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Economics and policies in formulating renewable power development plans

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Economics and policies in formulating renewable power development plans

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Editorial: Economics and policies in formulating renewable power development plans

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Editorial on the Research Topic
Economics and policies in formulating renewable power development plans

Introduction

Energy production is considered as the pillar of the national security and foundation of the economy (Li and Wang). Fossil fuel consumption leads to serious climate change and environmental pollution issues that results from carbon emissions and pollutants. Hence, renewable energy has been considered as an effective way to ameliorate these issues. Multiple international organizations such as the Intergovernmental Panel on Climate Change (IPCC) have invested a lot of effort to coordinate the benefits of countries. However, several countries, including developed and developing countries, have initiated certain policies to mitigate climate change and reduce carbon emissions. Consequently, increasing preferential policies are being formulated to accelerate the development of renewable power (Zhu and Jin). Energy security affected by the bottleneck of crude oil supply and the global issues ensuing from the fossil energy consumption are two compelling reasons for the rapid development of renewable energy (Liu et al.). In the past decades, the share of renewable energy in the energy mix has been steadily increasing, which indicates that the development and utilization of renewable energy has become the consensus policy of several nations.

In this perspective, this Research Topic intends to investigate the factors affecting the development of renewable power, and explore the optimal pathway for different economies, which may provide countermeasures and suggestions for academic research and policy drafts. This paper will introduce the contributions made by the accepted papers from three viewpoints, *viz.*, the development path of renewable power, the incentivizing factors, and the obstacles to the development of renewable power.

Discussions on the development path

Energy transformation is a difficult issue encountered by all countries. The critical concern is to explore the optimal development path for renewable power development. There are several studies focusing on the gradual goals of the transformation and upgrading of China's power industry, in which the conditions of technical judgment, specific profile, and moderate agenda have been incorporated Lu et al. The achievement of the energy-saving and emission reduction goals is a gradual pathway instead of a single stroke accomplishment. Xu et al. (2020) explored the optimal development path of China's solar photovoltaic power during the period 2018–2050, and found that the development goals set by governments can be achieved under different scenarios. Of course, all studies do not arrive at the same conclusion. Zhang X. et al. analyzed the optimal development path of Concentrated Solar Power (CSP), and found that the government cannot not achieve the target for the cumulative installed capacity by 2050.

Besides the domestic analysis, the international experience can also shed light on the development of the renewable power for a country. A comparative study of the international renewable power development paths can offer us certain suggestions, though the countries may vary in development paths owing to the differences in the resources and environment. Numerous studies have discussed the development path of the renewable energy from an international perspective. The examples include research on the relationship between renewable energy development and carbon emission efficiency in developed countries (Dong et al., 2022), and research on the long-term equilibrium nexus between renewable energy development and economic growth in European countries (Kasperowicz et al., 2020). Lan et al. measured the efficiency of China's green investment in the Belt and Road countries from 2011 to 2018 from both the static and dynamic perspectives, and provide an in-depth analysis regarding the differences, changes, and influential factors in the regional coordination of industries with the environment.

Analysis of the factors that incentivize renewable power development

Policy and regulation have always been an important factor in boosting the development of renewable power. To mitigate climate change and cope with the energy shortage, many countries around the world have formulated a series of policies to strengthen investment in research and development. The experience in related fields may tremendously benefit the development of renewable power (Dou et al.). Three papers in this Research Topic discuss their impacts on renewable power, including the combined game of subsidy and penalty policy, carbon quota policy, and subsidy policy for electric vehicles.

Subsidies and penalties are the two main regulation methods adopted by authorities to promote the development of renewable power. Many challenges, such as subsidy fraud and effectiveness exist while adjusting the polices. Dou et al. incorporated the subsidy and penalty policies into a sequential game theory model to explore the impact of the different regulatory mechanisms on the promotion of renewable energy. The findings demonstrate that higher fines or profits from the legal production are more likely to stimulate renewable power production than the subsidies. Zhu and Jin focused on the impact of the carbon quota on enterprises in implementing the efficiency power plant (EPP). Liu and Wang estimated the impact of the different subsidy policy intensities on the change in consumer demand for EVs, obtains the corresponding subsidy policy agent response and treatment effect, and proposes corresponding policy optimization countermeasures and suggestions. According to those results, the study proposes reasonable suggestions, including the supervising subsidies, the adoption of incentive regulations, and the design of a targeted regulatory mechanism.

The development of renewable power has been influenced by several other factors besides policy measures. Along with the analysis of the optimal development path of CSP, Zhang X. et al. discussed the impact of the factors such as Gross Domestic Product (GDP) growth, incentive policies, technological advances, grid absorptive capacity, and emission regulation schemes on the development of CSP generation. Mu et al. focused on the analysis of the relationship between China's photovoltaic development and grid parity. Li and Wang focused on the analysis of the impact of the public environmental concerns on green innovation in China's automobile industry.

Analysis of the obstacles to the development path

There are also several obstacles that hinder the development of renewable power, and the most important one is the unbalanced resource distribution and power consumption. The uneven distribution between the resources and electricity load has resulted in an increasing curtailment of the renewable energy source, which strengthens environmental pollution (Tan et al., 2020). Liu et al. explored the issue of unbalanced energy development in China and analyzed the impact of the regional energy development levels on the high-quality economic development in China, from 2016 to 2017. Liu et al. considered that it is necessary to evaluate the level of energy development in different regions and explore the policies and measures to adjust the energy structure. Accordingly, this is the only way to solve the issue of unbalanced regional energy development, and hence, to realize the coordinated development of renewable power and economy in different regions. The same result was confirmed by Zhang Y. et al. (2021b).

Power load shifting is considered as a critical approach to boost the development of renewable power as it can effectively counteract the intermittent characteristic of wind power and solar power. Zhang et al. systematically calculated the peak power load and the demand for gas-fired power generation capacity in China. They made theoretical contributions for applying the cooperative game model to overcome this difficulty.

Conclusion

The papers published in this Research Topic illustrate an in-depth understanding and fresh perspectives on the renewable power development path, influencing factors, and obstacles. This is intended for employing a set of quantitative models, such as the SBM-undesirable model (Lan et al.), learning curve model, technology diffusion model (Zhang X. et al.), structural equation model (Liu et al.), and sequential game theory model (Dou et al.). We believe that these studies can replenish the existing literature and contribute to the understanding and response of the policy makers on renewable power development. Furthermore, it provides a reference for us to study the development of renewable power from an international perspective (Zhang et al.). These papers develop the theories of renewable power in terms of the model, and offers several reasonable development suggestions with respect to practice.

Author contributions

B-CX, H-ZL, KA, and XT contributed to conception and design of the study. BL wrote the first draft of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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ORIGINAL RESEARCH
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Will Public Environmental Concerns Foster Green Innovation in China's Automotive Industry? An Empirical Study Based on Multi-Sourced Data Streams

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This study explores the impact of public concerns on green innovation in China's automotive industry and examines whether the effect varies based on firm size, ownership, and time phase. The study investigates 151 automobile enterprises and provides a novel, large-scale, and data-based perspective and estimation method for exploring critical factors of green innovation. By applying transition probabilities matrix (TPM) model, this paper finds that for different-sizes automotive enterprises there are significant differences in innovation sustainability, non-innovation sustainability, and liquidity between innovation and non-innovation, and such differences also exist for state-owned and non-state-owned enterprises. Then, based on the dynamic panel random probit (DPRP) model, the paper further analyzes the possible reasons for these differences, and particularly focuses on exploring the impact of public environmental concern on the environmental technology innovation. The empirical results show: 1) public concerns encourages green innovation emerging in all automotive firms, but only affects innovation persistence in medium and large companies. 2) public concerns encourages non-innovator state-owned companies to become innovators and motivates them to maintain continuous innovation. 3) the impact of public concerns changes over time. In the periods of 2002–2007 and 2012–2013, the role of public concerns is not significant. However, in the 2007–2012 period, public concerns significantly stimulate enterprises to move from non-innovators to innovators and promotes continuous innovation.

Keywords: green innovation, public concerns, innovation transition, innovation persistence, China's automotive industry, large-scale web search data

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INTRODUCTION

Global warming, which is caused by relentless increases in greenhouse gas, especially CO_2 emissions, has become a key challenge for the society worldwide (Liu et al., 2020a). Alongside with the rapid economic growth, China has overtaken the United States as the world's largest CO_2 emitter in around 2007 (Fu et al., 2021); According to the International Energy Agency (IEA), China's CO_2 emissions accounted for 29% of the world's total in 2019. Energy consumption in the transportation industry has become one of the significant contributor to the rapid increase in China's CO_2 emissions (Song et al., 2019). With hindsight, experiences in a large number of developing countries show that the growth rates of emissions in the transportation industry are faster than those of aggregate CO_2 emissions (Loo and Li, 2012; Li et al., 2019). At the same time, among the different modes of transportation, road transport is the biggest contributor to CO_2 emissions in many countries (Cai et al., 2011; Solaymani, 2019). In China, total carbon emissions from the freight industry increased 25.81 times from 3.7352 Mt in 1988 to 96.4158 Mt in 2016, and the road freight was the sector with the largest increase in carbon emissions, with a 119.38-fold increase (Lv et al., 2019).

Related statistics depict that the energy consumption of the transportation industry has been grown steadily and rapidly in China (Zhu et al., 2020). As a consequence, the environmental pollution caused by automobile industry is serious in China, and the emission of the automobile industry has been recognized as a key culprit for haze and photochemical smog pollution (Lu et al., 2021). Therefore, promoting green innovation in the automotive industry is imperatively important for controlling greenhouse gas emissions and improving the atmospheric environment (Gohoungodji et al., 2020).

Green innovation is also named as environmental innovation and sustainable innovation (Schiederig et al., 2012; Meng et al., 2020). However, it has yet formed a widely recognized definition of green innovation. Existing literature has proposed different definitions based on various perspectives and theoretical underpinnings. One strand of literature defines the green innovation with a specific emphasis on the object, content and objective of green innovation. For example, both Chen (2008) and Liao (2017) hold a similar view that green innovation involves hardware innovation or software innovation activities related to green products or processes, such as technology innovation in energy conservation, energy saving, pollution prevention, waste recycling, green product design or enterprise environmental management. Tarnawska (2013) argued that the goal of enterprises green innovation is to improve resource use efficiency, reduce production costs and enhance competitiveness of the enterprises. Another strand of literature defined green innovation based on the innovation effect. For example, Ghisetti et al. (2017) defined green innovation as the solution for new or important products (or services) and processes that reduce the consumption of natural resources and the release of harmful substances throughout the life cycle. Berrone et al. (2013) proposed that green innovation refers to the development of products, processes and services that can reduce environmental hazards by using new methods to deal with emissions, recycle or reuse waste, and find cleaner sources of energy. Combing the above two points of view, Schiederig et al. (2012) concluded that green innovation is driven by economic or ecological benefits, guided by meeting market demand or achieving market competitiveness, and results in reducing negative environmental impact.

Present literature on green innovation in the automobile industry mainly focuses on the following aspects. On the one hand, some literature have concerned on the poor innovation motivation of automobile enterprise. The poor innovation motivation can be attributed to various factors. First, environmental externality may deter enterprises from engaging green innovation activities. To be specific, investment and efforts to mitigate climate change and reduce air pollution exhibit a strong positive environmental externality, and the benefits received by climate change contributors (enterprises) are usually significantly lower than those received by the society (Gohoungodji et al., 2020; Qi et al., 2021), which discourages enterprises' concerns and commitments in green innovation. Second, inadequate green innovation capacity is another key impediment for green innovation. In some circumstances, some first movers of green innovation in the automotive industry does not generate apparent price advantages or performance features due to the inadequate capacity, which discourages green innovation incentives (Penna and Geels, 2015; Gupta and Barua, 2018). Third, a mismatch between innovation and traditional system is another barrier for simulating and fostering green innovation (Hao et al., 2019). In the process of green innovation, some new elements are usually incompatible with the rules, infrastructure, users' custom of the traditional or existing socioeconomic and technological systems, which may lead to a high sunk cost (Freeman, 1995; Gupta and Barua, 2018).

On the other hand, in views of the poor internal incentive, some scholars have studied how to use external factors to motivate green innovation in the automobile industry. Existing literature focuses on the effect of three aspects, including industrial policy, environmental policy and market demand on green innovation. For example, based on the number of new energy vehicles patents in China's automobile industry, Liu et al. (2020b) found that China's industrial policy has a significant impact on green innovation in the automobile industry. Cristina De Stefano et al. (2016) studied innovation in the automotive industry from the perspective of climate change policy and argued that it is necessary for automotive companies to continue to innovate in product stewardship in order to survive in a carbon-constrained market. Using data from 145 companies belonging to automotive parts manufacturing sector in Spanish, Leal-Rodríguez et al. (2018) links market orientation, green innovation and enterprise performance and finds that market positioning is a key factor for green innovation and maintaining a company's competitive advantage.

To summarize the above, most of the existing literature focuses on the poor innovation motivation of automobile enterprise and the effect of policy and market demand on stimulating green innovation. However, some scholars began to study the impact of public attention on green innovation in the automobile industry. Public concerns is an important concept in risk perception, communication and management literature, and a reason for policy attention (Fellenor et al., 2020). Penna and Geels (2015) argued that with the advent and prevalence of big data technologies such as social media, the external pressure from the public and the media has become an important driving force to promote green innovation in the automotive industry. Olson (2013) argued that China is the top automobile production and consumption market and the largest greenhouse gases emitter in the world. It is of great importance to evaluate the influence of public concerns on the green innovation of China's automobile industry. Empirical evidence of China is valuable to shed the light of the effects of public environmental concerns on green innovation in developing countries.

This study aims to explore the effect of public concerns on green innovation of automobile enterprises in China. Three specific research questions are investigated. 1) Does public concerns motivate automobile companies to transform from non-innovators (without green patents) to innovators (with green patents)? For most companies, the first patent is more difficult to obtain than subsequent ones (Cefis, 2003), making that transformation more challenging. 2) Does public concerns improve innovation commitment of automobile companies? Some studies have shown that companies with experience of innovation activities are of high possibility to engage innovation in future developments (Raymond et al., 2010), which can be attributed to state dependence (Ayllón and Radicic, 2019). This study also aims to examine whether public concerns will increase the probability that a company will pursue further innovation. 3) Does the effect of public concerns vary depending on enterprises' attributes such as enterprise size, ownership, and time phase? First, public concerns may take heterogenous effects on different enterprises. For example, small and medium enterprises usually have to face more impediments and challenges to innovation than large enterprises (Raymond et al., 2010). Second, ownership is an important determining factor of green innovation. The intention and capacity of green innovation of state-owned companies may generally differ from those of private or foreign-owned companies (Hu et al., 2020). Third, the effect of public concerns on green innovation may show temporal characteristics at different stages. For example, according to the dialectic issue life cycle (DILC) model (Geels and Penna, 2015; Sillak and Kanger, 2020), the public's response to environmental issues occurs and vary in several typical phrases. Thus, we study the impact of public concerns on green innovation at different stages.

The contributions of this study are as follows. First, the perspective of public environmental concern is introduced to the research domain of industrial green innovation, which enrich the research paradigms of green innovation. Green innovation studies primarily focus on the economy, policy, and technology aspects, whilst the effect of public concerns is largely omitted. The rapid development of social media platforms has enabled public environmental concern become a key driving force for promoting green innovation in different industries. Estimation results of this study shed light on the effect of public environmental concern on green innovation. Second, a novel quantitative-based evaluation framework based on multi-sourced data is proposed to explore the effect of public concerns on industrial green innovation. By using transition probabilities matrix (TPM) model, two important measurable indicators of innovation dynamics in Chinese automotive enterprises, including innovation transition and innovation persistence, are systematically investigated in this study. By using dynamic panel random probit (DPRP) model, this study quantitatively analyzes the impact of public attention on industrial green innovation, which complements the current case studies and deepens the understanding of external pressures to promote corporate green innovation.

The rest of this paper is organized as follows. Section *Theoretical Framework and Hypotheses* introduces theoretical framework and research hypotheses. Section *Research Methods* illustrates the research methods. Section *Indicators and Data* describes variables and data. Section *Empirical Results* presents the empirical results and robustness checks. Section *Discussion and Conclusion* concludes the study.

THEORETICAL FRAMEWORK AND HYPOTHESES

This section reviews relevant theories and research hypotheses are proposed.

Impact of Public Concerns on Green Innovation Emerging

The public's concerns on environmental issues essentially form an either formal or informal supervision on pollution emitter (enterprises), and such supervision involves a variety of stakeholders, including environmental protection enthusiasts, community residents, consumers, non-governmental organizations, etc. (Blackman and Bannister, 1998). By influencing the election and voting, the public's concerns on environmental issues can promote the legislation of environmental policy in some countries (Kahn, 2007).

In addition to the supervision effects, public environmental concerns can forester green innovation by affect consumer's behavior and lifestyle (Leonidou et al., 2017). The public environmental concerns of consumers can be transformed to buying preference for green product (Rugman and Verbeke, 1998). Therefore, enterprises with a good reputation of green innovation can improve the sales and competitiveness by meeting the demand of consumers (Revell et al., 2010). Environmental policy can promote enterprises' green innovation in the short term, whilst the changes of consumer's behavior and lifestyle toward environment-friendly ones are the sustainable force to encourage green innovation (Geels, 2010; Lin et al., 2019).

As to China's situation, this study assumes that environmental problems affect the regular life to people, thereby changing the cognitive roles of the public (e.g., raising public concerns on environmental issues) and promoting the emergence of green innovations. Thus, the following assumption hypothesis is proposed:

H1: Public concerns about environmental issues encourages green innovation emerging in Chinese automobile companies.

Impact of Public Concerns on the Persistence of Green Innovation

If the previous technological innovative activities of enterprises can significantly increase the probability of performing innovative practices in the future, then the continuity of technological innovative activities is considered persistent (Cefis, 2003; Clausen et al., 2012). Triguero and Córcoles (2013) further developed this concept in the context of conditional probability; that is, technological innovation sustainability refers to the probability of technological innovation in year t + 1 when there is technological innovation in year t. This theory does not emphasize the technological innovative activities in year t + 1 but the potential of enterprises to conduct technological innovative activities in year t + 1.

The theory of planned behavior (TPB) was proposed by Ajzen (1985), who incorporated perceived behavioral control into the theory of reasoned action. According to the TPB, the main determinant of behavioral intention is attitude (Ajzen, 1991). Attitude results from behavioral assessment while behavior and result are functions of behavioral attitude. The TPB has been successfully used to explain both general pro-environmental behavior (Chao, 2012) and specific behaviors such as organic food purchasing (Yazdanpanah and Forouzani, 2015), cleaner production technology adoption (Zhang et al., 2013), and environmental activism (Fielding et al., 2008). Thus, in the context of global warming and serious air pollution in China, the public will focus on measures to tackle pollution, including green innovation (Hu et al., 2020). Green products are environmentally friendly and can help to reduce pollution problems (Yu and Han, 2019), so the public will increase their demand for green products based on rational health considerations. In other words, public concerns about green innovative activities often indicates a potential demand for green products.

Two theories have been proposed for the relationship between market demand and technological innovation: the "demand-pull model" and the "technological innovation and demand interaction." Demand-pull model theory refers to the phenomenon that occurs when enterprises conduct technological innovative activities to earn high profits as they face actual or potential high market demand (Schmookler, 2013). Technological innovation and demand interaction theory holds that the potential market demand can stimulate enterprises' technological innovation activities. With forthcoming solutions to technical problems, product functions have rapidly increased; these new functions continue to stimulate and guide changes in market demand, and strong demand can entice enterprises to continue technological innovation for improved functionality (Mowery and Rosenberg, 1979). This suggests the following hypothesis:

H2: Public concerns on environmental issues positively affects the sustainability of green innovation.

Time Characteristic Factor

Penna and Geels (2012) established a DILC model by combining insights into life cycle theory. They argued that external pressure can be divided into five stages performed by different major players based on qualitative research of the repositioning of United States carmakers in response to global warming issues (1943–1985) and traffic accidents/safety issues (1900–1995) (Penna and Geels, 2012; Geels and Penna, 2015). In the first three stages, companies are reluctant to undergo substantive changes to solve their problems because they are "locked in" to four industry-specific systems: 1) industry beliefs and mentality, 2) identity and mission, 3) regulations and formal policies, and 4) competence and technical knowledge. Companies utilize social culture and political strategies to resist this pressure. When environmental problems affect the economic environment, the life cycle moves through the last two stages. In the fourth stage, the mounting public concerns pushes the issue toward the macro-political stage. Moreover, radical legislative policies will essentially change the economic framework. In the fifth stage, environmental issues affect the preferences of mass consumers, thereby resulting in strong market demand for new technologies.

On the basis of DILC theory, the following hypotheses are proposed:

H3a: The impact of public concerns on green innovation in China's automobile industry varies over time.
H3b: The impact of public concerns on the persistence of green innovation in China's automobile industry varies over time.

Influence of Enterprise Characteristic Factors

Consumers want to buy high-quality and safe products, but they also want to know if they are produced in a responsible way. These aspects are related to Corporate Social Responsibility (CSR). Corporate Social Responsibility is often defined as "the concept of a company on a voluntary basis that incorporates social and environmental issues into its business operations and interaction with stakeholders." Therefore, socially responsible practices include environmental responsibility measures related to natural resources management and eco-innovation implementation (Kesidou and Demirel, 2012).

However, corporate social responsibility may vary depending on different industries, companies, and departments (Cramer, 2005). The theory of corporate social responsibility shows that large companies should take a high degree of social responsibility (McWilliams and Siegel, 2000). In China, state-owned enterprises should take more social responsibility (Garde Sánchez et al., 2017). Zeng et al. (2011) believes that in China, the influence of environmental organizations and media attention on state-owned enterprises is much greater than that on non-state-owned enterprises. In fact, current national plans and policies related to sustainable development, such as energy conservation in China, are mainly concentrated on the regulation of state-owned enterprises (Kostka et al., 2013). Therefore, the following assumptions are made:

H4a: Public concerns has a greater impact on promoting green innovation in large enterprises than in small companies.
H4b: Public concerns has a greater impact on innovation persistence in large enterprises than in small companies.

H4c: Public concerns has a greater impact on promoting green innovation of state-owned enterprises than non-state-owned enterprises.

H4d: Public concerns has a greater impact on innovation persistence of state-owned enterprises than non-state-owned enterprises.

RESEARCH METHODS

Transition Probabilities Matrix Model

Several studies on the determinants of innovation have focused on the distribution of innovative and non-innovative enterprises in a given period. However, the distribution of a cross-section may refer to the coexistence of different transfer modes because enterprises may change from one innovative status to another over time. In general, this dynamic change is distinguished by an autoregressive process and TPM model. However, the time series of patent data is short, and biased estimates of the persistence of technological innovation are obtained using an autoregressive process. In addition, patent data are affected by several other factors, except for one-period lagged variables. Thus, the regression coefficient cannot fully reflect the extent of persistence. TPM can simultaneously consider cross-sectional and time series information and can thus effectively reflect the continuity of technological innovation. Thus, the TPM method is utilized in this study.

TPM is an important concept in the Markov chain. The basic assumption is that the probability distribution of the system status of the t + 1 phase is only related to the status of the t phase and independent of the status prior to that phase. This assumption is expressed as $F_{t+1} = p.F_t$. Transition probability refers to the possibility of transitioning from one status to another in the course of development. Assume that the development process of an event possesses m possible states, and p_{ij} is defined as the probability of transitioning from status i to status j. Then, considering the conditional probability in mathematical statistics, p_{ij} can be expressed as

$$p_{ij} = P\left(x_{t+n} = j | x_t = i\right) \quad (i, j = 1, 2, \ldots, m), \tag{1}$$

Where n represents the length of the interval.

Accordingly, TPM P is a matrix consisting of p_{ij} as elements and is expressed as follows:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix}. \tag{2}$$

All TPMs satisfy the following two conditions: **Eq. 1** the elements of the matrix are non-negative numbers and less than or equal to 1, and **Eq. 2** the sum of the elements of each row equal 1. That is,

$$\begin{cases} 0 \le p_{ij} \le 1, \quad (i, j = 1, 2, \ldots, m), \\ \sum_{j=1}^{m} p_{ij} = 1, \quad (i = 1, 2, \ldots, m). \end{cases} \tag{3}$$

Patent data are used to investigate industrial green innovation and establish two patent statuses based on relevant patents (i.e., without patents and with at least one patent). Therefore, TPM would be expressed as follows:

$$P - P\left(\mathrm{Innov}_{t+1} - j | \mathrm{Innov}_t - i\right), \quad (i, j - 1, 2, \ldots, m). \tag{4}$$

Specifically, this study focuses on the probability that a company changes from being a non-innovator to an innovator (p_{01}) and the probability of the sustainability of innovation (p_{11}). Geels and Penna (2015) method is used to divide time periods. Multi-angle indicators should be considered when dividing periods by using the DILC model. If different variables show strong changes in similar time points, then the visual examination of the plotted time series provides a quantitative-based stage division method.

Dynamic Panel Random Probit Model

The dynamic panel random probit model is used to analyze whether public concerns affects industrial green innovation. In this model, the probability of an event depends on its outcome at the previous time node and non-observed heterogeneity. Moreover, the model allows "status dependency" in the innovation process. Cross-multiplying terms of public concerns (Pubatn) and two innovative transfer statuses are combined. The specific model can be expressed as follows:

$$\begin{aligned} \Pr\left(\mathrm{Innov}_{it} = 1\right) = \alpha + \beta_1 \mathrm{Innov}_{i,t-1} + \beta_2 \big(&\mathrm{Pubatn}_{i,t-1} \\ &\times \mathrm{NOInnov}_{i,t-1}\big) + \beta_3 \left(\mathrm{Pubatn}_{i,t-1} \times \mathrm{Innov}_{i,t-1}\right) \\ &+ Z_{it}\psi + \mu_i + \varepsilon_{it}, \end{aligned} \tag{5}$$

where $\Pr(\mathrm{Innov}_{it} = 1)$ denotes the probability that the enterprise i is an innovator in period t. When the enterprise is not an innovator during period t − 1, $\mathrm{NOInnov}_{i,t-1}$ is one; otherwise, it is 0. When the enterprise is an innovator during period t − 1, $\mathrm{Innov}_{i,t-1}$ is one; otherwise, it is 0. α is the constant variable, β_2 and β_3 determine the probability of green innovation (from being a non-innovator in period t − 1 to being an innovator in period t) and its sustainability, respectively.

μ_i is unobservable enterprise heterogeneity. To solve the endogeneity of the dynamic random panel model, Wooldridge (2005) propose μ_i as a function of $\mathrm{Innov}_{i,0}$ and include $\mathrm{Innov}_{i,0}$ as the control variable. In this article, μ_i is substituted by $\mathrm{Innov}_{i,0}$ and the unobservable enterprise heterogeneity v_i which is uncorrelated with $\mathrm{Innov}_{i,0}$, where $\mathrm{Innov}_{i,0}$ identifies the presence or absence of innovative activities by the firm when the firm was observed. ε_{it} is a heterogeneous error term. Control variables Z_{it} include lagged R and D input intensity, government regulation, and company age. Furthermore, the square of age is added as a variable in Z_{it} because innovation output and age may have a non-linear relationship (Cefis and Marsili, 2015).

According to Cefis and Marsili (2015), a random effects model is selected for estimation as the dynamic panel random probit model assumes that individual effects are independent of explanatory variables.

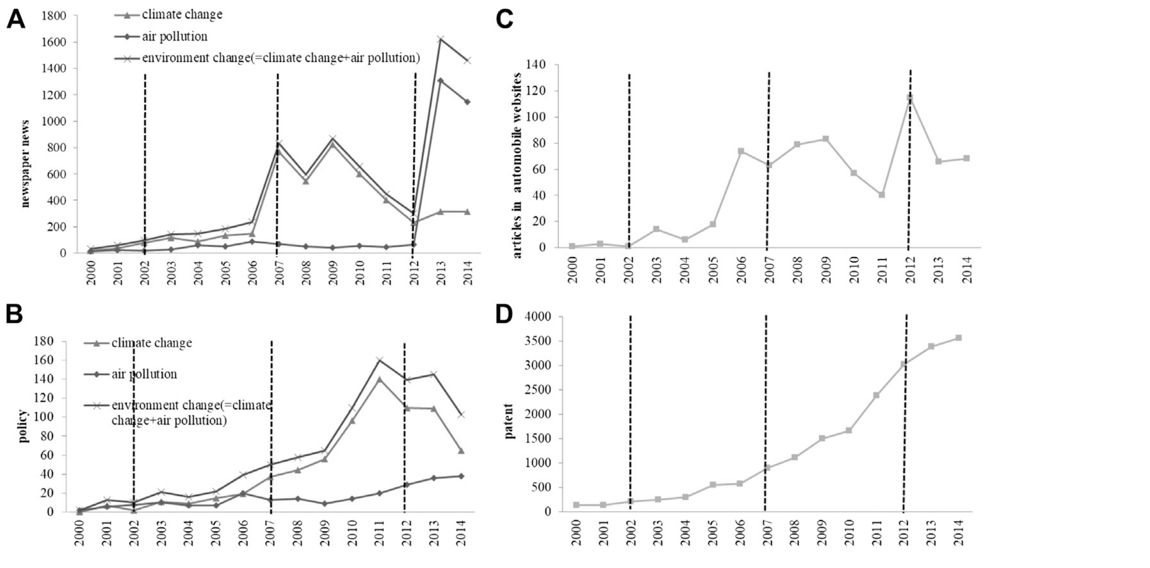

FIGURE 1 | Indexes for time division.

INDICATORS AND DATA

Dependent Variable

The dependent variable $\Pr(\text{Innov}_{it} = 1)$ is the probability that an enterprise is an innovator in period t .

The innovation output (patents for automobile emission reduction, using the IPC numbers in Dechezleprêtre et al. (2015)) is applied to reflect whether the company is an innovator in the field of energy conservation. At the same time, represent innovation as a stochastic process of the two statuses to reflect the dynamic changes in enterprises. In $\{\text{Innov}_t\}_{t=1,L\ T}$, Innov_t is a binary variable. If an enterprise is an innovator in period t, it takes the value of one; otherwise, it is 0.

In addition to the aforementioned patent data, data from automobile companies must be obtained to calculate each company's transition probabilities. For information on how to obtain data of automobile enterprises and how to match enterprises and patents, please refer to **Supplementary Material 3**.

Independent Variables

Public attention: Traditional public attention measurements can be divided into two approaches, namely, the most important problem (MIP) test and the media coverage index across the country. The MIP test provides respondents with a series of representative investigative questions for answers on what they consider the most important issue in the country at present. Subsequent information is collected, and the questions that are more important than others are summarized. McCombs and Zhu (1995) argued that the MIP test can force testers to respond to a limited number of questions that are prepared in advance. Henry and Gordon (2001) claimed that the MIP test has methodological deficiencies, while Wlezien (2005) argued that the MIP test has reliability and validity problems.

Considering the limitations of MIP, some scholars have proposed a dynamic media coverage index as the measurement method. The media coverage index refers to the number of instances of media coverage on a particular problem within a period. Public and media attention is generally believed to be strongly relevant, and the media coverage index is a lower cost, more flexible approach than the MIP test. However, some researchers have questioned the causal relationship between media coverage and public concern; that is, whether the media reports attract public attention or public concern leads to media coverage.

To address the shortcomings of the two methods, researchers have proposed a method of measuring public attention using search engines. Ripberger (2011) used Google for public attention because this search engine possesses the largest market share in the United States. Therefore, this study selects Baidu, which has the largest market share in China.

The Baidu index is a data-sharing platform based on the behavior data of a massive number of Internet users. Baidu uses search volume as the database for analyzing and calculating the weighted sum of each keyword in web search frequency. Search users can determine the search scale of a keyword and the spatial distribution of Internet users using the Baidu index (Zhao et al., 2015). In this study, the search volume in the Baidu index of the keywords "climate change," "global warming," "greenhouse effect," "air pollution," and "haze" is used as the proxy variable for public concern in each year.

Control Variables

Regulation: Government policy usually plays an important role in green innovation. However, the number of government policies alone is insufficient for evaluating this role. The emergence of new energy vehicles primarily deals with environmental problems; thus, environmental regulations reflect the role of the

TABLE 1 | Data description.

Stats	Patent (t)	Pubat	Age	Regu	rd
Max	170	1,620	58	1.47	18.39
Min	0	30	3	0.70	0
Mean	2.42	609.20	13.18	0.96	7.20
p50	0	446	11	0.97	8.57
sd	11.49	438.80	13.22	11.49	6.23
N	332	332	332	332	332

TABLE 2 | Composition of innovators and non-innovators by year.

	2000–2002		2002–2007		2007–2012		2012–2013	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Innovators	35	34	367	63	854	70	1,237	83
Non-innovators	67	66	216	37	363	30	257	17
Total	102	100	583	100	1,217	100	1,494	100

government. At present, most scholars measure environmental regulations from a governance point of view (Brunnermeier and Cohen, 2003; Wu et al., 2011) but with less concern for the effectiveness of the regulations. Ben Kheder and Zugravu-Soilita (2008) used Energy/GDP to measure the extent of environmental regulation. They claimed that the advantage of using this indicator is the capability of measuring the actual impact of the government's rules and terms on the environment. Given the superiority of the index, this study uses Energy/GDP to measure the degree of environmental regulation; that is, smaller Energy/GDP indicates stricter environmental regulations. GDP refers to the national gross domestic product (unit: billion yuan), and energy is the national energy consumption over the years (unit: million tons of standard coal).

R&D: R&D investment is an important factor in patent output. In the 11 years of the data set, nearly 80% of enterprises have no R&D investment. This phenomenon may be caused by two things. First, a large number of small-scale enterprises lack R&D departments, R&D funds, innovation capability, or demand for technological innovation. Second, some companies do not report the cost of R&D. In this case, it is unable to take the log of R&D input. Thus, use R&D expenditure divided by sales to represent R&D density.

Age: Company age is calculated by $(\text{year}_{now} - \text{year}_{start})$. Existing studies have shown that the impact of enterprise age on innovation is highly nonlinear. In young or newly established companies, the innovation rate is high; however, this rate decreases as the company ages (Huergo and Jaumandreu, 2004).

Moreover, enterprise size is classified in China Industry Business Performance Database (CIBPD); specifically, one represents large enterprises, two denotes medium enterprises, and three represents small enterprises.

In addition, state-owned and non-state-owned enterprises are distinguished by verifying H5 (a/b). State-owned enterprises are set to 1, whereas non-state-owned enterprises are set to 0.

Time Division

Multi-angle indicators should be considered when dividing periods using the DILC model. The indicators used in this study include media attention, government concern, vendor response, and patent activity. The sources of these indicators are described as follows.

(1) Media attention: This indicator is represented by the number of newspaper articles related to environmental change. Search titles in the newspaper database of China National Knowledge Infrastructure (http://www.cnki.net/) for news containing the following keywords: "climate change," "global warming," "greenhouse effect," "air pollution," and "haze."
(2) Government concern: Use the "advanced search" command in the Peking University Law database (http://www.pkulaw.cn/) to locate full texts of the central laws and regulations that contain at least one of the five keywords mentioned above.
(3) Vendor response: According to automotive media studies in China, vertical websites, where automobile manufacturers publish their announcements, have the greatest impact on new car purchase decisions. This study selects the following four representative vertical sites: Car Home (http://www.autohome.com.cn/), Pacific Car Network (http://www.pcauto.com.cn/), Sina Car (https://auto.sina.com.cn/), and Transaction Car Network (http://www.yiche.com/). The number of articles with topics including at least one of the above-mentioned keywords on different websites each year measures the vendor response.
(4) Patent activity: The data sources and collection procedures of enterprises patent activities, which are introduced specifically in the section of **Supplementary Material 3**.

A visual examination of the plotted time series provides a quantitatively-based stage division method. Based on a comprehensive investigation (see **Supplementary Material 1**), this study divided the green innovation period of the automobile industry in China into the following four stages: 2000–2002, 2002–2007, 2007–2012, and 2012–2013. The division follow the way proposed by Penna and Geels (2015), who used a DILC model to research the development of the United States automotive industry. As shown in **Supplementary Material 1**, four variables demonstrate the similar time trend. These stages serve as the foundation for studying the effect of public concerns on green innovation in different periods.

Data

Information on green information is obtained from Chinese patent database (CPD).

According to seven innovation directions provided by Dechezleprêtre et al. (2015), automotive emission reduction technology and every relevant International Patent Classification (IPC) patent number can be found (See **Supplementary Material 2**). Then, by searching the IPC from 1985 to 2014 in the CPD this study obtained 27,932 patent data from 3,303 agencies. The total number of patents eligible for

TABLE 3 | Transition probabilities between innovative statuses by size and ownership.

	Small firms		Medium firms		Large firms		State-owned firms		Non-state-owned firms	
	t + 1 period		t + 1 period		t + 1 period		t + 1 period		t + 1 period	
t period	Non-innovator	Innovator	Non-innovator	Innovator	Non-innovator	Innovator	Non-innovator	Innovator	Non-innovator	Innovator
Non-innovators	73.63	26.37	68.75	31.25	53.49	46.51	67.03	32.97	75	25
Innovators	68.18	31.82	48.39	51.61	32.2	67.8	55.96	44.04	12	88

TABLE 4 | Impact of different sizes and ownerships of enterprises on green innovation.

	All firms	Small firms	Medium firms	Large firms	State-owned firms	Non-state-owned firms
Innovative status (t–1)	5.18***	0.76	6.55*	5.61*	8.92*	−6.49
	(1.80)	(0.73)	(3.36)	(3.32)	(4.70)	(4.98)
Innovative status (t0)	0.50***	−0.06	0.58***	0.47***	0.62***	0.83
	(0.05)	(0.05)	(0.10)	(0.08)	(0.10)	(1.06)
Public concerns (t–1)* innovator (t–1)	0.76***	0.18	0.96*	0.95*	1.32*	1.08
	(0.28)	(0.13)	(0.52)	(0.56)	(0.74)	(0.78)
Public concerns (t–1)* non-innovator (t–1)	0.38***	0.46**	0.22**	0.10*	1.78**	−0.34
	(0.12)	(0.22)	(0.10)	(0.06)	(0.80)	(0.20)
Regulation	−3.31	−1.75*	−11.98	10.46	1.01***	1.13
	(3.82)	(1.06)	(10.80)	(9.75)	(4.51)	(1.04)
R&D intensity (t–1)	0.30**	−0.04	0.47	0.41*	0.46	−0.04
	(0.14)	(0.05)	(0.39)	(0.22)	(0.34)	(0.15)
Enterprise age	0.11	0.12**	−0.18	0.28	0.97*	1.66
	(0.21)	(0.06)	(0.66)	(0.40)	(0.54)	(4.85)
Square of age	−0.00	−0.00*	0.00	−0.01	−0.02*	−0.05
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.18)
Constant	0.54	−0.26	−0.80	−3.55	−18.13***	−11.01
	(2.40)	(0.68)	(7.16)	(4.26)	(6.08)	(29.79)
N	188	78	58	52	177	11
Wald Chi2	124.18***	19.86***	43.53***	52.23***	119.27***	31.44***
Rho	0.74	0.42	0.51	0.49	0.69	0.05
Pseudo R-Squared	0.33	0.28	0.32	0.35	0.31	0.34

Standard errors in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

green innovation represents the enterprise's annual innovation statues.

Automobile enterprise characteristic data are obtained from the China Industry Business Performance Database (CIBPD). CIBPD is established by the National Bureau of Statistics, and the data are mainly from sample enterprises' quarterly and annual reports to the local statistical bureau. Specific methods for screening automotive enterprises as well as the steps for matching data in different databases are described in the **Supplementary Material 3**. After data collection and matching, 151 automobile enterprises are identified that applied at least once for energy-saving automotive technology between 2003 and 2013.

EMPIRICAL RESULTS

Descriptive Analysis

Table 1 presents the descriptive statistics of each variable of 151 automobile enterprises in this study. The maximum number of patents related to car emission reduction is 170, and the minimum is 0, with a mean value of only 2.416, which implies that the green innovation capacity of most companies is very low. The average public concerns is 609.2, which indicates that the average of each enterprise concerned is approximately 609 times and the variance is 438.8. This finding shows considerably different degrees of public concerns.

Table 2 shows that the proportion of companies with innovative behavior increases, which is a positive situation. When enterprises innovate continuously, they become powerful and strong in the market. Accordingly, green innovation in the macro-environment can be accelerated.

Transition Probabilities

Tables 3 shows the transition probabilities of companies of different sizes and different ownership properties.

In terms of persistence (e.g., innovative and non-innovative statuses), the rate of sustained innovative status is highest in large enterprises (67.8%), followed by that in medium enterprises (51.61%), with small enterprises the least (31.82%). Accordingly, sustainability of non-innovative status declines as enterprise scale increases from small to large. Small enterprises present high probability of sustaining their non-innovative status at 73.63%, whereas medium and large companies are at 68.75% and 53.49%, respectively. Considering different ownerships, the rate of sustained innovative status in non-state-owned enterprises (88%) is two times as high as that in state-owned enterprises (44.04%). However, the rate of sustained non-innovative status in non-state-owned enterprises (75%) is also 8% higher than that in state-owned enterprises (67.03%). Accordingly, non-state enterprises exhibit a stronger tendency to sustain their status and continue innovations.

Concerning the liquidity between innovative and non-innovative statuses, the probabilities of innovation for small, medium, and large enterprises are 26.37%, 31.25%, and 46.51%, respectively, based on enterprise scale. Small enterprises exhibit high probability of withdrawing from innovation. Transition probabilities are 68.18%, 48.39%, and 32.2% for small, medium, and large enterprises, respectively. With regard to different ownerships, state-owned enterprises (32.97%) have higher probability of entering innovative status than non-state-owned enterprises (25%). Meanwhile, state-owned enterprises (55.96%) exhibit higher probability of retreating from innovation than non-state-owned enterprises (12%).

When comparing innovation entrance and withdrawal, large companies have higher probability of changing from non-innovative status to innovative status (46.51%), whereas they exhibit low probability of changing from innovative status to non-innovative status (32.2%). Small and medium companies demonstrate the opposite performance, which indicates that small enterprises encounter difficulties when attempting or sustaining green innovations because of limited resources (Geroski et al., 1997). Considering different ownerships, state-owned enterprises have higher probability of entering and withdrawing from innovation than non-state-owned enterprises. This finding shows that state-owned enterprises possess advantages in policy support and financing channels, and they can easily accomplish green innovation (Choi et al., 2011).

TABLE 5 | Stage analysis of influencing factors of green innovation of enterprises.

	2002–2007	2007–2012	2012–2013
Innovative status (t−1)	4.02*	−4.91***	9.76*
	(5.75)	(1.13)	(10.73)
Innovative status (t0)	0.16***	1.50***	0.47***
	(0.03)	(0.08)	(0.06)
Public concerns (t−1)* innovator (t−1)	0.84	3.74***	1.68
	(1.22)	(0.17)	(1.78)
Public concerns (t−1)* non-innovator (t−1)	0.22	0.72***	0.10
	(0.55)	(0.22)	(0.46)
Regulation	15.70	−3.47	−19.01
	(30.29)	(8.19)	(76.74)
R&D intensity (t−1)	0.39**	−0.07	0.35**
	(0.16)	(0.12)	(0.16)
Enterprise age	−0.66	0.02	0.10
	(0.51)	(0.31)	(0.24)
Square of age	0.02	−0.00	−0.00
	(0.02)	(0.01)	(0.00)
Constant	1.56	5.05*	−2.34
	(3.97)	(2.93)	(2.73)
N	32	82	74
Wald Chi2	35.66***	983.36***	76.55***
Rho	0.42	0.75	0.52
Pseudo R-Squared	0.26	0.40	0.35

Standard errors in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Regression Results

Innovations of Different Sizes

This paper uses dynamic panel random probit models, including the innovative status in the previous year, the initial innovative status of companies, and a set of control variables, to measure the impact of public concerns on the green innovation of enterprises. The regression results of different size enterprises, different ownership forms, and different periods are shown in **Table 4**.

In the models including all companies, the coefficient of innovative status in the previous year ($Innov_{i,t-1}$) is significantly positive. This result indicates that innovative behavior is influenced by the status in the previous period and presents serial correlation. The coefficient of $Pubatn_{i,t-1} \times Innov_{i,t-1}$ is significantly positive. Therefore, if the enterprise acts as an innovator in period t−1, then receiving public concerns will influence its innovative status in period t; that is, public concerns encourage the company to innovate continuously. The coefficient of $Pubatn_{i,t-1} \times NOInnov_{i,t-1}$ is significantly positive, which indicates that receiving public concerns in period t−1 also promotes the transformation of companies from non-innovative status to innovative status. Therefore, public concerns promotes green innovation of companies, and overall, public concerns promotes green and continuous innovation.

When enterprises are classified by size, strong heterogeneity of innovative status exists. The coefficient of $Innov_{i,t-1}$ is significantly positive at the 10% level only for medium and large companies, which shows that innovative status could be sustainable for both. When interaction with public concerns is considered, the coefficient of $Pubatn_{i,t-1} \times Innov_{i,t-1}$ is significantly positive only for medium and large companies and not for small companies. This finding suggests that small companies will not increase the probability of continuous innovation because of public concerns. However, in relation to the probability of green innovation, the coefficient of $Pubatn_{i,t-1} \times NOInnov_{i,t-1}$ is significantly positive for all enterprise sizes. This result shows that public concerns encourages automobile companies to cross the innovation threshold and transforms them from non-innovators to innovators.

Innovation of Different Ownerships

This paper primarily analyzes state-owned companies because the sample size of non-state-owned companies is extremely small, and the Rho value of the model is considerably low. The results are presented in **Table 4**.

For state-owned enterprises, the coefficient of $Innov_{i,t-1}$ is statistically significantly positive at 10% level, indicating that the innovative status of companies in the previous year could further innovative behavior in the current period. As previously mentioned, state-owned companies have greater probability of promoting innovation than non-state-owned companies. Once innovation starts in state-owned companies, their innovative

TABLE 6 | Summary of the research hypotheses and testing results.

Hypothesis	Result
H1: Public concerns about environmental issues encourages green innovation in Chinese automobile companies.	Accepted
H2: Public concerns about environmental issues positively affects the sustainability of green innovation.	Partially Rejected The hypothesis is supported by medium and large companies
H3a: The impact of public concerns on green innovation in China's automobile industry varies over time.	Accepted The effect only exists in 2007–2012
H3b: The impact of public concerns on the persistence of green innovation in China's automobile industry varies over time.	Accepted The effect only exists in 2007–2012
H4a: Public concerns has a greater impact on promoting green innovation in large enterprises than in small companies.	Rejected Public concerns has a greater impact on promoting green innovation in small companies than in large enterprises.
H4b: Public concerns has a greater impact on innovation persistence in large enterprises than in small companies.	Accepted
H4c: has a greater impact on promoting green innovation of state-owned enterprises than non-state-owned enterprises.	Accepted for state-owned enterprises. The results for non-state-owned enterprises can not be tested because of the small sample size.
H4d: Public concerns has a greater impact on innovation persistence of state-owned enterprises than non-state-owned enterprises.	Accepted for state-owned enterprises. The results for non-state-owned enterprises can not be tested because of the small sample size.

TABLE 7 | The effect of enterprise size on green innovation based on Baidu index with keywords replaced.

	All firms	Small firms	Middle firms	Large firms
Innovative status (t−1)	9.52***	4.33	8.83	6.27
	(3.60)	(3.47)	(8.54)	(6.00)
Public concerns (t−1)* innovator (t−1)	0.66**	0.57*	0.38	1.41
	(0.26)	(0.34)	(4.43)	(1.86)
Public concerns (t−1)* non-innovator (t−1)	0.12	0.06	1.76*	−0.64
	(0.13)	(0.14)	(1.05)	(0.47)
Constant	1.11	−2.21	5.88	−7.24
	(4.19)	(3.88)	(11.57)	(7.62)
N	188	78	58	52
Wald Chi2	55.41***	20.32***	39.43***	32.17***
Rho	0.33	0.11	0.63	0.32
Pseudo R-Squared	0.37	0.23	0.31	0.28

Standard errors in parentheses.
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

status becomes sustainable. The coefficient of $\mathrm{Pubatn}_{i,t-1} \times \mathrm{Innov}_{i,t-1}$ is also positive at the 10% significance level. Therefore, when companies are innovators in the previous year, receiving public concerns in that year may exert a positive effect on current innovative status. Public concerns, which is an external supervision mechanism, can monitor the company for continuous innovation. The coefficient of $\mathrm{Pubatn}_{i,t-1} \times \mathrm{NOInnov}_{i,t-1}$ is positive and significant at the 5% level. Thus, when companies in period t−1 are not innovators, receiving public concerns in period t−1 can encourage companies to change from non-innovators to innovators in period t. This allows companies to create a breakthrough and accelerate the pace of green innovation. In general, public concerns promotes sustainable innovation and initial green innovation of state-owned companies.

Phase Analysis

The results of the phase analysis are shown in **Table 5**. Due to the small sample size in the period 2000–2002, we omitted this period in the specific analysis. In the period of 2007–2012, the coefficient of $\mathrm{Innov}_{i,t-1}$ is negative, showing that the innovative status of companies in period t−1 restrains innovative behavior in period t, which may be related to a financial crisis. Companies need to invest a large amount of money to innovate, and innovation is characterized by large investment, slow effects, high risk, and long duration. The total amount of corporate capital is reduced as a result of a financial crisis, and the innovation investment in period t−1 crowds out the innovation investment in period t, exerting a negative effect. The coefficient of $\mathrm{Pubatn}_{i,t-1} \times \mathrm{Innov}_{i,t-1}$ is significantly positive. Thus, when the company is an innovator in the previous year, receiving public concerns will positively affect the probability of innovation in the current period. Although the capital of companies is limited, the decision to decrease innovation investment will be made cautiously when much public concerns is received. Public concerns, which is an external supervision mechanism, can monitor the company for continuous innovation. The coefficient of $\mathrm{Pubatn}_{i,t-1} \times \mathrm{NOInnov}_{i,t-1}$ is significantly positive, which shows that receiving public concerns in the previous year transforms companies from non-innovators to

TABLE 8 | The effect of ownerships and stages on green innovation based on Baidu index with keywords replaced.

	State-own firms	Non-state-own firms	2002–2007	2007–2012	2012–2013
Innovative status (t–1)	23.88**	13.20	4.79	–6.50**	5.22*
	(11.13)	(31.01)	(46.88)	(3.13)	(2.74)
Public concerns (t–1)* innovator (t–1)	1.68**	3.84	–0.53	3.99***	9.47
	(0.80)	(3.10)	(3.96)	(0.49)	(36.53)
Public concerns (t–1)* non-innovator (t–1)	0.73**	0.18	0.36	0.48**	-0.47
	(0.34)	(0.30)	(0.73)	(0.23)	(0.42)
Constant	–13.81	–16.66	–30.21	–14.20	–61.40
	(10.50)	(13.48)	(107.24)	(22.33)	(136.92)
N	177	11	32	82	74
Wald Chi2	33.24***	29.01***	24.18***	27.81***	27.99***
Rho	0.42	0.19	0.28	0.39	0.27
Pseudo R-Squared	0.34	0.19	0.26	0.28	0.30

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

TABLE 9 | the effect of public concerns on green innovation based on Public Environmental Awareness data and World Values Survey data.

	Public environmental awareness	World values survey
	All firms	All firms
Innovative status (t–1)	31.30**	21.14*
	(14.91)	(11.75)
Public concerns (t–1)* innovator (t–1)	2.41**	12.36*
	(1.22)	(6.62)
Public concerns (t–1)* non-innovator (t–1)	1.60	8.19*
	(1.12)	(4.50)
Constant	45.01**	1.18
	(21.22)	(4.82)
N	57	152
Wald Chi2	63.21***	107.00***
Rho	0.25	0.35
Pseudo R-Squared	0.32	0.38

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

innovators. In general, public concerns promotes sustainable innovation and the initial green innovation of companies. For the two periods of 2002–2007 and 2012–2013, the coefficients of $\text{Pubatn}_{i,t-1} \times \text{Innov}_{i,t-1}$ and $\text{Pubatn}_{i,t-1} \times \text{NOInnov}_{i,t-1}$ are insignificant.

The above empirical analysis tests the hypothesis respectively, and the test results are summarized in **Table 6**.

Robustness Analysis

As previously mentioned, the Baidu index of related keywords can be used to represent public concerns. However, the resulting robustness is sensitive to the appropriate selection of keywords. The impact of variations in keywords and different methods of measuring public concerns should be analyzed to ensure the robustness of the tests. Thus, the following procedure is conducted.

Changing Public Concerns' Proxy Variable

(1) Using the Baidu index, keywords are replaced by "sewage," "green," "energy saving," "energy consumption," "emission reduction," "sustainable," "new energy," and "green." The new empirical results (See **Tables 7**, **8**) are similar to those reported.

(2) The "public environmental awareness" score of China's public environmental protection livelihood index (state environmental protection administration and China Environmental Culture Promotion Association) is used as an indicator of public concerns. The index surveys public perceptions of food safety, drinking water pollution, air pollution, waste disposal, greening, noise pollution, pollution of rivers and lakes, sustainable development, land pollution, global warming, land

TABLE 10 | Statistic description for Listed automobile enterprises.

Stats	Max	Min	Mean	p50	sd	Obs
patent (t)	13	0	0.35	0	1.39	601
Pubat	2857	80	703.12	353	867.4	601
Age	29	3	12.38	12	4.56	601
rd	22.47	0	6.95	0	8.9	601
Regu	1.47	0.70	0.96	0.97	11.49	601

TABLE 11 | The effect of public concerns on green innovation of different size of listed automobile enterprises.

	All firms	Small firms	Middle firms	Large firms
Innovative status (t–1)	2.62***	1.93*	2.67*	2.08**
	(0.97)	(1.06)	(1.53)	(1.13)
Public concerns (t–1)* innovator (t–1)	0.26**	9.07	0.29***	0.27**
	(0.13)	(32.55)	(0.11)	(0.12)
Public concerns (t–1)* non-innovator (t–1)	0.50***	0.78*	0.31*	0.24
	(0.21)	(0.45)	(0.17)	(0.34)
Constant	−11.17***	−21.98	−74.26	−7.81*
	(3.44)	(20.13)	(58.78)	(4.16)
N	520	114	207	199
Wald Chi2	44.97***	29.63***	28.51***	32.51***
Rho	0.64	0.46	0.52	0.57
Pseudo R-Squared	0.27	0.18	0.23	0.25

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

TABLE 12 | The effect of public concerns on green innovation of listed automobile enterprises with different ownership and for different time periods.

	State-own firms	Non-state-own firms	2002–2007	2007–2012	2012–2013
Innovative status (t–1)	0.41**	0.09*	2.02**	7.52*	7.21***
	(0.21)	(0.05)	(0.98)	(4.30)	(4.37)
Public concerns (t–1)* innovator (t–1)	0.56*	1.94	0.13	2.31**	0.91
	(0.32)	(1.84)	(0.12)	(0.92)	(1.45)
Public concerns (t–1)* non-innovator (t–1)	1.08*	-0.02	0.35	1.72**	0.54
	(0.63)	(0.07)	(0.15)	(0.84)	(0.38)
Constant	−2.85	0.13	2.85	7.83	−3.50
	(9.82)	(0.58)	(2.52)	(16.64)	(2.43)
N	306	214	122	252	146
Wald Chi2	32.27***	33.54***	40.53***	58.12***	41.25***
Rho	0.60	0.57	0.42	0.54	0.33
Pseudo R-Squared	0.22	0.26	0.34	0.41	0.28

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

desertification, thinning of the ozone layer, species reduction, and 14 other issues using field surveys and telephone surveys. However, the index only includes data obtained from 2005 to 2007. Thus, conduct the analysis with the three-year data for the corresponding years of green innovation of enterprises. Although the model involves lagged variables with a small sample size, the positive impact of public concerns on green innovation and the role of enterprise scale can still be proven (See **Table 9**). However, the impact of corporate ownership and time heterogeneity cannot be proven because of the lack of data.

(3) According to the World Values Survey (http://www.worldvaluessurvey.org), the use of the 2000–2004, 2005–2009, and 2010–2013 rounds of surveys is related to the issue of environmental awareness in the study; two are selected as representative issues: "Aims of country: Enterprises choice" and "Protecting environment vs. economic growth." In terms of the small number of environmental awareness issues, this study assigns weights of 50% to each of the two problems, thereby calculating the Chinese public awareness of environmental protection level on the basis of each round of survey per year for the index of environmental awareness. The results are similar to those obtained using the Baidu index; however, the coefficients become large. This result is related to the high scores in the Baidu index (100–several thousand) compared to the much smaller World Values Survey data (typically ranging from 1 to 10) (See **Table 9**).

Using Data of Listed Companies

The research data is mainly sourced for Chinese industrial enterprises databased and most of the enterprises in the database are non-listed companies. Therefore, the use of such data may lead to biased estimation results. In order to test the robustness of the research findings, this study used the data of listed companies for robustness check. The data of listed companies, including patent data and enterprise characteristic data, are sourced from CSMAR database. In this paper, all the 81 automobile manufacturing enterprises data are sourced from the database covering the period between 2003–2013. The statistic description of these companies is shown in **Table 10**. Then, based on the dynamic panel random probit model, the data of listed companies are empirically analyzed. The specific empirical results are shown in **Tables 11**, **12**. It can be found that for listed companies, the public concerns takes heterogenous effects on innovation depending on the size of enterprise. Public concerns only has a statistically significant effect on the innovation sustainability of large and medium-sized companies, and this effect will not affect small companies. Public concerns has different effects on enterprises with different ownership. Public concerns only has a significant positive effect on the innovation sustainability and the transformation of innovation state of state-owned enterprises. In addition, in different time stages, the role of public concerns is different. Only in the period of 2007–2012, public concerns will significantly promote enterprises to carry out green innovation.

DISCUSSION AND CONCLUSION

Conclusion

This study analyzes the impact of public concerns on green innovation of Chinese automobile companies and examines whether the effect varies depending on enterprise size, ownership, and time phase.

Firstly, obtain data for 151 automobile enterprises by matching the data of the CIBPD and the CPD. TPM is then used to analyze the sustainability of company innovation. Subsequently, use a dynamic panel random probit model to analyze the impact of public concerns on the green innovation of enterprises. Afterward, use a DILC model to illustrate that the impact of public concerns on green innovation in the automobile industry varies with time.

Based on TPM, which describes the dynamic change in innovation status, the results show that for persistence (e.g., innovative and non-innovative status), innovation sustainability increases as company size increases from small to large. In contrast, the sustainability of non-innovative status decreases as company size increases from small to large. For different ownership forms, non-state-owned companies exhibit higher probability of maintaining their present innovative status than state-owned companies. Specifically, if the enterprise is an innovator (non-innovator) in the previous period, its likelihood of remaining an innovator (non-innovator) in the subsequent period is high with few dynamic changes.

Concerning the liquidity between innovative and non-innovative statuses based on company scale, the probability of becoming innovative increases with increases in company size from small to large. On the contrary, the probability of withdrawing from innovation decreases with an increase in company size from small to large. In terms of ownership, state-owned companies have higher probability of entering or withdrawing from innovative status than non-state-owned companies.

The dynamic panel random probit model is used to analyze the impact of public concerns on green innovation of Chinese automobile companies and examines whether the effect varies depending on enterprise size, ownership, and time phase. The results show the following:

In terms of company scale, the innovative status of medium and large companies is sustainable. Public concerns only affects the continuous innovation of medium and large companies, whereas small companies exhibit low probability of sustained innovation as a result of public concerns. However, public concerns encourages companies of all sizes to experience innovation threshold breakthroughs and green innovation.

For different ownerships, once innovation of state-owned companies begins, their innovative status becomes sustainable. Public concerns can monitor state-owned companies for continuous innovation and enable them to experience breakthroughs and accelerate the pace of green innovation.

Considering different periods, the innovative status of companies is not sustainable in the 2007–2012 period. This situation may be related to the financial crisis. Moreover, the total amount of corporate capital decreases. Thus, the company can no longer innovate in the current period because of the previous period of innovation. Public concerns relaxes the company as it cuts innovation funding and monitors and encourages the company to sustain green innovation. In the periods of 2002–2007 and 2012–2013, the innovative status of companies is continuous, and enterprises' R&D plays a significant role; however, the role of public concerns is minimal.

Public Policy Implications

About the green transformation of automobile industry in China, the result of this paper reveals that it has not been conducted for most enterprises, no matter divided by scale (26.37% of small businesses, 31. 25% of medium-sized and 46. 51% of large-scale enterprises), or by ownership (25% of non-state-owned enterprises and 32.97% of state-owned enterprises). For this situation, first, government shall realize the severe situation, and there is a long way to go for the greenization of the automobile industry in China. The enterprises' green innovation can be encouraged or promoted through measures such as government procurement, subsidies and stronger regulation etc. Second, government should realize the differences in enterprises' size and ownership during making policies, and more supporting policies shall be given to small enterprises and non-nationalized enterprises which with low green transformation probability. Third, public concerns is a very important driving force for enterprises' green innovation. Therefore, the government can strengthen the public's environmental awareness through various methods, and promote the enterprise's green transformation through external pressure.

About the innovation persistence, 68.18% of small enterprises will quit innovation even if they had green innovation in last time phase. It shows that it is not easy to maintain an innovative state for them. Innovation requires a high demand for R&D capability and fund support, but both of them are great disadvantages for small enterprises. Therefore, the government can play the positive role in personnel training, employment policy making, technology platform construction etc., and try to solve the problem of difficult financing for small enterprises.

Managerial Implications

The findings can be used by enterprises to consider how public concerns may impact their business decisions about enterprise activities, such as public concerns will facilitate the green transformation of enterprises. Furthermore, it will reinforce persistent innovation for large and medium enterprises, which demonstrates that the public has potential power to affect enterprise behavior.

Currently, environment issues are the core factors for the competitiveness in product markets (McDonagh and Prothero, 2014). This research is capable of assisting managers to exploit the implements, so as to acquire the competitive advantage of the market. For instance, the enterprise can take actions as the followings:

(1) The empirical results show that public attention is the key driving force to promote green innovation in enterprises. Meanwhile, according to the TPB theory referred in this paper, public concerns about green innovative activities often indicates a potential demand for green products. Therefore, before making a decision, the enterprise can have a good command of the development tendency of public opinions by virtue of online forum, Weibo as well as other social media, from which it can obtain the public opinions, reaching an agreement with the public before making a decision. What the enterprise observes for the perception of the public provides an opportunity of taking the public aspiration and the public concerns into consideration in the early stage of innovation and development, so as to bring the most potential benefits to the users in the future, acquiring the competitive advantage.

(2) However, according to the conclusion of this study, the impact of public concerns on automobile enterprises of different sizes and ownerships varies. The innovation of large and middle-sized enterprises and state-owned enterprises is more sustainable, which may be due to their stronger ability to bear innovation failures. If these enterprises want to be more competitive in the future market, they should analyze the public concerns to predict the possible green development trend of the industry and invest in innovation of this regard. For small enterprises and non-state-owned enterprises, green innovation is less sustainable, which may be related to financial constraints. Therefore, the main objective of such enterprises is to imitate existing green products, which can help them survive in the market by coping with increasingly strict environmental policies at a lower cost of innovation.

Limitations and Future Research

Although this paper comprehensively analyzes the impact of public concerns on the green innovation of enterprises, some limitations still exist.

Frist, public is a comprehensive concept. Future research should classify the public. For example, the public can be divided into corporate stakeholders (investors, creditors, suppliers, customers, etc.) and general public with no corporate interests and study the influencing mechanism of different actors on green innovation of enterprises.

Second, due to the data accessibility restrictions and using IPC of patent to identify "green" innovation, patents are used as indicators of innovation. But it is questionable. After viewing other literature, it is obvious to find that "eco-labeling product certification" as an index of "Green product innovation" (Lin et al., 2014), "ISO 14001 certification" is used as an index for "Green process innovation" (Lin et al., 2014) in some articles on measure "Green Innovation" and take other industries as research objects. But these data are not available in the automobile industry database. However, it is possible to use it in other industries in the future.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

Writing and method: YL. Data and review: ZW.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2021.623638/full#supplementary-material.

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The Effects of Subsidy Policy on Electric Vehicles and the Supporting Regulatory Policies: Evidence From Micro Data of Chinese Mobile Manufacturers

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Subsidy policy to electric vehicles in China was initially launched in 2001. This study uses the perspective of the characteristics of subsidy policy and applies generalized propensity score matching (GPS) to estimate the impact of different subsidy policy intensities on the change in consumer demand for EVs and find the interval to optimize. The study shows that the optimization interval of the policy is in the 40%–70% treatment level, which maximizes the effect of the subsidy on China's EVs. For a treatment effect lower than 40%, it is difficult to effectively create an incentive to enter the EVs market in China because consumers think that the product is difficult to satisfy the demand of too low technology; by contrast, for the treatment level higher than 70%, the cost of the high endurance mileage power battery increases exponentially, and the complementary effect of subsidies is insufficient. Consequently, we propose three suggestions: The government should 1) use big data technology to supervise subsidies and design a real-time reporting mechanism and punishment mechanism for subsidy-misuse; 2) adopt the incentive regulation to promote the battery range of new energy vehicles (e.g., optimizing the subsidy ladder, innovating the form of subsidies) and gradually eliminate low-technology product; and 3) reasonably design a targeted regulatory mechanism that increases the cost of fraud and breach of contract to encourage firms to truthfully report technical indicators.

Keywords: structural effect of subsidy policy, Chinese electric vehicles, generalized propensity score matching, regulatory polices, micro data of chinese mobile manufacturers

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INTRODUCTION

Electric vehicles (EVs) are the main types of new energy vehicles in China and are the target of financial subsidies implemented by governments. Under many policy incentives, China's EVs, especially domestic EVs, are among the world's best in terms of the level of scale development and the speed of technological progress. In 2018, the International Energy Agency (IEA) published the paper "IEA Global Electric Vehicle Outlook, 2018." According to its data, China's EV ownership in 2017 was approximately 40% of the world's, which in that year was approximately 3.1 million. These achievements are inseparable from the Chinese government's sustained financial policy support. However, the subsidy policy of EVs has also led to price distortions and serious deception; thus, the government and academia have started to review the effectiveness of the subsidy policy. The EVs subsidy policy was proposed in 2017, various ministries and commissions of China have adjusted the subsidy policies for EVs for many times to improve technical efficiency and achieve technological progress. Therefore, how to adjust subsidy policies that change the demand and future development of China's EVs industry has become a common topic of concern in practice and academia and the focus of the Chinese government's policymaking. Hence, from the perspective of the characteristics of subsidy policy, we use generalized propensity score matching (GPS) to estimate the impact of subsidy policy intensities on the change in consumer demand for EVs. The aim of this study is twofold: On the one hand, this study overcomes a gap in the literature, namely, studies have not focused on factors of subsidy policy; on the other hand, we provide an important theory and recommendation for the government to optimize the structure of subsidy policy.

The existing researches on government subsidies for China's EVs have focused on the effect of subsidy policies (Helveston et al., 2015; Li et al., 2016; Li et al., 2019; Sheldon and Dua, 2019a; Sheldon and Dua, 2019b). Some researchers claim that subsidies do not affect the willing to adopt today's BEVs and mid-range PHEVs in China, whereas consumers prefer low-range PHEVs despite subsidies (Helveston et al., 2015). (Yang et al., 2019). compare two kinds of subsides by establishing Cournot duopoly model and Stackelberg model to find that subsides policy can effectively expand the market share of domestic new energy vehicles with less technology. Beresteanu and Li (2011), Li et al. (2016), Li et al. (2019) analyzed the impact of subsidy policy on the uptake of product and subsidy modes, and found that the overall subsidy policy has significant effect. As incentive subsidies policies will have a significant impact, policy-makers should introduce policies aimed at ensuring a smooth transition to the electrification of China's vehicle fleet (Ouyang et al., 2020). Based on the data of China's plug-in electric vehicles, (Sheldon and Dua, 2020), adopt the choice model to predict PEV market share under various subsidy scenarios, they find that PEVs have improved China's new vehicle fleet fuel economy by roughly 2%, reducing total gasoline consumption by roughly 6.66 billion liters under expensive subsidies. On the contrary, reviewing the feasible fuel and/or electricity energy intensity of LDVs and arguing that the severity of impending anthropogenic global warming merits, (Harvey, 2020), think that subsidies for EVs should be scaled back or eliminated.

However, little is known about effectiveness of targeted designs of subsidy policy. Xiao et al. (2020a), Xiao et al. (2020b) find that the optimal subsidies should include the environmental cost of GHG emissions and the enterprise's profits excluding the innovation risk. Targeted subsidy designs for PEVs will have a greater impact than blanket subsidies (Sheldon and Dua, 2019a; Sheldon and Dua, 2019b). So, this paper adopts micro data to analyze the impact of targeted designs of subsidy policy on consumer demand. Therefore, the two marginal contributions of this paper are as follows: First, this study attempts to manage the new energy subsidy policy, analyze the influence of different subsidy policy intensities on the market's consumer demand, avoid the problem in the literature of entire adjustment, and study how to adjust the policy, to provide recommendations for the government to formulate and optimize the subsidy policy. Second, from the perspective of research data, this study uses monthly micro data collected from motor manufacturers from 2017 to 2018 for empirical research. Compared with the research that has used the data of listed companies, this study overcomes the corresponding research selectivity bias and other problems; compared with the research on industry-level data, this study attempts to relax the homogenization hypothesis to conduct microcosmic and unbiased research.

The arrangement of the remainder of this paper is as follows: *Methodology* mainly introduces the use of the model and GPS statistical strategy; *Data* mainly shows how we managed the data preprocessing and the descriptive analysis; *Empirical Analysis and Discussion* mainly analyzes and discusses the results of empirical research, to ensure the overall robustness of the model and avoid false regression; and *Sensitivity Test* adopts the method of eliminating the control variables to test the robustness of the model. The final part summarizes the whole paper, and based on the conclusion, offers corresponding suggestions and supporting regulatory policies.

METHODOLOGY

Econometric Model

In this paper, the construction method of demand estimation variables mainly refers to the construction of a demand estimation model in the empirical analysis of industrial organization theory. Due to the strong heterogeneity of the products consumed by the representative consumers studied in this paper, which is mainly reflected in different brands, classes, and types of vehicles, simply using the LOGIT demand model would inevitably create the problem of the unrelated choice independence hypothesis (Berry, 1994). Therefore, this paper adopts the nested logit demand model often used in the empirical model of industrial organizations (Deng and Ma, 2010; Dai and yuan, 2013; Zhou, 2017; Li et al., 2019).

