# UPSCALING LOW-CARBON ENERGY RESOURCES: EXPLORING THE MATERIAL SUPPLY RISK, ENVIRONMENTAL IMPACTS AND RESPONSE POLICIES

EDITED BY: Jianliang Wang, Mikael Höök and Fan Tong
PUBLISHED IN: Frontiers in Energy Research

frontiers Research Topics

ISSN 1664-8714
ISBN 978-2-88971-983-9
DOI 10.3389/978-2-88971-983-9

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# UPSCALING LOW-CARBON ENERGY RESOURCES: EXPLORING THE MATERIAL SUPPLY RISK, ENVIRONMENTAL IMPACTS AND RESPONSE POLICIES

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**Citation:** Wang, J., Höök, M., Tong, F., eds. (2021). Upscaling Low-Carbon Energy Resources: Exploring the Material Supply Risk, Environmental Impacts and Response Policies. Lausanne: Frontiers Media SA. doi: 10.3389/978-2-88971-983-9

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frontiers in Energy Research

EDITORIAL
published: 12 November 2021
doi: 10.3389/fenrg.2021.792797

# Editorial: Upscaling Low-Carbon Energy Resources: Exploring the Material Supply Risk, Environmental Impacts and Response Policies

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**Keywords: low-carbon energy, material supply, environmental footprints, energy-water-climates nexus, policies**

**Editorial on the Research Topic**

**Upscaling Low-Carbon Energy Resources: Exploring the Material Supply Risk, Environmental Impacts and Response Policies**



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**Specialty section:**
*This article was submitted to Sustainable Energy Systems and Policies, a section of the journal Frontiers in Energy Research*

***Received:*** *11 October 2021*
***Accepted:*** *25 October 2021*
***Published:*** *12 November 2021*

***Citation:***
*Wang J, Tong F and Höök M (2021) Editorial: Upscaling Low-Carbon Energy Resources: Exploring the Material Supply Risk, Environmental Impacts and Response Policies. Front. Energy Res. 9:792797. doi: 10.3389/fenrg.2021.792797*

## INTRODUCTION

Continued reliance on high-carbon fossil fuels in the face of increasing climate change casts a grand threat for modern society (Le Quéré et al., 2021). The global society has joined forces to address climate change, showcased by the UN Sustainable Development Goals and ambitious efforts to mitigate climate change stated in the Nationally Determined Contributions (NDC) for the Paris Agreement. Major countries have agreed to embark on a transition towards sustainable energy systems, where high-carbon fossil fuels would be replaced by low-carbon alternatives to reach carbon neutrality eventually. Although the development and deployment of low-carbon energy resources and technologies have achieved considerable success in the past decades, the scale to achieve carbon neutrality worldwide requires a rapid upscaling of low-carbon energy resources and technologies at speed unseen in human history (World Economic Forum (WEF), 2019).

The transition to sustainable energy systems is not an easy road, as broad and complex social and environmental implications would emerge during the transition. In particular, material supply risk and environmental impacts are the most significant challenges. In this Research Topic, we selected nine recent studies investigating environmental and social impacts caused by the development of low-carbon energy resources and proposing policy suggestions to address these challenges in the transition towards low-carbon energy systems.

### Material Supply Risk

Raw materials, including heavy-metal elements such as Lithium and Cobalt, are essential inputs for developing low-carbon energy resources and form the bedrock of low-carbon energy systems. The upscaling of low-carbon energy resources and technologies would induce exponential increases in material demands, which has led to uneven price dynamics and elevated supply risks. For example, Liu's work *Renewable Energy and Material Supply Risks: A Predictive Analysis Based on An LSTM Model* (Liu et al.) points out that improving the energy density of metals plays a crucial role in China's transition to a low-carbon energy system. Furthermore, Hu's work *An Explanation of*

*Energy Return on Investment From an Entropy Perspective* (Hu et al.) finds that improving resource extraction efficiency would facilitate renewable energy development. Finally, Wang's work *Accounting and Management of Natural Resource Consumption Based on Input-Output Method: A Global Bibliometric Analysis* (Wang et al.) presents a systematic review of recent natural resource consumption accounting and management studies. This overview clearly shows the increasing research interest and upward trend of research outputs related to upscaling low-carbon energy resources.

## Environmental Impacts

The upscaling of low-carbon energy resources and the transition to sustainable energy systems is crucial to address the global sustainability challenges but may also bring unexpected environmental impacts if managed poorly. For instance, natural gas is a low-carbon energy resource when replacing coal but could induce methane leakage, water pollution, and landscape impacts (Qin et al., 2018). Fu's work *Identifying and Regulating the Environment Risks in the Development and Utilization of Natural Gas as a Low-Carbon Energy Source* (Fu et al.) analyzes the environmental risks in the whole process of natural gas exploitation to utilization and put forward policy recommendations to manage these risks. The water-energy-carbon nexus has attracted increasing interest as these environmental impacts are intertwined, and no single solution could solve it all. Li's work *Water Use for Energy Production and Conversion in Hebei Province, China* (Li et al.) quantifies the relationship between energy production and water consumption in a Chinese province in the context of three future emissions reduction scenarios. On the other hand, well-designed low-carbon energy systems have the potential to mitigate carbon emissions as well as other environmental impacts. Xue's work *Environmental Benefit and Investment Value of Hydrogen-Based Wind-Energy Storage System* (Xue et al.) estimates the environmental benefits of hydrogen-based wind-energy storage systems, promoting renewable energy integration.

## Response Policies

Researchers have investigated response policies to support the low-carbon energy transition to address the material supply risks and the environmental impacts that may impede the upscaling of low-carbon energy resources. Wang's work *China's Energy Transition Policy Expectation and It's $CO_2$ Emission Reduction Effect Assessment* (Wang et al.) estimates carbon emissions reductions from China's energy transitions. Zhang's work *Analysis of Performance Deviation of Wind Power Enterprises in China* (Zhang and Qi) disentangles the impacts of policy measures and market conditions in the dynamics between carbon reduction efficiency and the financial performance of wind power enterprises. Finally, Hu's work *The Impact of Policy Intensity on Overcapacity in Low-Carbon Energy Industry: Evidence From Photovoltaic Firm* (Hu et al.) investigates the overcapacity issue (i.e., the bust-and-boom cycle) in the photovoltaic industry in China and examined the role of government subsidies and policies in the development of the low-carbon energy industry.

# CONCLUSION

A rapid and large-scale upscaling in developing and deploying low-carbon energy resources and technologies is essential to address climate change. Findings from studies in this Research Topic would help industry and governments better understand and manage the material supply risks and environmental impacts in the process of upscaling low-carbon energy resources. As highlighted by the selected studies, cross-discipline experts and practitioners need to work together to address the multi-dimensional challenges in the transition to sustainable energy systems towards carbon neutrality.

# AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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**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.

frontiers in Energy Research

ORIGINAL RESEARCH
published: 30 June 2020
doi: 10.3389/fenrg.2020.00126

# Analysis of Performance Deviation of Wind Power Enterprises in China

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Considering increased global emphasis on energy security, low-carbon economy and environmental governance, the proportion of renewable energy will increase in national power grid systems. Wind power generation will play an important role in China's future power systems. Environmental uncertainty will affect the time-varying correlation between carbon efficiency and the performance of the wind power enterprises. Panel data from 2011 to 2018 is used to analyze the development status and existing problems of the wind power industry; further, with the data, the dynamic conditional correlation coefficient is calculated through the DCC-GARCH model, and the breakpoint analysis method is used to analyze the impact of policy and the economic environment on the time-varying correlations between carbon efficiency and the performance of wind power enterprises. The results show that during the China-US trade war, the sudden trade policy changes that increased tariffs led to a sharp rise in interdependence. The relevant polices inspiring the wind power industry are positively correlated with the dynamic conditional correlation coefficient, while the financial performance of alternative fossil fuels is negatively correlated with the dynamic conditional correlation coefficient.

**Keywords: time-varying, DCC-GARCH, environmental uncertainty, wind power, deviation**

OPEN ACCESS

**Edited by:**
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**Specialty section:**
*This article was submitted to Sustainable Energy Systems and Policies,*
*a section of the journal Frontiers in Energy Research*

**Received:** *22 April 2020*
**Accepted:** *27 May 2020*
**Published:** *30 June 2020*

**Citation:**
*Zhang T and Qi X (2020) Analysis of Performance Deviation of Wind Power Enterprises in China.*
*Front. Energy Res. 8:126.*
*doi: 10.3389/fenrg.2020.00126*

## INTRODUCTION

China is currently ranked first in carbon dioxide emissions worldwide. In 2017, coal consumption accounted for 60.4% of China's energy consumption, while this number ranges from 5 to 25% for several developed countries. The typical coal-dependent economic model not only aggravates air pollution and harms the global ecological environment, but it also becomes an obstacle to sustainable development (Hongtao and Wenjia, 2018). Therefore, considering the current urgent situation of environmental governance, the shift of major energy sources away from coal and toward renewable energy is meaningful, and there is a close relationship between urbanization and renewable energy (Yang et al., 2016); the Chinese government has issued a series of documents to promote the development of renewable energy (Yuan et al., 2018). Wind power has grown most rapidly in Europe (Bonou et al., 2016), it provides energy in a cost-effective manner and have great potential and (Dawn et al., 2019), while it has become a promising renewable energy source in China (Shen et al., 2019), with wind power generation capacity having increased from 8.555 MW in March 2014 to 176 MW in September 2018.

According to the analysis of the current situation of China's wind power industry in the electricity market based on data from the State Grid, the relevant data from Clean energy installed capacity (solar, wind, hydropower) shows that hydropower is the largest three types of clean energy power generation capacity, followed by Wind power, and finally solar power, but the growth rate of wind power and solar power is higher than that of hydropower.

In terms of power generation, based on the total value over the past 8 years, thermal power generation is still the largest power generation route in China, and the proportion of renewable energy increases year by year. Taking power generation in September 2018 as an example, thermal power, hydropower, wind power and nuclear power generation accounted for 69.98%, 21.13, 4.31, and 4.58% of total power generation, respectively. However, the growth rate for wind power (from August 2010 to December 2018) is 90.5%, which is higher than the other three categories.

The carbon equivalent of a wind power project (the amount of carbon converted from various alloying elements in steel to the actual eutectic point carbon content) for its entire life cycle is ∼2.5 to 7.5 times higher than that of a nuclear power and hydropower projects. It makes significant contributions to alleviating environmental acidification during the operational stage (Wang et al., 2018), and human toxicity, eutrophication and ecological toxicity indicators are significantly reduced (Xu et al., 2018). Hence, wind power will play an important role in clean energy development. In addition, wind power generation is an indispensable part of future power systems.

Policy and economic uncertainties affect business decision-making by influencing the external conditions of business operations and consumer behavior. Policies promote corporate cost reduction, reduce emissions, and encourage enterprises to participate in wind power development (Hitaj and Löschel, 2019). And industrial policies or related countermeasures can help the industry to solve the obstacles in the development of low-carbon energy, thereby achieving low-carbon economy and sustainable development. But uncertainty in economic policies is an economic risk in that enterprises cannot accurately predict the timing and scope of policy implementations (Gulen and Ion, 2015). Economic policies frequently impact enterprises in the Chinese market, and some strategic emerging industries need policy support from the government during the process of development, but policy support and specific implementation times are ambiguous; further, some policies may even restrict development for a period of time, bringing challenges to decision-making for wind power enterprises. Meanwhile, macroeconomic fluctuations have always existed, and financial risks are also unavoidable. It is difficult for enterprises to accurately predict the mode of risk occurrence, the scope of coverage and the degree of risk. Therefore, policies and economic uncertainty lead to unstable responses by enterprises.

In cross-market interdependence research, interdependence is dynamic and unexpected events are the main reasons for the change. Energy prices and the carbon market have an impact on the performance of clean energy enterprises. Some relevant research shows that clean energy stock returns are highly sensitive to crude oil volatility (Dutta, 2017), but international oil prices have little impact on China's new energy stocks (Broadstock et al., 2012). Analysis of the impact of fossil fuels (coal, oil, and natural gas) on clean energy stocks by using the Divisia energy price index (Sun et al., 2018) shows that a slight negative correlation was found between fossil fuels and clean energy stocks. Oil prices have a greater influence on clean energy stocks than technological factors (Henriques and Sadorsky, 2008). Measure-Correlate-Predict (MCP) models and artificial neural network methods are often used to predict wind power potential (Vargas et al., 2019). Methods such as GARCH or Copula are widely using to analyze the dynamic interdependence between markets. As a classic method, GARCH is used when studying the dynamic fluctuations of two factors. Some scholars have studied the relationship between European Union Allowance (EUA) and clean energy stocks by VAR-GARCH (Sadorsky, 2012), and multivariate GARCH is used to analyze oil prices and clean energy and technology company stock prices.

At present, the development of low-carbon energy has a wide and profound social impact, and its related deployment and the corresponding changes in government policies will also have an impact on the development of energy companies, and its mechanism of action is particularly important in environmental protection and low-carbon energy development. As a renewable energy source, wind power has great potential for development, but the development of wind power enterprises is affected by many factors, such as talent technology, capital costs, fluctuations in relevant economic interest rates, etc., among which the policy and economic environment are the key factors affecting the decision-making of wind power enterprises. This paper analyzes the development status of the wind power industry with panel data, the dependence relationship between carbon efficiency (tons of the company's $CO_2$ equivalent divided by the company's annual revenue) and wind power enterprise performance, the sudden changes of dependence and the causes of the impacts.

## CURRENT STATUS OF WIND POWER

According to a report issued by the National Energy Administration, during 2014 and 2015, the largest grid-connected capacity of wind power was in the northwest of China. The province with the greatest grid-connected capacity in 2014 was Xinjiang, and its proportion reached 22%. The added grid-connected capacity of Shanxi and Shandong declined slightly during the period from 2015 to 2017, but it began to rise again in 2018. The implementation of offshore wind power projects in Weifang and other areas is an important factor for the increase in the wind power capacity of Shandong. The province with the largest grid-connected capacity in 2015 was Gansu Province (15%), followed by Ningxia Province (14%). Ningxia Province and Inner Mongolia had large amounts of new wind capacity in the period of 2014-2015, but over the next 3 years, this new capacity quickly returned to a low level.

In 2016, the new grid-connected capacity from wind power was mainly in Yunnan (28%). Yunnan's share in the previous 2 years increased steadily. After a surge in 2016, it quickly declined to below 5%. Jiangsu's new grid-connected capacity accounted for 9% of total capacity in 2016. Since 2014, the new grid-connected capacity of wind power in Jiangsu has been relatively stable, but it has only plummeted since 2017. At the same time, the new grid-connected capacities for Qinghai, Hebei and Henan were all quite close, at ∼10% of total capacity. Henan and Hebei had less grid-connected capacities during 2014-2016, and they

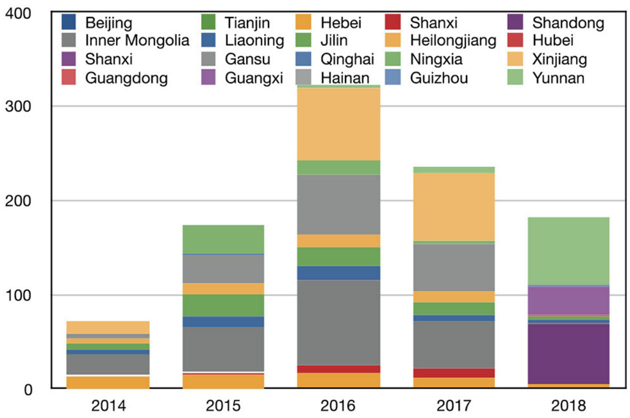


**FIGURE 1 |** Abandoned wind volume (100 million kWh).

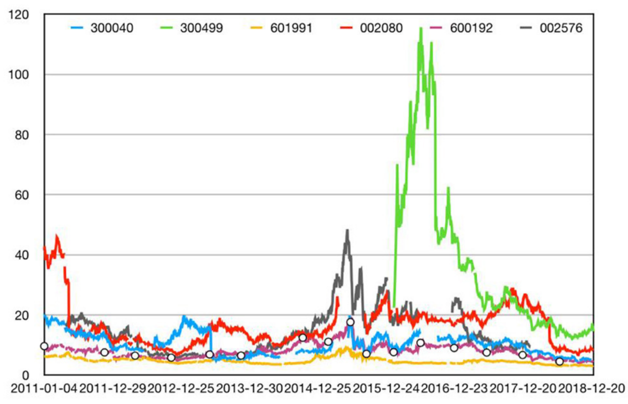


**FIGURE 2 |** Performance of wind power generation enterprises.

gradually expanded this capacity after 2017. In 2018, the largest grid-connected capacities from wind power were in Shanghai (12%), followed by Hainan (11%) and Shandong (11%), which was also related to the recent development of offshore wind power projects.

Abandoned wind energy and abandonment rate have always been important factors in recent years and hinders further development of wind power. Both of them are due to the large installed capacity of the power station where the wind power generation is located, which exceeds the local electricity consumption. In addition, the power grid configuration is low, and the electric energy cannot be sent out, resulting in the abandonment of wind power. Abandonment rate refers to the percentage of waste electricity to total wind power. The **Figure 1** shows the amounts of abandoned wind power for each province in the first half of 2014-2018. Cities or provinces without wind abandonment can be divided into two categories. One represents those cities with more developed economies, represented by Shanghai, Jiangsu, Zhejiang, and Fujian. They have sufficient capacity to utilize the generated wind power, and the other category is represented by cities with small installed wind power capacities, such as Chongqing, Sichuan, Anhui, and Jiangxi.

During the years from 2014 to 2017, the northwest and northeast regions exhibited extremely serious abandoned wind problems. Inner Mongolia exhibited the largest amount of abandoned wind power from 2014 to 2016, and the amount of abandoned wind accounted for 32, 27, and 28%, respectively for these years, but this amount decreased slightly in 2017; however, the problem of wind abandonment in Inner Mongolia greatly improved in 2018. The proportion of abandoned wind power dropped rapidly to 1%. Xinjiang is also a region showing a serious problem with abandoned wind power. The proportion of abandoned wind power increased gradually from 19 to 31% from 2014 to 2017. In 2016, the rate of abandoned wind power was the highest, reaching 45%. The abandonment of wind power in Gansu and Xinjiang were similar, with both showing gradual increases in 2014-2017; the highest rate of windfall reached 47%. Ningxia's proportion of abandoned wind power in 2015 was 17%, but it declined rapidly in the next few years and fell to 1% in 2017. Since 2014, Heilongjiang, Liaoning, and Jilin in the northeastern region have shown a gradual decline in the proportion of abandoned wind power, but the abandonment rate in 2015 and 2016 has increased, indicating that the utilization rate of wind power in these areas is decreasing.

After 2017, the problem of wind power abandonment in the northwestern and northeast regions has greatly improved. The new abandonment problem is in Yunnan, Guangxi, and Shandong, which have recently begun to vigorously develop wind power projects. The levels of abandoned wind power in Shandong Province between 2014 and 2015 have been fluctuating by 1%. In 2018, the abandoned wind power surged to 6.31 billion kWh and the rate of abandoned wind power reached 16.7%. The abandonment rate for Yunnan during the period from 2014 to 2017 remained below 5%, but increased to 28.9% in 2018 and the abandonment of wind power has reached a total of 7.13 billion kWh. In Guangxi, the amount of abandoned wind power in 2018 was 3.01 billion kWh, and the rate of abandoned wind power reached 20.5%.

**Figure 2** shows the daily closing price fluctuations of some representative wind power company stocks from 2011 to 2018, that is the performance of wind generation manufacturers, and the legend shows the stock codes. Codes 300040, 300499, and 601991 belong to power generation companies, while codes 002080, 600192, 002576 belong to wind power equipment production companies. **Table 1** is a statistical description of the daily closing price for these stocks.

Among these, the highest average is for 600499, but this is also the stock showing the largest variance, indicating that the daily closing price fluctuates drastically and that its price is unstable. The kurtosis for stock code 600040 is negative, indicating that there are extremes on both sides of the sample set. The stock price data of the six companies is greater than zero, which proves that the stock price data is right-biased. From the time series, the stock price average near the current time node is larger.

**TABLE 1 |** Descriptive statistics of wind power enterprise performance data.

| Index | 300040 Jiuzhou electric | 300499 Gaolan shares | 601991 Datang power generation | 002080 Sinoma technology | 600192 Greatwall technology | 002576 Accessible power |
|---|---|---|---|---|---|---|
| Average | 10.255 | 36.637 | 4.695 | 16.165 | 7.983 | 14.073 |
| Standard error | 0.086 | 0.989 | 0.025 | 0.165 | 0.052 | 0.200 |
| Median | 10.000 | 25.370 | 4.470 | 14.980 | 7.760 | 12.230 |
| Mode | 8.600 | 14.200 | 3.890 | 18.050 | 7.710 | 6.800 |
| Standard deviation | 3.563 | 26.340 | 1.085 | 7.047 | 2.307 | 7.744 |
| Variance | 12.698 | 693.793 | 1.178 | 49.666 | 5.321 | 59.964 |
| Kurtosis | −0.464 | 0.736 | 1.688 | 3.512 | 2.122 | 2.244 |
| Skewness | 0.488 | 1.338 | 1.161 | 1.611 | 1.023 | 1.416 |
| Minimum | 4.580 | 12.210 | 2.990 | 6.690 | 4.000 | 5.400 |
| Maximum | 20.290 | 115.600 | 9.440 | 45.800 | 19.350 | 48.500 |
| Numbers of observations | 1,711.000 | 710.000 | 1,924.000 | 1,825.000 | 1,935.000 | 1,501.000 |

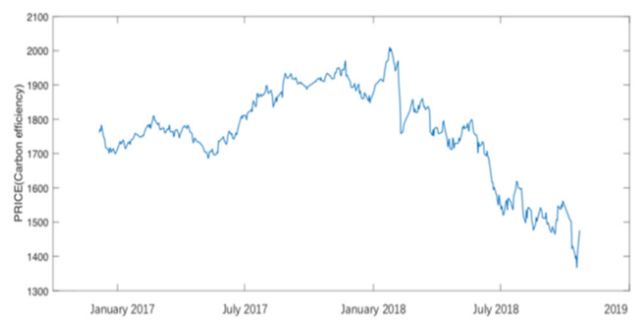


**FIGURE 3 |** Carbon efficiency.

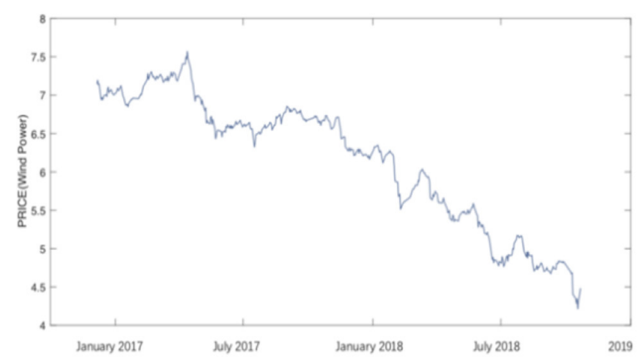


**FIGURE 4 |** Wind power daily closing price.

## DATA AND METHODS

### Data Sources and Description

For the empirical analysis of the relationship between carbon efficiency and wind power enterprise performance from the financial perspective, the characterization indicators selected the SSE 180 carbon efficiency index from December 2016 to November 2018 and the daily closing price data of the wind power sector (data is from tonghuashun database), as shown in **Figures 3–6**. The SSE 180 carbon efficiency index is a type of green index. The difference from other environmental protection indexes is that the SSE 180 carbon efficiency index mainly reflects carbon emissions from enterprises.

A statistical description of the daily closing price of wind power enterprises and carbon efficiency data is shown in the **Table 2**.

Both carbon efficiency and wind power data are negatively distributed, and the skewness is less than 0, indicating that the data to the left side of the mean are more dispersed. The kurtosis of both datasets is less than zero, indicating that the two datasets are flatter than the positive distribution, the extreme data at both ends is greater, and the wind power data is flatter than the carbon efficiency data.

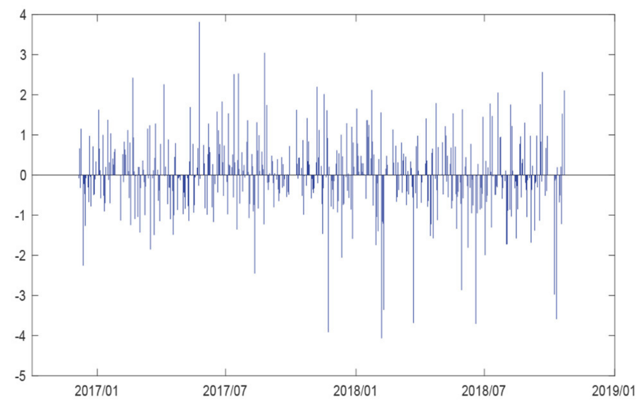


**FIGURE 5 |** Residual sequence of carbon efficiency.

### Model Specifications

The multivariate DCC-GARCH model is used in this paper. The research object is two time series $y_{1,t}$ and $y_{2,t}$($t$=1, 2, … $T$). In related research in the financial field, the GARCH (1,1) model is

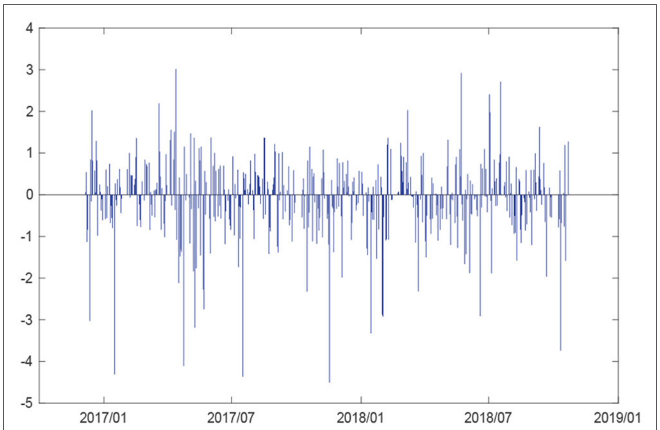


**FIGURE 6 |** Residual sequence of wind power.

**TABLE 2 |** Statistical description.

| | Carbon efficiency | Wind power |
|---|---|---|
| Average | 1,762.89 | 6.16519081 |
| Standard error | 6.386359288 | 0.039190344 |
| Median | 1,771.04 | 6.4579 |
| Mode | 1,782.98 | 7.0729 |
| Standard deviation | 136.3109926 | 0.837793864 |
| Variance | 18,580.6867 | 0.701898559 |
| Kurtosis | −0.175354825 | −0.973430091 |
| Skewness | −0.689443803 | −0.504312268 |
| Minimum | 1,367.7621 | 4.2174 |
| Maximum | 2,009.4118 | 7.5691 |
| Numbers of observations | 457 | 457 |

used according to the AIC (Akaike Information Criterion), and the mean equation is ARMA (1,1), which is stated as:

$$Y_t = \lambda + \Phi_1 Y_{t-1} + \varepsilon_t + \theta\varepsilon_{t-1}$$

where, $Y_t = \begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix}$, and $Y_{t-1}$ represents the previous period in the time series, $\lambda$ is an n×1 constant matrix, $\Phi_1$ is an n×1 autoregressive coefficient matrix, $\theta$ is an n×1 moving average coefficient matrix, and $\varepsilon_t$ is a residual sequence, given by:

$$\varepsilon_t = \sqrt{H_t} z_t$$

where, $\sqrt{H_t}$ is a positive definite matrix, so $H_t$ is the conditional covariance matrix of $y_t$. $z_t$ is i.i.d. $H_t$ is written as:

$$H_t = D_t R_t D_t = \rho_{ij}\sqrt{h_{ii,t} h_{jj,t}}$$

where, $D_t = diag(h_{ii,t}, h_{jj,t})$. In actual analysis, it is difficult to achieve a constant conditional correlation. Therefore, Engle (2002) and Tse and Tsui (2002) proposed the DCC model to achieve a dynamic condition correlation, so that $R_t$ can change with time, and $R_t$ is the correlation matrix.

$h_{ii,t}, h_{jj,t}$ are based on GARCH(1,1), its conditional variance is:

$$h_{ii,t} = w_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i h_{i,t-1}$$
$$h_{jj,t} = w_j + \alpha_j \varepsilon^2_{j,t-1} + \beta_j h_{j,t-1}$$

In the DCC-GARCH model, $R_t$ needs to be transformed and positive at each time point, so the process of constraining through $Q_t$, $\overline{Q}$ is the mean value, and $a + b < 1$.

$$Q_t = \overline{Q} + a(z_{t-1}z'_{t-1} - \overline{Q}) + b(Q_{t-1} - \overline{Q})$$
$$Q_t = (1 - a - b)\overline{Q} + a z_{t-1}z'_{t-1} + bQ_{t-1}$$
$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$$

The parameters in the model are estimated by the quasi-maximum likelihood method.

$$ll = \frac{1}{2}\sum_{i=1}^{T}(N\log(2\pi) + 2\log|D_t| + \log|R_t| + z'_t {R_t}^{-1} z'_t$$

# EMPIRICAL RESULTS AND DISCUSSION

## Results of Relevance

The calculation results using the r software are shown in the **Table 3**.

The residual sequence is shown below.

**Figure 7** shows the trends in the dynamic relationship of carbon efficiency and wind power enterprise performance from December 5, 2016 to October 19, 2018. As shown in the **Table 4** below, the mean value of the dynamic condition correlation is 0.66, which is greater than 0.5; this result proves that there is a clear dynamic dependence between carbon efficiency and wind power enterprise performance. In December 2016, the average dynamic condition correlation was 0.69. The average value of the dynamic condition correlation coefficient in 2017 was 0.59, which is below the average. The average dynamic condition correlation

**TABLE 3 |** DCC-GARCH model fitting results.

| | Parameter | Estimated value | Std. Error |
|---|---|---|---|
| Carbon efficiency | $\lambda_{ce}$ | 7.146380 | 0.008299 |
| | $\phi_1^{ce}$ | 1.000000 | 0.002324 |
| | $\theta_{ce}$ | −0.012951 | 0.043739 |
| | $w_{wp}$ | 0.000404 | 0.000241 |
| | $\alpha_{wp}$ | 0.045505 | 0.042064 |
| | $\beta_{wp}$ | 0.829461 | 0.089613 |
| Wind power | $\lambda_{wp}$ | 1,762.235870 | 1.687648 |
| | $\phi_1^{wp}$ | 0.998580 | 0.006638 |
| | $\theta_{wp}$ | 0.001062 | 0.051269 |
| | $w_{wp}$ | 3.281226 | 3.237692 |
| | $\alpha_{wp}$ | 0.093937 | 0.042802 |
| | $\beta_{wp}$ | 0.903851 | 0.042756 |
| DCC | a | 0.054626 | 0.027774 |
| | b | 0.918879 | 0.053063 |

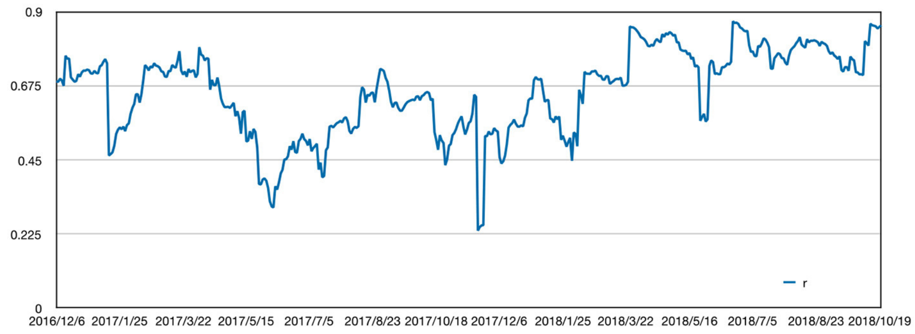


**FIGURE 7 |** Dynamic condition correlations.

**TABLE 4 |** Dynamic condition correlation statistical description.

| Index | Value |
|---|---|
| Average | 0.65698107 |
| Standard error | 0.006014795 |
| Median | 0.689249789 |
| Standard deviation | 0.128581625 |
| Variance | 0.016533234 |
| Kurtosis | −0.0824298 |
| Skewness | −0.582566794 |
| Minimum | 0.235569103 |
| Maximum | 0.872602755 |
| Numbers of observations | 457 |

coefficient in 2018 was 0.74, indicating that carbon efficiency and wind power enterprise performance were more closely related in 2018.

## Analysis of the Change of Dependence Relations

According to **Figure 8**, the immediate timing of sudden drops or surges in the correlation coefficient corresponds to the moments when China and the United States make important decisions regarding their trade relations. As shown in **Table 5**, on March 22, the Trump administration announced that it might impose a $60 billion tariff on China. After that, China and the United States entered the first round of negotiations. On May 19, the two governments issued a joint statement and the two sides agreed to take certain measures that have reduced the trade deficit with the United States. However, on May 29, the White House suddenly issued a statement that it would impose a 25% tariff on $50 billion of goods imported from China, and the two governments then entered a second round of negotiations. On June 15, the United States issued a list of tariffs.

The Shanghai Composite Index is at a concave inflection point for three rising time points, which may be partly reflected by the fact that the financial markets did not perform poorly after the trade war officially began. At the same time, before March 22, the Trump administration issued a statement that it would tax the Chinese steel industry. As an indispensable raw material for construction in the wind power industry, the competitive price advantage in US market will be weakened, overseas demand will decrease, and domestic supply will increase, leading to a short-term price decline. This reduces the costs for wind power enterprises and improves their profitability, which is beneficial to their performance. Similarly, in the stock market, the wind power sector is divided into trade warfare earnings shares, which can also benefit. The trade war also influences investor sentiment. The Shanghai Composite Index has generally declined since March, investors have become more cautious, their investment behavior in the wind power industry will be reduced from the perspective of economic profitability, and the influence of green preferences by investors on the performance of wind power enterprises will be strengthened. On March 22, the China Energy Administration stated at a meeting that it will further promote the development of renewable energy, deepen reform of the power system, promote the healthy development of industries including wind power and that the policy is industrial encouragement. These are reasons for increasing correlations.

On May 19, the correlation between carbon efficiency and the performance of wind power enterprises dropped sharply. This may be due to the joint statement by the two governments on May 19 that measures would be taken to reduce the deficit. The statement temporarily eased tensions in the trade war and alleviated investor concerns regarding the Chinese economy, resulting in a sharp decline in dynamic dependency, which was almost the same as the increase in the sudden announcement of tariffs on $50 billion on May 29. After two rounds of trade war negotiations, the government and the market have psychological expectations due to the uncertain consequences. Therefore, the impact of policy uncertainty on the correlation between carbon efficiency and wind power enterprise performance will decrease.

When the relevant policy is conservative or tight for the wind power market, the correlation decreases. For example, the National Development and Reform Commission issued an announcement (No. 2, 2017), suspending the application for voluntary greenhouse gas emission reduction projects, due to a non-standard carbon trading market, and the Interim Measures for the Management of Voluntary Greenhouse Gas Emission Reduction Transactions, issued in 2012 were revised,

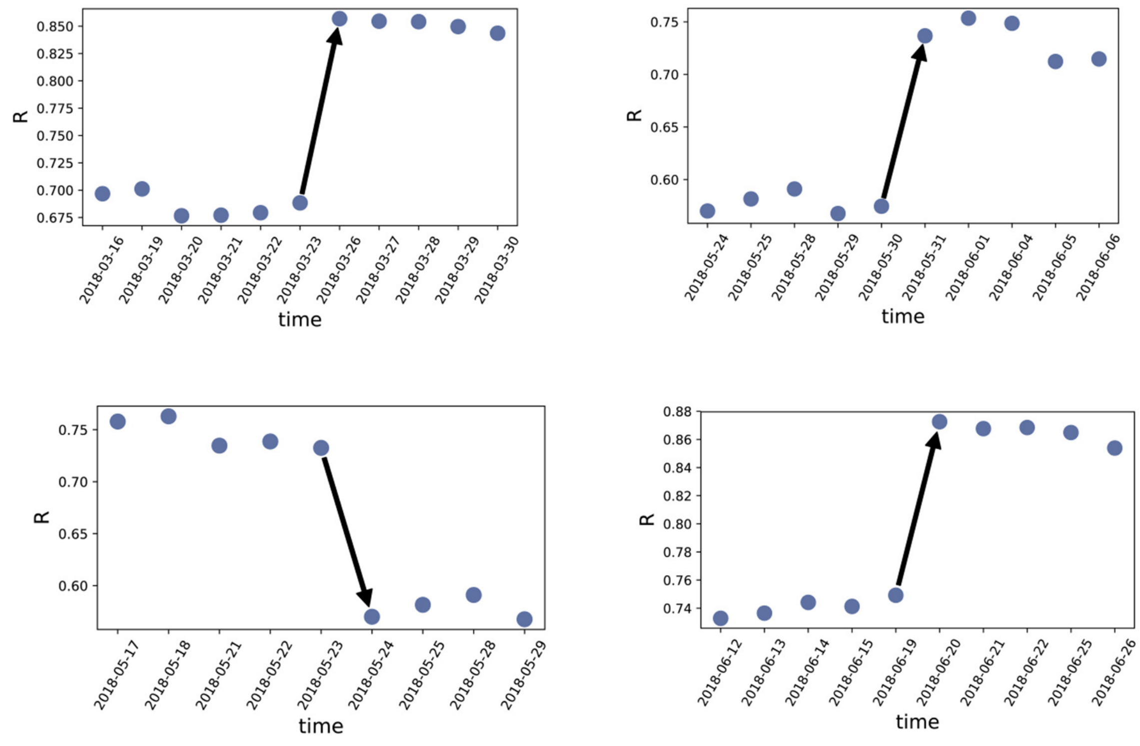


**FIGURE 8 |** Impact of the trade policy.

**TABLE 5 |** Relevant policies.

| Time | Policies |
|---|---|
| March 17, 2017 | Suspending the application for voluntary greenhouse gas emission reduction projects |
| March 22, 2018 | U.S. Tariff Increase on China |
| May 19, 2018 | Two governments reach a joint statement |
| June 15, 2018 | U.S. issued a list of tariffs |
| July 16, 2018 | China issued notice on actively promoting power market trading and further improving the trading mechanism |
| September 19, 2018 | China issued notice on combing information on wind and photovoltaic power projects |

the carbon trading market is facing reorganization. At that time, the relationship between carbon efficiency and wind power enterprise performance weakened. On September 19, 2018, the General Department of the State Energy Administration issued the first Notice on Combing Information on Wind and Photovoltaic Power Projects since the Twelfth Five-Year Plan, which abolished some of the wind power projects that had been planned but had not yet been completed. This policy aims to improve the problem of wind abandonment and prevent short-term over construction leading to energy waste. However, the relationship between carbon efficiency and the performance of wind power enterprises has dropped sharply because the information conveyed by this policy to the market is that the development of clean and carbon-efficient enterprises is limited, thus the dynamic conditions correlation coefficient decreases, as shown in **Figure 9**.

Conversely, when the relevant policies are to encourage the wind power market or low carbon emission, the correlation will increase. On July 16, 2018, the National Development and Reform Commission and the National Energy Administration jointly issued the "Notice on Actively Promoting Power Market Trading and Further Improving the Trading Mechanism," proposing to promote the optimization of large-scale resource allocation and the usage of clean electricity, and to establish a clean energy quota system as soon as possible. On September 28, 2018, the North China Regulatory Bureau of the State Energy Administration promulgated the Beijing-Tianjin-Hebei Green Power Market Trade Rules (Trial Implementation). The policy is to take the approach of guaranteed acquisition of part of the renewable energy power generated and to strengthen the market-oriented transaction of parts other than the guaranteed acquisition of electricity.

Measures to protect the wind power industry and to promote the market-oriented trade of wind power and the decline in the raw materials market have led to a sharp increase in the dependence of carbon efficiency and the performance of wind power enterprises, as shown in **Figure 10**.

Market changes in traditional energy and raw materials also have an impact on the correlations. When the futures market for

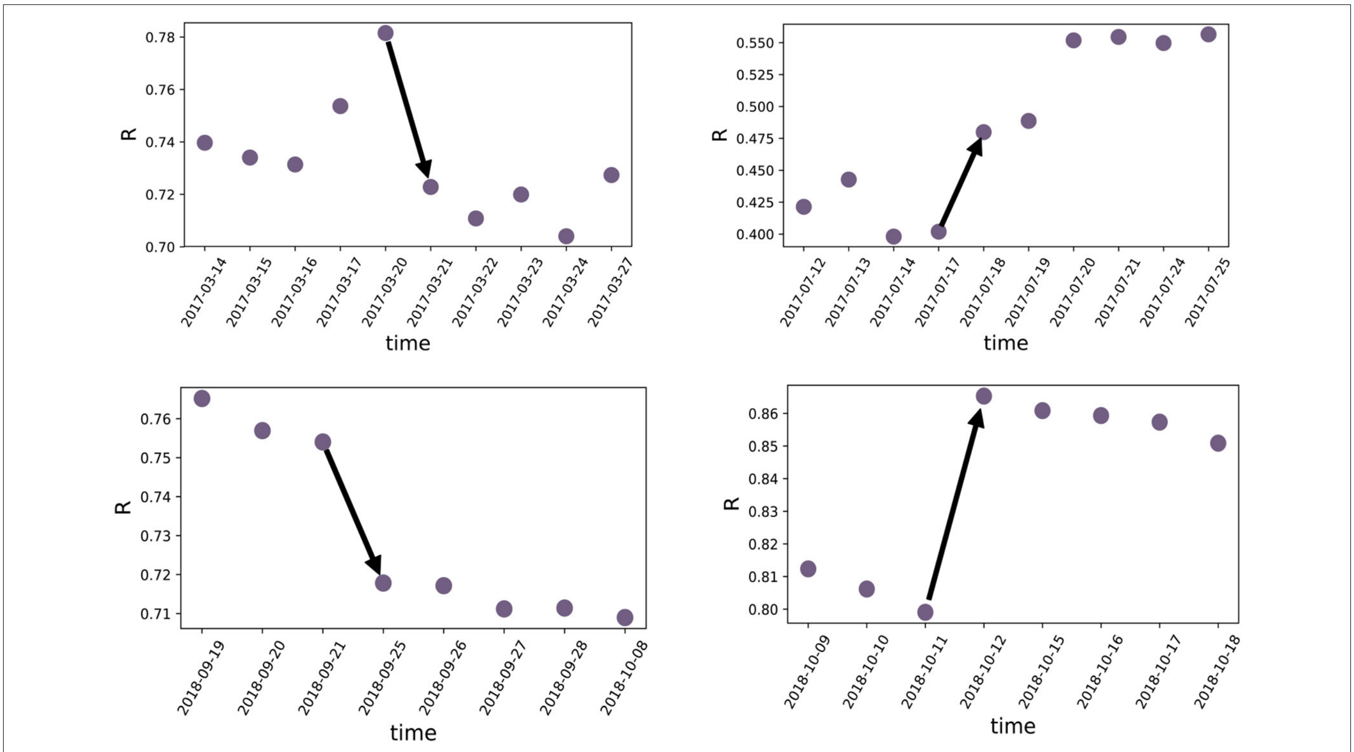


**FIGURE 9 |** Impacts of economic policy.

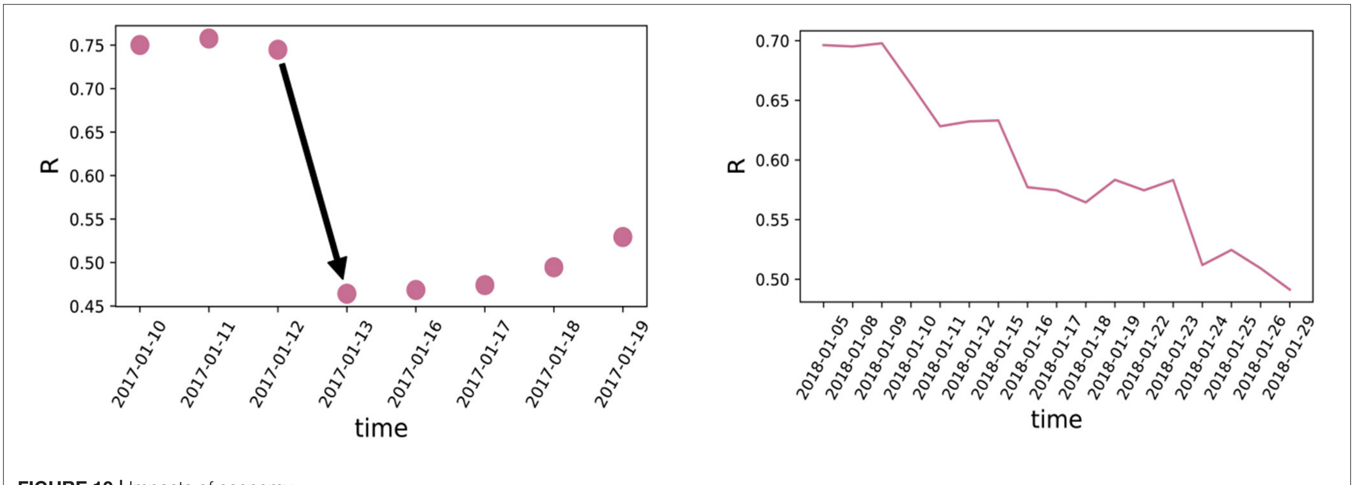


**FIGURE 10 |** Impacts of economy.

traditional energy and raw materials rises sharply, the correlation weakens. For example, on January 11, 2017, coke, iron ore and threaded steel futures rose sharply, increasing by 8.98, 8, and 6.99%, respectively. The dynamic conditions correlation coefficient declined sharply. From Jan. 4 to Jan. 29, 2018, the prices of oil, coal and liquefied natural gas increased due to climate and other factors, and the correlation decreased.

However, there do exist several special situations, when the correlation not only changes by the fluctuation of trade or economic policy and related raw material market. For example, on January 16, 2017, there was a significant decline in correlation of about 39%, but no relevant policies were issued at that time, and the change may be due to the sharp fluctuation of the stock market.

## CONCLUSIONS

According to the fitting results, the dynamic condition correlation coefficient shows that the average dependence degree is highest in 2018 (0.74) over these 3 years, and the minimum value was 0.59 in 2017. The maximum difference of the dynamic condition correlation coefficient reached 0.6371, and there were some sharp fluctuations at some time nodes.

Policy and economic changes can lead to fluctuations in dynamic conditional correlation coefficients. Policy uncertainties mainly affect the correlations through national economic policies and international trade policies. Sudden international trade policy changes, such as the tariff increase during the trade war, have a short-term impact on this relationship, which is reflected in the sudden drops or surges in the dynamic condition correlation coefficient. The domestic industrial policy also impacts the relationship between carbon efficiency and wind power enterprise performance over short periods of time.

When the national policies are positive for the wind power industry, such as promoting a clean electricity quota system, market-oriented transactions, and urging the implementation of subsidies, the correlations have become tight; when the state adopts austerity policies for the wind power industry, such as restricting the addition of wind power projects and suspending applications for voluntary emission reduction projects, the dynamic condition correlation coefficient plummets. The impact of trade channels on the correlations is mainly reflected by the fluctuations of alternative energy prices of wind energy. When the prices of oil, coal, or steel rise or the clean energy sector falls, the dynamic condition correlation coefficient tends to decline gradually. The speculative psychology of investors is greatly affected by the macroeconomic environment and by short-term financial trends. The price of energy and the updated status of related policies may also face uncertain effects throughout the industrial life cycle. These effects will produce a series of deviations from the performance of the company and accumulate effects. As a result, energy companies fully understanding these impacts and actively paying attention to government industrial policies will avoid unnecessary deviations from plans, thereby achieving harmonious and stable sustainable development between the company and the environment.

Therefore, wind power enterprises should pay close attention to sudden trade policy changes and to changes in the macroeconomic environment, and they should respond to environmental uncertainties by formulating different business decisions. The government can establish an effective incentive mechanism for carbon emission efficiency and introduce a moderate competition mechanism into the electricity market. Then through low-carbon energy management, maintain the coordination and common development of economy and environment.

## 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

TZ: conceptualization, methodology, software, supervision, writing-reviewing and editing. XQ: data curation and writing-original draft preparation. All authors contributed to the article and approved the submitted version.

## FUNDING

This research was supported by the NSFC (Grant No. 71801224) and the Fundamental Research Funds for the Central Universities of P. R. China (20CX04002B).

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**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.

frontiers in Energy Research

ORIGINAL RESEARCH
published: 11 September 2020
doi: 10.3389/fenrg.2020.577515

# The Impact of Policy Intensity on Overcapacity in Low-Carbon Energy Industry: Evidence From Photovoltaic Firms

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OPEN ACCESS

**Edited by:**
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**Reviewed by:**
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**Specialty section:**
*This article was submitted to Sustainable Energy Systems and Policies, a section of the journal Frontiers in Energy Research*

***Received:*** *29 June 2020*
***Accepted:*** *14 August 2020*
***Published:*** *11 September 2020*

**Citation:**
*Hu H, Tang P, Zhu Y, Hu D and Wu Y (2020) The Impact of Policy Intensity on Overcapacity in Low-Carbon Energy Industry: Evidence From Photovoltaic Firms. Front. Energy Res. 8:577515. doi: 10.3389/fenrg.2020.577515*

This study evaluates the impact of policy intensity on overcapacity using 55 listed photovoltaic (PV) firms from 2011 to 2019 in China. We divide PV industrial chain into three segments, which are upstream, midstream, and downstream. Results show that China's PV industry is diminishing returns to scale with low level of capacity utilization (20%). The enhancement of policy intensity can significantly promote overcapacity, but its impact varies in different policies and different enterprises. Fiscal subsidy has the largest positive effect in promoting overcapacity, followed by tax preference and land support. For three segments of PV industrial chain, fiscal subsidy, land support, and tax preference play a significant role in promoting overcapacity in each segment; the increase in financial support exacerbates overcapacity in midstream. The present study also tests the effectiveness of an important PV policy posed by the Chinese government in 2013. The results show that the policy is inefficient in the short term. Nevertheless, it promotes the development of PV industry in the long term. It takes a long time to reduce positive effect of policies on overcapacity. This study provides a guide for the government to make comprehensive use of different policies.

**Keywords: photovoltaic industrial chain, low-carbon energy, capacity utilization, overcapacity, policy intensity, subsidy**

## INTRODUCTION

Overcapacity in industrial production has become a huge drag on Chinese economic growth. As the growth rate of economy gradually slows down, its harm has also been increasingly apparent. From a microperspective, overcapacity is reflected in low-capacity utilization of enterprises, which will directly lead to the deterioration of their operation. From a macroperspective, large-scale and sustained overcapacity could lead to economic recession.

Some Chinese scholars believe that, in addition to the cyclical factors of economy, another important cause of overcapacity is the improper intervention of local governments (Zhang et al., 2017; Yang et al., 2019). This improper intervention shows in blindly following central government's instructions to carry out industrial planning while ignoring local development needs (Dai and Cheng, 2016; Wu S. et al., 2016; Zhou et al., 2017). Such tendency often leads to two consequences. First, industries that the government is eager to develop and support are more likely to witness overcapacity in a short time. Second, these industries are large in scale but insufficient in innovation ability and high risk of overcapacity exists.

In China, the National Development and Reform Commission and the National Energy Administration jointly issued *The Strategy for Energy Production and Consumption Revolution* (*2016–2030*). The document pointed out that we should adhere to the production and consumption of renewable energy, vigorously develop low-carbon industries, and reduce environmental damage. It also suggested promoting renewable and low-carbon energy development, for example, focusing on research and development of solar cell materials, photovoltaic conversion, and smart photovoltaic power stations. The renewable energy power generation in China, covering wind power, small hydropower, and solar photovoltaic, has experienced tremendous growth in the last decade (Zhao et al., 2013, 2016; Yi and Liu, 2014; Hu et al., 2015, 2018; Sahu, 2015; Xue, 2017). As a late entrant, the Chinese PV manufacturing sector has managed not only to catch up but also to become the world leader in the PV industry (Huo and Zhang, 2012; Huang et al., 2016; Lin and Chen, 2020). The dominance of photovoltaic among renewable energy technologies is owed mostly to its noiselessness, non-toxic emission, and relatively simple operation and maintenance (Moosavian et al., 2013). One square meter of PV power generation system installation is equivalent to 100 $m^2$ of afforestation in terms of carbon emission reduction. Photovoltaic power generation is a low-carbon energy and has significant environmental protection and economic benefits (Lei et al., 2019; Ouedraogo and Yamegueu, 2019; Sovacool et al., 2020; Walch et al., 2020).

However, it cannot be ignored that the rapidly developing photovoltaic industry is facing the dual pressure of overcapacity and deteriorating international trade environment (Sun et al., 2014; Wang et al., 2014, 2016, 2018; Shen and Luo, 2015). The industrial overcapacity problem is more prominent in China's solar PV sector than in the wind sector (Zhang et al., 2013). The excess capacity of Chinese photovoltaic enterprises is characterized by concentrated low-end links in the industrial value chain, surplus of various photovoltaic products, low-efficiency capacity cluster in the short run, and staged excess capacity (Zhao et al., 2015; Yang et al., 2017). Overcapacity is seriously affecting healthy development of the industry, resulting in a waste of resources. PV product prices and capacity utilization continued to decline; many companies fell into operating difficulties. Some giant PV enterprises, like SUNTECH and LDK, had been ruled by the local court to bankruptcy.

In this case, the Chinese government issued successive adjustment and transformation policies. In 2013, the State Council issued *Some Suggestions on Promoting the Healthy Development of Photovoltaic Industry* (hereinafter referred to as *Suggestions*). The main contents of *Suggestions* can be summarized as expanding the domestic PV market, controlling total PV capacity, and improving industrial technology level. This policy can improve the capacity utilization rate of PV industry, save materials and energy, and promote the healthy development of PV industry. Furthermore, since local officials in governments paid too much attention to gross domestic product (GDP) in their assessment and promotion, the central government has repeatedly stressed downplaying the GDP assessment. It aims to strengthen the inspection to local economic structure, resource consumption, and environmental protection rather than GDP and the economic growth rate. By 2014, more than 70 counties and cities had abolished the GDP assessment.

However, the effectiveness of *Suggestions* is full of doubt. According to the statistics of Chinese PV Industry Association, in 2015, the average capacity utilization of PV industry was only 77%, which was lower than the international empirical judgment on the normal range of 79–83%. Average capacity utilization of enterprises with an annual output below 200 MW was only about 50% (Wu et al., 2019).

Why does the policy restraining overcapacity of PV industry still play no role in mitigating overcapacity under the tight control? In the literature, the effect of government intervention on overcapacity has been fully studied, but most studies focus on overall industry while they ignore the research on a single industrial chain. Since characteristics vary in terms of different segments of PV industrial chain, government intervention efforts are also varied. Therefore, this study starts from the effect of government intervention on overcapacity of PV enterprises and tries to explore different effects of industrial policy on the three industrial segments. We calculate the capacity utilization rate of China's PV industry in recent years by applying production function. The empirical results show that the enhancement of policy intensity can significantly promote overcapacity, but its impact varies in different policies and different types of enterprises. Furthermore, we tested the effectiveness of *Suggestions* issued by the Chinese government in 2013 by piecewise regression. Hence, this article could provide basis for the reform of government in recent years.

This paper has three contributions. First, it calculates capacity utilization using the production function method, and it estimates the capacity utilization of the PV industry, which provides a clear explanation of the PV industry's overcapacity. Second, we provide new estimation of capacity utilization rate. We find that the capacity utilization rate calculated by the latest data is lower than that in the literature. It means the overcapacity is worsening, which should be attached more importance. Third, it also analyzes the correlation of policy intensity and overcapacity in the low-carbon energy industry and analyzes the different policy instruments' effects. It studies the effect of different policy intensity on overcapacity of different enterprises. The paper provides a basis for the government to make comprehensive use of different policy instruments. Fourth, this paper investigates the effectiveness of an important PV policy in 2013 via piecewise regression. it is the first study to test the effectiveness of *Suggestions* issued by the Chinese government in 2013.

The rest of the study is organized as follows. *Literature Review* lays out a review of relevant literature. *Empirical Model* introduces the methods used in the empirical studies. *Data and Variables* gives an introduction to data source, sample selection, and variable definition. *Empirical Results* reports the measurement of capacity utilization and the empirical regression results. *Extended Regression* tests the effectiveness of *Suggestions*. The final section provides the main conclusions.

## LITERATURE REVIEW

### Theoretical Causes of Overcapacity in PV Industry

For the sake of coping information asymmetry, preventing potential entrants and conspiring, enterprises have motivation to maintain excess capacity (Kamien and Schwartz, 1972; Zhong and Pan, 2014). Accordingly, a certain degree of overcapacity is normal. Lin et al. (2010) put forward a classic argument that the advantage of backwardness in developing countries makes it easy for enterprises to form correct consensus on the industry with good prospects, causing "Wave Phenomena" of investment and forming overcapacity.

For overcapacity in PV industry, most researchers believe that periodical overcapacity, structural overcapacity, and institutional overcapacity coexist. In China, institutional overcapacity is the main performance. The initial motivation that the government supported PV industry was to adjust industrial structure and stimulate economic growth. But as a policy maker, the central government has a principal–agent relationship with the local government, the policy executor who seeks to maximize its own utility. Under the double principal–agent relationships between the central government, local governments, and enterprises (Holmstrom and Milgrom, 1991), local governments have strong impulsion to help enterprises expand in order to pursue performance in a GDP-centered promotion system. As a strategic emerging industry, PV has naturally become an expansion object favored by local governments (Zhao et al., 2011). This expansion impulsion is most evident in the critical period of promotion after 3–5 years' official tenure (Guo, 2009; Gan et al., 2015). Zhang et al. (2014) found that the massive overcapacity in the solar PV industry has largely been driven by the government's overzealous pursuit of industrial growth.

Meanwhile, local governments in economic transition gradually possess the ability to intervene the economy. After the Tax Sparing System Reform, local governments gained more stable and free power to control local finance. Ambiguous land property right, soft constraint of financial institutions, and serious defects in environmental protection system make it possible for local governments to mobilize funds, sacrifice environment, and blindly assist PV enterprises to expand their capacity (Geng et al., 2011). In spite of the widely accepted fact that the government's improper intervention contributes to overcapacity in PV industry, the strength and mode of government intervention vary in terms of different PV segments. Blonigen and Wilson (2010) proved that the industrial policy that provides protection and subsidy to upstream would increase production cost and reduce technical efficiency of downstream.

### Fiscal Subsidy and Overcapacity

Photovoltaic is a strategic industry mainly supported by the country. The central government of China has given huge amount of subsidy to PV investment in a long period, causing a national investment boom in PV industry. In the early stage of the boom, the governmental subsidies can promote the technological innovation and the growth of photovoltaic enterprises and maximize the social and economic effects (Xiong and Yang, 2016; Zhang, 2018; Lin and Luan, 2020). Nevertheless, the government uses the subsidize-in-advance approach and one-size-fits-all approach to subsidize without supervision and neglecting the particularity of different enterprises. Therefore, under another principal–agent relationship between local governments and enterprises, subsidies flow to capacity expansion rather than technical innovation. Many researches indicate that government subsidies and investment contribute to overcapacity (Zeng et al., 2014; Chen, 2015; Lei, 2017). China's investment policy, regarded as subsidy, on PV industry investment should be reduced properly or even canceled, or at least, it should be combined with deployment and R&D (Yuan et al., 2014). However, Qin and Song (2019) believed that the influence of government subsidies on excess capacity is not deep.

### Tax Preference and Overcapacity

As a strategic emerging industry, governments also provide PV industry large tax preferences. Most PV enterprises have been recognized as high-tech enterprise and can enjoy 15% corporate income tax reduction every year. For some start-ups, the government even promises their tax exemption in the first three operating year; they only need to pay half tax in the following 3 years. In order to encourage export, the government adopts "exemption, offset, and refund" policy for the export of PV products; tax reimbursement rate is 5–17% (Wu T. et al., 2016; Zhang, 2018). Notice on the added-value tax policy of photovoltaic power generation rules that PV solar products enjoy 50% added-value tax reimbursement rate. These policy rules mean an extremely low tax burden for PV enterprises in comparison with other industries. For a strong green policy, a tax is the dominant instrument to achieve environmental goals (Droge and Schroder, 2005). However, tax preference may cause other problems. Janeba (2000) sets a mathematical model and proves that tax competition that reduces tax rate will result in overcapacity.

### Financial Support and Overcapacity

Since 1983, governments providing low-interest loans to state-owned enterprises has become a common phenomenon. Currently, local governments usually guide investment by applying the "loan with interest rate discount" and "financial products." Once a bank credit is obtained at a low interest rate, the proportion of owned capital in total capital would reduce. Jiang et al. (2012) proved that the decrease in owned capital will externalize business risk and increase the probability of overcapacity. In the PV industrial chain, local governments and banks are also more inclined to lend to enterprises in the upstream and midstream, which can help to push GDP forward in the short run.

## LAND SUPPORT AND OVERCAPACITY

In China, the local government is usually the main constitutor of local land prices. The ambiguous land property right also provides possibility for the government to allocate land.

Incentives such as low-interest loans and land at reduced cost provided by local governments have largely targeted at enhancing GDP and employment. Indeed, these policies appear to have been successful in assisting Chinese solar PV power manufacturers to rapidly expand over a short period of time (McCarthy, 2014). In addition, once receiving land, PV enterprises can utilize them to obtain mortgage loan from a bank, reducing the proportion of owned capital, thus increasing the probability of overcapacity. Huang et al. (2015) find that the distortion of land price has a significant effect on overinvestment in enterprises, and it has greater effect on enterprises with more new land assets.

## EMPIRICAL MODEL

### Measurement Model of Capacity Utilization

The common calculation methods of capacity utilization include direct measurement method, peak-to-peak, cost function method, data envelopment analysis, and production function method. These methods have been widely used in previous studies (Klein and Preston, 1967; Charnes et al., 1979; Morrison and Berndt, 1981; Fare et al., 1989; Garcia and Newton, 1997). This study chooses production function method to measure potential output of enterprises. The reasons are as follows: compared with peak-to-peak, this method is not only more accurate but also can analyze the contribution rate of each input factor. Compared with DEA, production function method avoids the problem of weight setting. Compared with cost function method, the production function method does not need to consider factor prices but only need to use capital, labor, and output data, which makes it more direct and objective. Moreover, the production function method is set on the basis of growth theory, so it has a solid theoretical foundation.

It is necessary to set production function form first. In this study, production function is set as the most commonly used Cobb–Douglas production function:

$$Y_{i,t} = f\left(K_{i,t}, L_{i,t}\right) = A_i K_{i,t}^{\alpha} L_{i,t}^{\beta} e^{-\mu},\ \ \mathrm{i} = 1, 2, 3;\ \ \mathrm{t} = 1, 2, \ldots, \mathrm{T} \tag{1}$$

where $i$ presents three different segments in the PV industry chain, and $t$ is for sample years. $Y$ is the output of an enterprise, and we measure $Y$ using operating receipt. $A$ is the Solow Residual, which represents the level of technology and is generally considered to be a constant in the short run. $K$ the is capital used by the enterprise, and we measure $K$ using annual net fixed assets. $L$ is the corresponding labor use. We use annual headcount as an indicator of labor use. $\mu$ is the residual. We assume that it is mutually independent and obeys the standard normal distribution. $\alpha$ and $\beta$ are the output elasticity of capital and labor, respectively. If $\alpha + \beta = 1$, it is constant returns to scale; if $\alpha + \beta < 1$, it is decreasing returns to scale; if $\alpha + \beta > 1$ with $\alpha, \beta < 1$, it is increasing returns to scale. Take the logarithm to Eq. (1):

$$\ln Y_{i,t} = lnA + \alpha lnK_{i,t} + \beta lnL_{i,t} - \mu \tag{2}$$

Let $lnA = \delta$, $E(\mu) = \varepsilon$, since $E(\varepsilon - \mu) = 0$, perform OLS on Eq. (2):

$$ln\hat{Y}_{i,t} = \hat{\alpha} lnK_{i,t} + \hat{\beta} lnL_{i,t} + \left(\delta - \hat{\varepsilon}\right) \tag{3}$$

Eq. (3) is the average production function. Adjusting the constant (namely $lnA$), the estimated value of $\bar{\varepsilon}$ can be obtained by the next equation:

$$\begin{aligned}\hat{\varepsilon} &= \max\left(\ln Y_{i,t} - \ln\hat{Y}_{i,t}\right)\\ &= \max\left\{lnY_{i,t} - \left[\hat{\alpha} lnK_{i,t} + \hat{\beta} lnL_{i,t} + \left(\delta - \hat{\varepsilon}\right)\right]\right\}\end{aligned} \tag{4}$$

Return to Eq. (3) and get the estimated value of $\hat{\delta}$ : ()

$$\hat{\delta} = ln\hat{Y} - \hat{\alpha} lnK - \hat{\beta} lnL + \hat{\varepsilon} \tag{5}$$

Then, the estimated boundary production function is:

$$\hat{Y}_{i,t} = e^{\hat{\delta}} K_{i,t}^{\hat{\alpha}} L_{i,t}^{\hat{\beta}} \tag{6}$$

Thus, the capacity utilization is:

$$cu = Y_{i,t} / \hat{Y}_{i,t} \tag{7}$$

### Regression Model Setting and Variables Measurement

Applying alternative indicators to measure policy is frequently used to measure policy intensity. Yu and Lv (2015) used enterprises' subsidized income to measure government subsidy and used cash inflow in fund-raising activities to represent financial support level. Zhang et al. (2017) used currency investment and tax subsidies to represent government interventions. In this paper, we select alternative indicators to quantify policy intensity. Given the multidimensional feature of policy instruments, we take all the four main policy tools into consideration.

Based on the above analysis, we construct the following regression model to examine the impact of government policy intensity on overcapacity of PV enterprises:

$$ovcp_t = \beta_0 + \beta_1 subsidy_{t-1} + \beta_2 tax_{t-1} + \beta_3 gainfund_{t-1} + \beta_4 land_{t-1} + \beta_5 X_{t-1} + \beta_6 \sum year + \sigma_t \tag{8}$$

where $ovcp_t$ is the enterprise's spare capacity at $t$, $subsidy_{t-1}$ is the fiscal subsidy obtained by the enterprise at $t-1$, $tax_{t-1}$ is the corresponding tax preference, $gainfund_{t-1}$ is financial support, $land_{t-1}$ is land support, $X_{t-1}$ is a series of control variables, and $\sum year$ is the dummy variable of year.

## DATA AND VARIABLES

### Data Source and Sample Selection

Photovoltaic is a heavy asset industry, which is categorized as two fields: PV manufacture and PV power generation. We divide

PV industry into three segments: upstream, midstream, and downstream. Upstream includes the extraction and manufacture of crystal silicon materials and related equipment. Midstream consists of the solar cell, solar component manufacture, and related equipment. Downstream contains the installation and establishment of the PV system.

We choose listed companies belonging to the concept of photovoltaic in Shanghai and Shenzhen A-share markets between 2011 and 2019 as the sample. Because a lot of data were missing before 2011, we excluded the enterprises that enter the photovoltaic field later than 2011 or those with serious lack of financial data. Finally, we have 55 PV enterprises altogether. According to the first main business of the listed company, we classify them into upstream, midstream, and downstream of PV industry. Twelve of them belong to the upstream, 22 companies belong to the midstream, and 21 enterprises belong to the downstream. Referring to Yu and Lv (2015) research, this study also adjusts operating receipt and estimated potential output on the basis of Industrial Producer Price Index in 2011; other financial data are also adjusted on the basis of Fixed Asset Investment Price Index in 2011. The list of photovoltaic concept public companies is from the Tonghuashun dataset. Other financial data and annual reports come from Wind database. Price indexes are from the National Bureau of Statistics of China. The statistical work of this study is completed by Excel 2019; graphics and tables are completed by Excel 2019; and regression analysis is completed by Stata16.0.

## Variable Definition

(1) Dependent Variables

We use the gap between estimated potential output and actual output, that is, (6) minus the operating receipt, as dependent variable. We define this value as spare capacity, which indicates the gap that enterprises fail to achieve their maximum output due to various reasons. Considering the stability problem of microdata, we take the logarithm to the difference.

(2) Independent Variables

According to the analysis above, this study uses the four main policies (fiscal subsidy, tax preference, financial support, and land support) as independent variables. These four policies can represent the overall policy intensity of government intervention to PV industry. We use government subsidy in non-recurring profit and loss to represent fiscal subsidy, use tax returns in cash flow statements to represent tax preference, use cash inflow in fund-raising activities in cash flow statements to represent financial support, and use land-use right in intangible assets to represent land support. In order to keep the data stable and unify statistical unit, the above variables are taken into the logarithm. Furthermore, considering the time-lag effect of policy on the influence of overcapacity (Hu et al., 2014), the above independent variables are all lagged one period behind.

(3) Control Variables

Enterprise investment decision is not only determined by government policies but also affected by the factors of enterprises themselves. Therefore, these two effects need to be separated. With regard to the enterprise characteristics that affect its investment level, this study refers to the setting of enterprise investment in Richardson (2006) study over the investment model. We use enterprise duration (age), enterprise growth (growth), enterprise asset–liability ratio (lev), enterprise stock yield (ret), and year dummy variables (year) to control the normal investment of enterprises. Since all enterprises belong to the PV industry, the industry dummy variable is omitted. We use accumulated listed year of enterprise, from the listing year to 2019, to represent enterprise duration, and use growth rate of operating receipt to represent enterprise growth. In order to make regression results easier to analyze, enterprise growth opportunity, enterprise asset–liability ratio, and enterprise stock yield are magnified 100 times. The entry of year dummy variable mainly aims to control the impact of economic fluctuations at home and abroad. Referring to the original model, the above control variables are also lagged one period behind except year.

(4) Instrumental Variables

Since there is a positive correlation between subsidy and revenue, considering the possible endogenous problem in the regression model, we use some instrumental variables. The ultimate purpose of government intervention is to achieve its economic, political, and social goals. Compared with private enterprises, state-owned enterprises need to bear a greater "policy burden." Meanwhile, state-owned enterprises can get more government financial support (Yu and Lv, 2015). The size of the firm also affects the subsidy received each year. The enterprise size and type will not directly affect capacity utilization of enterprises. Therefore, we choose enterprise size (size) and enterprise type (state) as instrumental variables. We use the log of total assets to represent enterprise size. As for enterprise type, state-owned enterprises are set at 1 and non-state enterprises are set at 0. **Table 1** shows the definition and calculation method of each variable.