The econometric model is as follows:

First, we describe the strategic process for consumers to purchase Chinese EVs. Based on the assumption that consumers have decided to buy EVs, the process is mainly divided into three decision-making levels. In the first decision-making level, consumers mainly consider whether to buy Chinese EVs by comparing these EVs with foreign EVs, of which Tesla is the main brand; thus, the brand of foreign EVs is used as the control group of the Chinese EVs market. At the second decision-making level, consumers mainly consider pure EV manufacturers (Firms), that is, various manufacturers' brands in the market, where firm$_a$ means manufacturer $g, g \in G, G = \{0, 1, \ldots, 33\}$, for example, firm$_0$ = Tesla Motors. In the third decision-making level, consumers buy the corresponding EVs' series $j \in J$, in which J represents the car series space. Therefore, on the whole, consumer i will select an EV j from all available EVs' space J in the market. This overall decision logic of consumers is summarized in **Figure 1**.

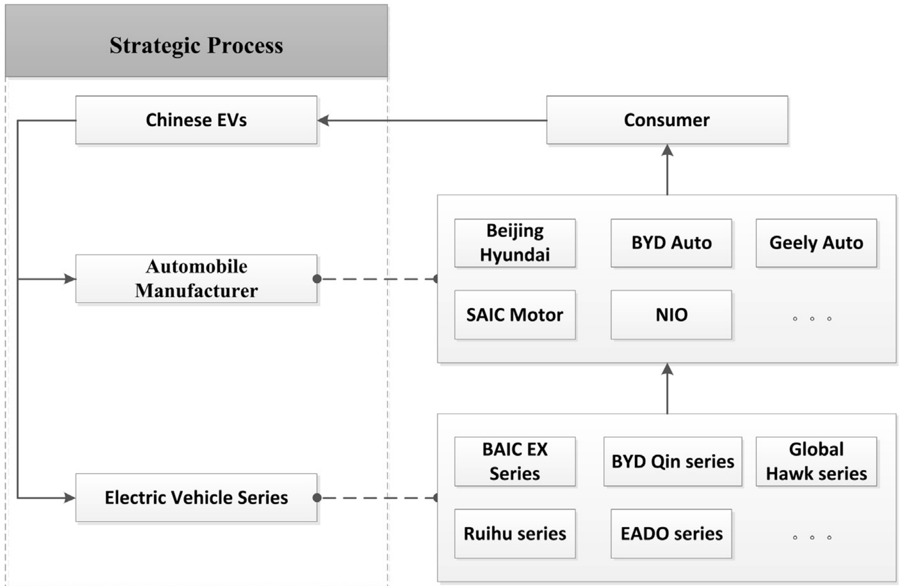

FIGURE 1 | Decision-making of consumers purchasing Chinese EVs.

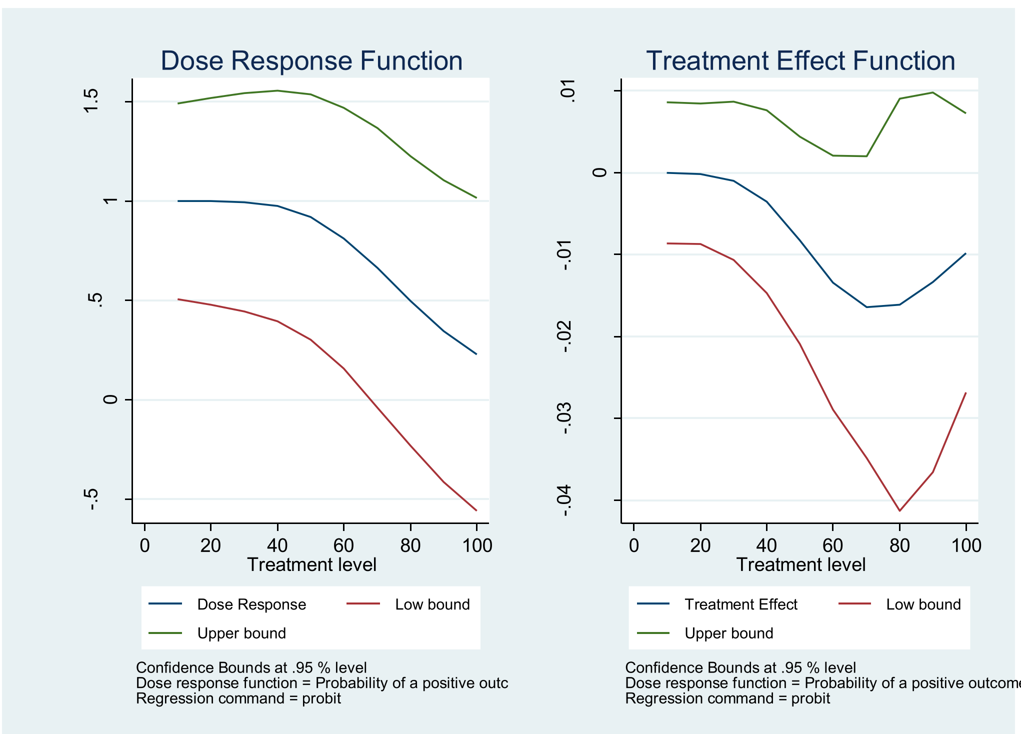

FIGURE 2 | Does-response and treatment effect of EV purchase probability.

Second, the utility function of Chinese EVs is designed. In this paper, Tesla Motors is set as the control group of Chinese EV manufacturers. For other EVs' series $j\,(j \neq 0)$, the corresponding utility obtained by consumer i is

$$U_{ij} = \beta_0 p_j + \beta_1 \text{subsidies}_j + \gamma X_j + \varepsilon_j + \mu_{ig} + (1-\delta)\varepsilon_{ij}, \qquad (1)$$

where, U_{ij} is the corresponding effect value of consumers. p_j refers to the price of the Chinese EVs of j, and subsidies$_j$ indicates that

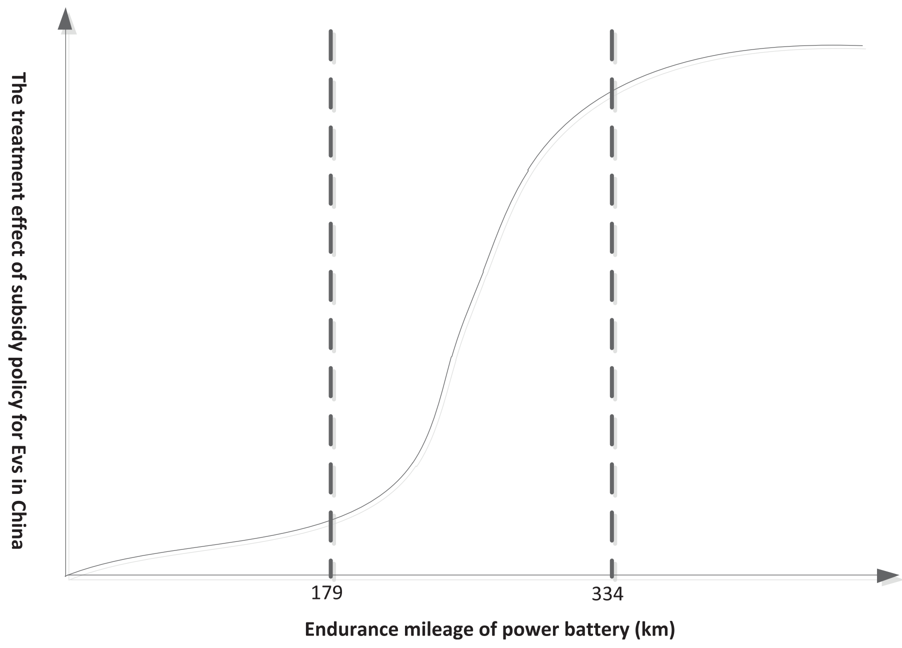

FIGURE 3 | Effect of EVs subsidy policies on consumers' willingness.

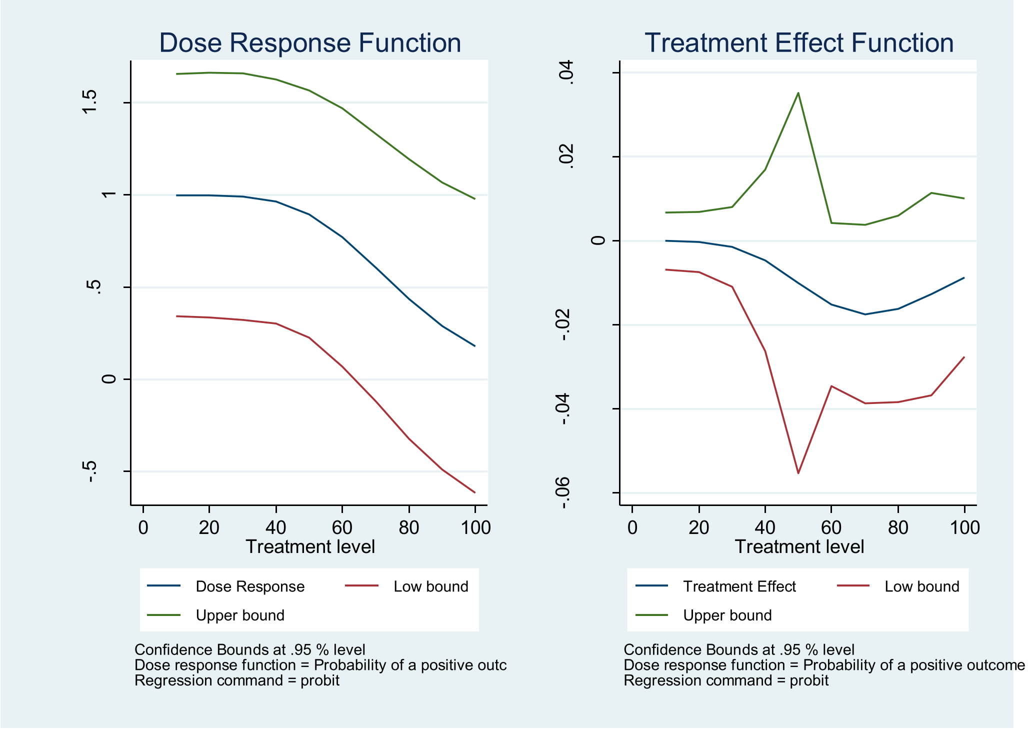

FIGURE 4 | Does-response and treatment effect of EV purchase probability without type.

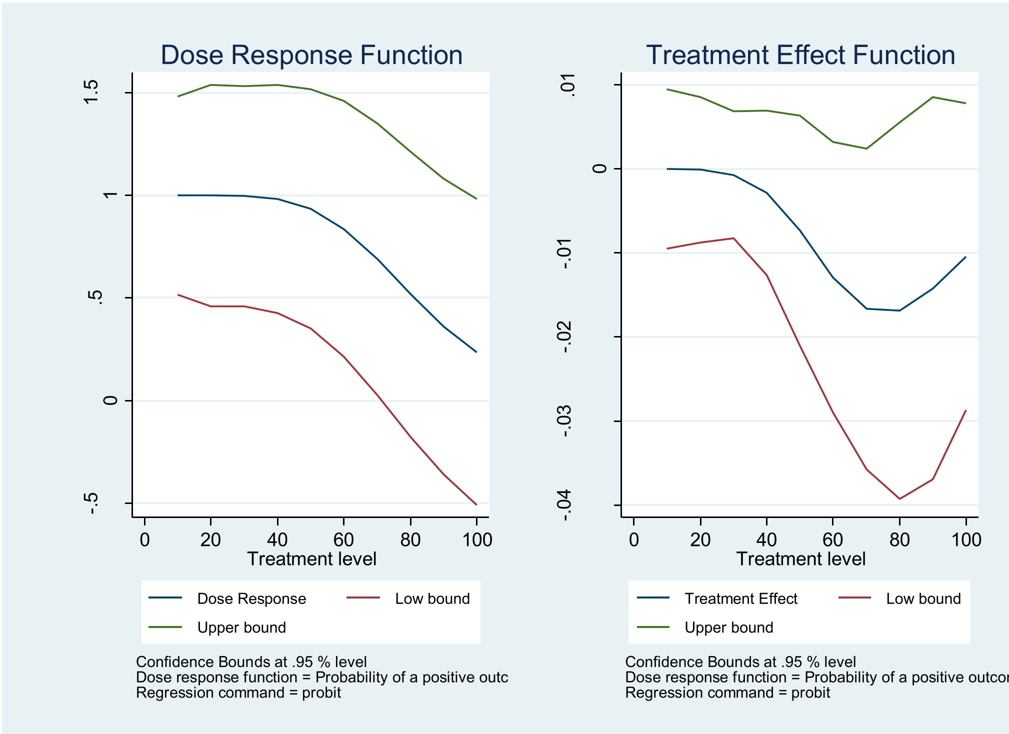

FIGURE 5 | Does-response and treatment effect of EV purchase probability without class.

TABLE 1 | Detailed list of national subsidy policies for EVs in China (10,000 Yuan).

Endurance mileage of power battery R (km)	$100 \leq R < 150$	$150 \leq R < 200$	$200 \leq R < 250$	$250 \leq R < 300$	$300 \leq R < 400$	$R \geq 400$
2017	2	3.6			4.4	
Transition period in 2018	1.4	2.52			3.08	
After the transition period in 2018	—	1.5	2.4	3.4	4.5	5

Note: the subsidy standard in 2018 is divided into three stages: the first stage is from January 1 to February 11, the subsidy is implemented according to 2017; the second stage (the transition period) is from February 12 to June 11; the third stage (the new policy in 2018) is implemented from June 12 to December 31.

TABLE 2 | Descriptive statistics of related variables.

Variables	Observations	Mean value	Standard deviation	Minimum value	Maximum value
Sale	3,114	222.932	875.753	0	15,719
Price	3,114	10.738	8.527	0	41.72
Subsidies	3,114	2.328	1.865	0	5.5
Battery	3,114	257.121	83.336	100	460
Firm	3,114	19.399	8.469	1	33
Series	3,114	44.861	24.457	1	88
Class	3,114	2.474	1.579	1	7
Type	3,114	2.445	0.657	1	3

Note: Three significant digits after the decimal point shall be reserved in the table.

TABLE 3 | K-S normal distribution test.

Sample	D-statistics	*p* value	Adjustment value
Condition treatment group	0.083	0.088	—
Cumulative treatment group	−0.088	0.070	—
Joint K-S	0.088	0.140	0.119

Note: Three significant digits after the decimal point shall be reserved in the table.

TABLE 4 | GPS value of the intervals of the treatment effect.

Interval of treatment effect[a]	Mean value	Std.	Minimum value	Maximum value
[0,150]	0.091	0.033	0.010	0.262
(150,250]	0.139	0.032	0.023	0.259
(250,460]	0.213	0.035	0.010	0.263

[a]In this paper, the treatment effect is divided into four intervals according to the subsidy policy. However, in the actual statistical process, the system automatically combines the small sample distribution between [0,100] and [100,150]; thus, it is only reflected in three intervals in the table. Three significant digits after the decimal point shall be reserved in the table.

the Chinese EVs j purchased has obtained the subsidy amount provided by the national support subsidy policy. X_j is the corresponding control variable of the j EV, for example, the wheelbase, grade, standard endurance mileage (determined by the European endurance test standard); ε_j represents the individual effect of EV j, which cannot be directly observed by the observer; μ_{ig} and ε_{ij} refers to the effect of consumer i on different vehicle types of the same manufacturer and different vehicle j, where ε_{ij} is subject to the mean value of zero and the same independent distribution. According to Cardell (1997), μ_{ig} and $[\mu_{ig} + (1-\delta)\varepsilon_{ij}]$ are set as independent and identical distribution with zero mean. The corresponding average treatment is conducted for **Eq. 1** with respect to vehicle j, we will obtain

$$\overline{U}_j = \beta_0 p_j + \beta_1 \text{subsidies}_j + \gamma X_j + \varepsilon_j. \tag{2}$$

Combining **Eqs 1**,**2**, we also find that

$$U_{ij} = \overline{U}_j + \mu_{ig} + (1-\delta)\varepsilon_{ij} \tag{3}$$

Third, according to Berry (1994), we obtain the market share of all types of automobile brands in all Chinese EV markets and build the demand model, which comprises the corresponding market share and consumer demand. The market share of corresponding model j of the same manufacturer can be expressed as follows:

$$\text{share}_{jg}\left(\overline{U}_j, \delta\right) = \frac{e^{\frac{\overline{U}_j}{(1-\delta)}}}{\sum_{t\in\vartheta} e^{\frac{\overline{U}_j}{(1-\delta)}}}. \tag{4}$$

In the same manner, the market share among the corresponding manufacturer groups can be also expressed as:

$$\text{share}_g\left(\overline{U}_j, \delta\right) = \frac{\left[\sum_{t\in\vartheta} e^{\frac{\overline{U}_t}{(1-\delta)}}\right]^{(1-\delta)}}{\sum_{\tau\in G}\left[\sum_{t\in\vartheta} e^{\frac{\overline{U}_{t\tau}}{(1-\delta)}}\right]^{(1-\delta)}}. \tag{5}$$

Combining **Eqs 4**,**5**, we will obtain the market share of corresponding vehicle j in Chinese EVs, as follows:

$$\text{share}_j = \text{share}_{jg} \cdot \text{share}_g. \tag{6}$$

We will assume that consumers choose the foreign EV (Tesla) that is imported, regarding this type of vehicle as a benchmark, and assume that $\overline{U}_0 = 0$, $\sum_{t\in\vartheta} e^{U_t/(1-\delta)} = 1$. Hence, the market share of the control group can be obtained as follows:

$$\text{share}_0 = \frac{1}{\sum_{\tau\in G}\left[\sum_{\tau\in G} e^{\overline{U}_{t\tau}/(1-\delta)}\right]^{(1-\delta)}}. \tag{7}$$

Here, by calculating **Eqs 6**,**7**, we can obtain:

$$\ln\left(\text{share}_j\right) - \ln\left(\text{share}_0\right) - \delta\ln\left(\text{share}_{jg}\right) = \overline{U}_j. \tag{8}$$

Consequently, we can obtain the corresponding statistical model (9) by substituting **Eq. 8** into corresponding **Eq. 2**.

$$\begin{aligned}\text{demand} &= \ln\left(\text{share}_j/\text{share}_0\right)\\ &= \beta_0 p_j + \beta_1 \text{ subsidies}_j + \delta\ln\left(\text{share}_{jg}\right) + \gamma X_j + \varepsilon_j.\end{aligned} \tag{9}$$

For the corresponding share difference on the left side of **Eq. 9**, we can calculate the corresponding EVs' market sales volume. Therefore, the overarching variables of this paper are transformed into the corresponding market share natural logarithm difference through the demand estimation model and can then be processed through the sales data (sale) of various manufacturers and vehicle types in the market to achieve the research purpose.

However, in the actual measurement and statistics process, because the measurement model involves price, market share, and intragroup market share, and other factors. OLS and other methods cannot overcome the endogenous problems; thus, the coefficients estimated must be biased. For this reason, we considered using propensity score matching (PSM) to eliminate the endogenous problems. In addition, this study is based on the analysis of the characteristic effect of subsidy policy, and traditional PSM is inappropriate for the treatment of continuous variables[1]; thus, this paper adopts GPS as the method for improvement.

Statistical Strategy of the Generalized Propensity Score Matching Method

GPS was first proposed by (Hirano and Imbens, 2004). Since traditional PSM is only applicable to 0–1 treatment variables and cannot solve the problem of continuous treatment variables, GPS has been widely used since it was proposed, especially in international trade, R&D cooperation intensity, and targeted poverty alleviation (Yang et al., 2019). Based on

[1]Although traditional propensity score matching (PSM) can well solve the endogenous problem, its assumption must be set up as a binary variable of 0–1, which is difficult to deal with continuous variables.

TABLE 5 | Balancing test of three treatment intervals.

Variables	Interval of treatment effect					
	(0,150)		(150,250]		(250,460]	
	Mean difference	*t* statistic	Mean difference	*t* statistic	Mean difference	*t* statistic
Firm	4.214	1.288	−0.259	−0.217	−0.623	−0.490
Series	−10.085	−1.164	−0.937	−0.669	3.934	1.155
Class	−0.170	−0.293	0.139	0.501	−0.101	−0.429
Type	0.093	0.431	−0.038	−0.552	0.021	0.234
Share2017m1	−0.239	−0.360	−0.184	−0.460	0.044	0.439
Share2017m2	0.959	0.999	−0.269	−0.583	0.101	0.430
Share2017m3	0.790	1.353	−0.233	−0.689	0.063	0.417
Share2017m4	1.137	1.836	−0.272	−0.755	0.062	0.327
Share2017m5	0.597	0.619	−0.359	−0.723	0.215	0.873
Share2017m6	2.610	2.496	−0.850	−1.686	0.386	1.201
Share2017m7	2.117	2.269	−0.683	−1.240	0.322	1.114
Share2017m8	2.050	2.053	−0.092	−0.182	−0.319	−0.305
Share2017m9	2.176	2.047	0.575	0.950	−1.001	−1.296
Share2017m10	2.011	2.007	−0.045	−0.083	−0.288	−0.099
Share2017m11	2.204	1.687	−0.129	−0.203	−0.273	0.087
Share2017m12	2.313	1.734	0.493	0.902	−0.997	−1.248

Note: According to the standard double-tailed t *test, the data have significantly the balance feature at the 99% confidence level; three significant digits after the decimal point are reserved in the table. In addition, Share2017m1 represents the relative market share in January 2017.*

TABLE 6 | Estimation of the dose-response model.

Variables	Coefficient	Std.	Statistic	Upper	Lower
T	−0.0789**	0.058	−1.37	−0.192	0.034
T^2	0.0002**	0.0002	1.32	−0.0001	0.0007
T^3	−2.98*e* − 07**	2.37*e* − 07	−1.26	−7.64*e* − 07	1.67*e* − 07
R	39.032**	27.782	1.40	−15.419	93.484
R^2	−230.888**	181.299	−1.27	−586.228	124.453
R^3	453.740*	369.947	1.23	−271.342	1178.821
TR	−0.003*	0.031	−0.09	−0.064	0.058
Constant	4.701**	4.557	1.03	−4.229	13.632
—	Log-likelihood -116.392		p value (F statistic) 0.017		Pseudo R2 0.782

*Note: Three significant digits after the decimal point shall be reserved in the table. In the table, *, **, and **, respectively represent the significant confidence levels of 90%, 95%, and 99%.*

our review of the literature, we propose that the advantage of this method is its management of specific policies in a structured manner; thus, this method is consistent with the goal of this study.

Therefore, the corresponding statistical strategies of this study are as follows:

First, we construct the conditional distribution of the treatment variables and calculate the GPS of the variables. The treatment variable analyzed is the amount of the government subsidies. Because the research object is Chinese EVs, there is no case when the subsidy amount is 0; thus, the distribution of variables conforms to the normal distribution hypothesis proposed by Hirano and Imbens, (2004). Thus, we will obtain the corresponding conditional distribution of treatment variables as follows:

$$g(T_i)\big|X_i \sim N\left[l(z, X_i), \sigma^2\right], \tag{10}$$

where $g(T_i)$ in **Eq. 10** represents the conditional distribution function of the treatment variables, also known as the discrimination function of the treatment variables[2]. $l(z, X_i)$ represents the corresponding covariance function of the control variable X_i. z is the corresponding higher-order coefficient, and σ^2 is the variance of the corresponding variable. According to Hirano and Imbens, (2004), this paper constructs the statistics of GPS, as follows:

$$\widehat{R}_i = \frac{1}{\sqrt{2\pi\widehat{\sigma}^2}}\exp\left\{-\frac{1}{2\widehat{\sigma}^2}\left[g(T_i) - l(\widehat{z}, X_i)\right]\right\}, \tag{11}$$

where, $\widehat{z}$ and $\widehat{\sigma}^2$ in **Eq. 11** are the corresponding parameter estimated in **Eq. 10**. Therefore, the unbiased statistics $\widehat{R}_i$ is defined as GPS.

Second, based on the first step of estimating the corresponding GPS value and treatment variable subsidy amount, we will

[2]The appellation of this discriminant function is mainly from the appellation of Michela BIA and other scholars in the official journal of Stata supporting by Bia and Mattei (2008), and then the scholars retain this appellation.

TABLE 7 | Consumer's willingness to buy Chinese EVs and prediction of the turning point.

Treatment level (%)	Willingness to buy (does−response model)	Treatment effect	Std. (does−response)	Std. (treatment effect)
10	0.999	−1.4*E* − 05	0.279	0.005
20	0.999	−0.000	0.290	0.006
30	0.995	−0.001	0.309	0.008
40	0.975	−0.004	0.335	0.005
50	0.920	−0.008	0.344	0.012
60	0.814	−0.013	0.349	0.016
70	0.663	−0.0164	0.363	0.011
80	0.498	−0.0161	0.371	0.012
90	0.347	−0.0134	0.377	0.010
100	0.229	−0.010	0.376	0.012

Note: The shaded part in the table indicates the area of the turning point of the corresponding marginal processing effect; the three significant digits after the decimal point are reserved in the table.

TABLE 8 | Optimal contribution range and contribution value of subsidy policy for EVs.

Rapid descent interval	Interval of the turning point	Optimization interval	Contribution
[38.9%, 42.2%] (179, 194)	[65%, 72.5%] (299, 334)	[40%, 70%] (179, 334)	65.823

Note: [] in the table represents the percentage of the corresponding interval, and () represents the corresponding endurance mileage, with the unit of kilometer; three significant figures after the decimal point are reserved in the table.

construct the conditional expectation of the corresponding consumers demand for EVs; thus, we can obtain:

$$E(\text{demand}_i|T_i, R_i) = \alpha_0 + \alpha_1 T_i + \alpha_2 T_i^2 + \alpha_3 T_i^3 + \alpha_4 R_i + \alpha_5 R_i^2 + \alpha_6 R_i^3 + \alpha_7 T_i R_i, \tag{12}$$

where, demand_i in **Eq. 12** represents the demand for pure EVs in China. According to the aforementioned estimation of the demand model, demand_i is expressed as the left part of **Eq. 9**, that is, the relative share difference between each manufacturer and the reference group. $E(\text{demand}_i|T_i, R_i)$ indicates the conditional expectation under the condition of the treatment variable and GPS value, which mainly tests whether the treatment effect and corresponding GPS value have a significant influence effect. Notably, the GPS value in **Eq. 12** actually uses (R_ I), namely, the estimated value of GPS.

Third, the dose-response function is estimated and used to assess the average potential outcome for each level of the treatment in which the scholars are interested. According to the corresponding multiple coefficients $\widehat{\alpha}$ estimated in **Eq. 12**, we will construct the expectation function equation of the consumer demand estimation corresponding to the variable with different treatment steps, and we can obtain

$$E\left[\widehat{\text{demand}}(t)\right] = \frac{\sum_{i=1}^{N}\left(\widehat{\alpha_0} + \widehat{\alpha_1} t + \widehat{\alpha_2} t^2 + \widehat{\alpha_3} t^3 + \widehat{\alpha_4} r(t, X)_i + \widehat{\alpha_5} r^2(t, X_i) + \widehat{\alpha_6} r^3(t, X_i) + \widehat{\alpha_7} T_i r(t, X_i)\right)}{N}, \tag{13}$$

t in **Eq. 13** represents the level of treatment variables, and $r(t, X_i)$ represents the corresponding density function of R_i. Through **Eq. 13**, we must set the corresponding level value when calculating $E[\widehat{\text{demand}}(t)]$. According to the needs of this research, a range of 10%–100% of the treatment variables with asynchronous length is selected for statistical analysis. Additionally, we compare and analyze the differences in consumer demand under different levels of subsidy intensity and obtain the characteristics of the average treatment effect on each node of the subsidy policy, that is, average treatment effect, which is as follows:

$$AT(t) = E\left[\widehat{\text{demand}}(t)\right] - E\left[\widehat{\text{demand}}(0)\right], \tag{14}$$

where $AT(t)$ in **Eq. 14** represents the average treatment effect of subsidy policies on different nodes; next, we assess whether there is a significant difference in the characteristics of subsidy policies.

DATA

The data used in this paper are mainly the monthly micro data released by the China Automobile Association and China Passenger car Federation and published research from January 2017 to December 2018, including the price data of Chinese EVs for two years, the sales data of different series of vehicles of various manufacturers and so forth; the data of Tesla cars in the group is mainly from the global import and export data, which is from China Customs micro database. The main purpose of using micro data is to solve the problem of subsidy heterogeneity that has been difficult to resolve at the industry level, for example, different financial subsidies for EVs with different endurance mileage, and when the same manufacturer continuously introduces the same series to fulfill the subsidy policy. In

TABLE 9 | Sensitivity test of the model estimated.

Control variables eliminated	Interval of treatment effect	Rapid descent interval	Optimal interval of subsidy effect	Contribution (%)
Type	[66%,72.5%]	[39%,43.2%]	[42%,72.1%]	66.015
Class	[64.5%,71.5%]	[37.6%,41.6%]	[39.6%,67.8%]	65.772

Variables	Without type			Without class		
	Coefficient	Std.	Statistics	Coefficient	Std.	Statistics
T	−0.0777	0.0584	−1.33	−0.0818	0.0581	−1.41
T^2	0.0003	0.0002	1.24	0.0003	0.0002	1.35
T^3	0.0000	0.0000	−1.14	0.0000	0.0000	−1.27
R	43.5529	28.2543	1.54	38.3343	27.2032	1.41
R^2	−269.6387	181.9056	−1.48	−217.8324	174.3206	−1.25
R^3	526.8460	366.1422	1.44	414.5679	350.1449	1.18
TR	0.0054	0.0312	0.17	−0.0022	0.0304	−0.07
Constant	4.5276	4.6192	0.98	4.9415	4.5749	1.08

summary, this paper uses this data to conduct in-depth analysis of different series of EVs, and this method not only conforms to the consistent research ideas of the automobile industry but also overcomes the difficulty of capturing and characterizing the heterogeneity subsidy intensity.

In addition, to make a detailed description of each EV series, this study collects and matches the corresponding vehicle technology variables, for example, vehicle wheelbase, vehicle use, vehicle grade, and pure electric vehicle range, from websites, for example, those for automobile homes, the Sohu automobile network, and first electric. Due to the corresponding subsidy policies of the government, there are corresponding subsidy regulations, subsidy intensities, and subsidy starting times for different subsidy endurance mileage, especially in 2018, which is more detailed regarding the specific implementation span, namely, the starting and ending time, which the government defined as February 12 to June 11, 2018, for the new energy vehicle subsidy transition period. Accordingly, this study collects and sorts the subsidy standard (**Table 1**).

In this paper, 3,114 observations are collected, and each includes the monthly data of a vehicle model, including the sales volume, price, subsidies, battery, firm, series, class, and type of EVs. The descriptive statistics of each main variable are presented in **Table 2**.

EMPIRICAL ANALYSIS AND DISCUSSION

This study focuses on the impact of subsidy policies on the demand for Chinese EVs. Therefore, the empirical process of this paper is mainly divided into the following four parts: First, this paper structures the national subsidy policy for EVs by partitioning the endurance mileage of the battery (km) into four intervals—[0.100], (100,150], (150,250], (250,460]—by referring to "The Requirements of The Notice on Adjusting and Improving The Financial Subsidy Policy for The Promotion and Application of New Energy Vehicles" (CJ [2018] No. 18). Second, according to the estimation strategy of the GPS, we test whether the GPS statistics fulfill the requirements of data balance and the normal distribution hypothesis and then obtain the corresponding GPS values if the results satisfy the condition. Third, the PROBIT model is used to measure the relative purchase ratio of the control group (imported pure EVs) and Chinese pure EVs. The results of the dose-response function and treatment effect show that different levels of subsidies affect consumers' willingness to buy imported pure EVs, and this is used to determine the relative willingness of subsidy policies to purchase Chinese pure EVs. Finally, we adjust and determine the optimal subsidy interval.

Normal Distribution of the Treatment Variable Distribution Test

$g(T_i)|X_i$ in **Eq. 10** is the conditional distribution function of the treatment variables for the normal distribution test (See **Table 3** for the characteristics of the conditional distribution of the treatment variables.). From the result of the distribution characteristics, we cannot directly assess that it does not conform to the corresponding normal characteristics because of its peak degree of 1.986. Therefore, we must further analyze it using the Kolmogorov–Smirnov (K–S) normal distribution test and accordingly assume the testing hypothesis, namely, H0: The test data is consistent with the classical theoretical data.

The results in **Table 3** show that the distribution of the treatment effect variables adopted in this paper obeys the normal distribution. Specifically, the p values of the conditional treatment group and the cumulative treatment group in **Table 3** are 0.088 and 0.070, respectively, and the p value of the corresponding joint K-S is 0.140. Even for the modified joint K-S, the p value is still 0.119. Therefore, the results show that it is difficult to reject the corresponding principle hypothesis. In other words, the conditional expectation distribution of treatment effect variables is consistent with that of the classical normal distribution.

Balancing Test for the Treatment Interval

Through the calculation of the corresponding GPS values of each interval, the corresponding results presented in **Table 4** are captured. Notably, this paper sets four intervals according to the national subsidy policy division standard, but the number of samples where there is endurance mileage in the [0,100] is rare. Thus, we merge [0,100] and (100,150] in the statistical process, and there are three effect intervals (**Table 4**).

However, only satisfying the aforementioned normal distribution characteristics is insufficient to provide a sufficient condition for further research and statistics; thus, we must test the overall stability property of the treatment interval. After the corresponding GPS values are estimated, the double-tailed *t* test of trend matching is conducted to determine whether all the data satisfy the significant balance characteristics of trend matching. The results are presented in **Table 5**, which reflects the mean value difference of the corresponding control variables and corresponding t statistics. Stata 14.0 assesses that the data characteristics fulfill the corresponding data balance test at the 99% confidence level according to the standard double-tailed *t* test. At this point, we obtain the corresponding GPS values that fulfill the requirements.

Dose-Response Function

In this subsection, the parameters of the dose-response function are estimated according to **Eq. 12** in the measurement strategy. Specifically, the corresponding coefficient estimated in **Table 6** is used into **Eq. 12** to obtain **Eq. 15**:

$$E(\text{demand}_i|T_i, R_i) = 4.701 - 0.0789T_i + 0.0002T_i^2 - (2.98e-07)T_i^3 + 39.032R_i - 230.888R_i^2 + 453.74R_i^3 - 0.003T_iR_i. \tag{15}$$

Accordingly, the F statistic of the dose-response function is 0.017, which is significant at the 95% confidence level, and its relative R-square value is as high as 78.2%. This result shows that the model has a strong, steady interpretation ability. In a later chapter, we conduct a robustness test to prevent false regression and other problems.

Treatment Effect and Discussion

On the basis of the aforementioned premise hypothesis and model test, this paper calculates the expected probability of consumers purchasing EVs at different processing levels and then draws the corresponding does-response curve (see the left side of **Figures 2**). The right side of **Figures 2** shows the marginal treatment effect at different treatment levels. According to the curve change in **Figures 2**, China's new energy subsidy policy has three arrangements for the consumption demand of Chinese EVs.

In the first arrangement, in which the range is mainly concentrated in the range of 0%–40% of the treatment level, the corresponding battery endurance mileage is approximately 0–179 km. From the perspective of the actual subsidy process, the amount of subsidy in this arrangement does not affect the decision-making of consumers very well. We can say that with the interval of a subsidy, it is difficult to achieve the role of stimulating consumption and supporting Chinese automobile brands. Therefore, the subsidy effect in this level is relatively low and only plays a basic role in the subsidy threshold.

In the second arrangement, the range is mainly 40%–70% of the treatment level, and the corresponding battery endurance mileage is approximately 179–334 km. This arrangement is the area with the fastest decline rate of the reagent reaction curve.

Combined with **Table 3**, we observe that although the willingness to buy imported pure EVs continues to decline under the impact of subsidy policies, when the treatment level is 70%, there is a significant turning point in the treatment effect. In the third column of **Table 3**, when the treatment level is 70%, the corresponding treatment is only -0.0164, reaching the bottom of the treatment effect curve. According to the actual situation and data, this interval is the best level for the effect of subsidy policy because the core of the subsidy policy is shifted backward; thus, the consumers have more price preference, and the consumers' preference for the subsidized Chinese EVs is significantly affected. By contrast, the battery technology level is relatively mature in this level, EVs categories are relatively rich; thus, consumers have sufficient choice space. This paper also estimates that the contribution of this level to consumer impact accounts for approximately 66%.

In the third arrangement the range shows that after 70% of the treatment level, the corresponding endurance mileage is more than 334 km. According to the information in **Figures 3** and **Table 8**, the pharmaceutical reaction in the third interval continues its downward trend, which shows that the impact of the subsidy policy continues to promote the consumption demand of Chinese EVs, but the acceleration of effect has declined. According to the curve of the treatment effect, after the turning point, the effect of the subsidy policy in this interval is obviously reduced, and the main reasons for this phenomenon are as follows: first, because of the rapid increase in the cost of high-performance vehicles with endurance of more than 334 km, the corresponding high subsidy amount has declined in the attraction of this part of consumers. Second, consumers of higher performance pure EVs are not so sensitive to the product price, and this part of consumption focuses more on the corresponding services, concepts, and supporting aspects. Therefore, when subsidies act on this level, the consumers at the top of the pyramid weaken the effect of the subsidy policy.

Based on these three arrangements, this paper considers that the effect of the subsidy policy in promoting the development of Chinese EVs and the distribution of consumer preferences form an "s"-type feature (**Figures 4**).

SENSITIVITY TEST

In this section, we conduct a sensitivity test to prevent the phenomenon of pseudo regression and ensure that the model is steady. This study mainly tests the stability of the model by eliminating the different control variables.

The results show that regardless of which control variable is eliminated, the overarching indicators do not change which they are the interval where the inflection point of the treatment effect appears, the rapid descent interval, the optimal interval of the subsidy effect, and the relative contribution. Specifically, the inflection point of the treatment effect of the subsidy policy is basically between 66% and 72% of the treatment level, approximately 70% of the horizontal position; the rapid settlement area reflected by medicament is basically between 38% and 43%; the optimal contribution range of the subsidy effect can be determined between 40% and 70%; finally, the optimal contribution range can increase to approximately 66%. The information in **Table 9** show that the overall robustness of the model is not significantly affected by the change in the corresponding control variables. To more intuitively express this conclusion, this paper draws the drug response curve and treatment effect curve after the two relaxation condition assumptions (**Figures 5**).

CONCLUSION AND REGULATORY POLICY

As an important starting point for the government to support the rapid development of China's EVs industry, the subsidy policy has attracted extensive attention from academic and practical circles. During the ten years of the implementation of the subsidy policy, the policy has been continuously adjusted and has thus evolved; there have been two stages: adjustment of the total amount of the subsidy policy, and adjustment of the "" subsidy policy. Notably, the literature has not emphasized the adjustment of the policy; thus, how to optimize the policy was unknown. This study is based on the aforementioned problems and analyzes the impact of consumer demand of domestic pure electric enterprises in China by using the GPS method, obtains the corresponding subsidy policy agent response and treatment effect, and proposes corresponding policy optimization countermeasures and suggestions.

The corresponding research conclusions are as follows: the current new energy subsidy policy has three levels of effects, the first level focuses on the range of 179 km, which is the worst, and is mainly reflected in the threshold effect; the second level focuses on the range of 179 km–334 km, which is the most likely to cause consumer demand, and its main contribution value is more than 65%, which should be regarded as the key area of optimization and inclination; the final level mainly focuses on more than 334 km, the policy effect of this level is affected by factors such as price and consumer group characteristics, and its contribution degree is approximately 30%.

According to these research conclusions, we propose the following two suggestions:

First, the government must understand the adjustment of subsidy policy, optimize and establish the structure of subsidy policy, and use the role of subsidy policy on the demand side. First, we propose that based on the annual decline of China's new energy subsidy policy, it should be adjusted and reshaped, and the understanding of the total decline mechanism should be abandoned. Whether it is China's new energy subsidy policy or its decline mechanism, if the difference and structure are not measured and evaluated, equalization will be misunderstood. Second, on the basis of reshaping the understanding of subsidy policy, this paper considers that an accurate measurement of the effect level of different interval subsidy policies is the key factor. Timely optimization and adjustment are formed for the different effect intervals, especially in the demand effect stimulation at the demand end, which is the most important premise when forming the pattern of "market leading and policy effective support."

Second, the government should formulate supporting regulatory policies and design a signal mechanism to ameliorate the cheating behavior through which firms mislead consumers by overstating endurance mileage to eliminate consumers' concerns about purchasing Chinese pure EVs, and promote the technological progress and sound development of the industry. In the development of the Chinese EV industry, consumers are most concerned about the durability of the power battery and the authenticity of the endurance mileage. In the analysis, we also found that the marginal treatment effect of Chinese EVs appears to be an obvious turning point in the higher mileage range. This conclusion suggests that the increasing cost of index weakens the subsidy effect. By contrast, what is more important is to show that consumers' concern about the higher mileage parameters also affects the effect of the subsidy policy. Therefore, the government should strengthen the supervision of the endurance mileage of EVs, use the national supervision and management platform of China's new EVs to regularly publish the product verification to the public, and increase the symmetry and transparency of market information. On the one hand, the supporting regulatory policy would eliminate the purchase concerns of consumers and potential customers; on the other hand, it would effectively stimulate EV manufacturers and battery suppliers to improve management and industry technology and promote the sound development of the industry.

Third, using big data technology to regulate subsidies, the government should design a real-time reporting mechanism and a punishment mechanism for subsidy misuse. With the traditional government regulation, it is difficult to track the usage of the subsidy effectively because of technical limitations; thus, the subsidy policy can only be modified and adjusted after the occurrence of fraud and cannot be optimized and prevented in advance. However, big data technology can be supported by a lot of data to analyze the changes of corporate behavior and performance in real time after the grant of subsidies, to form anticipation and inference in advance, accurately identify the possible fraud and compensation behavior, and design a real-time feedback mechanism. Additionally, the government should also use mechanism design theory to design the punishment mechanism for subsidy misuse, which increases the cost of a firm's breach of contract and cheating, to make the enterprise lack the probability of deception because of the incentive's compatibility. In addition, the government should design a regulatory mechanism for regulatory agencies, to improve the efficiency of supervision and implementation by influencing the interests of regulators. In summary, by adopting big data technology and mechanism design theory, the government could form a supervision system and tracking mechanism to prevent problems, improve regulatory efficiency in the middle of the event and afterward, and ensure the effective implementation of subsidy policy.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

X-fL supplies the data and methods for the research. LW supplies the idea for researching the relation between the subsidies policy and regulation policy. All authors contributed to the article and approved the submitted version.

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A Study on the Comprehensive Evaluation and Analysis of China's Renewable Energy Development and Regional Energy Development

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The problem of unbalanced energy development in China still exists. How to adjust the energy structure is the key to high-quality economic development in China. This paper analyses the impact of regional energy development levels on high-quality economic development in China from 2016 to 2017, with the global ML methodology and structural equation model. Firstly, from two aspects of environmental and technological factors, the Global Malmquist-Luenberger (GML) production function is used to measure the environmental endowment index of regional energy development in China. Secondly, the evaluation system of China's energy development is established. The structural equation model is used to measure and evaluate the degree of China's regional energy development. Combined with the environmental endowment index of regional energy development, the gap between the proportion of regional renewable energy and the optimal energy structure is analyzed. Thirdly, this paper explores the supporting effect of different energy development levels on high-quality economic development. It is concluded that the environmental endowment index of energy development varies among different regions in China, most of which are still underdeveloped, but a few of which have redundant technical elements of renewable energy development. China's regional energy development model is still dominated by fossil fuel energy, and the proportion of renewable energy driving economic growth is relatively low. Renewable energy can effectively replace the use of fossil fuel energy and have a higher impact on high-quality economic development. Finally, on the basis of the above study, the paper puts forward policy suggestions for Chinese governments to adjust energy structure and promote high-quality economic development.

Keywords: China's energy development level, renewable energy, energy development environmental endowment index, high-quality economic development, GML production function, structural equation model

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INTRODUCTION

Energy is considered as the cornerstone of national security and the foundation of national economy. From a global perspective, new trends on the energy development mode have emerged, and the renewable energy has been developing rapidly: Many countries have successively issued energy reform measures led by renewable energy. Among various forms of renewable energies, photovoltaic power and wind power are the main forms of energy conversion, and hydropower is the second choice. The transformation of the global energy structure is inevitably called forth by the renewable energies. There are two reasons for the rapid development of the renewable energy in the global market. One is the bottleneck of crude oil supply, caused by the unstable oil production, the violent fluctuation of international oil price, and the challenged energy security. The other one is the global problems caused by the fossil energy consumption, such as the climate change issue, the health and safety issue, and the economic loss issue (Abbasi et al., 2020; Ahmed et al., 2020). China, as a major energy consumer, has attracted wide attention on its energy development mode from the other countries. During the 13th 5-Year Plan period, China has accomplished remarkable achievements on the development of the renewable energy. The power generation of renewable energy in 2019 is 1.7 times that of 2015. In terms of consumption and utilization, the target of 95% utilization was achieved 1 year ahead of schedule (Chen et al., 2019). Still, there are some problems on the renewable energy development, such as the difficulties on implementing plans, the increased subsidy fund gap and the power restriction in some local areas. The current energy system in China that relies heavily on fossil fuels contradicts the strategic requirements of sustainable development and accelerates the transformation of renewable energy (Dong et al., 2018). How to adjust the regional energy development mode, so as to improve the utilization of renewable energy and to promote economic growth steadily, is the key to China's high-quality development in the new era.

In the existing papers on the impact of China's regional energy development level on high-quality economic development, there are two main problems: Firstly, based on the static theory, the weight of renewable energy and non-renewable energy is the same, and the environmental compensation benefits of renewable energy are ignored (Hacıimamovglu and Sandalcılar, 2020). Secondly, for the more abstract problems such as measuring the level of development, the traditional weighting method is lack of objectivity, the classical hypothesis model does not have a high degree of identification of the direction of variables, and the measurement results are often difficult to be convinced (Jin and Li, 2017). In order to solve the above problems, firstly, from two aspects of environmental and technological factors, the Global Malmquist-Luenberger (GML) production function is used to measure the environmental endowment index of regional energy development in China. Secondly, the evaluation system of China's energy development is established. The structural equation model is used to measure and evaluate the degree of China's regional energy development. Combined with the environmental endowment index of regional energy development, the gap between the proportion of regional renewable energy and the optimal energy structure is analyzed. Then, this paper explores the supporting effect of different energy development levels on high-quality economic development. Finally, on the basis of the above study, the paper puts forward inspiring policy suggestions for the Chinese government. This study has important implications for China's energy structure transformation, renewable energy utilization, and high-quality economic development in the new era.

LITERATURE REVIEW

Regarding the level of regional energy development and its impact on high-quality economic development, relevant scholars and departments at home and abroad have conducted some studies and achieved certain results.

At present, there are many researches using evaluation system to measure the level of regional energy development. For example, Li et al. (2011) comprehensively evaluated China's renewable energy development level from four aspects–economy, technology, resources, and environment–by using an analytic hierarchy process. Byrne et al. (2007) used GIS technology to explore the prospect of renewable energy demand of rural residents in China from the aspects of resources, economy, technology, and residents' life. Heo et al. (2010) used an analytic hierarchy process and fuzzy comprehensive evaluation to measure the popularization level of new energy in South Korea by selecting five indicators: technology, market, economy, environment, and policy. To a certain extent, the above research objectively reflects the energy development level of the region, but for measuring the development level, the traditional hypothesis model does not have a high degree of direction identification of variables, and the measurement results are often difficult to be convincing (Lu et al., 2019); at the same time, the scientificity and operability of the measurement index of regional energy development level and the weight determination method also need to be further improved (Wang and Chen, 2012). Therefore, the evaluation system of regional energy development level includes three aspects: renewable energy, non-renewable energy, and economic development (Wang, 2008); the structural equation model is selected as a quantitative analysis method, because it contains both explicit and latent variables, which can more comprehensively analyze the influence path and effect between variables. It is an important supplement to the traditional quantitative analysis method that cannot analyze the influence effect of potential factors in the evaluation system.

Renewable energy has strong technological dependence, high initial cost, dense industrial agglomeration, and high adaptability to regional environmental resources (Dranka et al., 2020; Khan et al., 2020). The regional economic growth might be inhibited if the regional energy structure is not properly allocated, the proportion of renewable energy structure is too large, and the fossil fuel energy utilization is inefficient (Ji and Zhang, 2019. For example, Ocal and Aslan (2013) thinks that, compared with the traditional fossil fuel energy system, the renewable energy development currently does not have either technological or cost advantages. Ocal's paper also uses the autoregressive lag model for analysis and concludes that for every 1% increase in renewable energy development, the regional GDP decreases by 0.3%. Qi and Li (2018) believes that the energy transformation is economically costly and the technology advantage of renewable energy is not great enough to recover the cost of energy transformation. In China, the internal motivation of energy development is the subsidy policy, and excessive renewable energy subsidies limit economic growth. Dong et al. (2020) clams that if we want to maintain a high economic growth rate, it may inhibit the utilization rate of renewable energy. The above research demonstrates that the unreasonable energy structure inhibits the high-quality development of regional economy, which is mainly caused by the improper allocation of renewable energy. However, there are still two limitations in the current research on how to improve the regional energy structure: first, based on the static theory, the weights of renewable energy and non-renewable energy are consistent, ignoring the environmental compensation benefits of renewable energy (Wang et al., 2020); second, the optimal proportion of energy structure is deduced without considering the regional environmental resource endowment (Yan et al., 2018; Zhang, 2019). In order to solve the above problems, this paper puts forward the hypothesis: moderately increasing the proportion of renewable energy can promote the overall level of regional energy development and can be conducive to high-quality economic development. On this basis, two factors of technology and environment are selected to calculate the environmental endowment index of regional energy development, which is used as the weight to estimate the optimal energy structure of the region, and to explore the gap between the proportion of regional renewable energy and the optimal energy structure.

From the existing literature, due to the different understanding of the energy development path, the selected evaluation index, the measurement method, and the constructed evaluation system are different, so the research conclusions are often inconsistent. Meanwhile, the scientificity and operability of the measurement index of regional energy development level and the weight determination method also need to be further improved; some literatures only measure the structure proportion or economic benefit of renewable energy, which lacks systematic analysis on the impact path and effect of regional energy development. This paper uses the global ML production function to measure the environmental endowment index of China's regional energy development. On this basis, the structural equation model is used to measure and evaluate the degree of regional energy development in China. Combining the regional energy development environmental endowment index, this paper analyses the gap between the proportion of regional renewable energy and the optimal energy structure and then explores the supporting role of different energy development levels on high-quality economic development, so as to provide reference for local governments to adjust the energy structure and improve relevant policies and measures.

MODEL SPECIFICATION

Energy Development Environmental Endowment Index (GML)

Global Malmquist-Luenberger (GML) Production Function Based on SBM Model Framework

The traditional productivity index method primarily has four weaknesses: (1) There is no transitivity in the geometric form. (2) If the research objects are samples from different periods, there may be no solution to the linear solution in the calculation process. (3) In the process of factor decomposition, there might be too large or too small factors. (4) There are two kinds of problems: laxity and radiality. Radiality refers to the idea that the traditional radial DEA model framework may overestimate the efficiency of the research object when the input and output are scaled up or down in equal proportion (Kim et al., 2019). In order to solve these problems and reduce measurement errors, this paper firstly uses the global ML production function to measure the environmental endowment of regional energy development in China (Liu et al., 2019). Compared with the traditional production function, the technology set of global ML production function includes the observation samples of the whole period, which avoids the situation that linear programming has no feasible solution. At the same time, its non-circular geometric form also solves the transitive problem of the traditional production function. Secondly, the SBM model is selected as the framework. The advantage of the SBM model is that it is non-radial considering the influence of non-balance variables. It can reduce the impact of non-pure efficiency of energy development by finding the minimum ratio to reach the optimal efficiency frontier and can distinguish the scale effectiveness. Compared with other analysis models, the SBM model is better to evaluate the reasonableness of resource allocation. The above model calculation formulas are expressed as follows:

$$D^G x, y, b; g_y, g_b) = \max\left\{\beta \left| (y + \beta g_y, b - \beta g_b) \in P^G(x) \right.\right\} \quad (1)$$

$$GML^{t,t+1} x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D^G x^t, y^t, b^t)}{1 + D^G x^{t+1}, y^{t+1}, b^{t+1})} \quad (2)$$

$$GML^{t,t+1} x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = EC^{t,t+1} \times BPC^{t,t+1} \quad (3)$$

In Eq. 1, $P^G(x) = P^1 \cup P^2 \cup \ldots \cup P^t$. T represents the reference yield set in cycle t. P^G encloses all P^t by constructing a single PPS through panel data on the input and output of all relevant DMU. Therefore, P^G is called the global technology set. In Eq. 2, $D^G x^t, y^t, b^t)$ represents $D^G x, y, b; g_y, g_b)$, which is the DDF defined on the global technology set P^G . If $GML^{t,t+1}$ of the DMU is greater than 1, the production activities of this DMU will increase the expected output and reduce the undesired output. Similarly, if $GML^{t,t+1}$ of the DMU is less than 1, the production activities of the DMU will reduce the required output. Equation 3 represents the factor decomposition part, and $EC^{t,t+1}$ is the efficiency change item, which is used to measure the technological change of the DMU in the t and $t+1$ period; $BPC^{t,t+1}$ is the best practice gap by measuring the gap between the technological frontier in the same period and the global technological frontier and estimates whether the technological frontier in the same period is closer to the whole technological frontier.

Variable Selection

With reference to Zhang's (2014) practice of building total factor productivity of new energy consumption, hydroelectric power generation (I_1), wind power generation (I_2), solar power generation (I_3), and thermal power generation (I_4) are selected as input indicators; electricity consumption (Q_1) is regarded as expected output; and carbon dioxide (CO_2), sulfur dioxide (SO_2), and chemical oxygen demand

($_{COD}$) emissions are regarded as non-expected output to build energy development environmental endowment index. According to the carbon emission accounting method of IPCC 2006 Guidelines for National Greenhouse Gas Inventory, the formula of carbon dioxide emission is as follows: $CO_2 = \sum_{i=3}^{3} E_i \times NCV_i \times CEF_i \times COF_i \times 44/12$, where i represents kerosene, oil, and natural gas; E represents the above energy consumption; NCV represents the low calorific value of the three energy sources; CEF represents the carbon emission coefficient; COF represents the carbon oxidation factor, among which, the factor coefficients of coal, oil, and natural gas are 0.99, 1.44, and 12, respectively; and 44/12 is the molecular weight ratio of carbon dioxide and carbon element.

Regional Energy Development Level

Overview of Structural Equation Model

The structural equation model uses generalized linear equation to represent the causal relationship between latent variables and explicit variables. The explicit variables can also be called measurable variables, which often represent the objective and essential factors of the analysis object. The latent variables are also called unmeasured variables. Because there are many existing indicators in real life that cannot be quantified, the introduction of the latent variables is necessary to specify the immeasurable index variables and to represent the potential factors of the analysis object. This consists with the objectivity of the economic and social research and improves the accuracy and comprehensiveness of the actual analysis. The advantage of the structural equation model is that the model introduces the concepts of latent variables and explicit variables, which can analyze the immeasurable variable model and study the endogeneity between variables and possible path dependence. It is perfect for the regional energy development mode study, which is a multifaceted and complex industrial economic problem (Hong, 2019).

Variable Selection

Based on the energy system constructed by China's energy statistics department, on the premise that there is a clear causal relationship between renewable energy, non-renewable energy, and economic growth variables, *a priori* hypothesis is put forward according to the nature of various types of energy so as to establish a reasonable energy development model evaluation index system. **Table 1** shows the results.

Model Assumption

Variables are selected and assumed conditions are set according to the structural equation model:

(1) "Non-renewable energy," "renewable energy," and "regional economic growth" are latent variables of the structural equation model. Among them, "non-renewable energy" and "renewable energy" are the endogenous latent variables of energy development level. They influence each other and jointly affect "regional economic growth." Therefore, the latter is the exogenous latent variable of the structural equation model.

(2) The nine indicators, i.e., "raw coal production," "crude oil production," "natural gas production," "hydroelectric generation," "wind power generation," "solar power generation," "gross regional product," "per capita disposable income," and "per capita electricity consumption," are the observed variables of the structural equation model. Among them, "gross regional product," "per capita disposable income," and "per capita electricity consumption" are exogenous explicit variables that directly determine the level of regional economic development, while the other six observed variables are endogenous explicit variables of the structural equation, which indirectly affect regional economic growth.

Based on the above assumptions and evaluation factors, the following models are established to analyze China's energy development level:

$$x = \Lambda_x \xi + \delta \tag{4}$$

$$y = \Lambda_y \eta + \varepsilon \tag{5}$$

$$\eta = B\eta + \Gamma\xi + \zeta \tag{6}$$

Among them, Eq. 4 represents the measurement equation of the exogenous variables of the energy development level; x is the vector set consisting of the explicit variables of "gross regional product," "per capita disposable income," and "per capita electricity consumption"; ξ represents "regional economic growth" vector set; Λ_x represents the factor loading matrix of x on ξ; and δ is the error of the exogenous variable measurement

TABLE 1 | Evaluation index system of China's regional energy development level.

Indirect influence factor	Latent variables	The variable name	Observation variable	The variable name	Unit
	Non-renewable energy	Lv_1	Raw coal production	A_{11}	Ten thousand tons
			Crude oil production	A_{12}	Ten thousand tons
			Natural gas production	A_{13}	Ten million cubic meters
	Renewable energy	Lv_2	Hydroelectric power generation	A_{21}	Ten million kilowatt hours
			Wind power generation	A_{22}	Ten million kilowatt hours
			Solar power generation	A_{23}	Ten million kilowatt hours
Direct influence factor	Regional economic growth	Lv_3	Gross regional product	A_{31}	One hundred million yuan
			Per capita disposable income	A_{32}	Yuan
			Per capita electricity consumption	A_{33}	Kilowatt hour

equation. Similarly, Eq. 5 represents the measurement equation of endogenous variables. The letter y is the set of explicit variables composed of "raw coal production," "crude oil production," "natural gas production," "hydroelectric power generation," "wind power generation," and "solar power generation"; η is the latent variable set composed of endogenous variables of "non-renewable energy" and "renewable energy"; Λ_x represents the factor loading matrix of y on η ; and ε is the error of the endogenous variable measurement equation. The structural equation model assumes that there is a causal relationship between the endogenous latent variables and exogenous latent variables in the model. Therefore, Eq. 6 is a description of this relationship. According to the above conditions, η represents the endogenous latent variable, ξ represents the external latent variable, B represents the relationship matrix of the interaction between the endogenous latent variables η, Γ is the relationship matrix of the influence of the exogenous latent variable ξ on its endogenous latent variable η, and ζ represents the part that the equation cannot explain.

According to the needs of practical research, the evaluation results of the energy development model evaluation index system are different for different evaluation purposes. Therefore, the evaluation results of the energy development level in the empirical analysis vary according to the established index system. It is necessary to have different evaluation purposes and extract valuable information according to the actual needs. To this end, the energy development mode evaluation index system is divided into three groups according to different evaluation purposes, i.e., "the impact of non-renewable energy development on regional economic growth," "the impact of renewable energy development on regional economic growth," and "the impact of comprehensive energy development on regional economic growth." These purposes match the corresponding indicator of explicit and latent variables. **Table 2** shows the results.

EMPIRICAL ANALYSIS

Data Sources

Structural equation model is suitable for the analysis of cross-section data, so this paper takes the energy development of 31 provinces in China during 2016–2017 as the research sample. The data in this paper are from China Statistical Yearbook, China Energy Statistical Yearbook, China Industrial Statistical Yearbook, and annual report data of relevant provinces from 2017 to 2019. In order to eliminate the impact of price factors, all prices in this paper accounted for the constant price in 2011. Data processing was completed with the help of SPSS 20, Stata14.0 and DEAMAX.

Energy Development Environmental Endowment Index

The global ML production function is used to calculate and decompose the total factor productivity of energy, of which GML is the environmental endowment index of energy development. The results are shown in **Table 3** (the global ML production function is estimated in a backward period, so the calculation results in 2016 are not shown).

The following conclusions can be reached from **Table 3**:

(1) The environmental endowment index of energy development has two connotations: technology and environment. From the perspective of regional endowment indexes, the environmental endowment index of energy development in various regions in China is different, but the average index is below 1, indicating that the overall level of China's regional energy endowment has become worse, and energy development technology and environmental problems are becoming increasingly serious. In terms of the environment, the average value of CO_2 emissions decreased by 380.8 million tons, indicating that China's energy production and pollution treatment capacity have improved. However, from the perspective of regional CO_2 emissions, carbon emissions in Shanxi, Inner Mongolia, Shaanxi, and other provinces are still relatively large, the energy structure mainly using fossil fuels has not been improved, and regional energy development environmental problems are still serious. From the perspective of technology, China's energy technology level fluctuates, but the average level of technological progress is below 1, and the scale efficiency of technology is above 1, indicating that the technological frontier has decreased compared with the previous year. The general trend is technological regression, but the energy utilization efficiency has improved. Among them, Beijing, Shanghai, Zhejiang, Sichuan, Yunnan, Tibet, and other provinces made relatively large progress, indicating that these provinces had attached importance to the development of energy science and technology innovation and taken technological progress as the major driving force of energy structure transformation. Regional energy production has become increasingly environmentally friendly, with low consumption and high efficiency. Different from previous regions, provinces such as Tianjin, Hebei, Shanxi, Jiangsu, and Anhui had relatively low technological progress in

TABLE 2 | Evaluation objectives of energy development level.

Serial number	Evaluation purpose	Explicit variables	Latent variables
1	The impact of non-renewable energy development on regional economic growth	$A_{11}.A_{12}A_{13}A_{31}A_{32}A_{33}$	$Lv_1\ ._{Lv_3}$
2	The impact of renewable energy development on regional economic growth	$A_{21}.A_{22}A_{23}A_{31}A_{32}A_{33}$	$Lv_2\ ._{Lv_3}$
3	The impact of comprehensive energy development on regional economic growth	$A_{11}.A_{12}A_{13}A_{21}A_{22}A_{23}A_{31}A_{32}A_{33}$	$Lv_1\ ._{Lv_2}\ Lv_3$

TABLE 3 | China's regional renewable energy structure and energy development environmental endowment index in 2017.

Provinces	Hydroelectric generating	Wind power generation	Solar power generation	Proportion of renewable energy	Reduction of CO_2 emission	GML	EC	TC
Beijing	11.320	3.460	1.360	4.16	503.31	1.000	1.000	1.000
Tianjin	0.070	5.910	1.610	1.24	822.45	0.417	1.000	0.417
Hebei	18.640	257.540	56.220	11.80	1739.05	0.974	1.069	0.911
Shanxi	42.220	146.060	46.540	8.32	−15320.57	1.030	1.166	0.884
Inner Mongolia	19.990	551.430	114.190	15.46	−21742.87	1.991	1.000	1.991
Liaoning	34.530	143.500	6.170	10.07	1834.43	0.975	1.079	0.904
Ji Lin	67.090	87.640	1.860	19.57	1218.73	0.864	0.959	0.901
Heilongjiang	18.620	90.700	1.220	12.05	26.60	0.718	0.829	0.866
Shanghai	0.000	16.640	0.620	2.01	12.11	1.000	1.000	1.000
Jiangsu	29.020	116.650	61.940	4.22	306.25	1.017	1.259	0.808
Zhejiang	198.730	23.590	23.520	7.42	27.67	1.984	1.000	1.984
Anhui	52.970	39.740	45.250	5.62	1890.22	0.964	1.202	0.802
Fujian	454.610	62.400	2.380	23.60	923.36	0.967	1.009	0.958
Jiangxi	144.170	29.840	15.390	16.78	2243.52	0.979	0.884	1.108
Shandong	6.260	166.080	73.600	4.76	−919.80	1.140	0.980	1.163
Henan	102.320	33.290	26.910	5.93	899.29	0.813	0.817	0.994
Hubei	1499.390	52.180	11.540	59.77	1025.74	1.113	1.152	0.966
Hunan	597.370	45.240	4.730	45.11	−4495.41	0.396	0.389	1.018
Guangdong	307.650	55.070	10.550	8.29	7545.18	0.908	1.143	0.795
Guangxi	629.340	24.290	2.690	46.85	54.48	0.297	0.321	0.927
Hainan	20.810	5.470	3.010	9.80	167.04	1.261	1.422	0.887
Chongqing	250.990	6.000	0.550	35.38	4071.65	0.535	1.000	0.535
Sichuan	3041.200	37.800	16.920	88.96	2399.52	1.000	1.000	1.000
Guizhou	699.910	60.150	4.610	40.27	1807.25	0.758	0.787	0.963
Yunnan	2493.430	194.400	27.580	91.89	−320.69	1.317	1.000	1.317
Tibet	48.290	0.000	4.490	94.25	0.97	1.000	1.000	1.000
Shaanxi	142.130	50.860	34.250	12.53	−20359.67	0.901	0.866	1.040
Gansu	374.150	187.600	73.480	47.09	1813.58	1.086	0.921	1.178
Qinghai	334.220	18.610	112.570	74.23	−375.31	1.000	1.000	1.000
Ningxia	15.450	149.320	71.790	17.13	−2055.76	0.964	1.034	0.932
Xinjiang	243.500	288.760	109.640	21.32	−7043.37	0.779	0.672	1.160
Mean	383.819	95.168	31.199	27.29	38077.77	0.973	0.967	1.013

2016–2017, with their level of technological progress below 1, manifesting as technological retrogression. Taking into account the distribution characteristics of regional environmental resources, most of the retrogressing provinces are located in Central China, having rich coal resources and using fossil fuel energy as the major energy production mode. They still lag on the energy structure transformation and the technology-driven transformation and the energy structure needs to be improved urgently.

(2) From the perspective of the main types of renewable energy in various regions of China, hydroelectric power generation is in the leading position, with an average power generation of 3.8382 billion kWh in 2017, mainly consumed by Hubei, Sichuan, Yunnan, and some other provinces. Solar power generation is at the end of renewal energy structure, with an average power generation of 312 million kWh in 2017, which is mainly consumed by Inner Mongolia, Qinghai, Xinjiang, and some other provinces. Wind power generation is at the middle position, with an average power generation of 951.7 million kWh in 2017 and Hebei, Inner Mongolia, Gansu, Xinjiang, and some other provinces as the major consumers. From the perspective of the proportion of renewable energy in various regions of China, the average proportion of China's renewable energy power generation in 2017 reached 27.29%, and renewable energy consumption accounted for 11.7%, which is higher than the global average level of renewable energy development. Tibet is the province with the largest proportion of renewable energy, accounting for 94.25%. Hubei, Sichuan, Yunnan, and Qinghai also have comparatively large proportion of renewable energy, indicating that these provinces have obvious energy structure transformation and are able to rationally use regional resources. For example, there is the Three Gorges Dam water conservancy project in Hubei Province, the Xiluodu Hydropower Station in Yunnan Province, and the Longyangxia

Hydro-Photovoltaic Complementary Photovoltaic Power Station in Qinghai Province. These provinces are mostly located in western China. The exploitation of fossil fuel energy in these regions is poor, yet the utilization rate of water power, wind power, and solar energy is relatively high.

Comprehensive Evaluation of Regional Energy Development Mode

The Impact of Non-renewable Energy Development on Regional Economic Growth

Based on the above indicator system and model assumptions, the authors standardize the original data and construct the structural equation model of the impact of non-renewable energy development on regional economic growth by using structural equation method and Amos 24 software. The results can be found in **Figure 1**.

Figure 1 shows that the standardized path coefficient of non-renewable energy development affecting economic growth is 0.21, the impact is significant, and the direction is positive. This conforms to the assumption of structural equation model (1), which is to say that non-renewable energy development is one of the influencing factors of regional economic growth. The path coefficients of raw coal production, crude oil production, and natural gas production that affect the development of non-renewable energy are 0.51, 0.54, and 0.36, respectively, and the degree of impact is significant, which conforms to the assumption of the structural equation model (2). **Table 4** shows the parameter estimation of the structural equation of the impact of non-renewable energy development on regional economic growth.

Table 4 shows that the model fits well, the variables and their correlations can be explained reasonably, and the settings of exogenous and endogenous variables are reasonable. The estimated value of the regression coefficient for non-renewable energy standardized development is 0.283, which indicates that the development and use of fossil fuel energy destroys the natural environment, but it is still a promoting factor of regional economic growth.

The Impact of Renewable Energy Development on Regional Economic Growth

Figure 2 is the structural equation model of the impact of renewable energy development on regional economic growth we construct.

Figure 2 shows that the standardized path coefficient of renewable energy development affecting economic growth is 0.11, the impact is significant, and the direction is positive, which conforms to the assumption of structural equation model (1). It means that renewable energy development is one of the influencing factors of regional economic growth. The path coefficients of hydroelectric power generation, wind power generation, and solar power generation affecting the development of renewable energy are 0.49, 0.71, and 0.70, respectively, which are significant and conform to the assumption condition of structural equation model (2). **Table 5** shows the parameter estimates of the structural equation of the impact of renewable energy development on regional economic growth.

Table 5 shows that the model fits well, all variables and their related relationships can be reasonably explained, and the settings of exogenous and endogenous variables are reasonable. The estimated value of standardized regression coefficient of renewable energy development is 0.418, which indicates that renewable energy can effectively replace fossil fuel energy and is a driving factor for regional economic growth.

The Impact of Comprehensive Energy Development on Regional Economic Growth

Figure 3 is the structural equation model of the impact of comprehensive energy development on regional economic growth.

Figure 3 shows that the standardized path coefficient of non-renewable energy development affecting economic growth is 0.41, and the standardized path coefficient of renewable energy development affecting economic growth is 0.36. Both effects are significant and the direction is positive, which conforms to the assumption of structural equation model (1). This means that non-renewable energy and renewable energy development are both influencing factors of regional economic growth. The path coefficients of each explicit variable are relatively large, indicating that the influence of each component is significant, which conforms to the assumption condition of structural equation model (2). **Table 6** shows the parameter estimates of the structural equation of the impact of comprehensive energy development on regional economic growth.

Table 6 shows that the model fits well, the variables and their correlations can be explained reasonably, and the settings of exogenous and endogenous variables are reasonable. The estimated value of the standardized regression coefficient for non-renewable energy development is 0.263, and the estimated value of the standardized regression coefficient for renewable energy development is 0.431, indicating that the development of renewable energy has a greater impact on economic growth. At the same time, the development of non-renewable energy and renewable energy influences each other, and the estimated value of the standardized regression coefficient is 0.177. This proves that renewable energy can effectively replace the fossil fuel energy. Although the initial cost of renewable energy development is relatively high, the research results show that the development of renewable energy is better for regional economic growth. From the perspective of long-term energy development, China should try to accelerate its regional energy structure transformation with renewable energy centered.