# EMPIRICAL RESULTS

## Measurement of Capacity Utilization

This study uses a balanced panel data to estimate capacity utilization of PV enterprises. Due to the heterogeneity between enterprises, the direct use of OLS could bring about autocorrelation and heteroskedasticity problems. Thus, we use panel corrected standard error (PCSE) to estimate the potential capacity. The estimated average production function is as follows:

$$lnY = 4.035 + 0.253lnK + 0.678lnL$$
$$(27.33) \quad (21.46) \quad (33.91) \tag{9}$$

Parentheses below Eq. (9) report the z statistical value of three parameters, which are significant at the level of 1%. Furthermore, the frontier production function is:

$$Y = e^{5.953}K^{0.253}L^{0.678} \tag{10}$$

Estimated production function shows that the output elasticity of labor is 0.678, which is higher than the capital's output elasticity of 0.253. It means that the contribution rate of labor to output growth is higher than the capital. One fact that it may indicate is

**TABLE 1 |** Variable definitions and calculation methods.

| | Name | Abbreviation | Measurement method |
|---|---|---|---|
| Dependent Variable | Idle capacity | *ovcp* | Ln[(9)-operating receipt] |
| Independent variable | Fiscal subsidy | *subsidy* | Non-recurring profit and loss—ln(government subsidy) |
| Independent variable | Tax preference | *tax* | Cash flow statements—ln(tax returns) |
| Independent variable | Financial support | *finance* | Cash flow statements—ln(cash inflow in fund-raising activities) |
| Independent variable | Land support | *land* | Intangible assets—ln(land use right) |
| Control variable | Enterprise duration | *age* | Total listed years, from listing time to 2019 |
| Control variable | Enterprise growth | *growth* | Growth rate of operating receipt × 100 |
| Control variable | Enterprise asset-liability ratio | *lev* | Asset–liability ratio = total liability/total asset × 100 |
| Control variable | Enterprise stock yield | *ret* | Profit statement—basic earnings per share × 100 |
| Control variable | Year dummy variables | *year* | Set 2011 as reference group; 2012–2019 as the other one |
| Instrumental variable | Enterprise size | *size* | Balance sheet—total assets |
| Instrumental variable | Enterprise type | *state* | Set state-owned enterprises as 1 and non-state enterprises as 0 |

**TABLE 2 |** Capacity utilization of photovoltaic (PV) from 2011 to 2019.

| | Whole industry | | | Upstream | | | Midstream | | | Downstream | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Min** | **Max** | **Mean** | **Min** | **Max** | **Mean** | **Min** | **Max** | **Mean** | **Min** | **Max** | **Mean** |
| | **(%)** | **(%)** | **(%)** | **(%)** | **(%)** | **(%)** | **(%)** | **(%)** | **(%)** | **(%)** | **(%)** | **(%)** |
| 2011 | 4.89 | 68.67 | 17.31 | 6.57 | 42.62 | 20.59 | 4.89 | 51.73 | 15.23 | 5.42 | 68.67 | 17.63 |
| 2012 | 3.20 | 40.84 | 13.94 | 3.20 | 40.84 | 13.77 | 5.20 | 37.83 | 12.03 | 6.26 | 25.58 | 16.04 |
| 2013 | 3.58 | 40.00 | 14.84 | 3.58 | 36.45 | 14.53 | 4.79 | 36.28 | 12.86 | 5.60 | 40.00 | 17.09 |
| 2014 | 2.39 | 100.10 | 17.52 | 2.39 | 36.62 | 16.03 | 4.64 | 100.10 | 18.03 | 4.64 | 52.63 | 17.83 |
| 2015 | 3.91 | 68.75 | 17.68 | 3.91 | 37.37 | 15.02 | 4.47 | 39.87 | 15.82 | 5.17 | 68.75 | 21.15 |
| 2016 | 2.99 | 59.22 | 19.27 | 2.99 | 38.61 | 15.98 | 5.88 | 54.09 | 18.03 | 4.05 | 59.22 | 22.44 |
| 2017 | 4.16 | 56.55 | 20.63 | 4.67 | 34.16 | 16.70 | 6.99 | 56.55 | 20.01 | 4.16 | 52.57 | 23.53 |
| 2018 | 0.45 | 70.56 | 21.64 | 0.45 | 44.08 | 19.50 | 9.61 | 70.56 | 21.02 | 5.10 | 56.01 | 23.53 |
| 2019 | 1.04 | 58.18 | 21.68 | 1.04 | 34.54 | 17.95 | 10.57 | 58.18 | 22.07 | 5.10 | 56.22 | 23.40 |
| N | | 495 | | | 108 | | | 198 | | | 189 | |

that, in spite of years of development, China's PV industry still relies heavily on labor input; most enterprises assemble at the bottom of the value chain. The sum of two elasticities is 0.931 and is $<1$, which means that China's PV industry is an industry of diminishing returns to scale, and the only way to improve productivity is innovation.

**Table 2** and **Figure 1** list the capacity utilization of China's PV industry between 2011 and 2019. The capacity utilization estimated by the production function method is the relative value rather than the absolute value. Therefore, the capacity utilization calculated in this study is lower than the actual value but can be compared between enterprises. We conclude from the statistics that:

Overall, the capacity utilization of PV industry in China is generally low during the study period; overcapacity exists in every segment. Among the three segments, overcapacity is serious in both midstream and upstream. Downstream has the highest capacity utilization. These all present structural overcapacity, which are also consistent with the economic facts.

For the upstream, although China is huge in silicon chips (which take over more than 90% of the whole world), due to the lack of technical input for purifying polysilicon materials, domestic enterprises are higher in production costs and poorer in product quality. Polysilicon is still heavily dependent on imports, resulting in the coexistence of import and excess. Recently, with the improvement of technical level of domestic enterprises, the cost of production of some advanced enterprises has been lower than that of foreign competitors. This will gradually ease the overcapacity situation in the upstream.

For the midstream, as solar cells and PV modules are mainly for export, the productivity utilization of midstream is kept at a low level in the case of the slump of international market and overlay of trade barriers. Although the situation has gradually improved since 2015, the capacity utilization of midstream is still at a low level.

For the downstream, since it faces customer directly, this part performs better in capacity utilization. But in recent years, there are still more and more enterprises blindly constructing power plants. According to data released by the State Energy Bureau, the average rate of discarding PV power plants among the Northwest five provinces reached 14.1% in 2017, up to 26.5%, which made the overcapacity situation in downstream also aggravated.

Since Europe and the United States launched some antidumping and countervailing actions, China's PV industry suffered a serious shock. The capacity utilization of the industry dropped 3.37%. Among the three segments, capacity utilization

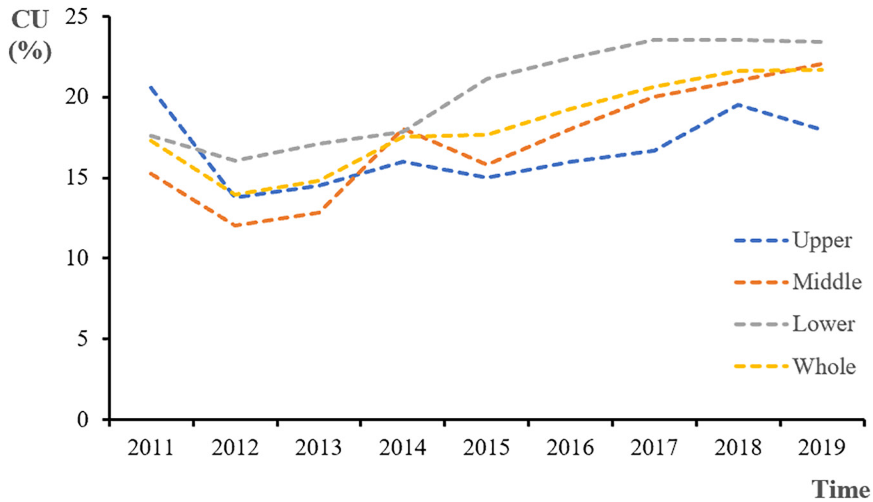


**FIGURE 1 |** Variation of photovoltaic (PV) capacity utilization through 2011–2019.

of upstream enterprises fell most dramatically, which decreased by 6.82%; while the downstream enterprises are relatively less affected. The utilization rate started to rise slowly from 2015, probably mainly because of rising demand. On the one hand, domestic demand is growing rapidly. On the other hand, the implementation of One Belt and One Road strategy has brought about a rebound in international market demand. However, the overall level is still not satisfactory. Capacity utilization of 95% enterprises is centralized below 70%.

## Basic Regression Analysis

In this section, this study uses a balanced panel data of PV enterprises to establish four panel models and then carries out basic regression analysis on the overcapacity situation about the three segments and the whole PV industry (see **Table 3**). Through Hausman test, this study uses fixed effect to regress models (1) and (4) and uses random effect to regress models (2) and (3). In order to provide a robust result, this study uses robust standard error in each model.

Considering the endogeneity of subsidy, this study chooses enterprise state and size as the instrumental variables of subsidy. This study uses the generalized method of moments (GMM) to re-regress models (1)–(4). Since GMM is a robust estimation method whose assumptions are weak; the autocorrelation and heteroscedasticity can be allowed (see **Table 4**). The number of instrumental variables is more than the number of endogenous variables, which means that there is an overidentification problem. According to the results of the Sargan test, there is no over identification problem in models (1)–(3). In model (4), due to the collinearities, the instrumental variable (state) is dropped, and there is no overidentification problem in model (4). The $p$ value of LM statistics is $<0.01$, indicating that there is no underidentification problem. The value of Cragg-Donald Wald F shows that the instrumental variables are valid.

Results in column (1) of **Table 3** show that the coefficients of four explanatory variables are all positive and significant. It means that no matter which policy is, the enhancement of policy intensity has exacerbated overcapacity of PV industry. The generalized method of moments (IV-GMM) regression results in **Table 4** are largely consistent with it. Specifically, the most "powerful" policy is *subsidy*, coefficient of which is 0.638 and is

**TABLE 3 |** Basic regression results.

| Ovcp | Whole industry (1) | Upstream (2) | Midstream (3) | Downstream (4) |
|---|---|---|---|---|
| Subsidy | 0.122*** | 0.227*** | 0.094*** | 0.158*** |
| | (0.018) | (0.047) | (0.022) | (0.035) |
| Tax | 0.059*** | 0.050*** | 0.037*** | 0.090*** |
| | (0.009) | (0.018) | (0.012) | (0.019) |
| Finance | 0.022** | 0.004 | 0.045*** | 0.014 |
| | (0.010) | (0.023) | (0.017) | (0.014) |
| Land | 0.213*** | 0.395*** | 0.179*** | 0.221*** |
| | (0.030) | (0.070) | (0.033) | (0.069) |
| Age | 0.000 | −0.025 | 0.044** | 0.000 |
| | (0.000) | (0.023) | (0.020) | (0.000) |
| Growth | 0.001 | 0.000 | 0.001* | 0.000 |
| | (0.000) | (0.001) | (0.001) | (0.001) |
| Lev | 0.007*** | 0.010*** | 0.007*** | 0.004 |
| | (0.001) | (0.003) | (0.002) | (0.003) |
| Ret | −0.001** | −0.001 | −0.000 | −0.001 |
| | (0.000) | (0.001) | (0.001) | (0.001) |
| Year | −0.170*** | −0.291*** | −0.154** | −0.100 |
| | (0.046) | (0.103) | (0.066) | (0.084) |
| Constant | 10.030*** | 8.001*** | 9.969*** | 9.618*** |
| | (0.267) | (0.557) | (0.386) | (0.592) |
| Observation | 495 | 108 | 198 | 189 |
| Method | FE | RE | RE | FE |
| $R^2$ | 0.658 | 0.798 | 0.614 | 0.650 |

*t/z statistics in parentheses. *p < 0.1; **p < 0.05; **p < 0.01.*

**TABLE 4 |** Instrumental variable–generalized method of moments (IV-GMM) regression results.

| | Whole Industry | Upstream | Midstream | Downstream |
|---|---|---|---|---|
| Subsidy | 0.638*** | 1.169*** | 0.521*** | 0.476*** |
| | (0.081) | (0.197) | (0.117) | (0.112) |
| Tax | 0.030** | −0.061 | 0.044** | 0.055** |
| | (0.015) | (0.044) | (0.018) | (0.024) |
| Finance | −0.029 | −0.084 | −0.042 | −0.010 |
| | (0.019) | (0.047) | (0.035) | (0.024) |
| Land | 0.020 | −0.132 | 0.097 | 0.079 |
| | (0.058) | (0.137) | (0.080) | (0.092) |
| Age | 0.010 | −0.056*** | 0.035*** | 0.010 |
| | (0.006) | (0.019) | (0.009) | (0.009) |
| Growth | 0.000 | 0.002 | 0.005*** | −0.003* |
| | (0.001) | (0.002) | (0.002) | (0.001) |
| Lev | 0.003* | 0.016*** | 0.001 | 0.005 |
| | (0.002) | (0.005) | (0.003) | (0.003) |
| Ret | −0.001 | −0.004*** | −0.002** | 0.001* |
| | (0.247) | (0.001) | (0.001) | (0.001) |
| Year | −0.035 | −0.407* | 0.074 | 0.024 |
| | (0.104) | (0.243) | (0.149) | (0.154) |
| Constant | 8.766*** | 7.731*** | 8.833*** | 8.861*** |
| | (0.244) | (0.660) | (0.394) | (0.361) |
| Observation | 495 | 108 | 198 | 189 |
| Method | GMM | GMM | GMM | GMM |
| $R^2$ | 0.487 | 0.596 | 0.519 | 0.563 |
| F | 75.85*** | 23.70*** | 28.93*** | 32.97*** |
| LM | 74.274*** | 23.767*** | 25.458*** | 32.565*** |
| Cragg–Donald Wald F | 42.735 | 13.684 | 13.802 | 37.262 |
| Sargan | 0.267 | 3.014* | 5.363** | Exactly identified |

*t/z statistics in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.*

significant at the level of 1%. The possible reason is that it is difficult to supervise the use of funds because of the improper subsidize ways, such as "subsidize in advance" and "one size fits all." When one enterprise obtains government's industrial support fund, scientific research subsidy, or project subsidy, it has incentive to use funds for short-term expansion, which makes the effect of *subsidy* is not ideal. Furthermore, under another principal–agent relationship between local governments and enterprises, subsidies flow to capacity expansion rather than technical innovation (Zeng et al., 2014; Chen, 2015; Lei, 2017). The second one is *tax*, whose coefficient is 0.030 and is significant at the level of 5%. Possibly because the government provides PV industry large tax preferences. In comparison with other industries, the tax burden on the PV industry is relatively low. Therefore, low-tax burden would attract many enterprises to enter the photovoltaic field and increase the overcapacity (Haley and Haley, 2013; Shi et al., 2018). The third one is *land*; its coefficient is 0.020 with a low significance level. This indicates that when the land-use right of PV enterprises increases by 1%, spare capacity will increase by 0.020% on average. It is found in some annual reports that enterprises take some land as collateral to get loans from banks (Shepherd, 2016). The last one is *finance*, whose policy effect in IV-GMM is contrary to our expectation, but it is not significant.

The study turns to regression of four policies on three segments of PV industry; see models (2)–(4). The following can be concluded:

In columns (2)–(4), the coefficients of fiscal subsidy are all positive with the significance level of 1%, which indicates that fiscal subsidy leads to overcapacity in the three segments of PV industry. Specifically, the coefficient of *subsidy* is 1.169, 0.521, and 0.476 in upstream, midstream, and downstream, respectively (see **Table 4**). The positive effect of fiscal subsidy on overcapacity of upstream enterprises is greatest and that of downstream enterprises is lightest (Zhang et al., 2017). The potential reason is that the entry threshold of PV enterprises in upstream and midstream is low, and they can obtain return in a short time. Most of fiscal subsidies flood to the PV enterprises of upstream and midstream with the aim of massive production. Therefore, fiscal subsidy leads to the capacity expansion of PV enterprises rather than technological innovation, and the overcapacity in upstream and midstream is greater than in downstream.

The coefficient of *tax* in midstream and downstream is positive and significant at the level of 5% (see **Table 4**). The effect of *tax* on spare capacity of upstream is contrary to the result of basic regression, but it is not significant. The coefficient of *tax* in model (3) is 0.044, indicating that when tax policy intensity increases by 1%, spare capacity of enterprises in midstream would increase 0.044% on average. The coefficient of *tax* in model (4) is 0.055, which means that for every 1% increase in tax policy intensity, idle capacity of enterprises in downstream would increase 0.055% on average. The one possible reason is that tax preference makes enterprises have more capital to support massive production. Another significant reason could be that tax preference attracts more enterprises entering photovoltaic field (Zhang et al., 2018).

Financial support has positive effect on spare capacity of PV enterprises in upstream and downstream with a low significance level and in midstream at the level of 1% (see **Table 3**), which means that financial support results in the overcapacity of PV enterprises. The financial support reduces the capital cost of PV enterprises and further helps them expand (Jiang et al., 2012). The result of IV-GMM is contrary to it, but not significant.

The coefficient of land support in models (2)–(4) is positive with the significance level of 1% (see **Table 3**). It indicates that land support is also a negative policy in reducing overcapacity. The land support would attract more enterprises to establish factories, which would give rise to redundant construction and overcapacity. In addition, the PV enterprises can use land to obtain mortgages from banks, reduce their own capital, and expand capacity. The results of IV-GMM are not significant.

With respect to other control variables, *age* is significant in models (2) and (3) but with opposite sign. It means that the effect of *age* is vague. Similarly, the effect of *growth* is also ambiguous. *Lev* is significant in model (2) with a positive sign. It indicates that *lev* has a positive effect on PV enterprises' spare capacity. The higher the *lev*, the less their own capital, so the PV enterprises are more inclined to expand capacity. *Ret* is significant in models (2) and (3), with a negative sign, which shows that *ret* could reduce PV enterprises' overcapacity. A high *ret* represents a good business status and strong competitiveness of PV enterprises, so enterprises with higher *ret* are not prone to excess capacity. It is worth noting that *year* is significant with a negative sign in model (2). It proves that comparing the spare capacity in 2011, the spare capacity is gradually reduced in recent years.

## EXTENDED REGRESSION

Facing the "chronic and stubborn" overcapacity in strategic emerging PV industry of China, the State Council issued *Suggestions* in July 2013. The main contents of *Suggestions* can be summarized as expanding domestic PV market, controlling total PV capacity, and improving industrial technology level. The policy varies much in terms of diverse segments of PV industrial chain. Specifically, for the upstream and midstream, polysilicon, solar cell, and component projects, which are newly declared by enterprises, are strictly controlled with the aim of expanding capacity, accelerating enterprises merger and reorganization, and raising the industry access threshold. For the downstream, major efforts are devoted to exploit PV applications on the user side, encourage local governments to use financial funds to support PV power generation, increase financial support, and provide more land to those PV power plants located in desert. As an important adjustment for PV industry, it has been more than 6 years since *Suggestions* was implemented, but few researches on PV have mentioned it. Thus, this study attempts to examine the implementation effect of the policy in this part.

Since all the observations in this study were affected by the policy at the same time, they cannot be divided into the control group and experimental group. Therefore, difference-in-difference (DID) method fails to evaluate policy effectiveness in this study. The study turns to the method of piecewise regression to compare the changes of estimation coefficients before and after the implementation of *Suggestions*. This study regards the implementation of *Suggestions* as a policy shock that took place in 2013. Considering the sample size matching and the time lag for the policy to take effect, this study regards year 2011–2013 as the investigation period before the occurrence of policy shock, the following 3 years, 2014–2016, as the investigation period after the shock occurred, and the following 3 years, 2017–2019, as the investigation period after the shock occurred to research the time effect of policy comparing with years 2014–2016.

**Table 5** shows the piecewise regression results of the whole PV industrial chain. Through the Hausman test, this study uses fixed effect to regress models (1) and (3) and uses random effect to regress model (2). In the first 3 years after implementing *Suggestions*, the coefficient of *subsidy* increased with the significance level of 1%. It indicated that the increase in fiscal subsidy would promote overcapacity. In the second 3 years after *Suggestions* was implemented, the coefficient of *subsidy* decreased with a low significance level. In 2014–2016, the coefficient of *tax* decreased with the significance level of 5% and then continued to decline in 2017–2019 but with a low significance level. The coefficient of *finance* decreased with a low significance level. In the first 3 years after *Suggestions* was implemented, the coefficient of *land* increased with the significance level of 1%. Then, the coefficient decreased in the second 3 years. Generally, on the one hand, the short-term effectiveness of *Suggestions* is not satisfactory. On the other hand, *Suggestions* will promote healthy development of PV industry in the long term. It takes a lot of time to reduce positive effect of policies on overcapacity.

**TABLE 5 |** Whole industry piecewise regression.

| | 2011–2013<br>(1) | 2014–2016<br>(2) | 2017–2019<br>(3) |
|---|---|---|---|
| Subsidy | 0.054** | 0.114*** | 0.041 |
| | (0.027) | (0.031) | (0.027) |
| Tax | 0.064*** | 0.035** | 0.013 |
| | (0.013) | (0.014) | (0.017) |
| Finance | 0.013 | 0.002 | 0.009 |
| | (0.015) | (0.012) | (0.015) |
| Land | 0.019 | 0.392*** | 0.300*** |
| | (0.064) | (0.055) | (0.076) |
| Age | 0.000 | 0.014 | 0.000 |
| | (0.000) | (0.013) | (0.000) |
| Growth | 0.001 | 0.001 | −0.001 |
| | (0.001) | (0.001) | (0.001) |
| Lev | 0.007*** | 0.004* | −0.008** |
| | (0.003) | (0.002) | (0.004) |
| Ret | −0.001** | −0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) |
| Year | −0.125*** | 0.000 | 0.000 |
| | (0.043) | (0.000) | (0.000) |
| Constant | 12.269*** | 8.829*** | 11.062*** |
| | (0.602) | (0.438) | (0.694) |
| Observation | 165 | 165 | 165 |
| Method | FE | RE | FE |
| $R^2$ | 0.451 | 0.656 | 0.571 |

*t/z statistics in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.*

**Table 6** shows the piecewise regression results of upstream. Through the Hausman test, this study uses random effect to regress models (1) and (2) and uses fixed effect to regress model (3). The coefficient of *tax* and *land* decreased in 2017–2019 with a low significance level compared to 2011–2013. It indicates that it would take some time for *Suggestions* to play positive effect on promoting healthy development of PV enterprises in upstream.

**Table 7** shows the piecewise regression results of midstream. Through the Hausman test, this study uses random effect to regress models (1) and (3) and uses fixed effect to regress model (2). After the *Suggestions* was implemented, the coefficient of *subsidy* decreased with a low significance level. In the first 3 years after the *Suggestions* was implemented, the coefficient of *tax* was negative, which means that *tax* had a positive impact on reducing overcapacity. However, the coefficient of *tax* increased between 2017 and 2019, which means that the positive effect of *tax* on reducing overcapacity was limited. The coefficient of *finance* first increased and then decreased, which means that the implementation of *Suggestions* helped reduce the positive impact of *finance* on

**TABLE 6 |** Upstream piecewise regression.

| | 2011–2013 (1) | 2014–2016 (2) | 2017–2019 (3) |
|---|---|---|---|
| Subsidy | 0.093 | 0.197** | 0.135 |
| | (0.067) | (0.084) | (0.100) |
| Tax | 0.013 | 0.075** | −0.087 |
| | (0.023) | (0.032) | (0.076) |
| Finance | −0.024 | 0.003 | 0.052 |
| | (0.042) | (0.022) | (0.042) |
| Land | 0.383*** | 0.192 | 0.355 |
| | (0.135) | (0.136) | (0.269) |
| Age | 0.027 | 0.006 | 0.000 |
| | (0.043) | (0.039) | (0.000) |
| Growth | 0.000 | 0.002 | 0.002 |
| | (0.001) | (0.001) | (0.002) |
| Lev | 0.012** | −0.001 | −0.030* |
| | (0.005) | (0.006) | (0.015) |
| Ret | −0.001 | −0.000 | −0.004* |
| | (0.001) | (0.001) | (0.002) |
| Year | −0.108 | 0.000 | 0.000 |
| | (0.090) | (0.000) | (0.000) |
| Constant | 8.823*** | 10.101*** | 11.120*** |
| | (1.203) | (1.091) | (2.025) |
| Observation | 36 | 36 | 36 |
| Method | RE | RE | FE |
| $R^2$ | 0.687 | 0.803 | 0.180 |

*t/z statistics in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.*

**TABLE 7 |** Midstream piecewise regression.

| | 2011–2013 (1) | 2014–2016 (2) | 2017–2019 (3) |
|---|---|---|---|
| Subsidy | 0.058* | 0.000 | 0.010 |
| | (0.033) | (0.028) | (0.036) |
| Tax | 0.028 | −0.031** | 0.028 |
| | (0.018) | (0.013) | (0.021) |
| Finance | 0.016 | 0.051** | 0.015 |
| | (0.025) | (0.022) | (0.024) |
| Land | 0.122** | 0.778*** | 0.434*** |
| | (0.051) | (0.102) | (0.087) |
| Age | 0.080*** | 0.000 | 0.035 |
| | (0.023) | (0.000) | (0.024) |
| Growth | 0.002** | −0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) |
| Lev | −0.000 | 0.002 | −0.003 |
| | (0.003) | (0.002) | (0.004) |
| Ret | −0.002*** | −0.002** | 0.002 |
| | (0.001) | (0.001) | (0.001) |
| Year | −0.110* | 0.000 | 0.000 |
| | (0.058) | (0.000) | (0.000) |
| Constant | 11.020*** | 6.205*** | 9.116*** |
| | (0.563) | (0.901) | (0.830) |
| Observation | 66 | 66 | 66 |
| Method | RE | FE | RE |
| $R^2$ | 0.620 | 0.537 | 0.586 |

*t/z statistics in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.*

**TABLE 8 |** Downstream piecewise regression.

| | 2011–2013 (1) | 2014–2016 (2) | 2017–2019 (3) |
|---|---|---|---|
| Subsidy | 0.063 | 0.135** | 0.171*** |
| | (0.046) | (0.061) | (0.038) |
| Tax | 0.104*** | 0.034 | 0.062*** |
| | (0.023) | (0.048) | (0.022) |
| Finance | 0.012 | 0.001 | −0.021 |
| | (0.022) | (0.020) | (0.019) |
| Land | 0.232* | 0.320** | 0.337*** |
| | (0.125) | (0.120) | (0.081) |
| Age | 0.039 | 0.000 | −0.012 |
| | (0.025) | (0.000) | (0.020) |
| Growth | −0.002 | 0.001 | −0.001 |
| | (0.002) | (0.001) | (0.001) |
| Lev | −0.011** | −0.002 | −0.003 |
| | (0.005) | (0.006) | (0.004) |
| Ret | −0.001 | −0.003 | 0.002*** |
| | (0.001) | (0.002) | (0.001) |
| Year | 0.030 | 0.000 | 0.000 |
| | (0.083) | (0.000) | (0.000) |
| Constant | 9.385*** | 9.842*** | 9.526*** |
| | (0.948) | (1.130) | (0.632) |
| Observation | 63 | 63 | 63 |
| Method | RE | FE | RE |
| $R^2$ | 0.648 | 0.455 | 0.762 |

*t/z statistics in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.*

overcapacity in a long time. Furthermore, the coefficient of *land* first increased and then decreased but still remained high. On the whole, the effectiveness of *Suggestions* is not satisfactory in midstream.

**Table 8** shows the piecewise regression results of downstream. Through the Hausman test, this study uses fixed effect to regress model (2) and uses random effect to regress models (1) and (3). The coefficient of *finance* decreased after *Suggestions* was implemented. Specially, the coefficient of *finance* showed a negative sign in 2017–2019. It denoted that the implementation of *Suggestions* would enable *finance* to play a positive role in reducing overcapacity. The coefficient of *tax* decreased and then increased a little, which means that the positive effect of *tax* was limited. It is a pity that the coefficient of *subsidy* and *land* increased after the *Suggestions* was implemented. It means the role of fiscal subsidy and land support in promoting overcapacity has been significant enhanced in downstream of PV industry.

## CONCLUSION

Based on the construction of overcapacity mechanism of PV industry in China, this study uses the data of 55 listed PV companies in Shanghai and Shenzhen A-share markets between 2011 and 2019. It aims to investigate the impact of policy intensity on overcapacity via production function and empirical model (9) and conduct the heterogeneity analysis by dividing the PV industrial chain into upstream, midstream, and downstream. Our main research work includes (1) using production function to estimate capacity utilization of PV enterprises, (2) analyzing the impact of major policies on overcapacity of PV industry, (3) conducting the heterogeneity analysis to estimate the impact of major policy instruments on different segments of PV industrial chain through piecewise regression, and (4) investigating the policy effectiveness of *Suggestions*.

The findings suggest that the following: first, China's PV industry belongs to the industry of diminishing returns to scale, and the improvement of economic efficiency depends on technological progress. Second, the capacity utilization rate of PV industry in China is generally low during the study period; overcapacity exists in every segment and presents structural overcapacity. The utilization rate has been rising slowly since 2015, probably mainly due to the increase in domestic demand and foreign demand. However, the overall level is still not satisfactory. Third, from 2011 to 2019, the increase in policy intensity exacerbates the overcapacity of PV industry. Fiscal subsidy has the largest positive effect in promoting overcapacity, followed by tax preference and land support. For the three segments of PV industrial chain, fiscal subsidy, land support, and tax preference play a significant role in promoting overcapacity in each segment; the increase in financial support exacerbates overcapacity in midstream. Finally, the short-term effectiveness of *Suggestions* is not satisfactory. However, *Suggestions* will promote healthy development of PV industry in the long term. It takes a lot of time to reduce positive effect of policies on overcapacity.

Based on the conclusions, we can draw the following recommendations.

First, the government needs to set up innovation-promoting incentives to encourage PV enterprises to conduct R&D activities and promote technological progress of enterprises. Technological progress can improve economic efficiency, save materials and costs, and improve competitiveness. China's PV industry is an industry of diminishing returns to scale, and the only way to improve productivity is innovation. The PV industry is urgent for independent research and development to convert "Made in China" into "Created in China."

Second, the government should pay attention to the increase in capacity utilization rate. The capacity utilization rate of PV industry in China is generally low during the study period. On the one hand, government should attach importance on the cultivation of talents in related majors. The talents can provide technical support for the increase in capacity utilization rate. On the one hand, for different enterprises and different production processes, the government should adopt different and well-directed policies.

Third, it is essential for the government to encourage small-scale and distribute solar photovoltaic power generation to expand the domestic demand. On the one hand, it can reduce overcapacity. on the other hand, it can reduce the dependence on the international market. In addition, enterprises should make scientific and reasonable production decisions to meet market demand. In 2020, the National Energy Administration issued a notice on the formulation of the 14th Five-Year Plan for the development of renewable energy. The 14th Five-Year is a critical period for wind and photovoltaic power generation to achieve full unsubsidized parity.

Fourth, the government should synthetically utilize various policies to achieve the purpose of promoting healthy development of the industry. For ineffective policy instruments, it should continue to perfect the implementation of policies and improve policy efficiency. Furthermore, it is necessary to reinforce demand-type policies and improve green certification transactions which are forms of incentive policies instead of subsidies (Yan et al., 2019; Zhou et al., 2020).

Finally, the government should deal with the inconsistency between central policy formulation and local policy implementation. Corwin and Johnson (2019) found that the future development of China's solar PV market will dependent upon enforcement of central policy and aligning the policy objectives and incentives between the central and local levels. Changing evaluation mechanisms is necessary for local government.

## DATA AVAILABILITY STATEMENT

All datasets presented in this study are included in the article/supplementary material.

## AUTHOR CONTRIBUTIONS

HH and YW finished the research and wrote the manuscript. PT and YW are responsible for data collection and analysis. YZ and DH worked with the other authors for the *Empirical Results*. All authors contributed to the article and approved the submitted version.

## ACKNOWLEDGMENTS

We would like to thank Ms. Y. Qu for great contributions to manuscript writing. Many thanks to Mr. Y. Wei, Dr. J. Yu, and Dr. B. Li for helpful comments.

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**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.

frontiers in Energy Research

ORIGINAL RESEARCH
published: 23 September 2020
doi: 10.3389/fenrg.2020.558536

# Water Use for Energy Production and Conversion in Hebei Province, China

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In recent years, with the socio-economic development, energy production and water consumption have been given more and more scientific, political and public concern. Taking Hebei Province, China as, an example, this paper performs an in-depth analysis of the energy production and water consumption. In this study, the water withdrawals and water consumption associated with energy production in Hebei Province from 2015 to 2050 were estimated by using the bottom-up Long-range Energy Alternative Planning model, which established three scenarios based on three different development models. The results show that the energy production and their associated water requirements would continue to grow at a high speed in the Reference Scenario. The energy production and their associated water withdrawals and water consumption were found to have decreased sharply in the coordinated development scenario and the strong emission reduction scenario compared to the reference scenario. It shows that industrial restructuring, energy structure optimization and the renewable energy replacement have played an important role in energy-efficient and water-efficient in coordinated development scenario and strong emission reduction scenario. Further coordinated management policy on water and energy should be fully considered to promote the sustainable management of water and energy in Hebei Province.

**Keywords: energy production, water requirements, energy–water nexus, Long-range Energy Alternative Planning model, Hebei**

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***Edited by:***
*Fan Tong,*
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***Reviewed by:***
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***Specialty section:***
*This article was submitted to Sustainable Energy Systems and Policies, a section of the journal Frontiers in Energy Research*

***Received:*** *03 May 2020*
***Accepted:*** *27 August 2020*
***Published:*** *23 September 2020*

***Citation:***
*Li X, Dong D, Lin G, Yan R and Li S (2020) Water Use for Energy Production and Conversion in Hebei Province, China. Front. Energy Res. 8:558536. doi: 10.3389/fenrg.2020.558536*

## INTRODUCTION

Water and energy resources are significant material foundations for the development of human society and a powerful driving force for the modernization process (Spang et al., 2014; Qin et al., 2015). However, in the context of global climate change and an increasing population, we are facing many problems regarding the demand for water resources and energy. The UN Sustainable Development Goals proposed in 2015 pointed out that, as the global economy grows year by year, despite the improvement in energy efficiency, energy use will have grown by 35% by 2020, and the world's energy consumption will increase by nearly 50% over the next 30 years (Bureau for Workers' Activities, 2014). At the same time, <3% of the world's water will be fresh, and it is estimated that two-thirds of the world's population will face water shortages by 2025 (Lu et al., 2015). Therefore, one of the objectives of the United Nations (UN) World Water Day, which has the theme of "Water and Energy," is to call on countries to implement more "coordinated, coherent, and consistent" sustainable development policies for energy and water resources.

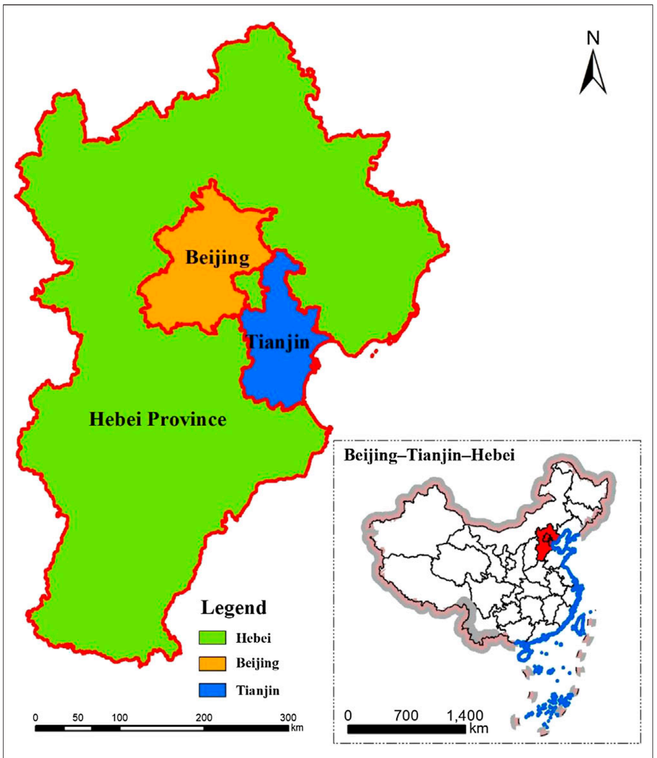


**FIGURE 1** | The location of the study region in China.

Hebei Province (E 113°27′–119°50′, N 36°05′–42°40′) is located on the shores of the Bohai Sea. Its inner ring contains the cities of Beijing and Tianjin, and it is one of China's primary industrial bases (**Figure 1**). It holds a critical strategic position in the integrated development of Beijing–Tianjin–Hebei (Jing-Jin-Ji). Hebei is a major energy and industrial center and faces population pressure, resource shortages, and environmental pollution. Hebei Province is rich in energy resources but seriously lacks water resources, and there is typically a serious mismatch between the energy and water resources distribution patterns. The energy industry is responsible for a large part of the water use of the industries in Hebei province. The exploitation and processing of traditional energy consumes a lot of fresh water every year, but Hebei Province is seriously deficient in water resources. The water resources per capita are 386 $m^3$, the water resources per acre are 243 $m^3$, and the water resources per capita and acre are equivalent to one-eighth of the national average value (Ministry of Water Resources of China, 2015).

The continuous increase in demand for energy poses enormous challenges for water use and safety in Hebei Province. In the functional orientation of the "Beijing–Tianjin–Hebei (Jing-Jin-Ji) Collaborative Planning Outline," Hebei Province is considered to be an area that supports the Beijing–Tianjin–Hebei ecological environment and plays an important role in the utilization of ecological resources and environmental protection. It is a typical regional economic area and a significant hub for the integration of Jing-Jin-Ji. However, the primary industry and the secondary industry require a large amount of imported water due to the fact that the local water resources cannot meet their total water demand. Considering the implement of the recent development plan ("The development of Xiongan New Area" and the "Two-child Policy"), hosting the Winter Olympic Games, and the technological innovation in the energy sector, without a doubt, it will exert great influence on the tense relationship between water and energy in Hebei Province. At this stage, studies focused on Hebei is commonly found on water-energy nexus and the decomposition analysis of water utilization in Jing-Jin-Ji region (Wang et al., 2015; Sun et al., 2018; Li X. et al., 2019). Specifically, for Hebei Province, Lv et al. (2018) identified optimal strategies for the energy-water nexus system under multiple uncertainties and various water-saving scenarios (Lv et al., 2018). However, few studies are employed to perform an in-depth analysis of the energy production and their associated water consumption under a multi-scenario analysis considering the low-carbon and sustainable policy in Hebei Province. Thus, this study established a multi-scenario analysis of water requirements for energy production in Hebei province using the Long-range Energy Alternative Planning (LEAP) model via comprehensively considering the corresponding policy of the development of a low-carbon economy. Furthermore, the paper explores the trend of change in water demand for energy production under the influence of the corresponding greenhouse gas emission policies in Hebei Province as well as the water use problems in the energy industry. The results of this study may provide a scientific basis for decision-making to improve the management of energy and water use and implement sustainable energy and water resource development policies, and be conducive to the sustainable development of the Beijing–Tianjin–Hebei region.

The paper is organized as follows: *Introduction* section introduces motivation and objective and contribution of this study; *Literature Review* briefly reviews the previous literatures; *Methodology and Data* describes the methodology and data; *Empirical Results and Discussion* present the empirical results and discussion of this work; conclusions and policy implications are presented in the final section.

## LITERATURE REVIEW

In recent years, energy production and water restrictions have attracted more and more scientific, political and public concern. Water withdrawals and water consumption for energy production always serve as key indicators for assessing the water use in energy production. Water withdrawals refer to the diverted or withdrawn water from a surface or groundwater source while water consumption is the consumed part (evaporation, absorbed by a product, or other losses) of withdrawn water from natural water bodies (Strzepek et al., 2012).

To date, researches on water use for energy extraction, processing, and conversion widely reported, including traditional fossil fuel production (coal, oil, and natural gas), heat and electricity generation, the production of energy from biomass, and the impact of water use in the energy production process on the ecological environment (Veil et al., 2004; Mielke et al., 2010; Zhou et al., 2016). In addition, the policy implications for managing the two resources have been assessed at the national level, where energy and water management are generally independently regulated (Pate et al., 2007). Many scholars have commented on the content of sustainable development policies for both energy and water resources, including the sustainable development of wind, solar, and biomass energy sources, an energy conservation policy, a climate policy, the sustainable development of water resources, the three Red Lines water policy, and technological innovation (Kiparsky et al., 2013; Qin et al., 2015; Zhou et al., 2016). The results of most of the abovementioned energy production studies are based on the research results of other studies and not on regional policies. For example, according to the energy strategy scenario of China's International Energy Agency (IEA), Cai et al. (2014) evaluated the water withdrawals for energy production from 2011 to 2030 (Cai et al., 2014), and Qin et al. (2015) assessed the water use in the energy industry and its impact on the "3 Red Lines water policy" (Qin et al., 2015). Based on a multiregional input-output analysis, Jin et al. (2019) investigated the water—energy nexus networks in China, which provided valuable reference for synergetic development of water and energy resources (Jin et al., 2019). However, few of the studies are employed to performs an in-depth analysis of the energy production and their associated with water consumption with a multi-scenario analysis considering the low-carbon and sustainable policy in Hebei Province.

There are three main approaches to calculate the water requirements for energy production. One is to use a technology-based bottom-up approach to calculate water use (water withdrawals or water consumption) in the energy sector, which is calculated by multiplying the energy production by the water use coefficients of a range of energy technologies, including fossil-fuel-based energy production and power generation (Veil et al., 2004; Kenney and Wilkinson, 2011; Nicot and Scanlon, 2012; Zhou et al., 2016; Zhou et al., 2019). Another approach is to use a hybrid strategy consisting of a lifecycle approach and an input—output approach (Cooper and Sehlke, 2012; Fang and Chen, 2016). The third approach is to use the scenario analysis method, which simulates water requirements in the medium- and long-term for energy production by setting different conditions (Cooper and Sehlke, 2012; Shang et al., 2016). The bottom-up approach is a simple and effective way to calculate local and overall water usage. The hybrid approach is more rigorous, but its data requirements are strict. The scenario analysis method can be used to set changes in different conditions and conduct medium- and long-term simulations of energy production and water requirements.

## METHODOLOGY AND DATA

### Methodology

#### The Framework of the Model

In view of the complex relations between water use, energy production, and socio-economic factors, the LEAP-Hebei model was adopted in this research to perform a systematic analysis of current and future energy production and the associated water use. **Figure 2** presents the model's framework, which was applied to assess the water use for energy production in Hebei Province.

#### The Long-range Energy Alternative Planning Model

The bottom-up approach can be used to calculate a local or an overall water use value. At this stage, most studies on water use for energy production use bottom-up accounting methods to calculate the water use value in the energy sector. These studies multiply the energy production by the water use coefficient of a range of energy technologies. The LEAP model was developed by the Stockholm Environment Institute in Boston. It is a bottom-up model and can be applied to perform a comprehensive analysis of the energy-economy-environment nexus based on different planning scenarios (Clark and Heaps, 2012). Different scenarios can be set up in the model, and different policy measures and technical means can be adopted to carry out medium- and long-term simulations of energy supply, energy consumption, and environmental conditions by linking the environmental emissions and the driving factors in the study area (Cai et al., 2008). It is widely used on global, national, and local scales to predict energy supply and demand and the impact of energy policy changes on the environment. Based on the LEAP model, Chen et al. (2020) established four scenarios to estimate China's energy demand and carbon emissions from 2020 to 2050. Katta et al. (2019) simulated energy demand and supply of Canada's oil sands from 2007 to 2050. Agrawal et al. (2018) developed an integrated framework to analyze the impact of climate change on water consumption and greenhouse gas emissions. Zhao et al. (2011) analyzed the path of China's development of a low-carbon economy by 2050. Hong et al. (2016) used the LEAP model to discuss the effectiveness of policies imposed on the Korean transportation sector, and the chain effect on Korea's energy and environment by 2050. Rahman et al. (2016) combined SMAA (Stochastic Multicriteria Acceptability Analysis) with the LEAP model to promote multi-sector-related interests and plan energy policies to achieve a sustainable low-carbon path. Emodi et al. (2017) used the LEAP-Ningbo model to simulate the greenhouse gas emissions of the six energy sectors in Ningbo, which is a pilot low-carbon city. In summary, the LEAP model is a bottom-up, long-term energy planning model. Most current research focuses on energy forecasting and carbon emissions simulation, but there is relatively little research on water use for energy production using the LEAP model. In this study, we combined the LEAP model with energy production forecasting to analyze water use for the energy sector.

#### Water Withdrawals and Consumption

Most of the energy scenarios that are currently used to study energy production and water use are based on the research results of other studies and do not fully integrate the policies in the study area. In this paper, we concentrate on current and future water use for energy production by first applying policies on economic growth, energy utilization (clean energy), industrial structure,

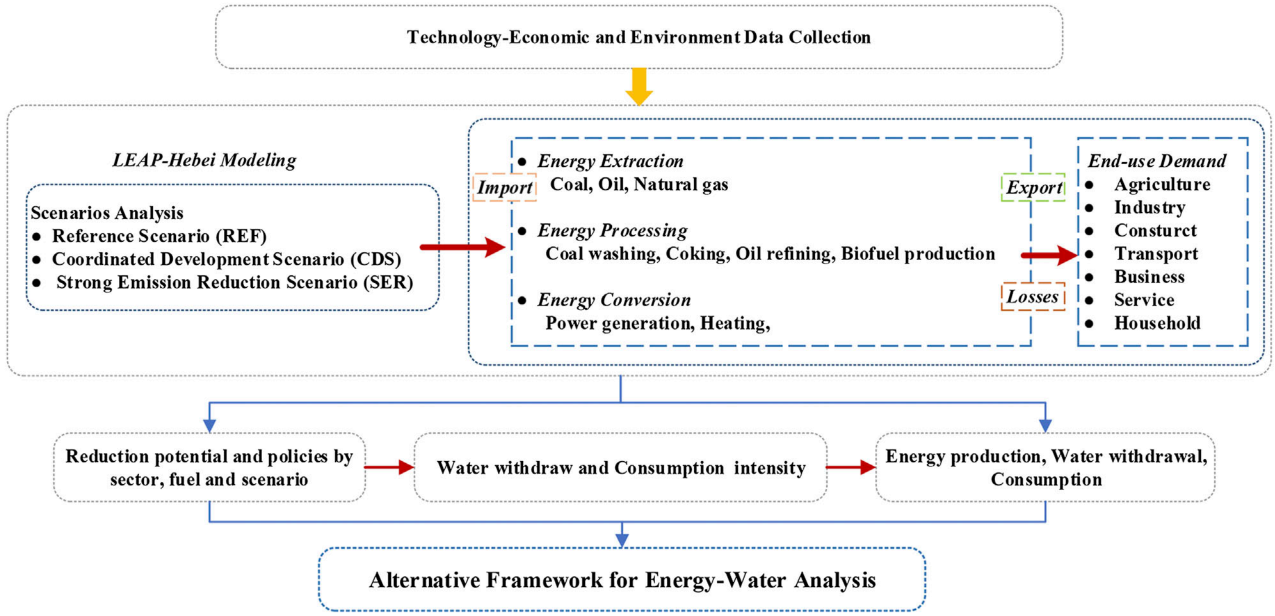


**FIGURE 2 |** The model's framework.

and innovative technology in a bottom-up approach based on the establishment of the LEAP-Hebei model. The water use for energy production was calculated by multiplying the energy production of each sector by the intensity of water withdrawals and the intensity of water consumption to calculate the water withdrawals and water consumption, respectively, of various types of energy production.

$$W = \sum_{i=1}^{n} E_i \alpha_i \tag{1}$$

$$C = \sum_{i=1}^{n} E_i \beta_i \tag{2}$$

where $E_i$ represents the $i$-type energy production, $W$ represents the water withdrawals for the energy production, $C$ represents the water consumption for the energy production, $n$ represents the total number of energy production types, and $\alpha_i$ and $\beta_i$ indicate the $i$-type intensity of water withdrawals and consumption for the energy production, respectively.

## Scenario Settings

The proposed scenario is based on the Hebei 13th Five-Year Plan, the Hebei Town Planning System, China's recent "Climate Planning," and the 2050 China Energy and Carbon Emissions Report. Three scenarios were established based on the activity level of each energy sector, the energy intensity, and the energy structure by the bottom-up approach. The key data and assumptions, including Gross Domestic Product (GDP), population, and urbanization, were set to be the same in order to compare the results from the three scenarios. Regarding the settings of the scenarios in Hebei province, reference was made to the research of Li Z. et al. (2019). As a basic scenario, the reference (REF) scenario is consistent with the REF scenario of Li Z. et al. (2019), representing the existing development status of Hebei Province. The coordinated development scenario (CDS) comprises the industry structure optimization scenario and the terminal consumption structure optimization scenario, which are based on the REF scenario, and optimize the industrial structure and energy structure, inhibit the development of the secondary industry, vigorously develop the tertiary industry, improve energy efficiency, implement natural gas instead of coal, develop renewable energy, and increase the proportion of renewable energy. The strong emission reduction (SER) scenario is referenced to the low-carbon development scenario, and the other key parameters refer to the settings described in this article. The SER scenario is based on the CDS scenario, and further improves energy efficiency, implements natural gas instead of coal, develops renewable energy, focuses on the development of wind and solar energy, which, in this scenario, become the energy sources with the dominant proportion of power generation, and introduces advanced carbon capture and storage (CCS) technology to reduce carbon emissions from thermal power generation. The major parameters that were used in the sub-sectors of the REF, CDS, and SER scenarios in the LEAP-Hebei model are given in Supplementary Tables S2–S6.

There are many technologies that can reduce the amount of water use for energy production, most notably cooling technology. In this paper, the parameters for change in consideration of the development of water-saving technology were set for the future. The intensity of water withdrawals and water consumption remained unchanged at the base year in REF. The other two scenarios take into account the development of water-saving technology, and the intensity of water withdrawals and the intensity of water consumption are estimated from the

**TABLE 1 |** The cooling technology in the future setting [the coordinated development scenario and the strong emission reduction scenario] in the model.

| Cool technology | 2015 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|
| Once-through cooling | 0.05 | 0.04 | 0.03 | 0.02 | 0.01 |
| Cyclic cooling | 0.66 | 0.61 | 0.55 | 0.50 | 0.42 |
| Air-cooling | 0.12 | 0.18 | 0.25 | 0.31 | 0.40 |

scenario. The proportion of the three cooling technologies in the three scenarios is based on (Zhang et al., 2014; Zhou et al., 2016). The future cooling technology development ratio parameters (excluding seawater cooling) were set as shown in **Table 1**.

## Data Acquisition

### Data Collection

The data for the modeling process that were collected for this research included: historical data on Hebei Province, baseline data from 2015, trend data, and reference parameters. The historical data were used for key assumptions and scenarios, such as industry added value, urbanization, population, and GDP, and were primarily statistics from the Hebei economic statistics yearbook (2000–2016) (Li et al., 2018), the sixth Hebei population census, and town planning in Hebei province (Wang and Yang, 2015; Department of Housing and Urban-Rural of Hebei, 2017). The baseline data from 2015 were statistics taken from the Hebei Economic Yearbook of 2016 and the China Energy Statistics Yearbook of 2016 (China Electric Power Yearbook Editorial Committee, 2016) regarding energy supply, imports and exports, transformations, input, and demand in seven sectors. The trend data (changes in industrial structure and changes in energy efficiency) and some binding indicators were obtained from government and special department planning documents. The government department survey data were taken from Hebei's 13th five-year energy development plan, reports from academic institutions in various departments of Hebei, the program for the coordinated development of Beijing–Tianjin–Hebei, and China's Energy and Carbon Report 2050 (China energy and Carbon Emission Research Group, 2009; Department of Housing and Urban-Rural of Hebei, 2017; Zhou et al., 2017). The reference parameter data were derived from the "General Calculation Rules for Integrated Energy Consumption" (GB/T-2589-2008), the energy conversion standard coal coefficient, and the average low heat generation of energy, which are all contained in Appendix 4 of the China Energy Statistics Yearbook of 2016 (China Electric Power Yearbook Editorial Committee, 2016).

The estimations of water withdrawals and consumption for energy production were found to vary widely across the following sources of information: the National Pollution Source Survey of China (Zhang et al., 2013), The Chinese Environmental Statistics Database of 2011 (Lv et al., 2018), and other research data (Qin et al., 2015). In this study, the water withdrawals coefficient was based on (Zhang et al., 2013; Lv et al., 2018), and the water consumption coefficient was based on (Zhang and Anadon, 2013; Zhou et al., 2016). The water withdrawals and consumption factors that were used in this paper are provided in **Supplementary Table S1**.

### Accounting Scope

In this study, water withdrawals and water consumption were assessed in the energy sector. Energy production included primary energy (coal, oil, and natural gas) extraction. The primary energy processes included processes for washing coal, coking, refining oil, and biofuel production. Primary energy conversion included coal power generation, natural gas power generation, biomass power generation, nuclear power, hydropower, wind power, and solar power generation and heating.

Considering that wind energy and nuclear energy are not widely used in Hebei, the water use for wind energy and nuclear energy were not taken into consideration (Chen et al., 2016). In the future, the use of solar energy and photovoltaic power generation will continue to grow in Hebei, and about 0.019 $m^3$/MW h of water will be used when cleaning the surfaces of battery components (Macknick et al., 2012). Hydropower, according to some studies, is considered to be a water-intensive energy carrier (Liu et al., 2015; Zhou et al., 2016). Biomass power generation only accounts for a small part of the total power generation in Hebei Province, and uses crop straw and garbage as fuel. In this study, we did not consider the water that was used in the production of biological raw materials; we only considered water consumption during power generation (Cai et al., 2014). In this paper, we analyzed the use of fresh water in energy production in Hebei Province; accordingly, the utilization of seawater fell outside the accounting scope. A power plant's cooling technology has a great impact on water withdrawals and water consumption. Three types of cooling systems were considered in our research: once-through, cyclic, and air-cooling. Only the "operable" water withdrawals and the water consumption that was directly related to energy production were considered in this research.

# EMPIRICAL RESULTS AND DISCUSSION

## Results and Analysis

### The Predicted Results for Energy Demand and Production

**Figure 3** shows the long-term energy demand trend in Hebei Province. There are no inflection points in any of the three scenarios. There is an increasing trend during the projection period in the REF and CDS scenarios. The SER scenario also shows an upward trend; however, the growth rate is slow. The total energy demand in the SER scenario increased from 321,618 Mtce in 2015–2,253.13 Mtce in 2050, with an average annual growth rate of 5.72%.

**Figure 4** shows the energy production in Hebei Province. There is an increasing trend during the projection period in the REF and CDS scenarios; however, in the SER scenario, the energy production peaked around 2030 due to strict control policies and then slowly declined. The energy production in the SER scenario decreased significantly compared to the REF and CDS scenarios. The energy production in the REF, CDS, and SER scenarios reaches 826.04, 547.01, and 340.30 Mtce, respectively, in 2050. In the REF scenario, traditional fossil fuels dominate the period

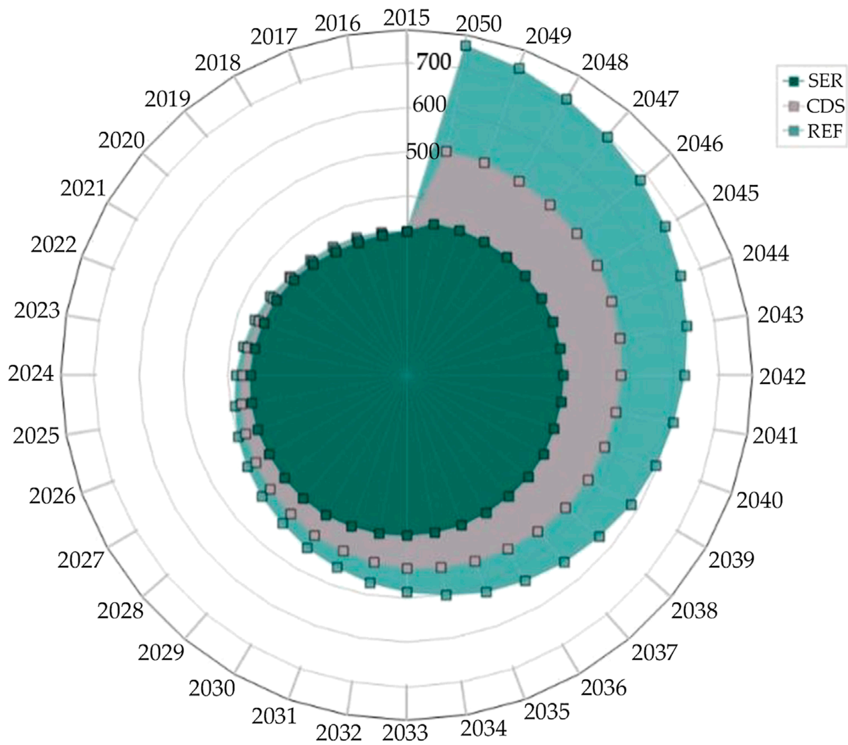


**FIGURE 3 |** The energy demand in the three scenarios during the period 2015–2050.

2015–2050; consequently, in this scenario, the coal industry accounts for the highest proportion of energy production among the various industries. In the CDS scenario, the total coal output and energy production in 2030 and 2050 decreased by approximately 19.78 and 39.47%, respectively, compared with the REF scenario. In the SER scenario, the production of natural gas shows an upward and then a downward trend. Renewable energies, such as wind and solar energy, become the main

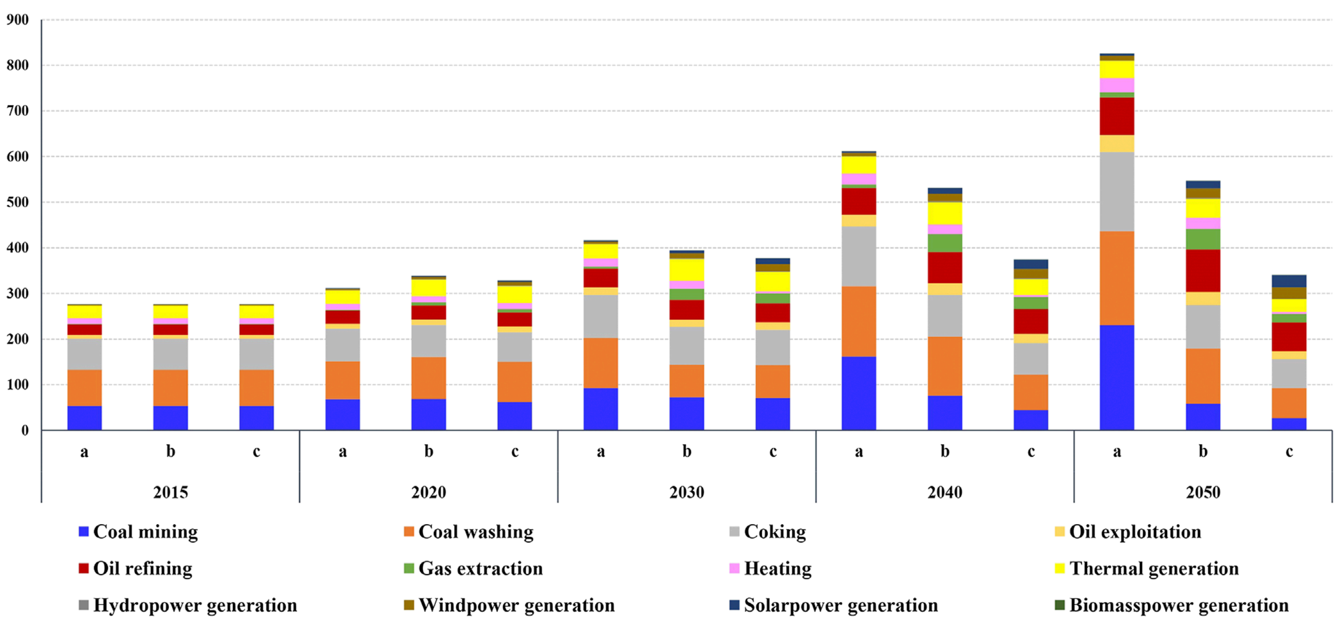


**FIGURE 4 |** The energy production of each sector in the three scenarios: (a) reference, (b) coordinated development scenario, (c) strong emission reduction (the detailed data was shown in **Supplementary Table S7**).

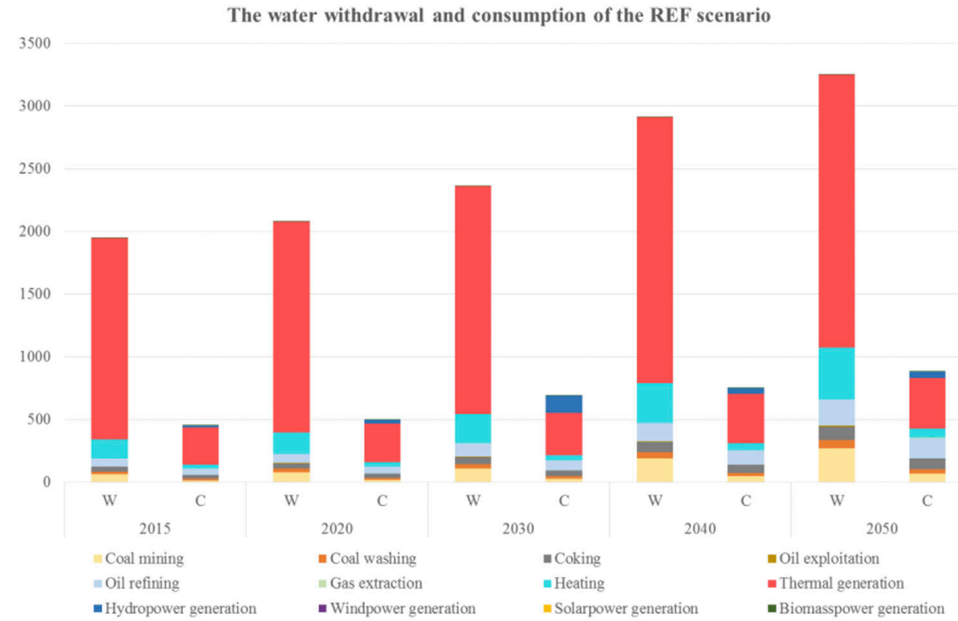


**FIGURE 5 |** The water withdrawal and water consumption of each sector in the reference (REF) scenario. Note: *W* represents water withdrawal, and *C* represents water consumption.

sources of energy. The production of coal, oil, and natural gas decreased by approximately 43.09, 34.34, and 59.60%, respectively, the production of wind energy increased by approximately 28.45%, and the production of solar energy increased by approximately 62.96% compared with the CDS scenario in 2050. Renewable energy gradually becomes an important energy, and the gradual expansion of renewable energy use also effectively reduces $CO_2$ emissions.

## Water Withdrawals and Water Consumption for Energy Production

The amount of water required for energy production is affected by changes in energy production and different policies will have different effects on energy production. Three different scenarios, as shown in Figures 5–7, were analyzed in this paper. A comparison of the three scenarios shows that, in the REF scenario, the energy structure was not adjusted, energy production is on the rise, and water withdrawals and water consumption for energy production are also on the rise. In the CDS scenario and the SER scenario, the water withdrawals and water consumption for energy production first increase and then decrease, and reach their peak in 2020 and 2030, respectively.

As shown in **Figure 5**, the REF scenario represents a continuation of the existing status. The water withdrawals requirements for energy production will increase to 2.08, 2.36, 2.91, and 3.25 billion $m^3$, and the water consumption for energy production will increase to 0.45, 0.50, 0.59, 0.75, and 0.88 billion $m^3$, in 2020, 2030, 2040, and 2050, respectively, Comparing 2015 with 2050, the water withdrawals and water consumption will increase by 66.80 and 95.68%, respectively, and the average annual growth rate of water withdrawals and water consumption will increase by 5.60 and 5.72%, respectively. This will pose a serious challenge to the protection of water resources in Hebei province. In terms of water withdrawals by 2050, about 72.43% of the water will be used for thermal power generation, and 7.76% of the water will be used by the heating industry. Coal mining, coal washing, coking, oil extraction, oil refining, and natural gas extraction account for 9.80% of the total water consumption. In terms of water consumption by 2050, coal mining, coal washing, coking, oil extraction, oil refining, and natural gas mining account for approximately 36.19%, the heating industry accounts for approximately 5.55%, and power industry's water consumption accounts for approximately 58.25%, of which thermal power accounts for approximately 56.06% of the total water consumption.

As shown in **Figure 6**, the water withdrawals and water consumption for energy production decreased sharply compared with the REF scenario. The water withdrawals and water consumption first increased and then decreased, and both the water withdrawals and the water consumption peaked around 2030. The water withdrawals decreased by 33.58 and 73.09% and the water consumption decreased by 26.95 and 57.58% compared with the REF scenario in 2030 and 2050, respectively. In the CDS scenario, the project to replace coal with natural gas is adopted, which causes the water used in coal mining and coal washing to reach a peak around 2040, with an inflection point. The amount of water used for thermal power generation peaks around 2030, then slowly declines, and the other sectors continue with an upward trend. In terms of water withdrawals by 2050, the proportion of thermal power generation will remain the largest, accounting for approximately 50.30% of the total value, and approximately 20.14% will be used by the heating industry. Coal mining, coal

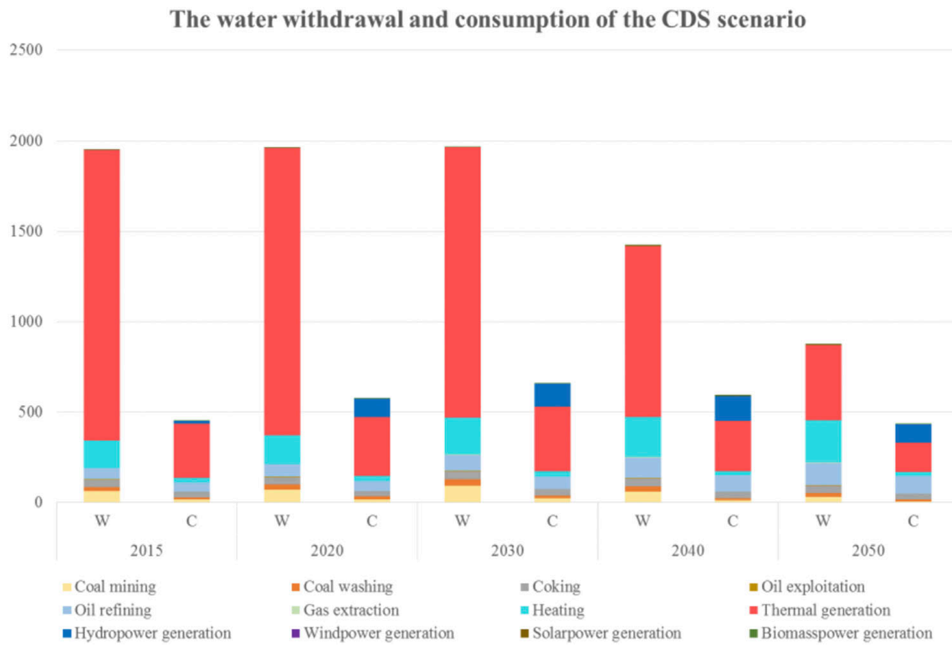


**FIGURE 6 |** The water withdrawals and water consumption of each sector in the coordinated development scenario (CDS) scenario. Note: *W* represents water withdrawal, and *C* represents water consumption.

washing, coking, oil extraction, oil refining, and natural gas extraction will account for approximately 29.16% of the total water withdrawals, which is 6.85% lower than in the REF scenario. In terms of water consumption by 2050, the proportion of coking and oil refining will have increased. Thermal power generation will account for approximately 39.54%, and this industry will be the sector with the largest water withdrawals and water consumption.

As shown in **Figure 7**, compared with the CDS scenario, the water withdrawals and water consumption for energy production decreased sharply in the SER scenario, and the water withdrawals and water consumption peaked around 2020. The water withdrawals decreased by 17.06 and 18.41% and the water consumption decreased by 46.05 and 37.96% compared with the CDS scenario in 2030 and 2050, respectively. However, in order to further reduce carbon emissions, the introduction of

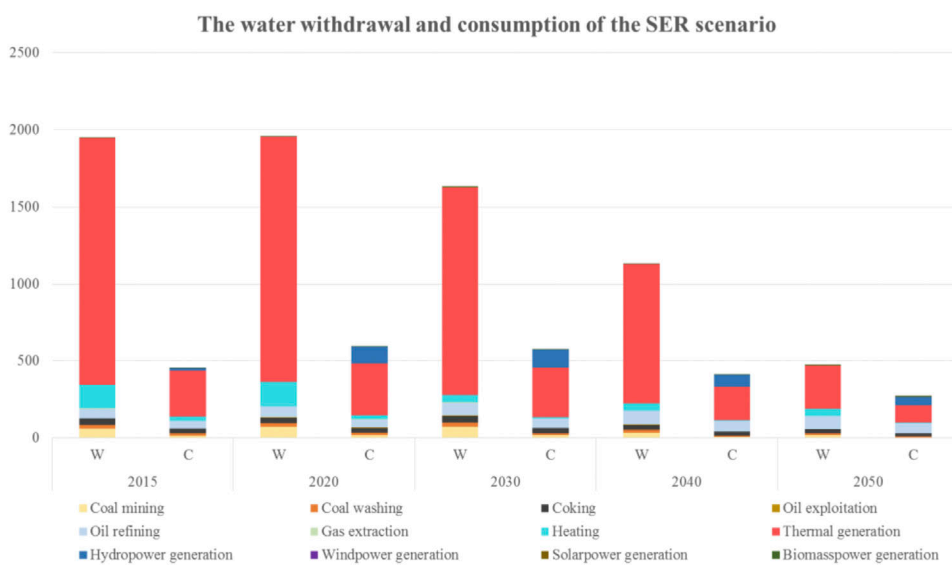


**FIGURE 7 |** The water withdrawal and water consumption of each sector in the strong emission reduction (SER) scenario. Note: *W* represents water withdrawal, and *C* represents water consumption.

advanced CCS technology will increase from 10 to 60% from 2030 to 2050. The additional water withdrawals and water consumption required for CCS technology will be 52.34 million $m^3$ in 2030, which will increase to 184.93 million $m^3$ in 2050, an increase of 2.53 times compared with 2030. Although the application of CCS technology reduces carbon emissions, it increases the use of water resources and reduces the efficiency of electricity production; hence, the limits of water resources should be weighed against reductions in carbon emissions. In the SER scenario, the amount of water used in coal mining and coal washing peaked around 2030, and there was an inflection point. The amount of water used for thermal power generation peaked around 2020, and then slowly declined. The amount of water used in the coking process peaked around 2030, and other sectors continued in an upward trend, while the growth rate slowed down noticeably. In terms of water withdrawals by 2050, the results are basically consistent with the CDS scenario. The proportion of thermal power generation remained the largest. About 44.40% of the water is used for thermal power generation, and 29.44% is used by the heating industry. Coal mining, coal washing, coking, oil extraction, oil refining, and natural gas extraction account for approximately 25.66% of the total water withdrawals. In terms of water consumption by 2050, the proportion of water consumption for oil refining increased. Thermal power generation accounts for approximately 36.22% of the total water consumption, which is the largest proportion of water consumption. The proportion of water consumption for hydropower generation increased, accounting for approximately 18.34% of the total water consumption in 2050. However, this proportion was decreased in comparison to the CDS scenario; in the CDS scenario, the further development of wind energy and solar energy increased the proportion again. The thermal power generation sector remains the sector with the largest water withdrawals and water consumption, and should be considered by the local government in the future.