Comprehensive Score of Regional Energy Development Mode

According to the fitting results of the structural equation model, the mode of China's regional energy development is modeled as follows:

$$Lv(T_1) = w_{1i}\sum_{i=1}^{3} A_{1i}f_{1i} + w_{3i}\sum_{i=1}^{3} A_{3i}f_{3i} \tag{7}$$

TABLE 4 | Parameter estimation of the structural equation of the impact of non-renewable energy development on regional economic growth.

Explicit variables	The path	Latent variables	The estimate	Standard error	Critical ratio	Significant
Economic growth	←	Non-renewable energy	0.283	0.139	2.040	***
Gross regional product	←	Economic growth	1.000			
Per capita disposable income	←	Economic growth	0.609	0.203	3.004	***
Per capita electricity consumption	←	Economic growth	0.675	0.218	3.097	***
Raw coal production	←	Non-renewable energy	1.000			
Crude oil production	←	Non-renewable energy	0.776	0.240	3.231	***
Natural gas production	←	Non-renewable energy	0.660	0.213	3.100	***
Goodness of fit of model	Chi-square = 10.135		*P* = 0.000			

*"***" indicates that the significance is less than 0.01, and the fitting effect is quite good.*
"←" means the path points between variables.
"Chi-square" indicates chi-square statistic. Under the premise of significance, the smaller, the better.

$$Lv(T_2) = w_{2i}\sum_{i=1}^{3} A_{2i}f_{2i} + w_{3i}\sum_{i=1}^{3} A_{3i}f_{3i} \tag{8}$$

$$Lv(T_3) = w_{1i}\sum_{i=1}^{3} A_{1i}f_{1i} + w_{2i}\sum_{i=1}^{3} A_{2i}f_{2i} + w_{3i}\sum_{i=1}^{3} A_{3i}f_{3i} \tag{9}$$

The above equations are the regional energy development mode evaluation model corresponding to each group of evaluation purposes. $f_{ji}(i = 1, 2, 3; j = 1, 2, 3)$ is the weight coefficient of each explicit variable, and $w_{ji}(i = 1, 2, 3; j = 1, 2, 3)$ is the weight coefficient of each latent variable.

According to the fitting results of the structural equation model and the evaluation purpose of the energy development mode, we standardize the data. In order to have the evaluation standard of energy development level, nine components, i.e., "raw coal production," "crude oil production," "natural gas production," "hydroelectric power generation," "wind power generation," "solar power generation," "gross regional product," "per capita disposable income," and "per capita electricity consumption," are adopted to represent high, medium, and low level of energy development:

High–Medium: (−0.3, −0.5, −0.4, −0.3, −0.3, −0.1, 0.0, −0.3, 0.0)

Medium–Low: (−0.5, −0.6, −0.4, −0.5, −0.7, −0.8, −0.7, −0.6, −0.8)

The score of 0.0 is the intermediate degree, the positive direction is the higher degree, and the negative direction is the lower degree.

According to the structural equation evaluation model and the normalized results of the weights of each group of variables, the scores of regional non-renewable energy development, renewable energy development, and comprehensive energy development on economic growth are calculated. The three scoring results are then averaged to obtain the final score results and the comprehensive ranking of China's regional energy development level. According to the results of regional non-renewable energy impact score and renewable energy score, the proportion

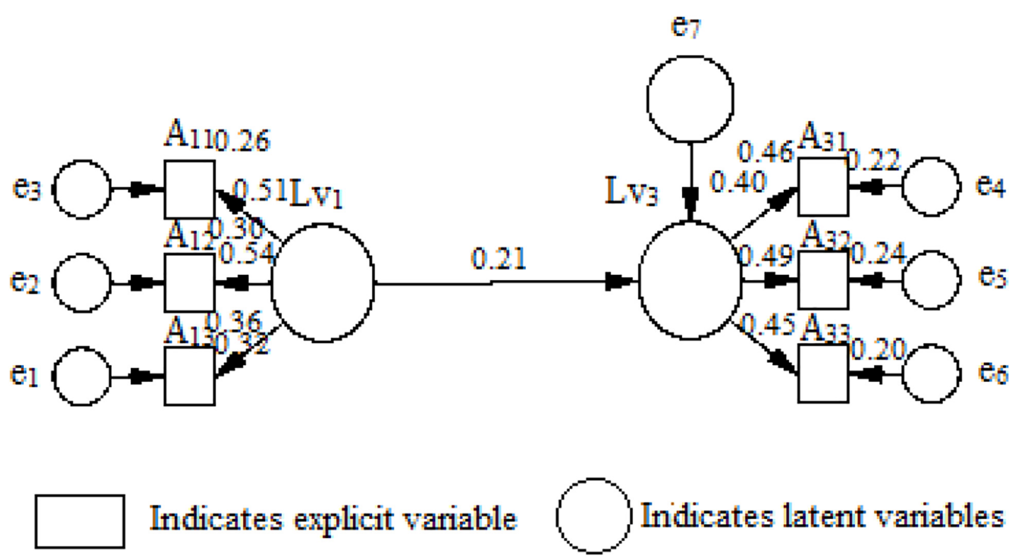

FIGURE 1 | Structural equation model of the impact of non-renewable energy development on regional economic growth.

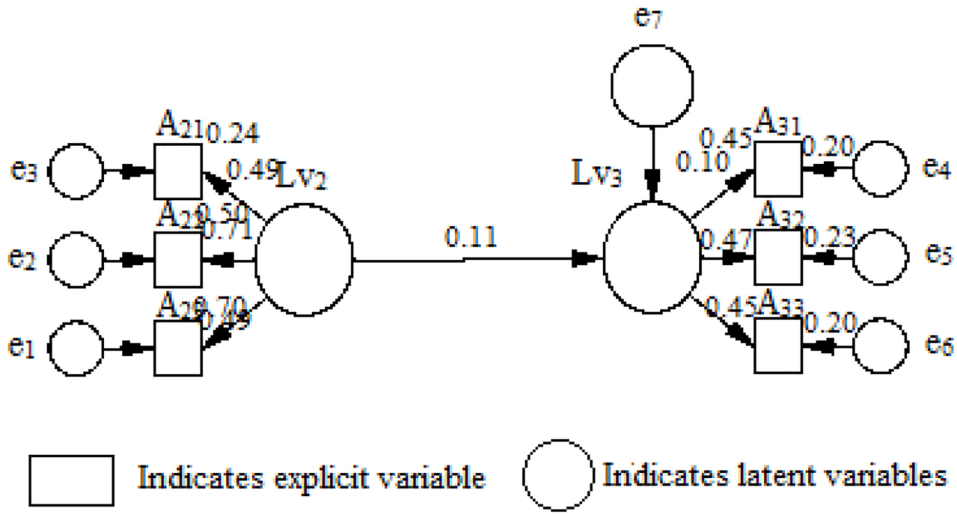

FIGURE 2 | Structural equation model of the impact of renewable energy development on regional economic growth.

of regional renewable energy is calculated with the regional energy environment endowment index as the weight. Finally, according to the evaluation criteria of structural equation of energy development level and the weight coefficient of each group, the definition standard of higher energy development level to medium energy development level is 0.00, and the definition standard of medium energy development level to low energy development level is −0.10. The energy development level accordingly is further grouped, and the results are shown in **Table 7**.

Table 7 tells us that among the 13 provinces with high degree of regional energy development in China, only Sichuan, Qinghai, and Yunnan provinces have achieved the expected proportion of renewable energy development, indicating that the energy development mode of provinces such as Inner Mongolia, Xinjiang, Shanxi, and Shandong is still dominated by fossil fuel energy and their proportion of economic growth driven by renewable energy is relatively low. Among the six provinces with low energy development, Chongqing, Guangxi, and Tibet have higher utilization rate of renewable energy, indicating that there is redundancy in the technical elements of renewable energy development in some regions of China, and the development of renewable energy restricts the growth of regional economy. Therefore, local governments in these provinces should strengthen the import and use of fossil fuel energy.

Distribution Characteristics of China's Regional Energy Development Level

According to the comprehensive score of China's energy development level and the results of energy development degree, a vector diagram is made for the distribution of China's regional energy development level. The results can be found in **Figure 4**.

Figure 4 shows that regions with a high degree of energy development are mostly located in western China. Firstly, northwestern China has a vast land area, low population density, sufficient sunshine, and photovoltaic conditions, which are more suitable for the development of large-scale wind and solar renewable energy industries. Also, the coal resources in these regions are relatively rich and are, therefore, the main source of China's energy output. Secondly, southwestern China is located in the upper and middle reaches of the Yangtze river and Yellow river. It is rich in freshwater resources and has a big drop between different rivers, which is suitable for the development of large-scale hydropower projects. Regions with low energy development are mostly located in central China. On the one hand, the population of central China is comparatively dense, and its sunlight, wind energy, and river resources have no significant advantages. It is therefore difficult for central China to form a large-scale renewable energy industry. The energy-driven economic growth mode mainly relies on the fossil fuel energy. On the other hand, the economic foundation of the central region is relatively weak, the investment in renewable energy development technology is comparatively insufficient, the transformation of the energy structure is difficult, and the energy development does not play an important role in economic growth.

CONCLUSION AND SUGGESTIONS

Conclusions

The problem of unbalanced energy development in China still exists. How to adjust the energy structure is the key to high-quality economic development in China. The main tasks of this study are as follows: one is to evaluate the level of China's regional energy development, and the other is to explore how to adjust the energy structure to promote high-quality economic development. In this paper, the abovementioned two problems have been studied in depth. Taking China's regional energy development level from 2016 to 2017 as the research object, the environmental endowment index of China's regional

TABLE 5 | Parameter estimation of structural equation of the impact of renewable energy development on regional economic growth.

Explicit variables	The path	Latent variables	The estimate	Standard error	Critical ratio	Significant
Economic growth	←	Renewable energy	0.418	0.160	2.608	***
Gross regional Product	←	Economic growth	1.000			
Per capita disposable income	←	Economic growth	0.414	0.164	2.676	***
Per capita electricity consumption	←	Economic growth	0.675	0.159	2.600	***
Hydroelectric generating capacity	←	Renewable energy	1.000			
Wind power generation	←	Renewable energy	0.793	0.244	3.248	***
Solar power generation	←	Renewable energy	0.699	0.222	3.151	***
Goodness of fit of model	Chi-square = 54.981		P = 0.000			

*"***" indicates that the significance is less than 0.01, and the fitting effect is quite good.*
"←" means the path points between variables.
"Chi-square" indicates chi-square statistic. Under the premise of significance, the smaller, the better.

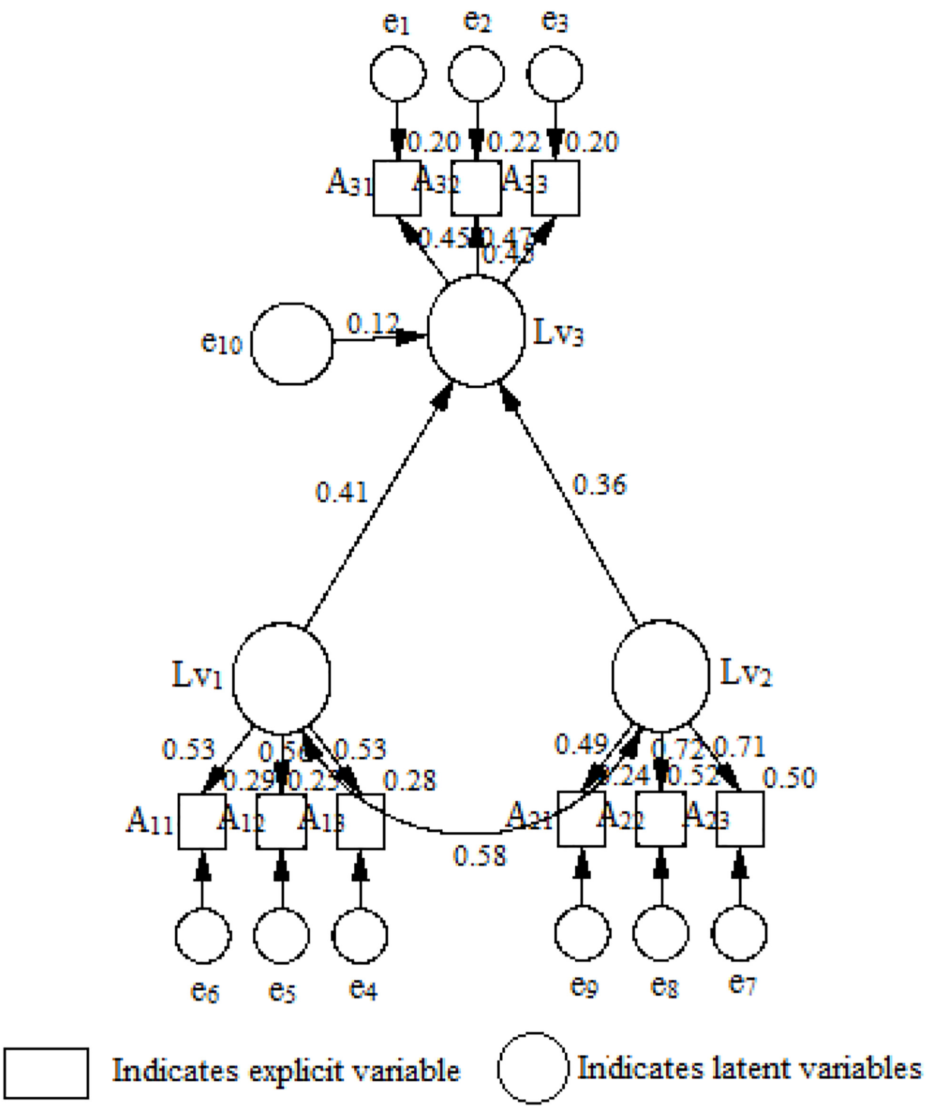

FIGURE 3 | Structural equation model of the impact of comprehensive energy development on regional economic growth.

TABLE 6 | The parameter estimates of the structural equation of the impact of comprehensive energy development on regional economic growth.

Explicit variables	The path	Latent variables	The estimate	Standard error	Critical ratio	Significant
Economic growth	←	Non-renewable energy	0. 263	0.136	1.940	***
Economic growth	←	Renewable energy	0.431	0.162	2.656	***
Renewable energy	↔	Non-renewable energy	0.177	0.131	1.350	***
Gross regional product	←	Economic growth	1.000			
Per capita disposable income	←	Economic growth	0.797	0.244	3.263	***
Per capita electricity consumption	←	Economic growth	0.804	0.246	3.269	***
Raw coal production	←	Non-renewable energy	1.000			
Crude oil production	←	Non-renewable energy	0.684	0.214	3.188	***
Natural gas production	←	Non-renewable energy	0.784	0.239	3.287	***
Hydroelectric power generating	←	Renewable energy	1.000			
Wind power generation	←	Renewable energy	0.424	0.156	2.717	***
Solar power generation	←	Renewable energy	0.403	0.152	2.652	***
Goodness of fit of model	Chi-square = 85.082		*P* = 0.000			

*"***" indicates that the significance is less than 0.01, and the fitting effect is quite good.*
"←" means the path points between variables.
"Chi-square" indicates chi-square statistic. Under the premise of significance, the smaller, the better.

TABLE 7 | Comprehensive score and development level of China's energy development level.

Provinces	Non-renewable energy impact score	Renewable energy impact score	Composite impact score	The average score	Ranking	Development degree	The proportion of renewable energy	The actual proportion of renewable energy
Inner Mongolia	0.81	1.57	1.21	3.59	1	High degree	42.67	15.46
Xinjiang	1.07	0.98	1.24	3.29	2	High degree	40.43	21.32
Shanxi	1.92	−0.15	1.30	3.07	3	High degree	21.77	12.53
Shandong	0.54	0.39	0.49	1.42	4	High degree	41.11	4.76
Shanxi	0.69	0.13	0.49	1.31	5	High degree	38.28	8.32
Sichuan	0.26	0.43	0.51	1.20	6	High degree	45.66	88.96
Heilongjiang	0.55	−0.34	0.18	0.40	7	High degree	21.06	12.05
Hebei	−0.18	0.46	0.08	0.36	8	High degree	59.30	11.8
Qinghai	−0.19	0.40	0.08	0.29	9	High degree	55.17	74.23
Yunnan	−0.47	0.72	0.02	0.27	10	High degree	60.00	91.89
Jiangsu	−0.03	0.22	0.05	0.24	11	High degree	45.83	4.22
Tianjin	0.57	−0.51	0.10	0.17	12	High degree	14.93	1.24
Ningxia	−0.19	0.34	0.02	0.16	13	High degree	54.12	17.13
Gansu	−0.49	0.49	−0.09	−0.09	14	Medium degree	66.77	47.09
Guangdong	0.06	−0.22	−0.06	−0.23	15	Medium degree	31.02	8.29
Liaoning	−0.06	−0.16	−0.13	−0.35	16	Medium degree	34.91	10.07
Hunan	−0.05	−0.26	−0.17	−0.48	17	Medium degree	30.14	45.11
Zhejiang	−0.13	−0.23	−0.22	−0.58	18	Medium degree	34.65	7.42
Hubei	−0.41	0.04	−0.26	−0.63	19	Medium degree	52.89	59.77
Henan	−0.20	−0.25	−0.26	−0.71	20	Medium degree	36.33	5.93
Anhui	−0.33	−0.12	−0.28	−0.73	21	Medium degree	39.67	5.62
Shanghai	−0.09	−0.46	−0.31	−0.86	22	Medium degree	25.63	2.01
Guizhou	−0.34	−0.21	−0.32	−0.88	23	Medium degree	45.08	40.27
Beijing	−0.11	−0.49	−0.32	−0.92	24	Medium degree	21.45	4.16
Fujian	−0.33	−0.26	−0.35	−0.93	25	Medium degree	41.59	23.6
Ji Lin	−0.35	−0.33	−0.38	−1.06	26	Low degree	35.48	19.57
Chongqing	−0.35	−0.47	−0.42	−1.25	27	Low degree	30.03	35.38
Guangxi	−0.50	−0.32	−0.48	−1.30	28	Low degree	44.70	46.85
Jiangxi	−0.49	−0.34	−0.48	−1.31	29	Low degree	45.83	16.78
Hainan	−0.53	−0.52	−0.59	−1.64	30	Low degree	39.06	9.8
Tibet	−0.64	−0.53	−0.65	−1.82	31	Low degree	42.56	94.25

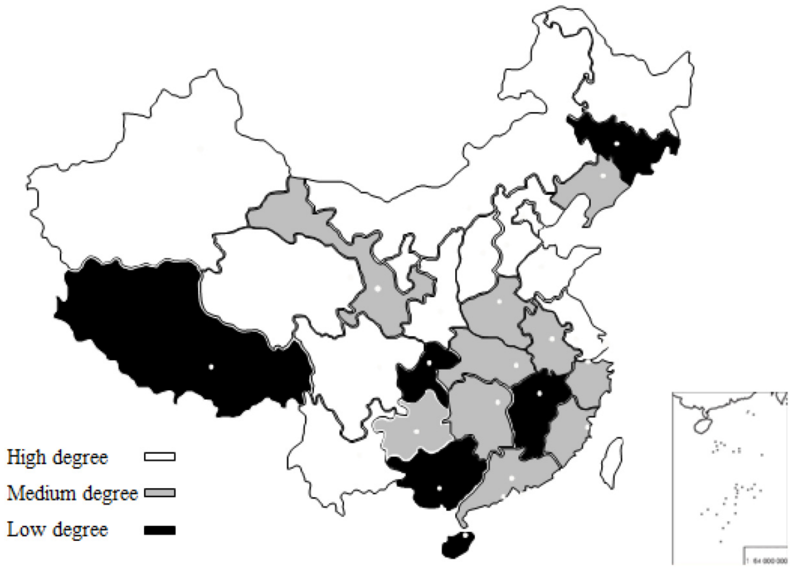

FIGURE 4 | Distribution diagram of China's regional energy development level.

energy development has been measured by using the global ML production function from the aspects of environmental and technological factors. Combined with the environmental endowment index of regional energy development, the gap between the proportion of regional renewable energy and the optimal energy structure is analyzed. Then, this paper explores the supporting effect of different energy development levels on high-quality economic development. It is concluded that the environmental endowment index of energy development varies among different regions in China, most of which are still underdeveloped, but a few of which have redundant technical elements of renewable energy development. China's regional energy development model is still dominated by fossil fuel energy, and the proportion of renewable energy driving economic growth is relatively low. Renewable energy can effectively replace the use of fossil fuel energy and have a higher impact on high-quality economic development.

Suggestions

Based on the above study conclusions, the following policy suggestions are proposed:

(1) Reasonable determination of the renewable energy development goals. The government needs to have an overall consideration of the production costs of the energy system and reasonably determines the proportion of various renewable energy resources. It is suggested to consider the energy structure of renewable resources from the perspective of energy structure and regional environmental resources. For example, the consumption space of the regional energy system should be fully considered to improve the efficiency of renewable energy. The mixed energy supply mode is recommended for densely populated areas, and the self-supplied energy mode is recommended for areas with low population density. In addition, it is suggested that the national energy development goals should be implemented by relevant parties and various regions with specific responsibilities to achieve the best results.

(2) Appropriate Adjustment of the regional energy production factors structure. The result of the factor production research shows that the renewable energy production factors in western China are excessive, while the factors in the central area are insufficient. To solve the imbalance problem of the regional-production-factor allocation, it is necessary to reduce the proportion of renewable energy development in the western region, while increasing the proportion of fossil fuel energy, so as to enhance the efficiency of regional energy and to avoid unnecessary energy waste. At the same time, it is necessary for the government to give policy and technical support on renewable energy in the central region, so as to increase the efficiency of renewable energy and to promote the coordination between economy and ecology.

(3) The enhancement of the energy market circulation. Promoting the renewable energy development is primarily for solving the problems of regional cooperation and market mechanism. From the perspective of regional energy development, the imbalance of regional production capacity can be solved through various measures, such as tapping active resources of electricity load, improving the flexibility of interprovincial energy trade and energy transmission, reducing interprovincial trade barriers, and incorporating energy forecasting systems, so as to gradually establish a regional energy market mechanism.

(4) The importance of the integration of energy development. It is suggested that the government systematically deals with the structural imbalance issue, avoids fragmentation

and contradiction in regional regulation, makes good use of the complementarily between different regions and different energy types, and further improves the efficiency of regional energy development.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author/s.

AUTHOR CONTRIBUTIONS

All authors have significantly contributed to the manuscript. WL was the leader of the research group that conceived and designed the study. YH completed the model design and simulation analysis. WF and CC were responsible for data collection and the writing of part I and part II.

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SUPPLEMENTARY MATERIAL

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frontiers in Energy Research

ORIGINAL RESEARCH
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Efficiency Power Plant Implementation Decision-Making Based on the Profit Function and Its Numerical Simulation

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The efficiency power plant (EPP) is a kind of virtual power plant with zero emission, zero pollution, and low cost and exhibits a high-quality low-carbon production behavior in input-output analysis. In the process of implementing EPP, enterprises not only save electricity but also reduce carbon emissions, while increasing the cost of R&D and equipment. Therefore, it is very necessary to study relationships between carbon quota and EPP implementation decision. In this paper, we build the profit functions of three different types of enterprises implementing EPP and analyze the relationship of main parameters, such as the probability of implementing EPP, electricity saving, income, cost, and carbon quota, and obtain nine relative results. Then, we use 'Maple' software to simulate the results by drawing images of parameters, and all the above nine results passed the simulation test verification. At last, we collect the actual survey data and use VC++ programming to carry out an empirical study in China to prove the practicability of the model and the results. The results show that, under the carbon quota trading system, enterprises should tend to implement EPPs and increase investment in R&D and acquisition of EPPs and are needed to adjust the intensity of implementing EPPs according to the change of carbon quota and unit carbon quota income, to obtain higher income.

Keywords: efficiency power plants, implementation decision, carbon quota, relationship analysis, maple

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INTRODUCTION

Background

Electricity demand side management (DSM) is to let enterprises and users manage their own enterprise electricity situation through the construction of electricity fine management platform. Efficiency power plant (EPP) is a representative DSM energy efficiency resource project. EPP can be considered as a collection of some DSM energy efficiency resource projects with better combination. EPPs use high-efficiency electrical equipment and products, based on the energy-saving transformation plan of an industry or a regional enterprise, to form a regional electricity utilization efficiency optimization in different ways, which has the same important significance with the construction of a new power plant.

Over the past 10 years, the development of DSM has achieved abundant energy conservation and emission reduction effects and formed a certain scale. For example, the State Grid Energy Research Institute of China counts that the generation capacity of the DSM project is 640.7 billion kWh in China from 2011 to 2015 and estimates that the same in 2016–2020 is 1.3254 trillion kWh. It can reach 1.9661 trillion kWh during the period of 2010–2020, equivalent to a reduction of 22,598 kWh in generation capacity, and nearly 57 billion USD in investment compared with the conventional power plants (Energy Research Institute of State Grid of China, 2010).

The China government has introduced a carbon quota management system (Chang et al., 2020), which has a significant impact on the implementation of EPP. Under the carbon quota system, enterprises must control the greenhouse gas emissions, mainly carbon dioxide (CO_2). The implementation of EPP cannot only reduce power consumption but also reduce carbon emissions, which, to some extent improves the willingness of enterprises to implement EPP (Li et al., 2016). Moreover, as the EPP grew in size, massive fiscal and tax subsidies became unsustainable, and carbon quotas became the government's main means of controlling carbon emissions.

In this paper, on the basis of predecessors' research summarized, we further combine government carbon quota with EPP, through the establishment of EPP implementation decision model based on the profit function, analyze the decisions of enterprises under different carbon quota, and verify the correctness and rationality of the results through system simulation. We hope this article could provide a reference for enterprises to make correct decisions under different carbon quota and different technology maturity when implementing EPPs.

Literature Review

EPP and DSM are hot topics in energy management, as they grew in size; they encountered economic, technological, and managerial problems in the development process (Haydt et al., 2014). Thus, most scholars prefer to focus on the three aspects of EPPs, such as in the economic field, such as billing (Çakmak and Altaş, 2020), pricing (Venizelou et al., 2020), and cost-benefit analysis (Wang and Zhu, 2014); in the field of mathematics, such as scheduling (Chamandoust et al., 2020) and planning (Zhu et al., 2017) and energy efficiency (Wang et al., 2015; Wang et al., 2016; Chakraborty et al., 2020); and in the field of technology, such as renewable energy (Kalair et al., 2020), smart distribution system (Reddy et al., 2020), and others (Mendes et al., 2020).

Among the field of energy management, the game analysis of low-carbon investment behavior is meaningful and necessary. Rai and Beck (2017) stated the importance of using behavioral science to address the persistent gaps between the technical potential of low-carbon technologies and the actual adoption of these technologies. The game analysis in low-carbon environment is derived from the low-carbon supply chain research. Du et al. (2015) conducted a game-theoretical analysis and gave low-carbon supply policies for supply chain management (Du et al., 2017). Chen et al. (2014) investigated a practical demand side management scenario where the selfish consumers compete to minimize their individual energy cost through scheduling their future energy consumption profiles using an aggregative game approach. Li et al. (2017) examined the influences of different game structures on the optimal decisions and performance of a low-carbon closed-loop supply chain (CLSC) with price and carbon emission level-dependent market demands. Then, the scholars put forward the game behavior of each participant in low-carbon investment. Du et al. (2013) considered the emission cap of emission-dependent manufacturer allocated by the government as a kind of environmental policy and formally investigated its influence on decision-making within the concerned emission-dependent supply chain and distribution fairness in social welfare. Luo et al. (2016) derived the optimal solutions for the two manufacturers in the purely competitive and co-opetitive market environments, respectively. Based on non-cooperative and cooperative games, Huang et al. (2018) proposed a hierarchical game playing scheme and a simplified multienergy system optimization method to assist stakeholders to participate in technoeconomic analysis process. Sun et al. (2020) constructed a Stackelberg differential game model (dominated by manufacturers) under both centralized and decentralized decisions considering the lag time of emission reduction technologies and the low-carbon preferences of consumers. Zhu et al. (2018) investigated how to optimize the strategy of low carbon investment for suppliers and manufacturers in supply chains and discussed the impacts of various factors on evolutionarily stable strategies. Arai et al. (2014) proposed a comprehensive framework for evaluating the performance of demand-side actors in a demand-side management system using each control scheme according to both communication availability and sampling frequency. Liu et al. (2017) proposed a scenario for DSM programs to schedule household energy consumption considering bidirectional energy trading of PEVs by a Bayesian game approach. Mahmoudi et al. (2019) evaluated the performance of Iranian thermal power plants combined with multivariate data analysis techniques, game theory, Shannon entropy, and the technique for the order of preference by similarity with ideal solution. Dou, 2015, established a dispatching optimization model of regional integrated power and gas energy system and analyzed the node energy price through the node energy balance equation and a demand response model based on evolutionary game.

Implementing EPP is a special low-carbon behavior, which can not only reduce carbon emission but also reduce electricity consumption. Therefore, the decision analysis of EPP needs to consider both low carbon and power-saving benefits. The author puts forward EPP implementation by government and enterprise, but it is far from enough (Zhu et al., 2019). Research on decision analysis among EPP enterprises is likewise important, but unfortunately, there is a lack of research on this aspect, especially about the EPP implementation decision with carbon quotas and carbon reduction benefits. Above all, the literature that analyzes the decision analysis among EPP enterprises urgently needs to be supplemented. Therefore, this study of relationship analysis for EPP implementation decision and carbon quota is innovative and of practical value.

THEORETICAL BASIS

Efficiency Power Plant

EPP is a packaged set of DSM items or collections. The brief summary is EPPs realize energy saving transformation of

TABLE 1 | Comparison of conventional power plants and efficiency power plants.

Parameter	Conventional power plants	Efficiency power plants
Capacity (10,000 kV)	30	30
Electricity produced/saved per year (one billion million kWh)	1.5	1.5
Fuel (standard coal) consumption (g/kWh)	340	0
CO_2 emission (g/kWh)	940	0
$SO_{2.}$ emission (g/kWh)	4	0
Average power generation and supply cost (dollar/kWh)	2.2–2.8	1

energy-consuming equipment, and the energy saved is equivalent to the electricity generated by conventional coal-fired power plants (Zhu et al., 2017). Compared with conventional power plants, which are power plant entities, EPPs are designed to save electricity, not produce electricity, and save as much electricity as they produce. Although an EPP is not a real power plant, compared with power generation resources, it has the same importance in the optimal allocation of regional power supply and demand resources. It is an effective and convenient way to realize energy conservation and emission reduction and control power consumption (Maria et al., 2020). EPPs have many advantages, such as zero emission, zero pollution, low cost, non-land occupation construction cost, and operation benefit. Based on these advantages, EPPs can be used to optimize regional power resource allocation and improve the reliability and stability of the power system.

Table 1 compares fuel consumption, pollution emissions, and cost comparisons, and the comparison is about producing (or saving) per 1 kWh electricity between conventional power plants and energy-efficient power plants (source: Castro et al., 2020). The conventional power plant in the table takes a typical coal-fired power plant with an installed capacity of 300,000 kW as an example, and the annual utilization hours of its power generation equipment are about 5000 h.

Carbon Quota

Carbon quota refers to the greenhouse gas emission reduction targets that must be completed according to the regulations. For an EPP, it refers to the carbon dioxide emission reduction during the implementation of EPP. Many scholars have conducted research studies on carbon quota, but they almost took carbon quota as a constraint condition, and few literature studies have studied it as an endogenous variable. Carbon cap-and-trade was first proposed by J.H.Dales in his book "*Pollution, Property and Price*" (Dales, 1968), which pointed out that the government could consider pollution as a transfer of the right through the process of mutual trading of emission rights by enterprises and the regulation of the market, so as to improve the efficiency of energy use. At present, the carbon quota trading system is a relatively effective incentive means in the market, which can urge enterprises to take emission reduction measures. There are three typical distribution methods: free distribution, priced sale, and full market (Chen, 2003). There are mainly four typical carbon emission trading systems in the world (Zhang et al., 2014), namely, the European Union Carbon Emission Trading System (EUETS), the United States Regional Greenhouse Gas Initiative (RGGI), Australia's New South Wales Greenhouse Gas Emission Reduction System (NSWGGAS), and Japan's Tokyo Carbon Emissions Trading System (Tokyo ETS).

METHODOLOGY

The Behavior of Implementing Efficiency Power Plant

In China, the initial government subsidies are one of the impetuses of the enterprises implementing EPPs. With the increase of the size of the EPP, government financial subsidies began to gradually withdraw from the market, and carbon quota, as another kind of subsidies for the development of enterprises, began to appear. The government sets different carbon quota levels according to the ability of different enterprises to implement EPP, thus encouraging the development of EPP. The government stipulates a certain amount of carbon quota at the initial stage of the enterprise. With the implementation of the EPP, the government will subsidize a certain amount of carbon quota for unit reduction of electricity consumption. When not implementing the EPP, a certain amount of carbon quota will be consumed in normal enterprise production. At the end of each year, the total amount of carbon quota of the enterprise is accounted. The excess carbon quota can be exported by the enterprise to obtain funds. If the excess carbon quota is less than zero, the enterprise needs to buy excess carbon quota, or it will have to pay high compensation to the government.

This paper takes the government carbon quota level as an endogenous variable and studies how enterprises should formulate EPP implementation decision with the change of carbon quota level to ensure the maximization of their own income.

1) For enterprises that choose to implement EPP, we analyze the carbon quota level that enterprises will reach the critical value of R&D investment, and with the constant change of the carbon quota level, we research how the electricity reduced and the income obtained by implementing EPP will change with the change of carbon quota. 2) For enterprises that do not choose to implement EPP, we study the carbon quota level that enterprises will start to tend to implement EPP and research what extent will they continue to ignore EPP. 3) For enterprises that are uncertain whether to implement EPP or not, we study how should they make EPP decision with the change of carbon quota, that is, determine the tendency (probability) of implementing EPP, so as

to maximize their own income, and research the change trend of enterprise output and income with the change of carbon quota.

Assumptions

1) Subject

There are three different types of enterprises, namely, enterprise E_1 which always implements EPP, enterprise E_2 which never implements EPP, and enterprise E_3 which implements EPP as the case may be.

2) Electricity saved or consumed (unit: kWh, MWh, and GWh)

Set the electricity saved in enterprise E_1 as Q_1; enterprise E_2 does not save electricity, but consumes electricity, so the electricity consumed by enterprise E_2 can be set as Q_2; when EPP is implemented for enterprise E_3, electric energy is saved; when EPP is not implemented, electric energy is consumed, so set the electricity saved by enterprise E_3 at last as Q_3.

In addition, we can set the probability, tendency, or strength $\lambda(0<\lambda<1)$ of enterprise E_3 to implement EPP, and then, the probability of not implementing EPP is $1 - \lambda$.

3) Price (this is the price at which EPP saves electricity, not the market price)

In fact, the electricity reduced by implementing EPP has exactly the same function as the electricity generated by the power plant, and the products can be completely replaced. But unlike electricity prices, which are controlled by the government, we assume that the price of electricity reduced by EPP is affected by market supply and demand, and its price can be expressed as P. $P = \alpha - bQ$, where α is the market acceptable price caps and b is the market demand-back coefficient. The larger the demand-back coefficient is, the smaller the market is.

4) Cost

It is assumed that the cost of EPP implementation is mainly divided into two parts: R&D cost and operation cost. R&D cost includes the costs of key processes, technologies, and equipment of EPP, expressed as C_1; operating costs include energy-efficient processes and equipment produced or purchased for EPP implementation, as well as personnel inputs, etc., expressed as C_2. For enterprise E_1 and E_3, the unit R&D cost and unit operation cost decrease with the increase of power saving. For enterprise E_2, this kind of enterprise has no R&D cost but only has operation cost.

4) Carbon quotas

It mainly refers to the carbon emission quota determined by the government according to the situation of enterprises. Assume that the carbon quota stipulated by the government for each enterprise is H. The government will subsidize the carbon quota of h for every 1 kWh of electric quantity reduced by EPP. The government will deduct the carbon quota of h for every 1 kWh of electric quantity consumed by the enterprise without EPP. The carbon quota can be sold or purchased, and the economic benefit of carbon quota of h unit is d.

The main parameters and implications of the above assumptions can be represented in **Table 2**, and the revenue, costs, and variable returns of three different kinds of enterprises implementing EPP are presented in **Figure 1**.

Building the Profit Functions

1) Business revenue functions for three types of enterprises:

1) Set π_1 as the revenue function of enterprise E_1, according to the hypothesis; then,

$$\pi_1 = PQ_1 + hdQ_1 + \frac{H}{h}d - C_1 - C_2Q_1. \tag{1}$$

Put $P = \alpha - bQ$, $P = a - bq$, and $Q = Q_1 + Q_2 + Q_3$ into **Eq. 1** to get

$$\pi_1 = aQ_1 - bQ_1^2 - bQ_1Q_2 - bQ_1Q_3 + hdQ_1 + \frac{H}{h}d - C_1 - C_2Q_1. \tag{2}$$

Take the derivative of Q_1 first order and set it equal to 0 in **Eq. 1**.

$$\frac{\partial\pi_1}{\partial Q_1} = a - 2bQ_1 - bQ_2 - bQ_3 + hd - C_2 = 0. \tag{3}$$

Thus, the optimal power saving Q_1^* can be obtained:

$$Q_1^* = \frac{a - bQ_2 - bQ_3 + hd - C_2}{2b}. \tag{4}$$

2) Set π_2 as the revenue function of enterprise E_2, according to the hypothesis; then,

$$\pi_2 = PQ_2 + \frac{H}{h}d - hdQ_2 - C_2Q_2. \tag{5}$$

In the same way, take the derivative of Q_2 first order and set it equal to 0 in **Eq. 5**. Thus, the optimal power consumption Q_2^* of enterprise E_2 can be obtained:

$$Q_2^* = \frac{a - bQ_1 - bQ_2 - hd - C_2}{2b}. \tag{6}$$

3) Set π_3 as the revenue function of enterprise E_2, according to the hypothesis; then,

$$\pi_3 = PQ_3 + \frac{H}{h}d + \lambda Q_3hd - (1 - \lambda)Q_3hd - C_1 - C_2Q_3. \tag{7}$$

In the same way, take the derivative of Q_3 first order and set it equal to 0 in **Eq. 7**. Thus, the optimal power consumption Q_3^* of enterprise E_3 can be obtained.

$$Q_3^* = \frac{a - bQ_1 - bQ_2 + 2\lambda hd - hd - C_2}{2b}. \tag{8}$$

Joint establishment of optimal power consumption of three kinds of enterprises, which can be simplified to

TABLE 2 | Variables and meanings in the assumptions.

	Enterprise E_1	Enterprise E_2	Enterprise E_3
Electricity saved	Q_1	Q_2	Q_3
Research and development costs	C_1	0	C_1
Operating costs	C_2	C_2	C_2
Initial carbon quota	H	H	H
Carbon quota for saving electricity per unit	h	$-h$	h
Carbon quota revenue for saving electricity per unit	d	$-d$	d
Probability of choosing to implement EPP	1	0	λ

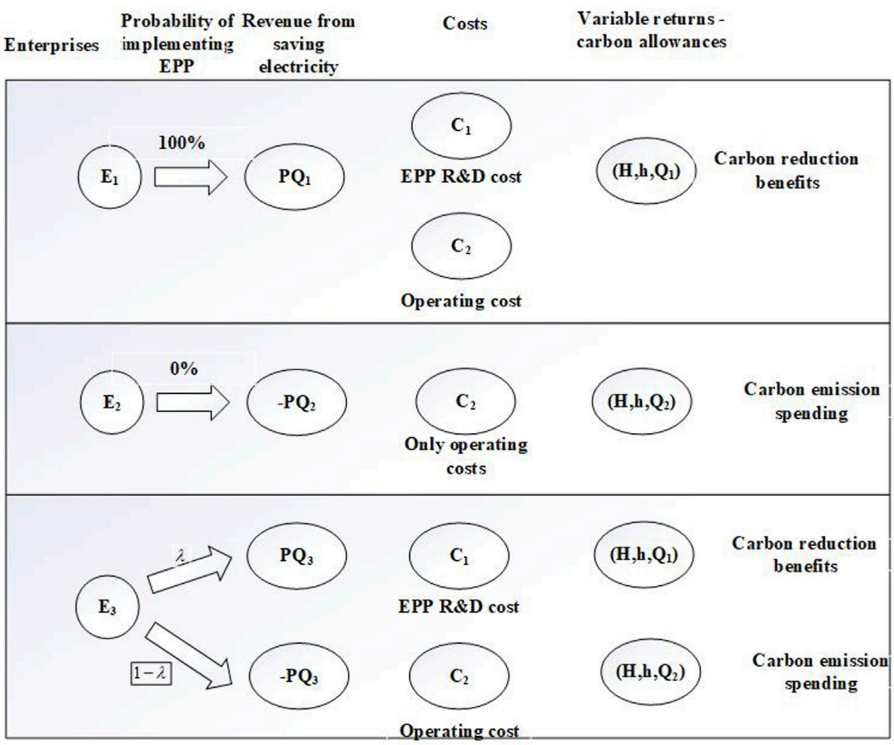

FIGURE 1 | The revenue, costs, and variable returns of three different kinds of enterprises implementing EPP.

$$\begin{cases} Q_1^* = \dfrac{a - 2\lambda hd + 5hd - C_2}{4b} \\ Q_2^* = \dfrac{a - 2\lambda|hd - 3hd - C_2}{4b} \\ Q_3^* = \dfrac{a + 6\lambda hd - 3hd - C_2}{4b} \\ Q^* = \dfrac{3a + 2\lambda hd - hd - 3C_2}{4b} \end{cases}. \tag{9}$$

By substituting the optimal solution of the above formula into the profit function of the respective enterprises, the optimal earnings of the three types of enterprises can be further obtained as follows:

$$\begin{cases} \pi_1^* = \dfrac{(a - 2\lambda hd + 5hd - C_2)^2}{16b} + \dfrac{Hd}{h} - C_1 \\ \pi_2^* = \dfrac{(a - 2\lambda|hd - 3hd - C_2)^2}{16b} + \dfrac{Hd}{h} \\ \pi_3^* = \dfrac{(a + 6\lambda hd - 3hd - C_2)^2}{|16b} + \dfrac{Hd}{h} - C_1 \end{cases}. \tag{10}$$

RESULTS

Relationship Analysis of Main Parameters

1) For enterprise E_1

According to **Eq. 9**, the electricity saved by enterprise E_1 has no relationship with the total carbon quota set by the government for the enterprise and is related to the carbon quota obtained by saving each unit of electricity and the benefit of unit carbon quota. In **Eq. 9**, the optimized first-order derivative of Q_1^* to h can be obtained as follows:

$$\frac{\partial Q_1^*}{\partial h} = \frac{5d - 2\lambda d}{4b}. \tag{11}$$

Then, result 1 can be obtained as follows. Result 1: the income of enterprise E_1 is directly related to the carbon quota for implementing EPP. There is a unit of carbon quotas h_0. When the carbon quota obtained by the implementation of EPP is higher than h_0, the income of enterprise E_1 will increase with the increase of unit carbon quota, and enterprise E_1 will continuously increase its sales volume to obtain greater income. When the carbon quota obtained from the implementation of EPP is lower than h_0, the enterprise income decreases with the increase of unit carbon quota, and the enterprise reduces the intensity of the implementation of EPP to ensure its own interests within a reasonable range.

Then, we analyze the relationship between revenue and R&D investment. The optimized first derivative of revenue π_1 with respect to R&D investment C_1can be obtained as follows:

$$\frac{\partial \pi_1}{\partial C_1} = -1. \tag{12}$$

Then, result 2 can be obtained as follows. Result 2: in **Eq. 12**, $\frac{\partial \pi_1}{\partial C_1} < 0$, therefore, for enterprise E_1, its incomes are negatively correlated with R&D investment, and enterprise income π_1 decreases with the increase of R&D investment C_1. In order to ensure the normal operation of the enterprise, there must be a critical value of the R&D investment. Below this value, the enterprise can operate normally and obtain profits. If the R&D investment exceeds this value, the enterprise will be unprofitable and gradually eliminated by the market.

Then, we analyzed the relationship between income π_1 of enterprise E_1 and income d from the unit carbon quota. In **Eq. 10**, the optimized first derivative of the enterprise income with respect to the unit carbon quota income can be obtained as follows:

$$\frac{\partial \pi_1}{\partial d} = \frac{(10 - 4\lambda)ah + 8\lambda^2 h^2 d + (50 - 40\lambda)h^2 d + 4\lambda h C_2}{16b} + \frac{H}{h}. \tag{13}$$

Then, result 3 can be obtained as follows. Result 3: in **Eq. 13**, all the unknowns are positive values, and we know $0 < \lambda < 1$; so, $(10 - 4\lambda)ah > 0$, $(50 - 40\lambda)h^2 d > 0$, and so $\frac{\partial \pi_1}{\partial d} > 0$. There is a positive correlation between the income of enterprise E_1 and the income of unit carbon quota, that is, with the increase of the income of unit carbon quota formulated by the government, the income of enterprises is gradually increasing. Similarly, the income of enterprise E_1 is positively correlated with the total carbon quota set by the government and the higher the carbon quota set by the government, the higher the profit obtained by the enterprise.

2) For enterprise E_2

In **Eq. 10**, the optimized first-order derivative of revenue π_2 of enterprise E_2 with respect to revenue d of the unit carbon quota can be obtained as follows:

$$\frac{\partial \pi_2}{\partial d} = \frac{-(6 + 4\lambda)ah + 8\lambda^2 h^2 d + 24\lambda h^2 d + 4\lambda h C_2 + 18h^2 d + 6hC_2}{16b} + \frac{H}{h}. \tag{14}$$

We cannot determine if $\frac{\partial \pi_2}{\partial d}$ is greater than 0 in **Eq. 14**. Let $\frac{\partial \pi_2}{\partial d} = 0$, we can get

$$d_0 = -\frac{16bh}{8\lambda^2 h^3 + 24\lambda h^3 + 18h^2} + \frac{6a + 4\lambda a + 4\lambda C_2 + 6h}{8\lambda^2 h + 24\lambda h + 18h}. \tag{15}$$

In **Eq. 15**, when $d = d_0$, $\frac{\partial \pi_2}{\partial d} = 0$. Therefore, the second derivative of **Eq. 14** can be obtained as follows:

$$\frac{\partial^2 \pi_2}{\partial d^2} = \frac{8\lambda^2 h^2 + 24h^2 + 18\lambda h^2}{16b}. \tag{16}$$

Then, result 4 is obtained as follows. Result 4: in **Eq. 16**, h and b are constants greater than 0, $0<\lambda<1$. That is, $\frac{\partial^2 \pi_2}{\partial d^2} > 0$, and the second derivative is greater than 0, indicating that the first derivative is monotonically increasing function. When $d > d_0$, the first derivative is greater than 0, and the first derivative is a monotonically increasing function. Therefore, the original function π_2 is a monotonically increasing function, that is, enterprise E_2 and incomeπ_2 increase with the increase of income d of the unit carbon quota. When $d < d_0$, the first derivative is less than 0, that is, the original function π_2 is a monotonically decreasing function, and the enterprise incomeπ_2 decreases with the increase of income d of the unit carbon quota. Enterprise E_2 income decreases first and then increases with the increase of the carbon quota income, and when $d = d_0$, the enterprise income is the smallest.

Similarly, in order to study the relationship between enterprise E_2, income π_2, and carbon quota h consumption, the modeling process is similar to the above contents. Taking the second derivative of income π_2 and carbon quota h of consumption,h_0 can be obtained; making $\frac{\partial \pi_2}{\partial h} = 0$ and then judging the monotonicity of the function, result 5 can be obtained as follows.

Result 5: there is a negative correlation between enterprise E_2 income and consumed carbon quota, that is, the income decreases with the increase of unit carbon quota. Within a certain range of unit carbon quota h, enterprise E_2 income will increase with the increase of carbon quota consumed, but beyond a certain range, the enterprise income will decrease with the increase of carbon quota consumed. For the government, the carbon quota of E_2 per unit enterprise determined must be greater than h_0, so that enterprises can be urged to reduce energy consumption in traditional production and then transform to implement EPP.

2) For enterprise E_3

In this part, we analyze the electricity saved and the revenue from enterprise E_3 and discuss how the parameter changes with carbon quota and the value of the probability a of implementing EPP, so as to maximize the enterprise revenue. That is, to study the electricity saved by enterprise E_3 and analyze the variation trend between electricity saved and carbon quota h, revenue d per unit carbon quota, and probability λ of EPP implementation.

Firstly, in **Eq. 9**, the first derivative of electricity quantity Q_3 consumed by the enterprise with respect to carbon quota h and revenue d of the unit carbon quota can be obtained as follows:

$$\begin{cases} \dfrac{\partial Q_3}{\partial h} = \dfrac{12\lambda d - 6d}{8b} \\ \dfrac{\partial Q_3}{\partial d} = -\dfrac{12\lambda h - 6h}{8b} \end{cases}. \tag{17}$$

Then, result 6 can be obtained as follows. Result 6: in **Eq. 17**, h, d and b are constants greater than 0, and $0<\lambda<1$. When $0<\lambda<0.5$, $12\lambda d-6d<0$, and $12\lambda h-6h<0$, that is, $\frac{\partial Q_3}{\partial h}>0$ and $\frac{\partial Q_3}{\partial d}>0$, the electricity saved by enterprise E_3 decreases with the increase of the unit carbon quota h and unit carbon quota income d; when $0.5<\lambda<1$, $12\lambda d-6d>0$, and $12\lambda h-6h>0$, that is, $\frac{\partial Q_3}{\partial h}>0$ and $\frac{\partial Q_3}{\partial d}>0$, the electricity saved by enterprise E_3 increases with the increase of unit carbon quota d and unit carbon quota revenue d.

Secondly, we analyze the income in **Eq. 10** of enterprise E_3 and find that the factors affecting enterprise income are related to the development cost, the total carbon quota given by the government, the income of carbon quota per unit, and the carbon quota obtained (or consumed) from energy saving (consumption). The relationship between the enterprise income and unit carbon quota income is analyzed as follows. In **Eq. 10**, the first derivative of the enterprise income π_3 with respect to revenue d of the unit carbon quota can be obtained as follows:

$$\frac{\partial \pi_3}{\partial d} = \frac{12\lambda ah - 6ah + 72\lambda^2 h^2 d - 72\lambda h^2 d + 18h^2 d + 6hC_2 - 12\lambda hC_2}{16b} + \frac{H}{h}. \tag{18}$$

We cannot determine whether $\frac{\partial \pi_3}{\partial d}$ is greater than 0 in **Eq. 18**. Therefore, the second derivative of d can be obtained as follows:

$$\frac{\partial^2 \pi_3}{\partial d^2} = \frac{72\lambda^2 h^2 - 72\lambda h^2 + 18h^2}{16b}. \tag{19}$$

In **Eq. 19**, h and b are constants greater than 0, and $0<\lambda<1$. So, $\frac{\partial^2 \pi_3}{\partial d^2}$ is greater than 0 is equal to $72\lambda^2 h^2 - 72\lambda h^2 + 18h^2$ is greater than 0. Because h^2 must be greater than 0, we just need to determine whether $72\lambda^2 h^2 - 72\lambda h^2 + 18$ is greater than 0. Let $72\lambda^2 h^2 - 72\lambda h^2 + 18 = 0$, we get $\lambda = 12\lambda = 12$; in other words, this quadratic opens up and only intersects the X-axis at one point. Therefore, it can be concluded that $\frac{\partial^2 \pi_3}{\partial d^2} \geq 0$ is always true, that is, the first derivative function is monotonically increasing function. Set the first derivative function equal to 0, and we can get $d_0^{'}$:

$$d_0^{'} = -\frac{8Hb}{36\lambda^2 h^3 - 36\lambda h^3 + 9h^3} - \frac{2a\lambda - a + C_2 - 2\lambda C_2}{12\lambda^2 h - 12\lambda h + 3h}. \tag{20}$$

Then, result 7 can be obtained as follows. Result 7: when $d<d_0^{'}$, $\frac{\partial \pi_3}{\partial d}<0$, and the second derivative function $\frac{\partial^2 \pi_3}{\partial d^2}$ is a monotonically increasing function, so the original function π_3 is a monotonically decreasing function. That is, enterprise E_3 income π_3 is negatively correlated with unit carbon quota income d, that is, the enterprise income decreases with the increase of unit carbon quota income. When $d>d_0^{'}$, $\frac{\partial \pi_3}{\partial d}>0$, and the second derivative function $\frac{\partial^2 \pi_3}{\partial d^2}$ is a monotonically increasing function, so the original function π_3 is a monotonically increasing function. In other words, enterprise E_3 income $\pi_3$increases with the increase of unit carbon quota income d. With the increase of the unit carbon quota income, enterprise E_3 income shows a trend of decreasing first and then increasing, and when unit carbon quota income $d=d_0^{'}$, the enterprise income is the lowest and then increases with the increase of the unit carbon quota. When $d<d_0^{'}$, the enterprise income decreases with the increase of the unit carbon quota. The main reason is that enterprises are unwilling to implement EPP in the early stage; the higher the income of unit carbon quota increases, the higher the government punishment the enterprises will accept. When $d>d_0^{'}$, the enterprise begins to implement EPP, and the increase of unit carbon quota income will greatly increase the income brought by power saving, so the enterprise income will gradually increase.

Similarly, the change trend between enterprise benefit and unit carbon quota h is as same as the relationship between enterprise income and unit carbon quota income d, and we would not analyze separately. In other words, enterprise E_3 income will decrease first and then increase with the increase of the unit carbon quota, and when $h=h_0$, the income reaches the minimum value.

Next, we analyze the relationship between the corporate income and total carbon quota. In **Eq. 10**, the first derivative of enterprise E_3 incomeπ_3 with respect to the total carbon quota H can be obtained as follows:

$$\frac{\partial \pi_3}{\partial H} = \frac{d}{h}. \tag{21}$$

Then, result 8 can be obtained as follows. Result 8: in **Eq. 21**, d and h are constants greater than 0, so $\frac{\partial \pi_3}{\partial H}>0$. And, the original function is a monotonically increasing function. In other words, there is a positive correlation between enterprise E_3 income π_3 and total carbon quota H, and enterprise E_3 income increases with the increase of the total carbon quota given by the government.

Then, the first derivative of enterprise E_3 income π_3 with respect to the probability λ of EPP implementation can be obtained as follows:

$$\frac{\partial \pi_3}{\partial \lambda} = \frac{3hd(a + 6\lambda hd) - 3hd - C_2}{4b}. \tag{22}$$

In **Eq. 22**, we cannot determine whether $\frac{\partial \pi_3}{\partial \lambda}$ is greater than 0, so the second derivative of λ can be obtained as follows:

TABLE 3 | The value setting of some parameters in simulation.

a	b	C_1	C_2	H	h	d
10	2	3	2	5	0.03	0.2

$$\frac{\partial^2 \pi_3}{\partial \lambda^2} = \frac{27h^2 d^2}{2b}. \tag{23}$$

In **Eq. 23**, h, d, and b are constants greater than 0, so $\frac{\partial^2 \pi_3}{\partial \lambda^2} > 0$. The first derivative $\frac{\partial \pi_3}{\partial \lambda}$ is a monotonically increasing function. Let $\frac{\partial \pi_3}{\partial \lambda} = 0$, we get λ_0:

$$\lambda_0 = \frac{C_2 + 3hd - a}{6hd}. \tag{25}$$

Then, result 9 can be obtained as follows. Result 9: when $\lambda < \lambda_0$, $\frac{\partial \pi_3}{\partial \lambda} < 0$, and the first derivative function is monotonically increasing function. Therefore, the function π_3 is a monotonically decreasing function, and enterprise E_3 earnings π_3 decreases with the increase of λ. When $\lambda > \lambda_0$, the first derivative is a monotonically increasing function, and $\frac{\partial \pi_3}{\partial \lambda} > 0$, the function$\pi_3$is a monotonically increasing function, that is, enterprise E_3 earnings $\pi_3$increases with the increase of λ. In the change process of probability λ of implementing EPP, the enterprise income first gradually decreases and then increases. The previous enterprise income will decrease with the increase of λ, The main reason lies in the large investment in the research and development of EPP technology and equipment in the early stage. With the increase of λ, EPP is gradually recognized and promoted by the government and enterprises due to its advantages of zero emission and energy saving. After a period of promotion and gradual improvement of government policies, the benefits brought to enterprises by the implementation of EPP are gradually reflected. Therefore, when$\lambda > \lambda_0$, the enterprise income will increase with the increase of λ.For enterprise E_3, λ should not be set asλ_0 because the enterprise income is the lowest at this time; if the enterprise prefers not to implement EPP, the ratio λ should be set below λ_0; if the enterprise is inclined to implement EPP, the production ratio λ should be set above λ_0 $(0 < \lambda_0 < 1)$, and the higher the proportion is set, the greater the profit of the enterprise will be.

Verification of Results

The previous nine results are mainly obtained through mathematical model construction and derivation. In order to verify the validity of the results, this part uses Maple, simulation software, to verify the validity of the results. Maple software is one of the most general mathematical and engineering computing software in the world and is widely used in the field of mathematics and science, among which the application of Maple software to test the correctness of decision results is one of its main applications. Main steps of Maple simulation include four steps, namely, assignment of variables, establishment of simulation model, analysis model, and conclusion. Among them, numerical setting plays a crucial role in the establishment of the simulation model, which determines whether the simulation model can correctly verify the decision results.

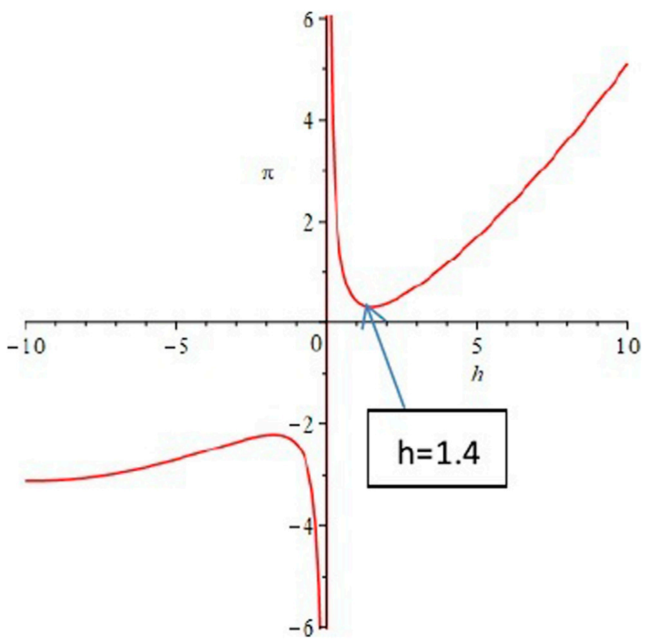

FIGURE 2 | The relationship between enterprise E_1 income π_1 and h.

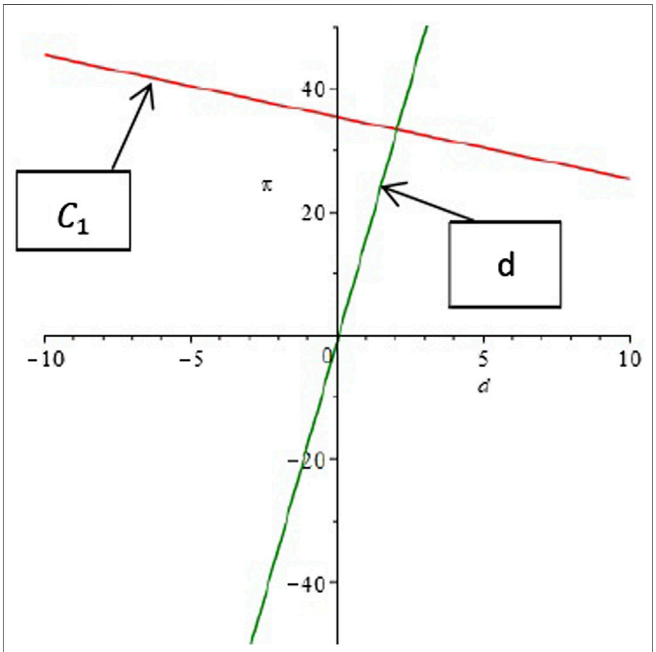

FIGURE 3 | The relationship between enterprise E_1 income π_1 with $C_1$and d.

According to the above parameter setting and requirements and referring to literature studies (Du et al., 2015; Luo et al., 2016; Huang et al., 2018), we set the values of each parameter as shown in **Table 3**.

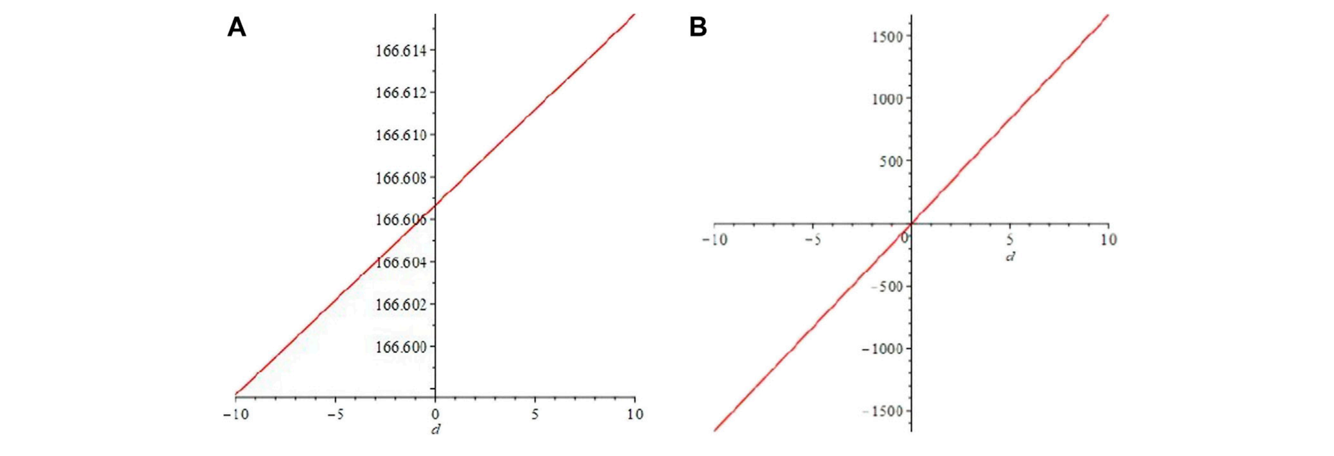

FIGURE 4 | (A) The function image of the derivative of π_2 with respect to d. **(B)** The relationship between π_2 and d.

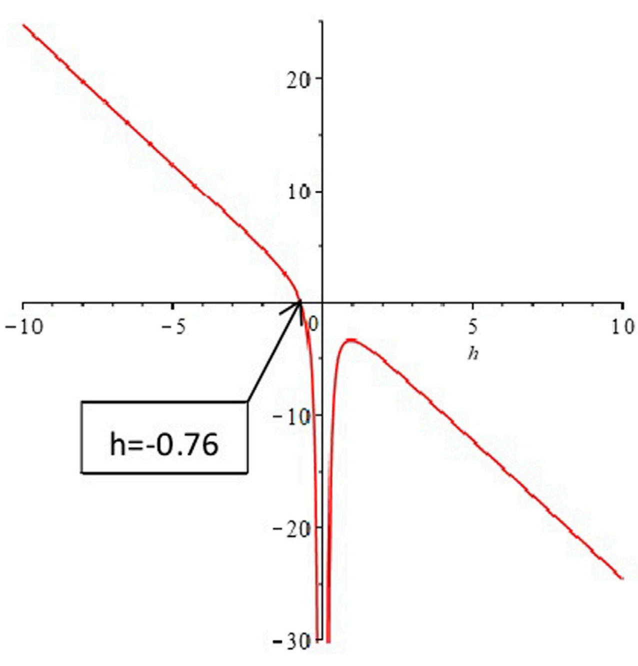

FIGURE 5 | The function image of the derivative of π_2 with respect to h.

Now, Maple software was used to verify nine results of the changes of industry income, output, and other variables of three kinds of enterprises, respectively, and the verification processes are as follows.

1) For enterprises E_1

Verification of result 1: the relationship image between enterprise E_1 income π_1 and unit carbon quota h is plotted according to known conditions, as shown in **Figure 2**. It can be seen that when $0 < h < 1.4$, the enterprise income decreases with the increase of the unit carbon quota. When $h > 1.4$, the enterprise income increases with the increase of the unit carbon quota, and the increasing amplitude is gradually expanding. When $h = 1.4$, the enterprise income reaches the minimum, which is consistent with result 2.

Verification of results 2 and 3: similarly, we set $\lambda = 0.5$ and plot the relationship image between enterprise E_1 income π_1, R&D cost C_1, and unit carbon quota income d, as shown in **Figure 3**. It can be seen that π_1 decreases with the increase of R&D cost and increases with the increase of the unit carbon quota income. In other words, the larger the income per unit carbon quota is, the higher the income from implementing EPP to save electricity will be, and the more enterprises tend to implement EPP, the more conducive to the development of EPP, which is consistent with result 3 and result 4. It should be noted that the above situation does not hold indefinitely because in the actual cases, the enterprise income will increase with the increase of carbon quota income over a period of time. However, after a certain range, under the influence of some factors such as policies, market saturation, and diminishing marginal return, the enterprise income will not continue to increase with the increase of carbon quota income.

2) For enterprise E_2

Verification of result 4: let $\lambda = 0.5$ and draw the graph of the first-order derivative function of enterprise E_2 income π_2 with respect to unit carbon quota income d, as shown in **Figure 4A**. According to the image, when $d > 0$, only the value of the first derivative function of enterprise E_2 income π_2 with respect to unit carbon quota income d is constant when the value is greater than 0. In other words, the enterprise income is positively correlated with the unit carbon quota income, which increases with the increase of the unit carbon quota income. When the first derivative is equal to $d = d_0 < 0$, in the actual operation of an enterprise, the income per unit carbon quota will not be negative. So, the function of $d_0 < 0$ is not analyzed. Plot the relationship image between enterprise E_2 income π_2 and unit carbon quota income d, as shown in **Figure 4B**. The analysis based on **Figure 5A** shows that when $d_0 > 0$, enterprise the income

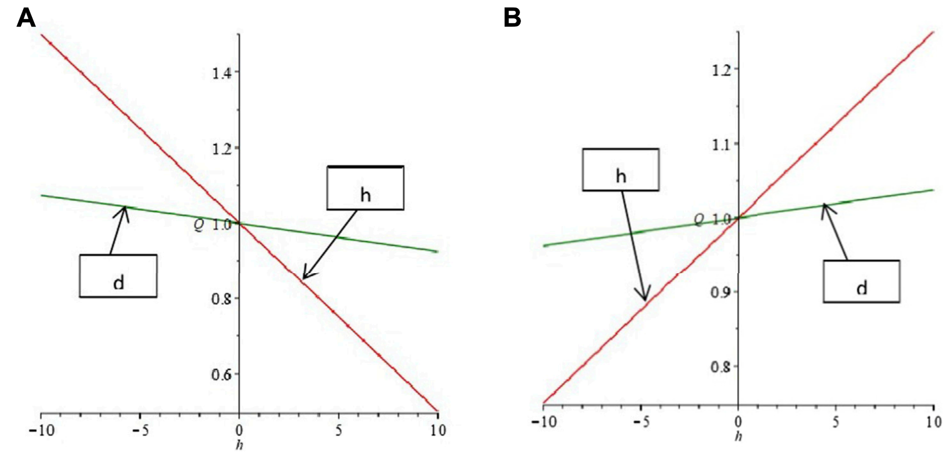

FIGURE 6 | (A) The relationship between electricity Q_3saving in enterprise E_3 with h and $d\,(0 < \lambda < 0.5)$. **(B)** The relationship between electricity Q_3saving in enterprise E_3 with h and $d\,(0.5 < \lambda < 1)$.

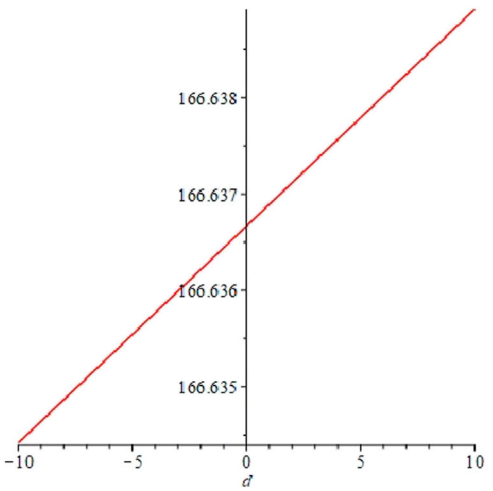

FIGURE 7 | The function image of the derivative of π_3 with respect to d.

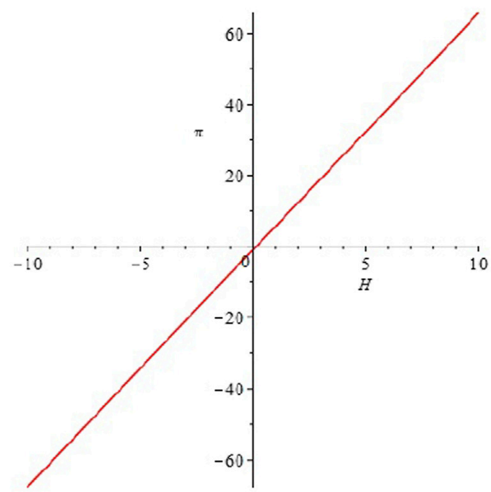

FIGURE 8 | The relationship between π_3 and total carbon quota H.

increases with the increase of unit carbon quota, which is consistent with result 4.

Verification of result 5: let $\lambda = 0.5$ and draw the graph of the first-order derivative function of enterprise E_2 income π_2 with respect to unit carbon quota h, as shown in **Figure 5**. In practice, it is impossible to take a negative value of carbon quota h, so the function image is taken as the function image of $h > 0$. According to the image, when $h <-0.76$, $\frac{\partial \pi_2}{\partial h} > 0$, that is, enterprise E_2 income π_2 increases with the increase of carbon quota h consumed; when h > -0.76, $\frac{\partial \pi_2}{\partial h} < 0$, that is, enterprise E_2 income$\pi_2$decreases with the increase of carbon quota h consumed, which is consistent with result 5.

3) For enterprise E_3

Verification of result 6: we analyze the relationship between electric quantity Q_3 saved by enterprise E_3 with unit carbon quota d and unit carbon quota income h. In this model, there are two stages according to whether λ is greater than 0.5. When $0<\lambda<0.5$, set $\lambda = \frac{1}{6}$, and draw the changing trend image of the relationship between Q_3, d, and h. As shown in **Figure 6A**, Q_3 decreases with the increase of d and h. However, since the slope of curve h is significantly higher than that of curve d, the degree of influence of h is higher than that of d. When the two factors influence the output of an enterprise at the same time, the range of change of variable h should be given the priority. When $0.5 < \lambda < 1$, set $\lambda = \frac{2}{3}$, and draw the changing trend image of the relationship between enterprise electric saved quantity Q_3, d, and h, as shown in **Figure 6B**. Q_3 increases with the increase of d and h, similarly, h has a higher influence on Q_3 than d. The result of this part is consistent with result 6, which verifies the correctness of result 6.