# Discussion

## Energy Transformation and Technological Innovation

A comparison of the CDS scenario with the SER scenario shows that the SER scenario further improved the energy efficiency and developed renewable energy sources, such as wind energy and solar energy, to replace traditional thermal power generation. The water withdrawals by the electricity sector in the SER scenario decreased by approximately 18.02 and 32.30% compared with the CDS scenario in 2030 and 2050, respectively. The water consumption decreased by approximately 17.90 and 36.84% in 2030 and 2050, respectively. This is due to the fact that almost no water is used in wind power generation and solar power generation, and the water-saving benefits increase as the scale of development expands. Hebei Province's geographical advantages and natural resources should be fully exploited to increase the use of renewable energy. In this paper, we considered three main types of cooling techniques (once-through cooling, cyclic cooling, and air-cooling) whose water withdrawals and water consumption vary greatly. The results of the scenario analysis indicate that a change in cooling technology (from once-through cooling to air-cooling) will have an obvious water-saving effect, which can effectively reduce the water withdrawals and water consumption of the thermal power generation sector.

## Impact on the "Three Red Lines" Water Policy

In 2011, the Ministry of Water Resources selected Hebei Province to pilot the most stringent water resources management system, the "three red lines" target system (the red line used to control the total amount of water, the red line used to control water efficiency, and the red line used to control the water function area to limit pollution). In terms of the red line used to control the total amount of water, the total water use value will be limited to 21.7, 22.1, and 24.6 billion $m^3$ in 2015, 2020, and 2030, respectively, in Hebei Province (The State Council of the People's Republic of China, 2012).

The ratio of water use for energy production to provincial water abstraction was calculated to illustrate the impact of water use for energy production on the limited water resources in Hebei. Although the water use for energy production only accounts for a small portion (approximately 8.7%) of the total water use in Hebei, it would have a greater impact on local water resources. Hebei is a region with a serious shortage of water resources, and the water use in agriculture is huge. An increase in water use for energy production, especially an increase in water use for traditional fossil fuel energy production and thermal power generation, will pose a serious threat to the local ecological environment. The amount of water used in agricultural and other industrial production processes will be reduced as more water will be used for energy production, which poses a high risk of local water shortages. Optimizing the industrial and energy structure, inhibiting the development of the secondary industry, vigorously developing the tertiary industry, improving energy efficiency, implementing natural gas instead of coal, developing renewable energy, increasing the proportion of renewable energy, and making use of advanced water-saving technologies will alleviate this trend. We estimated the impact of the policy measures adopted in the SER scenario on the "three red lines" water policy in Hebei. The water withdrawals for energy production accounted for approximately 8.7, 12.3, and 20.7% of the total water use control target in 2015, 2020, and 2030, respectively, in the REF scenario. A series of corresponding policy measures were taken in the SER scenario, where the water withdrawals accounted for approximately 8.7, 7.9, and 6.2% of the control targets, respectively. The water use for energy production in the SER scenario decreased by 4.4 and 14.5% compared with the REF scenario in 2020 and 2030, respectively. These results indicate that these policy measures can effectively save water and help to achieve the control target of the "three red lines." But it is worth noting that the water saving measures like the air-cooling technology might bring a risk of high economics cost for this region. The coordinated management of energy-water-economy needs further attention. Anyhow, air-cooling technology is still a better choice of thermal power station in the area like Hebei Province rich in coal but short of water.

## Uncertainty in the Scenario Analysis Results

This study used a series of parameters that were selected in accordance with the requirements of the 13th Five-Year Plan of Hebei Province. The LEAP model was adopted to predict the energy production, and the water intensity was derived from other studies. The selection of parameters was too simple and was not optimized. In addition to not including all of the influencing factors, there were also uncertainties in the setting of the future parameter values for the selected driving factors, including GDP growth rate, industrial structure, population growth rate, and energy import and export volume. The economy, population, and urbanization rate of Hebei were predicted according to the overall development trend in China for the period 2015–2050. As Hebei has no perfect plan for or information that would allow us to discuss its development trend, the average development trend of China's provincial-level regions was derived from other references. It was not subdivided into the detailed terminal equipment planning of each department, thus causing uncertainty in the accuracy of the results. There is a direct relationship between energy production and import and export volume, which is significant to the model that was used in this research, and as the energy import and export volume was based on a statistical analysis of historical data on Hebei Province, it is uncertain and therefore could cause uncertainty in the estimated energy production values. The estimations of the intensity of water withdrawals and water consumption were made using a predictive analysis that considered technological progress every 10 years. Detailed changes in each year were not considered, partly due to limited data, but also because we made a general estimate for the three scenarios based on the set conditions, which would not affect the comparison between the scenarios.

There is still another limitation to this study. The water use for nuclear energy were not taken into consideration in Hebei Province, since the first planed nuclear power station in Cangzhou of Hebei hadn't been put into operation to date. But anyway, the nuclear plant is going to be a very important factor to water resource stress in Hebei Province if the planned nuclear power plants will come into service in the next couple of years. Thus, if reliable data become available, future work on this topic will be carried out thoroughly and deeply.

# CONCLUSIONS AND POLICY IMPLICATIONS

## Conclusions

(1) In this study, the bottom-up LEAP model was applied to estimate the water withdrawals and water consumption associated with energy production for each sector in Hebei Province from 2015 to 2050. Our main conclusions are as follows.

(2) The energy production and the water requirements for energy production would continue to grow at a high speed in the REF scenario (the business-as-usual scenario); the energy production, the water withdrawals, and the water consumption for energy production decreased sharply in the CDS and SER scenarios compared with the REF scenario due to optimization of the industrial structure and the energy structure, inhibition of the development of the secondary industry, vigorous development of the tertiary industry, improvements in energy efficiency, implementation of natural gas instead of coal, development of renewable energy, and an increase in the proportion of renewable energy.

(3) The water withdrawals and water consumption would peak around 2030 and 2020 during the forecast period in the CDS and SER scenarios, respectively, indicating that these measures can effectively reduce energy production and water requirements. The thermal power generation sector remains the sector with the largest water withdrawal and water consumption; however, there is a decreasing trend with the implementation of policies and the development of renewable energy. The water use of the heating sector gradually increases with the improvement of people's living standards.

(4) The results of the comparison of the SER scenario and the CDS scenario indicate that advances in energy technology, optimization of the energy structure, and an increase in the proportion of renewable energy will play an increasingly significant role in Hebei's long-term development. Therefore, the development of a low-carbon economy is not only an urgent problem due to climate challenges and air pollution, but is also necessary in order to reduce the pressure on water resources. The government should adopt stricter policies to reduce the production of traditional fossil energy (especially by the coal industry), vigorously develop renewable energy technology, and reduce the pressure on Hebei's limited water resources.

(5) The selection of cooling technology for use in electricity generation should consider specific geographical factors. The promotion of air-cooling technology must consider the trade-off between energy efficiency and water use. In addition, the choice of electricity generation and cooling technologies should also consider the trade-off between funding and operating costs and between water conservation and greenhouse gas emissions. CCS technology should be carefully developed in areas where water resources are currently scarce. The trade-off between emissions reductions and water use by methods that reduce $CO_2$ should also be carefully considered.

## Policy Implications

Combing the above analysis and the industrial structure, energy structure and energy efficiency of Hebei Province, this paper put forward the following policy implications to improve energy efficiency and reduce water consumption:

Firstly, Hebei Province should speed up the adjustment of industrial structure, reduce the dependence of traditional industrial structure on energy consumption, promote the optimization of industrial structure, reduce the proportion of the primary and secondary industries gradually, develop the tertiary industry such as modern service industry vigorously, and promote the integration of the tertiary industry and other industries. Secondly, for the future development, Hebei Province should increase the proportion of cleaner alternative energy, continue to replace raw coal and coke with natural gas and electricity, improve the energy efficiency of thermal power generation, and focuses on the development of wind and solar energy. Finally, Hebei Province should increase investment in technologies, encourage the innovation in energy technologies, carry out the research on energy technologies, and increase the introduction and deployment of clean energy technologies on both the demand and supply, such as use cooling technology to reduce water consumption and improve energy efficiency of each sectors. At the same time, according to the current policy of Hebei Province, there may be some barriers for the above policy implications: for the adjustment of industrial structure, the large-scale industrial bases provided favorable conditions for the development of the secondary industries in Hebei Province, and it is difficult to reduce the dependence of economic development on the secondary industry in the short term. For cleaner alternative energy, there are still some problems in Hebei Province, such as insufficient development and low energy utilization of cleaner alternative energy, serious shortage of energy allocation management system. The photovoltaic power generation in Hebei Province is also in the initial stage. For energy technologies, the development of energy technologies is slow in Hebei Province, and the water saving measures like the air-cooling technology need higher economic cost, while the government lacks funds for relevant investment.

## DATA AVAILABILITY STATEMENT

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

## AUTHOR CONTRIBUTIONS

XL and GL contributed to all aspects of this work. DD and GL conducted data analysis. DD and RY wrote the main manuscript text. SL gave some useful comments and suggestions to this work. All authors reviewed the manuscript.

## FUNDING

This work was supported by a grant from State Key Laboratory of Resources and Environmental Information System, Fundamental Research Funds for the Central Universities (Grant No. 2019QD01 and 2019QD03).

## ACKNOWLEDGMENTS

We greatly thank "MDPI English editing" (English-15278) for the editing assistance to the paper.

## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2020.558536/full#supplementary-material

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**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.

frontiers in Energy Research

ORIGINAL RESEARCH
published: 23 September 2020
doi: 10.3389/fenrg.2020.00163

# Renewable Energy and Material Supply Risks: a Predictive Analysis Based on An LSTM Model

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OPEN ACCESS

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**Specialty section:**
This article was submitted to Sustainable Energy Systems and Policies, a section of the journal Frontiers in Energy Research

**Received:** 14 June 2020
**Accepted:** 26 June 2020
**Published:** 23 September 2020

**Citation:**
Liu B, Chen J, Wang H and Wang Q (2020) Renewable Energy and Material Supply Risks: a Predictive Analysis Based on An LSTM Model.
Front. Energy Res. 8:163.
doi: 10.3389/fenrg.2020.00163

In response to climate change and continued reliance on traditional high-carbon fossil fuels, promoting the transition toward sustainable energy systems by development of low-carbon energy resources has been seen as the main strategy for mitigating and solving global climate change. However, the promotion of low-carbon energy also faces material supply risks. To provide a reference for the steady and rapid development of renewable energy and other energy in the future energy market, this paper considers renewable energy prediction based on a long- and short-term memory network model as well as the growth rate changes of crude oil, natural gas, nuclear energy, financial revenues, and expenditure. In the prediction process, it is found that natural gas will be a strong competitor for the development of renewable energy in the future. When natural gas grows too quickly, the growth of renewable energy will be negative. On the other hand, when the monthly growth rate of natural gas and crude oil is smaller than that of nuclear energy, renewable energy will display a growth trend, and the rate will increase with the growth of natural gas and nuclear energy. What is more, wind and solar energy will be limited by metallic materials, such as Dy, Nd, Te, and In. Improving the energy density of metals plays a key role in China's transition to a low-carbon energy structure.

**Keywords: renewable energy, critical metals, sustainability, LSTM model, forecasting**

## INTRODUCTION

Renewable energy is an important means to control and reduce carbon emissions in the process of heat generation and transportation. Its main output form is power supply, which can be directly put into production and application. It does not need a large amount of investment in transportation infrastructure like traditional energy required in the past. China's overall electricity demand has been growing rapidly, according to the International Energy Agency (IEA). The total electricity generation capacity in China increased significantly from 621.268 TWh in 1990 to 6282.607 TWh in 2016. During the same period, the renewable energy generation capacity increased from 126.788 to 1570.566 TWh, among which wind power generation capacity increased from 0.002 to 237.071 TWh and solar photovoltaic power generation capacity increased from 0.002 to 75.256 TWh. The data show that China's electricity consumption and demand for renewable energy have been growing steadily.

In terms of electricity supply, hydropower accounts for a large proportion of China's total renewable energy generation, compared with wind and solar. For now, however, China's main means of generating electricity is still through the burning of fossil fuels. According to the IEA's statistics on China's electricity generation from fossil fuel combustion, the share of thermal power generation in China's total electricity generation decreased from 79.59% in 1990 to 70.40% in 2016. Although China has gradually attached importance to nuclear power plant construction and renewable energy power generation since 1990, it has gradually realized that coal, oil, and natural gas, which will eventually run out, cause great harm to the environment and are the key factors leading to the greenhouse effect and global warming. However, the data show that China's dependence on traditional energy sources remains a serious problem.

In 2016, China issued the 13th 5-year plan for renewable energy development, which aims to achieve emission reduction targets and accelerate the construction of a low-carbon and safe modern energy system. In the same year, the share of renewable energy in the total power generation rose from 16.14% in 2005 to 25% in 2016, which was largely dependent on national investment in renewable energy. According to statistics from the national energy administration of China, in 2018, when the total electricity consumption was 6844.9 TWh, the year-on-year growth was 8.5%, indicating that China's electricity demand is still on the rise. However, in 2017, China abandoned 55 TWh of water energy, 41.9 TWh of wind energy, and 7.3 TWh of solar energy, and the total amount of waste exceeded 100 TWh, equivalent to the annual electricity output of the Three Gorges power station in 2018, the world's largest power station. As a result, the capacity of renewable energy has not been perfectly matched with that of the energy storage equipment in the past few years.

More than that, the development and utilization of renewable energy are inseparable from many mineral resources, especially critical metals which are under high supply owing to high concentration of production and lack of available suitable substitutes. This issue has aroused worldwide concern. For the German wind industry, Shammugam et al. (2019) sees copper and dysprosium as the most critical materials for development, both of which clearly exceed Germany's quota for renewable energy technologies and will face stiff competition from other sectors for access to raw materials. In the United States, renewable energy (mainly wind and solar) is particularly constrained by Te and Dy (Nassar et al., 2016). However, the concern of China's energy–mineral nexus is far behind the environmental benefits and costs brought by renewable energy.

The characteristics of renewable energy are production of energy from renewable sources and environmental protection. The development of renewable energy is an important way to reduce traditional energy dependence and economic decarbonization. At the same time, Apergis et al. (2018) concluded in his research that investing in renewable energy and medical treatment would help reduce carbon emissions, and abundant renewable energy could cope with climate change and improve citizens' health. Therefore, it is particularly important to ensure the technology supply of renewable energy and promote the transformation of China's energy system. Forecasting the generation capacity of renewable energy can't only prevent the waste of power resources, such as the excess capacity of electric power and the mismatch between the power supply and the development speed of the power grid, but also further promote the healthy development of China's renewable energy power generation industry. Therefore, this paper adopts the long- and short-term memory network (LSTM) renewable energy generation prediction method to try to determine an accurate prediction value and then further discuss the key metal demand on this basis, hoping to provide an important basis for China's future renewable energy policy.

## LITERATURE REVIEW

### Selection of Relevant Indicators for Renewable Energy Prediction

Many renewable energy prediction studies began in 2000 (Tsai et al., 2017). Because of the uncertainty of renewable energy (Notton et al., 2018), the perspective of its prediction is diversified, which prompts each study to selectively consider different factors in its prediction, such as traditional energy (Nadimi and Tokimatsu, 2017), nuclear energy (Kok and Benli, 2017), policy (Black et al., 2014), installed capacity (Zhou et al., 2018), technology (Ruedabayona et al., 2019), and economy (Ozcan and Ozturk, 2019). Therefore, it is very difficult to accurately summarize and classify existing studies, but summarizing and reviewing existing studies is helpful to highlight the characteristics of this study.

The application of renewable energy can replace the burning of fossil fuels. Some studies have predicted that increasing the proportion of renewable energy in energy consumption can reduce traditional energy consumption and reduce carbon emissions (Chen et al., 2019). Research on the prediction of renewable energy based on production cost shows that the extraction time and technological cost of fossil fuels are gradually increasing, and the investment yield of renewable energy is expected to be lower than that of oil and natural gas production (Baranes et al., 2017). The advantages of renewable energy power production are increasingly prominent. So, the difference between renewable energy and traditional energy mainly lies in the sustainable use of energy and the low cost and impact on the environment (Craig et al., 2019). There are many forms of renewable energy sources that provide electricity, such as solar energy, wind energy, biological energy, and hydropower, and can provide power in an isolated or mixed way (Amri, 2019). This has led to many parts of the world making use of renewable energy sources. For example, solar energy is the easiest way to get free energy and is friendly to the environment; solar radiation on the surface of the earth is about 1.5 × 1018 KWh/year, which is about 10,000 times the global energy consumption (Sharma and Kakkar, 2018). In addition, for renewable energy resources, the extraction, processing, and power generation operations tend to be a single operation (Stokes and Breetz, 2018). Hydropower stations only need to collect water from rivers and mountain runoffs to provide power. Wind farms can generate electricity simply by turning blades with the force of the wind.

However, renewable energy also has its shortcomings and brings difficulties to its prediction. The associated research found that the dependency of solar and wind energy resources on the weather, with its randomness and volatility, makes electric power production and distribution uncertain and intermittent (Das et al., 2018), and can lead to sudden emergency power supply problems. Therefore, other forms of energy are needed to serve as a necessary supplement (Jenkins et al., 2018). For this reason, research on the prediction of renewable energy by nuclear energy shows that the joint investment return rate of nuclear energy, natural gas, and renewable energy is higher than 30%, whereas the investment return rate of only using renewable energy is only between 5 and 30% (Walmsley et al., 2018). It is expected that when building an energy system that relies on primary natural resources such as hydropower, wind power, geothermal power, and solar energy, this can make up for the shortage of natural resources that cannot meet the power supply demand.

High energy dependence and environmental degradation can provide strong incentives for the utilization of renewable energy. Cadoret and Padovano (2016) find that when the government only considers the environment and does not pay enough attention to the energy market, renewable energy may increase, and these environmental policies ignore energy costs which will have an impact on economic development. From this perspective, government financial support can also play an important role. In developed countries, economic efficiency is an important factor for the success of renewable energy projects (Belaid and Youssef, 2017). A major problem with renewable energy production is its direct economic cost (Newbery, 2016), which also depends on economic development. Renewable energy technology is a capital-intensive technology (Huh and Lee, 2014), so it needs a lot of investment, especially in the early stages of its development. The cost for developing countries is much higher than that of developed countries (Moriarty and Wang, 2015). In addition, in developing countries, labor force is often insufficient and the investment environment is more unstable, which makes the economic value created by renewable energy uncertain (Reddy, 2018). However, economic growth usually leads to an increase in renewable energy production (Narayan and Doytch, 2017). As a result, the government is making investments in renewable energy more valuable by changing the direction of the market through fiscal and policy measures.

National or regional renewable energy forecasting research should be a comprehensive study of all types of energy and fiscal policies. Through the analysis of the above renewable energy prediction research, it can be found that this only focuses on the advantages of renewable energy from an environment perspective, and mostly lacks the consideration of its intermittent power supply, which can easily cause a sudden power supply shortage. However, nuclear energy can only compensate for the shortage of renewable energy in a limited way owing to the construction cycles of the nuclear power industry and the limitations of its safety problems (Dong et al., 2018). The prediction of government finance and policy support can indeed achieve the purpose of accurately predicting renewable energy, but it ignores the impact of other energy sources. This paper forecasts renewable energy from a more comprehensive perspective based on comprehensive indicators such as traditional energy, nuclear energy, and fiscal revenue and expenditure, and further discusses its impact on renewable energy.

## Prediction Methods for Renewable Energy

Renewable energy prediction research can be divided into two categories. One kind is the medium- and long-term forecast which takes the social economic index or some depend on long-term measurements as the characteristic input. The other is a short-term prediction based on wind speed or illuminance. The two types of prediction use different methods because of different data volumes. The first kind of prediction research mentioned earlier is relatively mature; in this kind of study, the most widely used prediction method is the use of regression model (Wu et al., 2019) as well as fuzzy logic-based prediction (Sivaneasan et al., 2017), autoregressive integrated moving average model (ARIMA) (Aasim et al., 2019), Gray model (GM) (Liu et al., 2016), support vector regression (SVR) (Almusaylh et al., 2018), and artificial neural network (ANN) (Ghimire et al., 2019). These prediction methods have their own advantages. For example, for short-term prediction, linear multivariable prediction, fuzzy logic prediction, and neural networks based on regression models are the most accurate, whereas the SVR model is the most appropriate for a single variable. For long-term prediction, ARIMA and GM are the most accurate models for linear univariate prediction. The accuracy and stability of the prediction model can be improved, and accurate judgment can be made quickly and with high probability. Although these prediction models each have advantages, they also have disadvantages. The results obtained by the regression prediction method cannot reflect the periodicity, and the fuzzy logic prediction lacks specific algorithm formula. Although the GM is accurate, it cannot reflect the dynamic change, whereas the SVR and the ANN often fail to show high accuracy because of insufficient data.

In the second category of short-term prediction research, the methods are relatively uniform, mostly using LSTM. The LSTM model has the ability to memorize the characteristics of time series. Compared with other neural networks, LSTM models can effectively use historical data to predict future time points. This is widely used in prediction because of its prominent advantages for time series prediction. Zheng et al. (2019) used an LSTM model to predict electricity consumption. Zhang et al. (2019) used an LSTM model to predict short-term power generation. Cortez et al. (2018) confirmed that an LSTM model is more suitable for predicting emergencies than traditional time series models and machine learning methods. Srivastava and Lessmann (2018) applied an LSTM model to predict solar energy and concluded that this is a reliable prediction model. Yu et al. (2019) used a combined LSTM-EFG model to predict wind speed.

Recently, China's national bureau of statistics released monthly renewable energy supply data to provide support for relevant researchers. In this paper, an LSTM model is introduced that combines five characteristic inputs: crude oil output, natural gas output, nuclear power generation, and fiscal revenue and expenditure. It is expected that the construction of a prediction model that factors in the interaction of traditional energy, nuclear energy, and financial support will enable the prediction and comparison of the generation of renewable energy.

## Key Metal for Renewable Energy

In recent years, many official reports and academic studies have shown concern about the mineral density of renewable energy (Phadke, 2017; Vidal et al., 2017). For example, the European Union formulated the Strategic Energy Technology Plan (SET-Plan) to ensure the competitiveness of industrial enterprises in the new energy supply value chain. The plan prioritized six techniques: nuclear fission, solar photovoltaic (PV) and concentrating solar power, wind energy, biological energy, carbon capture and storage, and power grid. Some scholars further studied on the metal materials in the use of the six low-carbon energy technologies for large-scale technology deployment and identified the five metals with high risk (Moss et al., 2013). Although a comprehensive deployment of renewable energy is necessary, considering the development of renewable energy in China, this study focuses on sorting out metal material requirements related to hydropower, wind, and solar energy.

### Hydropower

Installed hydropower capacity is the largest source of renewable energy in the power sector, accounting for about 17% (Mallin, 2018) of global electricity demand. In terms of electricity supply, hydropower also accounts for a larger share of China's total renewable energy generation than wind and solar. Hydropower plants are mainly divided into four categories: run-of-river, reservoir, pumped storage, and in-stream technology. Each type requires different materials as a result of different scenarios of technical application. Roughly, steel and concrete make up the largest proportion of the pipes and pressure pipes used in the construction of hydropower stations. Steel is the main material for turbines, copper (about 8%) is needed for generators and aluminum is the main component for transmission lines.

### Wind and Solar Power

Nassar et al. (2016) analyzed the by-product metal demand of wind and solar PV power generation in the United States by 2040 and summarized 11 by-product metals related to 5 key renewable energy technologies (crystalline silicon solar cells (c-Si), cadmium telluride solar cells (CdTe), copper indium gallium (di), selenide solar cells (CIGS), amorphous silicon germanium solar cells (a-SiGe), and wind turbines with Nd2Fe14B permanent magnets), as follows: silver (Ag), cadmium (Cd), selenium (Se), tellurium (Te), indium (In), germanium (Ge), neodymium (Nd), praseodymium (Pr), dysprosium (Dy), terbium (Tb), and gallium (Ga). Shammugam et al. (2019), who studied wind turbines, conducted a comprehensive assessment of the metals used in the development of the German wind industry and identified steel as the most needed material for wind turbines, followed by copper and alloys such as chromium, manganese, and nickel. In addition, copper and dysprosium, which form the basis of wind turbines, will face particular competition from PV technology on a large scale. Based on the deployment of China's six wind and solar PV technologies, Wang et al. (2019) proposed eight key materials (neodymium, dysprosium, cadmium, tellurium, indium, gallium, selenium, and germanium). He believed that in the future, wind energy–related materials will increase by 230 to 312 times, and solar energy–related materials will increase by 20 to 137 times. In addition, China needs more critical materials to support future renewable energy targets than Germany and the United States.

# DATA AND METHODS

## Data Sources and Methods

The data used in this paper are all from the monthly data from nuclear power generation, crude oil, natural gas, renewable energy generation, fiscal revenue, expenditure, and six other indicators in the China national statistical yearbook. Considering the historical stage of China's renewable energy development, here, renewable energy generation is the sum of hydropower generation, wind power generation, and solar power generation. The data are divided according to a 9:1 ratio, which is determined by sample experiments. The research sample in this paper is a total of 108 sets of data from September 2009 to August 2018. For training, 90% of the data were used; that is, 97 sets of data from September 2009 to September 2017 were taken as the training samples. The remaining 10% were used as test samples, i.e., 11 sets of data samples from September 2017 to August 2018. Of the training samples, 90% are used for model construction, and the assessment of prediction accuracy is performed with the remaining 10%.

As the country with the largest population and consumption, China is the cradle of "digital capital." In recent years, China has continuously released more detailed data to facilitate research on various issues, especially monthly data concerning energy and fiscal revenue and expenditure. This can provide a new perspective for the prediction of renewable energy. A large amount of macro data supports the research and enables the use of more advanced LSTM prediction models. Compared with the traditional time series approach, which requires only a small amount of data to achieve a very high accuracy, training with more data will also make the results more accurate and reliable. To illustrate the function of the LSTM storage unit, in **Figure 1** we use arrows to indicate the operation of a single local LSTM unit in a layer of the network at time step $t$. Through activation functions *sigmoid*, *tanh*, and $\phi$, the corresponding Input Gate ($i_t$), Cell ($C_t$), Output Gate ($o_t$), and Forget Gate ($f_t$) values of the gate are calculated at the same time with the previous time step ($h_{(t-1)}$). The output is the same but also receives the input data related to the current time step ($x_t$). These are shown in Eqs 1–6. Here, $\theta_{xn}$ and $\theta_{hn}$ are the values before the input and output data of the unit weight matrix, and $b_n$ with $n \in (i, g, f, o)$ of the bias vector identify the gate.

$$f_t = \text{sigma}\left(\theta_{xf} x_t + \theta_{hf} h_{t-1} + b_f\right) \tag{1}$$

$$i_t = \text{sigma}\left(\theta_{xi} x_t + \theta_{hi} h_{t-1} + b_i\right) \tag{2}$$

$$\widetilde{c_t} = \tanh\left(\theta_{xg} x_t + \theta_{hg} h_{t-1} + b_g\right) \tag{3}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \widetilde{c_t} \tag{4}$$

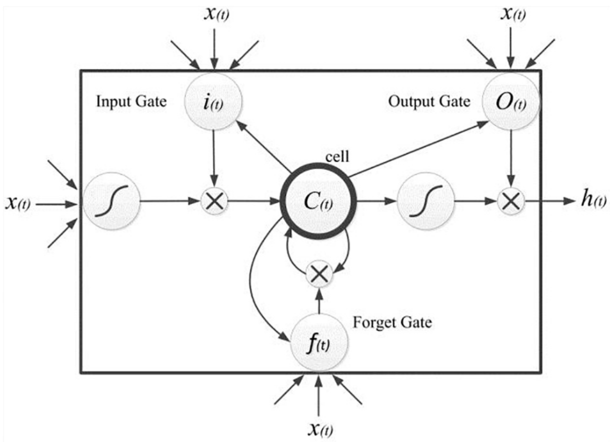


**FIGURE 1 |** LSTM unit structure (Graves, 2013).

$$o_t = \text{sigma}\left(\theta_{xo}x_t + \theta_{ho}h_{t-1} + b_o\right) \tag{5}$$

$$h_t = o_t \odot \phi(c_t) \tag{6}$$

## Model Building and Scenario Setting

In their forecast of China's energy demand and self-sufficiency, Xie et al. (2015) proposed that the self-sufficiency of crude oil would drop from 40.6 to 35.9% and that of natural gas from 73.1 to 68.6% from 2015 to 2020. From **Figure 2**, it can be seen that renewable energy, crude oil, natural gas, and nuclear power vary over time regarding financial revenue and expenditure, but from 2015 to 2018 there is a downward trend for crude oil and the other data. This confirms Xie et al. (2015) on the study of the self-sufficiency rate of crude oil, but the trend of natural gas production has not declined over the same period, but gradually rose in more than 10 years. Perhaps because natural gas is a clean source of energy, it can be regarded as a supplement to renewable energy without being restricted in exploitation. Thus, to ensure the integrity of experiments and the reliability of the forecasting model, based on 2.1, 2.2, and 2.3, the data are divided into three types of prediction index of renewable energy. The first category is crude oil, natural gas on behalf of non-renewable energy, and nuclear energy forecast of renewable energy (Merge1). The second is the projections of renewable energy by nuclear energy and fiscal revenues and expenditures (Merge2). The third category is the prediction of renewable energy by crude oil, natural gas, and financial balance (Merge3). In the end, seven methods can be used to predict renewable energy in a single and combined form.

The results can be seen in **Table 1**. The RMSE is the root mean square error, as shown in Eq. 7. The emergence of abnormal points (such as abnormally large and abnormally small values) will lead to errors in the model. According to the characteristics of intermittent renewable energy, abnormal values are considered to be normal, so the use of RMSE to measure the error is not reasonable. MAPE obtains the ratio between the true value and the predicted value, which is more appropriate for determining the accuracy of renewable energy prediction, and is shown in Eq. 8. In similar studies, Lu (2019) used MAPE as an indicator to measure the accuracy of the model. Thus, it is concluded that the three indexes are the most accurate in predicting renewable energy (Merge4), and the best prediction model is shown in **Figure 2**.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - x_i)^2} \tag{7}$$

$$\text{MAPE} = \sum_{i=1}^{N}\left|\frac{y_i - x_i}{y_i}\right| \times \frac{100}{N} \tag{8}$$

where $N$ is the total number of data samples, $y$ is the actual value, and $x$ is the predicted value.

According to the IEA, the share of the world's energy supply for renewable energy will be 22% by 2015 and 31% by 2035. In the medium- and long-term development plan for renewable energy, the key areas for development from 2010 to 2020 are hydropower, bio-energy, wind energy, solar energy, and other renewable energy, including geothermal energy and marine energy. In recent years, the utilization of renewable energy has been assigned great importance in China. Renewable energy rose 15.1% from 2014. China's renewable energy now accounts for 16.7% of the world's total, up from 1.2% a decade ago. According to the 13th 5-year plan (2015–2020), non-fossil energy will account for 15% of the total primary energy consumption by 2020. Data shows that China's renewable energy generation capacity (including hydropower generation) has reached 14,386.7 TWh in 2017, indicating that renewable energy resources are very rich, but using them involves some special technical, economic, and environmental issues. In BP's 2019 energy outlook forecast for China's energy market in 2040, demand for almost all fuels is growing, with oil up 19%, natural gas up 1.66 times, nuclear up 4.05 times, and renewable power up 5.84 times. Renewable energy is becoming a bigger part of the global energy mix, especially in the power sector. Therefore, in the discussion concerning renewable energy growth trends, three scenarios are considered:

Scenario 1: although China's major energy and fiscal monthly data show an overall upward trend in recent years, as a result of the implementation of the tax reduction policy, the pressure of balance of fiscal revenues and expenditures has gradually increased, as shown in **Figure 3**. Therefore, the lowest growth rate (non-negative) of the fiscal revenue and expenditure and other data is calculated based on the growth of the historical data, so as to predict the future trend of renewable energy and provide the basis for scenarios 2 and 3.

$$R_1 = \min\left\{R_i = \frac{N_{i+1}}{N_i}\middle| R_i \geq 0\right\} \tag{9}$$

Scenario 2: considering the intermittency of renewable energy and the difficulty in matching power production

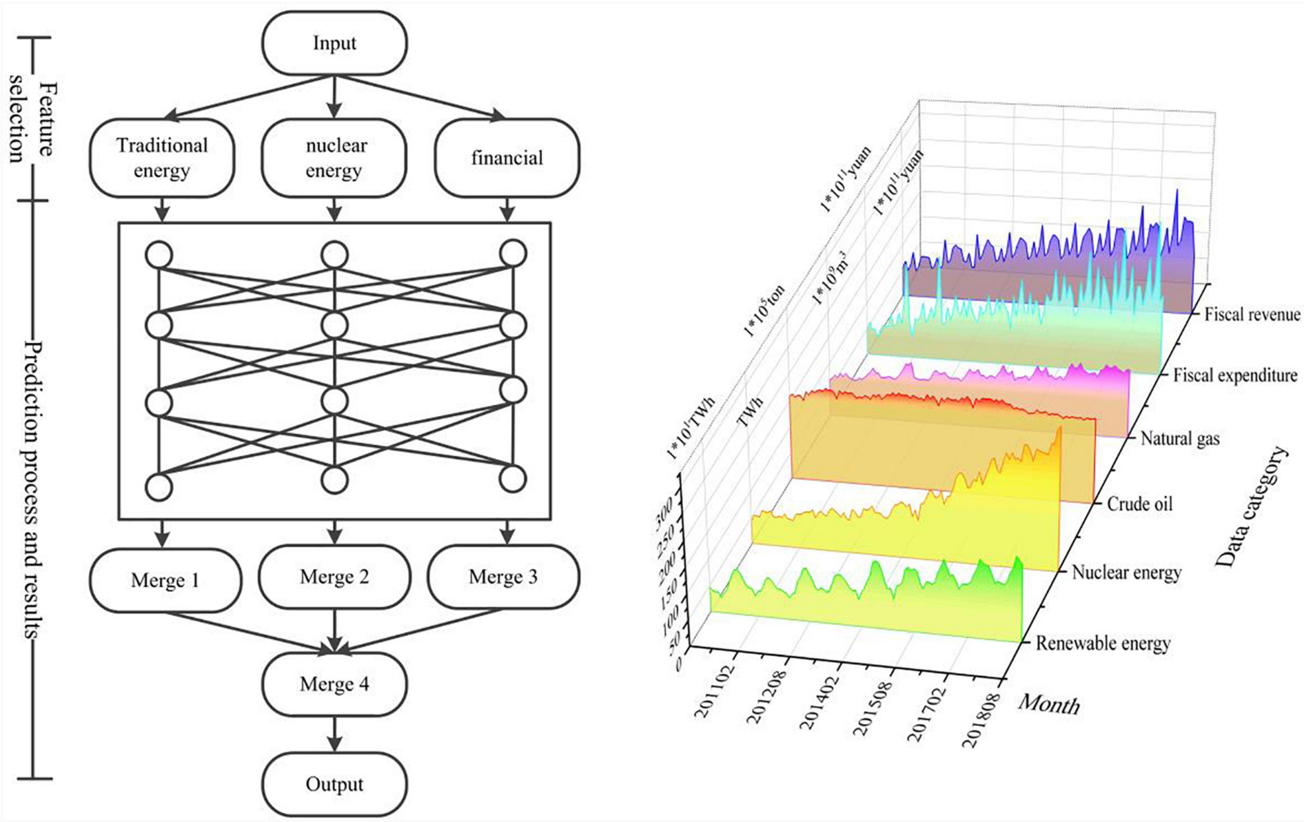


**FIGURE 2 |** Model structure and historical data analysis.

and actual installed capacity, it is assumed that the renewable energy power supply displays stable growth under the restraining effect of historical crude oil, natural gas exploitation and nuclear power supply and the constraint of financial revenue and expenditure.

$$R_2 = \frac{1}{N}\frac{N_{i+1}}{N_i} \tag{10}$$

Scenario 3: to recognize the role of renewable energy in environmental improvement and emissions reduction, assuming that the development of renewable energy is based on financial incentives, this presents a kind of average (non-negative) rate of additional growth.

$$R_3 = \left(1+\frac{1}{N}\frac{N_{i+1}}{N_i}\right)^n \tag{11}$$

$$V(t_n) = V(t_0)(1+R_q)^n, \quad q = 1, 2, 3 \tag{12}$$

In Eqs (9–12), $R_1$, $R_2$, and $R_3$ are the monthly growth, rates of scenario 1, scenario 2, and scenario 3, including crude oil, natural gas, nuclear energy, fiscal expenditure, and fiscal revenue. $V(t_0)$ is the value of the starting month, $V(t_n)$ is the value of the ending month, $n$ is the number of months in the range, and $N$ is the number of data samples.