Verification of result 7: study the relationship between enterprise E_3 income π_3 and unit carbon quota revenue d, set

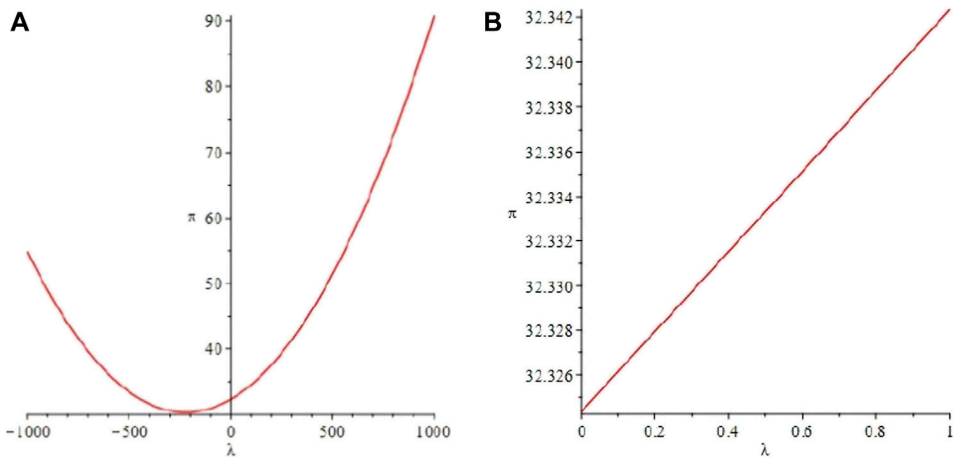

FIGURE 9 | (A) The relationship between enterprise E_3 earnings π_3 and $\lambda(-1000 \le \lambda \le 1000)$. **(B)** The relationship between enterprise E_3 earnings π_3 and $\lambda(0 \le \lambda \le 1)$.

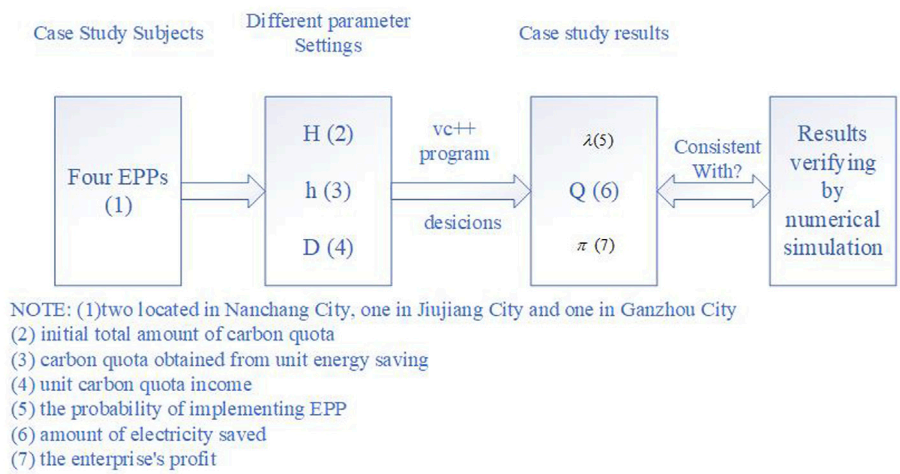

FIGURE 10 | The block diagram of the case study.

$\lambda = \frac{1}{6}$, and draw the first-order derivative function image of π_3 with respect to d, as shown in **Figure 7**. According to the figure, when d is small enough, the first-order derivative function will be less than 0. At this time, the enterprise income will decrease with the increase of unit carbon quota. Subsequently, with the gradual increase of d, the enterprise income will increase with the increase of the unit carbon quota income, which is consistent with result 7.

Verification result 8: now, study the relationship between enterprise E_3 income π_3 and total carbon quota H, set $\lambda = 0.5$, and draw the changing trend diagram between π_3 and total carbon quota according to known data, as shown in **Figure 8**. According to **Figure 8**, the enterprise income is positively correlated with the total carbon quota, that is, the enterprise income continues to increase with the increase of the total carbon quota, which is consistent with result 8. In addition, for every unit of change in the total carbon quota obtained from the image, the enterprise income will change by $\frac{20}{3}$ units, that is, the total carbon quota has a great impact on the enterprise income, which is a key factor that enterprises must consider in production.

Verification of result 9: finally, we study the relationship between enterprise E_3 income π_3 and total carbon quota H, set $\lambda = 0.5$, and draw the changing trend diagram between π_3 and willingness (probability) λ to implement EPP according to known data, as shown in **Figure 9A**. According to **Figure 10A**, the enterprise income first decreases and then increases with the gradual increase of λ. However, the effective value range of λ in this paper is $0 \le \lambda \le 1$. Therefore, we select part of the function images in **Figure 10A** to obtain **Figure 9B**, and when $0 \le \lambda \le 1$, the enterprise income π_3 continues to increase with the increase of λ. It can be seen from the figure that when $\lambda = 0$ and the enterprise does not implement EPP, the enterprise has a certain income, and with the gradual increase of λ, the enterprise income

TABLE 4 | The survey object descriptions and fixed parameter setting.

Respondents	Description	Remark
Four representative EPP projects in Jiangxi	Two located in Nanchang City: one in Jiujiang City and one in Ganzhou City	
Basic information data	Unit	Value
Average annual power saving (from 2015–2019)	kWh	$6.325*10^6$
[1]Sales price of power saved by EPP	Dollar/kWh	0.042
The market power price	Dollar/kWh	0.057
[2]Average annual carbon emissions	Ton	2,500
[3]Average annual cost of EPP implementation	Dollar	180,000

TABLE 5 | The probability λ of EPP implementation and its power saving Q and revenue π_3 under different H, h, and d.

H (ton)	h (kg/kWh)	d (dollar/t)	λ	Q (10^3 kWh)	π_3(10^3USD)
2,500	0.11	15	0.6839	688	171.71
2,500	0.11	13	0.5050	634	156.20
2,500	0.11	11	0.4632	609	132.61
2,500	0.15	13	0.712	763	189.63
2,500	0.11	13	0.5050	634	156.20
2,500	0.07	13	0.4154	482	107.45
1,500	0.11	13	0.7021	742	175.42
2,500	0.11	13	0.5050	634	156.20
3,500	0.11	13	0.3870	394	94.31
2,500	0.15	11	0.6132	658	164.89
2,500	0.11	13	0.5050	634	156.20
2,500	0.07	15	0.4732	617	143.57

continues to increase. When $\lambda = 1$, enterprise income reaches the maximum, which is consistent with result 9.

CASE STUDY

To prove the practicability of the model and the results, this part will use a case study to analyze the influence on the initial total amount of carbon quota H, carbon quota h obtained from unit energy saving, and unit carbon quota income d to the probabilityλ the enterprise implementing EPP. The authors and their research team members conducted a 2-month field survey at four EPP projects in Jiangxi Province in July and August 2019, to collect two kinds of original data as follows, aiming at providing basic data for VC++ program operation:

1) The basic information and data of the EPP project, such as project name, investment amount, annual power saving, annual carbon emission, equipment life, and other information come from field investigation of EPP project in Jiangxi province.
2) The common parameters, such as sales price of power saved by EPP, cost of EPP implementation, and other data are referred to recent data released by authorities and Energy Statistics Yearbook.

Table 4 shows the survey object descriptions and fixed parameter setting.

Note: [1]Sales price of power saved by EPP fluctuates with the market, but this part does not take electricity price as the focus problem. In order to simplify the problem, we take the average selling electricity price during the observation period as the final value. [3]For the cost of EPP implementation, which is also variable, we take the average value.

[2]The implementation of EPP has zero carbon emission, and enterprises only have carbon emissions when they do not implement EPP. Therefore, the carbon emission of the investigated enterprises is much lower than that of ordinary small or medium-sized manufacturing enterprises.

Next, we will adjust the initial total amount of carbon quota H, carbon quota h obtained from unit energy saving, and unit carbon quota income d, which will influence the decision of enterprises to implement EPP, and finally calculate the power saving and income of enterprises under the specified decision. Because the data in this study are complex and there are multifarious index operations, the VC++ (version 6.0) is used to construct a program to achieve the solution of this case study. The main code of VC++ program can refer to the code in the attachment of a previous article by Zhu et al., 2019. The block diagram of this case study can be shown in **Figure 10**.

The results are shown in **Table 5**.

According to **Table 5**, lines 1 through line 3 show that unit carbon quota income d has a positive effect on power saving Q and revenue π_3. With the increase of d, enterprises are more inclined to implement EPP. Line 4 through line 6 show that carbon quota h obtained from unit energy saving has a positive effect on power saving Q and revenue π_3. With the increase of h, enterprises are more inclined to implement EPP. Line 7 through line 9 show that initial total amount of carbon quota H has a positive effect on power saving Q and revenue π_3. With the increase of H, enterprises are more inclined to implement EPP. Line 10 through line 12 show that h has a greater influence than d, and the change of h plays a more important role in the decision of enterprises to implement EPP.

The results in **Table 5** are consistent with those obtained in *Relationship Analysis of Main Parameters*, that is, we prove the above results from the perspective of empirical analysis.

DISCUSSION

In this paper, three important contents are put forward:

Firstly, we build the profit functions of three types of enterprises, analyze the relationships of main parameters, and get nine results.

Secondly, we use Maple, the simulation software, to verify the validity of the results by drawing images of parameters. All the above nine results passed the simulation test.

Finally, we carry out an empirical analysis of a Chinese case and verify the practicability of the profit functions and the results of parameter relationship analysis through the actual survey data, which has practical guiding significance.

Compared to Zhu et al.'s, 2018, study about the general study of low-carbon investment, low-carbon investment is translated into implementation of EPP, and specific research conclusions and specific recommendations are given. Compared to literature studies by Li et al., 2017 and Sun et al., 2020, about the income study of carbon emission, the carbon emission energy savings are considered as one of the benefits of implementing EPP. Compared to (Arai et al.'s, 2014, study, correlation analysis of parameters is constructed based on three different types of enterprises and under different carbon quota constraints. Compared to literature studies by Zhu et al., 2018 and Dou et al., 2020, a simulation by Maple software and a case study in China are put forward to verify the research results.

Above all, this paper has three innovation points or improvements:

First, most research objects in literature studies about general low-carbon investment only have the function of reducing carbon emission or pollutant emission, while our research object-EPP in this paper is a special low-carbon behavior, which can reduce power consumption and carbon emission at the same time.

Second, the correlation analysis of parameters we constructed takes into account not only three types of different enterprises but also different carbon quota constraints.

Finally, through simulation and empirical analysis, we double test the profit function model and relevant results to verify their scientific effectiveness.

CONCLUSION AND SUGGESTION

Conclusion

Firstly, the paper analyzed the factors affecting the earnings and output of EPP enterprises, non-EPP enterprises, and selective EPP enterprises by establishing the profit functions, and then, we studied how the income and output of three kinds of enterprises change with the carbon quota. Thus, production decisions of different types of enterprises under different carbon quotas are obtained, and the results through Maple simulation software and empirical analysis are verified, in order to provide theoretical reference for different types of enterprises to make production decisions under different carbon quotas.

Suggestions

1) As the carbon quota given by the government and the carbon quota obtained by implementing EPP increase, the enterprise will gain more disposable carbon quotas, so enterprises can sell excess carbon quotas to reap the benefits and their profits will soar. At this time, enterprises should increase the investment in EPP research and input to acquisition, continuously improve the ability of EPP core technology, so as to expand their market share, and obtain the long-term development of the enterprise.
2) The effect of carbon quota obtained by implementing EPP on the output of enterprises is much greater than that of carbon quota income per unit. When both factors have an impact on the output of an enterprise, the enterprise should give priority to the carbon quota obtained by implementing EPP, so as to ensure the maximum income of the enterprise.
3) According to the change of carbon quota and unit carbon quota income, enterprises should adjust the intensity of EPP implementation to obtain higher income. Enterprise income is positively correlated with total carbon quota, carbon quota income per unit, and the intensity (probability) of EPP implementation. Therefore, when the total carbon quota and revenue per unit of carbon quota given by the government increase, enterprises should enhance the implementation of EPP, so that enterprises can obtain higher revenue.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

YZ constructed the theoretical framework of the manuscript. YJ collected the data and made statistical analysis.

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The LCOE Evolution and Grid Parity Analysis of Centralized Solar Photovoltaic: A Case Study of Ningxia, China

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Achieving grid parity in 2021 is the goal of China's photovoltaic development, which is not only on the user side but also on the generation side. Relevant studies indicated that distributed PV has realized grid parity basically in China, while centralized PV, which belongs to the generation side, still has some difficulties in achieving grid parity. Therefore, this paper takes Ningxia Province, which is abundant in solar resources, as the research object and compares LCOE with the traditional coal-fired price to analyze the situation of grid parity of the Pingluo project. It is found that this project cannot reach the goal of grid parity. Then, the future evolution of the local LCOE is analyzed, so as to determine the time of grid parity of Ningxia's centralized PV power stations. In the calculation of LCOE, the presence and absence of environmental benefits and the general and optimistic forecast of cumulative installed capacity are combined into four scenarios. The results show that the centralized PV in Ningxia cannot achieve grid parity in 2021 under the four scenarios. However, in addition to the scenario that there are no environmental benefits and the cumulative installed capacity is generally forecasted and will reach grid parity of the generation side in 2023, the other three situations can achieve the goal in 2022. Moreover, the LCOE value is the lowest under the scenario of considering environmental benefits and the optimistic forecast of future installed capacity.

Keywords: grid parity, centralized PV, LCOE, environmental benefits, Ningxia

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INTRODUCTION

In order to alleviate the energy crisis caused by the increase in electricity consumption, it is necessary to carry out energy transformation. Especially, the signing of the *Paris Agreement* in 2016 has made each country around the world to pay more attention to the importance of the renewable energy industry. Clean and abundant solar energy resources have great potential compared with fossil fuels (Lin and Luan, 2020). Every country has taken steps to promote the use of solar photovoltaic (PV). Germany is the most developed and mature country in the PV industry (Karakaya et al., 2015). In 2020, the *Renewable Energy Law* was enacted to stimulate large-scale growth of PV-installed capacity with fixed feed-in-tariffs (FITs) and subsidies. Then, in order to bring renewable energy into the power market to compete with traditional energy, the fixed subsidy was gradually changed into bidding, until it was finally canceled (Yu et al., 2016). It has been concluded that Germany has achieved grid parity in 2012 (Spertino et al., 2014). In the United States, each state has different incentives for the PV industry, but tax incentives are the most direct measure to guide their development. Moreover, it implemented the SunShot plan to encourage the research of PV technology which reduces the cost of PV power generation. Solar power generation accounted for 43% of U.S. power generation in 2020[1]. By the end of 2019, the cumulative installed capacity of global PV had reached 626 GW, more than a thousand times that of a decade ago.

China has been guided by the conviction that lucid water and lush mountains are invaluable assets. To promote the comprehensive green transformation of economic and social development, *the 14th five-year plan for national economic and social development of the People's Republic of China* further emphasizes in promoting clean, low-carbon, safe, and efficient utilization of energy, reducing the intensity of carbon emission (NDRC, 2021). As important clean energy, solar PV has become one of the renewable energy resources that China strongly supports. Since China implemented the FIT policy in 2011 and provided subsidies for PV in 2013, the cumulative installed capacity of PV in China has grown rapidly and surpassed Germany in 2015, becoming an important contribution to the global PV industry, as shown in **Figure 1** (NDRC, 2011a; NDRC, 2013; Tu et al., 2020). However, the massive growth of solar PV power plants has increased the financial burden of the Chinese government, resulting in a high subsidy gap (Zhang et al., 2020a). This subsidy gap reached 45.5 billion CNY by 2017 and exceeded 60 billion CNY in 2018 (NEA, 2019b; Zhang et al., 2020a). It not only increases the burden of China but also affects the enthusiasm for investment in the solar PV industry. To accelerate the decline of subsidies and promote the sustainable development of the PV industry, China has continuously lowered the PV FIT and subsidy standards and changed the centralized PV price to the guidance price in 2019, actively promoting the transformation of PV power generation to the era of grid parity. **Figure 2** shows the changes in PV electricity prices and subsidies. The electricity price has been falling year by year. Subsidies have also been reduced until they are abolished in the era of grid parity.

The grid parity of PV power generation can be divided into two sides: the centralized PV directly sends the generated power through the transmission network, which is the generation side of the grid parity; distributed PV power plants sell the power to users, so it belongs to the user side (Bhandari and Stadler, 2009; Yan et al., 2019; Zhang and Zhang, 2020). The levelized cost of electricity (LCOE) model is a commonly used tool for evaluating the cost-effectiveness of power generation technologies and determining whether emerging technologies are realizing grid parity (Hernandez-Moro and Martinez-Duart, 2013; Zhao et al., 2017; Zhang and Zhang, 2020). It represents the cost per kilowatt hour (kW h) of electricity generated by energy technology. If the LCOE is equal to or lower than the traditional generation price or retail price, it indicates that the emerging technologies are competitive and can achieve grid parity on the generation side or the user side (Castillo-Ramirez et al., 2017). The calculation and application of the LCOE method have been studied in pieces of literature. Allouhi et al. (2019) measured the LCOE of three different types of PV systems in 20 cities in Morocco and found that the lower cost of PV modules and higher solar radiation had a positive effect on reducing LCOE. Castillo-Ramirez et al. (2017) decomposed the operation and maintenance cost of PV specifically and calculated the LCOE of two large PV power plants in Colombia in 2015. Ouyang and Lin (2014) compared the LCOE of wind power, PV power, and biomass power in China. Liu et al. (2020) not only compared the LCOE of wind power and PV power in Guangdong but also studied the economic relationship between them under different load conditions. Some other papers used Monte Carlo simulation to conduct global sensitivity analysis on the LCOE of energy technologies to obtain the LCOE with the maximum probability (Darling et al., 2011; Pillot et al., 2018; Tran and Smith, 2018; Aldersey-Williams and Rubert, 2019). These papers calculated the LCOE of PV projects and other energy technologies under static conditions, and some other papers considered the changes in LCOE of renewable energy in the future and the time to achieve grid parity from a dynamic perspective. The learning curve is a power function, which is widely used to study the future evolution of energy technology power generation, reflecting that the cost of energy technology decreases with the increase in cumulative installed capacity (Yao et al., 2021). The single-factor learning curve was used to describe the relationship between the PV system cost and cumulative installed capacity, so as to obtain the future evolution of LCOE (Hernandez-Moro and Martinez-Duart, 2013; Wang et al., 2014; Vartiainen et al., 2020). Some papers used the two-factor learning curve to consider the dual effects of cumulative installed capacity and technological progress on the realization of PV grid parity (Zhang et al., 2020a). Yao et al.

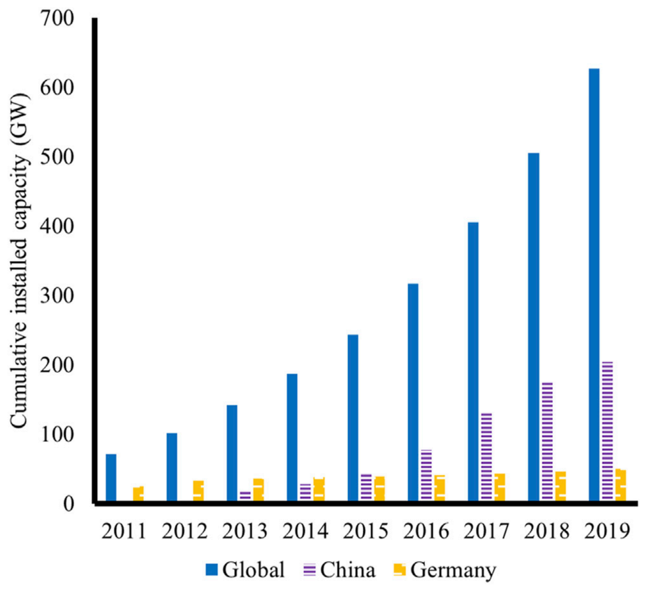

FIGURE 1 | Cumulative installed capacity of PV in the world, China and Germany from 2011 to 2019.

[1]https://www.xianjichina.com/special/detail_479192.html

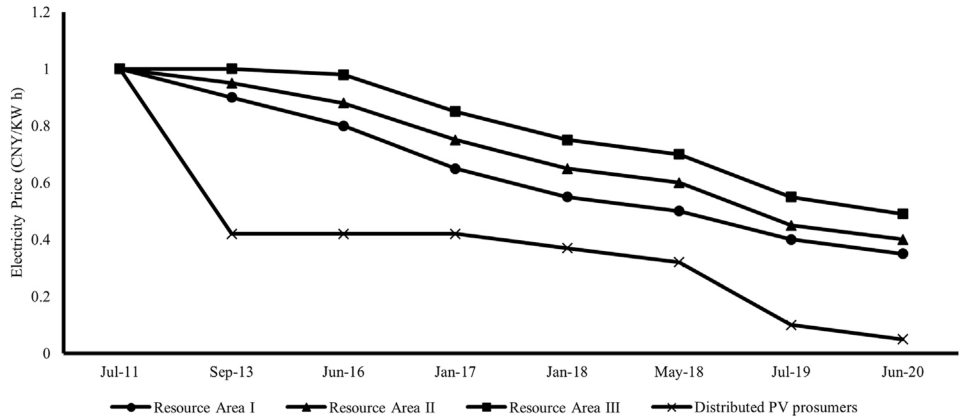

FIGURE 2 | FIT and guidance price of centralized PV and full on-grid distributed PV power stations and subsidy standard for distributed PV prosumers.

(2021) constructed a four-factor learning curve to measure the main driving factors of different renewable energy technologies.

At present, with the decrease in subsidy intensity in China, new energy is in the postsubsidy period, but the subsidy has not been completely canceled (Zhang et al., 2019). Qualified renewable energy such as wind and PV power can obtain the subsidy qualification by bidding and strive to achieve the goal of grid parity in 2021 (NEA, 2019a). Although the gradual decline of subsidies can reduce the financial pressure of the government, it has affected the passion of building PV to a certain extent. It needs follow-up incentive policies, for example, the tradable green certificate (Tu et al., 2020) and carbon emission trading (Tran and Smith, 2018; Tu et al., 2019), to ensure the sustainable development of PV projects (Jia et al., 2020). Since the provisions of the *Kyoto Protocol*, the European Union (EU) has established the European Union Emission Trading Scheme (EU-ETS) (Ge et al., 2019), which is the largest and most influential greenhouse gas emission reduction mechanism. In 2011, China also started the pilot work of carbon emission trading (NDRC, 2011b). Key emission units can use emission reduction indicators such as China Certification Emission Reduction (CCER). CCER comes from renewable energy, carbon sequestration, and methane and other emission reduction projects. One unit of CCER can offset one ton of carbon dioxide emissions (MEE, 2020b). The transaction of CCER not only reflects the carbon reduction and green development of renewable energy investments but also increases the profitability of renewable energy projects such as wind and solar PV (Tu et al., 2019).

In the study of the grid parity of PV projects, it is found that distributed PV projects have good economic feasibility by calculating the LCOE and internal rate of return (IRR) (Bhandari and Stadler, 2009; Pillot et al., 2018; Zhang et al., 2020b). The grid parity of distributed PV on the user side in China has been basically realized (Yan et al., 2019; Zhang and Zhang, 2020). The Development Research Center of the State Council also obtained this finding and considered that it is still very difficult for the generation side of centralized PV to reach grid parity (Zhou and Mu, 2020). However, centralized PV projects have always been the main force of China's PV development, accounting for more than half of China's PV industry, as shown in **Figure 3**. Moreover, China PV Industry

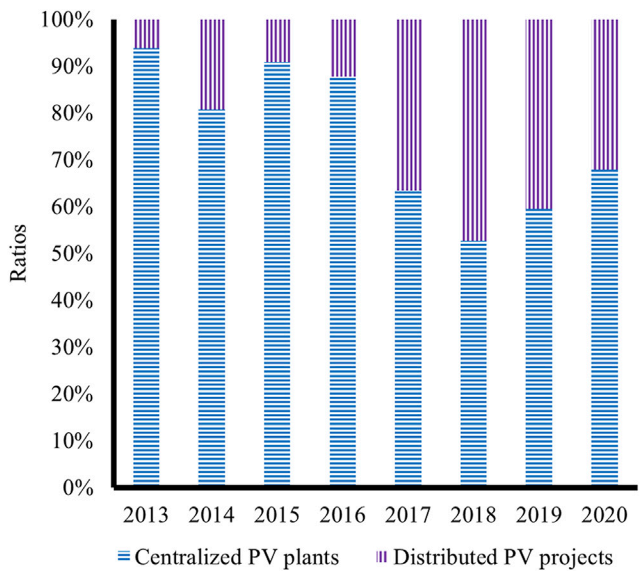

FIGURE 3 | Proportion of new installed capacity of centralized PV and distributed PV in China from 2013 to 2020.

Association (CPIA) predicted that a new round of development upsurge will appear in centralized PV power plants in 2021 (CPIA, 2020). Therefore, the generation-side grid parity of centralized PV will promote the realization of comprehensive grid parity. It is necessary to study the cost benefit and the time of grid parity of centralized PV power plants. At the same time, the cost offsetting effect of environmental benefits on PV projects cannot be ignored.

This paper takes Ningxia Province as the research object, which is in the leading position of PV power generation in China. The Datang Pingluo Gaoren 55 MW project is selected, the cost factors of this centralized PV power station in the whole life cycle are comprehensively considered, and the LCOE value of the project under the two conditions of whether to obtain the additional environmental benefits brought by carbon emission trading is calculated. The purpose is to analyze whether it can reach grid parity in 2021. Then, the absence and presence of environmental benefits and the general and optimistic forecast of cumulative installed capacity are combined into four scenarios to analyze the future LCOE evolution and the time of grid parity in Ningxia from the dynamic perspective of considering the learning effect. There are two contributions of this paper. One is analyzing the grid parity of centralized PV in Ningxia Province, which is abundant in solar resources. The other is considering the impact of environmental benefits and future cumulative installed capacity and dividing them into four scenarios when estimating the evolution of LCOE.

The structure of this paper is as follows. *Methodology* introduces the research method LCOE and learning curve. *The Development of Centralized PV: The Case of Ningxia Province in China* provides the relevant parameters involved in the calculation of LCOE in Ningxia Province. *Results and Discussion* shows the analysis of the centralized PV grid parity in Ningxia Province under different scenarios. *Conclusion and Policy Implications* shows the conclusion and policy implications.

METHODOLOGY

Levelized Cost of Electricity

LCOE is widely used in the estimation of power generation costs. It is a common tool to evaluate the cost-effectiveness of different energy generation technologies (Ouyang and Lin, 2014) and also a common method to study the grid parity of emerging technologies (Hernandez-Moro and Martinez-Duart, 2013). LCOE is a critical price when the sum of the present value of income is equal to the sum of the present value of costs in the whole life cycle of PV power generation (Tu et al., 2020), which is written as follows:

$$\sum\nolimits_{n=0}^{N}\frac{(\boldsymbol{Revenue})_n}{(1+\boldsymbol{r_d})^n}=\sum\nolimits_{n=0}^{N}\frac{(\boldsymbol{Cost})_n}{(1+\boldsymbol{r_d})^n}, \tag{1}$$

$$\sum\nolimits_{n=0}^{N}\frac{\boldsymbol{LCOE}\times\boldsymbol{G_n}}{(1+\boldsymbol{r_d})^n}=\sum\nolimits_{n=0}^{N}\frac{(\boldsymbol{Cost})_n}{(1+\boldsymbol{r_d})^n}, \tag{2}$$

where n is the year n during the operation of centralized PV power stations, N is the life cycle of centralized PV power stations, r_d is the discount rate, and G_n is the solar power generation in the year n.

Two scenarios are set to determine when the centralized PV power stations will achieve grid parity in this paper: without environmental benefits and with environmental benefits.

Generally, the basic LCOE of centralized PV projects is calculated without environmental benefits brought by carbon emission trading, as shown in **Eq. 3**.

$$\boldsymbol{LCOE}=\frac{\sum_{n=0}^{N}\frac{(\boldsymbol{Cost})_n}{(1+\boldsymbol{r_d})^n}}{\sum_{n=0}^{N}\frac{\boldsymbol{G_n}}{(1+\boldsymbol{r_d})^n}}=\frac{\boldsymbol{CI}+\sum_{n=1}^{N}\frac{(\boldsymbol{C0})_n}{(1+\boldsymbol{r_d})^n}}{\sum_{n=o}^{N}\frac{\boldsymbol{G_n}}{(1+\boldsymbol{r_d})^n}}, \tag{3}$$

where CI is the initial investment cost and $(C0)_n$ is the operational cost in the year n.

Under the scenario of introducing environmental benefits, the centralized PV power stations can not only obtain the electricity sale income but also obtain the additional benefits brought by carbon emission trading. Environmental benefits can offset the cost of centralized PV in the whole life cycle, as shown in **Eq. 4** and **Eq. 5**.

$$\sum\nolimits_{n=0}^{N}\frac{\boldsymbol{LCOE}\times\boldsymbol{G_n}+(\boldsymbol{R_E})_n}{(1+\boldsymbol{r_d})^n}=\sum\nolimits_{n=0}^{N}\frac{(\boldsymbol{Cost})_n}{(1+\boldsymbol{r_d})^n}, \tag{4}$$

$$\boldsymbol{LCOE}=\frac{\boldsymbol{CI}+\sum_{n=1}^{N}\frac{(\boldsymbol{C0})_n}{(1+\boldsymbol{r_d})^n}-\sum_{n=1}^{N}\frac{(\boldsymbol{R_E})_n}{(1+\boldsymbol{r_d})^n}}{\sum_{n=o}^{N}\frac{\boldsymbol{G_n}}{(1+\boldsymbol{r_d})^n}}, \tag{5}$$

where R_E denotes the environmental benefits.

It should be noted that the power generation in the equations seems to be discounted. In fact, it is obtained by rearranging the equations (Hernandez-Moro and Martinez-Duart, 2013).

Learning Curve

The increase in the cumulative installed capacity of energy technology leads to cost reduction, which is influenced by the "learning by doing". It can be represented by the learning curve, which is shown as **Eq. 6**.

$$\frac{\boldsymbol{C_{n_2}}}{\boldsymbol{C_{n_1}}}=\left(\frac{\boldsymbol{Q_{n_2}}}{\boldsymbol{Q_{n_1}}}\right)^{-\boldsymbol{b}}, \tag{6}$$

where C_{n_1}, Q_{n_1}, C_{n_2}, and Q_{n_2} are the unit power generation cost and the cumulative installed capacity of centralized PV in time n_1 and n_2, respectively, and $-b$ is the slope of **Eq. 6**. The learning rate (LR) can be calculated according to $-b$, as shown in **Eq. 7**.

$$\boldsymbol{LR}=1-2^{-\boldsymbol{b}}, \tag{7}$$

$$-\boldsymbol{b}=\frac{\boldsymbol{log}(1-\boldsymbol{LR})}{\boldsymbol{log}2}. \tag{8}$$

According to **Eqs 6–8**, the future unit generating cost can be predicted as follows:

$$\boldsymbol{C_n}=\boldsymbol{C}_0\left(\frac{\boldsymbol{Q_n}}{\boldsymbol{Q}_0}\right)^{\boldsymbol{log}(1-\boldsymbol{LR})/\boldsymbol{log}2}, \tag{9}$$

where C_0, Q_0 C_n, and Q_n are the unit power generation cost and cumulative installed capacity in the base year and the year n, respectively.

Therefore, the initial investment cost in the year n is

$$\boldsymbol{CI}=\boldsymbol{C}_0\left(\frac{\boldsymbol{Q_n}}{\boldsymbol{Q}_0}\right)^{\boldsymbol{log}(1-\boldsymbol{LR})/\boldsymbol{log}2}\boldsymbol{Q_n}. \tag{10}$$

THE DEVELOPMENT OF CENTRALIZED PV: THE CASE OF NINGXIA PROVINCE IN CHINA

Ningxia Province is located in Northwest China with high altitudes. The annual sunshine can reach more than 3,000 h. It

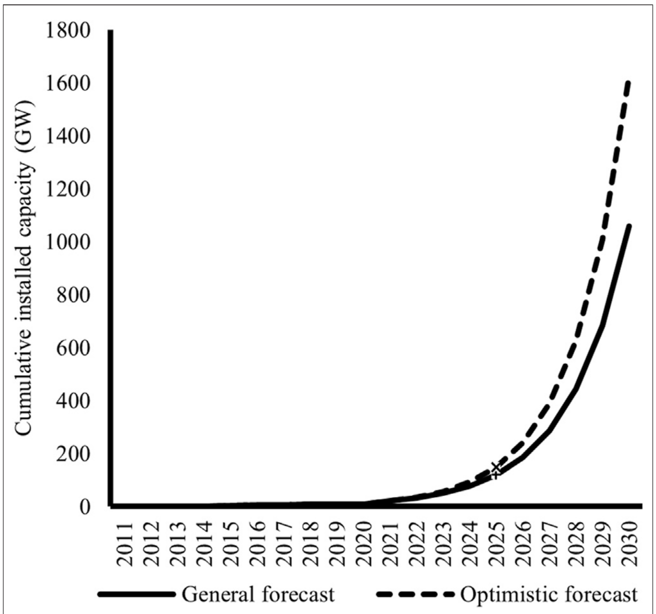

FIGURE 4 | Cumulative installed capacity of centralized PV in Ningxia from 2011 to 2030 under two conditions of general forecast and optimistic forecast.

is one of the areas with the most abundant sunshine and solar radiation in China. Its unique geographical conditions are conducive to the development of solar energy and wind energy. In 2012, the National Energy Administration (NEA) agreed to establish the first National Comprehensive Demonstration Zone of new energy in Ningxia, which promoted the rapid and orderly development of the new energy industry. At present, Ningxia has eight large-scale wind power and PV industry clusters, which are important bases for promoting clean energy in China. Therefore, the grid parity of Ningxia PV will be a strong driving force for the national grid parity. The following is about the centralized PV system in Ningxia Province.

Cumulative Installed Capacity

The learning effect of unit initial investment of the PV project is affected by the cumulated installed capacity. The cumulative installed capacity of centralized PV projects in Ningxia was 0.49 GW in 2011 and then soared to 8.44 GW in 2019. Based on the forecast of the CPIA, China's average annual installed capacity of new PV projects during the 14th Five-Year Plan period (2021–2025) is generally expected to be 70 GW, while the optimistic estimate is 90 GW (CPIA, 2020). Therefore, according to the proportion of Ningxia PV in China, it can be estimated that the cumulative installed capacity of centralized PV in Ningxia in 2025 is generally expected to be 120 GW and is expected to be 150 GW under the optimistic forecast. The most suitable description for the change in cumulative installed capacity is the logistic function ("s" curve) (Hernandez-Moro and Martinez-Duart, 2013; Tu et al., 2020). **Equations 11, 12** are logistic functions of the cumulative installed capacity of centralized PV in Ningxia Province under general and optimistic forecast, respectively, which are simulated using MATLAB software. n is the forecast year, and 2011 is the base year of the evolution of PV cumulative installed capacity. The fitting degrees are 0.9971 and 0.9977, separately. In **Figure 4**, the cumulative installed capacity curve of centralized PV in Ningxia is drawn under these two conditions from 2011 to 2030.

$$\boldsymbol{Q_n} = \frac{273800}{1 + 1027000\boldsymbol{e}^{-0.4364(\boldsymbol{n}-2011)}}, \tag{11}$$

$$\boldsymbol{Q_n} = \frac{195100}{1 + 1048000\boldsymbol{e}^{-0.478(\boldsymbol{n}-2011)}}. \tag{12}$$

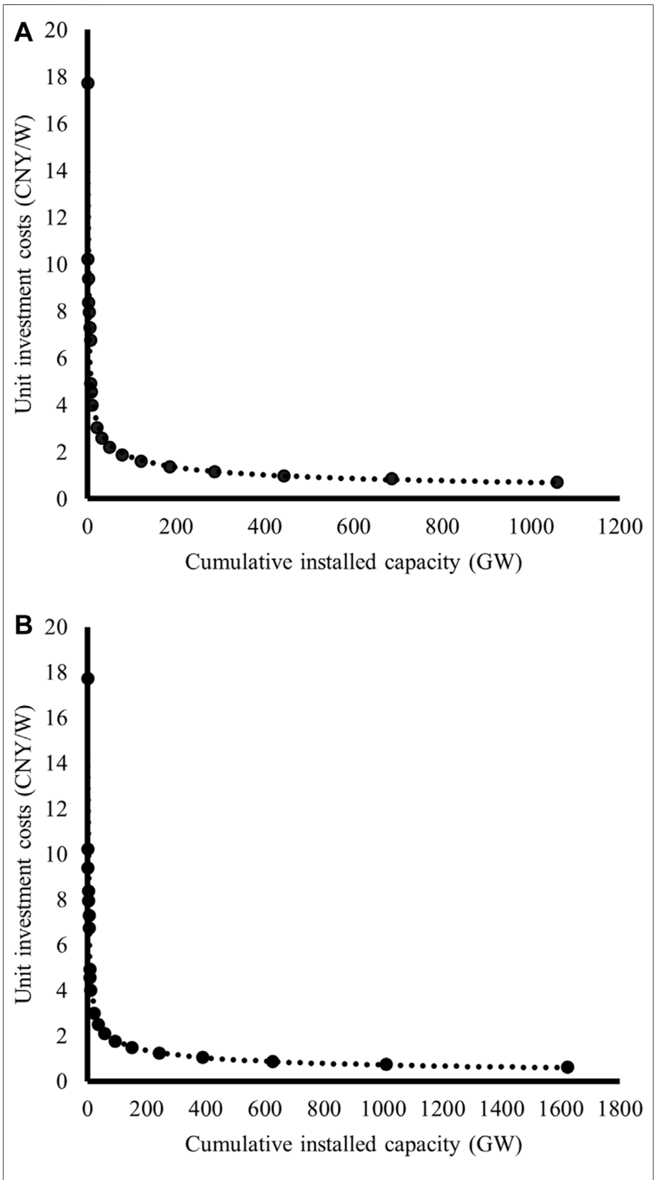

FIGURE 5 | Learning curve function of the cumulative installed capacity (GW) and unit investment costs (CNY/W) of centralized PV projects in Ningxia Province from 2011 to 2030 under the general forecast **(A)** and optimistic forecast **(B)**.

Initial Investment

The costs of centralized PV power stations during the construction period include equipment installation costs, construction engineering costs, basic reverse fund, and other expenses. Equipment installation costs mainly consist of the purchase costs and installation costs of generation equipment, distribution equipment, protection equipment, and auxiliary equipment related to PV power station operation. According to the arrangement of initial investment of ground PV power stations in the *China PV Industry Development Roadmap*, the costs of PV modules and equipment account for about 82% of the initial investment (CPIA, 2020). Construction costs contain the expenses of infrastructure facilities such as housing and transportation. The investment of environmental protection and conservation of water and soil can also be included. Other expenses include land use costs, production preparation costs, survey and design fees, and related management expenses.

The CPIA calculated the unit average investment costs of China's centralized PV power plants from 2011 to 2020. It has decreased year by year between the last 10 years, and by 2020, it decreased by about 77%. The cumulative installed capacity of centralized PV in Ningxia increased from 0.49 GW to about 10 GW during this period. In the future, with the growth of cumulative installed capacity, the unit investment costs will continue to decline. The single-factor learning curve model is used to fit the power-law relationship between them to obtain the learning rate and predict the change in unit investment costs from 2021 to 2030. It is found that the fitting degree between the cumulative installed capacity and the unit investment costs is 0.8502, and the slope of the learning curve −b is −0.366, so the learning rate is estimated at 22% correspondingly. According to **Eq. 9**, unit investment costs can be predicted through the learning rate and future cumulative installed capacity under general forecast and optimistic forecast from 2021 to 2030, which is shown in **Figure 5**.

Operation Costs

Operation costs refer to all expenses incurred during the operating phase of centralized PV power stations, including equipment repair costs, panel cleaning costs, all taxes payable, and so on. According to the *China PV Industry Development Roadmap* in 2020, the annual operation and maintenance cost (O&M) of centralized PV power stations is 0.046 CNY/W, which will remain at this level but slightly decrease in the future (CPIA, 2020). In order to simplify the calculation, it is determined that the unit operation and maintenance cost remain unchanged at 0.046 CNY/W.

This paper also takes into account the possible tax costs during the operation phase of centralized PV projects. According to the *Regulations on the Implementation of Enterprise Income Tax*, the tax costs include the income tax, urban construction tax, and education surtax, as shown in **Eq. 13** (CCTAA, 2010b).

$$\boldsymbol{TAX} = \boldsymbol{TAX_{Income}} + \boldsymbol{TAX_{Urban}} + \boldsymbol{TAX_{Edu}}. \tag{13}$$

The calculation of the urban construction tax and education surtax is based on the value-added tax (VAT). VAT is the difference between the output tax and input tax. The calculation of the VAT, urban construction tax, and education surtax is shown in **Eqs 14–16**.

$$\boldsymbol{VAT} = \boldsymbol{TAX_{Output}} - \boldsymbol{TAX_{Input}} = \left(\boldsymbol{p} \times \boldsymbol{G} - \boldsymbol{CI} - \boldsymbol{C_{O\&M}}\right) \times \boldsymbol{r_{VAT}}, \tag{14}$$

$$\boldsymbol{TAX_{Urban}} = \boldsymbol{VAT} \times \boldsymbol{r_u}, \tag{15}$$

$$\boldsymbol{TAX_{Edu}} = \boldsymbol{VAT} \times \boldsymbol{r_e}. \tag{16}$$

The enterprise income tax is the total income minus costs and expenses. According to the *Enterprise Income Tax Law*, the calculation of the income tax should deduct all taxes except the VAT (CCTAA, 2010a). The calculation is shown in **Eq. 17**.

$$\boldsymbol{TAX_{Income}} = \left[\boldsymbol{p} \times \boldsymbol{G} - \left(\boldsymbol{C_{O\&M}} + \boldsymbol{Dep} + \boldsymbol{TAX_{Urban}} + \boldsymbol{Tax_{Edu}}\right)\right] \times \boldsymbol{r_i}. \tag{17}$$

As the environmental protection projects, PV stations can enjoy the preferential income tax, which will be exempted in the first to third years and halved in the fourth to sixth years. The tax rates of related tax costs are shown in **Table 1**.

Therefore, the cost of PV projects during the operation period is

$$\begin{aligned}\boldsymbol{CO} &= \boldsymbol{C_{O\&M}} + \boldsymbol{TAX}\\ &= \boldsymbol{C_{O\&M}} + (\boldsymbol{TAX_{Income}} + \boldsymbol{TAX_{Urban}} + \boldsymbol{TAX_{Edu}}).\end{aligned} \tag{18}$$

Power Generation

The *Specification of Performance Evaluation for Photovoltaic Power Station* stipulates the calculation of annual power generation of PV power stations (SAC, 2021a):

$$\boldsymbol{G_n} = \boldsymbol{IC} \times \frac{\boldsymbol{H}}{\boldsymbol{H_S}} \times \boldsymbol{PR} \times (1 - \boldsymbol{d})^{\boldsymbol{n}}, \tag{19}$$

where H is the total amount of solar radiation for the best-inclined area of the PV array (kW h/m^2), H_S is the irradiance under standard conditions, which is generally a constant of 1 kW/m^2, and PR is the performance ratio, which is influenced by PV module conversion efficiency, PV inverter conversion efficiency, power generation efficiency, line and transformer loss, and other factors. PV's PR generally fluctuates between 70 and 80% (Brecl and Topic, 2016; Xu et al., 2018). In this paper, we assume that PR is 80% (Zhang and Zhang, 2020). d is the annual decay rate of PV modules. According to the *Specification of Photovoltaic Power Generation Efficiency*, it is stipulated that the annual decay rate of crystalline silicon PV modules shall not be higher than 0.7% (SAC, 2021b).

Electricity Price

According to the *Notice on Issues Related to Feed-in-tariff Policy of PV Power Generation in 2020*, the FIT (electricity price) of newly added centralized PV power stations shall be determined through the market competition. The part lower than the local coal price is settled by the provincial power grid, and the part

TABLE 1 | Relevant parameters of the Pingluo project.

Parameter	Meaning	Value
IC	Installed capacity (MW)	55
CI	Initial investment cost (million CNY)	285
N	Lifetime (year)	25
r_v	Residual value rate	5%
$O\&M$	Unit operation and maintenance cost (CNY/W)	0.046
r_{VAT}	VAT rate	13%
r_u	Urban construction tax rate	1%
r_e	Education surtax rate	3%
r_i	Enterprise income tax rate	0 (1–3 years) 12.5% (4–6 years) 25% (after 7 years)
H_P	Peak hours (h)	1763.82
PR	Performance ratio	80%
d	Decay rate	0.7%
p_{coal}	Coal-fired power price in Ningxia (CNY/kW h)	0.2595
p	Declared price (CNY/kW h)	0.2868
EF	Emission factor (tCO_2/MW h)	0.7793
p_{CO_2}	Carbon price (CNY/ton)	29.19
r_d	Discount rate	8%

higher than the local coal price is subsidized by the state. Therefore, the declared electricity price consists of the current coal price and state subsidies (**Figure 6**). If the declared electricity price of the PV project is equal to or lower than the coal price, the state subsidy cannot be obtained (**Figures 6B,C**) (NDRC, 2020). **Eq. 20** reflects the relationship between the declared electricity price and the coal price.

$$\begin{gathered} \boldsymbol{if\ p > p_{coal},\ p = p_{coal} + p_{subsidy}} \\ \boldsymbol{if\ p \le p_{coal},\ p_{subsidy} = 0}, \end{gathered} \tag{20}$$

where p is the declared electricity price of PV projects; p_{coal} is the local coal-fired price; and $p_{subsidy}$ is the state subsidy.

In order to adapt to the market orientation, China decides that the coal-fired power price will be determined by the current benchmark price fluctuation from 2020, with the upward floating not exceeding 10% and the downward fluctuation not exceeding 15% (NDRC, 2019). The current benchmark price of coal-fired electricity in Ningxia is 0.2595 CNY/kW h, so the floating range of the coal-fired price is 0.2206 CNY/kW h to 0.2855 CNY/kW h, which is the comparative standard of whether Ningxia-centralized PV can achieve grid parity.

Environmental Benefits

In 2020, the Ministry of Ecological Environment (MEE) proposed that renewable energy projects such as wind power and PV power could trade CCER and receive additional revenue in *the National Carbon Emission Trading Management Measures* (MEE, 2020b).

The carbon emission reduction (CER) of PV power stations is the product of the power generation (G) and the carbon emission factor (EF) of the area where this project is located (MEE, 2016).

$$\boldsymbol{CER = G \times EF}. \tag{21}$$

The environmental benefits are

$$\boldsymbol{R_E = CER \times p_{CO_2}}, \tag{22}$$

where CER is the carbon emission reduction of PV projects and EF is the carbon emission factor of the area where the PV project is located. Ningxia belongs to the northwest regional power grid, and its baseline EF is 0.7793 tCO_2/MW h (MEE, 2020a). p_{CO_2} is the carbon trading price. The average transaction price of China's eight carbon markets is 29.19 CNY/ton[2].

Discount Rate

The discount rate is an important parameter affecting LCOE, which reflects not only the expected revenue of PV projects (Ren et al., 2018) but also the time value and investment risks (Zhao et al., 2017). China's social discount rate is 8%. It is the benchmark discount rate for most investment projects in China. The discount rate most commonly used in the new energy industry is 8% (Ouyang and Lin, 2014; Lai and McCulloch, 2017; Abdelhady, 2021). Therefore, the cost and power generation of LCOE is discounted at an 8% discount rate in this paper.

Therefore, the prediction of future LCOE without and with environmental benefit impacts can be written as **Eq. 23** and **Eq. 24**, respectively.

$$LCOE = \frac{C_0\left(\frac{Q_n}{Q_0}\right)^{\log(1-LR)/\log 2} Q_n + \sum_{n=1}^{N} \frac{CI\times O\&M + \left[p\times G - \left(CI\times O\&M + Dep + TAX_{Urban} + TAX_{Edu}\right)\right]\times r_i + TAX_{Urban} + TAX_{Edu}}{(1+r_d)^n}}{\sum_{n=0}^{N} \frac{IC\times\frac{H}{H_S}\times PR\times(1-d)^n}{(1-r_d)^n}}, \tag{23}$$

$$LCOE = \frac{C_0\left(\frac{Q_n}{Q_0}\right)^{\log(1-LR)/\log 2} Q_n + \sum_{n=1}^{N} \frac{CI\times O\&M + \left[p\times G - \left(CI\times O\&M + Dep + TAX_{Urban} + TAX_{Edu}\right)\right]\times r_i + TAX_{Urban} + TAX_{Edu} - G\times EF\times p_{CO_2}}{(1+r_d)^n}}{\sum_{n=0}^{N} \frac{IC\times\frac{H}{H_S}\times PR\times(1-d)^n}{(1-r_d)^n}}. \tag{24}$$

In order to transition to the era of grid parity, China stipulated in 2019 that the PV projects requiring subsidies should determine the price and scale of subsidies in a competitive way and give priority to the projects with strong subsidy regression (NEA, 2019a). In this paper, the Datang Pingluo Gaoren 55 MW PV power station (Pingluo project) in Ningxia is also selected as an

[2]Carbon K line: http://k.tanjiaoyi.com/

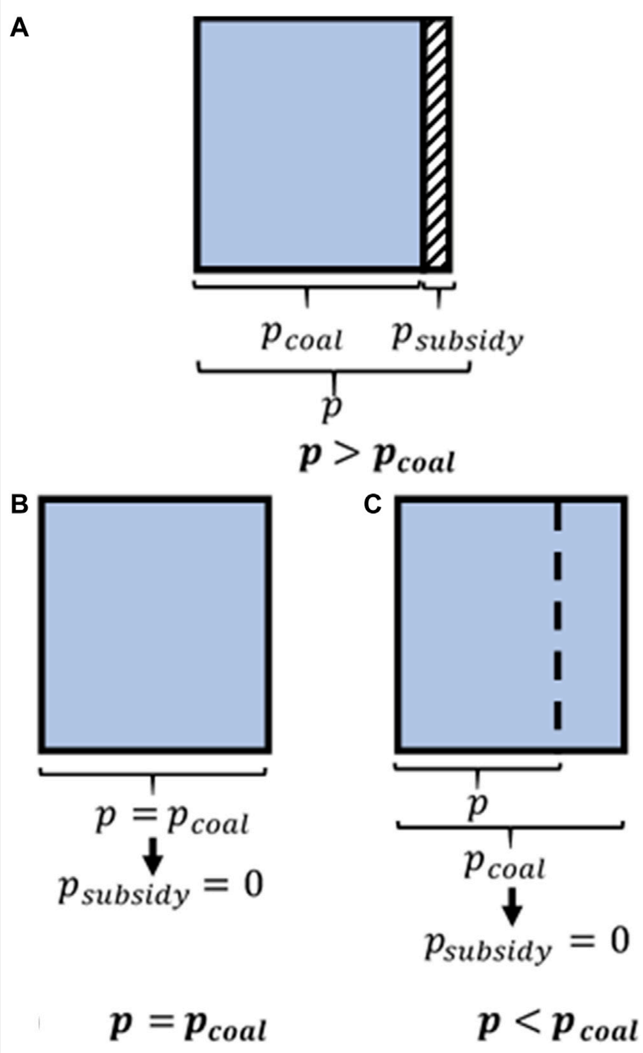

FIGURE 6 | Relationship among the declared electricity price of centralized PV projects (p), the coal-fired power price (p_{coal}), and state subsidies ($p_{subsidy}$).

example, which was included in the national bidding subsidy list in 2020. This project is located at the junction of Gaoren Township of Pingluo County and Yueyahu Township of the Xingqing District of Ningxia Province (38.39N, 106.39E). It is rich in solar energy resources, with an average annual solar radiation of 6349.75 MJ/m^2. The Pingluo project was a new project in 2020 and was planned to be completed by the end of 2020. **Figure 7** shows the location of this power station and the average annual sunshine hours in Ningxia Province. **Table 1** shows the relevant parameters of the Pingluo PV project.

RESULTS AND DISCUSSION

In this section, the LCOE value is calculated to analyze whether the Pingluo project can achieve grid parity in 2021 and the future situation of centralized PV grid parity in Ningxia. The effect of relevant green policies on achieving grid parity is also taken into account.

Grid Parity of the Pingluo Project in Ningxia

In this part, the LCOE value of the Pingluo project in 2021 without and with environmental benefits, respectively, is calculated based on **Eq. 23** and **Eq. 24** in *The Development of Centralized PV: The Case of Ningxia Province in China*, and it is analyzed whether this PV project can achieve grid parity in 2021.

The Pingluo project has been included in the national bidding subsidy list, so it can enjoy part of the support of state subsidies. The declared electricity price of the Pingluo project is 0.2868 CNY/kW h, and the coal-fired price in Ningxia is 0.2595 CNY/kW h. Therefore, this PV project can obtain a state subsidy of 0.0273 CNY/kW h. It can be calculated that the LCOE of the Pingluo project in 2021 is 0.4145 CNY/kW h, which is higher than the range of local coal-fired power prices. Therefore, the project cannot achieve grid parity in 2021. If the electricity price of the Pingluo project is determined to be 0.2595 CNY/kW h through market competition, which is the coal price in Ningxia, the price of 0.2595 CNY/kW h is settled by the provincial power grid and the state subsidy is 0 CNY/kW h according to the *Notice on Issues Related to Feed-in-tariff Policy of PV Power Generation in 2020*. The LCOE is 0.4102 CNY/kW h at this time. This is because the decline of the electricity price of the Pingluo project makes its tax costs and the LCOE decrease. The relationship among them can be seen in **Eq. 17** and **Figure 8**. Compared with the situation with state subsidies in the calculation, the LCOE is slightly lower but still far higher than the local coal price range, so it still cannot achieve grid parity.

Taking the nonsubsidy situation as the benchmark, the declared electricity price is continuously reduced based on the coal price until it is reduced to about 0.1661 CNY/kW h. The LCOE is 0.3956 CNY/kW h, which still cannot meet the standard of grid parity. However, the declared electricity price cannot be reduced continuously; otherwise, it will not get enough income. This is because if the electricity price of the Pingluo project drops below 0.1661 CNY/kW h, the tax costs of the project is 0 CNY/kW h according to the calculation of **Eqs 13–17**. It means that the costs only include initial investment and O&M costs when calculating the LCOE value at this time. **Figure 9** shows the LCOE of the Pingluo project after the electricity price drops below the current coal power price. The starting point of the vertical axis is 0.2595 CNY/kW h, which is the current coal price in Ningxia. It can be seen that there is a big gap between the LCOE of the Pingluo project and the local coal-fired power price in 2021.

If the Pingluo project does not qualify for a subsidy in 2021 but can obtain additional benefits through the CCER transaction, the environmental benefits can reduce the costs of this centralized PV power plant in the whole life cycle to some extent. When the current coal price is used as the declared electricity price and the carbon trading price is 29.19 CNY/ton, the LCOE value of the Pingluo project is 0.3903 CNY/kW h. Although it still does not reach grid parity, the LCOE value is relatively lower than that without carbon trading.

Under the dual effects of the rising carbon price and reduction of the electricity price, the decline of LCOE is gradually more

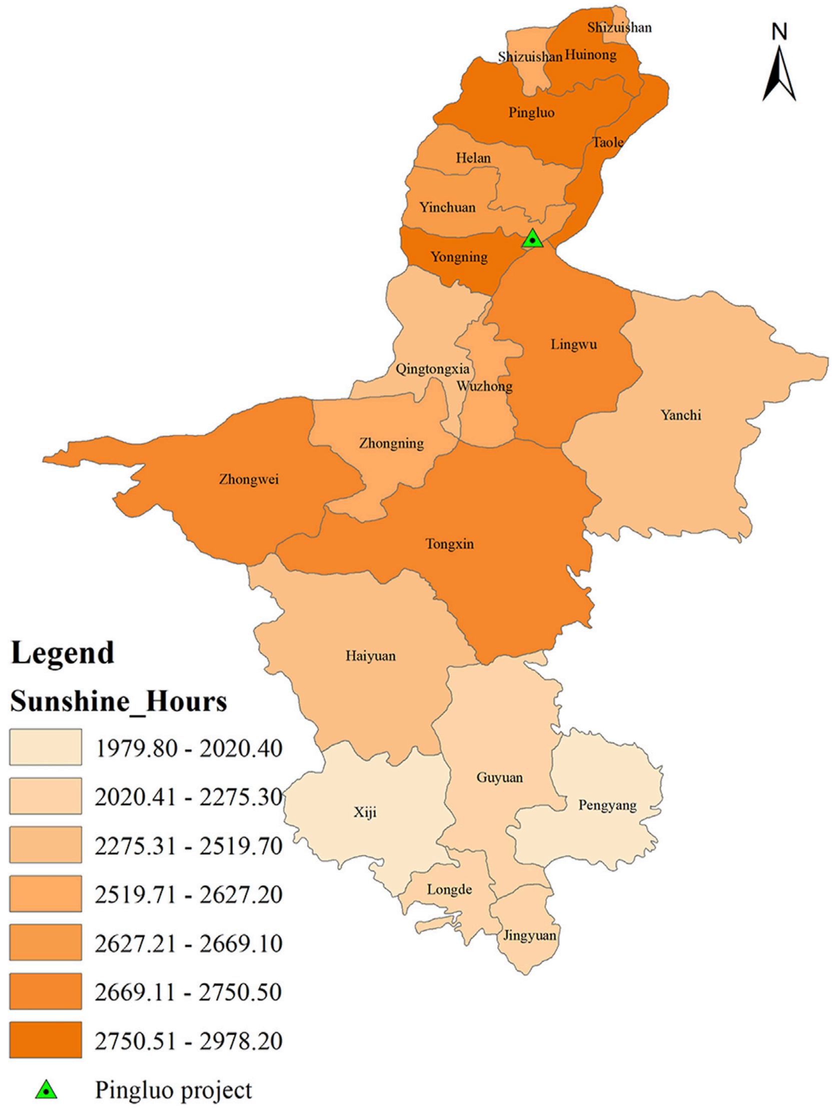

FIGURE 7 | Average annual sunshine duration in Ningxia Province.

obvious than that of only electricity price decline. Until the electricity price is reduced to about 0.1661 CNY/kW h, only the rise of the carbon price can promote the decline of LCOE, as shown in **Figure 10**. However, CCER trading is regarded as nonoperating income and needs to pay the income tax according to the *Interim Provisions on Accounting Treatment of Carbon Emission Trading* (MOF, 2019). Therefore, with the rise of the carbon price, it will bring more nonoperating income, which will lead to the corresponding increase of the cost in the calculation of LCOE and weaken the cost offsetting effect of environmental benefits.

For the Pingluo project in Ningxia Province, taking into account all possible costs incurred throughout its life cycle, the LCOE value is higher than the range of local coal power prices regardless of whether environmental benefits are introduced. Therefore, it is difficult to achieve grid parity in 2021.

Grid Parity of Centralized PV Projects in Ningxia Province

Some articles calculated the LCOE and IRR of large-scale PV power stations in China in 2019 and 2020 and found that the centralized PV projects in Ningxia did not have the economy of achieving grid parity (Lou et al., 2019). Moreover, after our calculation, we find that the Pingluo project in Ningxia will not be able to achieve grid parity in 2021 either, so when the whole Ningxia region can reach grid parity needs to be further measured and analyzed.

Without Environmental Benefits

The centralized PV projects in Ningxia Province will not be affected by additional environmental policies in this scenario. According to **Eq. 22**, the LCOE of centralized PV projects in

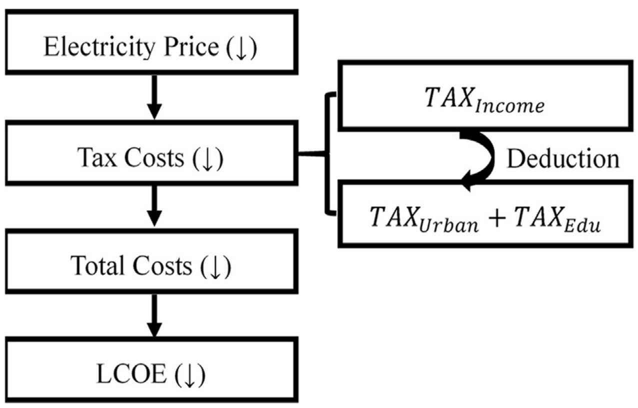

FIGURE 8 | Relationship among the electricity price, tax costs, total costs, and LCOE of the Pingluo project.

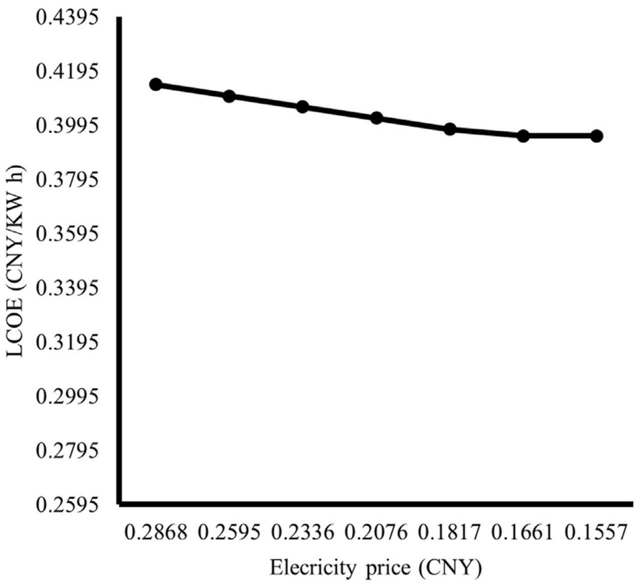

FIGURE 9 | LCOE of the Pingluo project when the electricity price is gradually decreasing.

Ningxia Province from 2020 to 2030 is calculated, as shown in **Figure 11**. The LCOE value was 0.3063 CNY/kW h in 2020 and has been developing with a decreasing trend.

When the cumulative installed capacity in the future is generally forecasted, the LCOE will drop to 0.2499 CNY/kW h and 0.2231 CNY/kW h in 2021 and 2022, respectively, which is between the upper and lower limits of the Ningxia coal-fired power price (0.2206 CNY/kW h to 0.2855 CNY/kW h). Ningxia can achieve grid parity compared with the ceiling of coal-fired prices. However, if the coal price goes down, it is not easy to achieve grid parity. The LCOE in 2023 is 0.2002 CNY/kW h, which is lower than the minimum limit of the coal-fired price in Ningxia. Therefore, the centralized PV in Ningxia can comprehensively realize the grid parity after 2023.

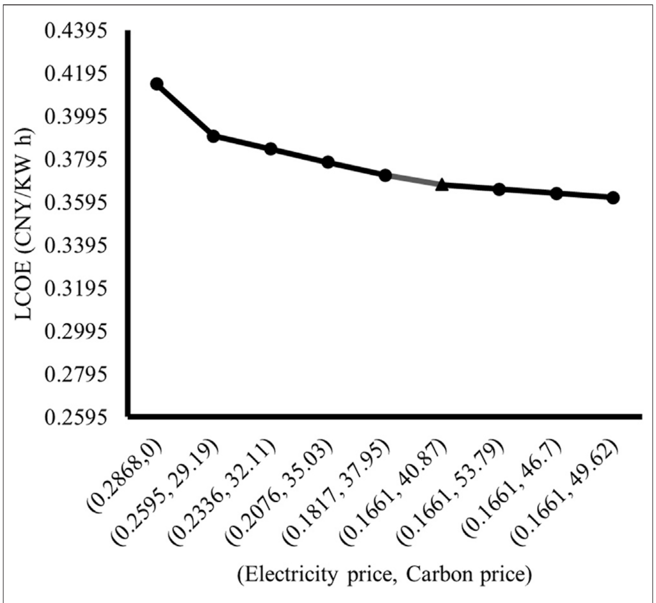

FIGURE 10 | LCOE of the Pingluo project under the combined effect of decreasing electricity price and rising carbon price.

When the forecast of future cumulative installed capacity is optimistic, the LCOE value is lower than the general forecast. At this time, the LCOE of centralized PV is 0.2461 CNY/kW h in 2021, which is still within the range of the coal price. However, the LCOE in 2022 will be lower than the minimum coal-fired price of 0.2206 CNY/kW h. Therefore, in the optimistic forecast of installed capacity, Ningxia's centralized PV will have the ability to access the grid parity from 2022.

In general, if environmental benefits are not taken into account in the calculation of LCOE, the centralized PV in Ningxia will achieve grid parity in 2023 when the cumulative installed capacity is generally predicted and 1 year in advance in the optimistic forecast scenario.

With Environmental Benefits

The additional environmental benefits brought by carbon emission trading will be included in the income of power generation projects, which will lead to a reduction of the LCOE of centralized PV to some extent. According to **Eq. 23**, to calculate the LCOE value considering environmental benefits of Ningxia centralized PV from 2020 to 2030, it is found that the introduction of environmental benefits can indeed reduce LCOE. As shown in **Figure 11**, the LCOE considering environmental benefits is lower than that without environmental benefits. The LCOE with environmental benefits of Ningxia centralized PV was 0.2873 CNY/kW h in 2020, which is higher than the local coal-fired price and cannot achieve grid parity.

When the future cumulative installed capacity is the general forecast, the LCOE in 2021 is 0.2309 CNY/kW h. Therefore, only when the local coal-fired price is lower than 0.2309 CNY/kW h can the centralized PV in Ningxia realize grid parity in 2021. In 2022, LCOE will drop to 0.2041 CNY/kW h, which is smaller than

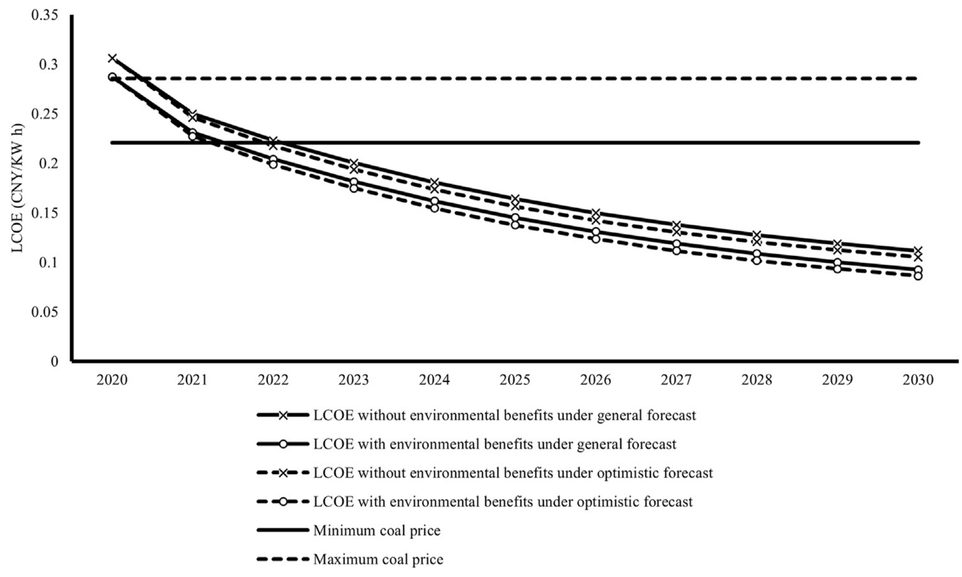

FIGURE 11 | LCOE of Ningxia centralized PV in four scenarios from 2020 to 2030.

the local minimum coal-fired power price. Therefore, centralized PV in Ningxia will achieve grid parity from 2022. Although the LCOE under the optimistic forecast scenario of future cumulative installed capacity is relatively lower compared with the general forecast scenario, it cannot achieve the goal of grid parity in 2021. The LCOE in 2022 will be 0.1987 CNY/kW h, which is significantly lower than the range of the local coal price. When the cumulative installed capacity is optimistically predicted, the conditions for generation side grid parity will also be met in 2022, consequently.

Therefore, the introduction of environmental benefits can not only bring additional benefits to the centralized PV projects and reduce the cost of the whole life cycle but also promote the realization of generation side grid parity (Tu et al., 2019).

CONCLUSION AND POLICY IMPLICATIONS

This paper analyzes whether the centralized PV power stations in Ningxia Province, the first comprehensive demonstration area of new energy in China, can achieve grid parity under four scenarios. The newly built PV power station, Pingluo project in 2020, is taken as an example, and its LCOE is calculated. In addition, the evolution of LCOE in the whole Ningxia Province is analyzed by considering the learning effect and is compared with the local coal price to determine whether it meets the requirements of grid parity.

This paper finds that the LCOE of the Pingluo project completed at the end of 2020 is much higher than the local coal-fired power price in 2021, so it cannot achieve grid parity on the generation side. Although reducing the electricity price and rising the carbon price with other conditions remain unchanged, it is still difficult to implement grid parity. The main reason is the high initial investment. The unit investment cost of the project is as high as 5.18 CNY/W, which is about twice the average investment cost. Since the Pingluo project in Ningxia Province cannot achieve grid parity in 2021, is it the same for the whole Ningxia region? Based on the prediction of Ningxia's future cumulative installed capacity and the learning effect, the evolution of LCOE is estimated. The results mainly include three parts. First, it is difficult for centralized PV to achieve grid parity in 2021 in Ningxia under these four scenarios. If the coal electricity price is reduced in the future, it is possible to achieve generation side grid parity. Second, the introduction of environmental benefits significantly reduces the LCOE value, which can achieve the generation side grid parity in 2022. However, under the general forecast of cumulative installed capacity, if the environmental benefits are not considered, the realization of grid parity will be delayed by 1 year in 2023. Third, the LCOE of the optimistic forecast of cumulative installed capacity is lower than the general forecast under the two scenarios of without environmental benefits and with environmental benefits. Moreover, it can achieve grid parity in 2022 in the optimistic forecast.

The results give us two enlightenments or policy implications.

On the one hand, the construction of the national carbon market is improved. First, the coordination between the carbon market and the PV power generation market is strengthened, the carbon quota of PV power generation enterprises is increased, and the energy enterprises with heavy pollution to buy more carbon quotas from the clean energy enterprises are encouraged. Second, in order to simplify the calculation, the carbon price in this paper adopts the average value of the pilots. However, in fact, the carbon price has different degrees of fluctuations, which will affect the profits of PV power generation projects. Therefore, it is very important to improve the price mechanism of CCER (Tu et al., 2019). Third, PV subsidies are gradually canceled and the national carbon trading market is not yet mature. In order to encourage and guarantee the enthusiasm of the PV industry to participate in the carbon market trading, the government needs to strengthen the leadership of the carbon market (Song et al., 2020).

On the other hand, the R&D expenses are increased to promote the progress of PV technology. The evolution of LCOE is also affected by the future target value of cumulative installed capacity (Hernandez-Moro and Martinez-Duart, 2013). The larger the installed capacity is, the lower the LCOE value will be. The large-scale increase in installed capacity promotes PV projects to use more advanced technology and equipment, which brings economies of scale and significantly reduces the investment cost. Therefore, to reduce the investment cost, PV projects should appropriately expand the scale of development, pay attention to technological progress (Zhang et al., 2020a), and give play to the learning effect of learning by doing. The government should also implement the responsibility of supervision of PV power stations so that the quality and safety of PV projects can be guaranteed (Zhang and Zhang, 2020).

Although this paper analyzes the grid parity of centralized PV projects in Ningxia, it still needs to be improved. For example, the investment cost is not only affected by the single factor of cumulative installed capacity but also influenced by other factors such as technology development and material price. The multifactor learning curve model can be built to analyze the effects of more factors on the investment cost. In addition, the role of other environmental policies such as tradeable green certificates can also be considered when calculating LCOE in the future.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article, and further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

All authors have significantly contributed to the manuscript. YaG was responsible for collecting relevant data. YiG carried out the calculation and analysis. LM guided this article. PL optimized the structure of this article.

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SUPPLEMENTARY MATERIAL

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A Theoretical Model of Sequential Combinatorial Games of Subsidies and Penalties: From Waste to Renewable Energy

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Subsidies and penalties are two main regulation methods adopted by authorities to promote the development of renewable energy. Due to the possibility of subsidy fraud, it is necessary to explore effective ways to combine these two policies. In this article, subsidy and penalty policies are incorporated into a sequential game theory model to explore the impact of different regulatory mechanisms on the promotion of renewable energy from recycled resources. We take biodiesel production from used cooking oil (UCO) as an example. UCO can be converted into environmentally friendly biodiesel or mixed with fresh cooking oil, resulting in inferior cooking oil containing harmful carcinogens but with huge profits. There are two mechanisms in the sequential combination model, spot checks after subsidy and subsidy after spot checks. Under both cases, fines are imposed if fraud is found during spot checks. The amounts of subsidies and fines also need to be determined. We show that the effects of subsidies depend on the implementation of the timing. The ex-ante subsidies have no effect. When spot checks are performed first, the larger subsidies will increase the probability of producing inferior cooking oil due to lower probability of spot checks. While combined with penalties, the ex-post subsidies have a positive effect on biodiesel production, that is, there exists synergy effect of penalty and subsidy on renewable energy production. In an infinitely repeated game, the shutdown threat of a grim trigger strategy (GTS) is much easier to induce biodiesel production than the penalty threat of a tit-for-tat strategy (TFT). When penalties are large enough, TFT can achieve the same goal of legal production effectively as GTS. The sooner illegal production is observed, the lower penalties are required to induce the processor to produce legally. Compared to subsidies, penalties are more effective in encouraging processors to produce renewable energy rather than illegal products. Moreover, our simulation results suggest that higher fines or profits from legal production are more likely to stimulate renewable energy production than subsidies. Our findings enrich our knowledge of the link between government regulations and the promotion of renewable energy.

Keywords: renewable energy, subsidy, penalty, game-theoretical analysis, biodiesel, used cooking oil

INTRODUCTION

Faced with the challenges of energy shortages and rising greenhouse gas emissions, countries around the world have gradually adopted various policies to stimulate the use of environmentally friendly renewable energy, among which subsidies and penalties are the main intervention means (al Irsyad et al., 2017; Saghir et al., 2019; Chen et al., 2021). For example, the Japanese government provides investment subsidies for solar energy projects to encourage clean energy supply (Kimura and Suzuki, 2006) and allocates direct subsidies for biofuel companies (Zhang et al., 2015). In Europe, Germany and Spain provide subsidies of around €60/MWH and €300/MWH, respectively, to wind and solar renewable energy producers (Abrell et al., 2019). At the same time, subsidy fraud has become a serious problem. Kumar (2019) stated that 70% of the subsidy was provided to ineligible solar rooftop projects in India. In 2017, the world's leading electric car maker, Tesla, lost the electric vehicle subsidies from the German government after it was accused of gaming the subsidy system (Lambert, 2017). Penalties are introduced to reduce misbehavior by renewable energy producers. The Chinese government fines three times money for solar photovoltaic subsidy fraud (Yuan et al., 2015; Liu et al., 2021).

Although both subsidies and penalties are widely followed, implementing them effectively remains a challenge. Chang et al. (2011) pointed out that direct subsidy is the main driving factor on solar water heater market expansion in Taiwan, but the high-level subsidy might cause a negative impact on users or a sustainable industry. Zhang et al. (2014) studied the subsidy effect of the biofuel processing industry in different stages from investment, raw material input to final product, and found that investment subsidy is less effective compared with the other two. A benefit–cost analysis of subsidizing residential solar panels in the United States was conducted by Tibebu et al. (2021) and the results showed that in comparison with the federal tax credit, the optimal subsidy schedule can raise net benefits by 250%. In terms of penalty, Lu et al. (2018) developed a penalty-cost-based design mechanism, which can reduce the cost of net zero energy building (NZEB) owners by half. Although a few studies attempt to design and apply the reward–penalty mechanism to lessen the over-generation from renewable energy systems (Md et al., 2017) and to reduce the risk in auctions of renewable energy support (Kreiss et al., 2017), the literature regarding the effective combination of subsidies and penalties is still limited.

From the perspective of sustainable energy use, biodiesel is increasingly being adopted as an important alternative to clean energy in the field of transportation, which is a key factor in global climate change (Fischer and Schrattenholzer, 2001). There are two main sources of biodiesel: oily plants, such as the nonedible Jatropha oil, and fatty acid-rich waste including UCO. On the basis of a life cycle assessment, biodiesel processed from UCO has nearly 74% reduced impact on the environment and 80% reduced global warming effect compared with nonedible Jatropha oil (Sajid et al., 2016). In addition, the usage of UCO as a feedstock in biodiesel production (Rincón et al., 2019) can lead to a cost reduction of 60–90% compared to other fatty acid–rich waste (Marchetti et al., 2008). According to Kharina et al. (2018), subsidizing UCO-to-biodiesel production can save the government 345 billion rupiahs (approximately US $24M) per year, in comparison with the subsidy of the same amount of palm biodiesel.

Due to the above reasons, many countries and regions have adopted incentive measures to promote the production of biodiesel from UCO and to reduce the possibility of illegal processing of UCO into other products. Mixing UCO with fresh edible oil can lead to higher profits for processors but serious health problems for consumers (Cai et al., 2015; Ortner et al., 2016; Liu, 2018; Tsai, 2019). For example, biodiesel produced from UCO can enjoy the double counting of carbon dioxide emission reduction in Europe. In Japan, the government subsidizes biodiesel companies to reduce incentives for illegal UCO processing. In China and Japan, restaurants can be fined or shut down if they buy processed UCO or sell it to illegal institutions. Zhang et al. (2017) stated that the penalty mechanism is one of the key determinants that affect the performance of biofuel companies.

The game modeling method is suitable for the theoretical study of the situation where stakeholders have different objectives. The dynamic game model developed by Zhang et al. (2014) compares the incentive effects of different subsidy modes on UCO supply for biofuel refining and sales of UCO-refined products. With a non-cooperate game-theoretical model, Wang et al. (2017) assess the promotion impact of the consumer's response capability on the penetration of distributed photovoltaic systems. A three-stage Stackelberg game model is used to explore the optimal subsidy policy for green energy trading among user residents, service providers, and the grid (Wu et al., 2021). However, it is still unclear that how governments should effectively combine subsidy and penalty measures and what effect it would be if subsidy and penalty measures are taken simultaneously. We integrate subsidy and penalty policies into one game-theoretical model to examine the influence of different regulatory mechanisms on the processing decisions of UCO processors.

The rest of this article is structured as follows. The ***Model Specification*** section discusses the specifications in the model. The ***Simulation Results*** section shows the simulation results. We offer concluding remarks and practical implications in the ***Conclusions and Practical Implications*** section.

MODEL SPECIFICATION

We assume that a processor can produce two kinds of products, one is a good product such as renewable energy with low profit under the government subsidy policy, and the other is a bad product such as unqualified products or carcinogens with high profit. For example, there is a financial support policy for the promotion of new energy cars from 2012 in China, and pure electric vehicles will be subsidized according to cruising range. In order to get a subsidy of up to US$14k, some car enterprises choose to make a false report of cruising range and produce low-standard

TABLE 1 | One-stage game when the subsidy is given before a spot check.

		Local government	
		Spot check	**No spot check**
Processor	Produce biodiesel	$(R^l - C^h + E_1, V^+ - C_g - E_1)$	$(R^l - C^h + E_1, V^+ - E_1)$
	Produce inferior cooking oil	$(R^h - C^l + E_1 - E_2, E_2 - C_g - E_1 - K)$	$(R^h - C^l + E_1, -E_1 - V^-)$

battery instead of high-standard battery. Take UCO as an example, we consider a waste UCO processor that can produce either biodiesel legally or inferior cooking oil illegally. A local government can perform a spot check to see whether the processor produces biodiesel rather than inferior cooking oil. The spot check can be implemented before or after providing subsidies[1]. To encourage the processor to convert the waste oil into biodiesel fuel through a chemical process, the government provides a subsidy to the processor if the processor produces biodiesel and otherwise punishes the processor with a fine.

One-Stage Game Model With Subsidy Given Before Spot Checks

Consider the static game with complete information. We assume that the cost of recycling waste oil is negligible and focus on the cost difference between the production of biodiesel and inferior cooking oil. The strategic-form representation of the game where the subsidy is given first and then a spot check is performed is in **Table 1**.

In this table, E_1 is the subsidy provided by the government if the government does not perform a spot check or confirms that the processor produces biodiesel during a spot check. C^h and C^l are the processor's production costs of biodiesel and inferior cooking oil, with $C^h > C^l$. R^l and R^h are the benefits for the processor to produce biodiesel and inferior cooking oil, with $R^l < R^h$. M is the difference in the profits of these two products, $M = (R^h - C^l) - (R^l - C^h)$. s and $(1 - s)$ are the probabilities of producing inferior cooking oil and biodiesel. r is the probability of a random check. E_2 is the penalty that is charged by the government if the processor is found to produce inferior cooking oil during a spot check. K is the recycling or disposal cost of inferior cooking oil. V^+ is the social benefit of prevention against the reuse of waste oils by restaurants and households, which makes the consumers better-off. V^- is the social cost of the reuse of waste oils by restaurants and households, which makes the consumers worse off. C_g is the cost of the random check and is an increasing function of the probability of a random check, $dC_g/dr > 0$.

Given these payoffs, we find the following pure and mixed Nash equilibria.

Scenario 1. When $E_2 - C_g - E_1 - K < -E_1 - V^-$, that is, $C_g + K > E_2 + V^-$, the sum of the cost of the spot check and the recycling or disposal cost of inferior cooking oil is larger than the sum of the fine and the social cost of the reuse of waste oils by consumers. In this case, there exists a unique pure Nash equilibrium (production of inferior cooking oil, no spot checks). Due to the limited technology for the differentiation between inferior cooking oil and normal cooking oil, the cost of the spot check is so large that it is not efficient for the government to check. Fortunately, the cost of the spot check decreases with the continuous development of techniques for identifying inferior cooking oil.

Scenario 2. Suppose $E_2 - C_g - E_1 - K > -E_1 - V^-$, that is, $C_g + K < E_2 + V^-$, then, if $R^h - C^l + E_1 - E_2 > R^l - C^h + E_1$, that is, $E_2 < M$, then the penalty is smaller than the difference in the profits of these two products. Because the penalty is not large enough and the profits from producing inferior cooking oil are far higher than from producing biodiesel, the processor benefits from producing inferior cooking oil instead of biodiesel even after paying the penalty. In this case, there is a unique pure Nash equilibrium (production of inferior cooking oil, spot checks). If $R^h - C^l + E_1 - E_2 < R^l - C^h + E_1$, that is, $E_2 > M$, there is no unique pure Nash equilibrium.

Scenario 3. There is a mixed Nash equilibrium as follows:

$$\boldsymbol{r}^* = \frac{(\boldsymbol{R^h} - \boldsymbol{C^l}) - (\boldsymbol{R^l} - \boldsymbol{C^h})}{\boldsymbol{E_1} + \boldsymbol{E_2}} = \frac{\boldsymbol{M}}{\boldsymbol{E_2}}, \tag{1}$$

$$\boldsymbol{s}^* = \frac{\boldsymbol{C_g}}{\boldsymbol{E_2} - \boldsymbol{K} + \boldsymbol{V^-}}. \tag{2}$$

The processor is indifferent between producing biodiesel and producing inferior cooking oil when

$$\left(\boldsymbol{R^l} - \boldsymbol{C^h} + \boldsymbol{E_1}\right) = \boldsymbol{r}\left(\boldsymbol{R^h} - \boldsymbol{C^l} + \boldsymbol{E_1} - \boldsymbol{E_2}\right) + (1 - \boldsymbol{r})\left(\boldsymbol{R^h} - \boldsymbol{C^l} + \boldsymbol{E_1}\right). \tag{3}$$

The government is indifferent between performing a spot check and not performing a spot check when

$$\begin{aligned} &\boldsymbol{s}\left(\boldsymbol{E_2} - \boldsymbol{C_g} - \boldsymbol{E_1} - \boldsymbol{K}\right) + (\boldsymbol{1} - \boldsymbol{s})\left(\boldsymbol{V^+} - \boldsymbol{C_g} - \boldsymbol{E_1}\right) \\ &= \boldsymbol{s}(-\boldsymbol{E_1} - \mathbf{V^-}) + (\boldsymbol{1} - \boldsymbol{s})(\boldsymbol{V^+} - \boldsymbol{E_1}). \end{aligned} \tag{4}$$

Equations 3, 4 pin down the equilibrium probabilities of performing a spot check and producing inferior cooking oil as given by **Eqs 1, 2**.

Lemma 1.

a) When $C_g + K > E_2 + V^-$, there is a pure Nash equilibrium with the processor producing inferior cooking oil and the government not checking.
b) When $C_g + K < E_2 + V^-$ and $E_2 < M$, there is a pure Nash equilibrium with the processor producing inferior cooking oil and the government always checking.

[1]The Shanghai government, for example, released a specific emergency subsidy method for promoting UCO-biodiesel conversion in 2016. According to the method, municipal governments provide companies subsidy based on the documents submitted by the companies. The governments can choose to implement spot checks before or after providing subsidies.

c) When $C_g + K < E_2 + V^-$ and $E_2 > M$, there is a mixed Nash equilibrium with $r^* = M/E_2$ and $s^* = C_g/\left(E_2 - K + V^-\right)$.

Lemma 1 says that there is a unique pure Nash equilibrium with the processor producing inferior cooking oil and the local government not checking the firm when the sum of the cost of the spot check and the recycling or disposal cost of inferior cooking oil is greater than the sum of the penalty the local government imposes on the processor and the social cost of the reuse of waste oils by consumers. This outcome makes sense because the cost of checking is so high for the government that no check is performed, so the processor's best response to the government's strategy is to produce inferior cooking oils because of the high profit. However, when the sum of the cost of the spot check and the recycling or disposal cost of inferior cooking oil is lower than the sum of the penalty and the social cost of the reuse of waste oils by consumers and the penalty is lower than the difference in the profits of these two products, the government always performs the spot check, but the processor's best response is still to produce inferior cooking oil to earn the higher profit. When both the costs and the difference in the profits of these two products are greater than the penalty, there is no unique pure Nash equilibrium. If the government performs the spot check, the processor produces biodiesel; if the government does not perform the spot check, the processor produces inferior cooking oil. If the processor produces biodiesel, the best response for the government is to not check; if the processor produces inferior cooking oil, the best response for the government is to perform the spot check and punish the processor. There is a mixed Nash equilibrium with the probabilities of the processor producing inferior cooking oil and of the government performing a spot check.

We take the partial derivatives of $r^*$and s^*, respectively, with respect to E_1, E_2, M, K, V^-, and find the following results.

(a) $\frac{\partial r^*}{\partial E_2} = -\frac{M}{E_2^2} < 0$, so r^* is a decreasing function of E_2, meaning that a larger penalty reduces the probability that the government performs the check. If the government wants to decrease the frequency of spot checks, it must increase the penalty on the production of inferior cooking oil. The intuition for this result is that to reduce the production of inferior cooking oil, and the direct policy is to reduce the incentive of the processor to produce inferior cooking oil by increasing the penalty. In the extreme case where the penalty is so high that it exceeds the extra benefits from producing inferior cooking oil, the processor has no incentive to produce inferior cooking oil, and there is no need to make a spot check. $\frac{\partial s^*}{\partial E_2} = \frac{-C_g}{(E_2 - K + V^-)^2} < 0$, s^* is a decreasing function of E_2, meaning that a larger penalty lowers the probability of the processor producing inferior cooking oil. If the penalty is sufficiently large, the processor has no incentive to take the risk of producing inferior cooking oil.

(b) $\frac{\partial r^*}{\partial M} = \frac{1}{E_2} > 0$, so r^* is an increasing function of M, meaning that an increase in the difference between the profits of the two products increases the probability of the government performing a spot check. To reduce the frequency of spot checks, it is best to shrink the difference in the profits of the two products by promoting technological progress in the manufacturing process, increasing exports to increase the market price of biodiesel, or improving the identification technology for consumers to decrease the demand for inferior cooking oil. $\frac{\partial s^*}{\partial C_g} = \frac{1}{E_2 - K + V^-} > 0$, s^* is an increasing function of C_g if $E_2 > K$, meaning that the higher the cost of the spot check is, the higher the probability of the processor producing inferior cooking oil is. Similarly, the higher the cost of the spot check is, the lower is the probability of the processor producing biodiesel. $\frac{\partial s^*}{\partial K} = \frac{C_g}{(E_2 - K + V^-)^2} > 0$, s^* is an increasing function of K, meaning that increasing the cost to the government of disposing inferior cooking oil increases the probability of the processor producing inferior cooking oil. As the cost to the government of disposing inferior cooking oil increases, the government's incentive to check the UCO process decreases and the processor has a higher probability of producing inferior cooking oil. $\frac{\partial s^*}{\partial V^-} = \frac{-C_g}{(E_2 - K + V^-)^2} < 0$, s^* is a decreasing function of V^-, meaning that the higher the social cost of the reuse of waste oils by consumers is, the lower is the probability of the processor producing inferior cooking oil. As the social cost of the reuse of waste oils by consumers increases, reflected in huge costs of public healthcare and a variety of diseases such as cancer, the probability of the government performing the spot check rises under the pressure of public concern over waste oils; as a result, the processor is less likely to produce inferior cooking oil.

Figure 1 shows that as the social cost, V^-, of the reuse of waste oils by consumers increases, the government increases the frequency of spot checks in the short run. The government reduces the frequency of spot checks in the long run as the probability of the processor producing inferior cooking oil decreases, which demonstrates how a higher social cost decreases the probability of the processor producing inferior cooking oil by increasing the incentive for the local government to increase spot checks to decrease the probability of the processor producing inferior cooking oil. A larger penalty, E_2, results in a lower probability of the government performing a check. To decrease the social cost of the reuse of waste oils by consumers, V^-, the government can increase the penalty for producing inferior cooking oil, E_2, proportionately[2] via reducing the probability of the processor producing inferior cooking oil, s^*, then further shrink the production of inferior cooking oil and the corresponding social cost related to public healthcare and a variety of diseases. When the cost of the random spot check is moderate[3] and the penalty for producing inferior cooking oil is small, $E_2 < M$, the government always checks. While the penalty is large enough, $E_2 > M$, the government will check with a positive probability no matter how much the cost of the random spot check is.

The two blue lines in **Figure 2** show that as the difference in the profits of the two products increases, so does the probability that the government performs a check. The two brown lines show that as the penalty for producing inferior cooking oil increases,

[2]Since $\frac{\partial s^*}{\partial V^-} = \frac{-C_g}{(E_2 - K + V^-)^2}$ and $\frac{\partial s^*}{\partial E_2} = \frac{-C_g}{(E_2 - K + V^-)^2}$, then $\frac{\partial V^-}{\partial E_2} = \frac{\partial s^*}{\partial E_2} / \frac{\partial s^*}{\partial V^-} = 1$, when $s^* = C_g / (E_2 - K + V^-)$ in equilibrium. That is, there is a one-to-one relationship between the social cost of the reuse of waste oils by consumers and the penalty for producing inferior cooking oil.

[3]When $C_g + K < E_2 + V^-$, the cost of the random spot check is moderate; when $C_g + K > E_2 + V^-$, the cost of the random spot check is large so that the government always chooses not to check.

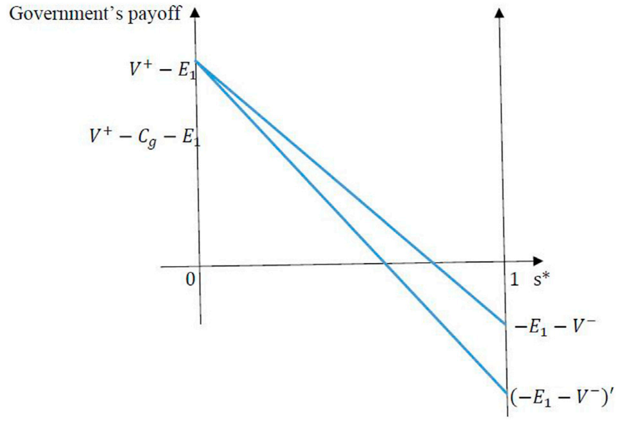

FIGURE 1 | Relationship between the government's payoff and the probability of producing inferior cooking oil.

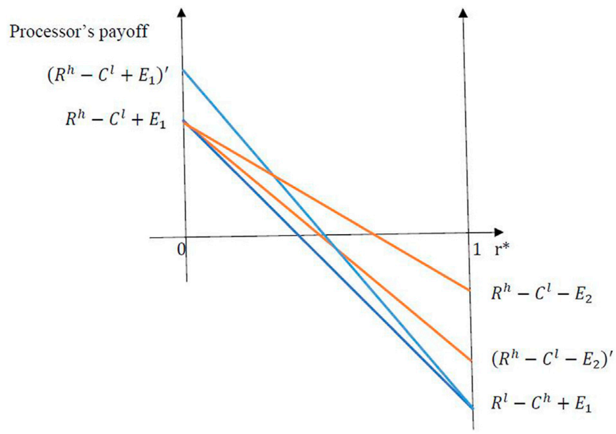

FIGURE 2 | Relationship between the processor's payoff and the probability of a spot check.

the frequency of spot checks decreases. In the short run, the processor is less likely to produce inferior cooking oil when the penalty is higher; however, a higher penalty increases rather than reduces the probability of the processor producing inferior cooking oil as r* decreases in the long run because the higher penalty decreases the probability of the government performing a spot check.

Proposition 2 (incentive paradox). Ex-ante subsidy has no effect on the probabilities of the processor producing inferior cooking oil or the government performing a spot check. Increasing the penalty for the processor does not deter it from producing inferior cooking oil in one-stage game but does reduce the frequency of spot checks by the local government. Increasing the social cost of the reuse of waste oils by consumers decreases the probability of the processor producing inferior cooking oil.

One-Stage Game Model With Subsidy Given After Spot Checks

The strategic-form representation of the game when the spot check is performed first, and then, the subsidy is given as follows in **Table 2**. Given these payoffs, we find the following pure and mixed Nash equilibria.

Scenario 1. When $E_2 - C_g - K < V^-$, that is, $C_g + K > E_2 + V^-$, the sum of the cost of the spot check and the recycling or disposal cost of inferior cooking oil is larger than the sum of the penalty and the social cost of the reuse of waste oils by consumers. In this case, there exists a unique pure Nash equilibrium (production of inferior cooking oil, no spot check). As shown above, there is no pure Nash equilibrium if the cost of the spot check is too small.

Scenario 2. When $E_2 - C_g - K > V^-$, that is, $C_g + K < E_2 + V^-$, and $R^h - C^l - E_2 > R^l - C^h + E_1$, which can be rewritten as $E_1 + E_2 < M$, there is a unique pure Nash equilibrium (production of inferior cooking oil, spot check). If $R^h - C^l - E_2 < R^l - C^h + E_1$, which can be rewritten as that is, $E_1 + E_2 > M$, there is no pure Nash equilibrium.

Scenario 3. In all other cases, there is a mixed Nash equilibrium with

$$r^{**} = \frac{(R^h - C^l) - (R^l - C^h)}{E_1 + E_2} = \frac{M}{E_1 + E_2}, \tag{5}$$

TABLE 2 | Spot check performed before the subsidy is given.

		Local government	
		Spot check	No spot check
Processor	Produce biodiesel	$(R^l-C^h+E_1,\ V^+-C_g-E_1)$	$(R^l-C^h,\ V^+)$
	Produce inferior cooking oil	$(R^h-C^l-E_2,\ E_2-C_g-K)$	$(R^h-C^l,\ -V^-)$

$$s^{**}=\frac{C_g+E_1}{E_1+E_2-K+V^-}\ . \tag{6}$$

The processor is indifferent between producing biodiesel and producing inferior cooking oil when

$$r\left(R^l-C^h+E_1\right)+(1-r)\left(R^l-C^h+E_1\right)\left(R^l-C^h\right)$$
$$=r\left(R^h-C^l-E_2\right)+(1-r)\left(R^h-C^l\right). \tag{7}$$

The government is indifferent between performing a spot check and not performing a spot random check when

$$(1-s)\left(V^+-C_g-E_1\right)+s\left(E_2-\ Cg-K\right)=(1-s)V-sV^-. \tag{8}$$

Equations 7, 8 can be solved to obtain the equilibrium probabilities of the government performing a spot check and the processor producing inferior cooking oil as given by **Eqs.5, 6**. We take the partial derivatives of $r^{**}$and s^{**} with respect to E_1, E_2, M, K, C_g, and V^- to find the following.

a) $\frac{\partial r^{**}}{\partial E_1}=\frac{-M}{(E_1+E_2)^2}<0$, so r^{**} is a decreasing function of E_1, meaning that a larger subsidy lowers the probability of the government performing a check. When a check is performed before the subsidy is given, a larger subsidy lowers the opportunity cost of the check. If the government wants to decrease the frequency of the checks, it must increase the subsidy for the production of biodiesel. Theoretically, if the subsidy is so high that it compensates for the difference in the profits of the two products, the processor has no incentive to produce the inferior cooking oil. However, the subsidy is also a cost of government supervision and the management of waste oil. The government faces a tradeoff between the cost of a spot check to reduce the production of inferior cooking oil and increase the production of biodiesel and the cost of a subsidy to increase the production of biodiesel and reduce the production of inferior cooking oil. $\frac{\partial s^{**}}{\partial \mathrm{E}_1}=\frac{\mathrm{E}_2-K+V^--C_g}{(\mathrm{E}_1+\mathrm{E}_2-K+V^-)^2}>0$, so s^{**} is an increasing function when $\mathrm{E}_2>K+C_g$, the larger the subsidy is, the higher the probability of inferior cooking oil producing. To deter the production of inferior cooking oil, the government may decrease the subsidy and increase the frequency of spot checks to the processor. For example, as the subsidy for new energy cars increases in China, more enterprises just make simple modification of unqualified electric cars to cheat subsidy. To eliminate the occurrence of subsidy fraud, the subsidy for new energy vehicles is reduced gradually from 2016. One of car enterprises received a total of more than US$0.5B higher than its profit from two national subsidies for new energy vehicles in 2020 (from the Ministry of Industry and Information Technology of China). In other words, it would lose money without these huge subsidies.

b) $\frac{\partial r^{**}}{\partial E_2}=\frac{-M}{(E_1+E_2)^2}<0$, so r^{**} is a decreasing function of E_2, meaning that a larger penalty decreases the probability that the government performs a check. A larger penalty deters the processor from illegally producing inferior cooking oil and increases the probability of the processor producing biodiesel legally, which decreases the probability and cost of a spot check. $\frac{\partial s^{**}}{\partial \mathrm{E}_2}=\frac{-(\mathrm{C_g}+\mathrm{E}_1)}{(\mathrm{E}_1+\mathrm{E}_2-K+V^-)^2}<0$, so s^{**} is a decreasing function of E_2. A larger penalty weakens the incentive of the processor to take the risk of producing inferior cooking oil and lowers the probability of the processor producing inferior cooking oil. Moreover, $\frac{\partial^2 r^{**}}{\partial \mathrm{E}_2\partial \mathrm{E}_1}=\frac{2M}{(\mathrm{E}_1+\mathrm{E}_2)^3}>0$, $\frac{\partial^2 s^{**}}{\partial \mathrm{E}_2\partial \mathrm{E}_1}=\frac{-(\mathrm{E}_2-K-\mathrm{C_g})-(V^--\mathrm{E}_1-\mathrm{C_g})}{(\mathrm{E}_1+\mathrm{E}_2-K+V^-)^3}<0$, the combined effect of penalty and subsidy is positive on the probability of spot checks and negative on the probability of producing inferior cooking oil. When two measures used on the case of spot checks performed first with penalty or subsidy, the processor has lower incentive to produce inferior cooking oil because of large penalties ($\mathrm{E}_2>K+C_g$) and huge social cost of the reuse of waste oils by consumers($V^->\mathrm{E}_1+\mathrm{C_g}$), and higher incentive to produce biodiesel because of increasing penalties and subsidies ($E_1+E_2>M$).

c) $\frac{\partial r^{**}}{\partial M}=\frac{1}{E_1+E_2}>0$, so r^{**} is an increasing function of M. Increasing the difference in the profits of the two products increases the probability of the government performing a spot check. A larger difference in the profits of the two products increases the probability of the processor producing inferior cooking oil illegally, which results in a higher probability of the government performing a spot check. This result is similar to the results when the subsidy is given before the spot check is performed. $\frac{\partial s^{**}}{\partial C_g}=\frac{1}{\mathrm{E}_1+\mathrm{E}_2-K+V^-}>0$, so s^{**} is an increasing function of C_g. A larger cost of performing a spot check results directly in a lower probability of a spot check which results in a higher probability of the processor producing inferior cooking oil. $\frac{\partial s^{**}}{\partial K}=\frac{-(C_g+\mathrm{E}_1)}{(\mathrm{E}_1+\mathrm{E}_2-K+V^-)^2}>0$, s^{**} is an increasing function of K, meaning that increasing the disposal cost of inferior cooking oil increases the probability of the processor producing inferior cooking oil. $\frac{\partial s^{**}}{\partial V^-}=\frac{-(C_g+\mathrm{E}_1)}{(\mathrm{E}_1+\mathrm{E}_2-K+V^-)^2}<0$, s^{**} is a decreasing function of V^-, increasing the social cost lowers the probability of the processor producing inferior cooking oil.

Proposition 3. Therelative timing of the subsidy and spot check is important. When the subsidy is given before the spot check is performed, ex-ante subsidies have no impact on the probabilities of the processor producing inferior cooking oil or the government performing a spot check. When a spot check is performed before the subsidy is given, ex-post subsidies have a negative effect on the probability of biodiesel producing, combined with penalties have a positive effect on the probability of producing biodiesel from UCO

The difference between these two timings is the effect of subsidies. When the subsidy is given before the spot check is performed, there is no effect of subsidies on the probabilities of the processor producing inferior cooking oil or the government performing a spot check. When the spot check is performed before the subsidy is given, a larger subsidy combined with large penalties decreases the probability of the processor producing inferior cooking oil. The government may increase the subsidy and penalty to lower the probability of the processor producing inferior cooking oil and increase the probability of the processor producing biodiesel.

Proposition 4. Comparing the two methods, the probability of biodiesel production caused by the first method (subsidy given before spot checks) is higher than that caused by the second method (spot checks are performed before subsidy given).

Given the probability of the government performing a spot check in the n^{th} stage and the probability of producing biodiesel we derived above, then the conditional probability of biodiesel production caused by the first method (subsidy given before spot checks) can be written as,

$$\begin{aligned} \boldsymbol{p}(\boldsymbol{Check}1|\boldsymbol{BIO}) &= \frac{\boldsymbol{p}(\boldsymbol{BIO}|\boldsymbol{Check}1)\boldsymbol{p}(\boldsymbol{Check}1)}{\boldsymbol{p}(\boldsymbol{BIO})} \\ &= \frac{(\mathbf{1}-\boldsymbol{s}^{*})\boldsymbol{r}^{*}}{(\mathbf{1}-\boldsymbol{s}^{*})\boldsymbol{r}^{*}+(\mathbf{1}-\boldsymbol{s}^{**})\boldsymbol{r}^{**}+0(\mathbf{1}-\boldsymbol{r}^{*}-\boldsymbol{r}^{**})} = \frac{(\mathbf{1}-\boldsymbol{s}^{*})\boldsymbol{r}^{*}}{(\mathbf{1}-\boldsymbol{s}^{*})\boldsymbol{r}^{*}+(\mathbf{1}-\boldsymbol{s}^{**})\boldsymbol{r}^{**}}, \end{aligned} \tag{9}$$

where $p(Check1)$and $p(Check2)$ represent the probabilities of the government performing a spot check after or before subsidy; $p(BIO|Check1)$ and $p(BIO|Check2)$ represent the probabilities of the government performing a spot check after or before subsidy and the processor producing biodiesel; and $p(BIO)$ is the total probability of the processor producing biodiesel. And the conditional probability of biodiesel production caused by the second method (spot checks are used before subsidy given) can be written as,

$$\boldsymbol{p}(\boldsymbol{Check}2|\boldsymbol{BIO}) = \frac{(\mathbf{1}-\boldsymbol{s}^{**})\boldsymbol{r}^{**}}{(\mathbf{1}-\boldsymbol{s}^{*})\boldsymbol{r}^{*}+(\mathbf{1}-\boldsymbol{s}^{**})\boldsymbol{r}^{**}}. \tag{10}$$

Substitute **Eqs 1, 2, 5, 6** into the following conditional probabilities, we have,

$$\boldsymbol{p}(\boldsymbol{Check}1|\boldsymbol{BIO}) = \frac{(\boldsymbol{E}_2-\boldsymbol{K}+\boldsymbol{V}^{-})\boldsymbol{E}_2}{(\boldsymbol{E}_2-\boldsymbol{K}+\boldsymbol{V}^{-})(2\boldsymbol{E}_2+\boldsymbol{E}_1)+\boldsymbol{E}_1(\boldsymbol{E}_1+\boldsymbol{E}_2)}, \tag{11}$$

$$\boldsymbol{p}(\boldsymbol{Check}2|\boldsymbol{BIO}) = \frac{(\boldsymbol{E}_1+\boldsymbol{E}_2-\boldsymbol{K}+\boldsymbol{V}^{-})(\boldsymbol{E}_1+\boldsymbol{E}_2)}{(\boldsymbol{E}_2-\boldsymbol{K}+\boldsymbol{V}^{-})(2\boldsymbol{E}_2+\boldsymbol{E}_1)+\boldsymbol{E}_1(\boldsymbol{E}_1+\boldsymbol{E}_2)}, \tag{12}$$

and $p(Check2|BIO) > p(Check1|BIO)$, since $(E_1+E_2-K+V^{-})(E_1+E_2) > (E_2-K+V^{-})E_2$. Which means that production of biodiesel is caused by the second method (spot check performed before subsidy given) of the probability is greater than production of biodiesel is caused by the first method (subsidy given before spot checks) of the probability. The spot check performed before subsidy has a greater effect on biodiesel production than that performed after subsidy. In order to improve the processor's incentive to produce biodiesel, the spot check is preferred to be used first and then subsidy or penalty will be performed accordingly.

Dynamic Infinitely Repeated Game Model

We assume as above that there is one waste oil processor that can produce either biodiesel legally or inferior cooking oil illegally. The local government encourages the waste oil processor to produce biodiesel legally and gives the processor a subsidy according to its reported biodiesel production. If the waste oil processor deviates from producing biodiesel and the inferior cooking oil illegally instead and this is discovered during a spot check, the local government punishes the waste oil processor with a fine.

Because government supervision is a repeated process, both the local government and the processor know the results of the most recent spot check. Both sides readjust their strategies given the outcome of the most recent stage of the game. The processor decides whether to produce biodiesel legally or inferior cooking oil illegally, and the local government adjusts its probability of performing a spot check to adjust its cost. The game between the local government and the waste oil processor is an infinitely repeated game of complete information.

The following two strategies, grim trigger strategy (GTS) and tit-for-tat strategy (TFT), can be used to punish the processor producing inferior cooking oil in the infinite repeated game.

First, GTS is as follows, start by cooperating, that is, the waste oil processor producing biodiesel and the government does not perform a spot check at stage 1, and continue to cooperate until the waste oil processor deviates to produce the inferior cooking oil, once a deviation observed, the government will immediately punish the waste oil processor to shut down and cannot produce either legal biodiesel or illegal inferior cooking oil any more.

Suppose both the government and the processor choose to cooperate at the beginning of the infinite repeated game, the government performs a spot check in the n^{th} stage and the processor continues to produce biodiesel.

To induce the processor to produce biodiesel to be a Nash equilibrium, the expected payoff to the processor of producing biodiesel must be no lower than the processor's expected payoff to producing inferior cooking oil. So it is only when the government punishes the processor for producing poor-quality cooking oil, the processor's profit is lower when producing inferior quality cooking oil than when producing biodiesel. The expected payoff to the processor of producing biodiesel is greater than and equal to the expected payoff to the processor of producing inferior quality cooking oil in the first n stages until the illegal production is discovered with shutting down in the n^{th} stage as shown in **Eq. 13**.

$$\sum_{i=1}^{\infty} \delta^{i-1}\left(R^l - C^h + E_1\right) \geq \sum_{i=1}^{n-1} \delta^{i-1}\left(R^h - C^l + E_1\right). \quad (13)$$

Which results in $\frac{1}{1-\delta}\left(R^l - C^h + E_1\right) \geq \frac{1-\delta^n}{1-\delta}\left(R^h - C^l + E_1\right)$, and we have the following results,

$$\delta^n \geq 1 - \frac{R^l - C^h + E_1}{R^h - C^l + E_1} = \frac{\left(R^h - C^l\right) - \left(R^l - C^h\right)}{R^h - C^l + E_1} = \frac{M}{R^h - C^l + E_1} \text{ and } 0 \leq \frac{R^l - C^h + E_1}{R^h - C^l + E_1} \leq 1 \quad (14a)$$

or

$$\delta \geq \left(\frac{M}{R^h - C^l + E_1}\right)^{\frac{1}{n}} \text{and } 0 \leq \frac{R^l - C^h + E_1}{R^h - C^l + E_1} \leq 1 \quad (14b)$$

where the numerator is the profit difference between legal biodiesel production and illegal inferior cooking oil production. Moreover, the denominator represents the benefit to cooperate to produce legal biodiesel, and the numerator represents the inventive to cheat to produce illegal inferior cooking oil.

Given the discount rate, δ, the smaller the incentive not to cooperate once M relative to the benefit to cooperate ($R^h - C^l + E_1$), the greater the probability of cooperation to produce legal biodiesel. Given the ratio of the incentive not to cooperate to the benefit to cooperate, the greater the discount rate, or the more important the future outcomes, the greater the probability of cooperation in the infinite periods. Moreover, given the ratio of the incentive not to cooperate to the benefit to cooperate, since $\frac{\partial \delta}{\partial n} = -\left(\frac{M}{R^h - C^l + E_1}\right)^{\frac{1}{n}} \ln \frac{M}{R^h - C^l + E_1} \frac{1}{n^2} > 0$, the bigger n, the greater the discount rate δ. Thus, the later production of illegal inferior cooking oil was observed, the greater the discount rate needed to cooperate, and the more patient, the more important to future benefits.

The second strategy is known as TFT, which starts by cooperating, that is, the waste oil processor producing biodiesel, and the government does not perform a spot check at stage 1, and continue to do (either cooperate or cheat) what the rival did in the most recent period. Once the waste oil processor deviates to produce the inferior cooking oil, the government will immediately revert to a period of punishment of the remaining period to perform a spot check definitely in order to push the waste oil processor back to cooperate and produce legal biodiesel again.

$$\sum_{i=1}^{\infty} \delta^{i-1}\left(R^l - C^h + E_1\right) \geq \sum_{i=1}^{n-1} \delta^{i-1}\left(R^h - C^l + E_1\right) + \delta^n\left(R^h - C^l + E_1 - E_2\right) + \sum_{i=n+1}^{\infty} \delta^{i-1}\left(R^l - C^h + E_1\right), \quad (15)$$

which is equivalent to $\frac{1-\delta^{n+1}}{1-\delta}\left(R^l - C^h + E_1\right) \geq \frac{1-\delta^n}{1-\delta}\left(R^h - C^l + E_1\right) + \delta^n\left(R^h - C^l + E_1 - E_2\right)$ and results in $\frac{1-\delta^{n+1}}{1-\delta}\left(R^l - C^h + E_1\right) \geq \frac{1-\delta^{n+1}}{1-\delta}\left(R^h - C^l + E_1\right) - \delta^n E_2$, then we have

$$\delta^n \geq \frac{1-\delta^{n+1}}{1-\delta} \frac{\left(R^h - C^l\right) - \left(R^l - C^h\right)}{E_2} = \frac{1-\delta^{n+1}}{1-\delta} \frac{M}{E_2} \text{ and } 0 \leq \frac{R^l - C^h + E_1}{R^h - C^l + E_1} \leq 1, \quad (16)$$

where $0 \leq \frac{(R^h - C^l) - (R^l - C^h)}{E_2} = \frac{M}{E_2} \leq 1$ represents profit differencepenalty ratio, as penalty increases the ratio tends to 0. This ratio is equivalent to $E_2 \geq M$, which means that the penalty is large enough to compensate the illegal profit difference between biodiesel and the inferior cooking oil production. Otherwise, when the penalty is not large enough, such that $E_2 < M$, the waste oil processor will always produce the inferior cooking oil even if the government performs a spot check at every stage.

Where the numerator is the profit difference between legal biodiesel production and illegal inferior cooking oil production and represents the inventive to cheat to produce illegal inferior cooking oil, in other words, it is also the cost of cheating in the future. It can be considered as a threat of cheating. Moreover, the denominator is the penalty, $E_2 = \left(R^h - C^l + E_1\right) - \left(R^h - C^l + E_1 - E_2\right)$, represents the benefit to cooperate to produce legal biodiesel in the future. It can be considered as a promise of cooperating in the future.

Given the discount rate, δ, the smaller the incentive not to cooperate once M relative to the benefit to cooperate E_2, the greater the probability of cooperation to produce legal biodiesel. Given the ratio of the incentive not to cooperate to the benefit to cooperate, the greater the discount rate, or the more important the future outcomes, the greater the probability of cooperation in the infinite periods.

Proposition 5. When the discount factor, δ, is sufficiently large, producing biodiesel is a perfect Nash equilibrium grim trigger strategy or tit-for-tat strategy for the processor in the infinitely repeated game. The discount rate, δ, is such that:

a) $\delta^n \geq \frac{M}{R^h - C^l + E_1}$, *and* $0 \leq \frac{R^l - C^h + E_1}{R^h - C^l + E_1} \leq 1$ *(GTS)*
b) $\delta^n \geq \frac{1-\delta^{n+1}}{1-\delta} \frac{M}{E_2}$, *and* $0 \leq \frac{M}{E_2} \leq 1$ *(TFT)*
c) If $\frac{M}{E_2} > 1$, producing illegal inferior cooking oil is a dominant strategy for the processor even there is a penalty.

Since GTS or TFT can be a Nash equilibrium, when $\delta \geq \left(\frac{M}{R^h - C^l + E_1}\right)^{\frac{1}{n}}$ and $\delta^n \geq \frac{1-\delta^{n+1}}{1-\delta} \frac{M}{E_2}$ respectively. Let $\delta^{GTS} = \left(\frac{M}{R^h - C^l + E_1}\right)^{\frac{1}{n}}$, only if the discount rate, $\delta \geq \delta^{GTS}$, GTS will be a Nash equilibrium in infinite repeated game. Let $f(\delta) = \delta^n(1-\delta) - (1-\delta^{n+1})\frac{M}{E_2} \geq 0$ and δ^{TFT}be the solution to $f(\delta)$, only if the discount rate, $\delta \geq \delta^{TFT}$, TFT will be a Nash equilibrium in infinite repeated game. Next, we substitute $\delta^{GTS} = \left(\frac{M}{R^h - C^l + E_1}\right)^{\frac{1}{n}}$ into $f(\delta)$ and have $f(\delta^{GTS}) = \left[\delta^n - \frac{M}{E_2}\right] + \delta^{n+1}\left[\frac{M}{E_2} - 1\right] = \left[\frac{M}{R^h - C^l + E_1} - \frac{M}{E_2}\right] + \left(\frac{M}{R^h - C^l + E_1}\right)^{\frac{n+1}{n}}\left[\frac{M}{E_2} - 1\right] < 0$, when $M \leq E_2 \leq R^h - C^l + E_1$, meaning that $\delta^{GTS} < \delta^{TFT}$. When $E_2 \geq R^h - C^l + E_1 \geq M$, it is ambiguous that either $\delta^{GTS} < \delta^{TFT}$ or $\delta^{GTS} \geq \delta^{TFT}$.

Proposition 6. The discount factor, $\delta^{GTS} < \delta^{TFT}$, is lower for GTS than that for TFT when the penalty is not big enough. Producing biodiesel is a perfect Nash equilibrium that is easier for GTS than TFT for the processor in the infinitely repeated game. Given the ratio of the incentive to produce illegal inferior cooking

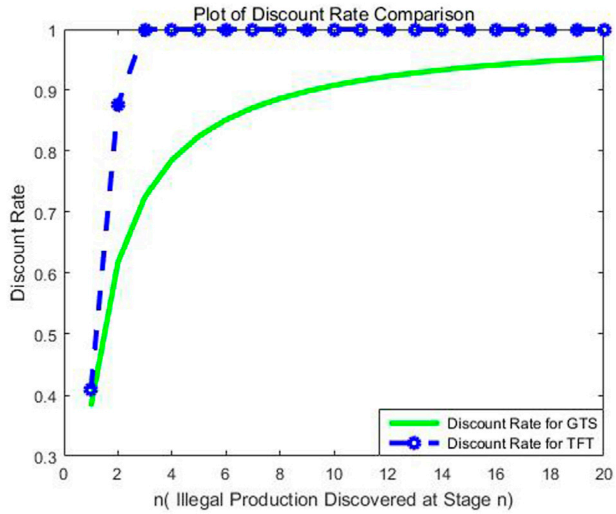

FIGURE 3 | Discount rate comparison between GTS and TFT.

oil to the benefit to produce biodiesel, the threat of shutting down is much easier to induce biodiesel production than the threat of penalty.

If we substitute $\delta^{GTS} = (\frac{M}{R^h - C^l + E_1})^{\frac{1}{n}}$into $\delta^n \geq \frac{1-\delta^{n+1}}{1-\delta}\frac{M}{E_2}$, we have $E_2 \geq \frac{M(1-\delta^{n+1})}{(1-\delta)\delta^n} = \frac{M(1-\delta^{n+1})}{(1-\delta)\delta^n} = (R^h - C^l \quad \frac{+E_1)^{\frac{n+1}{n}} - M^{\frac{n+1}{n}}}{(R^h - C^l + E_1)^{\frac{1}{n}} - M^{\frac{1}{n}}} \delta^n \geq \frac{M-E_1}{R^h}$ $-C^l,_{\frac{1}{n}} \delta^n \geq \frac{1-\delta^{n+1}}{1-\delta}\frac{M-E_1}{E_2}\delta^{GTS} = (\frac{M-E_1}{R^h}$ $-C^l) \delta^n \geq \frac{1-\delta^{n+1}}{1-\delta}\frac{M-E_1}{E_2} E_2 \geq \frac{(M-E_1)(1-\delta^{n+1})}{(1-\delta)\delta^n} = \frac{(R^h-C^l)^{\frac{n+1}{n}} - (M-E_1)^{\frac{n+1}{n}}}{(R^h-C^l)^{\frac{1}{n}} - (M-E_1)^{\frac{1}{n}}}$. That is, only if the amounts of penalties are large enough, the tit-for-tat strategy requires the discount rate as low as it for trigger strategy to be a perfect Nash equilibrium and produce biodiesel. We have the following Lemma.

Lemma 7. There exists a sufficient condition that ensures producing biodiesel when $E_2 \geq \frac{(R^h - C^l + E_1)^{\frac{n+1}{n}} - M^{\frac{n+1}{n}}}{(R^h - C^l + E_1)^{\frac{1}{n}} - M^{\frac{1}{n}}}$; the strategy of tit-for-tat will be a perfect Nash equilibrium in the infinitely repeated game, and producing inferior cooking oil is impossible. Moreover, the sooner production of illegal inferior cooking oil is observed, the lower penalty required to induce the processor to produce biodiesel in infinitely repeated game.

SIMULATION RESULTS

Policy makers want an efficient regulation method to achieve the objective of biodiesel production instead of inferior cooking oil production in the infinitely repeated game. Although this policy objective is clear and unique, the exact amount of subsidy or penalty for each outcome has not been calculated in the literature, to our best knowledge. We believe that the reason was that an analytic calculation is not possible, and one has to use simulations for this. Our simulation code is written in MATLAB. It begins with drawing net profits for the processor producing biodiesel and inferior cooking oil based on the current situation in Shanghai, China. Then, we adjust different levels of stages (from stage 1–20) at which the illegal production by the processor will be discovered to show the changes in discount rate for the GTS and TFT strategies in the long run and the changes in penalties. Finally, we adjust different levels of profit difference between biodiesel and inferior cooking oil production and subsidy to show that the effect of change in profit of illegal and legal production on penalties. One set of values and numbers corresponds to one strategy. Knowing these values, by using our theoretical model, we calculate different levels of discount rate, the amount of penalty and subsidy.

Figure 3 shows that the discount rates comparison between GTS and TFT which two strategies need to be Nash equilibria as the stage at which the illegal inferior cooking oil production is checked out, where stage n increases from 1 to 20, the corresponding different discount rates for GTS and TFT. The simulation parameters setting based on the case of Shanghai is as follows: net revenue for biodiesel is \$190/t and net revenue for inferior cooking oil is \$318/t; the annual UCO output is 35,000 tons; the amount of subsidy is \$0.63M per year, and penalty is \$6.17M. As we shown above, the bigger n, the greater the discount rate δ for both GTS and TFT strategies. However, the later production of illegal inferior cooking oil was observed, the greater the discount rate needed to cooperate to produce biodiesel for TFT strategy than GTS strategy. In other words, it is more difficult for FTF strategy to induce the processor to produce biodiesel than GTS strategy, since TFT needs more patience for future benefits with discount rate close to 1. **Figure 4** shows that as the stage at which the illegal inferior cooking oil production was observed increases from 1 to 20, the penalty will increase dramatically. That is, the later the illegal inferior cooking oil production is checked out, the higher the penalty required to force the processor to produce biodiesel.

Figure 5 shows that the discount rate comparison for GTS of the changes in profit of biodiesel and subsidy. As the profit of biodiesel and subsidy increase by the same amount per year, the corresponding discount rates show that it is higher for increase in subsidy than for increase in the profit of biodiesel production.

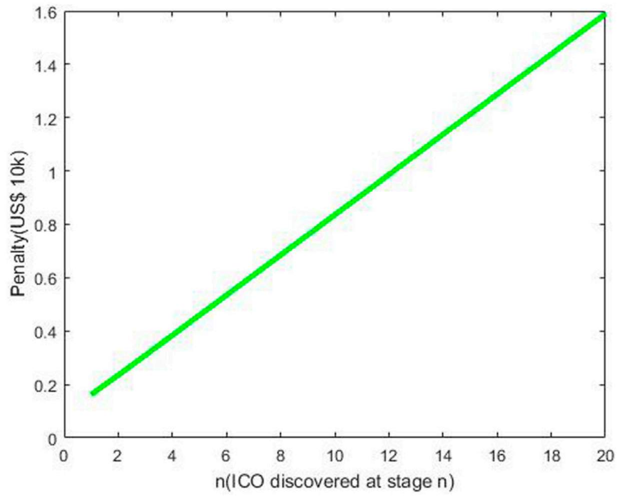

FIGURE 4 | Increase in penalties for TFT of the changes in stage at which illegal production is discovered.

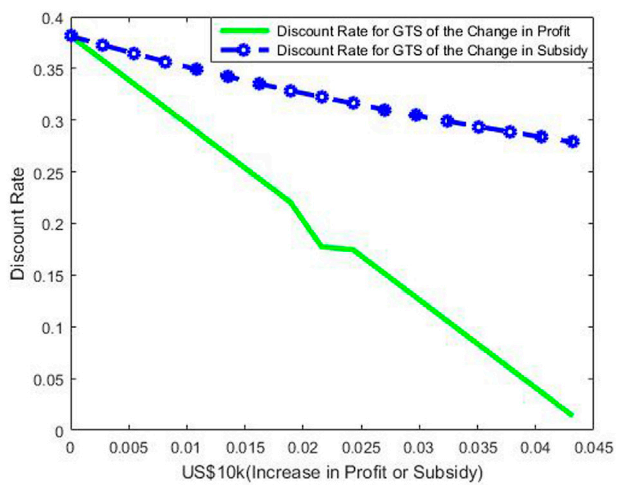

FIGURE 5 | Discount rate comparison for GTS of the changes in profit and subsidy.

Moreover, the effect of the increase of subsidies on the discount rate is far less than that of the increase in profit of biodiesel production. It is better to increase the profit growth of biodiesel or shrink the profit difference between biodiesel and inferior cooking oil to guide biodiesel production instead of increase in subsidies.

Figures 6, **7** show that the effect of change in profit of illegal and legal production on penalties when subsidy is given and on the sum of subsidies and penalties with $n = 1$. The blue line represents the changes in penalties and the sum of subsidies and penalties when there is a decrease in profit of legal biodiesel production from the highest value $318/t by $1.5/t and profit of illegal inferior cooking oil production remains constant at $318/t. Then, the green line represents the changes in penalties and the sum of subsidies and penalties when there is an increase in profit of illegal inferior cooking oil production from the lowest value $190/t by $1.5/t and profit of legal biodiesel production remains constant at $190/t. The changes in profit difference between inferior cooking oil and biodiesel production are the same for both cases and also increase from $1.5/t to $150/t which means that there are two ways to shrink the profit difference, either decrease profit of illegal inferior cooking oil production or increase profit of legal biodiesel production. Both lines increase as the profit difference increases, but the effect of same profit difference is different. The lower the blue line, the higher profit growth in legal biodiesel production and the lower penalties; the higher the green line, the higher profit growth in illegal inferior cooking oil production and the higher penalties. The green line is steeper and more elastic than the blue line. That is, the same amount changes in the profit difference resulting from an increase profit of illegal inferior cooking oil production will require more penalties or the sum of subsidies and penalties

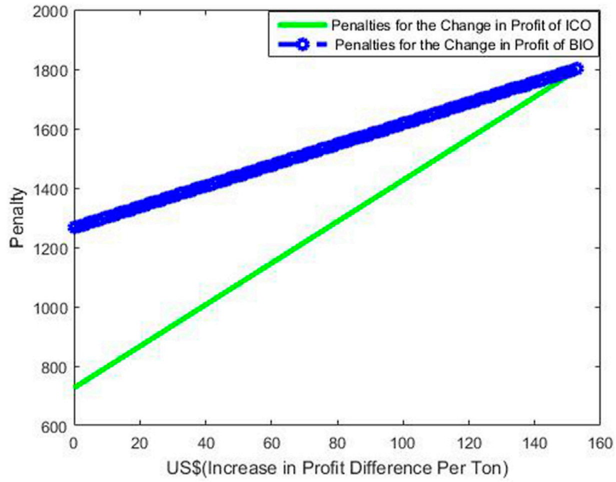

FIGURE 6 | The effect of changes in profit for TFT on penalties.

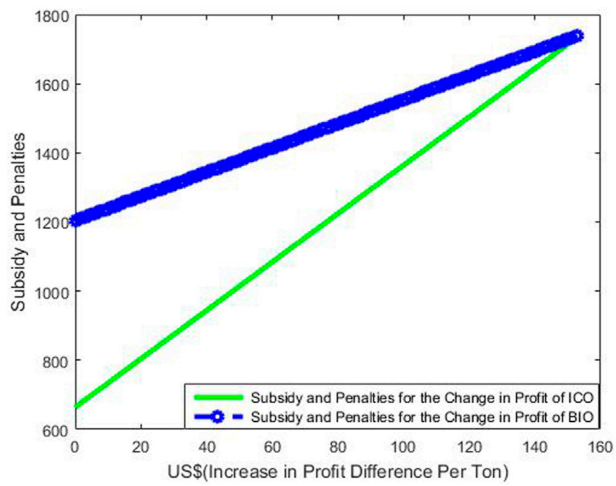

FIGURE 7 | The effect of changes in profit for TFT on the sum of subsidies and penalties.

than that resulting from a decrease profit of legal biodiesel production. As a result, an increase in profit of legal biodiesel production will reduce penalties/subsidies more than an increase in profit of illegal inferior cooking oil production. Given the amount of penalty, as the profit difference increases, the subsidy should increase too.

Lemma 8. The later production of illegal inferior cooking oil was observed, the higher patience required to cooperate for TFT strategy than GTS strategy to induce the processor to produce biodiesel in infinitely repeated game. Moreover, the effects of same increase in profit of biodiesel and subsidy are different, and it is much easier and better to increase the profit of biodiesel instead of subsidies to guide biodiesel production. Increasing profits from legal production is more effective in reducing penalties and subsidies than increasing profits from illegal production.

CONCLUSIONS AND PRACTICAL IMPLICATIONS

Conclusions and Discussion

In this article, a sequential game theory model is developed to study the combined effects of subsidies and penalties on the promotion of renewable energy production with an example of biodiesel production from UCO. This model considers three aspects, including the intensity of the government punishment, the relative timing of government subsidies, and the cost of government regulations. Regardless of the timing of the subsidy, it is more effective to raise penalties punishment and reduce the cost of spot checks. When the combined cost of spot checks and the recycling or disposal exceeds fines and social losses to consumers, governments do not spot check and processors tend to produce illegal outputs. Otherwise, the government conducts random checks, and the processor produces illegal products with a positive probability.

The timing of a subsidy or penalty also plays an important role in regulation. Ex-ante subsidies have no effect on the probabilities that processors produce illegal products or that the government conducts spot checks, so more subsidies are not always better. The results are consistent with Chang et al. (2011), who empirically find that high levels of subsidies may cause a negative impact on users or sustainability resource production. Larger penalties do not prevent more processing of illegal products, but they do reduce the need for spot checks. Ex-post subsidies reduce the probability of spot checks which will increase the illegal production.

Extending our model to an infinitely repeated game, we find a negative relationship between penalty and discount factor. A small discount factor makes processors less patient, so they are more willing to produce illegal products for short-term gain. In such cases, it is necessary to increase punishment like shutting down or heavy penalties. In such cases, severe penalties like closure or heavy fines may be necessary. In the infinitely repeated game, the earlier illegal production can be detected, the lower the penalty required to induce the processor to produce renewable energy products such as biodiesel.

Lu et al. (2018) show that a penalty-cost-based mechanism can reduce the cost of renewable energy users. Our study shows that the combination of subsidies and penalties can not only increase the production of renewable energy but also decrease the probability of negative output. In addition, the efficiency and effectiveness of misconduct monitoring can reduce the penalty needed to mitigate illegal products. Between the two combined regulation methods, ex-post subsidy is more effective than ex-ante subsidy. This can explain why China's solar photovoltaic incentive policy has changed from ex-ante subsidy such as "Golden Sun Plan" to ex-post subsidy such as feed-in tariff policy (Yuan et al., 2015).

Our results provide a theoretical basis for the government's regulatory (GTS or TFT) strategies. When the penalties are not large enough, it is easier for GTS than TFT strategy to induce renewable energy production in an infinitely repeated game. While the penalties are large enough, TFT achieves the same objective as GTS does in biodiesel production. The simulation results show that the high-profit margin of renewable energy is a better incentive for producers to process legal products than subsidies.

Previous researches mostly focus on the positive benefits of reward and punishment policies (e.g., Kreiss et al., 2017; Md et al., 2017), while our model can provide more detailed dynamic characteristics of the subsidy and penalty mechanisms. Our study further emphasizes the importance of policy environment. The subsidy and penalty mechanism should be adjusted dynamically in accordance with the change of policy environment such as renewable energy producers' cost structure, production and management efficiency, and technology levels.

Practical Implications

First, ex-post subsidies outperform ex-ante subsidies. In practice, a successful ex-post subsidy mechanism requires detailed subsidy rules and monitoring of sustainable energy projects throughout their life cycle. Participation of third-party organizations and timely evaluation of every subsidy can contribute to the success of regulation.

Second, the grim trigger strategy (GTS) outperforms the tit-for-tat strategy (TFT). Generally, GTS is superior to TFT when the penalty is not too severe. To achieve the same effect as GTS, the penalties in TFT must be severe enough and even requiring shutting down the business. It echoes a Chinese old saying, "desperate diseases need desperate remedies". A testimony is the case of Taiwan. In 2014, the maximum fine on illegal production of UCO increased from \$0.28M to \$3.13M after a severe scandal of mixing refined UCO with fresh cooking oil. Since then, the tougher penalty has greatly reduced the opportunism behavior of UCO processors. On the other hand, companies should not only comply with the environmental regulation but also take a more proactive approach by seeking competitive advantage from sustainability practices.

Third, synergized effect of subsidy and penalty measures on renewable energy production. Subsidies and penalties must be combined, since higher subsidies may lead to more illegal output in the absence of penalties. Regardless of the timing of providing subsidies, the imposition of penalties can always have a positive impact on sustainability production. Two other elements, namely the detection of misbehavior and profit margins, are important factors influencing the implementation of subsidies and penalties. The less punishment is needed if misbehavior can be detected in time. Hence, governments should pay more attention to the use of big data, information transmission, and other technologies to improve the efficiency and effectiveness of regulation. The less subsidy is needed if the more profit companies can gain from technological and managerial innovation. Thus, governments can provide corresponding research and development funds to incentivize technological and managerial innovation. The intensity of subsidies and penalties should also be adjusted according to governments' ability to detect misbehavior and companies' level of technological or managerial innovation.

There are some limitations on our model, such as the assumption of only one processor. However, there may be more than one processor in practice. If we extend this assumption, competition between processors might lower the profits. Our theoretical results may be revised. Furthermore, in future, our work will extend our model with complete information to the game with incomplete information.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, and further inquiries can be directed to the corresponding author. The codes generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

All authors have significantly contributed to the article. XM and YD are the leaders of this research team who organized and designed the study. XM completed the main model design and simulation analysis. ZT and YD were responsible for supervision and funding acquisition and the writing of part I and part II. All authors have read and agreed to the published version of the manuscript.

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Gradual Goals of Energy Transformation and Upgrading in China's Power Industry Considering Production Profiles

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As the largest processing sector of primary energy, the transformation and upgrading of the power sector is undoubtedly an effective way to alleviate the situation of energy and environment. This article studies the gradual goals of the transformation and upgrading of China's power industry, where the conditions of technical judgment, specific profile, and moderate agenda are incorporated. The empirical analysis of China's provincial power sectors based on the constructed models came to the following results. First, it is of great importance to consider the profile of each region's power sector in setting energy-saving and emission reduction targets. The analysis of variance demonstrates significant differences in the reference points of inputs and outputs under the 1% confidence level. Second, regardless of the specific quantity, the strongly consistent trends of the short- and long-term targets demonstrated the feasibility and effectiveness of the gradual goals. Finally, realizing the potential of energy-saving and emission reduction needs a gradual pathway instead of accomplishing in one stroke. The targets of this study, which are attainable for the power sector and still represent a best practice, could serve as transitional benchmarks in power supply and emission reduction. To further achieve carbon neutrality, the management strategy to coordinate power supply and renewable energy accommodation needs to be transformed.

Keywords: gradual goals, power mix optimization, development pathway, emission reduction, power industry

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INTRODUCTION

Energy issues and climate change are increasing concerns over the world. As an important energy processing and conversion sector, power industry plays a dominant role in supporting the national economic and social development. At the same time, it consumes a lot of energy, causing serious environmental pollution. The total electricity consumption was 7,511 billion kWh in 2020, and the installed capacity of power plants of 6,000 kW and above was 2.2 billion kilowatts to meet the ever-increasing power demand in China, of which thermal power and nonfossil energy (hydropower, wind power, and photovoltaics) accounted for 56.6 and 43.4%, respectively. As for CO_2 emissions, the power industry accounts for about 40% of the total emissions of the whole society, and the carbon emissions of other industries also come from their demand for electricity to a large extent (Holladay and LaRiviere, 2017).

Faced with the increasingly difficult situation of energy conservation and emission reduction, there has been an international effort to develop a low-carbon economy, especially in the power industry. For example, the growth rate of carbon emissions has declined in the United States due to the reduction in coal-fired power generation. European countries have also realized a continuous rate of reduction in emissions by reducing fossil fuel consumption in power generation (Mohsin et al., 2019). A relatively great potential of preserving the environment could be realized by more robust environmental policies and renewable energy resources for the set of 25 developing countries (Mohsin et al., 2021b). In China, the power development plan, the Sino-US joint statement on climate change, and the climate ambition summit have all put forward clear optimization goals for China's energy consumption structure, namely, by 2030, carbon emissions per unit of GDP will be reduced by 60–65% compared to 2005, and nonfossil energy will account for about 25% (Lo, 2014; 2020). In September 2020, China pledged at the United Nations General Assembly to reach the peak of carbon emissions by 2030 and achieve carbon neutrality by 2060. The carbon peak goal and the carbon-neutral vision have been listed as the key tasks of the Central Economic Work Conference. The proportion of electricity in the terminal energy consumption increased year by year, and accordingly, the total primary energy consumption of this sector increased. Electric power is the hub of energy consumption. The "30·60" targets put forward higher requirements for carbon emission reduction in the electric power industry. Therefore, it is very important to formulate a rational pathway for the power industry to take the lead in realizing the targets of emission peak and carbon neutrality.

The first step for the pathway design is to evaluate the present status and improvement potential of the decision-making units (DMUs). In this regard, the DMUs are usually compared to the benchmarks to determine the corresponding operation situation and the possible inefficiency levels. The nonparametric data envelopment analysis (DEA) (Charnes et al., 1978) is considered a popular tool to assess the relative efficiency of the DMUs (Xia et al., 2020). It is also applied to the aggregation of sub-indicators, taking the low-carbon finance index for example (Mohsin et al., 2020). Based on the efficiency analysis results, the potentials of input reduction or output expansion are evaluated (Bello et al., 2018; Li et al., 2019; Nakaishi et al., 2021a). The neighborhood approach is also used to estimate the potential (Aarakit et al., 2021). In an environmental efficiency analysis, various methods have sprung up to incorporate undesirable outputs, for example, carbon emissions, into the models (Monastyrenko, 2017; An and Zhai, 2020; Li et al., 2021; Zhang et al., 2021). Among them, directional distance function (DDF) (Chung et al., 1997) methods have come into focus recently due to their feasibility in dealing with multiple inputs and outputs and nonradial characteristics (Zhou et al., 2018; Wang et al., 2019; Sun et al., 2020). In practice, the directional vectors can serve as guidance for the policy implementation or promotion direction. Along the directional vectors, the potential on inputs or outputs can be captured with policy or economic implications (Long et al., 2018; Song and Wang, 2018; Xian et al., 2019). The growth potential of environmental efficiency in China's power generation sector was found to be 27% on average (Nakaishi et al., 2021b). However, it is a long-term task to realize the full potential of emission reduction, not to accomplish in one move, which has rarely been considered in the previous efficiency studies for the power industry. It needs to find an appropriate pathway to realize energy-saving and emission reduction targets for the DMUs of the power industry step by step. In addition, there exists regional diversity in the marginal abatement costs of China's power industry (Xian et al., 2019). There is a need to investigate the impacts of resource endowment, the technological level, economic development, and other factors in the efficiency analysis to find out the sources of difference in operation status.

In analyzing the influence of individual characteristics, external environment, and other factors on environmental efficiency, various forms of regression analysis were commonly used. Among them, some directly analyze the efficiency and some research on the impact of a certain function of efficiency. For example, Halkos and Polemis (2018) analyzed the relationship between the environmental efficiency of the power sector and economic growth through curve fitting. There are also studies using the production function to analyze the impact of factors such as the economic level, population, industrial structure, production scale, electricity price, and bargaining power on the efficiency of the power system (Lozano et al., 2019; Lin and Zhu, 2020; Eguchi et al., 2021). Mohsin et al. (2021a) combined DEA and the difference-in-difference method to study the impacts of power reforms on energy efficiency and found that energy reform can be a good means to achieve high energy efficiency. The drivers of CO_2 emissions in China's power industry were assessed by the production-theoretical decomposition analysis based on DEA. The emission efficiency changes and the growth in installed capacity are identified as key contributors (Wang et al., 2019; Xie et al., 2021). The above analysis could provide an important reference for the existing inefficiency levels. However, from the practical perspective, it is of more operation significance and reference value to find out goals than to determine the efficiency/inefficiency levels for the purpose of realizing the full potential of emission reduction.

From the perspective of performance management, DEA methods are extended to evaluate performance in the context of improvement plans where certain management goals are set (Ruiz and Sirvent, 2019). To avoid setting unachievable or unambitious goals, studies established various models for target setting. Taking the closest target setting as an example, it guarantees that the targets are achievable and represent best practices (An et al., 2015; Ramón et al., 2016). Zhou et al. (2019) used a DEA benchmarking approach to determine goals and designed the reward and penalty plan accordingly. The target setting approach was used in the case study of 10 cities of the Chinese Huaihe River Basin. The impacts of decision-maker's preferences on the target setting are investigated (Lim and Zhu, 2019; Chen and Wang, 2020). The above analyses of influencing factors and goal setting could provide important references for the targets of DMUs in the power industry in the case of inputs and desirable outputs. However, there exists correlation between the desirable and undesirable outputs in China's power industry. The most feasible transitional path is ensuring benefits and social awareness and at the same time realizing energy-saving and emission reduction (Chai et al., 2020); that is, both desirable and undesirable outputs should be considered in setting gradual goals for the power industry. In addition, the goals set in the initial stage would necessarily affect the operational process. The efficiency analysis should not neglect the impacts of initial goals.