# RESULTS AND DISCUSSION

## Results

It has been shown in section "Model Building and Scenario Setting" that the prediction of renewable energy by the LSTM model requires more accurate input of the five data indexes: crude oil, natural gas, nuclear energy, and fiscal revenue and expenditure. Therefore, the selection of input characteristics in various prediction studies is also an important factor affecting the accuracy of the model. On this basis, the monthly growth rate

**TABLE 1 |** Error comparison of each model.

| Input data | RMSE | MAPE |
|---|---|---|
| Non-renewable energy | 23.5893 | 16.39 |
| Nuclear energy | 16.91845 | 17.23 |
| Fiscal revenue and expenditure | 21.89596 | 21.29 |
| Non-renewable energy + nuclear energy (Merge1) | 45.6084 | 22.36 |
| Nuclear energy + fiscal revenue and expenditure (Merge2) | 34.10925 | 20.75 |
| Fiscal revenue and expenditure + non-renewable energy (Merge3) | 28.36976 | 21.55 |
| All (Merge4) | 25.68142 | 13.03 |

*Model parameters: epoch = 2000, step = 2, size = 1, lr = 0.001.*

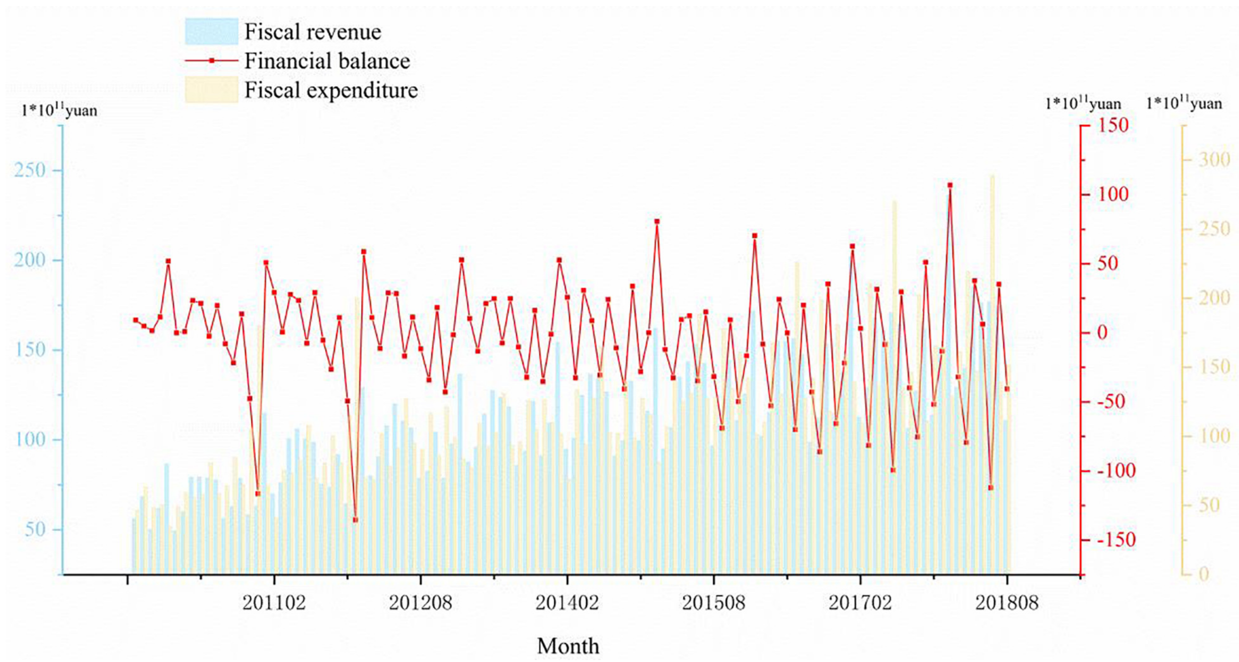


**FIGURE 3 |** Financial balance.

of renewable energy in 2019 is estimated from three scenarios according to the outlook of BP, an authoritative international institution, on renewable energy in China and the historical trend analysis concerning renewable energy related data, as shown in **Table 2**.

According to the different rate of all data, it can be divided into three different growth trends. The nuclear energy in scenario 1 will remain unchanged for the next 16 months, with the fastest growth in scenario 3. Natural gas, as a clean energy with higher core security, shows an increasing trend in all three scenarios, among which scenario 1 has the fastest growth rate of 3.3% per month. Crude oil grew the fastest in scenario 3 and the lowest in scenario 1, which was only 0.02%. In terms of fiscal revenue and expenditure, the growth rates of scenario 1 and scenario 2 are the same, respectively 0.28 and 0.87%, lower than scenario 3.

Based on the aforementioned scenarios, renewable energy output was predicted, and the trend variation and predicted values for the three scenarios were obtained as shown in **Figure 4**. The comparison of the growth rate of the predicted results for renewable energy under the three scenarios is shown in **Figure 5**. In scenario 1, the renewable energy fluctuates between 1288.81 and 1297.13 TWh, with the lowest and highest growth rates of −21 and 0.06%, respectively. In scenario 2, the renewable energy fluctuates between 1295.12 and 1513.07 TWh, with the lowest and highest growth rates of 0.28 and 1.55%, respectively. In scenario 3, the renewable energy fluctuates between 1295.12 and 1549.18 TWh, with the lowest and highest growth rates of 0.51 and 1.8%, respectively.

Here, we consider a comparative analysis of the indicators. For scenario 1, nuclear power remains the same, whereas other indexes show a state of growth. However, the predicted results indicated a decline. Also, in this scenario, the growth of natural gas is faster than other indicators. Therefore, it is concluded that gas is a strong competitor to the future development of renewable energy. In scenario 2, all the indexes showed an upward trend. Scenario 1 compared various indicators of growth, and the growth rate here reduced to 0.68% for natural gas, nuclear energy growth rose to 1.66%, and other indicators of growth essentially remained the same. The result showed an upward trend in sharp contrast to the results from scenario 1, and demonstrated the likely development of renewable energy in the future, the importance of nuclear energy to the synergy of renewable energy, and at the same time once again verified safe, clean energy is a development in the future of the enemy. In scenario 3, the monthly growth rate of the indicators is similar to scenario 2, where growth increased month by month. The renewable energy prediction results showed an upward trend to nearly the same extent as scenario 2, and the predicted values were higher than that month. This confirms that when crude oil, natural gas has increased less than nuclear power, regardless of the trend of financial revenue and expenditure, renewable energy will still increase. This growth is likely to increase with the increase of the indicators.

## Discussion

### Influence of Traditional Energy on Renewable Energy

China's energy demand is still rising, but environmental problems cannot be ignored. It is an inevitable trend to develop new energy sources to replace traditional energy sources and reduce environmental pollution. Nearly 200 parties to the 2015 Paris agreement agreed to limit global warming to 1.5°C, and China pledged to reduce its carbon intensity by

**TABLE 2 |** The rate of growth in each scenario.

| Data | Crude oil (%) | Natural gas (%) | Nuclear energy (%) | Fiscal expenditure (%) | Fiscal revenue (%) |
|---|---|---|---|---|---|
| **Scenario 1** | 0.02 | 3.30 | 0 | 0.87 | 0.28 |
| **Scenario 2** | 0.08 | 0.68 | 1.66 | 0.87 | 0.28 |
| **Scenario 3** | | | | | |
| September-2018 | 0.0800 | 0.7024 | 1.6600 | 0.8776 | 0.2808 |
| October-2018 | 0.0800 | 0.7256 | 1.6876 | 0.8852 | 0.2816 |
| November-2018 | 0.0800 | 0.7496 | 1.7156 | 0.8929 | 0.2824 |
| December-2018 | 0.0801 | 0.7743 | 1.7440 | 0.9007 | 0.2831 |
| January-2019 | 0.0801 | 0.7999 | 1.7730 | 0.9085 | 0.2839 |
| February-2019 | 0.0801 | 0.8262 | 1.8024 | 0.9164 | 0.2847 |
| March-2019 | 0.0801 | 0.8535 | 1.8324 | 0.9244 | 0.2855 |
| April-2019 | 0.0801 | 0.8817 | 1.8628 | 0.9324 | 0.2863 |
| May-2019 | 0.0801 | 0.9108 | 1.8937 | 0.9405 | 0.2871 |
| June-2019 | 0.0802 | 0.9408 | 1.9251 | 0.9487 | 0.2879 |
| July-2019 | 0.0802 | 0.9719 | 1.9571 | 0.9570 | 0.2887 |
| August-2019 | 0.0802 | 1.0040 | 1.9896 | 0.9653 | 0.2896 |
| September-2019 | 0.0802 | 1.0371 | 2.0226 | 0.9737 | 0.2904 |
| October-2019 | 0.0802 | 1.0713 | 2.0562 | 0.9822 | 0.2912 |
| November-2019 | 0.0802 | 1.1067 | 2.0903 | 0.9907 | 0.2920 |
| December-2019 | 0.0803 | 1.1432 | 2.1250 | 0.9993 | 0.2928 |

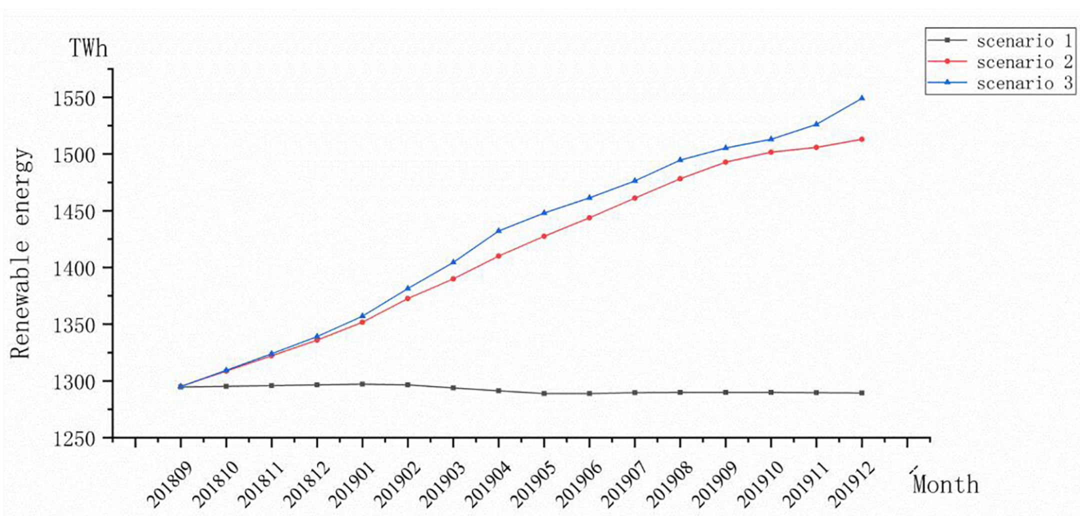


**FIGURE 4 |** Renewable energy sources providing power forecasts in various scenarios.

40 to 45% by 2020. To fulfill its commitment to the world, China has made efforts to develop renewable energy through a number of policies, making renewable energy increasingly competitive in terms of efficiency, energy production, and economic efficiency. Both in terms of investment efficiency and environmental factors, renewable energy has become the most suitable energy source for China's development, which is also the main reason for the reduction of carbon emissions. Similarly, although natural gas is a kind of non-renewable energy, it is undeniable that it is a kind of clean energy and plays an important role in reducing environmental pollution. Therefore, the competition between natural gas and renewable energy is the most obvious among non-renewable energy. Furlan and Mortarino (2018) have verified that renewable energy and coal, oil, natural gas, and nuclear power are competitors. The study in this paper also found that there is a negative relationship between natural gas and renewable energy, and that the conditions for the existence of this relationship, namely crude oil, mean that natural gas is growing faster than nuclear power indicators such as financial revenue growth. Therefore, the appropriate restriction of natural gas production in the future energy policies of the Chinese government may have a positive impact on the development of renewable energy.

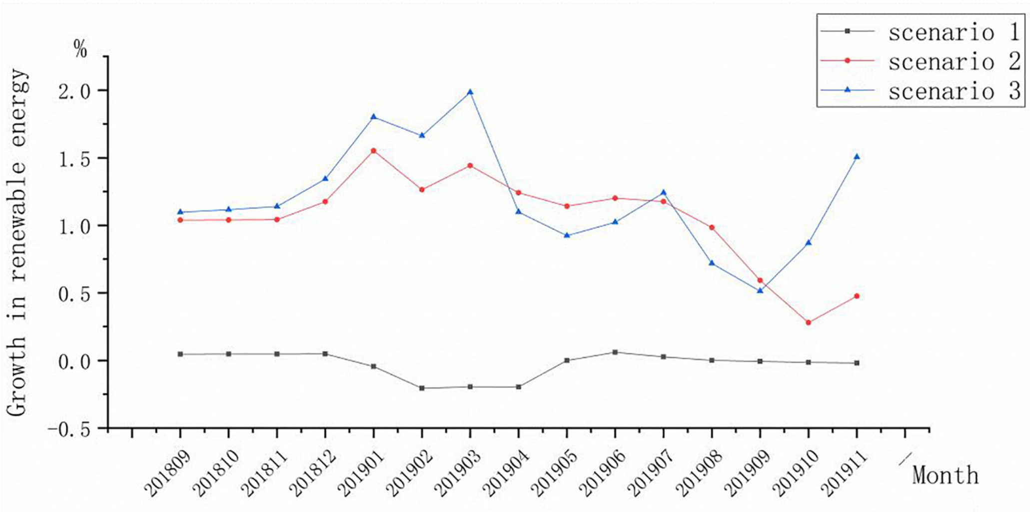


**FIGURE 5 |** The growth rate of renewable energy supply in each scenario.

**TABLE 3 |** Production and reserve of seven metals.

| Material | Dy | Nd | Te | In | Ga | Cd | Se |
|---|---|---|---|---|---|---|---|
| Annual production in China – 2015 (unit: tons) (Wang et al., 2019) | 1142 | 15,215 | 280 | 350 | 550 | 8090 | 920 |
| Reserve in China (unit: kt) (Wang et al., 2019) | 790 | 6784 | 6.6 | 1.3 | 16.3 | 92 | 26 |

## Influence of Nuclear Energy on Renewable Energy

In 2016, nuclear energy accounted for 2% of China's total power generation, and the IEA also announced that nuclear energy is expected to only account for 4% of China's total power generation in 2040. However, at the end of 2017, China's carbon intensity has been reduced by 46%, and non-fossil energy accounts for 14.3% of primary energy consumption in 2018. Compared with the target of reaching 15% by 2020, the gap is only 0.7%. It can be seen that China cannot solely rely on nuclear energy to reach the emissions reduction goal. Thus, renewable energy, as an energy market, is in a state of rapid development with remarkable achievements, but the intermittency problem will increase with the proportion of renewable energy power generation, with its long construction period and relatively small, but clean, energy. The stability of nuclear power can be used to supplement renewable energy sources. This research also found that when the nuclear growth is faster than for natural gas, renewable energy power will increase. In the case of fiscal revenue and expenditure, the growth rate of gas is less than the growth rate of nuclear energy, and renewable energy will increase. This means that the limited production of natural gas and control of its consumption can lead to more renewable energy, reducing carbon emissions. As Li and Lu (2019) proposed, natural gas consumption will be limited to between 9 and 14%; China's 2020 carbon intensity will be 15.27% lower than in 2015.

## Assessment of Supply Risks for Individual Metals

Based on the results mentioned previously, it is estimated that the cumulative supply of renewable energy in the next 16 months will be between 20,677.25 and 22,816.83 TWh. In 2018, China's renewable energy generation capacity reached 1.9 trillion KWh, including 1.2 trillion KWh of hydropower, 366 billion KWh of wind power, and 177.5 billion KWh of PV power, accounting for 63, 19, and 9%, respectively (Ministry of Ecology and Environment).[1] On this basis, it is roughly estimated that in the next 16 months, the cumulative wind energy supply will be between 3928 and 4335 TWh, and the cumulative solar energy supply will be between 1860 and 2053 TWh. Referring to the analysis of the most common metal requirements for each energy technology by Moss et al. (2013) and production and reserve of seven metals in **Table 3**, the demand of Te and In is more than two times that of the production in China in 2015. Both metals also face significant supply risks from their holdings in China. Dy and Nd, as key materials for wind energy, are close to the total amount of mining in 2015 and may face the threat of competition with other sectors in the future.

The future of solar energy in China will be limited by the need for metal materials, and the deployment of wind materials will need to be accelerated. To solve this dilemma, the transformation of China's energy system needs to proceed from the following aspects: (1) encouraging the application of technologies to improve the energy density of metals, thus easing the dependence on materials; (2) increase recycling techniques to improve mine recovery rates, mineral processing, and smelting recoveries; (3) promote the reasonable extension and combination of industrial chain of circular economy and improve the recycling of waste;

[1] http://www.mee.gov.cn/

(4) in terms of hydrogen energy infrastructure, promote the advanced system of hydrogen production, hydrogen supply, and hydrogenation and the main role of enterprises, and improve the technical standards and testing system.

## CONCLUSION

The accurate prediction of renewable energy can be achieved. It can provide a strong basis for the state to invest in the construction of capacitors in the power industry, and effectively solve the waste of wind, water, and solar energy and other energy caused by the lack of energy storage equipment in China's current renewable energy power supply field, and contribute to China's sustainable development. Based on non-renewable energy, nuclear energy, fiscal balance, and other factors related to the development of renewable energy, this paper establishes a prediction model and forecasts China's renewable energy consumption from September 2018 to December 2019 based on various monthly data recently released by the Chinese bureau of statistics. Through the verification and analysis in this paper, the following three important conclusions can be drawn:

(1) Through the process of selecting indicators through the LSTM prediction model, it is concluded that China's renewable energy is intrinsically related to five variables, including crude oil, natural gas, nuclear energy, financial revenue, and expenditure. The prediction of China's renewable energy consumption can be achieved by monitoring these five variables.
(2) In the process of data collection and experimental comparison, this paper concludes that in the future development of renewable energy, nuclear energy has an important synergistic effect on its development, and at the same time verifies that natural gas, a safe and clean energy source, is a strong competitor to the development of renewable energy in the future.
(3) It is confirmed that when the growth rate of crude oil and natural gas is smaller than that of nuclear energy, regardless of whether the financial balance remains unchanged or grows, renewable energy will still grow, and this growth may increase with the increase of various indicators. Conversely, when natural gas production increases rapidly, renewable energy capacity declines.
(4) The development of China's renewable energy, especially solar energy, is restricted by metal materials, among which Te and In are the most prominent. Improving the energy density of metals plays a key role in China's transition to a low-carbon energy structure.

In addition, there are some deficiencies in the prediction process of China's renewable energy. Although the Chinese government has provided researchers with a larger amount of data in recent years, the limited sample size caused by the relatively difficult data collection limits the prediction ability of the LSTM model adopted in this paper. Therefore, the prediction accuracy of renewable energy is not obviously superior to other traditional energy prediction models. It is hoped that with the accumulation of data, the LSTM approach will have more advantages in predicting renewable energy.

## DATA AVAILABILITY STATEMENT

Publicly available datasets were analyzed in this study. This data can be found here: https://data.stats.gov.cn/english/easyquery.htm?cn=C01.

## AUTHOR CONTRIBUTIONS

BL and JC carried out the concepts, design, definition of intellectual content, literature search, data acquisition, data analysis, and manuscript preparation. HW provided assistance for data acquisition, data analysis, and statistical analysis. JC carried out literature search, data acquisition, and manuscript editing. QW performed manuscript review. All authors have read and approved the content of the manuscript and have made substantial contributions to all of the following: (1) the conception and design of the study, or acquisition of data, or analysis and interpretation of data, (2) drafting the manuscript or revising it critically for intellectual content, (3) final approval of the version to be submitted.

## FUNDING

The funding sources of this work include the National Natural Science Foundation of China (grant number 71503180) and Science Foundation of Ministry of Education of China (grant number 20YJA630042).

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**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.

frontiers in Energy Research

ORIGINAL RESEARCH
published: 02 February 2021
doi: 10.3389/fenrg.2020.627096

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# China's Energy Transition Policy Expectation and Its $CO_2$ Emission Reduction Effect Assessment

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Measuring the expected impact of China's energy transition on carbon dioxide ($CO_2$) mitigation and identifying the key influencing factors in different economic sectors will help to provide better policy recommendations for $CO_2$ emission reduction. Based on the prediction results of China's $CO_2$ emissions in 2030 under the baseline scenario and the target scenario, this study constructs the control group and the treatment group of the energy transition policy quasinatural experiment and then uses the difference in difference (DID) model to evaluate the $CO_2$ emission reduction effect of China's energy transition policy. The results reveal that the energy transition policy has a significant impact on $CO_2$ emission reduction and helps to achieve China's 2030 carbon emission reduction target. The impact of energy structure transition on $CO_2$ emission reduction has significant sectoral heterogeneity, which has a positive reduction effect in the industry sector, wholesale and retail sectors, and accommodation and catering sectors, but its reduction effect is not obvious in transportation, storage, and postal sectors. It is suggested that China should implement the sector-differentiated $CO_2$ mitigation strategy, focus on improving the industrial sector's energy efficiency, and promote the clean, low-carbon transition of energy consumption structure in construction, transportation, storage, and postal industries.

**Keywords: China, energy transition, $CO_2$ emission, policy preassessment, DID model**

OPEN ACCESS

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***Specialty section:***
*This article was submitted to Sustainable Energy Systems and Policies,*
*a section of the journal Frontiers in Energy Research*

***Received:*** *08 November 2020*
***Accepted:*** *28 December 2020*
***Published:*** *02 February 2021*

***Citation:***
*Wang D, Liu X, Yang X, Zhang Z, Wen X and Zhao Y (2021) China's Energy Transition Policy Expectation and Its $CO_2$ Emission Reduction Effect Assessment.*
*Front. Energy Res. 8:627096.*
*doi: 10.3389/fenrg.2020.627096*

## INTRODUCTION

With the rapid growth of the fossil energy consumption in China, the $CO_2$ emission reduction has gradually become the focus of global attention (Ouyang and Lin, 2017). Constrained by the structure of energy endowments, China's economic growth is accompanied by the production and consumption of a large amount of coal, which has led to the emission of a large number of greenhouse gases and has a severe impact on the ecological environment. (Wang et al., 2016; Zhang et al., 2017; Li et al., 2019). As the world's second largest economy, China has become the world's largest energy consumer and the largest $CO_2$ emitter (Hao et al., 2015). In response to international calls for reducing carbon dioxide emissions, China is working hard to reduce carbon dioxide emission intensity (CEI). China promises that CEI in 2030 will be reduced by 60–65% compared to 2005 and strives to reach the peak of carbon dioxide emissions around 2030 as soon as possible. Considering the coal-based energy endowment constraints, the National Development and Reform Commission (NDRC) issued the "Energy Production and Consumption Revolution Strategy

(2016–2030)" at the end of 2016, clearly requiring that the coal consumption structure reaches 48% in 2030 (NDRC, 2016). What impact will this policy orientation have on China's $CO_2$ mitigation targets in 2030? What is the expected effect of the policy? To address these issues, this study conducts policy preassessment studies on the energy transition policy.

Scientific prediction of the future trend of $CO_2$ emissions is the fundamental basis for judging whether China's $CO_2$ emissions can peak in 2030 (Zhang et al., 2017). Mi et al. (2017) point out that under the scenario of an average annual GDP growth rate of 5%, China will achieve $CO_2$ emissions peak of 11.2 billion tons in 2026 and then fall to 1.084 billion tons in 2030. Elzen et al. (2016) indicate that China's current mitigation policies are challenging to achieve Paris emission reduction commitments in 2030. Zhang et al. (2019) found from past studies that China's energy consumption structure has improved during the past three FYP periods. It is expected that in the next decades, the energy consumption structure can be optimized further through future policies and become another factor in reducing $CO_2$ emissions. Under the baseline scenario, China's total $CO_2$ emissions in 2030 will reach 14.7–15.4 billion tons, while the policy scenario will be reduced to 13.1–13.7 billion tons. Based on the framework of scenario analysis, Wang et al. (2019a) considered that China will achieve the CEI reduction target in 2030 under the current mitigation policy and difficult to achieve the target of $CO_2$ emission peak, and it is expected that China's total $CO_2$ emissions will reach 11.289 billion tons in 2030. Therefore, whether China can achieve the CEI mitigation goals and the peak emission in 2030 depends on identifying the influencing factors.

Considering social development, economic growth, energy technologies, and other factors, many scholars have analyzed the influencing factors of $CO_2$ emission reduction based on the framework of the Kaya equation and IPAT model (Zhang et al., 2017; He et al., 2018). According to the consensus view, economic growth and population size are the promotion factors of $CO_2$ emissions, while energy intensity, energy structure, and industrial structure are the promotion factors of reducing $CO_2$ (Ang et al., 1998; Wang et al., 2005). Specifically, the regional economic growth and the energy technology progress have a relatively large impact on $CO_2$ emission reduction, while the total population, the industrial structure, and the energy structure optimization have a relatively small contribution to $CO_2$ mitigation (Ma et al., 2016; Zhu et al., 2017). As far as the mitigation contribution of each factor, the economic transition development, the energy technology progress, and the energy structure optimization will be the critical paths for China to realize $CO_2$ emission reduction (Wang et al., 2019a). In fact, many studies have shown that the mitigation effects of economic growth and energy technology progress are very significant. In contrast, the mitigation contribution of energy structure optimization is relatively small. However, considering China's high-carbon energy structure, the mitigation potential of energy structure optimization still has room for further improvement (Yi et al., 2016). Xu et al. (2020) pointed out that $CO_2$ emissions will not peak in the business-as-usual scenario, further revealing that adjusting the energy consumption structure is the key to reducing $CO_2$ emissions and achieving their peak. Based on the scenario prediction of China's $CO_2$ emission by 2030, Wang et al. (2019b) suggest that whether China's $CO_2$ emission reduction target in 2030 can be achieved lies in exploiting the mitigation potential of economic growth, energy technology progress, and energy consumption structure optimization, especially in the industrial sector.

The view that energy transition helps to promote $CO_2$ emission reduction has been widely recognized by scholars at home and abroad (Pan et al., 2017; Gölz and Wedderhoff, 2018). In terms of the existing research, many scholars believe that China's energy transition mainly involves the clean use of high-carbon energy and the structure optimization of the clean low-carbon energy (Pain, 2017; Chai et al., 2019). At the same time, there is also significant uncertainty in the direction of China's energy transition, especially in the determination of future clean energy (Ren and Sovacool, 2015; Wang et al., 2017). Besides, the issue of the energy transition has also attracted the attention of many scholars. Many studies have shown that there are many problems in China's energy transition from coal-based to renewable energy, which involves technological levels, cost constraints, and institutional obstacles (Zhou et al., 2012; Musa et al., 2018). From the perspective of the practice of international energy transition, the developed countries such as Europe and the United States have been leading the energy transition, and the proportion of clean energy in total energy consumption is relatively high. In addition, most of their policy goals of the energy transition are energy security, affordable, and environment friendly (Schmid et al., 2019). However, in a specific practice, the priorities of national energy transition objectives are not the same. For example, the U.S. energy transition's core motivation is to ensure energy security and reduce dependence on imported energy, and other motivations such as environmental protection are secondary. On the contrary, environmental protection has been the most important motivation for Germany's energy transition, although energy security motivation is also essential for Germany (Gölz and Wedderhoff, 2018; Karin et al., 2019). In view of this, as the world's largest energy consumer, China should pay attention to both energy security and acceptable costs as well as the environmental impact of the energy transition, especially its impact on carbon emissions.

Considering the necessity of reducing carbon dioxide emissions and the urgency of controlling air pollution, China's energy transition will inevitably require the efficient use of traditional fossil energy. Therefore, the energy consumption structure will eventually tend toward clean and efficient development (BP, 2017; Chai et al., 2019). In "Energy Production and Consumption Revolution Strategy 2016–2030," China puts forward the strategic orientation of energy transition (NDRC, 2016), which is "security first, conservation first, green, low-carbon, and proactive innovation." However, in the concrete implementation process, due to the significant sectoral differences in resource allocation and energy technology among China's economic sectors, the energy consumption structure and its transition process also have sectorial heterogeneity (Wang et al., 2019b). In conclusion, China's energy transition is still in the transition period of clean utilization of high-carbon energy and clean energy scale expansion. China's energy transition and sectorial differences will also affect the realization of $CO_2$ mitigation targets by 2030.

The research on the impact of the energy transition on $CO_2$ emissions can be divided into two categories. One is based on historical data and measures the $CO_2$ mitigation effect of energy structure optimization through econometric models, index decomposition, and other methods. For example, Qi and Li (2017) investigated the relationship between renewable energy consumption, carbon emissions, and economic growth in the EU based on the panel vector autoregressive (PVAR) model; Zhang and Da (2015) used the LMDI model to measure the emission reduction effect of energy structure. This kind of method is simple and easy to operate, but limited by data accessibility, the research conclusion can only provide a general direction for policy improvement (Yang et al., 2018). The other is the micropolicy effect evaluation research focusing on energy transition-related policies and using nonexperimental historical data. The policy evaluation methods mainly include the instrumental variable (IV) method, propensity score matching (PSM) method, regression discontinuity (RD) model, and difference in difference (DID) model (Dong et al., 2019; Zhang et al., 2019). Among them, the IV, PSM, and RD methods have certain problems in how to determine the instrumental variables, whether they meet the "one size fits all" threshold, whether there are sufficiently strong assumptions, and whether they have a large number of data samples (Campbell, 1991; Heckman et al., 1997; Angrist and Pischke, 2010; Rosenbaum, 2017).

In contrast, the DID method can solve these problems well and allow the existence of unobservable factors, thereby relaxing the conditions for policy evaluation and making the application of policy evaluation closer to economic reality (Zhang et al., 2019). However, as a major weapon in the policy effect evaluation method, DID has been applied to the effect evaluation of pilot policies that have been implemented for a period of time. Relevant studies on the evaluation of the future implementation effect of a certain policy are relatively rare, which may be limited by the absence of scientific prediction data. Therefore, based on the data obtained from Wang et al. (2019a), this study will use this method to investigate the heterogeneous impact of energy transition policies on $CO_2$ mitigation in China's different economic sectors. Not only can we make full use of the exogenous nature of explanatory variables but we can also control unobserved individual heterogeneity on the explanatory variables to better achieve unbiased estimates of the effects of policy interventions.

Furthermore, some scholars have conducted scenario prediction studies based on the framework of scenario analysis for the reduction effect of energy structure (Tan et al., 2018). For example, Wang et al. (2019a) predicted the trend of China's $CO_2$ emission under the baseline scenario and the target scenario based on the extended form of Kaya equation. Furthermore, they measured the $CO_2$ mitigation potential of China's energy structure optimization with the LMDI model. The scenario analysis method combines qualitative analysis with quantitative analysis, which can predict different trends in the development of things from a multidimensional perspective, which is helpful to explore the different influences of various factors on future trends of $CO_2$ emissions under different scenarios (Li et al., 2018; Song et al., 2018). However, this method also has some shortcomings. Although the scenario prediction results is helpful to provide multiple choices for the $CO_2$ mitigation policy, it is difficult to reveal the $CO_2$ emission reduction potential of various policy factors. Based on this consideration, this study uses the DID model to analyze the expected mitigation effect of China's energy transition policy on the basis of China's $CO_2$ emissions forecast results in the baseline scenario and target scenario (Wang et al., 2019a), so as to determine the policy effectiveness of the energy transition.

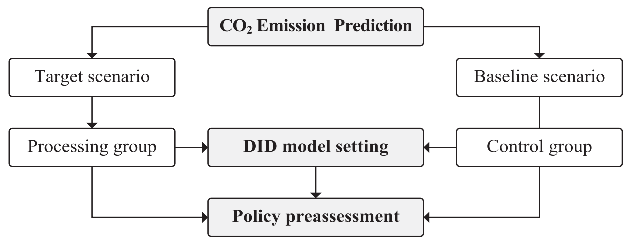


**FIGURE 1** | Research framework.

In summary, this study needs to verify whether the energy transition policy can effectively promote the development of carbon emission reduction in China, and if so, to what extent it will play a role in emission reduction. Furthermore, considering the difference of energy utilization modes in different sectors, whether there is heterogeneity in the impact of energy transition policy on different sectors remains to be evaluated. Therefore, according to the prediction results of China's $CO_2$ emissions in 2030 under the baseline scenario and the target scenario (Wang et al., 2019a), this study constructs the control group and the treatment group of the energy transition policy quasinatural experiment, uses the DID model to evaluate the expected impact of energy transition on $CO_2$ emission reduction, and further discusses the sectoral heterogeneity of the emission reduction effect of energy transition, so as to put forward some reasonable policy opinions to meet China's $CO_2$ mitigation target.