Given the above, this study expands the target model to include undesired outputs in recognition of benchmarking to monitor operation as well as plans (Stewart, 2010). The contributions of this work are twofold. First, it constructs short-term and long-term learning target models for the power sector under different goals and explores its energy conservation and emission reduction potential; it also explores reasonable steps to achieve energy conservation and emission reduction. The urgent need for a clean power structure and the structural characteristics of the provincial power sector itself, as well as the coordination between energy conservation and emission reduction, and power supply goals, are integrated into the constructed models. Second, in order to build realistic and feasible goals for the provincial power sector, it explores the emission reduction potential under different target systems based on the established efficiency analysis models and provides practical and feasible strategies and pathways for energy conservation and emission reduction in the provincial power sector based on the corresponding benchmark analysis.

The remainder of this article proceeds as follows. "*Methods*" section sets out the methods. In "*The Gradual Targets of China's Power Industry*" section, we investigate the short- and long-term goals of China's provincial power sector in energy-saving, emission reduction, and responsibility fulfillment, analyze the impacts of initial goal setting on efficiency, and explore feasible pathways. "*Conclusion*" section comes to conclusions.

METHODS

This study will investigate the gradual goals for China's provincial power sector in energy-saving, emission reduction, and responsibility fulfillment to explore feasible paths to realize the potential. To this end, we first apply the directional distance function to determine the energy-saving and emission reduction potential for the power sector. Second, we develop a target-setting model where the reference points are both attainable and representing best practice based on the closest target model.

Energy-saving and emission reduction targets based on the directional distance function.

Consider n DMUs in the electricity generation process, indexed by $j = 1, \cdots, n$, of which the distance function in a given period of time is evaluated in terms of m_x inputs, m_b desirable outputs, and m_b undesirable outputs denoted by (X_j, Y_j, B_j). Herein, $X_j = (x_{1j}, \cdots, x_{m_x j})' > 0_{m_x}$, $Y_j = (y_{1j}, \cdots, y_{m_y j})' > 0_{m_y}$, and $B_j = (b_{1j}, \cdots, b_{m_b j})' > 0_{m_b}$. We adopt the environmental DEA technology to conduct the following study. The corresponding production possible set T can be formulated by $T = \{(X, Y, B) | X \text{ can produce } (Y, B)\}$. The production set is assumed to be convex and closed, and the undesirable outputs are assumed to satisfy the weak disposability assumption and null-jointness condition (Shephard et al., 1970; Färe et al., 1985). Given the reference technology, the directional distance function for environmental efficiency assessment with variable returns to scale (VRS) in the DEA framework can be formulated as follows:

$$D(X_0, Y_0, B_0) = \max \beta$$
$$s.t. \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0} - \beta g_{i0}, & \forall i = 1, \cdots, m_x \\ \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0} + \beta g_{r0}, & \forall r = 1, \cdots, m_y \\ \sum_{j=1}^{n} \lambda_j b_{kj} = b_{k0} - \beta g_{k0}, & \forall k = 1, \cdots, m_b \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j \ge 0, & j = 1, \ldots, n \end{cases}. \tag{1}$$

Subscript *0* indicates the DMU being evaluated. λ_j is the weight of each DMU in constructing the production frontier. $(d_{i0}, d_{r0}, d_{k0})'$ is the directional vector along which DMU_0 will be projected to the production frontier. Upon obtaining the optimal solution $(\lambda_j^*, \beta^*)'$ to the linear programming, the reference point for the DMU under estimation on the best practice frontier is $(\sum_{j=1}^{n} \lambda_j^* x_{ij}, \sum_{j=1}^{n} \lambda_j^* y_{rj}, \sum_{j=1}^{n} \lambda_j^* b_{kj})'$. The potentials of inputs and/or outputs can be obtained directly by the difference between the reference point and the observation, which obviously include both radial and nonradial slacks.

Attainable and Best Practice Target Setting Model

As stated in the previous section, decision-makers usually set goals at the beginning of the period. Moreover, the goals will orient the operation process at that period of time. In this subsection, we will establish a benchmark model in the framework of DEA to find out the targets for the DMUs. The targets would satisfy the following features. The targets represent the best practice which are expressed in terms of inputs and/or outputs and are attainable with reasonable distance from the current situation of the DMU; that is, in the short term, the power industry will pursue goals similar to its current profile to some extent. We denote the targets by vector $(x_i^t, y_r^t, b_k^t)'$. It can be obtained by the following model:

$$\min \sum_i \left\| \frac{x_{i0} - x_i^t}{x_{i0}} \right\|_1 + \sum_r \left\| \frac{y_{i0} - y_i^t}{y_{i0}} \right\|_1 + \sum_k \left\| \frac{b_{i0} - b_i^t}{b_{i0}} \right\|_1$$
$$s.t. \begin{cases} \sum_{j \in E} \lambda_j x_{ji} = x_i^t, \quad \forall i = 1, \cdots, m_x & (2.1) \\ \sum_{j \in E} \lambda_j y_{jr} = y_r^t, \quad \forall r = 1, \cdots, m_y & (2.2) \\ \sum_{j \in E} \lambda_j b_{jk} = b_k^t, \quad \forall k = 1, \cdots, m_b & (2.3) \\ -\sum_i v_i x_{ji} + \sum_r u_r y_{jr} - \sum_k w_k b_{jk} + d_j = 0, \quad j \in E & (2.4) \\ \lambda_j \le M(1 - q_j), \quad j \in E & (2.5) \\ d_j \le M q_j, \quad j \in E & (2.6) \\ \sum_{j \in E} \lambda_j = 1, \quad j \in E & (2.7) \\ v_i, u_r, w_k \ge 1, \quad i = 1, \cdots, m_x, r = 1, \cdots, m_y, k = 1, \cdots, m_b \\ q_j \in \{0, 1\}, \quad j \in E \\ \lambda_j, d_j, x_i^t, y_r^t, b_k^t \ge 0 \end{cases}, \tag{2}$$

The objective function is to minimize a weighted L1 distance to the DMU under estimation. E is a set of the extremely efficient DMUs to construct the reference point for DMU0. M indicates a positive number large enough. The key constraints of the above model lie in Eqs (2.4)–(2.6). q_j is a 0–1 logical variable. If it equals 0, then $d_j = 0$, and it means that the reference point DMU_j falls on the production frontier of T by the constraint (2.4). Otherwise, if it equals 1, DMU_j is not on the efficient frontier subject (2.4), and simultaneously, the constraint (2.5) enforces λ_j to be zero, which indicates that the point will not participate in constructing the targets for the DMU under estimation. In addition, due to the L1 distance in the objective function, the model becomes a type of nonlinear program. With regard to its solving process, a set of instrumental variables would be introduced. For example, we introduce a pair of nonnegative variables x_i^+ and x_i^- for each i. The corresponding term $\|x_{i0} - x_i^t/x_{i0}\|_1$in the objective function would be equivalently transformed to $(x_i^+ + x_i^-)/x_{i0}$ by introducing additional constraint $x_{i0} - x_i^t = x_i^+ - x_i^-$ to model **Eq. 2**. Similarly, the other nonlinear terms can be transformed to linear ones by introducing instrumental variables and constraints. By means of the transformation we can obtain the targets $(x_i^{t*}, y_r^{t*}, b_k^{t*})'$ for each DMU.

THE GRADUAL TARGETS OF CHINA'S POWER INDUSTRY

Data Descriptions

We employ the methods introduced in the "*Methods*" section to explore the gradual pathway of China's power industry in 30 provincial administrative regions (PARs) in terms of energy-saving, CO_2 emission reduction, and responsibility fulfillment during the period 2010–2019; Tibet is not included due to data unavailability. The inputs include labor, installed capacity, and energy. Similar to the study of Duan et al. (2016), we take the sum of energy inputs as a single energy input indicator. The desirable output is electricity generated, and undesirable outputs are CO_2 emissions stemming from three primary fossil fuels include coal, petroleum, and natural gas. The data of labor, installed capacity, energy, and electricity generated are from the China labor statistical yearbook, China electric power yearbook, China energy statistics yearbook, and compilation of statistical data of the electric power industry. The CO_2 emissions are calculated through the method of IPCC. The descriptive statistics of the inputs and outputs are shown in **Table 1**.

Gradual Goals of the Power Industry

Environmental Efficiency Analysis of the Power Sector Under DDF

Based on the DDF, where the directional vectors are the quantity of inputs and outputs indicators of the observations, the values of the distance function of the power sector in China's 30 PARs during 2010–2019 are obtained. The distances of 2010, 2015, and 2019 and the average distances during the study period are shown in **Figure 1**. It shows that nine PARs get the lowest distance of zero on average, including Beijing, Tianjin, and Shanghai. Most of these areas are municipalities directly under the central government or located in the eastern developed areas. The corresponding power generation process is superior to others in terms of production and emission, and the observations are located on the production frontier. The lowest distance from the frontier of Sichuan and Yunnan might benefit from the advantages of energy resources and the development of external power transmission. The longest distance occurs in Heilongjiang Province. As an energy base, it is urgent to improve the environmental efficiency in power generation facing the pressure from primary energy-dominated energy mix and emission reduction. The trends of distance functions vary from one to another. Some have experienced growth, some have been declining, and some have risen before falling. Taking a new round of electric power reform in 2015 as the boundary, it shows that most of the regions have experienced the narrowing of the distance, which is inseparable from the promotion effect of power reform.

In order to more intuitively reflect the performance of each region's power sector, a scatter diagram of the environmental efficiency during the study period is shown in **Figure 2**. It shows that the relative efficiency has experienced a trend of slight decentralization around 2015. Most of the observations on the efficient frontier have always been in the lead. The slight changes in environmental efficiency indicate a catch-up effect among the regions in power generation and emission reduction.

From the perspective of practice, it is more meaningful to know the specific goals of each input/output indicator for the plans than the relative efficiency levels. Therefore, the reference targets for each DMU in terms of inputs, desirable outputs, and undesirable outputs are calculated by the weighted sum of the observations on the efficient frontier participating in constructing the benchmarks. Taking the ith input for example, the target can be obtained by $\sum_{j=1}^n \lambda_j^* x_{ij}$, where λ_j^* and x_{ij} are the weight and inputs corresponding to the jth observation, respectively. To make the targets of different inputs and/or outputs comparable, we transform the targets to gap ratios, that is, dividing the difference between the observation to the targets by the target value, that is, $(\sum_{j=1}^n \lambda_j^* x_{ij} - x_{i0})/\sum_{j=1}^n \lambda_j^* x_{ij}$ for the ith input. The average gap ratios of each indicator during the study period of 2010–2019 can be found in **Figure 3**. The results of labor, power generated, and carbon emissions correspond to the left coordinate, while the other two indicators correspond to the right for the sake of readability. What is worth noting is that the positive and negative signs mean the indicator should be increased or reduced, respectively. That is, the more, the better for the desirable outputs, and the opposite applies for the other indicators, including inputs and undesirable outputs.

For the input indicators, the gap ratio of installed capacity moves around 2.41%. The gap ratio of energy input slightly fluctuates around zero, which may be due to the energy input, and in this study, it is the total energy input rather than a certain energy type. The energy input needs to support the power supply and economic operation, and the way to further improve the environmental efficiency of the power generation sector is to optimize the power mix rather than simply reducing the energy

TABLE 1 | Descriptive statistics of inputs and outputs.

Variable	Unit	Mean	Std. dev	Type
Labor	Person	98041.71	54231.60	Input
Installed capacity	Megawatt	48879.93	30290.91	Input
Energy consumption	Million tons of coal equivalent (Mtoc)	57333.29	36699.51	Input
Power generated	Billion kWh	191.64	123.85	Desirable output
Carbon emissions	Thousand tons	125310.84	99021.91	Undesirable output

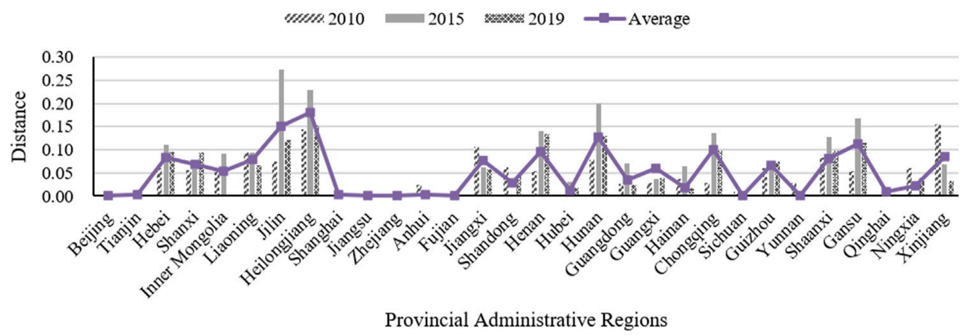

FIGURE 1 | Directional distance of the power sector of provincial administrative regions.

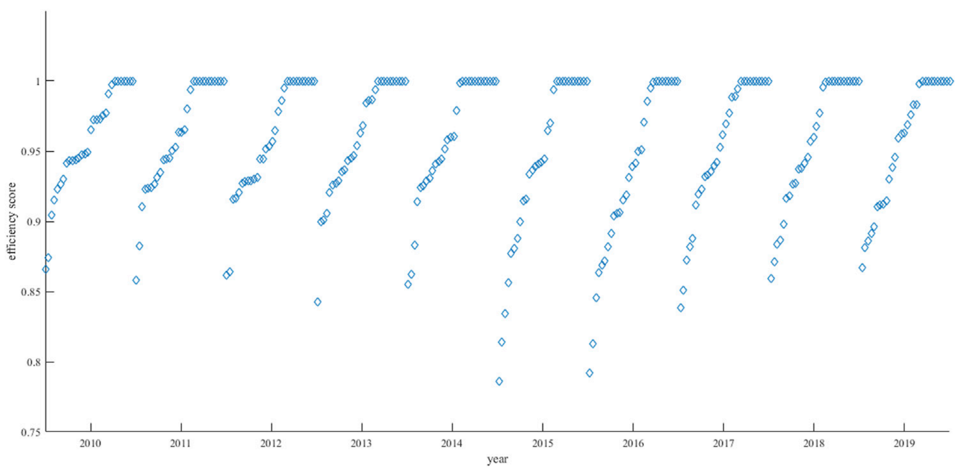

FIGURE 2 | Environmental efficiency of the power sector during 2010–2019.

input. As for the labor input, it is approximated by the total input in the production and supply of electric power and heat power industry. The fluctuation of the gap ratio needs to further clarify the exact values of the power generation industry. From the point of view of outputs, we can find that the gap ratio of electricity generated is relatively stable at 4% except for 2015 and 2016. It indicates that the relative gap among the regions regarding desirable output has not been widened or narrowed to some extent during the study period. When turning to the undesirable output, the gap ratio is larger than the desirable one. The maximum gap of 8.80% is in 2016, the year after the new round of power reform. On average, the carbon emissions could be reduced by 5.79% through environmental efficiency improvement.

In detail, we can obtain the specific quantity of targets in the inputs and outputs for each region to realize. From the perspective of serving society and emission reduction, the targets of desirable and undesirable output in the latest year of the study period 2019 are listed in **Table 2**. The emission reduction potentials of Heilongjiang and Henan were over

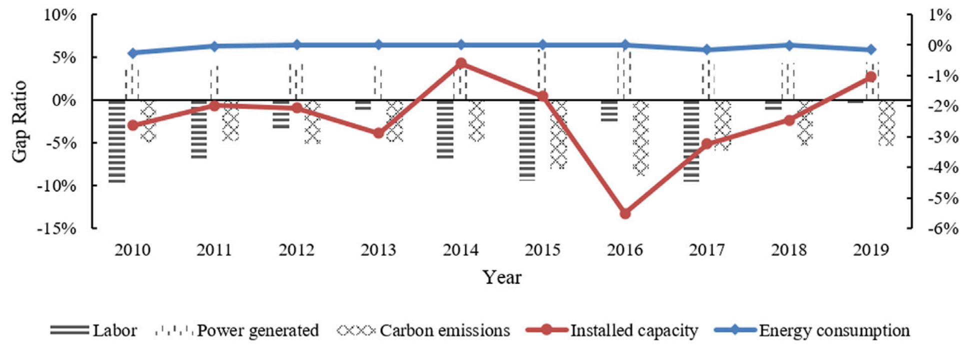

FIGURE 3 | Gap ratio of the inputs/outputs in the power sector during 2010–2019.

TABLE 2 | Reference targets of desirable and undesirable outputs for the power sector in 2019.

	Target-desirable (billion kWh)	Gap, %	Target-undesirable (thousand tons)	Gap, %
Beijing	46.10	0.00	13465.49	0.00
Tianjin	67.30	0.00	44559.93	0.00
Hebei	316.45	8.77	186601.19	−10.63
Shanxi	355.57	8.51	227746.34	−10.26
Inner Mongolia	545.10	0.00	412158.72	0.00
Liaoning	212.22	6.13	111092.31	−6.99
Jilin	103.86	10.84	50540.89	−13.84
Heilongjiang	125.51	13.31	65351.42	−18.15
Shanghai	83.70	0.00	62801.61	0.00
Jiangsu	506.20	0.00	341245.70	0.00
Zhejiang	355.20	0.23	205048.38	−0.23
Anhui	288.00	0.00	224838.44	0.00
Fujian	257.30	0.00	118938.50	0.00
Jiangxi	148.41	5.46	91291.02	−6.13
Shandong	550.88	4.06	387318.09	−4.42
Henan	319.45	11.85	185064.35	−15.53
Hubei	302.34	1.67	124100.32	−1.72
Hunan	175.10	11.42	69247.42	−14.80
Guangdong	497.34	2.44	252463.19	−2.57
Guangxi	189.79	3.74	82865.42	−4.04
Hainan	35.10	1.70	16913.57	−1.76
Chongqing	89.09	8.86	43482.61	−10.77
Sichuan	390.30	0.00	43269.85	0.00
Guizhou	242.62	6.98	114941.65	−8.11
Yunnan	346.20	0.00	29295.37	0.00
Shaanxi	244.18	8.96	155044.17	−10.92
Gansu	185.08	10.36	65148.13	−13.07
Qinghai	88.30	0.00	9506.41	0.00
Ningxia	177.03	3.80	119206.49	−4.12
Xinjiang	372.28	3.14	230943.73	−3.35

15% in the measurement of the gap ratio. Large potential abatement cost savings would be realized by trading emission permits for these regions (Xian et al., 2019). In terms of the total amount, the carbon emission reduction could have been up to 196.35 million tons in 2019 if the power sector of all regions achieved the best practice of that time. It is hard to realize the amount of emission reduction by a nonstop process. A feasible and smooth transition target for each provincial power sector needs to be investigated.

Closest Targets of the Power Sector

As stated in the "*Methods*" section, realizing the potential of input saving and emission reduction needs a gradual pathway instead of accomplishing in one stroke. For this reason, we applied the models of attainable and best practice targets setting in the previous section to the power generation sectors of 30 PARs. The gap ratios, of which the calculation process is the same as the "*Environmental Efficiency Analysis of the Power Sector Under DDF*" section, of each region during the study period 2011–2019

TABLE 3 | Gap ratios between the observations and the closest targets of the power sector (%).

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Beijing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Jiangsu	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hubei	0.00	0.00	0.00	0.29	0.01	0.06	0.00	0.00	0.00	0.00	0.04
Yunnan	0.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07
Zhejiang	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.81	0.00	0.08
Anhui	0.47	0.62	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11
Tianjin	0.00	0.00	0.00	0.00	1.45	0.00	0.00	0.00	0.00	0.00	0.15
Fujian	1.48	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.15
Guangdong	0.48	0.00	0.00	0.00	0.00	0.85	0.33	0.50	0.00	0.00	0.22
Hainan	1.20	0.00	0.23	0.00	0.00	0.60	0.00	0.00	0.75	0.00	0.28
Sichuan	3.56	0.00	0.35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.39
Shanghai	0.00	0.00	0.00	0.00	0.00	0.00	2.79	0.00	2.58	0.00	0.54
Shandong	2.28	2.95	1.73	1.03	0.00	0.00	0.00	0.00	0.00	1.71	0.97
Guangxi	0.23	0.75	0.55	0.92	1.59	2.19	3.55	1.89	0.64	0.26	1.26
Guizhou	2.23	2.85	0.71	2.31	0.33	0.82	1.22	0.49	1.32	0.74	1.30
Liaoning	2.77	3.16	2.49	1.95	0.62	1.31	0.93	0.10	1.05	0.75	1.51
Hebei	3.32	1.19	1.18	0.67	2.12	2.22	1.55	0.96	0.83	1.34	1.54
Shanxi	1.34	2.45	1.93	1.12	0.72	0.94	3.34	1.09	2.01	1.35	1.63
Inner Mongolia	4.24	4.69	2.03	1.96	0.36	1.77	2.79	1.38	0.00	0.00	1.92
Chongqing	0.97	2.17	2.13	1.93	0.77	2.45	3.22	2.22	2.34	1.38	1.96
Xinjiang	4.65	3.93	3.04	3.05	0.76	0.95	3.32	1.11	1.44	0.00	2.23
Qinghai	0.00	0.00	0.00	0.00	0.00	6.70	6.64	6.47	3.80	0.00	2.36
Ningxia	2.38	1.94	0.75	0.00	0.00	1.86	5.19	4.78	3.52	4.21	2.46
Shaanxi	1.94	1.14	0.64	0.80	6.51	4.71	4.00	1.45	1.50	2.05	2.47
Hunan	2.48	1.98	1.96	1.66	1.73	4.13	3.57	2.56	3.39	2.28	2.57
Henan	1.52	0.92	0.79	0.75	4.86	4.89	5.81	3.50	3.85	4.33	3.12
Gansu	0.86	1.24	1.27	2.87	3.20	6.17	8.06	4.77	3.36	2.03	3.38
Jiangxi	3.65	2.82	1.92	1.47	14.26	10.18	1.34	0.45	1.04	0.80	3.79
Jilin	6.16	7.59	7.22	6.47	5.71	11.24	9.12	5.70	5.34	2.92	6.75
Heilongjiang	3.50	4.09	3.58	5.87	16.18	16.63	14.38	13.36	5.74	8.94	9.23

are shown in **Table 3**. In order to compare the gap ratio of each region's power sector as a whole, the weighted sum of the gap ratios of each input/output indicator is constructed. Herein, the inputs (labor, installed capacity, and energy) and outputs (electricity generated and carbon emissions) are endowed with the same weight of 1/2, of which each input indicator gets a weight of 1/6. For the outputs, power supply and emission reduction are assumed to be equally important; that is, the weights of desirable and undesirable output are both equal to 1/4. The weighted sums of the indicators for the power sectors in **Table 3** are sorted by the average values of the 10 years in the last column.

On average, Beijing and Jiangsu have obtained the lowest gap ratio of zero during the study period, which means that these two regions provide an example in power generation for others in terms of environmental efficiency. If all the regions realized the closest targets, a 1.75% increase could have been achieved. The gap ratios for Hubei, Yunnan, and Zhejiang are all below 1%, which indicates the power sectors of these regions are near the best practice. The highest ratios for Heilongjiang and Jilin indicate that it is very urgent for these two regions to realize the transformation in the power industry. After all, the targets here are the closest ones of the best practice frontier for these regions with consideration of their specialties. The variance analysis of the gap ratios shows that there exist significant differences in both the regions and different years under the 1% confidence level, as shown in **Table 4**. It further enhances the importance of learning about each other's practices in terms of power generation and emission reduction.

TABLE 4 | ANOVA statistics of the gap ratios.

Source of variation	SS	df	MS	F	P-value	F Crit
Rows	0.14	29.00	0.00	17.24	0.00	1.51
Columns	0.01	10.00	0.00	3.32	0.00	1.86
Error	0.08	290.00	0.00			
Total	0.22	329.00				

The gap ratios of the inputs and outputs could provide strategic references for the improvement of environmental efficiency and transformation of the power industry. To realize the potential of input/undesirable output reduction and desirable output increase in the previous subsection, it needs a specific roadmap. **Figure 4** presents the gap ratios of each indicator compared to the closest targets, which are attainable and represent the best practice. The column charts (labor, installed capacity, and power generated) and line charts (energy consumption and carbon emissions) correspond to the left and the right coordinate, respectively. The empirical results also provide evidence for the importance of gradual goals by comparing the gap ratios of DDF results and closest targets in **Figures 3**, **4**.

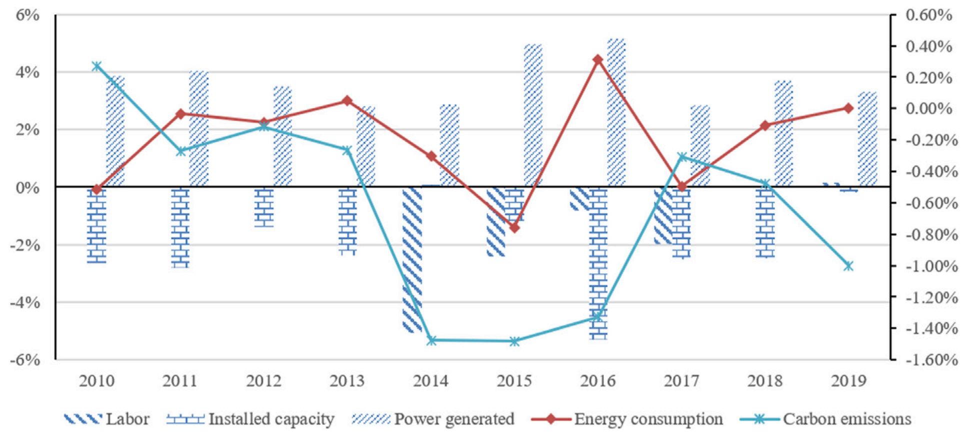

FIGURE 4 | Gap ratio of the inputs/outputs compared to the closest targets.

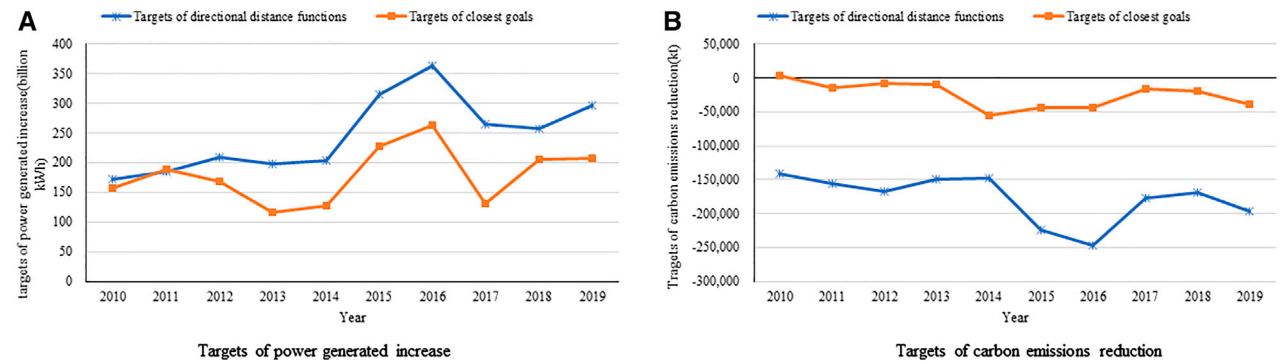

FIGURE 5 | Targets of desirable and undesirable outputs.

From the perspective of inputs, the gap ratios of energy input fluctuate around zero during the study period, which may be due to the total quantity of energy input that neglects the power mix. The gap existing in the labor input is relatively high during 2014–2017. For the installed capacity, we can find that the largest gap occurred in 2016 after the new round of power reform. The gap has been narrowed after 2017. As to the desirable output, a 3.71% increase could have been realized if the closest targets were reached. The line of carbon emissions shows that the gaps for the years around 2015 are the largest. The reform may promote the renewal and practice of emission reduction strategies in some regions.

The targets of desirable output increase and undesirable output decrease are calculated and shown in **Figure 5**. The quantities corresponding to DDF and the closest targets are presented, respectively. The positive and negative signs in the figure indicate the increase or decrease and cannot be calculated by simply adding up. There exists a clear gap between the two curves for both the desirable and undesirable outputs. That is, the closest targets are lower than the ones under directional distance functions without considering the profile of the regions under estimation. It again demonstrated the feasibility and necessity of periodical target setting. Regardless of the specific value, the trends of the short- and long-term targets have strong consistency. From the perspective of the transformation of the power industry, it provides gradual goals for power supply and emission reduction.

CONCLUSION

As a dominant industry in supporting the national economic and social development and realizing energy-saving and emission reduction targets, it is very urgent to formulate a rational pathway for the power industry to realize its transformation. In this study, we established models for target setting of the power industry in the framework of DEA where the reference sets participating in constructing benchmarks for the DMUs and the potentials of input and output adjustment were obtained first. Considering that it is a long-term task to realize the full potential of the indicators, the attainable targets in the short-term representing best practice were found out by a mixed-integer programming model. The models are used to analyze the gradual goals of the power sectors in China's 30 provincial administrative regions. Based on the empirical analysis, the main conclusions are as follows. First, it is of great importance to consider the profile of each region's power sector in setting energy-saving and emission reduction targets. The analysis of variance demonstrates significant differences in the reference points of inputs and outputs in both regions and different years under the 1% confidence level. Second, short- and long-term targets of inputs and outputs are investigated by the constructed models for each region's power sector. Regardless of the specific quantity, the strongly consistent trends of the targets demonstrated the feasibility and effectiveness of the gradual goals. In terms of the total amount, 196.35 million tons of carbon emission reduction could have been realized in 2019 if the power sector of all regions achieved the best practice of that time. Finally, realizing the potential of input saving and emission reduction needs a gradual pathway instead of accomplishing in one stroke. The targets of this study which are attainable for the present profile of the power sector and still represent best practice could serve as transitional benchmarks in power supply and emission reduction. To further achieve carbon neutrality, it needs to transform the management strategy to coordinate power supply and renewable energy accommodation.

There are still some deficiencies in our research. First, due to data availability, the labor input is the total number of employees of production and supply of electric power and heat power industry rather than electric power industry, which may affect the estimation results. Second, it lacks analysis on the influence of external environmental factors. The limitations will be addressed in future research.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

All authors have significant contributions to the manuscript. GL: conceptualization, writing—review and editing, and supervision. XY: supervision and writing—review and editing. ND: conceptualization, establishing models, empirical analysis, and writing—original draft, review, and editing.

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Study of China's Optimal Concentrated Solar Power Development Path to 2050

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As an important form of clean energy generation that provides continuous and stable power generation and is grid-friendly, concentrated solar power (CSP) has been developing rapidly in recent years. It is expected that CSP, together with wind and solar photovoltaic, will constitute a stable, high percentage of renewable energy generation system that will be price-competitive with conventional energy sources. In this study, a dynamic programming approach based on minimum cost was used to explore the optimal development path of CSP generation in China by 2050. A learning curve model and a technology diffusion model were used as constraints. The impact of factors such as Gross Domestic Product (GDP) growth, incentive policies, technological advances, grid absorptive capacity, and emission regulation schemes on the development of CSP generation was discussed in the context of sensitivity analysis and scenario comparison. This study has reached the following conclusions: 1) the government cannot achieve the target for cumulative installed capacity in 2050. Considering the interaction of relevant factors, the target would be hard to achieve even under favorable conditions; 2) as a key factor affecting the development of CSP, the incentive policy is closely related to construction cost. It is noteworthy that although the target can be achieved with a higher investment ratio, the CSP industry has failed to create a good ecological environment in the early stage of development; 3) GDP growth and learning rate are important factors influencing the development path in later stages; and 4) although they operate as potential factors affecting construction costs, grid absorptive capacity and carbon permit prices have limited impact on the development of CSP generation.

Keywords: concentrated solar power, development path, learning curve, innovation diffusion model, genetic algorithm, dynamic programming

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INTRODUCTION

Coping with global climate change and reducing dependence on non-renewable energy sources is of great significance today. Researchers around the world are striving to develop renewable energy to realize sustainable development (Lu et al., 2015). Renewable energy sources mainly include wind, hydro, geothermal, and solar energy, among which solar energy resources have great potential. The total solar radiation energy projected onto the Earth per second is about 5.9×10^6 tons of standard coal equivalent. China enjoys substantial solar energy resources, and the total solar radiation energy at its surface is 1.47×10^{16} kWh per year (Chen et al., 2017), which is equivalent to 1.7×10^{12} tons of standard coal (Zhang et al., 2009). The distribution of total solar radiation is uneven: plateaus and arid areas in western China have higher radiation than plains and humid areas in eastern China. The Qinghai–Tibet Plateau has the highest solar radiation density, with total annual radiation levels exceeding 1,800 kWh/m^2 and even 2,000 kWh/m^2 in some areas,[1] indicating that China has a great opportunity to develop solar energy.

Solar energy is used for power generation in two main ways: photovoltaic (PV) and concentrated solar power (CSP) (Desideri and Campana, 2014). At present, PV technology in China has become mature after decades of development. In 2019, new installed capacity and cumulative installed capacity were both the highest in the world, at 29.56 and 204.6 GW, respectively.[2] CSP is the process of converting solar energy into thermal energy, which is then converted into electricity by doing work (Wang et al., 2020). Basically, CSP shares the same power generation principle with fossil-fuel power stations (Liu et al., 2019). The difference is that fossil-fuel power stations use fuels such as coal, oil, and natural gas to generate heat. However, the process produces huge amounts of pollutants (flue gases, dust, sludge, and wastewater). In contrast, CSP generates heat by clean, renewable solar energy. CSP devices can be classified as parabolic troughs, solar towers, linear Fresnel lenses, and parabolic dishes based on the type of reflectors (Wang F. Q. et al., 2017). Parabolic trough concentrated solar power is one of the most developed solar technologies (Gonzalo et al., 2019), accounting for 95.7% of operational CSP projects (Baharoon et al., 2015).

CSP has the following characteristics: 1) it uses solar radiation to generate electricity. Solar energy is the most abundant and widely distributed resource on Earth. 2) Compared with hydropower, CSP faces fewer environmental problems and social objections. Moreover, installed CSP capacity is not constrained by topography. Because CSP facilities are often constructed in desert areas, there is no need to resettle local residents. Furthermore, they can boost the local economy (Chien and Lior, 2011). 3) Unlike wind power, CSP creates no noise pollution. 4) Compared with photovoltaic power generation, CSP has a long service life and is pollution-free (Liu et al., 2019).

The biggest advantage of CSP over other renewable energy sources is its ability to generate electricity in a stable and continuous manner. With reflectors or lenses to concentrate sunlight over a large area into a small light-collecting region, it converts irradiation to heat and then turns heat into electricity by doing work. The excess thermal energy is stored in a medium such as molten salt to generate electricity at night or when solar radiation is low, making CSP grid-friendly (Wang et al., 2020). In addition, from a long-term perspective, CSP can be used as a basic load regulator and can provide a stable and high proportional generation system combined with renewable energy generation technologies such as PV and wind power. Therefore, CSP is a highly competitive power generation technology (Liu et al., 2019).

CSP has drawn much attention for its stable power generation. Since 2008, CSP production has accelerated globally (Zhao et al., 2017). Over the past 20 years, approximately 20 solar thermal power plants over 500 kW have been manufactured, and some of these have been commercialized (Liu et al., 2019). Globally, CSP operates on a medium to large scale, with a focus on Spain and the United States (Zhang et al., 2013). By the end of 2019, the total installed global CSP generation capacity reached 6,289 MW, of which Spain accounted for 36.6% and the United States for 28%.[2] Due to a late start (the first solar thermal power demonstration projects launched in 2016) (Tang et al., 2018), China accounts for only a small fraction of CSP installations (6.7%).[2] However, China takes the lead in terms of CSP capacity under construction and in the planning stage (Zhao et al., 2017). **Figure 1** shows new and cumulative installed CSP capacities in China from 2012 to 2019.[3] In terms of distribution characteristics, solar thermal power stations in China are distributed over most of northwestern China and in a few areas in North China because of their need for particular natural conditions such as land and light resources. Existing solar thermal power stations are mainly distributed in Qinghai province (Delhi City and Gonghe County) and at Urad Middle Banner in the Inner Mongolia Autonomous Region. Solar thermal power stations under construction or being planned are mainly distributed in Gansu province (Yumen City, Dunhuang city, Aksay Kazakh Autonomous County, Jinta County, and Gulang County), Hami City in the Xinjiang Uygur Autonomous Region, Zhangjiakou city in Hebei province, and Urad Front Banner in the Inner Mongolia Autonomous Region.

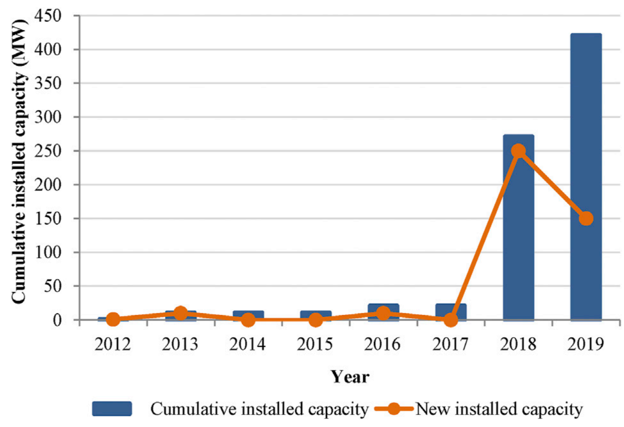

FIGURE 1 | New and cumulative installed capacities of China's CSP from 2012 to 2019.

CSP is a promising technology for solar energy utilization with far-reaching implications for China (Yang et al., 2010). However, an efficient and economical thermal energy storage (TES) system is one of the key factors determining the development of this technology (Pelay et al., 2017). CSP plants with large TES can be more economically competitive by generating stable and dispatchable power from intermittent solar energy (Ju et al., 2017). With high penetration of renewable energy, CSP plants with cheap TES will play a key role. However, with its low conversion efficiency of solar

[1]The data are collected from National Energy Administration (http://www.nea.gov.cn/2014-08/03/c_133617073.htm) [in Chinese].

[2]The data are collected from the IRENA (https://www.irena.org/solar).

[3]The data are collected from the IRENA (https://www.irena.org/solar).

energy, the CSP industry in China is still immature (Zhao et al., 2017). High cost is the main factor that hinders its large-scale development. Therefore, developing CSP at minimal cost is important research that can serve as a reference for policy-making.

To accelerate the construction of a clean, low-carbon modern energy system and meet the needs of sustainable economic and social development, China has occasionally adjusted its CSP generation targets. The Medium and Long-term Development Plan of Renewable Energy (National Energy Administration, 2007) requires the cumulative installed capacity of CSP to reach 200 MW by 2020. China's Renewable Energy Development Roadmap 2050 (Sino-Danish Renewable Energy Development Project Management Office, 2014) proposes that the cumulative installed capacity of CSP will reach 5, 30, and 180 GW by 2020, 2030, and 2050, respectively. The 13th Renewable Energy Development Five-Year Plan (National Energy Administration, 2016) predictes that cumulative installed CSP capacity will reach 13.9 MW in 2015 and 5,000 MW in 2020. Nonetheless, due to insufficient consideration of potential factors affecting CSP development in China and unreasonable targets that could not be optimally achieved, only a few targets were achieved by the end of 2019.

It is very important to forecast CSP investment cost because high cost is the main factor hindering its large-scale development (Zhao et al., 2017). The learning curve model is most commonly used to predict cost reductions (Van der Zwaan and Rabl, 2003; Viebahn et al., 2011). However, few studies have used the learning curve model to forecast cost reduction of CSP. In addition, only a few of the goals proposed have been achieved in China, which may have been due to unreasonable goal setting. Therefore, it is crucial to forecast the development trend of CSP. The technology diffusion model is most commonly used to predict the development trends of renewable energy sources (Kumar and Agarwala, 2016; Fadly and Fontes, 2019), but only a few researchers have predicted CSP development using this model (Xie and Fan, 2017). Furthermore, the goals cannot be achieved in an optimal manner, which may be due to insufficient consideration of potential factors affecting CSP development in China. Dynamic programming, as an optimization method for multi-stage decision problems, is more suitable for studying path-dependent problems under the influence of uncertain factors. Dynamic programming is also widely applied to studies of renewable energy (Lu et al., 2015; Ding et al., 2020; Xu et al., 2020), but rarely to CSP. To narrow these gaps, this study selected a 2050 target of 180 GW and investigated whether it was reasonable, as well as charting the optimal development path of China's CSP by using dynamic programming based on minimum cost, with a learning curve model and a technology diffusion model used as constraints. The impact of factors such as GDP growth, incentive policies, technological advances, grid absorptive capacity, and emission regulation schemes on the development of CSP generation is discussed in the context of sensitivity analysis and scenario investigation.

The rest of this paper is organized as follows. *Literature Review* reviews previous research on solar energy, particularly on CSP, and other renewable sources of energy. *Model and Hypothesis* introduces the research model used in this study and poses hypotheses. The results are presented in *Results*. *Discussions* discusses the influence of relevant factors on the CSP development path and makes some suggestions. Finally, *Conclusions* provide conclusions.

LITERATURE REVIEW

Due to increasingly severe energy shortages and environmental pollution, renewable energy sources are becoming a larger part of the global energy mix, especially in the power industry (Zhang et al., 2017). Therefore, CSP is drawing more attention from experts and researchers. The relevant literature covers several aspects, including cost forecasting as well as diffusion models and integrated utilization of technologies.

Cost is a key constraint to compete with conventional energy sources. Wang (2010) pointed out that significant cost reduction is the crux of market acceptance. Compared with the mature parabolic trough CSP technology, there is potential for the linear Fresnel CSP technology to be cost effective (Sun et al., 2020) due to its simple structure and lesser need for reflectors. The learning curve model proposed by Wright (1936) is most commonly used to predict cost reductions. It has also been widely demonstrated that the cost of products decreases continuously based on economies of scale (Wright, 1936; Yelle, 1979; Wene, 2000), especially in renewable energy generation (Hernández-Moro and Martinez-Duart, 2013). Specifically, this cost reduction can be described as a certain percentage decrease in cost when the cumulative installed capacity is doubled, which is also known as "the learning by doing approach." The approach assumes that changes in costs are generally attributable to experience, as verified in most of the literature on cost changes in renewable energy (Albrecht, 2007; Köberle et al., 2015; Elshurafa et al., 2018; Hong et al., 2020). Van der Zwaan and Rabl (2003) explored the cost-cutting potential of PV technology in the first decade of the 21st Century through the learning curve model. The same model was used to analyze the cost of CSP plants in Africa and Europe by Viebahn et al. (2011), and the cost reduction curves were derived. Consistently with these papers, this study also adopted the learning curve model to predict the investment cost of CSP generation in China.

Technology diffusion is a subsequent sub-process of the innovation process (Wu et al., 1997), which combines the complex technology with the economy and the market (Cao and Chai, 2013). Renewable energy, as a new form of energy, has a development trend that resembles that for new technology (Lu et al., 2015), with both following the S-shaped growth pattern (Sheng, 2002). Researchers have conducted many studies on renewable energy development based on technology diffusion models. Xie and Fan (2017) built a logistic model to determine the technology maturity of CSP and revealed that the CSP technology was still in the early stage of development. It is expected that global CSP technology will become highly mature and will enter the stage of large-scale commercial application around 2032. Grafström and Lindman (2017) provided a technical development model for economic analysis of the European wind power sector and suggested natural gas prices and feed-in tariffs as crucial factors in the spread of wind power. Other studies have analyzed renewable sources using technology diffusion models (Rao and Kishore, 2010; Popp et al., 2011; Pfeiffer and Mulder, 2013; Kumar and Agarwala, 2016; Fadly and Fontes, 2019). The Bass model plays an important role in the diffusion modeling. Since it was proposed in 1969, it has become the main research tool of market diffusion theory (Yang, 2006). Rao and

Kishore (2009) used the Bass model to study the growth patterns of wind power technology in several Indian states; the model which provided a good foundation for the study of capital-intensive equipment such as wind power generators. Radomes and Arango (2015) analyzed the diffusion of photovoltaic systems in Colombia using an extended Bass model in which the adoption rate was a function of promotional activities and social interactions. It can be concluded that technology diffusion modeling is generally mature in renewable energy research based on the above papers, but there is little research about CSP. Yang (2006) pointed out that the fitting result of the Bass model is better than that of the logistic model. Therefore, this study used the Bass model to explore the diffusion path of CSP in China.

Due to the strict data requirements of the Bass model, some studies have focused on parameter estimation methods. Generally speaking, the ordinary least-squares method (Satoh, 2001), the non-linear least-squares method (Wang et al., 2017), the maximum likelihood estimation method (Razo, 2017), the Kalman filtering method (Chow, 2004), and the grey theory method (Wang, 2013) can be used to estimate parameters when data are sufficient, whereas judgment and analogical methods can be used otherwise. However, when using judgment or analogical methods, much external information is required, leading to subjectivity in the estimated parameters. Because CSP development in China started late, this study had insufficient data. Due to the heavy reliance of the accuracy of Bass model prediction on the number of data points (Mahajan et al., 1990), more than 14 data points are usually required to produce reliable statistical results (Zhang, 2006). Yang (2006) indicated that the accuracy of estimating Bass model parameters using a genetic algorithm is higher, which is of great significance for forecasting product diffusion in the growth period. Genetic algorithms (GA), proposed by Holand (1975), are global search methods based on natural selection and genetic variation. Sohn et al. (2009) developed a dynamic pricing model using the Bass model with GA for Korean mobile phone manufactures, and this method was also applied to the optimal electric vehicle charging location problem by Akbari et al. (2018). Similar papers include (Venkatesan and Kumar, 2002; Wang and Chang, 2009; Kong and Bi, 2014). Therefore, the application of GA to estimate the parameters of the Bass model appears to be relatively mature. Hence, GA was used for parameter estimation in this study.

The studies discussed above considered the impacts of cost and technology diffusion on renewable energy development. Other uncertain factors may also influence progress. Therefore, researchers have been investigating the comprehensive development of renewable energy (Xu et al., 2020). For instance, Lund (2007), in a case study in Denmark, discussed the problems and prospects of switching an existing energy systems completely into a renewable energy (wind, solar, wave, and biomass) system. Incentive policies for renewable energy power generation in China were explored by Zhao et al. (2016), including R&D incentives, fiscal and tax incentives, grid-connection and tariff incentives, and market development incentives. The results showed that these policies indeed substantially promoted renewable energy power generation development. Dynamic programming, as an optimization method for multi-stage decision problems, is more suitable for studying path-dependent problems under the influence of uncertain factors. Dynamic programming has also been widely applied to renewable energy studies (Boaro et al., 2012; Marano et al., 2012; Feng et al., 2018; Jafari and Malekjamshidi, 2020). Ding et al. (2020) researched the sensitivity of cost and price elasticity and policy performance to renewable energy technology diffusion by constructing a dynamic programming model. Lu et al. (2015) and Xu et al. (2020) also took these two models as constraints to explore the optimal path of China's wind power and PV power development, respectively. They both took resource potential, economic development, incentive policies, emission regulatory schemes, and grid absorptive capacity into account. However, few researchers have studied the CSP development path by applying dynamic programming methods.

The studies just described have analyzed the progress of renewable energy from various perspectives, but there have been few studies on CSP, especially on its development path. Therefore, this study draws on the more mature theories and methods to build a dynamic programming model with the goal of cost minimization. Based on the 2050 development target, the optimal development path of CSP in China was studied under the constraints of a learning curve model, a technology diffusion model, economic development, policy incentives, emission regulation schemes, and grid absorptive capacity.

MODEL AND HYPOTHESES

Learning Curve Model

The learning curve, also known as the experience curve, describes the relationship between cumulative production and unit cost. Previous literature in the field of new energy was principally focused on the one-factor learning curve model (Lu et al., 2015). The functional form can be defined as follows (De La Tour et al., 2013):

$$\mathrm{C}(t) = C_0 \times n(t)^{-\alpha} \times e^{\mu_t}, \tag{1}$$

where, $\mathrm{C}(t)$ is the unit investment cost for concentrated solar power in year t, C_0 is the corresponding cost in the base year, $\mathrm{n}(t)$ represents the cumulative installed capacity of CSP at the beginning of the year t, α is the cumulative installed capacity elasticity coefficient of the unit investment cost, and e^{μ_t} is a stochastic error term.

$$\mathrm{PR} = 2^{-\alpha}, \tag{2}$$

$$\mathrm{LR} = 1 - 2^{-\alpha}. \tag{3}$$

The progress ratio (PR) is used to describe the ratio of current unit investment cost to original unit investment cost when cumulative installed capacity doubles; however, the learning rate (LR) is more commonly applied in newer literature (Zhou, 2015). The LR is the learning rate of the learning curve model, which denotes the proportional reduction in unit investment cost associated with a doubling in accumulative installed capacity. For example, if LR = 0.2, it means the unit investment cost will decline by 20% when the cumulative installed capacity is doubled.

Innovation Diffusion Model

The Bass model is a mathematical model proposed by Bass (1969), which represents the macroscopic diffusion process of new products (Cao and Chai, 2013). It was originally designed to predict sales of durable goods and has gradually been applied to the new energy sector. The logistic model and the Gompertz model are also typical S-shaped diffusion curves (Rao and Kishore, 2010). The basic form of these three models is as follows (Lu et al., 2015):

$$dN(t)/dt = F(t)[m - N(t)], \tag{4}$$

where, m is the theoretical maximum installed CSP capacity, $\mathrm{N(t)}$ is the possible maximum cumulative installed capacity in year t, and $\mathrm{F(t)}$ is a time function determined by the technology diffusion model. The basic form of the Bass model is as follows (Bass, 1969):

$$N'(t) = \left[p + \frac{q}{m}N(t)\right][m - N(t)]. \tag{5}$$

The Bass model assumes that the adoption of new products is influenced by both external and internal information. External information includes mass media and advertising, for which the effect is represented by p, and which is called the innovation coefficient; internal information includes social interaction and word-of-mouth, of which the effect is expressed by q, and which is called the imitation coefficient (Bass, 1969).

Dynamic Programming Model for China's CSP

It is difficult to study the optimal development path of CSP generation with conventional deterministic prediction methods because solar power forecasting is uncertain (Channon and Eames, 2014). Dynamic programming can decompose a complex multi-stage decision-making problem into a group of simple single-stage sub-problems to solve (Mahmoudimehr and Loghmani, 2016). Generally speaking, the cost of CSP generation consists of investment cost, operation cost, and emissions reduction benefit. Therefore, the total cost function is as follows:

$$\mathrm{TC}(S(t), x(t)) = C(t) \times x(t) + (V - M \times L) \times n(t) \times T, \tag{6}$$

where, $\mathrm{x(t)}$ is the new installed capacity of China's CSP in year t and also the decision variable of the dynamic programming model; $\mathrm{n(t)}$ is the cumulative installed capacity in year t; $\mathrm{S(t)}$ is the state variable, which is equivalent to the cumulative installed capacity gap between the target and $\mathrm{n(t)}$; $\mathrm{C(t)}$ and V represent the unit investment cost and the unit operating cost of CSP, respectively; T is the annual average operating hours; M is the trading price of the carbon emissions market; and L is the conversion coefficient between carbon emissions and thermal power generation (Lu et al., 2015).

According to the target proposed in the China Renewable Energy Development Roadmap 2050, cumulative installed CSP capacity will reach 180 GW by 2050. Based on this target, the relationship between $\mathrm{S(t)}$ and $\mathrm{n(t)}$ can be expressed as:

$$\mathrm{S}(t) + n(t) = 180. \tag{7}$$

Nowadays, the average service life of a CSP installation is 20 years (Piemonte et al., 2011). It is assumed here that the life cycle of a CSP system follows a uniform distribution ranging from 18 to 22 years. The retired installed capacity is described by the following equation:

$$\mathrm{r}(t) = \frac{1}{5}\sum_{i=18}^{22} x(t-i). \tag{8}$$

The state transition equation can then be written as follows:

$$\mathrm{S}(t+1) = \mathrm{S}(t) - x(t) + r(t). \tag{9}$$

Therefore, the dynamic programming model of China's CSP development under the minimum cost can be expressed as:

$$\begin{cases} f_t(S(t)) = min_{x(t)\in g(S(t))}\left\{TC(S(t), x(t)) + \frac{1}{1+r} f_{t+1}(S(t+1))\right\} \\ f_{2051}(S(2051)) = 0, t = 2050, \ldots, 2020 \end{cases}. \tag{10}$$

Constraints and Parameters

In the past decade, China's economy has shifted from fast growth to medium-high growth, and the GDP growth rate has gradually decreased from 10 to 6% (Qi and Li, 2020). The impact of COVID-19 reduced China's GDP growth rate to 2.3% in 2020 (National Bureau of Statistics, 2021). To reflect the moderate slowdown of China's economic development as well as the impact of the pandemic, the paper refers to Qi and Li (2020) for the GDP growth rate from 2021 to 2050.

As a renewable energy source, CSP is capable of continuous and stable power generation, thus becoming the focus of R&D in some developed countries. The development of CSP technology in China started late, with the first demonstration projects launched in 2016. However, CSP is more competitive than other renewable energy sources due to its low cost, long service life, and stable output power. Nevertheless, incentives and subsidies must be adopted to stimulate CSP development. For this reason, 25.7 billion dollars were invested in China's solar industry in 2019 (International Renewable Energy Agency, 2020a; International Renewable Energy Agency, 2020b), accounting for 0.18% of GDP. The percentage in 2017 was 0.69%, including 0.01% for CSP investment (International Renewable Energy Agency, 2018). Due to its large planned installed capacity, China is likely to invest more in CSP development. Therefore, the investment ratio for CSP was set at 0.02% of GDP.

The proportion of CSP generation should be continuously increased so that it can become a power source for peak load regulation and intermediate power loads and form a stable and high proportion of a renewable energy power generation system together with wind power and PV power generation to achieve price competitiveness with conventional energy. According to data released by the International Energy Agency, China's CSP

TABLE 1 | The parameters in the model.[a]

No.	Parameter	Value	Units	Description
1	C_0	3.46	USD/W	Unit investment cost of CSP in 2019
2	V	0.021	USD/kWh	Unit operation cost of CSP plant
3	n (2019)	421	MW	Cumulative installed capacity in 2019
4	T	4000	h	Annual average operational hours
5	M	12	USD/ton	Carbon trading permit price
6	L	0.36	ton/MWh	Carbon emission coefficient
7	r	0.06	None	Discount rate
8	GDP_0	1.43×10^{13}	USD	GDP in 2019
9	P (2020)	5	GW	Planned cumulative capacity in 2020
10	P (2030)	30	GW	Planned cumulative capacity in 2030
11	P (2050)	180	GW	Planned cumulative capacity in 2050
12	u	0.02%	None	Investment proportion of GDP
13	g	35%	None	Annual growth rate of CSP production

[a]Parameter 2 is obtained from Renewable Power Generation Costs in 2019 issued by the IRENA. Parameter 3 is obtained from the IRENA (https://www.irena.org/solar). Parameter 8 is acquired from the National Bureau of Statistics, 2020. Parameters 9–11 are collected from the China Renewable Energy Development Roadmap 2050. The others are estimates based on relevant reports and literature.

generation reached 300 GWh in 2019, accounting for 0.016% of renewable (non-combustible) power energy generation.[4] According to the target proposed in the China Renewable Energy Development Roadmap 2050, electric generation by CSP is expected to reach 720,000 GWh by 2050. Therefore, the annual growth rate of power generation must exceed 28.45% to achieve the above target. With the gradual development of the grid, the growth rate of power connected to the main grid is included in the constraint to reflect the absorptive capacity of the grid. In addition, because of its advantages such as stable and continuous power generation, CSP will certainly become the focus of future development. To reflect this trend, the paper assumed that the grid absorptive capacity would grow at a rate of 35% per year.

In the general debate of the 75th session of the United Nations General Assembly, President Xi Jinping emphasized that China would adopt stronger policies and measures to achieve carbon neutrality by 2060. In 2019, the power sector accounted for more than 40% of the country's total carbon emissions (National Energy Information Platform, 2020b). Therefore, during the 14th Five-Year Plan period, it is imperative to demonstrate and promote the carbon trading market mechanism in the power industry. The national carbon market is a policy tool based on market mechanisms, and neither a high nor a low carbon price can achieve the most cost-effective emission reductions. The carbon permit price in most Chinese cities (except Beijing) fluctuates between 1.5 and 7.5 USD/ton (Website of Carbon trading, 2020). Because the pressure to reduce emissions is increasing, this study set the price of carbon at 12 USD/ton for the baseline condition.

The related parameters to clarify the above statements are listed in **Table 1**, which will be used as a base case.

In view of the factors just described, the constraints in this model can be expressed as follows:

$$n(t) \le N(t), \tag{11}$$

$$C(t) \times x(t) + (V - M \times L) \times n(t) \times T \le GDP_t \times u, \tag{12}$$

$$\left(n(t) + \frac{x(t)}{2}\right) \times T \le \left(n(t-1) + \frac{x(t-1)}{2}\right) \times T \times (1+g), \tag{13}$$

$$C(t) = C_0 \times n(t)^{-\alpha} \times e^{\mu_t}, \tag{14}$$

$$n(t+1) = n(t) + x(t) - r(t), \tag{15}$$

$$\begin{aligned} &x(t) \ge 0 \\ &t = 2020, \ldots, 2050. \end{aligned} \tag{16}$$

Constraint **Eq. 11** says that the cumulative installed capacity cannot exceed the possible maximum development potential in year t. Constraint **Eq. 12** states that the total investment cost of the newly added capacity cannot surpass a certain percentage of GDP. Constraint **Eq. 13** expresses the limitation of grid absorptive capacity to avert explosive growth of CSP. Equality constraint **Eq. 14** is a forecast of investment cost, and **Eq. 15** is the state transition function of the dynamic programming model. Constraint **Eq. 16** expresses a non-negative constraint.

The flowchart of this section and the following two sections (*Models*, *Results*, and *Discussions*) is shown in **Figure 2**.

Hypotheses

With an increasing share of renewable energy in the grid, energy storage will be a key factor in further decarburization (Pelay et al., 2017). From the perspective of reality, the new energy base of 10 billion watts level will inevitably form a base with integrated wind, PV, and storage and will need to be equipped with flexible regulating power sources such as energy storage. A CSP station is a kind of power source with a regulating ability and a moment of inertia, and its regulating ability is better than battery energy storage. Therefore, CSP is bound to become a focus of future development (National Energy Information Platform, 2020a). However, the actual progress of CSP has not been as fast as expected (Zhao et al., 2017). Further development still needs the guidance and support of the government, which can be

[4]The data are collected from the IEA (https://www.iea.org/countries/china).

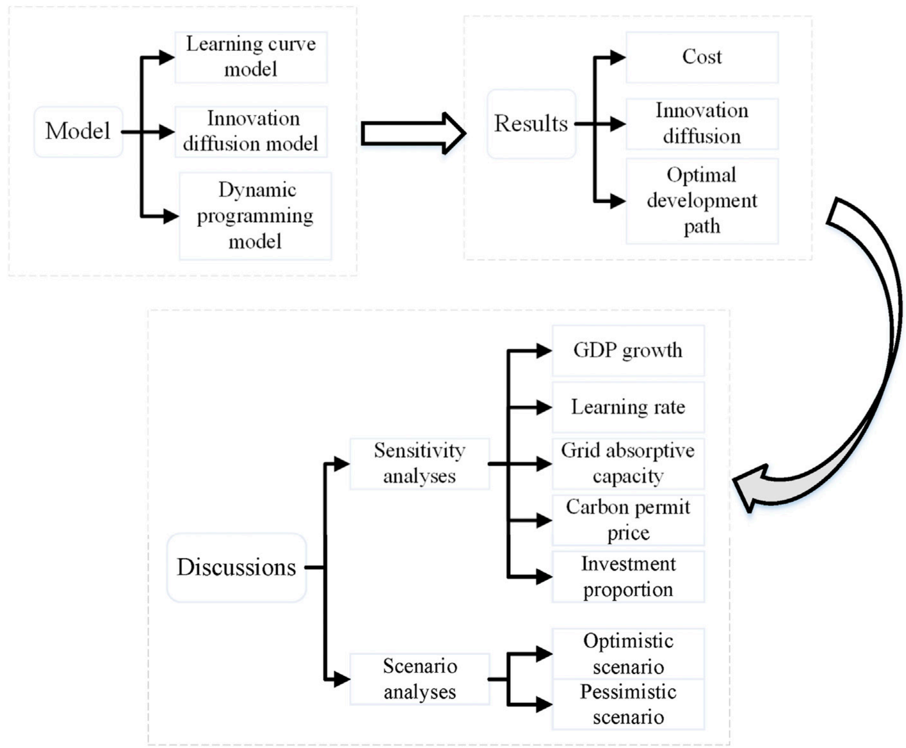

FIGURE 2 | Flowchart of models, results, and discussions.

reflected through incentive policies. Therefore, this paper hypothesizes that:

H1. Incentive policy is the key factor influencing CSP development.

Next, there is also a close relationship between GDP and social and economic development. The impact of economic development is reflected by analyzing different GDP growth rates (Lu et al., 2015; Xu et al., 2020). The more prosperous the economy, the higher is the GDP growth rate, and the greater will be the investment in CSP. Therefore, this paper proposes that:

H2. GDP growth rate is the key factor that influences CSP development.

Next, installed CSP capacity is small now. However, with large-scale deployment and the accumulation of industry experience, there is still much room to reduce investment cost (International Renewable Energy Agency, 2016). Therefore, the learning rate must necessarily be included in the analysis. Hence, this paper proposes that:

H3. The learning rate is the key factor influencing CSP development in the later phase.

Next, the absorptive capacity of the power grid is also an important factor affecting CSP development (Lu et al., 2015). Insufficient absorptive capacity leads to excess power generation, and excessive construction leads to waste of investment. However, the development of China's CSP is slow in the early stages, while the development of power grid construction is in step with it. Therefore, the following hypothesis is presented:

H4. The absorptive capacity of the grid is a potential factor influencing construction cost, but has limited impact on CSP development.

With the goal of being carbon-neutral by 2060, the pressure to cut emissions will increase further (Xu et al., 2020). The price of carbon permits directly affects the benefits of emissions reduction and thus the total cost. At present, China's carbon trading mechanism, relevant laws, and regulations are gradually improving. Therefore, this paper hypothesizes that:

H5. The carbon permit price is a potential factor influencing construction cost, but has limited impact on CSP development.

RESULTS

It is very important to forecast the investment cost of CSP because substantial cost reductions are the key to gaining market acceptance (Wang, 2010), as well as ensuring the rationality of goals due to the small number of stated goals that could be

TABLE 2 | Parameter estimation of the learning curve model and innovation diffusion model.

Parameter	Estimate	LR (%)	R^2
α	0.065	4.4	
m	3.5×10^5		
p	5.8×10^{-6}		0.9308
q	0.6		

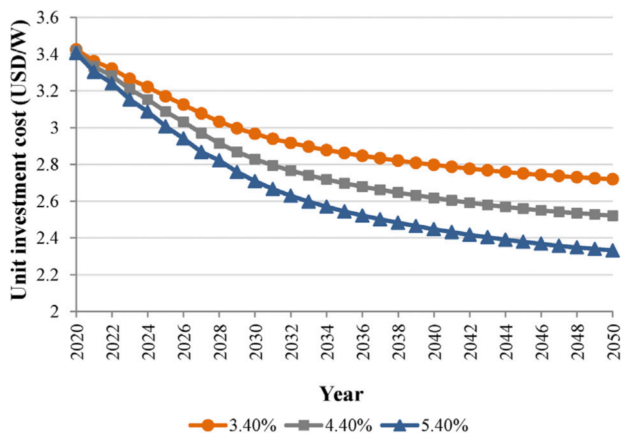

FIGURE 3 | Unit investment cost changes under different learning rates.

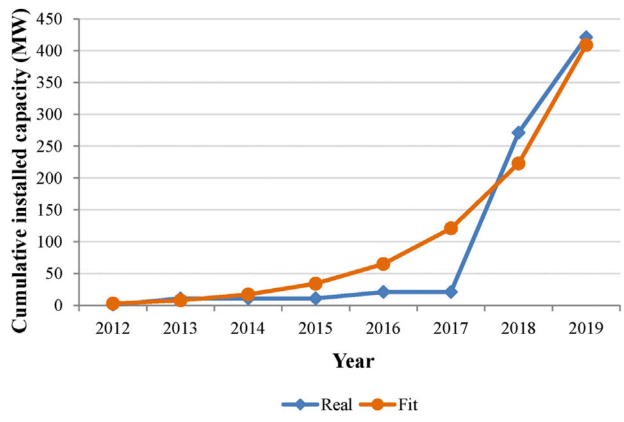

FIGURE 4 | Fitted model of cumulative installed capacity.

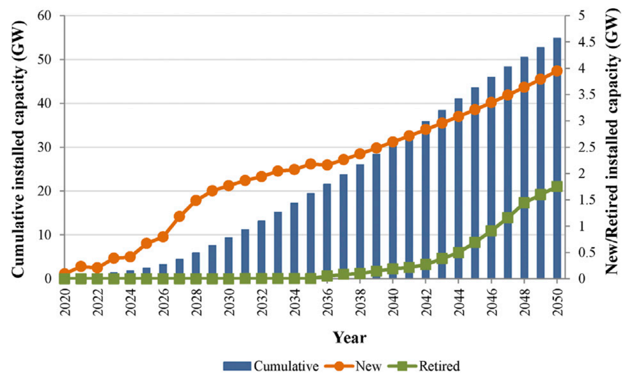

FIGURE 5 | Optimization path of CSP development in the base case.

attained in China. Therefore, the results for CSP cost forecasts, development trends, and the optimal development path under minimum cost are discussed in this section.

Cost of CSP

Data for the unit investment cost of CSP generation were derived from statistical reports released by IRENA and adjusted according to the actual situation in China. **Table 2** presents the parameter estimation results of the learning curve model. The learning rate LR was 4.4%, which shows that the unit investment cost will decrease by 4.4% for each doubling of CSP cumulative installed capacity. **Figure 3** reveals the change in CSP generation cost due to the learning curve model. The cost reduction trend is slowing down, which shows that the effect of experience accumulation on cost reduction is gradually being weakened. The unit investment cost is expected to fall to 2.521 USD/W by 2050, a reduction of 27.14% from the base year.

Innovation Diffusion of CSP Generation Technology

Estimated parameters have been shown in **Table 2**. It is apparent that the innovation diffusion model fits relatively well with the historical data in **Figure 4**.

This study used GA to estimate parameters of the Bass model. Correlative matrix is shown in **Table 3**. Consistently with previous literature, that the innovation coefficient p is far less than the imitation coefficient q (Xu et al., 2020). China's CSP market potential is about 350 GW, which is far less than the 1357 GW of solar PV power (Xu et al., 2020). This may be the case because CSP is still in its early development stage and the cumulative installed capacity is small in China. Therefore, these historical data led to relatively small results. However, the market potential of 350 GW is higher than the target of 180 GW in 2050, which demonstrates that CSP development in China has a long way to go.

TABLE 3 | GA settings.

Quantity	Setting
Population size	50
Crossover rate (Pc)	0.85
Mutation rate (Pm)	0.01
Crossover type	One-point crossover
Selection type	Roulette wheel selection
Generation	20,000

Optimal Development Path

Figure 5 shows the optimal CSP development path in the base case. Cumulative installed CSP capacity in China will attain

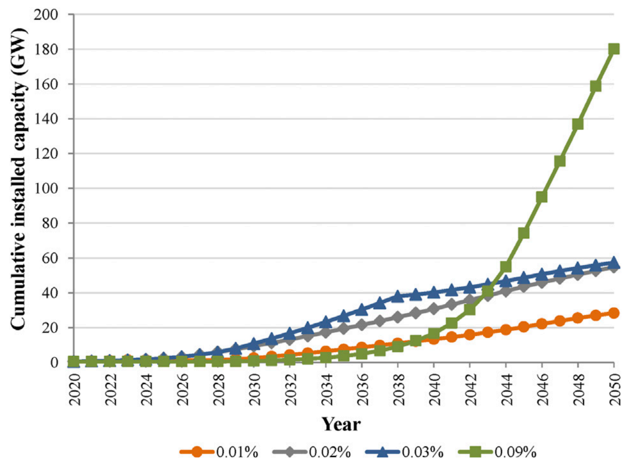

FIGURE 6 | Cumulative installed CSP capacity under different investment proportions.

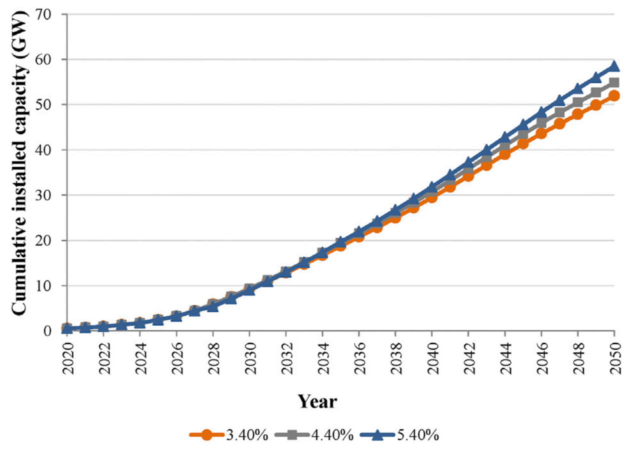

FIGURE 8 | Cumulative installed capacity of CSP under different learning rates.

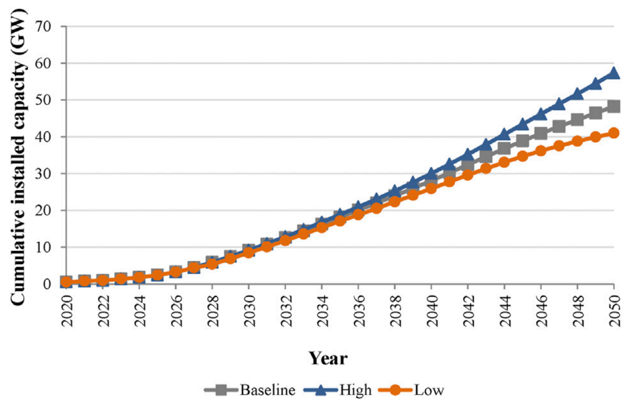

FIGURE 7 | Cumulative installed CSP capacity under different GDP growth rates.

54.84 GW in 2050 under this scenario, which leaves a big gap to reach the target of 180 GW. Furthermore, significant differences exist between forecasts and targets in 2020 and 2030, which illustrates the targets that were established could not be realized. **Figure 5** shows that the new installed capacity will increase rapidly before 2030 and then more steadily after 2030. The retired installed capacity will be very small until 2040 due to the small base of new installed capacity before 2020. The retired installed capacity will increase steadily after 2040, keeping in step with previous growth.

This study investigated a way to achieve the target in 2050 by adjusting parameters. The results show that the goal established for 2050 could be attained if the investment ratio were at least 0.09%. However, it is impossible to realize the stated goal by adjusting other parameters because of the limited impact of these parameters on CSP development (The analysis can be found in *Sensitivity Analyses*). According to **Figure 6**, CSP is expected to develop slowly before 2040 and rapidly after 2040 under this investment ratio. One possible reason is that strong government support leads to an influx of numerous investors and fierce market competition, which does not provide a good ecological environment for the CSP industry in the early stage.

DISCUSSIONS

In addition to the optimal path of CSP development, it is also crucial to study the potential factors affecting its development. The following section describes the application of sensitivity and scenario analyses to explore the key factors impacting CSP development under different conditions. In the various scenarios, there was little difference in the early path, with change occurring mainly in the later period. This conclusion was also reached in previous studies (Xu et al., 2020). Notably, the government's stated goal is not achieved in any of the following cases.

Sensitivity Analyses

GDP Growth

Based on Qi and Li (2020), China's GDP growth rate will fall to 3.81% by 2050. This study assumed that the base case GDP growth rate would decline by 0.07% per year from 2019 to 2050. Under the high-speed and low-speed scenarios, the annual growth rate would fall by 0.02 and 0.12%, respectively, which implies that the GDP growth rate would fall to 5.38% and 2.28% by 2050. **Figure 7** shows the variation in cumulative installed capacity under different GDP growth rates. The development path is the same under all growth rates until 2035, which implies that the economic growth rate is not a decisive factor for early CSP development. However, the higher the GDP growth rate, the more the cumulative installed capacity grows after 2035. This indicates that economic growth rate is one of the key factors affecting later CSP development, meaning that H2 is partially supported. One reason for this may be that PV power generation in China is in a period of rapid development (Xu et al., 2020), and that CSP is expected to flourish after 2035.

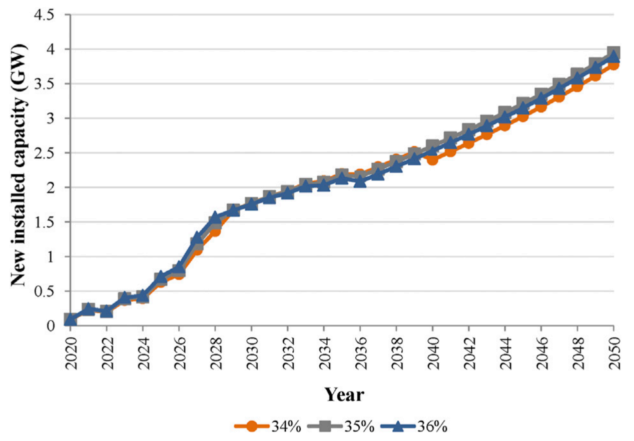

FIGURE 9 | New installed capacity under different grid absorptive capacities.

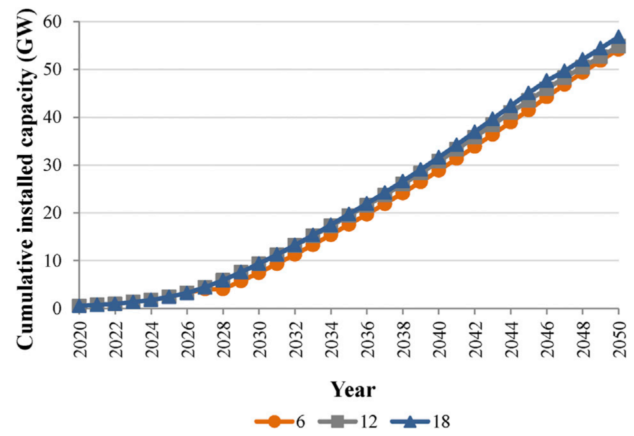

FIGURE 10 | Cumulative installed capacity under different carbon permit prices.

Learning Rate

The increase in cumulative installed CSP capacity (i.e., accumulated experience) leads to a decrease in costs according to the learning curve. The learning rate in the base case is 4.4% according to least-squares estimation. Lu et al. (2015) pointed out that the variation would not exceed 2% even if there was a technical breakthrough. Therefore, this study assumed that the variation in learning rate was 1%, that is, the learning rate in the favorable case was 5.4% and in the unfavorable case was 3.4%. **Figure 8** shows the variation of the development path for different learning rates. The paths are almost the same in the early stages. However, in the later period, a higher learning rate results in a larger cumulative installed capacity, indicating that learning rate is one of the key factors affecting the development of CSP in the later period, which supports H3. From **Figure 3**, the unit investment cost in 2050 will drop to 2.72, 2.521, and 2.332 USD/W when the learning rate is 3.4, 4.4, and 5.4%, respectively.

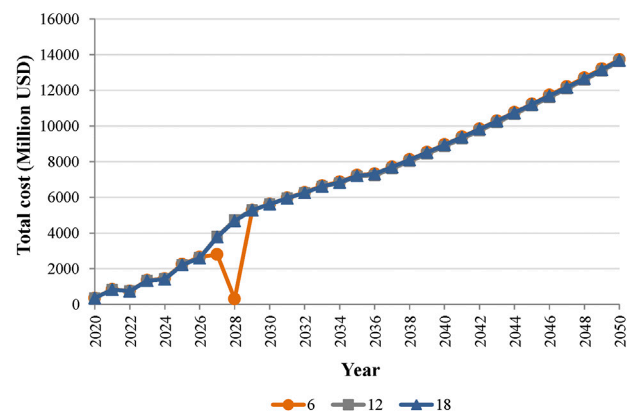

FIGURE 11 | Total cost changes under different carbon permit prices.

Grid Absorptive Capacity

Previous studies (Lu et al., 2015; Xu et al., 2020) have pointed out that insufficient grid absorptive capacity leads to excess generation and idle power plants, whereas overbuilding the grid results in wasted investment. Due to the large installed CSP capacity planned for the future, this paper has set a higher grid absorptive capacity in the base case, with an annual growth rate of 35%. The variation in the other two cases is 1%. The optimal development paths under different grid absorptive capacities are presented in **Figure 9**.

The development curves in different periods—before 2025 and from 2029 to 2039—are relatively flat, with essentially the same path for different absorptive capacities. The period 2025–2029 shows slight fluctuations, which implies that grid absorptive capacity is insufficient to keep up with the development of CSP generation. After 2040, the base case develops slightly better than the other two scenarios, indicating that grid absorptive capacity should develop in parallel with CSP generation. Taken together, there is no significant difference in new installed capacity among the three scenarios, and H4 is supported by the indication that grid absorptive capacity has a limited impact on CSP development.

Carbon Permit Price

The carbon permit price in the Chinese market (excluding Beijing) fluctuates between 1.50 and 7.50 USD/ton. With the vision of achieving carbon neutrality by 2060, there is increasing pressure to reduce emissions. Therefore, this study set the price at 12 USD/ton under the base condition, with a variation range of 6 USD/ton.

Figure 10 shows the optimal development paths under different carbon permit prices. The path remains the same until 2028, regardless of the changes in carbon permit price. After 2028, higher prices contribute to larger cumulative installed capacity. This indicates that the carbon permit price is one of the factors affecting later development of CSP, but that the impact is limited, which supports H5. The impact of different carbon permit prices on the total cost is shown in **Figure 11**. Under the unfavorable case, the total cost will fluctuate in 2028 because zero new installed capacity ensures that only operating cost is taken into consideration. Except for 2028, the development paths under different carbon permit prices are basically identical in other years, i.e., the new installed capacity and the cumulative installed capacity are essentially the same each year, and therefore the total costs under various carbon permit prices remain almost unchanged. This also confirms the limited impact of carbon permit prices on CSP development. Overall, total cost is trending upward by 2050, indicating that CSP in China is still immature at this stage and that the emissions reduction benefits are still lower than construction and operating costs.

Investment Proportion

The ratio of CSP investment to GDP can, to some extent, reflect the strength of government incentives. China currently invests a small percentage of GDP in CSP generation, at most 0.01%. Given the huge installed CSP capacity under construction and in the planning stage, it is highly possible that China will increase its investment in CSP. Therefore, in the base case, the investment ratio was set to 0.02%. In the other two cases, the ratios were 0.03 and 0.01%. The optimal development paths under different investment ratios are shown in **Figure 6**. There is a huge gap in the cumulative installed capacity for different ratios, indicating that strengthening the incentive policy is beneficial to accelerate the achievement of CSP goals. Therefore, H1, stating that incentive policy is the key factor influencing CSP development, is supported. Note that in the unfavorable case, the considerable gaps between cumulative installed capacity and the other two cases indicate that China should invest more to accelerate CSP construction. However, the gap between the base case and the favorable case gradually narrows in the later stage of development, which implies that the incentive effect of the policy gradually diminishes. This is when the influence of other factors such as grid absorptive capacity should be considered.

However, the government can achieve the established target of 180 GW by expanding the investment ratio to a minimum of 0.09%. Note the limited influences of learning rate, power grid absorption capacity, and carbon permit price on CSP development when the investment ratio is 0.09%. However, under this investment ratio, there is an exception that CSP develops steadily when GDP growth rate is low, but rapidly in the later stage when GDP growth rate is high. For higher investment ratio (e.g., 0.17%), the influence of GDP growth rate can be ignored. Therefore, the conclusion can be drawn that as investment in CSP is increased, the influence of all factors will be gradually weakened. (The figures can be seen in **Supplementary Materials**.)

Scenario Analyses

Some other possible development paths are explored in this section. The parameters of all elements are the medium-range values in the basic situation. For the sake of simplification, only two extreme cases are discussed, the optimistic scenario (all favorable conditions) and the pessimistic scenario (all unfavorable conditions). The development paths of the optimistic and pessimistic scenarios are greatly different. **Figure 12** shows the optimal CSP development paths under optimistic, basic, and pessimistic scenarios. CSP is predicted to enter a stable and fast growth period from 2042 under the optimistic scenario, but will maintain extremely slow growth from 2031 onward in the pessimistic scenario. Note that the government's stated target is still not achieved, even under the optimistic scenario. A detailed description and analysis of the development paths in the two scenarios are given in following paragraphs.

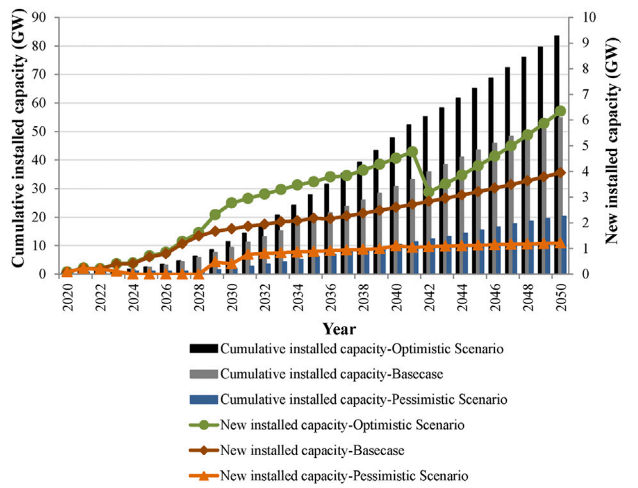

FIGURE 12 | Comparison of optimistic, basic, and pessimistic scenarios.

Optimistic Scenario

Considering the continuous progress of China's economy and of CSP technology, the increasing proportion of investment, the steady increase in grid absorptive capacity, and future pressure to reduce emissions, there is a growing call for sustainable development. Therefore, changes in these factors must be considered together. In this section, it is assumed that China's GDP growth rate will decline at 0.02% per year, the investment ratio will be 0.03%, the learning rate will be 5.4%, the grid absorptive capacity will be 36%, and the carbon emission permit price will be 18 USD/ton.

In the optimistic scenario, CSP development fluctuates in 2042 and then enters a period of steady growth; the process is faster than in the baseline case. Large-scale development starts from 2029. The cumulative installed capacity is expected to reach 83.46 GW by 2050, which is much larger than the 54.84 GW in the baseline case, but still far from the target of 180 GW. Therefore, the government should continue to create a favorable environment for CSP development to achieve the set targets.

Pessimistic Scenario

Contrary to the optimistic scenario, future funding for CSP research and development is likely to decrease in light of mature wind power and PV technologies that are competitive with conventional energy sources. For this reason, a comprehensive analysis of the relevant factors in the pessimistic scenario, i.e., considering all adverse conditions, is crucial. In this section, it is assumed that China's GDP growth rate decreases at 0.12% per year, the investment ratio is 0.01%, the learning rate is 3.4%, the grid absorption capacity is 34%, and the carbon emission permit price is 6 USD/ton.

In the pessimistic scenario, there is very little new installed capacity until 2028, and even a few years of zero growth. There will be a variation from 2028 to 2031, but after 2031, there will be a stable growth phase with a very low rate compared to the base case. By 2050, the cumulative installed capacity is expected to be 20.24 GW, which is well below the base case. CSP development costs will increase further under unfavorable conditions such as slow economic growth, weakening incentives, and slow grid construction. If the scenario worsens, China's planned development goals will be even harder to achieve.

CONCLUSIONS

Taking the cumulative installed capacity of 180 GW by 2050 as the target, a dynamic programming approach based on minimum cost has been used to explore the optimal development path of CSP generation in China. A learning curve model and a technology diffusion model were adopted as constraints. The impact of related factors is discussed in the context of sensitivity analysis and scenario analysis. The study has reached the following conclusions:

1) In the base case, the government will fail to achieve the set development target, with a projected cumulative installed capacity of 54.84 GW by 2050. New installed capacity will maintain a high growth rate until 2030 and enter a stable growth phase after 2030. The incentive policy is closely related to construction cost, which is the key factor impacting CSP development. Further development of CSP in China still needs guidance and support from the government, but the investment mainly comes from enterprises. Preferential policies will lead to an expanded proportion of investment, which in turn will help the government achieve its development goals more quickly. However, the incentive function of policies will weaken gradually in the later phase. Hence, other influencing factors should be considered, and the incentive policy should be gradually weakened. China's CSP is expected to usher in rapid development in the later period if the government maintains a more favorable support policy, and then the established goals of the government would be achieved. However, under this policy, market dominance is poor, and other factors have little influence on CSP development.
2) GDP growth rate and learning rate are important factors influencing the development path in the later stages. Affected by the learning curve, the cost decreases in these stages. Fast GDP growth ensures heavy investment in R&D and construction. The higher the learning rate, the easier it is to reach a certain installed capacity target. This indicates that in the later stages of development, industry experience can be accumulated, economies of scale can be realized, and the market will gradually gain more dominance. Grid absorptive capacity and carbon permit prices are potential factors affecting construction costs, but they have limited impact on CSP development, which is a slow process that must be synchronized with grid construction. With the gradual maturity of wind power and PV power generation, China's carbon trading mechanism and related laws and regulations are also developed gradually and therefore have a limited impact.
3) The scenario analysis shows that even under the optimistic scenario, the government cannot realize the 180 GW development target of cumulative installed capacity by 2050. However, the time required to achieve the target will be shorter than in the base case. This target will be achieved sooner if relevant factors are more favorable, such as better economic development and further increases in investment ratio and R&D funding. On the contrary, in the pessimistic scenario, economic growth will slow down, incentives and R&D will weaken, and the cost of CSP development will further increase. These developments will make the goal more difficult to achieve.

The main contributions of this study are as follows: 1) The impact of realistic factors on economic development is considered. China's GDP growth rate decreased to 2.3% in 2020 due to the impact of COVID-19. Many projects were put on hold, placing roadblocks in the path of CSP development in China. 2) A genetic algorithm was used to estimate the parameters of the technology diffusion model. By 2019, only eight years of data were available due to the late start of CSP in China. Because the parameter estimation is prone to large bias, using a genetic algorithm makes up for this deficiency and results in more accurate prediction. 3) Unit investment cost data for CSP are extremely hard to obtain. Only global data could be retrieved by consulting a large number of IRENA reports. Therefore, reviewing many references and adjusting global data according to the specific situation of China (e.g., low land acquisition cost, low labor cost) are the best means of estimating the unit investment cost of CSP in China. 4) The path of how to achieve the goal of 180 GW by 2050 and the related influencing factors have been explored.

In addition, the paper is instructive for the development of CSP generation in China, but improvement is still needed. The optimal CSP development path in China by 2050 has been explored with the goal of minimizing cost, and therefore the path may be stable with little variation in the early stages (Xu et al., 2020). Changing the goal, however, will lead to different results. The need remains to improve the accuracy of the forecast parameters (Lu et al., 2015), such as the theoretical maximum installed capacity and the learning rate, which will be improved in further studies.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**; further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

Data and review: XZ. Writing and methodology: XD. Proofreading and polishing text: XL.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2021.724021/full#supplementary-material

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Estimation of China's Green Investment Efficiency in Belt and Road Countries -Based on SBM-Undesirable Model and Malmquist Index Model

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Green and low-carbon development is an important element of the Belt and Road Initiative, and a reasonable and objective evaluation of China's green investment efficiency in B&R countries is of great significance to promote the sustainable development of those area. This paper applies the Slack-based measure model that considers undesirable outputs and Malmquist total factor productivity index to measure the efficiency of China's green investment in B&R countries from 2011 to 2018 from both static and dynamic perspectives, as well as provides an in-depth analysis of the differences, changes, and influential factors. The empirical results reveal that the overall efficiency of China's green investment in B&R countries is relatively low, showing a distinctly uneven trend and the main driving force of the decline in total factor productivity comes from technical change. Some significant differences have also been reported amongst these countries in terms of their industrial development and income levels. These findings provide a valuable reference for B&R countries to identify unique strategies that can promote their green total productivity factor.

Keywords: "The Belt and Road", green investment efficiency, SBM-undesirable model, Malmquist index, total factor productivity

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1 INTRODUCTION

At the second Belt and Road Forum for International Cooperation in April 2019, General Secretary Xi Jinping pointed out that we should put into practice the principles of common business, common construction and sharing, and build the "Belt and Road" with the concept of openness, green and honesty. The "Belt and Road" initiative (BRI) focuses on both economic prosperity and green development. China has always upheld the concept of green development in the practice of "Belt and Road" construction, promoted green and low-carbon infrastructure construction and operation management, emphasized the concept of ecological civilization in investment and trade, and strengthened cooperation in ecological and environmental management, biodiversity conservation and climate change.

According to World Bank, the greenhouse gases emitted during the construction and operation of infrastructure in Belt and Road (B&R) countries account for 70% of the total global carbon emissions, and once completed, their annual emissions will remain unchanged for decades to come, with an obvious "carbon lock-in effect". Apart from the energy consumption caused by the B&R project, most B&R countries are from the developing world whose economic development patterns are still

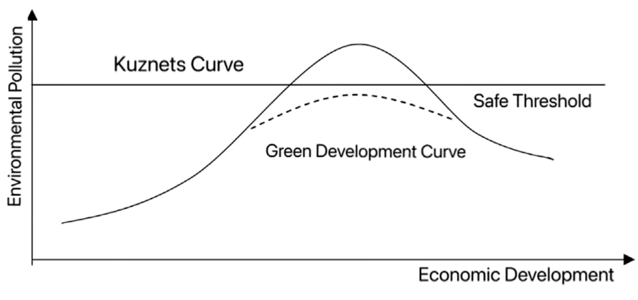

FIGURE 1 | Environmental Kuznets curve.

featured by "high inputs, high consumption, and high emissions" (Hou et al., 2019). With the outbreak of conflicts accumulated over years of uneven development, the crude development method can no longer maintain the original growth rate of the economy and brings a series of environmental and social problems. The specifics of socio-economic and technological development levels and systems vary greatly. An effective assessment of the relationship between the level of economic development (Wei et al., 2019) and environmental efficiency (Hu and Zheng, 2021) of B&R countries is essential to analyze the level of green development and its development trend. Green upgrade is an important support force to promote high-quality economic development and people's happiness. (Li and Zhang, 2021).

A recent report released by the United Nations Environment Programme (UNEP) shows that only $368 billion of the $14.6 trillion in announced recovery plan-related spending in 2020 meets the "green standards" and that most green spending is concentrated in a few high-income countries, which is likely to exacerbate the uneven development of the green economy that existed before the epidemic (Hu et al., 2018). After the COVID-19 epidemic, green development will be gradually centralized under the BRI, and the support of governments and financial institutions for the development of green industries will be further strengthened; highly-polluting and energy-intensive industries may be eliminated at an accelerated rate, and people will pay more attention to and support environmental protection, which may force the realization of green development. In the post-epidemic economic recovery phase, the Chinese government has proposed green low-carbon development initiatives such as the "China Carbon Neutral Commitment", calling on all countries to establish a new development concept of innovation, coordination, green, openness and sharing, seize the historic opportunity of the new round of technological revolution and industrial change, nurture new opportunities in the crisis, and take a series of green measures to promote a "green recovery" of the post-epidemic world economy.

2 LITERATURE REVIEW

American economist Simon Kuznets pointed out in 1995 that there is an inverted U-shaped curve between the income disparity and per capita income, called the "Kuznets Curve" (Kuznets, 1955). Through many empirical analyses, economists have found that the relationship between the degree of environmental pollution and the level of economic development also presents an inverted "U-shaped" curve (Grossman and Krueger, 1991), so this curve is called the environmental Kuznets curve (EKC) (Panayotou, 1993), as shown in **Figure 1**.

To a certain extent, the Environmental Kuznets Curve (EKC) can visualize the role of green investment in the relationship between environmental pollution and economic development. Along with economic globalization and the global spread of environmental pollution, scholars have focused on the analysis of environmental effects generated by foreign direct investment (FDI) in host countries covering the aspects of opening up, environment and green development. Classical studies have suggested that the mechanism of international trade affecting the environment consists of scale, structural and technological effects (Grossman, 1995), as is shown in **Figure 2** which also applies to the transmission path of outward foreign direct investment (OFDI) affecting the environment. In terms of scale effect, along with the entry of FDI, the input of natural resources and other factors will increase, and the scale of production will expand, but it may also lead to excessive input and more pollution emissions. Scholars have studied the structural effects by arguing that multinational companies move pollution-intensive industries to countries with low environmental standards for cost-saving purposes (Taylor, 2005), but FDI also drive industrial upgrading by improving the production efficiency of host countries (Feng, 2003). Some studies have confirmed the environmental improvement effect brought by FDI to the host country from the aspect of technological effect (Frankel, 2003; Sheng and Lv, 2012; Jing and Zhang, 2014; Shao et al., 2021), believing that environment-friendly new technologies and international environmental protection standards provided by FDI can promote the environmental improvement of the host country through learning effect and demonstration effect. The impact of FDI is closely related to the type and degree of environmental regulation, and appropriate environmental regulation helps to enhance the efficiency of green development (Tian and Hao, 2020). Another influencing factor is the size of FDI. The relationship between FDI and environmental pollution is a U-shaped curve that decreases and then rises, which is because the initial FDI mainly plays the advantage of green technology and produces the "pollution halo" effect, and as the scale of FDI expands, the technology of domestic and foreign investment gradually converges, and the impact of environmental pollutants brought by FDI exceeds the effect of technological improvement. (Gu et al., 2020).

The economic agglomeration caused by FDI will improve the efficiency of green economy through resource allocation optimization, industrial structure upgrading and technological progress of energy conservation and emission reduction (Jia and Lei, 2019). However, when agglomeration is excessive, crowding effect will be generated and environmental pollution will be aggravated (Zhou and Zhang, 2021). Meanwhile, most existing studies focus on the analysis of the impact of China's OFDI on domestic technological innovation, arguing that China's OFDI promotes domestic technological innovation capability, and the

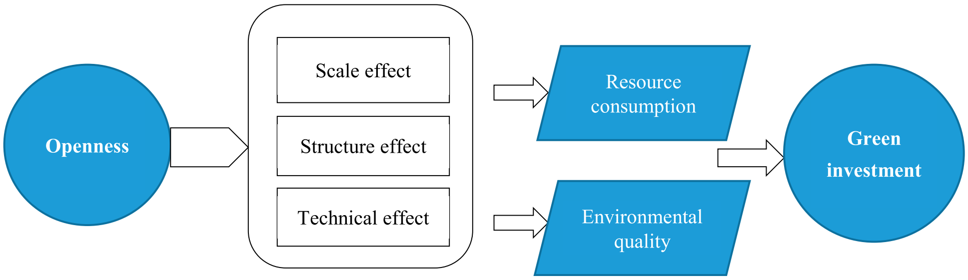

FIGURE 2 | The mechanism of openness on the efficiency of green investment.

impact mechanisms mainly include industrial transfer mechanism, high-end production link gathering in home countries, reverse technology spillover effect, and competition mechanism (Nie and Qi, 2019), and the reverse technology spillover effect of OFDI is influenced by the institutional quality (Ran et al.,2019). However, it has also been argued that the reverse technology spillover effect of China's OFDI has not yet emerged and is constrained by the structure of OFDI (Liang, 2019). With the rapid development of China's OFDI, its impact on the environment of B&R countries has become a controversial issue that needs to be resolved urgently. The "pollution transfer theory" argues that Chinese enterprises, under the pressure of increasingly stringent domestic environmental regulations (Jing and Zhang, 2014), will transfer polluting industries to B&R countries, especially those with poor environmental management (Tracy et al.,2017). Further, China's infrastructure investments can destabilize ecosystems and lead to new environmental risks for B&R countries (Teo et al., 2019). These studies are mainly theoretical in nature and are not yet supported by empirical studies. However, in fact, China's OFDI has a positive "pollution halo" effect (Huang et al., 2020). Firstly, those projects are mainly environment-friendly projects such as information technology, and the main investors focus on well-qualified enterprises, which have a strong sense of social responsibility and high level of green technology, which will produce obvious technology spillover effect in project implementation. Secondly, China's OFDI and the industrial structure of the B&R countries form a benign complementarity, which is in line with the industrial transformation and upgrading needs of the B&R countries and promotes the development of low-pollution and low-energy-consuming industries (Liu and Dai, 2017). Finally, there is a threshold effect of China's OFDI, which has a significant positive impact on the green total factor productivity of the B&R countries, which is affected by the ability to internalize advanced technology. (Xue and Ge, 2019).

China's outward foreign direct investment (OFDI) is not limited to simple currency flows but mainly the integration of resource elements, including technology, management, and systems, thus achieving the optimal allocation of production factors through industrial transfer and other methods (Huang et al., 2021). At the same time, B&R countries can also effectively learn, digest, and absorb advanced technologies, accumulate human capital, optimize industrial structure (Lei and Hong, 2019), and promote the growth of total factor productivity (TFP). In addition, the BRI runs through Asia, Europe and Africa, and there are differences in the overall economic scale, infrastructure quality and human capital accumulation among those countries, which may affect the ability of the host country to internalize Chinese advanced technologies and lead to the non-linear impact of China's OFDI on the GTFP of the B&R countries. However, there is a paucity of research in the literature on this issue. Throughout the existing literature on GTFP in the BRI, most of them have been developed from trade opening (Qi and Xu, 2018), scientific research and innovation (Ge et al., 2017), financial development (Ge et al., 2017) and urbanization (Wu and Ge, 2019), and no scholars have yet started from China's OFDI perspective to cut into.

How to choose a suitable theoretical perspective and research method to evaluate the green level of the countries reasonably and objectively and identify their influencing factors are yet to be studied in depth. Regarding the investment efficiency estimation method, Data Envelopment Analysis (DEA) was first proposed by Charnes and Cooper et al., in 1979, which is a non-parametric efficiency evaluation method that uses a mathematical planning model to calculate the distance between each Decision-Making Unit (DMU) and the production Frontier consisting of the best performing DMUs in practice, and further to calculate the efficiency score of each DMU. Tone (2001) proposed an SBM model considering the slack measure, which effectively overcomes the radial and angular deficiencies. Fukuyama and Weber (2009) and Fare and Grosskopf (1994), on the other hand, propose a more tractable directional distance function based on slack measures based on Tone's study (Tone and Tsutsui, 2010; Tone and Tsutsui, 2014), which is applicable to the Luenberger productivity index analysis first proposed by Chambers in 1996. With the application and expansion of DEA analysis by domestic scholars, research on environmental performance continue to emerge. Zheng et al. (2017) used DEA model with ML index to measure the eco-efficiency of Chinese provinces, and then examined the factors influencing eco-efficiency through panel Tobit model. Fang and Xiao (2019) measured ecological efficiency of 30 Provinces in China based on the S-DEA model and analyzed the factors influencing regional eco-efficiency using spatial panel regression. Undesirable outputs, such as CO_2 emissions, are inevitable in actual production processes. Therefore, one fundamental way of improving environmental efficiency is to generate desirable economic outputs whilst minimizing both inputs and undesirable outputs (Shen et al., 2019). In addition, TFP is usually regarded as an important evaluation indicator for the quality of economic growth of a country or region, but the traditional TFP measurement process ignores resource and environmental factors, which leads to bias in evaluating regional development performance, and it is advisable to refer to TFP with resource and environmental factors taken into account as green TFP. Regarding the GTFP estimation method, the Malmquist–Luenberger (ML) productivity index proposed by Chung (1997) has been widely applied in the previous studies. Wang and Wu, (2011) adopted the super-efficiency SBM model, emphasizing the dual objectives of economic production and environmental quality, with energy and carbon emissions as inputs, to measure the ecological efficiency and its temporal and spatial differences in East, West and Northeast China. Han et al. (2014) constructed a systematic GMM model, and a threshold panel model based on the SBM function to empirically investigate the spatial and temporal impact paths of environmental regulations on industries with heterogeneous pollution emissions, technology levels, and production cycles. Liu and Zeng (2018) adopted the Meta-Frontier-GML index method to measure the GTFP of 47 B&R countries based on data from 2003 to 2012. It is found that the GTFP in Central and Eastern Europe, Southeast Asia and CIS region is relatively high. Ran et al. (2019) revised the traditional TFP by constructing a comprehensive index of the discharges of industrial wastewater, industrial waste gas, and industrial solid waste ("three wastes") as undesirable output. Dong et al. (2019) measured and decomposed GTFP by using SBM function and ML index considering environmental pollution indicators under the constant constraint of return to scale.

A review of the literature reveals that there is room for improvement in the study of China's green investment efficiency in B&R countries. First, most of the existing studies focus on countries in a certain region, lacking green investment efficiency analysis based on the whole B&R region. Second, existing studies generally adopt the DEA method, which only stays at the level of static analysis of investment efficiency, lacking dynamic analysis decomposition of national investment dynamic efficiency research, thus failing to scientifically reflect the differences in investment as well as technical output contribution. Based on this, this paper will be improved in two aspects: first, to expand the vision of overall investment efficiency research, select the whole Belt and Road region, including 47 countries with complete data as research objects, comprehensively explore the current situation of China's green investment in B&R countries, systematically analyze the input and output problems, and propose corresponding strategies according to local conditions. It is an important reference for narrowing the green development gap of the B&R and solving the problems of unbalanced regional development. Secondly, we break through the single logical idea of traditional investment efficiency measurement and choose DEA-SBM model and Malmquist index method to conduct empirical research from a single investment process to an inter-period multidimensional input-output process, analyze the key factors affecting overall green investment efficiency based on previous research deficiencies, and comprehensively quantify the level of green investment efficiency and influencing factors.

3 METHODOLOGY AND DATA

3.1 Research Setting and Sample

To calculate the efficiency of China's green investment in B&R countries, this study constructs a set of production possibilities including input, desirable output, and undesirable output items. First, based on the static view perspective and using the SBM-Undesirable model, we analyse the general characteristics and country differences of green investment efficiency. Then, based on the dynamic perspective and using the Malmquist index method, we also analyse the dynamic evolution characteristics of China's green investment efficiency in B&R countries in time and space dimensions and then discuss the change in TFP in B&R countries from three aspects: total factor productivity, efficiency change, and technological progress.

3.2 Methods

3.2.1 The Slacks-Based Measure Model

DEA has become the most mainstream method for measuring production efficiency because it can consider multiple inputs and outputs simultaneously and does not require a specific functional form. (Sun et al., 2020). However, the traditional DEA model cannot deal with efficiency issues that include undesirable outputs. Then, a Slacks-Based Measure (SBM) model based on relaxation measures was proposed by Tone in 2001, which can solve the efficiency evaluation problem including undesired outputs.

Suppose there are n decision units $DMU_j\,(j = 1, 2, \ldots, n)$. According to the conventional SBM model, if $s^- \in R_m$ and $s^+ \in R_k$ denote input and output slacks, respectively, a certain DMU such as (x_0, y_0) can be expressed as:

$$x_0 = X\lambda + s^-, y = Y\lambda - s^+ \tag{1}$$

Matrixes X and Y are defined as $\mathrm{X} = (\mathrm{x}_{ij}) \in \mathrm{R}_{\mathrm{m}*\mathrm{n}}$ and $\mathrm{Y} = (y_{ij}) \in \mathrm{R}_{\mathrm{s}*\mathrm{n}}$, respectively. Assuming $\mathrm{X} > 0, \mathrm{Y} > 0$, the production possibility set is expressed as:

$$\mathrm{G} = \left\{ (\mathrm{x}, \mathrm{y}) | \mathrm{x} \geq \mathrm{X}\lambda, \mathrm{y} \leq \mathrm{Y}\lambda, \sum\nolimits_{\mathrm{i}=1}^{\mathrm{n}} \lambda \geq 0 \right\} \tag{2}$$

At the same time, Tone defines indicator ρ as follows:

$$\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{n}\sum_{i=1}^{m}\frac{s_r^+}{y_{r0}}} \tag{3}$$

Thus, the SBM model is defined as (Tone 2001):

$$min\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{n}\sum_{i=1}^{m}\frac{s_r^+}{y_{r0}}} \tag{4}$$

s.t: $x_0 = X\lambda + s^-$; $y = Y\lambda - s^+$; $\lambda \geq 0$, $S^+ \leq 0$, $S^- \geq 0$;
where, λ is the intensity vector and s^- and s^+ respectively represent slack of input and output. If and only if $\rho = 1$ and $S^- = 1$, $S^+ = 1$, DMU is efficient.

To measure the effect of negative externalities on efficiency, such as environmental factors, the SBM-Undesirable model, was proposed by Tone in 2003. x, Y^g, and y^b represent inputs, desirable outputs, and undesirable outputs, respectively. Matrix X, Y^g andY^b is defined as: $X = (x_{ij}) \in R_{m*n}$, $Y^g = (y_{ij}^g) \in R_{S1*n}$, $Y^b = (y_{ij}^b) \in R_{S2*n}$. Assuming $X > 0, Y^g > 0, Y^b > 0$, the production possibility set is expressed as:

$$G = \left\{ \left(x, y^g, y^b\right) | x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, \sum_{i=1}^{n}\lambda \geq 0 \right\} \tag{5}$$

The production possibility set is closed and bounded, so input and output can be disposed freely. When $\sum_0^n \lambda \neq 1$, the model is regarded as variable returns to scale; when $\sum_0^n \lambda = 1$, the model has a constant return to scale, and the model is regarded as constant returns to scale. Then, the SBM-Undesirable model is constructed as follows **Eq. 1** (Charnes et al., 1979):

$$\min\rho^* = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^{g+}}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{s_r^{b+}}{y_{r0}^{b+}}\right)} \tag{6}$$

s.t: $x_0 = X\lambda + s^-$, $y_0^g = Y^g\lambda - s^{g+}$, $y_0^b = Y^b\lambda + s^{b+}$, $\lambda \geq 0$, $s^- \geq 0$, $s^{g+} \geq 0$, $s^{b+} \geq 0$,
where λ is the weight vector, s^-, s^{g+}, and s^{b+} respectively represent the slacks of inputs and desirable and undesirable outputs, and ρ^* is the production efficiency of each DUM considering undesirable output. When and only when $\rho^* = 1$ and $s^- = 0$, $s^{g+} = 0$, $s^{b+} = 0$, and the DMU is efficient. If $\rho^* < 1$ it means DMU is ineffiicient.

3.2.2 The Malmquist Index

The Malmquist index is a nonparametric method based on a distance function compared to the effective Frontier, which can be regarded as the distance between a certain production point and the optimal production point. Fare et al. (1994) transformed the Malmquist index from a theoretical index to an empirical index based on the DEA method proposed by Charnes et al., 1979 et al. Since then, the Malmquist index has been widely used in the analysis of input and output. According to D.W. Caves et al. (1982), it can be expressed as follows:

$$M_j^t = \frac{D_j^t\left(x^{t+1}, y^{t+1}\right)}{D_j^t\left(x^t, y^t\right)} \tag{7}$$

where x^t and y^t are the output and input of period t, respectively; $D_j^t(x^{t+1}, y^{t+1})$ is the distance function of the production point in period t+1 with reference to the technological Frontier of period t; and M_j^t calculates the change in efficiency from period t to period t+1 under the technical conditions of period t.

According to R. Fare, S. Grosskopf, B. Lindgren and P. Roos, **Eq. 7** can be further decomposed into two parts (hereinafter referred to as FGLR decomposition), as follows:

$$\begin{aligned} M_j\left(x^{t+1}, y^{t+1}; x^t, y^t\right) &= \left\{\frac{D_j^t\left(x^{t+1}, y^{t+1}\right)}{D_j^t\left(x^t, y^t\right)} \cdot \frac{D_j^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_j^{t+1}\left(x^t, y^t\right)}\right\}^{\frac{1}{2}} \\ &= \frac{D_j^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_j^t\left(x^t, y^t\right)} \cdot \left\{\frac{D_j^t\left(x^{t+1}, y^{t+1}\right)}{D_j^{t+1}\left(x^{t+1}, y^{t+1}\right)} \frac{D_j^t\left(x^t, y^t\right)}{D_j^{t+1}\left(x^t, y^t\right)}\right\}^{\frac{1}{2}} \\ &= EC_{FGLR}\left(x^{t+1}, y^{t+1}; x^t, y^t\right) . TC_{FGLR}\left(x^{t+1}, y^{t+1}; x^t, y^t\right) \end{aligned} \tag{8}$$

That is,

$$TFP = EC(CRS) \times TC(CRS) \tag{9}$$

where x^t and y^t are the output and input of period t, respectively; $D_j^t(x^t, y^t)$ and $D_j^t(x^{t+1}, y^{t+1})$ represent the respective distance functions of the DMUs in periods t and $t + 1$ when the data in period t are used as the reference set; and the same as $D_j^{t+1}(x^t, y^t)$ and $D_j^{t+1}(x^{t+1}, y^{t+1})$.

The Malmquist index measures the dynamics of total factor productivity of green investment from period t to period t + 1. When M > 1, it indicates an increase in total factor productivity, and vice versa. TECFGLR (·) is the efficiency change (EC) index under the condition of fixed return to scale, which measures the degree of change in the relative technical efficiency of the DMU from period t to period t + 1, that is, the catch-up change to the technological Frontier, also known as the "Frontier movement effect" (Jamaluddin and David, 1997). When EC > 1, the relative efficiency of the DMU is improved in period t + 1 compared to period t; that is, a higher output level can be achieved under the same level of input factors, and vice versa. TCFGLR (·) is a technological progress (TC) index that measures the movement of the technological Frontier from period t to t + 1, also known as the "technological Frontier movement effect" (Jamaluddin and David, 1997), which reflects the impact of changes in relevant production technology levels on the investment efficiency index. When TC > 1, it indicates technological progress, that is, the technological Frontier has expanded, and vice versa.

The discussion above is carried out under the condition of fixed returns to scale. In the case of variable returns to scale, according to R. Fare, S. Grosskopf, M. Norris and Z. Zhang (1994) further decomposed the index into two parts, efficiency change (EC) and technical change (TC), of which EC can be further decomposed into the pure technical efficiency index (PEC) and scale efficiency index

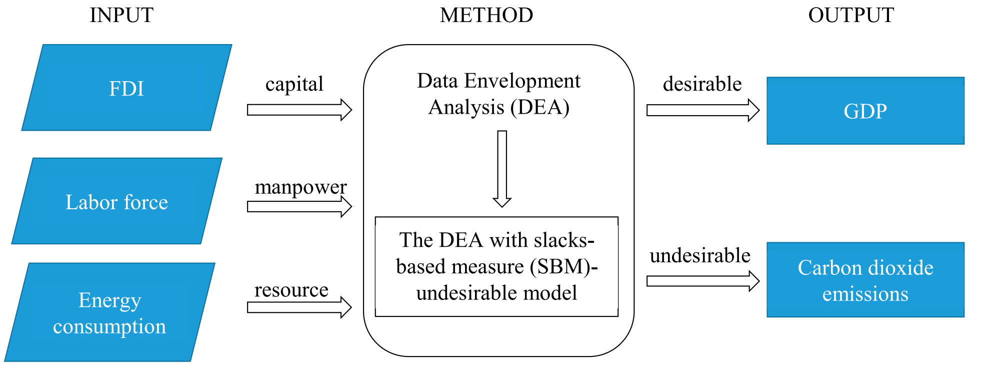

FIGURE 3 | Schematic diagram of SBM input and output.

TABLE 1 | The classification of B&R countries.

Type	Countries
Low-income countries	Tajikistan, Yemen
Lower-middle-income countries	Pakistan, Philippines, Kyrgyz, Cambodia, Mongolia, Bangladesh, Myanmar, Moldova, Serbia, Indonesia, Vietnam
Upper-middle-income countries	Albania, Azerbaijan, Belarus, Bulgaria, Macedonia, Bosnia and Herzegovina, Georgia, Kazakhstan, Montenegro, Lebanon, Malaysia, Sri Lanka, Thailand, Armenia, Iraq, Iran, Jordan
High-income countries	Arab Emirates, Oman, Estonia, Bahrain, Poland, Czech, Qatar, Kuwait, Croatia, Latvia, Saudi Arabia, Slovak, Brunei, Singapore, Hungry, Israel

TABLE 2 | The measurement indicators system.

Type	Indicators	Abbreviations	Amount	Units
	Foreign direct investment	FDI	423	ten-thousand dollars
Inputs	Labor force	LABOR	423	person
	Energy consumption	ENERGY	423	knte
Desirable outputs	Gross domestic product	GDP	423	ten-thousand dollars
Undesirable outputs	Carbon dioxide emissions	CO_2	423	knit

(SEC), hereinafter referred to as FGNZ decomposition, with the following expression:

Therefore, **Eq. 8** can be further decomposed into:

$$m\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \left(\frac{d_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{d_c^t\left(x^t, y^t\right)}\right) \times \frac{\frac{d_c^t\left(x^t, y^t\right)}{d_c^t\left(x^t, y^t\right)}}{\frac{d_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}{d_c^{t+1}\left(x^{t+1}, y^{t+1}\right)}} \times \left[\frac{d_c^t\left(\left(x^{t+1}, y^{t+1}\right)\right)}{d_c^{t+1}\left(x^{t+1}, y^{t+1}\right)} \times \frac{d_c^t\left(x^t, y^t\right)}{d_c^{t+1}\left(x^t, y^t\right)}\right]^{1/2} \tag{10}$$

That is,

$$\mathrm{TFP} = \mathrm{EC} \times \mathrm{TC} = \mathrm{PEC} \times \mathrm{SEC} \times \mathrm{TC} \tag{11}$$

When TFP >1, it means that the production efficiency is improved, and vice versa.

3.3 Data

Based on the relevant research literature and considering practicality, follow the principles of relevance and appropriateness, and combine the relevance of indicators and data accessibility, we select the data of 47 B&R countries excluding Maldives, Bhutan, Turkey, Egypt, Syria, Palestine, and Romania during 2010–2018 as the study sample As is shown in **Table 1**. And according to the 2018–2019 country classification by income level provided by the World Bank, these 47 countries are classified into four major categories: low-income countries, lower-middle-income countries, upper-middle-income countries, and high-income countries.

It should be noted that null values are not allowed to ensure the overall objectivity of the evaluation objects while considering the availability of data. However, due to the limitations of the DEA model, the input indicators should be no less than the output indicators (Yang and Wei, 2021), the input-output model is shown in **Figure 3**. Thus, a low-

TABLE 3 | Descriptive statistics of input and output variables.

Variables	Number	Mean	Stdv	Minimum	Maximum
FDI	423	155,814.272	21,318.962	20	5,009,383
LABOR	423	12,666,398.7	9,294.3714	191,157	132,584,070
ENERGY	423	27,262.2223	31.8472	655	199,796
GDP	423	1,230,214.345	50.6638	1,042	61,250,812
CO_2	423	90.2553	0.1021	2.1	579.2

TABLE 4 | Measurement results of green investment efficiency.

DUM	2010	2011	2012	2013	2014	2015	2016	2017	2018	MEAN
Philippines	0.0045	0.0084	1	1	1	0.2896	0.7836	0.5406	0.3086	0.5484
Malaysia	0.0069	0.0101	0.0071	0.0068	0.0067	0.1967	0.3478	0.2865	0.1981	0.1185
Myanmar	0.0017	0.0030	0.0012	0.0012	0.0012	0.0729	0.0704	0.0558	0.0802	0.0320
Thailand	0.0035	0.0052	0.0038	0.0036	0.0037	0.1152	0.2784	0.2502	0.1532	0.0908
Brunei	0.0197	0.0290	0.0240	0.0234	0.0217	0.3892	0.4373	0.4551	0.4101	0.2011
Singapore	0.0224	0.0262	0.0234	0.0240	0.0242	1	1	1	1	0.4578
Vietnam	0.0014	0.0026	0.0014	0.0014	0.0015	0.0644	0.1486	0.1379	0.0949	0.0505
Cambodia	0.0011	0.0014	0.0007	0.0008	0.0008	0.0441	0.0543	0.0536	0.0598	0.0241
Indonesia	0.0036	0.0059	0.0104	0.0031	0.0029	0.1258	0.3378	0.2644	0.0001	0.0838
Sri Lanka	0.0042	0.0070	0.0040	0.0039	0.0040	0.1942	0.4735	0.3773	0.2349	0.1448
Mongolia	0.0021	0.0031	0.0024	0.0027	0.0028	0.0748	0.0634	0.0613	0.0688	0.0313
Bangladesh	0.0032	0.0048	0.0045	0.0040	0.0044	0.2707	0.3614	0.2955	0.2535	0.1336
Pakistan	1	0.0029	0.5949	1	0.0016	0.0650	0.1497	0.1276	0.0730	0.3350
Turkmenistan	0.0029	0.0044	0.0044	0.0047	0.0052	0.1371	0.1887	0.1798	0.1219	0.0721
Kyrgyz	0.0011	1	1	1	0.0010	0.0323	0.0415	0.0482	0.0417	0.3518
Kazakhstan	0.0051	0.4163	0.2988	0.2974	0.0070	0.1273	0.1433	0.1556	0.0143	0.1628
Tajikistan	0.002	0.003	0.001	0.002	0.002	0.047	0.054	0.049	0.043	0.0226
Arab Emirates	0.2943	0.0174	0.2614	0.3312	0.0156	0.3199	0.4331	0.4238	0.4036	0.2778
Saudi Arabia	0.0138	0.0182	0.0166	0.0163	0.0158	0.3286	0.7033	1	0.3671	0.2755
Iraq	0.0069	0.0112	0.0082	0.0095	0.0095	0.3021	0.7245	1	0.3239	0.2662
Iran	0.0060	0.0080	0.0070	0.0051	0.0048	0.1027	0.2096	0.1771	0.1209	0.0712
Qatar	0.0241	0.0341	0.0287	0.0280	0.0286	1	1	1	1.0000	0.4604
Kuwait	0.0202	0.0278	0.0253	0.0274	0.0271	0.4544	0.6998	0.5550	0.3757	0.2459
Lebanon	0.0201	0.0181	0.0163	0.0150	0.0472	1	1	1	1	0.4574
Armenia	0.0076	0.0076	0.0075	0.0075	0.0077	0.2705	0.3034	0.2458	0.1999	0.1175
Israel	0.0269	0.0330	0.0307	0.0335	0.0333	1	1	1	1	0.4619
Jordan	0.0065	0.0085	0.0080	0.0083	0.0086	0.4133	0.4145	0.3255	0.2307	0.1582
Bahrain	1	0.0211	0.4565	1	0.0259	1	1	0.5796	0.3438	0.6030
Georgia	0.7882	0.0052	1	1	0.0026	0.0919	0.1376	0.1393	0.1082	0.3637
Yemen	0.0034	0.0064	0.0033	0.0031	0.0030	0.2985	1	0.2488	0.2231	0.1988
Azerbaijan	1	0.0100	1	1	0.0110	0.5032	0.2188	0.1969	0.4704	0.4900
Oman	0.3198	0.0136	0.3129	0.3117	0.0165	0.2595	0.3382	0.2888	0.2470	0.2342
Poland	0.4325	0.0127	0.7141	0.9582	0.0141	0.6040	0.0402	0.4180	0.4478	0.4046
Moldova	0.0079	0.0059	0.0072	0.0052	0.0106	0.1812	0.1811	0.2133	0.3161	0.1032
Hungry	0.0094	0.0128	0.0085	0.0087	0.0091	0.2639	0.7182	0.5532	0.3863	0.2189
Serbia	0.0100	0.0100	0.0104	0.0081	0.0096	0.2749	0.2603	0.2282	0.1796	0.1101
Bulgaria	0.5342	0.0083	0.8666	0.7276	0.0060	0.1634	0.3323	0.2896	0.2461	0.3527
Belarus	0.0050	1	1	1	0.0059	0.1013	0.1624	0.1707	0.1131	0.3954
Estonia	0.3804	0.0142	1	1	0.0330	1	1	1	0.4367	0.6516
Croatia	0.0214	0.0159	0.0160	0.0140	0.0241	0.6201	0.6778	0.5877	1	0.3308
Latvia	0.0273	0.0227	0.0269	0.0260	0.1891	1	1	1	1	0.4769
Montenegro	0.0136	1	1	1	0.0497	0.4226	0.3836	0.3779	0.2187	0.4962
Macedonia	0.0227	0.0217	0.0217	0.0161	0.0198	0.3084	0.3302	0.2919	0.2224	0.1394
Albania	0.0059	0.0075	0.0076	0.0066	0.0094	0.3385	0.3552	0.2984	0.5815	0.1790
Bosnia and Herzegovina	0.0062	0.0072	0.0079	0.0071	0.0133	0.2748	0.2727	0.3074	0.3592	0.1395
Czech	0.0140	0.0165	0.0170	0.0128	0.0131	0.4384	1	1	0.5008	0.3347
Slovak	0.0158	0.0144	0.0161	0.0121	0.0123	0.4480	1	0.5821	0.5289	0.2922

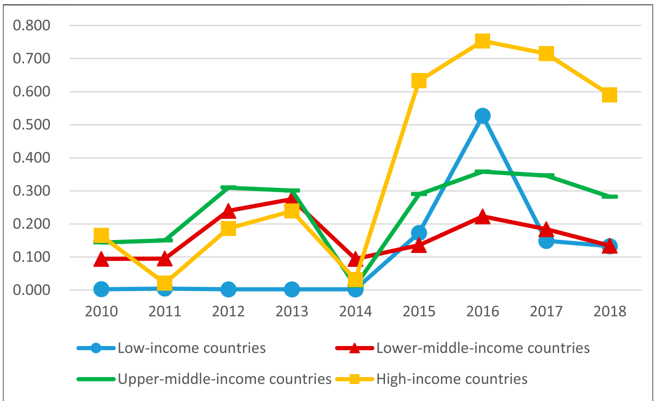

FIGURE 4 | Green investment efficiency by category in B&R countries.

carbon development efficiency evaluation system is established. The input-output indicator system is shown in **Table 2**.

The inputs and outputs are explained as follows:

1) Labor: the year-end employment of each country, obtained from Word Bank.
2) Capital: Since official data on capital stock cannot be obtained directly, we estimate capital stock by the stock of China's FDI in each country, sourced from the Statistical Communique of China's Outbound Investment 2019.
3) Energy consumption: energy consumption of each country, including coal usage, crude oil usage, refined oil usage, natural gas usage, wind energy, solar energy, electricity consumption, and biofuels, etc. obtained from the International Energy Agency.
4) Desirable output (GDP): the gross domestic product of each country is chosen as the proxy for the desirable output at the constant price of 2000, obtained from Word Bank.
5) Undesirable output (CO_2): the carbon dioxide emissions of each country, obtained from the Word Bank.

Table 3 represents the summary statistics of the input and output indicators for the study. There is a considerable gap between the minimum and maximum values among all the regions' capital and labour indicators during the study period. The wide gap observed in the summary statistics may highlight differences in the level of green development across the region.

4 RESULTS AND DISCUSSION

4.1 The Result of Green Investment Efficiency

This segment provides the description of the findings of the DEA and green investment efficiency. We adopt the SBM-undesirable model to measure the green investment efficiency of China in B&R countries between 2010 and 2018. **Table 4** shows the results, ignoring the effects of random errors. It can be seen that the efficiency of green investment has generally shown an upward trend, with the highest efficiency value in 2016. In 2016, for example, Singapore, Qatar, Lebanon, Israel, Bahrain, Yemen, Estonia, Latvia, the Czech Republic and Slovakia, had high green investment efficiency with an efficiency value equal to 1. However, the average investment efficiency has not reached the optimal level. The low level of comprehensive green investment efficiency indicates that the waste of resources and environmental pollution are still relatively serious, and the efficiency of energy use needs to be further improved.

As shown in **Figure 4**, the efficiency of green investment in B&R countries has recently shown a stable upward trend, with a small drop in the efficiency values in 2014, followed by a significant increase. Those countries are classified into four

TABLE 5 | Estimated results of green investment efficiency.

Countries	TE	PTE	SE
Philippines	0.5484	0.7012	0.7745
Malaysia	0.1185	0.1329	0.7825
Myanmar	0.0319	0.0357	0.6031
Thailand	0.0907	0.1797	0.6136
Brunei	0.2011	1.0000	0.2011
Singapore	0.4578	0.4660	0.8060
Vietnam	0.0504	0.0661	0.5989
Cambodia	0.0241	0.0384	0.4416
Indonesia	0.0838	0.3378	0.5041
Sri Lanka	0.1448	0.1672	0.5985
Mongolia	0.0313	0.0674	0.3735
Bangladesh	0.1336	0.3762	0.4980
Pakistan	0.3350	0.4003	0.7571
Turkmenistan	0.0721	0.0853	0.5890
Kyrgyz	0.3518	0.3766	0.5862
Kazakhstan	0.1628	0.2413	0.7241
Tajikistan	0.0223	0.2808	0.2408
Arab Emirates	0.2778	0.3303	0.8446
Saudi Arabia	0.2755	0.4550	0.7427
Iraq	0.2662	0.3374	0.6915
Iran	0.0712	0.1161	0.7124
Qatar	0.4604	0.4732	0.7791
Kuwait	0.2459	0.2660	0.7607
Lebanon	0.4574	0.4783	0.6663
Armenia	0.1175	0.2301	0.4218
Israel	0.4619	0.4683	0.8854
Jordan	0.1582	0.1880	0.5917
Bahrain	0.6030	0.6328	0.8175
Georgia	0.3637	0.4146	0.6792
Yemen	0.1988	0.2298	0.5534
Azerbaijan	0.4900	0.5019	0.8454
Oman	0.2342	0.2813	0.7626
Poland	0.4046	0.6756	0.6638
Moldova	0.1032	0.2539	0.3830
Hungry	0.2189	0.3409	0.5771
Serbia	0.1101	0.1272	0.6322
Bulgaria	0.3527	0.3930	0.7885
Belarus	0.3954	0.4035	0.8116
Estonia	0.6516	0.7648	0.7385
Croatia	0.3308	0.4703	0.5567
Latvia	0.4769	0.5906	0.6224
Montenegro	0.4962	1.0000	0.4962
Macedonia	0.1394	0.7993	0.2264
Albania	0.1789	0.4094	0.3749
Bosnia and Herzegovina	0.1395	0.2136	0.5127
Czech	0.3347	0.3950	0.7893
Slovak	0.2922	0.3516	0.6529

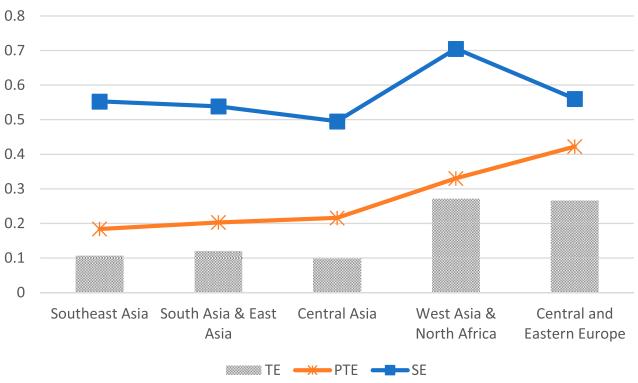

FIGURE 5 | Green investment efficiency and its decomposition trend.

major categories: low-income countries, lower-middle-income countries, upper-middle-income countries, and high-income countries. The green investment efficiency of high-income countries is the highest, followed by upper-middle-income countries, and the investment efficiency of lower-middle and low-income countries is relatively low. The green investment efficiency of high-income, lower-middle-income, and upper-middle-income countries all showed a significant increase during 2011–2013, while that of low-income countries was very low from 2010 to 2014. However, the green investment efficiency of both high-income and low-income countries showed a huge increase from 2014 to 2016, and the overall investment efficiency of all countries decreased slightly from 2016 to 2018, with the largest decrease in low-income countries. In general, there is still a huge space to improve the efficiency of green investment in B&R countries, and there is a large regional difference.

TE measures whether B&R countries utilize China's investment in an optimal way or at the most appropriate scale, reflecting the effectiveness of China's green investment, showing that the area can obtain the maximum output under the current factor input scale and combination structure through the current production technology, production organization and management of green investment.

Pure technical efficiency (PTE) is mainly related to factors such as production methods, production processes, technology and equipment levels, and organizational management levels. The area where the PTE is equal to 1 is the technical effectiveness area, showing that the area can obtain the maximum output under the current factor input scale and combination structure through the current production technology, production organization and management of green investment.

The scale effect (SE) is closely related to the factor input scale and its social allocation and combination level. The region with scale effectiveness equal to 1 is scale effectiveness, that is, marginal output equals marginal input, indicating that all kinds of resources can be effectively allocated and used in the region under the current factor input and production scale.

As shown in **Table 5**, the TE of relatively economically developed areas, the countries in Southeast Asia and Central and Eastern Europe, such as the Philippines (0.5484), Singapore (0.4578), Poland (0.4046), Estonia (0.6516) and Montenegro (0.492), have not yet reached the best production Frontier, indicating that although B&R countries attach great importance to green development, still do not utilize China's investment in an optimal way or at the most appropriate scale.

As shown in **Figure 5**, the average value of SE is less than 1, indicating that with the current factor inputs and production scale, all kinds of resources can still be inefficiently allocated and utilized in the region. The average value of PTE is far less than 1, indicating that the region cannot obtain the maximum output with the existing factor input size and mix structure through the existing green investments in production technology, production organization and management. The ability of Chinese companies to adapt to the market environment of B&R countries still needs to be strengthened. These results show that B&R countries all demonstrate inefficiency, among which that of Central Asia is particularly severe, indicating that there is still much room for improvement in the input or output level of factors.

To compare the differences in the green investment efficiency in various countries, according to the classification of the existing research results (Zhao et al., 2010), since the investment efficiency measured by the DEA model belongs to relative efficiency, which is dimensionless and has a value range of 0–1, the three types of investment efficiency of each country can be compared with the mean value to determine their relative status in B&R countries, and the green investment efficiency can be divided into four types, as shown in **Table 6**.

The first category refers to "high–high–high" development areas. In this type of area, technical factors and management factors have been fully utilized, and TE has reached or approached the best production Frontier (comparatively). From the above analysis results, there are fifteen such countries, mainly in Southeast Asia, West Asia and Central and Eastern Europe.

The second category refers to "low–high–low" development areas. Countries of this type have a high contribution of PTE but a low contribution of SE. The key to improving development efficiency in these areas is to further improve management elements that can bring SE. Examples of this type include Brunei Bangladesh, North Macedonia, and Albania, showing that the efficiency of green investment in those countries depends more on the technology effect than the scale effect.

The third category refers to "low–low–high" development areas. Countries in this category have a low contribution of PTE but a high contribution of SE. Six countries were classified as this type, showing that the efficiency of green investment in those countries depends more on the scale effect than on the technology effect.

The fourth category refers to "low–low–low" development areas, which were characterized by low comprehensive TE, low production technology, and insignificant scale effects. There were fifteen countries of this type.

4.2 Malmquist Index Analysis

This study applies the Malmquist Index to examine investment efficiency in a panel of 47 countries. For each pair of adjacent

TABLE 6 | Types of green investment efficiencies.

Type	TE	PTE	SE	Amount	Countries
1	high	high	high	15	Philippines, Singapore, Pakistan, Saudi Arabia, Qatar, Lebanon, Israel, Bahrain, Georgia, Azerbaijan, Poland, Bulgaria, Belarus, Estonia, Czech
2	low	high	low	4	Brunei, Bangladesh, North Macedonia, Albania
3	low	low	high	6	Malaysia, Kazakhstan, Iran, Kuwait, Oman, Serbia
4	low	low	low	15	Myanmar, Thailand, Vietnam, Cambodia, Indonesia, Sri Lanka, Mongolia, Turkmenistan, Tajikistan, Armenia, Jordan,Yemen, Moldova, Hungry, Bosnia and Herzegovina

TABLE 7 | Average productivity growth.

Countries	EC	TC	TFP
Philippines	1.6943	0.6112	1.0356
Malaysia	1.5204	0.6600	1.0035
Myanmar	1.6183	0.6237	1.0094
Thailand	1.6028	0.6467	1.0365
Brunei	1.4611	0.6691	0.9776
Singapore	1.6077	0.6424	1.0328
Vietnam	1.6936	0.6359	1.0769
Cambodia	1.6565	0.6426	1.0645
Indonesia	0.6670	0.6414	0.4278
Sri Lanka	1.6520	0.6203	1.0247
Mongolia	1.5436	0.6852	1.0577
Bangladesh	1.7257	0.6027	1.0401
Pakistan	0.7209	0.6336	0.4568
Turkmenistan	1.5934	0.6658	1.0610
Kyrgyz	1.5755	0.6484	1.0216
Kazakhstan	1.1370	0.6690	0.7606
Tajikistan	1.5067	0.6558	0.9882
Arab Emirates	1.0403	0.6694	0.6964
Saudi Arabia	1.5067	0.6684	1.0071
Iraq	1.6182	0.6382	1.0328
Iran	1.4561	0.6628	0.9650
Qatar	1.5930	0.6202	0.9880
Kuwait	1.4411	0.6703	0.9659
Lebanon	1.6298	0.6225	1.0146
Armenia	1.5043	0.6267	0.9427
Israel	1.5711	0.6426	1.0096
Jordan	1.5611	0.6368	0.9940
Bahrain	0.8751	0.6545	0.5728
Georgia	0.7802	0.6465	0.5044
Yemen	1.6878	0.6087	1.0275
Azerbaijan	0.9100	0.6045	0.5501
Oman	0.9682	0.6511	0.6304
Poland	1.0044	0.6263	0.6291
Moldova	1.5860	0.6085	0.9651
Hungry	1.5910	0.6381	1.0153
Serbia	1.4355	0.6467	0.9284
Bulgaria	0.9077	0.6395	0.5805
Belarus	1.4778	0.6528	0.9648
Estonia	1.0174	0.6475	0.6588
Croatia	1.6166	0.6104	0.9869
Latvia	1.5688	0.5776	0.9061
Montenegro	1.4151	0.6496	0.9192
Macedonia	1.3298	0.6294	0.8370
Albania	1.7761	0.5682	1.0092
Bosnia and Herzegovina	1.6597	0.6200	1.0290
Czech	1.5638	0.6389	0.9991
Slovak	1.5503	0.6262	0.9709

Abbreviations: Malmquist index averages are geometric means.
Source: *Authors' calculation.*

TABLE 8 | Average regional productivity changes (2010–2018).

	Region	Number of countries	EC	TC	TFP
1	Southeast Asia	9	1.4558	0.6412	0.9339
2	South Asia and East Asia	4	1.3348	0.6348	0.8510
3	Central Asia	4	1.4402	0.6597	0.1534
4	West Asia and North Africa	15	1.3009	0.6413	0.8115
5	Central and Eastern Europe	15	1.4080	0.6249	0.8914

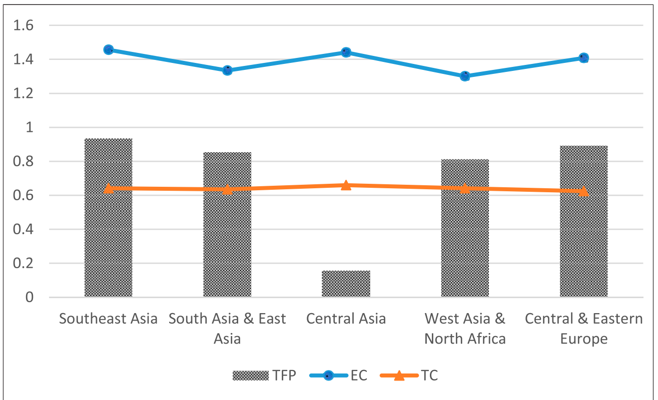

FIGURE 6 | Regional productivity changes.

years, measures of technical efficiency change, technical change and total factor productivity change have been calculated for each DMU. Only relevant sections of the results are presented in this research as there are a lot of computer output (Sun Y et al., 2020).

Table 7 displays the mean technical efficiency change, technical change, and total factor productivity change for all the countries under study from 2010 to 2018. Based on the DEA-Malmquist model, the MI is further decomposed to explore the main driving components of its dynamic changes. EC represents the index of change in efficiency change, which refers to the ratio of the actual output level to the potential maximum output level of the B&R countries at a certain amount of factor input level, which shows the ability of the countries to obtain the maximum potential production under the condition of certain input factors. TC represents the index of change in technological progress, which reflects the impact of changes in the relevant level of production technology on the investment efficiency index.

As shown in **Table 7**, Vietnam, Cambodia and Turkmenistan are countries with highest total factor output growth. Vietnam recorded an 7.7% average increase in total factor output attributable to a 69.4% increase in efficiency change. Indonesia, Pakistan, and Georgia, however, are countries with the least total factor output. Indonesia experienced a 57.2% decline in total factor output due to a 33.3% decline in the mean efficiency scores and a 35.9% decline in technical scores over the period. From the perspective of the average value of MI, that of Southeast Asia, South Asia, East Asia and Central and Eastern Europe is greater than 1, indicating that the overall productivity of these regions has increased, and of Central Asia, West Asia and North Africa is less than 1, especially the use efficiency of production inputs in Central Asian countries needs to be improved. The average value of the MPI from 2010 to 2018 was 0.845, which is less than 1, indicating that the growth rate of the efficiency of China's green investment in B&R countries declined and that there is still much room for improvement in resource use efficiency. Over the entire sample period, the mean value of EC is greater than 1, indicating that the desirable output (GDP) increases, and the undesirable output (CO_2 emissions) decreases in B&R countries due to their own technological progress or the lower cost of China's investment.

As shown in **Table 8**, all the regions recorded growths in efficiency changes over the period. The value of EC is greater than 1 throughout the sample period. South Asia reported the highest average efficiency changes of about 45.6%. However, all the regions recorded declines in total factor productivity changes as well as technical changes. West Asia and North Africa reported the hugest decline, 18.8% decline in total factor output due to a 35.9% decline in technical scores over the period.

Figure 6 shows the trends of technical change, efficiency change and total factor productivity change for regions during the years under study. Average total factor productivity change is attributable to the average decrease in technical change more than to the average growth in efficiency change in all regions. The technical change has therefore, been the predominant driver in global total factor productivity decline over the period.

5 CONCLUSION AND POLICY IMPLICATIONS

5.1 Main Conclusion

This study examines China's green investment efficiency in B&R countries from 2010 to 2018 using the SBM-Undesirable model and Malmquist total factor productivity index with labour, capital and energy consumption as inputs and GDP and carbon emission as desirable and undesirable output respectively to analyse the topic from both static and dynamic perspectives, as well as provides an in-depth analysis of the differences, changes, and influential factors in the regional coordination of industries with the environment. The following conclusions and policy implications may be extrapolated:

From a static analysis of green investment efficiency, we find that the overall green investment efficiency has generally maintained an upward trend but not reached 1, indicating that the efficiency of China's green investment in B&R countries is still not at its best, which show that most of the Chinese enterprises investing in the region have not been able to better adapt to the investment environment of the B&R countries or actively integrate into the local market. The average value of SE is less than 1, indicating that China's input of resources to those countries has not yet reached the optimal allocation. There are still many wasted investments and there is room for improvement in the optimization and improvement of the scale of green investment. In terms of decision-making technology, Chinese enterprises should also make adjustments as soon as possible to improve the efficiency of green investment with PTE less than 1. From the perspective of dynamic analysis of total factor productivity, the average total factor productivity change is attributable to the average decrease in technical change more than to the average growth in efficiency change in all regions, indicating that the main driving force of the decline in total factor productivity comes from technical change. This result implies that in order to promote green investment efficiency, it is more effective and appropriate to invest in environmental-related technologies than policies that aim to keep up with the global Frontier technology.

5.2 Policy Implication

Based on the above empirical results, some implications are proposed as follows:

1. The scale of green investment should be adjusted to create a global green value chain. 1) For Africa and Central Asia, scale up investment. In response to the huge investment gap in transportation and infrastructure in Central Asia and Africa, we should accelerate the delivery of China's excellent green products and advantageous effective production capacity, expand the number of high-quality sustainable projects in green energy, clean energy, green buildings and wastewater treatment on both sides, and build "China's business card" with high standards and quality. 2) For the Central and Eastern Europe region, maintain the steady development of the current investment scale. Focus on promoting technical cooperation with Central and Eastern Europe in the field of green science and technology and green standards, accelerate the speed of transformation and application of achievements in the field of sustainable development such as resource-saving, environment-friendly, safe, and efficient on both sides, and enhance the technology spillover effect. 3). For Southeast and South Asia, moderately reduce the scale of green investment. Green investment in the region should focus on playing a leading role in green technologies and reducing investment in high-emission, energy-consuming areas such as thermal power and copper and iron smelting. Expand high-quality cooperation in low-carbon areas such as high-speed rail and communications with key countries such as Malaysia and Indonesia to promote the optimization and upgrading of economic structures and green development in the region.
2. The domestic green governance system should be coordinated to promote and reshape the green governance cooperation model. A reasonable environmental regulation policy can effectively enhance the technological innovation capacity of each region

and promote economic growth while reducing environmental pollution. China should raise the green threshold for export technologies and reshape the green governance cooperation model according to the different levels of economic and social development of the B&R countries. In cooperation with countries at a lower level of economic development, the fiscal expenditure level of local governments should be appropriately increased by green investment and green financial cooperation, especially to strengthen green financial cooperation with such governments for environmental pollution control. When cooperate with countries at a higher level of economic development, we can introduce and exchange their experience in green governance by establishing cooperation mechanisms for green governance policies. At the same time, promote the establishment of a coordination mechanism for environmental protection, conduct performance assessment of sustainable development levels, and establish a consultation model for green governance cooperation in the construction of green infrastructure and green investment.