In fact, reasonable policy prediction is more conducive to realizing China's low-carbon development goals and improving the energy transition's policy effect. According to the previous research results, this study designs a quasinatural experiment of the energy transition policy and uses the DID model to evaluate the $CO_2$ mitigation effect of China's energy transition policy, in order to provide a basis for decision-making to achieve China's $CO_2$ mitigation target by 2030. Among them, the quasinatural experiment of energy transition policy involves the design of the control group and treatment group, which are based on the forecast results of China's $CO_2$ emissions under the baseline scenario and target scenario, respectively (**Figure 1**).

# METHODS AND DATA

## Model Setting

After implementing the energy structure optimization and transition policy in China, $CO_2$ emission intensity changes mainly come from three aspects. One is because of the "grouping effect" formed by China under different scenarios, and the other is the "time effect" caused by the inertia of time. The third is the "policy treatment effect" which is part of China's policy impact under the target situation. The DID method can effectively separate the "policy processing effect" and is widely used to evaluate the effect of policy implementation (Zhang, 2019).

In this study, based on the scenario prediction of China's $CO_2$ emissions (Wang et al., 2019a), the DID method is used to construct the binary virtual variable G = {0, 1}. When the object is China under the target scenario, G takes 1; otherwise, the value is 0; simultaneously, the year of the implementation of the policy is taken as the boundary and divided into before and after the experimental period. The binary dummy variable $T = \{0, 1\}$ is constructed. When entering the experimental period (2017), $T = 1$, and before the experimental period (2017), $T = 0$. Therefore, for China in the target scenario, when $T \geq 2017$, the corresponding dummy variable $G \times T$ is denoted as 1; otherwise, they are all 0. The interaction term $G \times T$ was defined to describe the policy treatment effect of China's energy structure transition. Based on the above ideas, considering that the reduction of $CO_2$ intensity is more in line with China's national conditions than the total $CO_2$ mitigation, this study selects the $CO_2$ emission intensity (CEI) to measure the performance of China's $CO_2$ emission reduction, so as to construct its basic hypothesis model:

$$\text{lnCEI}_{\text{it}} = \lambda_0 + \lambda_1 G_{\text{it}} + \lambda_2 T_{\text{it}} + \lambda_3 G_{\text{it}} T_{\text{it}} + \beta lnX_{\text{it}} + \varepsilon_{\text{it}}, \quad (1)$$

where subscript $i = 1, 2$, respectively, represents the baseline scenario and target scenario of China's $CO_2$ emissions, $t$ represents the time, and $\boldsymbol{X}$ represents other control variables. That is, China's CEI under the baseline scenario is changing under the current situation and historical development trend of China's society, economy, resources, and environment, while the target scenario is based on the implementation of certain energy policies. The development trend of the two scenarios before implementing the policy is identical, satisfying the conditions of the parallel trend of the control group and the experimental group used by the DID model. Therefore, the changes in the two groups before and after the experiment are purely caused by the policy treatment effect.

Regarding the selection of control variables, we mainly follow some suggestions and practices put forward by Bernerth and Aguinis (2016). In order to describe and explain the relationship between energy transition policies and carbon emission reduction, we need to control other related variables that may have an unnecessary impact on this relationship. As a systematic, complete, and simple method, the Kaya equation is recognized as an important tool for revealing the links between population, economy, energy, and environment (Kaya, 1989). It is generally believed that carbon emissions will be affected by demographic, economic, and technological factors. For example, Zhang and Da (2015), Wang et al. (2017), Tan et al. (2018), and Wang et al. (2019a) believe that the total population, economic level, economic structure, energy efficiency, and energy structure are the main factors affecting carbon emissions. Abadie (2005) believes that the addition of the control variable $\boldsymbol{X}$ is helpful to eliminate the interfering factors of the model, so as to make it meet the condition of "common trend." Without the loss of generality, this study selects total population ($P$), per capita GDP ($A$), industrial structure ($M$), and energy intensity (EI) as control variables. The final DID model was established.

$$\ln CEI_{it} = \lambda_0 + \lambda_1 G_{\text{it}} + \lambda_2 T_{\text{it}} + \lambda_3 G_{\text{it}} T_{\text{it}} + \beta_1 lnA_{\text{it}} + \beta_2 lnP_{\text{it}} + \beta_3 lnM_{\text{it}} + \beta_4 lnEI_{\text{it}} + \varepsilon_{\text{it}}. \quad (2)$$

According to the basic idea of the DID model, the interaction terms and their coefficients are mainly used to investigate the net effect of a certain policy implementation. In the model setting of this study, the coefficient $\lambda_3$ is the focus, and it takes into account the change in China's carbon intensity under the target scenario after the implementation of the energy transition policy. If the target policy does improve China's $CO_2$ emission reduction performance in the future, the sign of $\lambda_3$ will be significantly negative, otherwise nonsignificant or significantly positive. And as stated in the literature review, the fundamental factor affecting the implementation effect of the energy transition policy is the adjustment of the energy structure, increasing the proportion of low-carbon energy consumption and reducing the consumption of high-carbon energy, especially coal. Many studies have shown that 18 environmental indicators, including $CO_2$ emissions, are considered to have a certain time lag effect (Kais and Sami, 2016), and environmental impacts show dynamic sustainability. Based on the above research, it is fully considered that the CEI of this period is affected by the previous CEI, and the environmental impact is sustainable. Therefore, the dynamic panel data model is set based on the above model:

$$\text{lnCEI}_{\text{it}} = \lambda_0 + \lambda_1 G_{\text{it}} + \lambda_2 T_{\text{it}} + \lambda_3 G_{\text{it}} T_{\text{it}} + \beta_1 \text{lnA}_{\text{it}} + \beta_2 \text{lnP}_{\text{it}} + \beta_3 \text{lnM}_{\text{it}} + \beta_4 \text{lnEI}_{\text{it}} + \beta_5 \text{lnCEI}_{\text{it}-1} + \varepsilon_{\text{it}}. \quad (3)$$

## Data Sources and Processing

In order to investigate the expected impact of energy transition policy, this study empirically examines the expected $CO_2$ mitigation effect of energy transition policy in the "Strategy of Energy Production and Consumption Revolution (2016–2030)" by using the DID model based on the historical and projected data of $CO_2$ emissions in China and various sectors from 2000 to 2030. The data in this study include two parts: the historical data and the prediction data.

### Historical Data (2000–2016)

The relevant data of China's total population, economic growth, and energy consumption in various sectors source from the China

**TABLE 1** | Basic historical data.

| Time | Population | GDP | Energy demand | Energy intensity | $CO_2$ emission | $CO_2$ intensity |
|---|---|---|---|---|---|---|
| | $10^8$ person | $10^{12}$ yuan | $10^9$ tce | Ton/$10^4$ yuan | $10^9$ ton | Ton/$10^4$ yuan |
| 2000 | 12.67 | 10.03 | 14.70 | 0.87 | 32.85 | 1.95 |
| 2005 | 13.08 | 18.73 | 26.14 | 0.95 | 58.72 | 2.13 |
| 2010 | 13.41 | 41.30 | 36.06 | 0.76 | 78.75 | 1.67 |
| 2011 | 13.47 | 48.93 | 38.70 | 0.75 | 85.36 | 1.65 |
| 2012 | 13.54 | 54.04 | 40.21 | 0.72 | 87.27 | 1.57 |
| 2013 | 13.61 | 59.52 | 41.69 | 0.69 | 89.75 | 1.49 |
| 2014 | 13.68 | 64.40 | 42.58 | 0.66 | 90.29 | 1.40 |
| 2015 | 13.75 | 68.91 | 42.99 | 0.62 | 90.07 | 1.31 |
| 2016 | 13.81 | 73.73 | 45.07 | 0.61 | 95.70 | 1.30 |

**TABLE 2** | Basic prediction data.

| Scenario | Time | Population | GDP | Energy demand | Energy intensity | $CO_2$ emission | $CO_2$ intensity |
|---|---|---|---|---|---|---|---|
| | | $10^9$person | $10^{12}$yuan | $10^9$ tce | Ton/$10^4$ yuan | $10^9$ ton | Ton/$10^4$yuan |
| Baseline scenario | 2017 | 13.87 | 78.89 | 47.26 | 0.60 | 99.83 | 1.27 |
| | 2018 | 13.93 | 84.41 | 49.54 | 0.59 | 104.12 | 1.23 |
| | 2019 | 13.99 | 90.32 | 51.94 | 0.58 | 108.59 | 1.20 |
| | 2020 | 14.06 | 96.64 | 54.46 | 0.56 | 113.24 | 1.17 |
| | 2025 | 14.34 | 132.41 | 67.39 | 0.51 | 136.28 | 1.03 |
| | 2030 | 14.59 | 177.19 | 81.45 | 0.46 | 159.93 | 0.90 |
| Target scenario | 2017 | 13.93 | 77.42 | 45.26 | 0.58 | 93.04 | 1.20 |
| | 2018 | 14.02 | 82.07 | 46.45 | 0.57 | 94.49 | 1.15 |
| | 2019 | 14.11 | 86.99 | 47.66 | 0.55 | 95.92 | 1.10 |
| | 2020 | 14.20 | 92.21 | 48.90 | 0.53 | 97.32 | 1.06 |
| | 2025 | 14.35 | 120.52 | 55.74 | 0.46 | 106.33 | 0.88 |
| | 2030 | 14.50 | 153.81 | 62.05 | 0.40 | 112.89 | 0.73 |

*The detailed data can be found in the literature (Wang et al., 2019a).*

Statistical Yearbook (National Bureau of Statistics, 2016). Considering the comparability of the data, the relevant economic data are converted at constant prices in 2015. The $CO_2$ emission (CE) is calculated according to the IPCC model (IPCC, 2006). In addition, this study uses the improved model proposed by Li et al. (2017) to modify the $CO_2$ emission coefficient, which takes into account the actual calorific value and oxidation rate of fossil fuels in China and calculates the carbon dioxide emissions of each fossil fuel by multiplying the consumption of fossil fuels by its revised $CO_2$ emission coefficient and oxidation rate. The historical data of relevant indicators from 2000 to 2016 are shown in **Table 1**.

## Prediction Data (2017–2030)

The influencing factors of $CO_2$ emission are relatively complex, and its change trend is often affected by the uncertainty of social, economic, energy, and technology factors, so the prediction results of $CO_2$ emission should be multidimensional oriented. As an important tool to reveal the relationship among population, economy, energy, and environment, Kaya equation is widely used in scenario prediction of $CO_2$ emissions (Jung et al., 2012). For example, Wang et al. (2019a) used the Kaya extended model to identify the influencing factors of $CO_2$ emissions and then to predict the changing trend of China's $CO_2$ emissions in different scenarios. Based on this study, the control group and the treatment group of the energy transition policy quasinatural experiment according to the prediction results of China's $CO_2$ emissions in 2030 under the baseline scenario and the target scenario are constructed and then use the difference in difference (DID) model to evaluate the $CO_2$ emission reduction effect of China's energy transition policy. This study selects the scenario prediction results of China's $CO_2$ emission and its related factors from 2017 to 2030 as the basic experimental data, and some relevant data are shown in **Table 2**.

According to the forecast results in **Table 2**, under BS, China's economy will continue to grow at a moderate rate. China's $CO_2$ emissions will continue to grow at an average annual rate of 3.74% from 9.57 billion tons in 2016 to 15.95 billion tons in 2030. At the same time, the $CO_2$ emission intensity dropped from 1.29 tons/104 yuan to 0.903 tons/104 yuan, with an average annual decrease rate of 2.56%. In contrast, under TS conditions, China's total $CO_2$ emission and its growth trend slowed down significantly, from 9.57 billion tons in 2016 to 11.89 billion tons in 2030, with an average annual growth of about 1.51%, which was significantly lower than the baseline scenario. The $CO_2$ emissions intensity also dropped from 12,298 tons/million in 2016 to 0.73 tons/million in 2030, with an average annual decrease of 3.82%.

**TABLE 3** | Descriptive statistics of variables.

| Variable | Unit | Mean | Maximum | Minimum | Std. deviation |
|---|---|---|---|---|---|
| CEI | Ton/$10^4$yuan | 1.1667 | 1.6688 | 0.7340 | 0.2683 |
| *G* | — | 0.5000 | 1.0000 | 0.0000 | 0.5060 |
| *T* | — | 0.6667 | 1.0000 | 0.0000 | 0.4771 |
| *G* × *T* | — | 0.3333 | 1.0000 | 0.0000 | 0.4771 |
| *P* | $10^8$ person | 14.0455 | 14.5945 | 13.4091 | 0.3600 |
| *A* | $10^4$ yuan | 6.9794 | 12.1412 | 3.5191 | 2.4045 |
| *M* | % | 41.8690 | 46.6113 | 40.0000 | 2.0378 |
| *EI* | Tce/$10^4$ yuan | 0.5671 | 0.7643 | 0.4034 | 0.1030 |

## Variable Description

### Explained Variable

In the main text of this study, the CEI is chosen as the explained variable, which is calculated in terms of the $CO_2$ emissions per unit of GDP.

### Core Explanatory Variables

This study selects the grouping virtual variable ($G$), the time dummy variable ($T$), and the interaction item ($G \times T$) for the energy transition policy as explanatory variables. The variable $G$ measures the differences of the CEI between the baseline scenario and the target scenario. The variable $T$ measures the change of the CEI between the treatment group and the control group and the interactive item ($G \times T$) measuring the impact of policy implementation on the CEI of the treatment and control groups. It is the core explanatory variable.

### Control Variables

Through the analysis of the relevant literature on the factors affecting the intensity of $CO_2$ emission, the study finally selects the population size, per capita GDP, industrial structure (the proportion of the secondary industry in the regional GDP), and energy intensity as the control indicators. In addition, in order to eliminate possible collinearity and ensure the smoothness of the data, each indicator is logarithmic.

## Descriptive Statistics

This study takes China's $CO_2$ emissions and its related influencing factors from 2000 to 2030 as the research sample. The descriptive statistical results of the relevant indicators are shown in **Table 3**.

# PREASSESSMENT OF POLICY EFFECTS

In view of the policy target of 48% coal consumption structure in 2030, this study uses the DID model to investigate the impact of the energy transition policy on the future CEI. Based on the research paradigm of the quasinatural experiments, this study constructs the "treat group" under the target scenario after the policy intervention and the "control group" under the baseline scenario. Under the premise of controlling other factors that affect CEI, this study isolates the difference in $CO_2$ emissions performance between the "treatment group" and the "control group" after the energy transition policy has occurred. Furthermore, this study conducts regression tests for each of China's six major sectors, examining the heterogeneous impact of the energy transition policy on the reduction of CEI across China's economic sectors.

## Analysis of Empirical Results

The first two columns in **Table 4** are the full sample estimates for the model (2). The first column only examines the effect of each explanatory variable, and the second column adds the individual control variables to the first column. From the test results of **Eqs 1** and **2**, it is known that there is no substantial change in the sign and significance level of the core explanatory variable's estimated coefficient. The results show that the energy transition policy implementation has an inhibitory effect on China's CEI. In column (1), only the effect of the policy effect' dummy variable $G \times T$ on the CEI intensity is considered, and its $R^2$ value is relatively low, explaining efforts are weak, contributing 0.131% to the carbon emission intensity. After adding the control variables, the significance level is significantly improved, and the explanation is also significantly strengthened. According to the estimation results in column (2), after controlling the population size, the wealth of residents, the industrial structure, and the energy intensity variables, the estimated value of the energy transition policy impact is significantly negative, and the estimated value increases, indicating some control variables. The suppression of carbon emission intensity does not play a significant role and even has the opposite promotion effect. The implementation of the policy will reduce China's carbon emissions intensity by about 0.0111% each year. In general, the experimental results prove that the energy transition policy will have a more obvious suppression effect on future China's carbon emissions.

**TABLE 4** | Descriptive statistics of variables.

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *G* | −0.0050 | −0.0024 | −0.0050 | −0.0026 |
| | (0.0563) | (0.0034) | (0.0778) | (0.0031) |
| *T* | −0.3230*** | 0.0128** | −0.1820* | 0.0147** |
| | (0.0484) | (0.0050) | (0.0973) | (0.0058) |
| *G*×*T* | −0.1310* | −0.0111** | −0.0640 | −0.0150*** |
| | (0.0763) | (0.0043) | (0.0859) | (0.0047) |
| lnA | | 0.0647*** | | 0.0403*** |
| | | (0.0173) | | (0.0142) |
| lnP | | 0.0109 | | 0.1700* |
| | | (0.1380) | | (0.1000) |
| lnM | | −0.2100*** | | −0.1580** |
| | | (0.0525) | | (0.0639) |
| lnEI | | 1.4560*** | | 1.4040*** |
| | | (0.0225) | | (0.0295) |
| lnCEI_01 | | | 0.5430** | 0.0145** |
| | | | (0.2090) | (0.0065) |
| _Cons | 0.3900*** | -0.0562 | 0.1980* | −1.6630 |
| | (0.0384) | (1.4430) | (0.1140) | (1.0270) |
| *N* | 42 | 42 | 42 | 42 |
| $R^2$ | 0.7150 | 1.0000 | 0.8330 | 1.0000 |

*Standard errors in parentheses,* *p < 0.1, **p < 0.05, ***p < 0.01.

**TABLE 5 |** The results of the heterogeneity test in China's six sectors.

| Variables | 1st | 2nd | 3rd | 4th | 5th | 6th |
|---|---|---|---|---|---|---|
| *G* | −0.0007 | −0.0023 | 0.0012 | 0.0042 | −0.0024 | −0.0003 |
| | (0.0121) | (0.0038) | (0.0096) | (0.0187) | (0.0412) | (0.0074) |
| *T* | −0.0008 | 0.0147*** | −0.0105 | −0.0540** | 0.0171 | 0.0093 |
| | (0.0103) | (0.0050) | (0.0081) | (0.0212) | (0.0274) | (0.0073) |
| *G*×*T* | −0.0162 | −0.0130** | 0.0026 | 0.0823* | −0.0406 | −0.0141 |
| | (0.0179) | (0.0049) | (0.0135) | (0.0411) | (0.0498) | (0.0107) |
| lnA | −0.1370 | 0.1970*** | −0.3380*** | −0.0170 | −0.1670 | −0.3380*** |
| | (0.0865) | (0.0209) | (0.0641) | (0.2020) | (0.2250) | (0.0495) |
| lnP | −0.9150 | 0.7510*** | −2.8910*** | −5.4430*** | 1.6890 | 0.1060 |
| | (0.7290) | (0.1610) | (0.5760) | (1.7300) | (1.6600) | (0.4540) |
| lnM | −1.7620*** | −1.4480*** | −1.5440*** | −1.2620*** | −0.5120 | 1.0370*** |
| | (0.1550) | (0.0586) | (0.0920) | (0.2990) | (0.5810) | (0.0846) |
| lnEI | 1.0960*** | 1.9540*** | 0.3360*** | 0.3740 | 0.9310*** | 0.1340** |
| | (0.1030) | (0.0269) | (0.0758) | (0.2440) | (0.2860) | (0.0558) |
| _Cons | 9.4110 | −10.2400*** | 35.3100*** | 64.4700*** | −20.2700 | 2.0520 |
| | (7.685) | (1.6750) | (6.1700) | (18.2800) | (17.1200) | (4.8370) |
| *N* | 42 | 42 | 42 | 42 | 42 | 42 |
| $R^2$ | 0.9960 | 1.0000 | 0.9970 | 0.9870 | 0.9440 | 0.9980 |

*The 1st sector includes agriculture, forestry, animal husbandry, fishing, and water conservancy. The 2nd sector denotes the industry. The 3rd sector denotes the construction industry. The 4th sector includes transportation, warehousing, postal services, and communications. The 5th sector includes wholesale, retail, accommodation, and catering services. The 6th sector includes consumer goods and other industries. The standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.*

The estimated results of the control variables are shown in column (2) of **Table 4**. First, for China's per capita GDP, the impact of this variable on carbon emission intensity can be divided into positive and negative aspects. On the other hand, the growth of resident income leads to the improvement of living standards, and the needs of the people for the quality of life also increase. People pay more attention to clean energy consumption, which is conducive to reducing carbon emissions caused by energy consumption. The regression results show that the increase in per capita GDP significantly aggravates China's future carbon emissions, indicating that energy demand has increased during the policy implementation period, and there may be a shortage of clean energy supplies. People's daily activities are still mainly dependent on traditional energy.

Second, from the perspective of the population size, a control variable, it is expected that this variable may have two different influences. On the one hand, the population growth increases people's demand for transportation, housing, and various products, resulting in increased demand for energy consumption and aggravating overall carbon emissions. On the other hand, the increase of population enables the full utilization of public facilities and the development of economies of scale, thus improving the efficiency of energy use. The impact of future population growth on future carbon emissions levels is not apparent. Based on the current social status, the population growth rate is set to be small, and there is no massive population increase. Compared to other factors, the impact of normal population expansion on future carbon emissions intensity is negligible.

Third, in terms of the influence of the industrial structure variable on the result, the regression coefficient is significantly negative; it shows that this variable will inhibit carbon emissions in the future. The adjustment of China's industrial structure (reducing the secondary industry's proportion) in the target scenario will significantly reduce China's future carbon emissions intensity. Finally, for the variable of energy intensity, the regression results show that the continuous increase of energy intensity significantly promotes future carbon emissions, and the massive use of fossil fuels still inhibits low-carbon development.

The latter two columns in **Table 4** are the correlational regression results of **Eq. 3**, which adds a lag term of the CEI to examine the sustainable dynamics of environmental impacts. The results show that the estimated coefficient of the interaction term *G*×*T* is not significant after adding the lag term of the CEI without considering the control variables. This means that the energy transition policy is affected by the development inertia of CEI, and its expected effect of $CO_2$ emission reduction will decrease. Considering the control variables, the results of column (4) show that the coefficient of the core explanatory variable $G \times T$ is still negative, indicating that the carbon reduction effect of the energy transition policy is more significant. Moreover, the previous CEI's impact on the current CEI has decreased significantly, indicating that CEI's development inertia has been diluted. Meanwhile, the lag coefficient of CEI listed in (3) and (4) is significantly positive, indicating that the $CO_2$ emission in the previous period has a cumulative and sustainable effect, which will not be conducive to energy transition and $CO_2$ emission reduction in the future.

## Heterogeneity Test

In order to investigate the sectoral heterogeneity of the mitigation effect of the energy transition, this study has conducted a subsample regression on China's six sectors on the premise of controlling other influencing factors (**Table 5**). The results reveal that the impact of energy transition policy on the $CO_2$ mitigation in Chinas six sectors are significantly different, which means that

**TABLE 6** | Robustness test results.

| Variables | (1) lnCE | (2) lnCE | (3) lnCEI | (4) lnCEI |
|---|---|---|---|---|
| *G* | −0.0073 | −0.0024 | −1.56e−15 | −4.20e−16 |
| | (0.1440) | (0.0024) | (0.0240) | (0.0052) |
| *T* | 0.3740*** | 0.0071* | −0.3650*** | −0.0043 |
| | (0.0437) | (0.0037) | (0.0390) | (0.0058) |
| *G*×*T* | −0.2870*** | −0.0099 | −0.1080 | −0.0076 |
| | (0.0618) | (0.0069) | (0.0668) | (0.0062) |
| Control variables | NO | YES | NO | YES |
| _cons | 13.6900*** | −44.2300*** | 0.4870*** | −1.6930 |
| | (0.0357) | (4.2890) | (0.0170) | (1.6340) |
| *N* | 42 | 42 | 42 | 42 |
| $R^2$ | 0.7650 | 1.0000 | 0.4680 | 1.0000 |

*Standard errors in parentheses, *p < 0.1, **p < 0.05, ***p < 0.01.*

the formulation of the mitigation policies in different sectors should be differentiated in the future.

For the 1st sector, the interaction coefficient $G \times T$ is negative and not significant, indicating that the energy transition policy does not have an obvious inhibitory effect on the CEI. The reason may be that the energy demand in this sector is relatively small, and fossil energy consumption does not change much before and after the release of the energy transition policy.

For the 2nd sector, the coefficient of $G \times T$ is significantly negative, indicating that the energy transition policy has played a significant role in curbing the CEI. The root cause is that the industrial sector, as a high energy consumption sector, mainly depends on traditional fossil energy such as oil and coal, and energy transition plays an essential role in the efficient, clean, and sustainable use of energy.

As for the 3rd sector, the coefficient of $G \times T$ is positive and insignificant, indicating that the energy transition is not an effective way to reduce the CEI in the construction industry in the future.

In contrast, the 4th sector is mainly dependent on oil resources, which means that it is difficult to change the energy consumption structure and reduce the CEI in the short term. Therefore, the 4th sector should focus on the progress of new energy technologies in the future and fundamentally reduce its dependence on traditional high-carbon energy.

In terms of the 5th sector, except for the energy efficiency, which has a significant positive impact on the CEI, the impact of other indicators on the CEI is not significant. The root cause is that the proportion of carbon emissions in the 5th sector in the total carbon emissions is small, which leads to the relatively weak impact of energy transition policy on the CEI of the service industry in the future.

For the 6th sector, the impact of the energy transition policy on its CEI is positive, which means that people will focus on green consumption in the future, and the energy required for daily life will gradually shift to clean energy.

In addition, the effects of the control variables on the CEI in different sectors have been examined. The results show that the $CO_2$ mitigation effects of the economic level and the population size have sectoral heterogeneity, while industrial structure and energy efficiency are expected to have significant mitigation effects.

## Robustness Test

The above results show that the implementation of China's energy transition policy has effectively reduced the CEI in the future. In order to illustrate the robustness of the results, the following robustness tests were carried out in this study, and the results are shown in **Table 6**.

### Substitution Variable Test

In order to test the robustness of the foregoing conclusions, this study uses the variable substitution method to perform the robustness test. We replace the logarithm of the $CO_2$ emission intensity (lnCEI) with the logarithm of $CO_2$ emissions (lnCE) for the explained variables. The columns (1) and (2) of **Table 6** show that, under the influence of control variables, the overall effect of energy transition policy on $CO_2$ emission is moderate; the baseline regression without control variables is effective, but overall, the effect of energy transition policies on $CO_2$ emissions remains significant. This shows that the core conclusions of this study are not affected by the measurement method of explained variables, but it is more appropriate to choose the CEI as the control index.

### Counterfactual Test

Drawing on the existing research (Wang et al., 2019a), this study conducts a counterfactual test by changing the time of policy implementation. In fact, in addition to the influence of energy transition policy on China's CEI, some other factors may also cause the CEI change, which is not related to the implementation of the energy transition, thus affecting the establishment of the above conclusions. In order to avoid the interference of such factors, this study puts forward the policy implementation time. If the policy treatment effect is still significantly negative at this time, it indicates that the change of China's CEI in the future is influenced by other random factors and not all of which are caused by the energy transition policy. Columns (3) and (4) of **Table 6** show that, with or without the addition of control variables, the assumed policy implementation has no significant impact on future carbon emissions. Therefore, this indicates that the difference in the CEI between the treatment group and the control group is not caused by other factors but comes from the implementation of the energy transition policy.

# CONCLUSIONS AND POLICY IMPLICATIONS

## Conclusions

The energy transition is one of the important ways to reduce China's $CO_2$ emission, and evaluating its policy effect is of great significance for the realization of China's $CO_2$ mitigation target in 2030. Different from previous studies, this study preevaluates the mitigation impact of China's energy structure transition based on the scenario prediction results of China's $CO_2$ emission (Wang et al., 2019b) and further examines the heterogeneous impact of energy transition policy on $CO_2$ mitigation in various sectors in China.

The study shows that China's CEI under the target scenario is significantly reduced compared with the baseline scenario, which means that energy transition positively impacts China's expected CEI target in 2030. The study also reveals that the CEI has obvious development inertia during the inspection period, and the previous CEI has a significant impact on its current CEI. The effect of implementing the energy transition policy in the short term may not be obvious. Therefore, the Chinese government needs to pay close attention to it for a long time and strictly implement it to ensure the expected carbon emission reduction effect.

The heterogeneity test reveals that the policy effects of the energy transition on the CEI in China's six sectors are different. Still, on the whole, it has a positive policy impact on the CEI. As an essential way of $CO_2$ mitigation, the energy transition positively affects the $2^{nd}$ sector, and its expected mitigation contribution is the most obvious. In contrast, the $4^{th}$ sector is affected by the high oil and gas energy use patterns, and the mitigation effects of its energy transition are not obvious.

Meanwhile, energy technology has significant heterogeneous impacts on the CEI in different sectors. In terms of their expected mitigation effects, the energy intensity in the industrial sector has the most significant impact on the CEI, indicating that this sector's energy technology can effectively contribute to the decline in the CEI. In contrast, the impact of the $4^{th}$ sector energy efficiency on the CEI is not significant. The root cause is that the energy consumption of the $4^{th}$ sector is mostly oil and gas resources, and its energy consumption structure is difficult to change in the short term, which leads to the energy transition policy is difficult to affect the CEI of the sector significantly.

## Policy Implications

According to the research results, we can find that the energy transition policy has a significant influence on carbon emission reduction. To some extent, the current carbon emissions will still be affected by the previous period, so the implementation of the energy transition policy will not produce immediate effects. Therefore, the following policy suggestions are proposed in this study. First, China should resolutely implement the energy transition policy, and take into account the development demands and emission reduction potential of various economic sectors, so as to dynamically adjust the carbon reduction policy. Second, the government should strictly control coal-oriented total fossil energy consumption, ensuring a complete substitute of clean energy for incremental energy demand and gradually begin to replace stock. Third, according to the critical factors of $CO_2$ emission reduction in different sectors, China should implement a differentiated emission reduction policy in different sectors, focusing on promoting clean energy and improving energy utilization efficiency in the $2^{nd}$ sector and promoting the clean and low-carbon transition of energy consumption structure in the $4^{th}$ sector. On this basis, relevant departments should pay attention to the coordinated development of policy objectives of various industries and establish a compatible policies network system to reduce $CO_2$ emission.

# 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

DW, XL and YZ: conceptualization. DW, XL, YZ and XY: methodology. DW, XL, XY and ZZ: writing. XL, XY and ZZ: results. XY, ZZ and XW: validation. XW: artwork. All authors contributed to the article and approved the submitted version.

# FUNDING

The work described in this manuscript was supported by the National Natural Science Foundation of China (No.71974191), the National Social Science Foundation of China (No.19FGLB057), the Key Project of Jiangsu Universities' Philosophy and Social Sciences Research (No.2017ZDIXM162), and the Fundamental Research Funds for the Central Universities (No.2020ZDPYSK05).

# ACKNOWLEDGMENTS

We are thankful for the comments and advice which are given by the reviewers. They have improved the content of this work and pointed out some research directions of particular interest.

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**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
published: 10 March 2021
doi: 10.3389/fenrg.2021.629136

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# Environmental Benefit and Investment Value of Hydrogen-Based Wind-Energy Storage System

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Alongside the rapid expansion of wind power installation in China, wind curtailment is also mounting rapidly due to China's energy endowment imbalance. The hydrogen-based wind-energy storage system becomes an alternative to solve the puzzle of wind power surplus. This article introduced China's energy storage industry development and summarized the advantages of hydrogen-based wind-energy storage systems. From the perspective of resource conservation, it estimated the environmental benefits of hydrogen-based wind-energy storages. This research also builds a valuation model based on the Real Options Theory to capture the distinctive flexible charging and discharging features of the hydrogen-based wind-energy storage systems. Based on the model, simulation results, including the investment value and operation decision of the hydrogen energy storage system with different electricity prices, system parameters, and different levels of subsidies, are presented. The results show that the hydrogen storage system fed with the surplus wind power can annually save approximately 2.19–3.29 million tons of standard coal consumption. It will reduce 3.31–4.97 million tons of $CO_2$, $SO_2$, $NO_x$, and PM, saving as much as 286.6–429.8 million yuan of environmental cost annually on average. The hydrogen-based wind-energy storage system's value depends on the construction investment and operating costs and is also affected by the mean-reverting nature and jumps or spikes in electricity prices. The market-oriented reform of China's power sector is conducive to improve hydrogen-based wind-energy storage systems' profitability. At present, subsidies are still essential to reduce initial investment and attract enterprises to participate in hydrogen energy storage projects.

**Keywords: hydrogen storage system, wind power, environmental benefits, investment value, real options**

OPEN ACCESS

***Edited by:***
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***Specialty section:***
*This article was submitted to Sustainable Energy Systems and Policies,*
*a section of the journal Frontiers in Energy Research*

***Received:*** *13 November 2020*
***Accepted:*** *22 January 2021*
***Published:*** *10 March 2021*

***Citation:***
*Xue Q, Wang Z and Zhang Y (2021) Environmental Benefit and Investment Value of Hydrogen-Based Wind-Energy Storage System.*
*Front. Energy Res. 9:629136.*
*doi: 10.3389/fenrg.2021.629136*

## INTRODUCTION

In China, with the rapid development of renewable energy power, installed wind power capacity is increasing year by year. However, wind power generation has a high-frequency power curtailment phenomenon, making the renewable energy consumption problem more serious. The resulting contradictions between the on-grid load and the excess wind power generation become increasingly prominent. According to the statistics of *the National Energy Administration* of China, from 2011 to 2018, China's cumulative wind power curtailed totaled 215.1 billion kWh, suffering an economic loss of 116.5 billion yuan, and the average annual wind surplus ratio is as high as 12.89%. If energy storage systems are connected to the wind farms to shave the peak load, the electricity operators can better ensure the wind power output stability and improve the power output quality (Apostolou and

Enevoldsen 2019). The hydrogen-based energy storage system (HESS) provides a reasonable solution for wind power generation flaws—excess wind power can render the energy storage system. It will be used to electrolyze water to produce hydrogen. The hydrogen either returns to the grid through methods such as fuel cells or is used as energy carrier ending up in industrial or commercial application (Chen et al., 2009; Ipsakis et al., 2009; Bakke et al., 2016; Javed et al., 2020; Mayyas et al., 2020). According to the Global Energy Storage Database of the Department of Energy of the United States, as of June 2018, the world's total installed capacity of energy storage systems had reached 195.74 GW, and 1747 projects are running in operation. The number of hydrogen storage projects totals 14 with an installed capacity of 0.02 GW.

Chinese government has explicitly supported the development of the hydrogen energy industry since 2014. The State Council has issued policies to upscale developing the hydrogen fuel-cell motor vehicle (HFEV) industry. Subsidies compensate the whole industrial chain from hydrogen production and vehicle sales to hydrogenation station construction (see the **Supplementary Material**). As for the research and development of HESS, the government and the industry have carried out three demonstration projects of HESS in China. The first one is the "Technology Research and Demonstration Test Project of Direct Hydrogen Production by Wind Power and Fuel-Cell Power Generation System," which is put into practice by China Energy Conservation and Environmental Protection Group Corporation since April 2014. The project was projected with a hydrogen production power of 100 kW and a fuel cell electric power of 30 kW. The second is the demonstration project of a wind-power HESS operated by Sino-German cooperation since April 2015. Its hydrogen generation power reaches 200 MW, and the production capacity reaches 17.52 million standard cubic meters per year. The third one is a wind-power HESS invested by *Goldwind Technology Company* in *Jilin* Province. Its total installed capacity of wind power generation reaches 100 MW, and the maximum energy storage capacity is 10 MW.