3. The green science and technology cooperation should be strengthened to enhance technical efficiency and promote technological progress. China can cooperate by way of green investment through continuous improvement of its production process to promote technical efficiency, take the "Made in China 2025 policy" as an opportunity to internalize the upgrading requirements of green transformation and environmental standards embedded in the process of manufacturing in China, promote China's green technology standards, green technology products can be promoted out and jointly enhance sustainable development. The sustainable development information sharing and think tank platform should also be established in conjunction with existing international and regional organization cooperation mechanisms to jointly negotiate and improve green technology standards, promote the common upgrading of technology levels, and play the driving role of technological progress in enhancing sustainable development levels. New technologies such as artificial intelligence, satellite monitoring and big data will be used to real-time monitoring of the global carbon emissions of key projects and promote the construction of the ecological and environmental protection big data service platform.

4. The green capital chain should be supported. Strengthen the support and leadership of green financing for green investment, establish the Belt and Road Green Investment Fund, give full play to the synergy effect of its complementary advantages with bilateral and multilateral development funds and domestic financial institutions, and support green investment in countries and regions along the route in all aspects. For the key green investment projects and the green industrial chain formed around them, we will provide more choices of financing tools for green investment and build a green capital chain that "green financing supporting and leading green investment, and green investment returning to green financing".

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

QL: Conceptualization, Methodology, Writing–Review and Editing Supervision; WT: Writing–Original Draft, Data Curation, Formal analysis; The corresponding author is responsible for ensuring that the descriptions are accurate and agreed by all authors.

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Estimating Peak Shaving Capacity Demand of Gas-Fired Power in China From a Regional Coordination Perspective

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To meet the carbon neutralization goal and renewable energy development, it is of great significance to promote the construction of gas-fired power generation for power peak shaving. From the perspective of regional coordination (corresponding to three scenarios), this paper systematically calculates the power peak shaving demand and the demand for gas-fired power generation capacity in regions of China, by using Mathematical Programming and Shapley value. Compared with the existing research, this paper may make theoretical contributions to the following aspects: studying more spatial scopes and time scales of peak shaving, analyzing the complete system of "coal power—renewable energy—gas power", and applying cooperative game model to peak shaving issue. We find that, firstly, compared with the scenario of independent peak shaving in a single province (Scenario 1), the peak shaving demands of load and renewable energy are greatly reduced in the scenarios of areal coordination (Scenario 2) and national coordination (Scenario 3), especially renewable energy; secondly, abandonment of 110,766 MWh of renewable energy power occurring in Scenario 2 is avoided in Scenario 3. Compared with Scenario 2, the final peak shaving demands of seven areas in China are simultaneously reduced in Scenario 3. The largest reduction rate is 14% from East China. Thirdly, with deep peak shaving restricted by certain constraints, gas power generation for start-stop peak shaving is inevitable. Compared with Scenario 2, national coordination (Scenario 3) can eliminate 120,714 MW of start-stop peak shaving demand (SS-PSD); finally, flexibility retrofit of existing facilities can further significantly curtail SS-PSD. Based on the above research results, some recommendations are put forward, including developing areal coordination and national coordination mechanisms for peak shaving, clarifying allocation plan of SS-PSD based on the fairness principle (i.e., Shapley value) as soon as possible, encouraging East China, Central China, and North China to take the lead in establishing trading markets of SS-PSD, giving priority to meeting the most urgent and economic peak

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Abbreviations: D-PSD, deep peak shaving demand; F-PSD, peak shaving demand; id-PSD, intra-day peak shaving demand (PSD between hours in a day); ih-PSD, intra-hour peak shaving demand (PSD between minutes in an hour); iw-PSD, intra-week peak shaving demand (PSD between workdays and holidays or weekends); PSC, deep peak shaving capacity; PSD, final peak shaving demand, including the following L-PSD and REP-PSD; PSD, PSD of load, including the following iw-PSD and id-PSD; RC, required consumption-based capacity of renewable energy power (**subsection 3.1.2.1**); REP-PSD, PSD of renewable energy power, including the following id-PSD and ih-PSD; RG, required consumption-based generation of renewable energy power (**subsection 3.1.2.1**); SS-PSC, start-stop peak shaving capacity; SS-PSD, start-stop peak shaving demand.

shaving demand, and establishing a coordination mechanism between new and old units for flexibility retrofit.

Keywords: renewable energy, shapley value, peak shaving, gas-fired power generation, regional coordination, capacity allocation, capacity trading, flexibility retrofit

1 INTRODUCTION

To meet the carbon neutralization goal, vigorously developing renewable energy has been an important challenge worldwide, and China is no exception. **Table 1** shows the data of China's renewable energy power generation in 2020. According to **Table 1**, in 2020, there is a certain proportion of renewable power generation abandoned in China due to limited power peak shaving capacity. As rapid development of renewable energy power continues, China calls for more power peak shaving capacity. According to *The Letter on Soliciting the Weight of Responsibility for Renewable Energy Power Consumption in 2021 and the Expected Target Suggestions for 2022–2030,* which was issued by the National Energy Administration of China in 2021, the total installed capacity of wind and solar power is required to reach more than 12×10^8 kWh in 2030. According to the plan of National Energy Administration of China, each province ought to raise the proportion of renewable energy power consumption to 40% by 2030.

Renewable energy power generation is characterized by intermittency, randomness, and volatility, while the power system needs to keep balance at any time. If the supply sector lacks peak shaving capacity, end users have to cut down their power consumption under pressure of balancing the power system. The power rationing in California, United States and Northeast China in 2021 are two examples.

In addition to wind and photovoltaic power, there are many other ways to generate electricity including nuclear, hydro, coal, and gas power. However, not all of them are competent in power peak shaving. The nuclear power units need to operate stably for safety. Water resources' distribution is limited (Oil Observer, 2020). Coal power has many drawbacks such as high pollution and limited peak shaving ability (Zhang et al., 2011). Therefore, these power sources hardly function as start-stop peak shaving energy.

Compared with other types of traditional power, natural gas power has significant advantages of low carbon and pollution, outstanding flexibility, and greater depth of peak shaving. Consequently, it is the relatively ideal peak shaving resource. In terms of low carbon and pollution, gas power emits 50% less CO_2 and 80% less NO_x than coal power does. Moreover, there is almost no SO_x, particulate matter, solid waste, and heavy metals (such as Mercury) emission of gas power (Li and Bai, 2010; Staple and Bean, 2013; Chang et al., 2015). Meanwhile, gas power entails less water and land resources (Staple and Bean, 2013). With the promotion of coal to gas and the more natural gas utilization, China's particulate matter level has decreased significantly from 2015 to 2018 (IEA, 2019). In terms of outstanding flexibility, the ramping rate of gas power plants (especially OCGT) is higher than that of coal-fired power plants. Thus, the start-up time of gas power plants is shorter. Start-up time refers to the time required from start-up to achieve minimum stable load. Among the most commonly used techniques, the average hot-start (idle for less than 5 h) times (Agora, 2017; Glensk and Madlener, 2019) for OCGT, CCGT, hard coal, and lignite power plants are 8, 75, 165, and 300 min, respectively. The cold-start (idle for more than 40 h) time for all types of power plant is two to three times longer than hot-start time, except for OCGT. For OCGT, cold-start time are similar to hot-start time. Power plants' start-up time with the latest technology is 20–40% less compared to that in the current most commonly used technology, except for OCGT, whose start-up time remained unchanged. In addition to affecting start-up time, idle time of power plants also affects start-up costs. Gas power plant's start-up costs of hot-start, warm-start (idle time is between 5 and 40 h), and cold-start (Glensk and Madlener, 2019) are 57 €/MW, 83 €/MW, and 117 €/MW, respectively. Considering start-up cost, regional coordinated peak shaving is necessary for the smooth operation of power plants. In terms of greater depth of peak shaving, the minimum load of OCGT, CCGT, hard coal, and lignite is 20, 30, 25, and 35%, respectively in the latest technology. What's more, gas power can even reach an 100% peak shaving depth through start-stop operation, which is a huge advantage over coal power.

Natural gas power generation began in the first half of the 20th century and developed rapidly in the second half (Breeze, 2016).

TABLE 1 | China's power generation in 2020.

Power	Installed capacity (10^8 kW)	Generation (10^8 kW)	Capacity proportion (%)	Generation proportion (%)	Abandonment proportion
Hydro	0	13,552	2	17	3%
Wind	3	4,665	13	6	3%
Solar	3	2,605	11	3	2%
Biomass	0	1,326	1	2	—
Thermal	12	52,800	56	67	—
Nuclear	4	3,663	17	5	—
Total	22	78,611	100	100	—

Source: China Electric Power Council, China National Energy Administration.

As of today, gas-fired power generation keeps growing, but mainly in developed regions and major gas-producing regions, such as the US, Europe, and Russia. In case of confusion, "region" in the paper refers to any geographic scope, including a province, area, country and even country union like the European Union. Among them, "area" specifically refers to a certain geographical scope larger than a province but smaller than a country, such as the area of North China. Currently, natural gas is the second largest power source after coal worldwide. In 2019, gas-fired power generation in the US, United Kingdom, and Japan accounted for 38.63, 40.10, and 35% respectively of their total power generation (Li, 2021).

Fighting against atmospheric pollution is a universal driver of gas-fired power worldwide. For Europe and the US, increased resource availability and higher consumption ability are also important contributing factors. Unlike the US and Europe, air pollution control (e.g., haze) is the main driver of fuel switching in China (IEA, 2020a). In this context, coal-to-gas conversion in China has occurred mainly in the industrial and residential sectors (IEA, 2019), rather than in the power generation sector. Since it is not a priority field for natural gas utilization, gas-fired power in China has developed slowly (China Power Network, 2021) (Yang, 2021). (East China Energy Supervision Bureau, 2020). With large renewable energy power generation, China needs to change the status. The China Natural Gas Development Report (2021) published by the National Energy Administration of China states that gas power peak shaving has been positioned as an important part of future power systems dominated by renewable energy (Li, 2021).

For transformation to a zero-carbon society, natural gas, as a bridge energy, is a realistic option (Staple and Bean, 2013; Breeze, 2016; Cowell, 2020). This is reflected in the coal-to-gas trend in many countries. With the development of renewable energies, the trend of coal-to-gas conversion is replaced by transformation from fossil to renewable energies (IEA, 2018), especially in the power sector. As a result, gas power tends to provide flexible auxiliary services for renewable energy generation (Breeze, 2016). Detailed reasons are given as follows. Firstly, renewable energy power is cleaner than gas power. In this respect, renewable energy power is more suitable for base load power (IEA, 2019). Secondly, gas-fired power is already less economical than renewable energy generation (IEA, 2018, 2019, 2020), which drives gas-fired power plants to change their role voluntarily. Despite low investment (CAPEX), gas-fired power has higher operating costs (OPEX). Therefore, gas power should be used for start-stop peak shaving. Thirdly, compared to other types of conventional generation, the main advantages of gas power are the speed and cost of start-stop (especially OCGT). In this respect, gas power is the best alternative for start-stop peak shaving (at least for the near term).

In addition to gas-fired power, other potential flexible energies include hydrogen, batteries, and fuel cells. Given low-carbon development goals, using fossil energy in cleaner ways (e.g., combined with CCUS technology) is expected to reduce dependency on renewable energy. However, these technologies are not yet economically viable, especially in large-scale applications (Breeze, 2016; IEA, 2019; IEA, 2020b). Compared to the above technologies, gas-fired power has such advantages as being competent in all kinds of peak shaving like multi-time interval (short-term and long-term) and large capacity. All in all, gas-fired generation is undoubtedly the most desirable auxiliary energy source in the short to medium term.

As gas power is shifting to mainly provide ancillary services, it is necessary to measure peak shaving demand to help with planning and investing in peak shaving units. Unnecessary demand for peak shaving, a relatively expensive service, needs to be eliminated wherever possible. To this end, regional coordination is a good option. Here is an example: at a certain time, region A generates 10 MWh of power, although it only needs five MWh. Region B is in the opposite situation. When the two regions are not connected, both region A and B need five peak shaving power, adding up to 10. If the two regions are connected and trade power, the surplus power in region A will be transmitted to region B. As a result, the peak shaving power generation in both regions is 0. At the same time, both sides can also get additional benefits. Region A can increase revenue, and region B can also reduce power generation cost (the peak shaving power generation cost is generally higher than the price of foreign surplus power). Lacking electricity spot markets, China has established 14 electricity ancillary service markets, including four areal markets (North China, Northeast China, Northwest China, and East China) and 10 provincial markets (Xinjiang, Mengxi, Gansu, Guangdong, etc.,). From January to October 2020, the volume of inter-area and inter-province transactions amounted to 5,152 and 12,796 $\times$ 10^8 KWh respectively, accounting for 8.5 and 21% of national electricity generation (60,288 $\times$ 10^8 KWh) in that period. Therefore, regional coordination in power systems already has some practical basis. However, most of these transactions are long-term contractual ones. Moreover, China's power peak shaving and regional coordination currently relies on coal-fired power. Based on this, the regional coordination mechanism needs to be improved.

Based on the above-mentioned era background and development status, it is of great practical significance to study the gas-fired power demand for peak shaving from the perspective of regional coordination. The following section is structured as follows. **Section 2** reviews some literature on methods of calculating peak shaving capacity demand and its allocation among regions. **Section 3** establishes the methods of electricity peak shaving demand and the demand for gas-fired peak shaving capacity. **Section 4** presents the main calculation results and their analysis, followed by conclusions and recommendations in the last section.

2 LITERATURE REVIEW

2.1 Literature on Calculating Power Peak Shaving Demand

Before calculating peak shaving demand, it is necessary to introduce the definition. For a load curve, the peak shaving demand is the peak-valley difference of the curve (within a certain time) (Zhang et al., 2011). As renewable energy power is connected to the power grid, peak shaving demand changes (usually becoming larger). For example, wind power has an inverse peak shaving nature. Wind power output curve is inverse to load curve, calling for other units to reduce more output (for peak shaving). In an extreme but possible scenario, where load curve and wind power output curve move in the exact opposite directions, peak shaving demand equates to the sum of the peak-valley difference in load curve and the wind power capacity (Zhang et al., 2011). With renewable energy generation considered, the framework for calculating peak shaving demand of a power system (for a certain time horizon) is set up as follows (Chen, 2020). Firstly, the net load curve is derived. The net load is equal to the initial load minus renewable power generation. Secondly, the total peak shaving demand is determined after considering reserve capacity of power plants. Thirdly, the peak shaving ability (e.g., peak shaving depth) of power plants is determined. Finally, the peak shaving capacity demand of the whole power system is estimated. In determining the capacity of each peak shaving energy, certain technical and economic constraints need to be considered. When it comes to constraints, the commonly used calculation model, Mathematical Programming, is applicable (Fan et al., 2020).

For different time intervals (peak shaving cycle), peak shaving demand varies. The shorter the discussed time is, the smaller the fluctuation of net power load and peak shaving demand is. Time intervals can be divided into minutes, hours, days, weeks, months, seasons, and even years. Peak shaving techniques differ for different time intervals. For example, energy storage is more suitable for short peak shaving cycles (e.g., minutes), while thermal units function better for long peak shaving cycles (e.g., days and longer cycles) (Zhao et al., 2015). In a study of peak shaving demand of thermal units in eastern Inner Mongolia (Li, 2020), the author aimed at the peak shaving cycle of hours. Pimm et al. (2018) considered the temporal differences in loads and renewable energy generation, such as workday-holiday difference and summer-winter difference, when studying the peak shaving effect of distributed battery energy storage in a certain United Kingdom residential area.

For different targets, peak shaving demand differs. For example, Zhao et al. (2015) studied the capacity allocation of hybrid energy storage technologies under different peak shaving targets. Peak shaving targets were divided into three types. The first type is smoothing wind power output. By storing energy, the wind power output (after incorporating battery storage) curve is a flat line (without considering the load). Under this strategy, the charging and discharging thresholds are the same value. The second type is smoothing the net load (wind + load). It aims to flatten the net load curve, but only for one charge-discharge cycle. In this case, the continuous charging and discharging times are long. Charging and discharging thresholds depend on the long-term load curve, long-term wind power output forecast, and the battery status. The last type is smoothing the net load, and for multiple charging and discharging cycles. Each charging-discharging cycle is short. This target is applicable when frequent fluctuations of wind power output happens. The charging and discharging thresholds depend on the short-term load profile, short-term generation output forecast, and the battery status. The required battery capacity decreases sequentially in the three targets. For peak shaving with battery storage, the load threshold corresponding to the battery discharge is equivalent to peak shaving threshold of the battery.

How to select charging and discharging thresholds of battery is important, since it determines peak shaving demand. Although it is about batteries, this issue sheds light on calculating capacity of gas-fired power plants. Leadbetter and Swan (2012) used the quantile method to select the discharge threshold for the power load duration curve. The curve generally shows a decreasing trend. The higher the load, the shorter the duration occurs. The quantile is a load value whose corresponding duration is no less than the aggregated duration corresponding to a certain percentage of the load level. For example, there are only three possible load values, namely 10, 20, and 30 MW, and the corresponding duration is 3, 2, and 1 h. For this duration curve (frequency profile), 20 MW is the (2 + 3)/(1 + 2+3) = 5/6 quantile of the curve. Similarly, 10 and 30 MW are respectively 3/6 and 6/6 quantile. The quantile method of selecting the discharge threshold means that a certain quantile (load value) is selected as the threshold value, e.g., 98%. This method determines the discharge threshold based on discharge time. For example, with 98% quantile as the threshold value, the time required to discharge the battery to meet the peak load is 2% (the battery is required to discharge only when the real-time load exceeds the quantile point). With the discharge threshold value is determined, the total amount of power required to be released from the battery will be projected, as will the capacity of the battery.

For large scale peak shaving, it is necessary to consider the scale effect. The scale effect of peak shaving means that the cost or benefit to each member is different when they cooperate compared to acting individually. Generally, cooperation leads to cost saving or benefit increase for each member (economy of scale). When they investigated the peak shaving effect of distributed battery storage in the United Kingdom, Pimm et al. (2018) found that the larger the size of the residential cooperative group, the smaller the average load peak for the users. Mair et al. (2021) had similar findings. Some problems are significant at small scales but are mitigated or even eliminated at large scales. Jankowiak et al. (2020) studied the role and benefits of battery storage for a single residential day's load in Northern Ireland. The authors noticed short time but very high spike loads (generated when appliances are switched on), and real-time consumption fluctuation. In the large-scale case, these issues are no longer apparent for the following reasons. Firstly, the spike problem is attenuated due to the time differences and variability of each individual action. Secondly, the load profile for a large user group is relatively fixed and predictable.

2.2 Literature Related to Cooperative Game Theory

Given economy of scale, different regions should coordinate in peak shaving. Regionally coordinated peak shaving means that the overall peak shaving demand and capacity demand are calculated with the aggregate net load curve, and then the management center deploys them to each region. Therefore, the direct calculating result under regional coordination is the overall peak shaving demand and capacity demand of multiple regions, and how to allocate them to each region is an important issue. Shapley value is one of the core concepts in cooperative game theory, which is the allocation of the alliance value (benefit or cost) to each member. The core idea of this method is to allocate according to the marginal contribution of each member, which is relatively fair.

To the best of our knowledge, there are few studies on allocation of peak shaving demand, let alone applying Shapley value for the issue. In other issues, there are examples of using Shapley value to allocate cost or revenue. Examples of using Shapley value for cost allocation can be seen in the following issues: allocating cost to two facilities of a combined operating system, which consists of a cogeneration plant (CCHP) and power-to-gas (P2G) (Yang et al., 2020); allocating heating costs to three chemical plants (Jin et al., 2018); and allocating peak shaving costs to cogeneration units (Hu and Hu, 2015). Examples on revenue allocation are as follows: allocating operating profit to multiple cooperating power sales companies (Acua et al., 2018); allocating the revenue to six hydro power plants in Lancang River (Shen et al., 2018); and allocating revenue to thermal power plants (CHP) and virtual power plants (VPP) (Fang et al., 2020).

In addition to cost and revenue, there are articles using Shapley value to allocate air pollutants or CO_2 emissions. These articles cover the following issues: allocating carbon emissions to four key influencing factors of carbon emissions (e.g., population and economic output) to obtain the influence degree of each factor on carbon emissions (Yu et al., 2012); allocating carbon emission allowances in eight regions of China (Zhang et al., 2014; Chang et al., 2016); allocating CO_2 emissions from refineries across all products (Pierru, 2007); and analyzing the inter-region cooperation in carbon emission reduction problem in China (Zeng et al., 2021).

In the process of applying Shapley value, it is necessary to consider the computation time. For the game of n members, the number of coalitions to be discussed is 2^n (including the empty coalition). The cost or revenue of each coalition needs to be calculated, which will take long time if n is large. In this case, it is necessary to simplify Shapley value method. For example, it should be simplified when applying Shapley value to study the distribution of power losses and pollutant emissions among multiple distributed generation units, Ehsan et al. (2016) considers only two types of coalitions, namely the great coalition (including all units) and sub-great coalitions (including all units except a certain one). Fernando et al. (2017) used Shapley value to study the benefit allocation of transmission expansion projects, where two other methods, namely TOOT and PINT, are mentioned. The two methods also shed light on the simplification of Shapley value. TOOT (Take out one at a time) approach assumes that all projects (including the discussed one, i.e., project A) already exist. When project A is taken out from the system, the change of the system benefits is the contribution of project A. PINT (Put in one at a time) approach assumes that no other projects exist, and the impact of including project A on system benefits (relative to not including A) is the contribution of the project. The system benefits are the total cost of electricity generation (of all projects), carbon emissions, and unmet demand for electricity. Both TOOT and PINT are simplified forms of Shapley value approach, considering some certain coalitions, but not all possible ones.

Based on the above literature, this article may make theoretical contributions in the following aspects. Firstly, unlike the existing research focusing on peak shaving demand with a single small scope (such as a certain wind farm) (Zhang et al., 2011; Fan et al., 2020), this paper studies the demand in every province and area of China for the first time. Considering the differences in time and space, the paper analyzes the peak shaving demand in three scenarios of coordination. The research scope selected in this paper may provide a theoretical reference value for future research on peak shaving problems in other countries. Secondly, existing studies hardly systematically analyze the relationship among load, renewable energy, and various peak shaving power sources, but focus on one of them instead (Chen, 2020; Fan et al., 2020; Liu et al., 2020). This paper would fill the gap to an extent by comprehensively analyzing the constraint system of deep peak shaving and measuring the demand for start-stop peak shaving capacity as well as its sensitivity to deep peak shaving. This part of the research may provide a useful reference for the future discussion on more complex power peak shaving systems; Thirdly, most existing research focuses on the peak shaving demand of a single time interval. Although Pimm et al. (2018) mentioned load curves of different time intervals, they did not measure the peak shaving demand of different time intervals, but the peak shaving demand for a complete week and the capacity of the energy storage battery. This paper studies peak shaving demands of multiple time intervals, based on the following data sets: 24-h data of renewable energy power generation and 24-h data of typical load on workdays and holidays. Finally, learning from the research of other issues such as carbon emission allocation, the paper uses Shapley value in the peak shaving problem. With existing research, the paper establishes the simplified model of Shapley value, which may provide some extra references for the application of the method.

3 MATERIALS AND METHODS

Before calculating capacity demand of gas-fired peak shaving power generation (demand for power capacity. The power, generated in gas-fired plants, is used for peak shaving) in China, it is necessary to study the total peak shaving demand of China's power system. Focusing on these two demands, the main framework of the following research is shown in **Figure 1**.

3.1 Measurement Method of Peak Shaving Demand in Power System

Power peak shaving refers to the power dispatching behavior of peak shaving power that reduces output at low-load time, and increases power supply when a load peaks. Since the total design

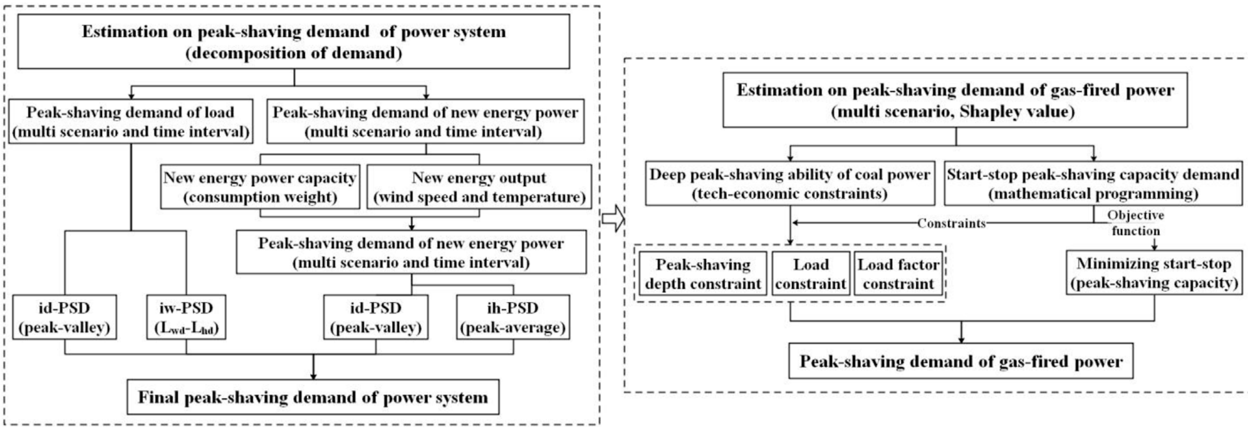

FIGURE 1 | The main frame of the research in this paper. Texts in parentheses show the research methods corresponding to the content above; "consumption weight" represents required proportion of renewable energy power consumption to total power consumption in each region; "id-PSD", "iw-PSD", "ih-PSD" respectively refers to intra-day peak shaving demand, intra-week peak shaving demand, intra-hour peak shaving demand; "L_{wd}-L_{hd}" means max load on weekdays minus that on holidays; More details are described below.

capacity of the peak shaving system is determined by the maximum load, the maximum output of the system is relatively fixed. The demand for peak shaving is mainly expressed as the demand for the peak shaving units to reduce the power output level. With renewable energy connected to a grid, peak shaving power units have to cope with both the load fluctuation and renewable energy generation randomness. Therefore, the final peak shaving demand (F-PSD) can be simplified as follows.

$$\begin{aligned} &Final\ peak\ shaving\ demand = Peak\ shaving\ demand\ of\ load \\ &+ Peak\ shaving\ demand\ of\ renewable\ energy\ power\ generation \end{aligned} \tag{1}$$

Due to the difference between load fluctuations and renewable energy fluctuations, the "+" in **Eq. 1** is not a simple addition, but mainly means the decomposition of peak shaving demand. The following section will first analyze the peak shaving demand of load (L-PSD) and renewable energy power generation (REP-PSD) separately, and then study the final peak shaving demand (F-PSD). The significance of simplifying the F-PSD is to clarify the main source of the final demand, which will help with search for corresponding peak shaving countermeasures. To stabilize power grid operation, if the peak shaving demand mainly comes from load fluctuation, then the peak shaving power may be mainly distributed to the areas with large load fluctuations, and vice versa. For China, renewable energy powers are mainly distributed in the west, with the power load in the east, thus the above discussion is meaningful. If the two peak shaving demands are similar, it is beneficial to coordinate them, that is, the F-PSD based on the net load may be significantly less than the sum of the two peak shaving demands considered separately.

3.1.1 Peak Shaving Demand of Load (L-PSD)

The load curves of China's provinces share the following characteristics. Firstly, periodicity. Within a day, the load curves generally have two peak periods: day peak and night peak. Secondly, volatility. The load curves fluctuate randomly from hour to hour and even from minute to minute. Thirdly, diversity. Diversity includes spatial diversity and temporal diversity. Spatial diversity means that load curve differs among regions. Time diversity can be further divided into two categories, namely time zone divergence and workday-holiday divergence. Due to the vast size of China, different regions are located in different time zones so that there is divergence of local times at the same global time. Obviously, time zone divergence is distinguished from spatial diversity. Load curve on workdays is higher than that on holidays. The workday-holiday divergence refers to the difference between the two load curves. The five provinces with the largest workday-holiday divergence are Zhejiang (Average value of load curve on workdays is larger than that on holidays by 100%. The values in following parentheses are similar), Shanghai (96%), Chongqing (92%), Guangdong (88%), and Jiangsu (81%). The specific load curves for each region can be found in the annex of "*Notice on the Signing of Medium- and Long-term Electricity Contracts in 2021*" (Development and Reform Operation No. 1784 (2020), in Chinese) of National Energy Administration of China.

According to the above characteristics of load curves and gas-fired power units, load peak shaving can be cataloged into intra-hour peak shaving, intra-day peak shaving, intra-week peak shaving, and so on. Due to data accessibility, only intra-day and intra-week peak shaving demand of loads (referred to as id-PSD and iw-PSD) are analyzed in the paper. As for seasonal peak shaving, other technologies are more applicable than expensive gas power.

id-PSD equates to the peak-valley difference of load in a 24-h interval. Coordination of peak shaving between regions will affect the overall peak shaving demand of China. iw-PSD equates to the difference in maximum loads between workdays and holidays (weekdays and weekends). Three scenarios of peak shaving coordination are considered in the paper, i.e., independent peak shaving in each province (referred to as "Scenario 1"), areal coordinated peak shaving ("Scenario 2"), and national coordinated peak shaving ("Scenario 3"). The setting of the three scenarios is mainly based on the following two facts. Firstly, China's Energy Administration has two sub levels: areal level and provincial level. Secondly, China's power trading market is generally divided into provincial market and regional market. Independent peak shaving by province means that each provincial load curve (see **Supplementary Table SA1** and **Supplementary Table SA2** in Appendix A) is an independent and complete peak shaving object, with no coordination between different provinces. Areal coordinated peak shaving means peak shaving for the cumulative load curve of each province in the same area (see **Supplementary Table SA3** and **Supplementary Table SA4**). National coordinated peak shaving means peak shaving for the cumulative load curve of all areas (and thus all provinces) in the country (see "total" indicators in **Supplementary Table SA3** and **Supplementary Table SA4**). As the degree of coordination increases (from Scenario 1 to 3), the overall national peak shaving demand decreases significantly.

3.1.2 Peak Shaving Demand of Renewable Energy Power (REP-PSD)

Should load not be considered, the peak shaving demand of renewable energy generation (REP-PSD) would be the difference between its maximum output (capacity) and its minimum output. Similar to the previous load peak shaving demand, REP-PSD comprises intra-day and intra-hour peak shaving demand (referred to as id-PSD and ih-PSD, respectively). id-PSD equates to the peak-valley difference in power output between different hours. For example, if the renewable energy output reaches its maximum value at 12:00 ~ 12:59 (assuming the average output of 10 MW during this hour) and its minimum value at 20:00 ~ 20:59 (assuming the average output of 1 MW), then the id-PSD is 10−1 = 9 MW. ih-PSD equates to the maximum positive deviation of renewable energy output within each hour, i.e., the difference between the maximum output and the average output of each hour. For example, for 12 o'clock (12:00 ~ 12:59), the average output is 10 MW and the maximum output is reached at 12:30 (assumed to be 10.5 MW). Then the ih-PSD of 12 o'clock is 10.5−10 = 0.5 MW. Obviously, id-PSD and ih-PSD are additive.

In conclusion, REP-PSD is calculated by the following steps: Firstly, calculate the capacity of renewable energy generation; Secondly, calculate the hourly output coefficient (percentage of capacity) of renewable energy generating units; Finally, calculate the REP-PSD including id-PSD and ih-PSD.

3.1.2.1 Calculation of Renewable Energy Generation Capacity

Due to scarcity, energy should be supplied based on demand. Therefore, renewable energy capacity should not be directly taken as the current capacity data, but needs to be calculated based on renewable energy consumption. For ecological construction, the central government of China formulates the required renewable energy power consumption (proportion of total power consumption) of each region every year, which grows year by year. In order to distinguish it from the current generation and capacity, the required consumption-based generation and capacity of renewable energy power are defined as the required generation and capacity of renewable energy generation (respectively referred to as RG and RC hereinafter). Energy demand includes local demand and external demand (from other regions), which are complementary. Based on the required consumption of renewable energy and connection between regions, the required generation (RG) and the required capacity (RC) of renewable energy power in each region are calculated as shown in **Eqss 2 to 4**.

For regions with export power and no import power, RG (corresponding to $rs_{\min}$) is calculated as in **Equation (2)**.

$$\begin{aligned} &\boldsymbol{d} = \boldsymbol{s} - \boldsymbol{o} \\ &\boldsymbol{rd}_{\min} = \boldsymbol{d} \times \boldsymbol{w} = (\boldsymbol{s} - \boldsymbol{o}) \times \boldsymbol{w} \\ &\Rightarrow \begin{cases} \boldsymbol{rs}_{\min} = \boldsymbol{s} \times \boldsymbol{w} \\ \boldsymbol{o}_{\min} = \boldsymbol{o} \times \boldsymbol{w} \end{cases} \end{aligned} \tag{2}$$

In **Equation (2)**, $\boldsymbol{d}, \boldsymbol{s}, \boldsymbol{o}$ represent respectively power consumption (local demand), power generation (supply), and power export (external demand); $\boldsymbol{rd}_{\min}$ and $\boldsymbol{w}$ represent respectively the minimum renewable energy generation consumption and consumption weight (required proportion of renewable energy power consumption in total power consumption); $\boldsymbol{rs}_{\min}$ and $\boldsymbol{o}_{\min}$ represent respectively the minimum renewable energy generation (RG) and the minimum power export.

For regions with import power, RG (corresponding to $rs_{\min}$) is calculated as in **Equation (3)**.

$$\begin{aligned} &\boldsymbol{d} = \boldsymbol{s} + \boldsymbol{i} \\ &\boldsymbol{rd}_{\min} = \boldsymbol{d} \times \boldsymbol{w} \\ &\boldsymbol{ir} = \boldsymbol{i} \times \boldsymbol{v} \geq \boldsymbol{i} \times \boldsymbol{w}' \\ &\boldsymbol{rs}_{\min} = \boldsymbol{rd}_{\min} - \boldsymbol{ir} \end{aligned} \tag{3}$$

In **Equation (3)**, i, ir, v, w' represent respectively import power, import renewable energy power, and proportion of renewable energy power generation in the total power generation at the import source (the region exporting power to the discussed importing region in **Equation (3)**), the weight of renewable energy power consumption at the import source. The other variables are connoted as above.

For all types of areas, the required renewable energy generation capacity (RC) is calculated as in **Equation (4)**.

$$\begin{aligned} &\boldsymbol{wp} = \boldsymbol{rs}_{\min} \times \lambda_{\boldsymbol{wp}} \\ &\boldsymbol{sp} = \boldsymbol{rs}_{\min} \times \lambda_{\boldsymbol{sp}} \\ &\boldsymbol{c_{wp}} = \boldsymbol{wp} \div \boldsymbol{h_{wp}} \\ &\boldsymbol{c_{sp}} = \boldsymbol{sp} \div \boldsymbol{h_{sp}} \end{aligned} \tag{4}$$

In **Equation (4)**, wp, sp represent respectively required generation of wind and PV power in a certain year; λ_{wp} and λ_{sp} represent the proportion of wind and PV power in the renewable energy generation (in addition to wind and solar energy, renewable energy also includes hydro and biomass energy); c_{wp} and c_{sp} represent the required capacity (RC) of wind and PV power; h_{wp} and h_{sp} represent the annual utilization hours of wind and PV power.

For any variable of **Eqss 2 to 4**, all types of power are included unless it is explicitly specified for renewable energy. For example, s means power generation of all types of energy in a region, including thermal, nuclear, and renewable energy power. As v is unknown, $i \times w'$ is used to estimate ir, in other words, $ir \approx i \times w'$.

Data on power generation and consumption of provinces were obtained from National Bureau of Statistics of China, and data on the weight of renewable energy power consumption were obtained from National Energy Administration of China (National Development and Reform Commission, 2020). Due to the lack of power trading data between provinces, this paper estimates it through the power trading between areas (China Electricity Union, 2019) and the geographical distance between provinces (see **Supplementary Appendix SB** for the estimation process and results). The utilization hours of wind and PV power in each province were obtained from reports on power construction and operation released by National Energy Administration of China.

3.1.2.2 Calculation of Renewable Energy Power Output

Lacking detailed data on the hourly output of renewable energy generation in each province, this paper uses the impacting factor of renewable energy generation to estimate it. The renewable energy output is equal to the product of renewable energy capacity and renewable energy output coefficient, where the latter is the standardized value of its impacting factor (the maximum value is 1, and it is a positive indicator). The impacting factor curve (unstandardized) used for renewable energy output coefficient is referred to as the coefficient curve.

The coefficient curve has both a trend and fluctuation nature. For this reason, the hourly values can be divided into two parts, i.e., trend value and fluctuation value. In the coefficient curve, value on the (estimated) trend line is trend value of each hour, while the part of the actual value above the trend value (positive deviation) is the fluctuation value. Considering randomness, the fluctuation rate (ratio of fluctuation value to max trend value) should be uniform for 24 h, although the rate calculated for each hour may vary. For example, if only 3 hours are considered, and the fluctuation rates measured based on actual data are 10, 20, and 30%, then the fluctuation rate for each hour is unified to 30% to better describe the peak shaving demand within any hour. For the best fitting of the trend line, this paper uses Taylor series in Excel, in other words, polynomial function.

For the coefficient curve of wind power output, the hourly data of wind force (see **Supplementary Table SC1**) is used. This data is taken from China Meteorological Administration (which publishes the data of the last few days every day) and covers 24-h wind force (corresponding to the indicator "2-min average wind speed") of each province on 24 July 2021. Based on this data, the trend value and fluctuation value of coefficient curve can be calculated. For coefficient curve of PV with obvious distribution characteristics (Li, 2020), the trend value is simulated according to the normal distribution. To calculate fluctuation values of PV coefficient curve, the hourly temperature data published by China Meteorological Administration is used (see **Supplementary Table SC2**).

The trend value of the coefficient curve is standardized to be the hourly average output coefficient of the renewable energy. The standardization of trend value is to divide the trend value for each hour by the largest trend value. The (uniform) fluctuation rate is used as the intra-hour fluctuation coefficient of renewable energy output. Based on the two coefficients above, the renewable energy generation output curve for each province consists of the following two components. Firstly, hourly average output, which is obtained by multiplying the required renewable energy generation capacity (RC) and the hourly average output coefficient. Secondly, intra-hour fluctuation, which is obtained by multiplying RC and the intra-hour fluctuation coefficient. In an areal coordination scenario (Scenario 2), the renewable energy output curve of each area is calculated as follows. Firstly, wind power output curve of each area is obtained by accumulating that of all provinces in the area. After that, trend value and fluctuation rate of the curve can be calculated to obtain the hourly average output and intra-hour fluctuation. Secondly, for PV output, the areal hourly average output is obtained by accumulating the hourly average output of all province in the area; the fluctuation rate is calculated by the areal average temperature curve, which is then multiplied by the maximum hourly average output to obtain intra-hour fluctuation. Thirdly, the hourly average output of different energies (wind and solar) is summed to obtain the hourly average output of renewable energies (wind and solar) as a whole. The overall intra-hour fluctuation of renewable energies is obtained in a similar way. For the renewable energy output curve of the whole country under a national coordination scenario (Scenario 3), the hourly average output of the whole country is obtained by summing up the hourly average outputs of all seven areas; the fluctuation rate is taken as the average value of that of all seven areas. The intra-hour fluctuation of renewable energy output is obtained by multiplying the max value of hourly average output and the fluctuation rate. Different output components correspond to different time intervals of peak shaving demand (see below).

3.1.2.3 Calculation of Peak Shaving Demand of Renewable Energy Power (REP-PSD).

Based on the calculation results of renewable energy output, and with the load unconsidered here, REP-PSD is calculated as follows. The peak-valley difference of hourly average output is the intra-day peak shaving demand (id-PSD), while the intra-hour fluctuation is the intra-hour peak shaving demand (ih-PSD). The sum of id-PSD and ih-PSD is the total REP-PSD.

3.1.3 Final Peak Shaving Demand (F-PSD)

Based on the above analysis, F-PSD can be calculated. Due to advantages of coordinated peak shaving, the paper only calculates the F-PSD of each area (not province) in Scenario 2 and 3. Since coordination means simultaneous action, the hourly data of load and renewable energy output involved is adjusted according to the time zone used before (with Xinjiang time as base time). The calculation steps of F-PSD are narrated as follows.

1) Calculate the load. The load is divided into two types: load on workdays and load on holidays. The loads of each province (corresponding to Scenario 1) are accumulated to generate the

areal coordinated loads of seven areas (corresponding to Scenario 2), which are then accumulated to form the national coordinated load (corresponding to Scenario 3).

2) Calculate the renewable energy power output. It includes the hourly average output and intra-hour fluctuation, as described in **Subsection 3.1.2**.
3) Calculate the backup power output (i.e., net load in some articles). The backup power is conventional generating units other than renewable energy (it has the priority to connect to the grid). Backup power output includes average output and fluctuating output. The average hourly output of backup power is equal to the difference between the hourly load and the average hourly output of renewable energy. Fluctuating output includes fluctuations on different time intervals: intra-week fluctuation (from load) and intra-hour fluctuation (from renewable energy). The areal and national average hourly output curves are obtained directly by adding up the average output curves of each province. The intra-week fluctuation and intra-hour fluctuation are described in the previous section (see **Subsection 3.1.1** and **3.1.2**).
4) Calculate the final peak shaving demand (F-PSD). Through the previous analysis, the F-PSD includes intra-week peak shaving demand (iw-PSD), intra-day peak shaving demand (id-PSD), intra-hour peak shaving demand (ih-PSD), and operating reserve capacity (peak shaving demand at any time), which are additive. iw-PSD comes from load curves (see **Subsection 3.1.1** for details). ih-PSD comes from renewable power output curves (see **Subsection 3.1.2** for details). id-PSD is equal to the peak-valley difference of average output of backup power (calculated in step 3). The operating reserve capacity is the product of maximum load and the reserve rate (8%) (Li, 2020).

In the national coordination scenario (Scenario 3), the direct calculation result based on the national backup power output curve is the total peak shaving demand of the country, which needs to be allocated to each area. For different peak shaving demands, the allocation method is different. For id-PSD, considering the different roles of each area in the national coordinated peak shaving demand, this paper adopts Shapley value to allocate the national coordinated peak shaving demand to each area. The traditional Shapley value requires discussion of all possible area alliances, with seven areas corresponding to as many as $2^7 = 128$ (ordered) alliances. To simplify the calculation, only two types of alliances are considered in this paper including the great alliance consisting of all areas and sub-great alliance consisting of all areas except the discussed area. In this way, the marginal contribution of each area is equal to the value of the great alliance minus that of the sub-great alliance, which is then divided by the number of areas to obtain Shapley value of the area (see **Supplementary Appendix SD** for details). For ih-PSD, because the national ih-PSD is related to the average of ih-PSD of each region, the national ih-PSD is linear with the that of each region. Therefore, we allocate the national ih-PSD obtained in Scenario 3 according to the proportion of ih-PSD of each area in Scenario 2. For allocation of iw-PSD, theoretically, Shapley value is applicable. As the difference between the overall national peak shaving demand in Scenario 2 and 3 is relatively small, the above-mentioned proportional allocation method is also used for the sake of simpler calculation.

3.2 Calculation of Demand for Gas-Fired Power Capacity

Bases on economy analysis, peak shaving priority is given to deep peak shaving of coal power, so that the start-stop peak shaving demand (SS-PSD) is equal to the final peak shaving demand (F-PSD) minus the deep peak shaving demand (D-PSD). D-PSD is subject to the following constraints. Firstly, peak shaving depth constraint. For deep peak shaving, there is a maximum peak shaving depth. In other words, there is a lower bound of D-PSD given a certain F-PSD, denoted as "lower capacity bound under depth constraint"; Secondly, load constraint. Since deep peak shaving units operate continuously, their capacity cannot be lower than the peak of the corresponding load curve (i.e., the above backup power curve), denoted as "lower capacity bound under load constraint"; Thirdly, load factor constraint. For economic efficiency, the operation of deep peak shaving units must meet a certain minimum average load factor, so there is a maximum capacity of the units given a certain load curve, denoted as "upper capacity bound under load factor constraint". Given the load curve, the above three capacity bounds of deep peak shaving units are determined by the capacity of start-stop units, which are able to shave peak of the backup power curve to an extent. In other words, the above capacity constraints need to be satisfied when deciding the start-stop capacity (SS-PSD). There are possibly many start-stop capacities that satisfy the above constraint, among which the smallest one should be taken due to natural gas resource limitations. Therefore, the following Mathematical Programming set (see **Supplementary Appendix SB** for the calculation process) is used to determine the SS-PSD. Firstly, the objective function is to minimize the SS-PSD, where the start-stop units include intra-day start-stop units (units that operate during peak hours and shut down during valley hours within a day) and intra-week start-stop units (units that operate on workdays and shut down on holidays); Secondly, the constraints are the above three constraints. Using the above programming model, the SS-PSD of each area in Scenario 2 and the national capacity in Scenario 3 are obtained. In Scenario 3, the total national capacity needs to be allocated to each area according to certain rules. Similar to the previous peak shaving demand allocation, this paper uses Shapley value as the allocation rule (see **Supplementary Appendix SD**) to meet the fairness requirement.

To calculate SS-PSD, the parameters related to deep peak shaving units (thus related to SS-PSD) are set as follows: Firstly, the peak shaving depth is assumed to be 70% (i.e., the minimum operating load is 30%); Secondly, based on existing coal power units (Wang et al., 2019), the minimum economic average load factors of deep peak shaving units in each area are listed as follows: North China (70.45%), Northeast China (59.26%), East China (71.75%), Central China (72.03%), South China (52.82%), Southwest China (63.17%), and Northwest China (69.05%).

TABLE 2 | Required capacity of renewable energy power (RC).

Province	Required capacity of wind power (MW)	Required capacity of PV (MW)	Total (MW)	Province	Required capacity of wind power (MW)	Required capacity of PV (MW)	Total (MW)
Beijing	200	100	200	Inner Mongolia	34,200	11,900	46,100
Tianjin	2,700	5,100	7,800	Jilin	7,200	2,900	10,100
Hebei	14,800	9,600	24,500	Heilongjiang	9,200	3,000	12,200
Liaoning	8,000	2,500	10,400	Anhui	8,900	26,400	35,200
Shanghai	800	100	900	Fujian	5,600	700	6,300
Jiangsu	9,300	8,200	17,500	Hubei	7,800	8,600	16,400
Zhejiang	2,200	5,800	8,000	Sichuan	7,300	4,400	11,700
Jiangxi	2,600	3,800	6,300	Guizhou	5,900	6,900	12,800
Shandong	25,000	14,000	39,000	Yunnan	16,600	6,700	23,300
Henan	12,000	12,100	24,000	Tibet	0	1,100	1,100
Hunan	5,100	2,100	7,200	Shaanxi	8,400	15,300	23,700
Guangdong	4,400	3,000	7,400	Gansu	12,800	8,400	21,100
Guangxi	4,300	1700	6,000	Qinghai	4,700	13,600	18,300
Hainan	1,100	4,400	5,500	Ningxia	16,300	13,400	29,700
Chongqing	600	600	1,100	Xinjiang	30,400	16,200	46,600
Shanxi	22,200	16,300	38,400	—	—	—	—

3.3 Sensitivity Analysis

The above parameters related to deep peak shaving units are the current (baseline) values. To take information uncertainty and future technology update into account, sensitivity analysis is required. Considering the benefits of regional coordination, the paper analyzes the sensitivity of national SS-PSD to deep peak shaving ability of deep peak shaving units in Scenario 3, and the detailed steps are given as follows: Firstly, calculate the change of national SS-PSD after deep peak shaving ability decreases by 20% (both minimum load and minimum average load factor increase by 20%); Secondly, calculate the change of national SS-PSD after deep peak shaving ability increases by 20% (both minimum load and minimum average load factor decrease by 20%).

4 RESULTS AND DISCUSSION

4.1 Results of Power Peak Shaving Demand

4.1.1 Results of Peak Shaving Demand of Load (L-PSD)

According to the load curves on workdays (**Supplementary Table SA1** and **Supplementary Table SA3**), in Scenario 1 ~ 3, the national intra-day peak shaving demands (id-PSD) are 246 × 1000 MW, 230 × 1000 MW, and 219 × 1000 MW, respectively. According to the load curves on holidays (**Supplementary Table SA2** and **Supplementary Table SA4**), in the above three scenarios, the national id-PSDs are 166 × 1000 MW, 155 × 1000 MW, and 143 × 1000 MW, respectively. Compared with Scenario 1, in Scenario 2, the load peak shaving demands on workdays and holidays are reduced by 2.35% ~ 13.6 and 0.01% ~ 2.21%, respectively, where the reduction rate varies in different areas. Compared with Scenario 1, in Scenario 3, the national id-PSD on workdays and holidays are reduced by 27 × 1000 MW and 23 × 1000 MW, or by 11 and 14%, respectively. 27 × 1000 MW exceeds the average load on workdays in 22 provinces, and 23 × 1000 MW exceeds the average load on holidays in 24 provinces. The results show huge economic benefit brought by national coordination.

According to the relevant data (**Supplementary Tables SA1–SA4**), the national intra-week peak shaving demands (iw-PSD) on holidays in the three scenarios are 272 × 1000 MW, 269.2 × 1000 MW, and 268.8 × 1000 MW. It can be seen that the iw-PSD has also been reduced by regional coordination. The max load on workdays in each province is greater than that on holidays, so there is no iw-PSD on workdays.

Given that there is no iw-PSD on workdays, the id-PSD is also the total load peak shaving demand (L-PSD) on workdays. The total L-PSD on holidays is the sum of the id-PSD and the iw-PSD. Under the three scenarios, the national L-PSDs on holidays are 438 × 1000 MW, 424.2 × 1000 MW, and 411.8 × 1000 MW, respectively. In the end, the total L-PSD shall be the larger one between L-PSD on workdays and that on holidays. In Scenario 3, the total L-PSDs in East and South China are significantly higher than that in other areas of China, accounting for 44 and 18% of the country's total demand respectively.

4.1.2 Results of Peak Shaving Demand of Renewable Energy Power (REP-PSD)

Table 2 shows the calculation results of the required capacity of renewable energy power (RC) of each province in China. The capacity is taken as the larger between the estimated value (**Eqs 2-4**) and actual value (2019).

Table 3 shows the calculation results of peak shaving demand of renewable energy power (REP-PSD) in each area in Scenario 1 and 2. Due to the time and spatial difference of renewable energy output, the REP-PSD in each area in Scenario 2 is smaller than that in Scenario 1. According to **Table 3**, regardless of area, the REP-PSD in Scenario 2 is reduced by more than 100% compared to Scenario 1. In other words, the REP-PSD in Scenario 1 is more than twice that in Scenario 2. In Scenario 3, the national REP-PSD is 349.6 × 1000 MW, with further decreases compared to that in Scenario 2.

TABLE 3 | Demand for peak shaving of renewable energy power (REP-PSD).

Area	Scenario 2 (MW)	Scenario 1 (MW)	Reduction rate (%)
NC	86,984	205,045	136
NE	22,916	54,336	137
EC	93,030	201,286	116
CC	34,117	81,924	140
SC	16,590	36,297	119
SW	36,210	93,654	159
NW	99,949	249,143	149
Total	389,797	921,684	136

NC, NE, EC, CC, SC, SW, NW, respectively represents North China, Northeast China, East China, Central China, South China, Southwest China, Northwest China; The reduction rate is the ratio of the reduction to the demand in Scenario 2.

In Scenario 3, the national L-PSD and REP-PSD are 411.8 × 1000 MW and 349.6 × 1000 MW, respectively. The above two peak shaving demands are not very different, which means that the they deserve similar degrees of attention, and that there may be economy of scope if they are considered in coordination as shown in the following paragraphs.

4.1.3 Results of Final Peak Shaving Demand (F-PSD)

It is calculated that the hourly average output of backup power in North China and Northwest China has negative values in some periods, representing renewable energy output exceeding the load in the areas. If there is no coordination (Scenario 2) between areas (e.g., North and Central China), then a negative hourly output of backup power means that renewable energy power that exceeds the load must be abandoned (the abandoned amount is calculated to be 110,766 MWh), and the peak shaving demand is the entire load. If there is coordination between areas (Scenario 3), then the renewable energy power that exceeds the load can be fully absorbed, reducing the amount of renewable energy abandonment and the areal peak shaving demand.

Table 4 shows the calculation results of final peak shaving demand (F-PSD). According to **Table 4**, the following further results can be obtained. Firstly, the F-PSD in Scenario 3 is less than that in Scenario 2, especially the F-PSD on workdays (the reduction rate reaches 7.21%). Compared with Scenario 2, the F-PSD on workdays in North China in Scenario 3 has the largest decrease rate, reaching about 14%. Secondly, the load on holidays in each area is lower than that on workdays, so the former has intra-week peak shaving demand, while the latter does not. Thirdly, East China has the highest F-PSD, followed by North China, and Northeast China has the lowest demand. The highest F-PSD in East China stems from the highest load and renewable energy capacity. The high F-PSD in North China is mainly due to high renewable energy capacity (mainly from Inner Mongolia). The lowest F-PSD in Northeast China is due to the lowest load.

According to **Table 4**, in Scenario 3, the national F-PSD is 656.3 × 1000 MW, which is the peak shaving demand when the load and renewable energy are considered in coordination. According to the previous results (the last paragraph of **Subsection 4.1.2**), the sum of the national L-PSD and the REP-PSD is 761.4 × 1000 MW, which is the peak shaving demand when the load and renewable energy are considered independently. The above two demands are significantly different. Thus, the coordinated consideration of load and renewable energy has economy of scope. The findings here would be of reference significance for peak shaving resource planning and investment decision-making.

4.2 Results of Demand for Gas-Fired Power Capacity

Even in Scenario 2 and Scenario 3, the start-stop peak shaving capacity (SS-PSC) of 0 is not a feasible solution. In other words, when the SS-PSC is 0, no deep peak shaving capacity (D-PSC) value can meet its three constraints (See **section 3.2**) at the same time. Therefore, in order to support the development of renewable energy, SS-PSC is inevitable. The calculation results of SS-PSC of each area in Scenario 2 and Scenario 3 are shown in **Table 5**. According to **Table 5**, compared with Scenario 2, the total SS-PSC in Scenario 3 is greatly reduced, the intra-day SS-PSC is sharply reduced to 0 MW, and the intra-week SS-PSC is slightly increased. Overall, nearly half (375,838-255,126 = 120,712 MW) of the SS-PSC investment has been avoided through national coordination. In Scenario 3, China's total demand for SS-PSC is 255,126 MW, accounting for about 11.6% of the total installed power generation capacity in China. The three areas with the largest demand for SS-PSC are East China (EC), North China (NC) and Northwest China (NW). **Figure 2A** intuitively shows the comparison of SS-PSC between areas.

TABLE 4 | Final peak shaving demand (F-PSD) in various areas in China.

Area	F-PSD in scenario 2 (MW)		F-PSD in scenario 3 (MW)		Reduction (MW)		Reduction rate	
	Workdays	Holidays	Workdays	Holidays	Workdays	Holidays	Workdays	Holidays
NC	99,560	94,386	94,836	93,365	4,724	1,021	5.0%	1.09%
NE	33,640	33,307	33,338	32,993	302	314	0.9%	0.95%
EC	164,228	234,468	143,918	215,731	20,310	18,737	14.1%	8.69%
CC	59,247	73,605	58,450	73,331	797	275	1.4%	0.37%
SC	60,151	89,958	58,785	88,107	1,366	1,851	2.3%	2.10%
SW	57,895	67,925	55,967	67,624	1,928	301	3.4%	0.45%
NW	78,662	77,954	70,887	75,898	7,775	2,056	11.0%	2.71%
Total	553,383	671,603	516,181	656,255	37,202	15,348	7.2%	2.34%

NC, NE, EC, CC, SC, SW, NW, respectively represents North China, Northeast China, East China, Central China, South China, Southwest China, Northwest China; The reduction rate is the ratio of the reduction to the demand in Scenario 2.

TABLE 5 | | Start-stop peak shaving capacity demand (SS-PSD) in each region.

Scenario	Scenario 2 (MW)				Scenario 3 (MW)			Reduction rate
Type	**Id-PSD.**		**Iw-PSD**	**Total-PSD**	**Id-PSD.**		**Iw-PSD (Total-PSD)**	**Total-PSD**
Time	**wd**	**hd**	**Wd-hd**	**Wd-hd**	**wd**	**hd**	**Wd-hd**	**Wd-hd**
NC	72,009	55,028	39,358	111,367	0	0	40,162	–63.94%
NE	1,297	964	0	1,297	0	0	372	–71.32%
EC	0	0	116,700	116,700	0	0	119,357	2.28%
CC	0	0	19,868	19,868	0	0	22,525	13.37%
SC	0	0	12,599	12,599	0	0	13,338	5.87%
SW	0	0	26,451	26,451	0	0	29,021	9.72%
NW	57,908	48,306	29,648	87,556	0	0	30,352	–65.33%
Total	131,214	104,297	244,624	375,838	0	0	255,126	–32.12%

NC, NE, EC, CC, SC, SW, NW, respectively represent North China, Northeast China, East China, Central China, South China, Southwest China, Northwest China; id-PSD, iw-PSD, respectively represents intra-day SS-PSD, and intra-week SS-PSD; wd, hd respectively represent workdays and holidays; The reduction rate is the ratio of the Total-PSD, reduction between Scenario 2 and 3 to the Total-PSD, in Scenario 2.

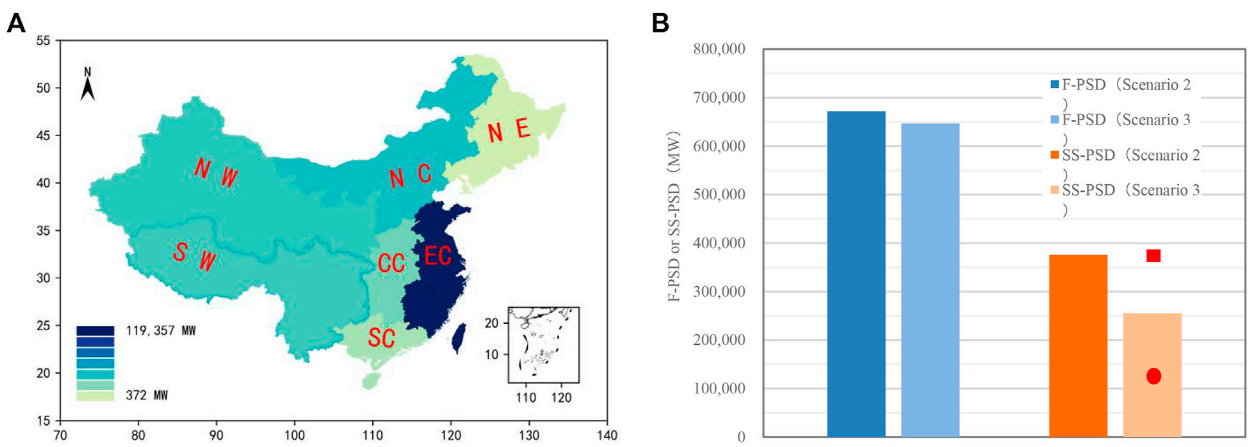

FIGURE 2 | Distribution of gas peak shaving capacity demand in areas in Scenario 3 **(A)** and National peak shaving demand (F-PSD) and capacity demand (SS-PSD) under Scenario 2 and 3 **(B)**. For the sake of simplicity, some islands are not drawn in the **(A)**. The darker color in the figure means the greater demand for peak shaving capacity in the area. In the **(B)**, the small red rectangles and circles represent the sensitivity analysis results of capacity demand on deep peak shaving capacity. The small rectangle represents the capacity demand (SS-PSD) when the deep peak shaving ability (D-PSA) decreases by 20% (Scenario 3). The small circle represents the SS-PSD when the D-PSA increases by 20% (Scenario 3).

Based on the allocation of SS-PSC according to Shapley value (fairness principle), it is also necessary to consider the efficiency of building SS-PSC. In other words, it should be constructed according to the efficiency principle, i.e., "who has lower cost, who builds more". According to the efficiency principle, the areal distribution of SS-PSC may not be consistent with that of the fairness principle, but this does not deny the necessity of the latter. This is because the allocation of SS-PSC under the fairness principle represents the responsibilities and rights of each region. When the economy of SS-PSC is poor, no area is willing to invest in construction under the efficiency principle. At this time, allocating mandatory construction indicators to each region according to the fairness principle is the premise of promoting the SS-PSC construction. At present, gas-fired power plants are mainly Combined Heat and Power plant (CHP), and there are few start-stop peak shaving power plants. Under the pressure of carbon neutralization and renewable energy power utilization, the construction of gas-fired peak shaving power plants is urgent. The current paid auxiliary power market in China is only for the operation of existing units, not for the allocation of SS-PSC among areas. Therefore, the results of SS-PSC allocation based on the above fairness principle has practical guiding significance.

As the living habits, industrial structure, and climate in each area are relatively stable, the load curves and renewable energy endowments remain relatively stable. Therefore, the allocation of SS-PSC in accordance with the fairness principle would not change significantly over time. Based on this, the allocation of SS-PSC can be clarified as early as possible in policy. SS-PSC allocation in fairness principle corresponds to the mandatory allocated indicators, and that in the efficiency principle corresponds to expected actual utilization of the indicators. The areas with high SS-PSC demand (East China, North China, and Northwest China) should be encouraged to take the lead in building areal trading market for SS-PSC. In this trading market, provinces owning allocated SS-PSC and failing to use them economic-efficiently should sell SS-PSC to provinces in the opposite situation. The nominal income of capacity sales may be either positive or negative. When a positive income can be obtained from start-stop peak shaving, the sales income is positive; otherwise, it is negative (corresponding to the cost of entrusting other provinces to build SS-PSC). Regardless of the nominal income, compared to self-built case, selling SS-PSC can increase the income or reduce the cost, which means the actual income is always positive. The final transaction price is formed spontaneously in the market. Since Scenario 3 can largely reduce the demand for SS-PSC, a national capacity trading market should be established on the basis of areal trading markets in the future.

In order to promote sufficient investment in flexible power generation, capacity market mechanism has been implemented by some countries (DECC, 2012; Hach and Spinler, 2016). It should be noted that the concept of the existing power capacity market is different from that in this paper. The former refers to the transaction of reserve power generation capacity between grid companies and power plants in order to stabilize power systems (Hou et al., 2015), while the latter refers to SS-PSC transactions between various regions.

Although better than other peak shaving technologies, the economy of gas-fired power generation are not yet satisfactory, especially for China. Firstly, it is difficult to guarantee gas supply. China is already the largest importer of natural gas, and its dependence on foreign gas in 2020 exceeded 43%. Thus, it is not easy to meet the demand for gas-fired power (Li and Bai, 2010). Secondly, carbon prices are not high enough. China's national carbon market has just started to operate in 2021, and carbon prices will not be strong enough for a certain period in the future, which is not conducive to the development of gas-fired power (IEA, 2020c). Thirdly, China requires much more investment in gas turbines. As of 2020, China's installed capacity of gas-fired power was 98,020 MW, which is about 40% of the estimated capacity demand (255,126 MW, **Table 5**) in this paper. In addition, China's existing gas-fired power plants are mainly (if not totally) CCGT units, rather than OCGT. OCGT is more suitable for start-stop peak shaving. In order to fill the gap of SS-PSC, substantial investment in OCGT units is required in future. Due to low utilization rates, the leveling cost of OCGT is approximately 1.6 times that of CCGT (IEA, 2020d). The economy of gas-fired power plant investment will also be potentially challenged by many new peak shaving technologies.

Facing the challenge of economy of gas-fired power, China may need the idea of grading peak shaving demand. In peak shaving demand, there are always some parts more urgent and economical than other parts, which should be met first. Of course, when it comes to specific investment, a detailed tech-economic evaluation needs to be carried out first.

4.3 Results of Sensitivity Analysis

When the deep peak shaving ability of existing power units increases by 20%, China's SS-PSC demand sharply drops to 102,659 MW (all of it is intra-week SS-PSC). Compared with the SS-PSC of the base case (255,126 MW), the drop rate is 60%, and the sensitivity coefficient is about 3. When the deep peak shaving ability of existing units drops by 20%, China's SS-PSC demand rises to 348,619 MW (including 56,591 MW of intra-day SS-PSC), and the sensitivity coefficient is 1.83. **Figure 2B** visually shows the sensitivity analysis results. It can be seen that SS-PSC demand is very sensitive to deep peak shaving ability of existing units. Flexibility retrofit of existing units can greatly reduce the demand for SS-PSC, which is good news for China (and maybe some other countries), where the cost of natural gas utilization is relatively high.

Flexibility retrofit has been seen in Chinese government documents. China's "*13*th *Five-Year Plan for Electric Power Development*" required that, during the 13th Five-Year Plan period (2015 ~ 2020), the min capacity for flexibility retrofit of CHP and condensing units in three north areas (Northeast, North China, and Northwest) are about 133 × 1000 MW and 82 × 1000 MW respectively, and that the retrofit capacity of condensing units in other areas is about 4.5 × 1000 MW, so the total required retrofit capacity is about 220 × 1000 MW. Shanxi Energy Bureau (2020) required that by the end of 2020, the retrofit capacity of coal power units of each power generation company should not be less than the company's renewable energy installed capacity.

However, flexibility retrofit of power plants was not progressing as expected. As of May 2019, coal-fired power generation units in the three north areas have only completed 24% of the goals of the "*13th Five-Year Plan for Electric Power Development*" (China Electricity Council, 2019). Among the 22 pilot projects, Northeast and North China completed 80 and 25% respectively. Northwest China completed less. Northeast China introduced ancillary service compensation policies in 2016 with reasonable compensation, which accounts for high retrofit motivation of local plants. For most areas of China, insufficient economic compensation for peak shaving is an important reason for the low completion degree of flexibility retrofit (China Electricity Council, 2019). In 2018, China's ancillary service compensation fee accounted for 0.83% of the total on-grid electricity fee, which is much lower than 2.5% in US PJM market and 8% in the United Kingdom. In addition, a lack of enthusiasm for flexible transformation in most parts of China may also be resulted from the fact that the past investment of some units has not been fully recovered. Compared with coal-fired power plants in developed countries, China's coal-fired power plants have shorter operating times. Coupled with the previous environmental protection retrofit, some units in China may need more time to recover their investment.

In terms of peak shaving compensation, it may not be the best strategy for each province to formulate compensation policies independently, especially for the situation that there is a large amount of power export in the three northern areas. Considering the economy of scale effect brought by regional coordination, formulating compensation policy coordinately for deep peak shaving may be better, as in Scenario 3. The details are given as follows. The overall demand for deep peak shaving is supposed to be determined from the perspective of national coordination. With the above overall demand, some reasonable rules (such as Shapley value) are used to allocate the peak shaving demand of each region. After that, the market determines the actual implementation of deep peak shaving and flexibility retrofit of power plants.

In terms of investment recovery, it may be reasonable to allocate more responsibility of flexibility retrofit to those coal-fired and renewable energy units that have recovered all (or the majority of) their investment. In other words, the new and old units should be coordinated.

5 CONCLUSIONS, RECOMMENDATIONS, AND OUTLOOKS

Faced with the requirements of carbon neutralization and the rapid development of renewable energy, it is more and more important to develop gas-fired power for peak shaving in China. However, the development of gas power in China is relatively slow. There are few existing studies on the peak shaving systems of large-scale spatial scopes and multi-time intervals. At the same time, some articles pointed out the economy of scale and the concept of different time intervals for peak shaving. Against this background, from the perspective of regional coordination and multi-time interval, this paper applies Taylor series, Mathematical Programming, and Shapley value to study the peak shaving demand of the power system and peak shaving capacity demand of gas-fired power in China. The main conclusions of the paper are as follows.

Regional coordination can greatly reduce the demand for peak shaving and the abandonment of renewable energy power generation. Firstly, compared with the scenario of independent peak shaving in each province (Scenario 1), the load peak shaving demand on workdays and holidays under the areal coordination scenario (Scenario 2) are reduced by 2.35% ~ 13.6 and 0.01% ~ 2.21%, respectively, where the reduction rates differ among areas. Secondly, compared with Scenario 1, the peak shaving demand of renewable energy power generation in each area is greatly reduced in Scenario 2, with reduction rates of 116% ~ 159%. Thirdly, coordination between provinces of the same area (Scenario 2) is not enough, since 110,766 MWh of renewable energy power would be abandoned in North China and Northwest China in the scenario. National coordinated peak shaving (Scenario 3) can completely avoid the above-mentioned abandonment of renewable energy power. Compared with Scenario 2, the final peak shaving demands on workdays and holidays in Scenario 3 are reduced by 0.91% ~ 14.11 and 0.37% ~ 8.69%, respectively.

Regional coordination (Scenario 2 or 3) fails to completely eliminate the demand for gas-fired power peak shaving, but is able to reduce it to a large extent. In any scenario, the pure deep peak shaving mode without start-stop peak shaving cannot meet the following constraints at the same time, namely peak shaving depth constraint, load constraint, and load factor constraint. Compared with areal coordination (Scenario 2), the national coordination (Scenario 3) avoids 100% (131,214 MW) of intra-day start-stop peak shaving capacity demand (SS-PSC) with minor increase of intra-week SS-PSC demand (4.29%, 10,502 MW).

Through flexibility retrofit of existing units, the demand for SS-PSC can be further reduced significantly.

Based on the previous analysis, the paper presents some policy recommendations as follows. Firstly, it is necessary to establish areal coordination and national coordination mechanisms for power peak shaving. Secondly, with the good stability of SS-PSC allocation under the fairness principle, SS-PSC allocation needs to be clarified as soon as possible in policy. This will help to promote the implementation of start-stop peak shaving responsibilities in regions, and preparation for the large-scale investment and construction of SS-PSC in the future. Thirdly, with large peak shaving demand, the three areas, including East China, Central China, and North China, are supposed to establish areal capacity trading markets. Fourthly, given the economy uncertainty, it is necessary to give priority to meeting the peak shaving demand with most urgency and economic-efficiency. Finally, in order to promote the flexibility retrofit of existing power units, both regional coordination mechanisms and coordination mechanisms between new and old units should be established.

However, there are some shortcomings in this paper, and further research is needed. Firstly, the renewable energy capacity in this paper is for the short-term future, and the medium-term or even long-term renewable energy capacity needs to be predicted in following research. Secondly, this paper ignores demand-side response or interruptible load, assuming that all loads need to be met. Load interruption as a way of peak shaving also requires costs (similar to peak shaving costs). Nonetheless, as technologies such as virtual power plants mature in the future, load interruption costs and peak shaving costs need to be compared and analyzed before calculating peak shaving demand.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

SZ and YW proposed the initial vision, outlined the research framework, and wrote the manuscript. XZ, XD, and DL provided guidance on methods and expression. Everyone collaborated in discussing and polishing the manuscript.

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SUPPLEMENTARY MATERIAL

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