However, the research and development of critical technologies for wind-power HESS in China are still in its infancy. The technical bottlenecks lie in critical technologies such as the efficient conversion of power to hydrogen, large-scale and low-cost hydrogen storage, and comprehensive energy utilization. Besides, unlike developed countries such as the United States and Japan, China has not yet regarded energy storage as an independent industry, it lacks the top-down design of energy storage payment mechanism, and the hydrogen energy storage industry has not yet achieved commercial development. However, it is essential to evaluate the resource value, environmental value, and investment value of the wind-power HESS from the perspective of sustainable development of wind power and large-scale hydrogen energy commercialization.

Some researchers adopted the cost-benefit analysis and discounted cash flow approach to evaluate the value of energy storage. The report published by American Electric Power Research Institute and Sandia Laboratories discussed the potential costs and benefits of energy storage applied to power generation, transmission, and distribution (Eckroad, 2003). Schoenung (2011) analyzed both the short-term and long-term applications of energy storage systems, including load balancing, peak load shaving, and power quality improvement. They analyzed the influence of various operating parameters such as time response, capital cost, efficiency, operating cost, and renewal cost on the energy storage system's application effects. Many scholars compared the economics of different energy storage technologies from a broader range of technical features, including service life, energy efficiency, power density, and degree of technology maturation (Harrison et al., 2009; Steward et al., 2009; Schoenung, 2011). With a deep understanding of energy storage technology, researchers introduced uncertainties in the economic evaluation of energy storage systems (Denholm and Sioshansi, 2009; Loisel et al., 2015; Parra et al., 2019). Yu and Foggo (2017) pointed out that the lack of understanding of investment risks related to energy storage is an obstacle to its application and popularization. They established a stochastic valuation model of energy storage in the large-scale electricity market. Bakke et al. (2016) suggested considering the uncertainty of electricity price fluctuation when conducting power storage investment evaluations. The spot price of electricity generally shows strong seasonality, mean recovery, high volatility, clustering effect, and extreme price changes. This high-frequency electricity market price fluctuation provides flexibility in operation of the energy storage system.

Foreign countries attach great importance to the economic research of hydrogen energy storage technology and wind-power HESS and have begun to develop the evaluation simulation software of wind-power HESS, including the following three software platforms: first, HOMER, a power system optimization platform developed by the Renewable Energy Laboratory of the United States Department of Energy, is mainly used to evaluate the effect of grid-connected power generation system and can effectively assess and analyze the economy and sensitivity of the integrated system of wind power and fuel cells hydrogen production (Bansal et al., 2020; Hassani et al., 2020). Second, TRNSYS, a system dynamic behavior simulation software platform designed and released by the New Energy Power Laboratory of the University of Wisconsin-Madison, United States, effectively quantifies and evaluates the operation effect of power system through simulation, and its standard database is composed by nearly 150 calculation models, including the simulation calculation models of hydrogen production system by wind power and fuel cell generation models (Bakić Vukman et al., 2012; Buonomano et al., 2018). Third, URHYS, a renewable energy grid-connected systems optimization platform, is mainly used for economic evaluation and decision-making optimization of wind-power HESS (Twaha and Ramli, 2018). All these models provide implications for the research and development of a comprehensive wind-power HESS appraisal model in China. Nevertheless, both the model and parameters should be adjusted to fit for the reality of Chinese wind-power HESS industry.

Overall, previous literature mostly used cost-benefit analysis and the traditional NPV method for energy storage evaluation. However, considering the uncertainties during the energy storage system's operation, static cost-benefit analysis and net present value calculation may underestimate the flexibility value of energy

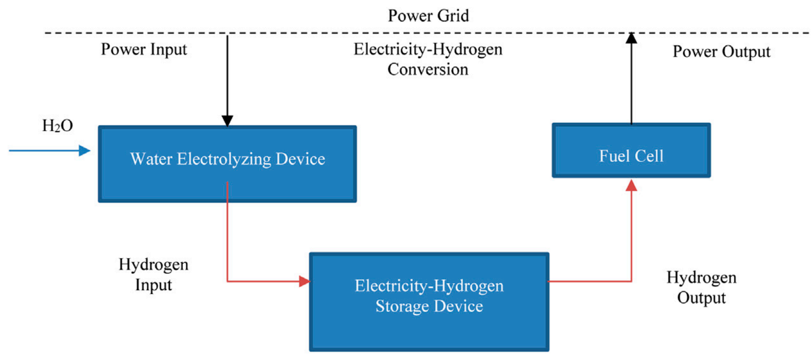


**FIGURE 1** | System configuration of wind-power HESS.

storage projects. The real options method can improve the accuracy and effectiveness of elastic valuation. Besides, most of the current research focused on the mature mechanical energy storage technology, quite few on the comprehensive evaluation of wind-power HESS. As a frontier energy storage alternative, HESS provides an alternative pathway that not only helps to integrate wind power generation, but also enables the decarbonization of the transportation and natural-gas sectors. A comprehensive appraisal of the wind-power HESS has particular theoretical and practical significance to unlock its environmental and investing potentials in China.

# STRUCTURE AND CHARACTERISTICS OF WIND-POWER HYDROGEN-BASED ENERGY STORAGE SYSTEM

Wind-power HESS usually includes wind power input, water electrolysis device, hydrogen storage device, fuel cell, and other power generation devices connected to the grid. The operation started from inputting excess wind power into HESS, electrolyzing water to produce hydrogen, and inputting hydrogen into the energy storage device. The system further increases the storage density by means such as high-pressure compression. Finally, hydrogen energy can be returned to the grid through the fuel cell at an appropriate time, thus improving the utilization of grid-connected wind power and ensuring the stable output of power system (see **Figure 1**).

In the wind power storage industry, traditional electrolyzers make difficult to maintain a stable hydrogen production because of the intermittence and fluctuation of power input. It is necessary to equip high-performance electrolyzers to ensure the HESS's hydrogen energy input safety. Under the current technical conditions, the proton exchange membrane (PEM) electrolyzer can meet the technical requirements of hydrogen production in the wind-power HESS. PEM electrolyzer can keep the hydrogen production rate stable under high intermittent and high fluctuation of electricity input. It can resist high voltage and digest a strong current density (Patrício et al., 2012).

The hydrogen storage device is the most critical component of the wind power-hydrogen storage system, and it can replace the traditional energy storage technology. Hydrogen can be compressed into a gaseous state, liquid state (such as metal hydride and carbon material), or solid state (such as methanol and ammonia) for storage. At present, compressed gaseous hydrogen is widely used in large-scale hydrogen energy storage systems because of low energy leakage (lower than 0.00033%·d$^{-1}$) and high conversion efficiency (higher than 90%). High energy efficiency can adequately compensate for the long time-consuming disadvantage of hydrogen production by water electrolysis (Bergen et al., 2009).

As the hydrogen-based wind-energy storage system's back-end, the fuel cell is responsible for power output and grid-connected sales. There are two alternatives: high-temperature fuel cells and low-temperature fuel cells. Generally speaking, low-temperature fuel cells are more suitable for the power generation of hydrogen energy storage system because of its flexible working hours and the ability to start and stop at any time (Andrijanovits and Beldjajev, 2012).

# RESOURCES AND ENVIRONMENTAL BENEFITS OF WIND-POWER HYDROGEN-BASED ENERGY STORAGE SYSTEM

As a backup facility of wind farms, the wind-power HESS plays the role as energy buffer. Its powerful resources and environmental benefits will bring a revolution to the energy storage industry.

## Energy-Saving Effect

According to the National Energy Administration of China, the energy loss of wind power curtailment in China was 16.9 billion kWh in 2019. The curtailment rate was 4%, which was the lowest level for the past decade. Take the year 2019 as the benchmark year, considering the increasing installed capacity of wind power, the improvement of grid-connected rate, and the further improvement of clean power incentive policies in the future. In that case, the average annual wind power curtailed may fluctuate by 20% based on the benchmark scenario. In the

**TABLE 1** | Coal consumption savings of wind-power HESS.

| Scenarios | Annual wind power curtailment (billion kWh) | Annual wind power saving (billion kWh) | Coal saving (million tons) | |
|---|---|---|---|---|
| | | | If unit coal consumption for 1 kWh = 300 g | If unit coal consumption for 1 kWh = 253 g |
| Baseline | 16.90 | 9.126 | 2.738 | 2.309 |
| Low curtailment rate | 13.52 | 7.301 | 2.190 | 1.847 |
| High curtailment rate | 20.28 | 10.951 | 3.285 | 2.771 |

*Note: wind power in baseline scenario = wind power curtailed of China in 2019; abandoned wind power with low curtailment rate = baseline scenario * 80%; abandoned wind power with high curtailment rate = baseline scenario * 120%. Available wind power = annual curtailed wind power * 60% *90%, where 60% is the efficiency of the hydrogen production unit and 90% is the efficiency of the hydrogen-electricity conversion in our estimation. In the report of* Research on China's Natural Gas Development Strategy *by the Development Research Center of the State Council (2015), the Unit Coal Consumption for large-capacity generating units in China is roughly 300 g/kWh. Considering the parameter of the most advanced 1000 MW supercritical coal-fired generators, this number will approach 253 g/kWh. See the news from http://news.cctv.com/2019/12/11/ARTIkCHyj9hDLKJuCl5WT3c3191211.shtml.*

**TABLE 2** | Environmental benefits of the wind-power HESS.

| | Emission rate (g/kWh) | Unit cost | Base scenario | | Low curtailment | | High curtailment | |
|---|---|---|---|---|---|---|---|---|
| | | | Annual emissions (ton) | Environmental cost (000 RMB) | Annual emissions (ton) | Environmental cost (000 RMB) | Annual emissions (ton) | Environmental cost (000 RMB) |
| $SO_2$ | 0.165 | 13.8 yuan/MWh | 1,506 | 125,939 | 1,205 | 100,751 | 1,807 | 151,127 |
| $NO_x$ | 0.239 | 8.2 yuan/MWh | 2,181 | 74,833 | 1,745 | 59,867 | 2,617 | 89,800 |
| $CO_2$ | 453 | 20.64 yuan/ton | 4,134,078 | 85,327 | 3,307,262 | 68,262 | 4,960,894 | 102,393 |
| PM | 0.028 | 7.9 yuan/MWh | 256 | 72,095 | 204 | 57,676 | 307 | 86,514 |
| Total | 453.432 | | 4,138,020 | 358,195 | 3,310,416 | 286,556 | 4,965,625 | 429,834 |

*Note: the emission rate and unit cost of pollution emissions ($SO_2$, $NO_x$, PM) are based on the work of Tang et al. (2019). They adopted the Continuous Emission Monitoring Systems Network to calculate the emission factors after the introduction of ultra-low emissions standards. The emission rate of $CO_2$ is obtained from the work of Zhao et al. (2020). Zhao et al. (2020) estimate the carbon emission factor of coal-fired power plants of China in 2020. Their estimation is founded on the base of the emission factors proposed by Shan et al. (2018), which are closer to China's actual survey value than that of IPCC (2015). The cost of $CO_2$ is estimated by using the transaction data of China Emissions Exchange (CEEX) in Guangzhou. The trading volume totals 0.196 billion tons with a total trading value of 3.489 billion yuan. So, we estimate the unit cost of $CO_2$ to be 20.64 yuan/ton.*

ideal situation, the wind power-hydrogen energy storage device would absorb all the surplus wind power.

This article takes the base-load coal-fired power as the reference to estimate the energy-saving effect of the wind-power HESS. The coal-fired power plants in China apply the 600-MW or 1000-MW ultrasupercritical units with an average standard coal consumption of 300 g/kWh. Suppose the efficiency of the hydrogen production unit is 60% and the efficiency of the hydrogen-electricity conversion is 90%, the energy storage system can save as much as 2.190–3.285 million tons of standard coal consumption. The calculation results are shown in **Table 1**.

The 1000 MW supercritical generators are the most advanced coal-fired power plants globally, highlighting high-efficiency and ultra-low emission. The generators' power efficiency is 47.82%, and the standard coal consumption for power generation is 253 g/kWh. If taking the 1000 MW supercritical generators as a reference, the total saving of standard coal consumption by the HESS will be as high as 1.847–2.771 million tons/year (see **Table 1**).

## Emission Reduction Effect

Wind power generation has outstanding environmental protection advantages because it has no emission of dust ($PM_{2.5}$), $SO_2$, $NO_x$, $CO_2$, or other toxic gases, which is also the highlight feature of the wind-power HESS. Here, we take the base-load coal-fired power generation as the reference and calculate the hydrogen energy storage system's emission reduction effect. In fact, substantial emission has been reduced from Chinese power plants after the introduction of ultra-low emissions standards (Tang et al., 2019). Suppose the coal-fired power plants apply the current mainstream ultrasupercritical generators, which emit about 453 g of $CO_2$ per kilowatt/hour (Zhao et al., 2020). The $SO_2$, $NO_x$, and PM emission rates are 0.165 g/kWh, 0.239 g/kWh, 0.028 g/kWh, respectively (Tang et al., 2019). **Table 2** summarizes conventional coal-fired power plants' pollutant emission rates and unit environmental costs.

The annual emission of pollutants is calculated by multiplying the annual wind power saving in **Table 1** by the pollutant emission rate. The environmental cost, which is the external environmental benefit of the wind-power HESS, can be obtained by multiplying the annual emission by the unit environmental cost. Based on the above parameter assumptions, the wind-power HESS can reduce the $CO_2$ emissions by 3.307–4.961 million tons and the pollutant emissions by 3,154–4,731 tons per year.

People pay lots of attention to the air pollution problem in China, and the air pollution emission standards are increasingly strict. China has implemented the new emission standard for air pollutants in thermal power plants (GB 13223–2011) since July 1, 2014, and the new National Ambient Air Quality Standard (GB

3095–2012) since January 1, 2016, with the emission limit of $PM_{2.5}$ being raised. The wind-power HESS will undoubtedly play a positive role in improving wind power utilization and reducing pollutants and greenhouse gas emissions from coal-fired power plants. However, no matter how much resource and environmental benefits the new storage system brings, it is the investment value that decides the commercialization and market prospects of the wind-power HESS.

# INVESTMENT VALUE OF WIND-POWER HYDROGEN-BASED ENERGY STORAGE SYSTEM

## Nature of Real Options

The critical advantage of wind power-hydrogen storage technology is its operational flexibility. The wind power plant operators can select different operation modes according to the price change in the power market, thus creating a time difference between wind power generation and on-grid sales. Therefore, wind-power HESS's maximum economic value is closely related to the operational decision. Operators can adopt reasonable charging and discharging strategies to earn maximum profits. As electricity price increases, the system releases hydrogen energy and convert it into electricity through fuel cells for on-grid sales to earn profits. As electricity price decreases, the system electrolyzes water to produce hydrogen, converts electric energy into hydrogen energy, replenishes the workload of the wind-power HESS, and sells it when the electricity price reverts to its high level. Operational flexibility is a kind of Compound Real Option since operators face many choices to delay charging and discharging decisions; thus, they can wait for more information and favorable prices to make better-informed decisions. It is necessary to set up a suitable valuation model to cover the Compound Real Options features of the wind-power HESS.

In the process of energy storage, a considerable volume of curtailed wind power is fed to the wind-power HESS, and this part of electric energy can be directly stored by electrolyzing water to produce hydrogen without purchase cost. Therefore, the fluctuation of input wind power will have a particular impact on the profit of the wind-power HESS, and, at the same time, it will affect the actual operating power of the energy storage system (the system is limited by rated capacity). Therefore, the wind-power HESS evaluation model needs to simulate this part of free wind input to quantify the system's economy accurately.

## Valuation Model Construction

### Cost-Benefit Analysis

For a wind-power HESS directly connected to the wind farms, its cost consists of fixed cost and variable cost. The fixed cost includes the depreciation and amortization of initial investment and the fixed operating and management expenses. The variable cost includes the unit operating cost of energy storage or release. It varies directly to the energy storage system's operating power and the input/output power. The operating income comes from the sales of on-grid electricity discharged from the wind-power HESS.

Assume that at time $t$, the working capacity of the hydrogen storage system is $I(t)$, $I(t) \in [0, I_{max}]$, where $I_{max}$ indicates the maximum working capacity (kWh) of the hydrogen storage system. $u(t)$ indicates the control variable of the hydrogen storage system, that is, the power of storing or releasing hydrogen energy, which satisfies $u_{min} \le u(t) \le u_{max}$. $u_{max} > 0$ indicates the maximum discharge power, and $u_{min} < 0$ indicates the maximum hydrogen storage power.

There is no purchase cost for the surplus wind power digested by the wind-power HESS. We use the mean-reverting model established by Kelouwani et al. (2005) to simulate the change in excess wind power input to the hydrogen storage system, as shown in **Eq. 1** follows:

$$Ei(t) = a + b\sin[2\pi(t - t_0)] + \alpha_1[Ei_0 - Ei(t-1)]dt + \sigma_1 Ei(t-1)dZ, \tag{1}$$

where $Ei(t)$ represents the input power of the surplus wind into the hydrogen energy storage system; $a$ and $b$ are two periodic variation parameters of excess wind power's input power; $t_0$ is the time of maximum input power in 1 year; $\alpha_1$ is the average recovery rate; $\sigma_1$ is volatility; $dZ$ is a standard Wiener process. The actual operating power after removing excess wind power's input power should satisfy $u_{min} - Ei(t) \le u(t) \le u_{max}$.

The energy storage capacity volatility is mainly determined by the power of charge and discharge energy and electrohydrogen conversion efficiency. Considering the uncertain consumption of excess wind power's input power, the change of energy storage working capacity is shown in .

$$\frac{dI}{dt} = [-u(t) + Ei(t)]a(u), \tag{2}$$

where $I$ represents the energy storage capacity of the wind-power HESS and $a(u)$ indicates the efficiency of electrohydrogen conversion when hydrogen is input or output, $a(u) \ge 0$.

We focus on the annual total cost during the operational stage, so set the time when the energy storage system is officially put into operation as $t_0$. Calculate the equivalent annual cost of the initial construction investment to allocate initial capital expenditure evenly among operational stage. Then discount the operating costs, subsidies, and the equivalent annual cost of the initial construction to $t_0$. The formula of the total cost is as follows:

$$C_D(t) = \begin{cases} c[-u(t) + Ei(t)]a(u), & u(t) < 0 \\ cu(t)a(u), & u(t) \ge 0 \end{cases},$$

$$\int_0^T e^{-r\tau} C_s d\tau = \int_{-t_1}^0 e^{-r\tau}(I_S - Sub)d\tau,$$

$$C_S = \frac{e^{-rt_1} - 1}{1 - e^{-rT}}(I_S - Sub),$$

$$C(t) = C_0 + C_D(t) + \frac{e^{-rt_1} - 1}{1 - e^{-rT}}(I_S - Sub),$$

$$C(t) = \begin{cases} C_0 + c[-u(t) + Ei(t)]a(u) + \frac{e^{-rt_1} - 1}{1 - e^{-rT}}(I_S - Sub), & u(t) < 0 \\ C_0 + cu(t)a(u) + \frac{e^{-rt_1} - 1}{1 - e^{-rT}}(I_S - Sub), & u(t) \ge 0 \end{cases}, \tag{3}$$

where $t_1$ indicates the investment period of the project and $T$ is the total operation period. $C(t)$ represents the operating cost of the system per unit time, including (1) $C_S(t)$, the net cost during the investment stage offset by subsidies; (2) $C_0$, the energy storage cost per unit time; and (3) $C_D(t)$, the charge and discharge cost per unit time, which is directly proportional to the unit cost $c$ and the real-time charge and discharge power. $I_C$ represents the one-time initial investment cost, $Sub$ means subsidies on the equipment purchase expense, and $r$ represents the discount rate.

## Fluctuations in Electricity Price

At present, China is deepening its power industry reform, gradually liberalizing the power sector from the government's macro-control. One of the reform's objectives is to abolish the fixed electricity prices into marketized electricity prices. Therefore, this research assumes that electricity price is a liberalized market price.

The electricity price in a liberalized market shows robust seasonal features and peaks and jumps in its movement. Soaring and jumping ups in price are related to supply interruption and abnormal incremental demand due to extreme weather. The severe dives in price are related to uncertain external factors, such as the excess power generated by the wind farms' failure of "shut down". This kind of price surge or plunge is usually short lived. Once the supply and demand interruptions are alleviated, the price will quickly return to its original level. The seasonal fluctuation of electricity prices is related to the demand, price rising in the period of high demand and falling in the period of low demand. To sum up, for most market-oriented electricity markets in the world, the characteristics of electricity prices are periodicity, seasonality, high volatility, mean reversion, and peak-jumping.

To establish a multifactor electricity price model, we modified the multifactor electricity price model of Borovkova and Schmeck (2017) to adapt to the Chinese power sector. The complex multifactor electricity price model of Borovkova and Schmeck (2017) is as follows:

$$Y_t = A_t + M_t^c + M_t^d$$

$$A_t = e^{-\theta T(t)} + \mu\left(1 - e^{-\theta T(t)}\right) - \theta \int_0^t \times \int_0^u e^{\theta T(s)} \sigma \sqrt{\tau(s)} dB(s) e^{-\theta T(u)} \tau(u) du + \int_0^t \int_R x v(dx, du) - \theta \int_0^t \int_0^u \int_R e^{\theta T(s)} x N(dx, ds) e^{-\theta T(u)} \tau(u) du$$

$$s(t) = a_1 \sin\left(\frac{a_2 + 2\pi t}{T}\right) + a_3$$

$$M_t^c = \sigma \int_0^t \sqrt{\tau(u)} dB(u)$$

$$M_t^d = \int_0^t \int_R x(N - v)(dx, du), \tag{4}$$

$Y_t$ is a spot price considering mean-reverting effect, seasonality, random volatility, jumping, and correlation of different random movements. $A_t$ describes the random walk trend considering mean reversibility, $s(t)$ describes periodic seasonal fluctuation, and $M_t^c$ and $M_t^d$ describe the fluctuation and jumping, respectively.

As China's power sector's marketization is still in its infant stage, Borovkova and Schmeck's (2017) model can be simplified. We can directly add the seasonal effect term to the reverting mean and reflect the random fluctuation and peak jumps with two parameters. Thus, the power market price model is established as follows:

$$dP = \alpha_2 [K(t) - P] dt + \sigma_2 P dB + \gamma P dZ_1, \tag{5}$$

$$K(t) = K_0 + \beta \sin[2\pi(t - t_{SA})], \tag{6}$$

where $P$ stands for electricity market price, $K(t)$ for long-term equilibrium price under seasonal effect, $K_0$ for long-term equilibrium price without seasonal effect, $\alpha_2$ for average price recovery rate, $\sigma_2$ for price fluctuation, $\gamma$ for the jumping parameter of electricity price, and $dB$ for standard Wiener process increment ($dB = \varepsilon\sqrt{dt},\ \ \varepsilon \sim N(0,1)$). $dZ_1$ represents the increment of the Poisson process ($dZ_1 = \lambda dt$), $\beta$ represents the seasonal parameter of electricity price, and $t_{SA}$ indicates the time when the seasonal electricity price is the highest.

Due to the surge in demand for heating in winter and cooling in summer, the power price reaches its peak then. So $K(t)$ in **Eq. 6**, which reflects the seasonal fluctuation of equilibrium price in the electricity market, is a periodic function for a half year.

## Valuation Model

Operators of the wind-power HESS can maximize the economic value by optimizing charge and discharge decisions. The operator's objective is as follows:

$$max_u E\left\{ \int_0^T e^{-rt} [u(t) a(u) P(t) - C(t)] dt \right\}, \tag{7}$$

where $u \in [u_{min}(t) - Ei(t), u_{max}(t)]$, and $E$ represents operators' expected profit.

We define V(P,t) as the economic value of the wind-power HESS. That is, the value of the wind-power HESS is a function that depends on the price and time variation of the electricity market.

$$V(P,t) = max_u E\left\{ \int_0^T e^{-rt} [u(t) a(u) P(t) - C(t)] dt \right\}, \tag{8}$$

To make the model intuitive, we establish a standard Bellman equation, which separates the energy storage system's value from $t$ to $t + dt$ and $t + dt$ to $T$ and then simplify the value formula with the rectangle method. See the detailed derivation process:

$$V(P,t) = \max_u E\left\{ \int_t^{t+dt} e^{-r(\tau - t)} [u(\tau) a(u) P(\tau) - C(\tau)] d\tau + \int_{t+dt}^T e^{-r(\tau - t)} [u(\tau) a(u) P(\tau) - C(\tau)] d\tau \right\},$$

$$V(P,t) = max_u E\left\{\int \left\{[u(t)a(u)P(t) - C(t)]dt + e^{-rdt}V(P+dP, t+dt)\right\}\right\},$$

Bring the cost (**Eq. 3**) into the above formula, and carry out Taylor's expansion. According to Ito's Lemma, we can get

$$V(P,t) = max_u E\left\{\int \left\{[u(t)a(u)P(t) - C_0 - C_D(t) - C_S]dt + (1-rdt)\left[V + \alpha\left(K_0 + \beta sin(2\pi(t-t_{SA})) - P\right)\frac{\partial V}{\partial P}dt + \frac{1}{2}\sigma^2\frac{\partial^2 V}{\partial^2 P}dt + \sigma\frac{\partial V}{\partial P}dB + \frac{\partial V}{\partial P}dZ + \frac{\partial V}{\partial t}dt\right]\right\}\right\},$$

Finally, take the expectation of the above equation and divide the value at $dt$.

$$\frac{\partial V}{\partial t} + \frac{1}{2}\sigma^2\frac{\partial^2 V}{\partial^2 P} + \alpha\left(K_0 + \beta sin(2\pi(t-t_{SA})) - P\right)\frac{\partial V}{\partial P} - rV - C_0 - C_S + max_u E[u(t)a(u)P(t) - C_D(t)] = 0. \tag{9}$$

The last part of the above formula contains the variable $u(t)$. To realize the optimal economic value of the wind-power HESS, the actual operating power, $u(t)$, which is also the buying and selling power, should meet the following requirements:

$$\begin{cases} max_u E\{u(t)a(u)[P(t) - c]\}, & u(t) \ge 0 \\ max_u E\{u(t)a(u)[P(t) - c] - cEi(t)a(u)\}, & u(t) - Ei(t) < 0 \end{cases},$$

where $u \in [u_{min}(t) + Ei(t), u_{max}(t)]$, $a(u) = \begin{cases} a_1, & u \ge 0 \\ a_2, & u - Ei(t) < 0 \end{cases}$.

Therefore, when $u(t)$ meets the optimal operation condition ($u^*$), the wind-power HESS will satisfy

$$\frac{\partial V}{\partial t} + \frac{1}{2}\sigma^2\frac{\partial^2 V}{\partial^2 P} + \alpha\left(K_0 + \beta sin(2\pi(t-t_{SA})) - P\right)\frac{\partial V}{\partial P} - rV - C_0 - C_S + u(t)a(u)P(t) - C_D(t) = 0. \tag{10}$$

Now the question comes to find the optimal control variable, $u^*$.

### Boundary Conditions

Assume that the energy storage system will stop working at the end of the project life, and then the system's real-time value will be zero.

$$v(P,t) = 0, \quad t = T.$$

When the market price of electricity is high, the optimal choice is to maximize the output power for grid-connected sales. When the market price of electricity is low, the optimal choice is to purchase power for energy storage for subsequent operation. However, if the market price stays still, the real-time value $v$ of the system will not change, so the optimal choice at this time will be no additional buying or selling. To sum up, the boundaries for the value of the wind-power HESS are defined as follows:

$$\begin{cases} V_{PP} \to 0, & P\ large \\ V_{PP} \to 0, & P \to 0 \end{cases},$$

Next, let us define the difference term's restrictions in the valuation model. Set $V_j^i$ as the value when the energy storage system operates at the time $i$ and the electricity market price $P$ is at its $j$th node, where $i = 1, 2,..., N$ while $j$ is a continuous variable with 0 as the lowest value. Therefore, take the discretized first-order difference of the value function with time $t$ and price $P$. The results are shown in **Eqs. 11**, **12**.

$$\frac{\partial V_j^i}{\partial t} = \frac{V_j^{i+1} - V_j^i}{\delta t}, \tag{11}$$

$$\begin{cases} \frac{\partial V_j^i}{\partial P} = \frac{V_{j+1}^i - V_j^i}{\delta P}, & if\ \alpha > 0 \\ \frac{\partial V_j^i}{\partial P} = \frac{V_j^i - V_{j-1}^i}{\delta P}, & if\ \alpha \le 0. \end{cases} \tag{12}$$

Then, take the discretized second-order partial difference in the value function with price $P$.

$$\frac{\partial^2 V_j^i}{\partial P^2} = \frac{V_{j+1,}^i - 2V_j^i + V_{j-1}^i}{(\delta P)^2}. \tag{13}$$

When the market price of electricity is zero or reaches its peak value, the second-order difference in the wind-power HESS's value is zero. Hence, the following boundary conditions determine the second-order difference term in **Eq. 13**.

$$\frac{\partial^2 V_0^i}{\partial P^2} = 0,$$
$$\frac{\partial^2 V_N^i}{\partial P^2} = 0.$$

The constraints include the energy storage capacity, $I$, and its first-order derivative. The specific boundary conditions are defined as follows:

$$\begin{cases} u(t)a(u) > 0, & I = I_{max} \\ [u(t) - Ei(t)]a(u) \le 0, & I = 0 \end{cases}.$$

The above formula indicates that the input power is zero when the wind-power HESS works at its maximum capacity. That is, operators should adopt the strategy of discharge or no operation. When the working capacity of the system is zero, there is no power output. That is, operators should adopt the strategy of charge or no operation. Based on the above objections and restrictions, the optimal control variable, $u^*$, can be solved with Monte Carlo simulations.

## SIMULATION OF THE INVESTMENT VALUE

### Simulation Assumptions

The operation and settlement cycle of the wind-power HESS is generally 1 year, so this resaerch studies the value and operation decision of the wind-power HESS within 1 year. According to the existing hydrogen storage technology

**TABLE 3 |** Wind power benchmarking price of four resource zones in China (yuan/kWh).

| Reference | NDRC No.[2009]1906 | NDRC No.[2014]3,008 | NDRC No.[2016]2,729 | NDRC No.[2016]2,729 |
|---|---|---|---|---|
| Effective date | 2009.08 | 2015.01 | 2016.01 | 2018.01 |
| Type I | 0.51 | 0.49 | 0.47 | 0.40 |
| Type II | 0.54 | 0.52 | 0.50 | 0.45 |
| Type III | 0.58 | 0.56 | 0.54 | 0.49 |
| Type IV | 0.61 | 0.61 | 0.60 | 0.57 |

*Source: documents released by the* National Development and Reform Commission *of China.*

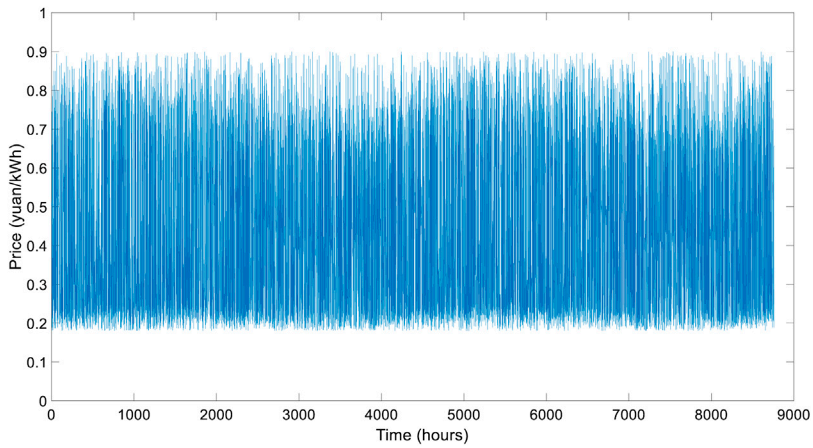


**FIGURE 2 |** Single simulation of electricity prices (for 1 year).

specifications, we set the maximum energy storage capacity to be 100 MWh, maximum released power to be 6 MW, and maximum stored power of the wind-power HESS to be 10 MW. For the direct transmission power model of excessive wind power consumption, assume that the periodic parameters $a$ and $b$ are 2000 and −5,000, respectively, the peak time $t_0 = 0$, the average stored power $Ei_0$ is 5,000 kW, the average recovery rate $\alpha_1$ is 0.5, and the volatility at $\sigma_1$ is 0.2. The long-term average electricity price, $K_0$, is based on the benchmark on-grid price of onshore wind power in the four resource zones (see **Table 3**) and set as 0.5 yuan/kWh. t is in hours.

We assume that the average recovery rate $\alpha_2$ is 0.5, the volatility $\sigma_2$ is 0.05, the jumping parameter $\gamma$ is 0.05, and the seasonal parameter $\beta$ is 0.1. The simulation results of the electricity price are shown in **Figure 2**.

Assuming unlimited operating time, the construction period ($t_1$) lasts for 4 years, = 1 (Yuan/kW), $C_0 = 10^4$ (Yuan), and the annual discount rate during the construction period is 10%,

$$a(u) = \begin{cases} 1/0.6\ , & if\ u < 0 \cdot \\ 0.9\ , & if\ u \geq 0 \end{cases}$$

Assume that the unit construction cost is 0.35 yuan/kWh and the total investment is 350 million yuan, that is, IC = 350 million yuan. For the convenience of calculation, assume that the subsidy is equal to the investment, that is, $Sub$ = 350 million yuan, then $Ic - Sub = 0$. Suppose the initial hydrogen energy storage system is at full working capacity, $I_0 = 10^5$ kWh.

## Simulation Results

**Figure 3** shows the value of the wind-power HESS under different electricity market prices and working capacities. When the electricity market price is high and the HESS reaches full load, the value of the wind-power HESS reaches its maximum. When the electricity market price is the highest and the HESS's working capacity is zero, then the value of the wind-power HESS reaches the minimum. This result can be understood as when the electricity price is very high, or the HESS is running at full capacity, the decision-makers always choose to produce hydrogen energy as soon as possible to obtain the maximum profit. When the HESS's working capacity is zero, no matter how high the electricity price is, the decision-maker has no available stored hydrogen energy for power generation output. In that case, it is not worth buying extra electricity for sale because of the high purchasing price. Besides the above two extreme cases, the decision-makers will choose to purchase electricity from the spot market and convert it into hydrogen energy for storage if the electricity price is relatively low and the HESS still has vacant working capacity. In this way, they can convert hydrogen to output electricity through fuel cells after the electricity price rises. Therefore, when the system's working

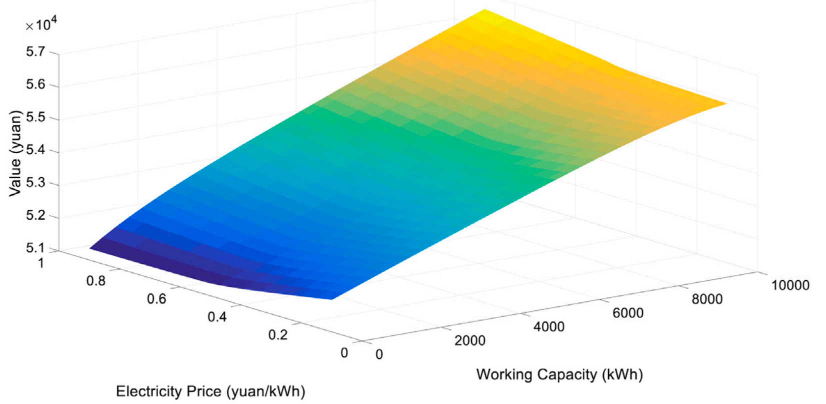


**FIGURE 3 |** Wind-power HESS value surface.

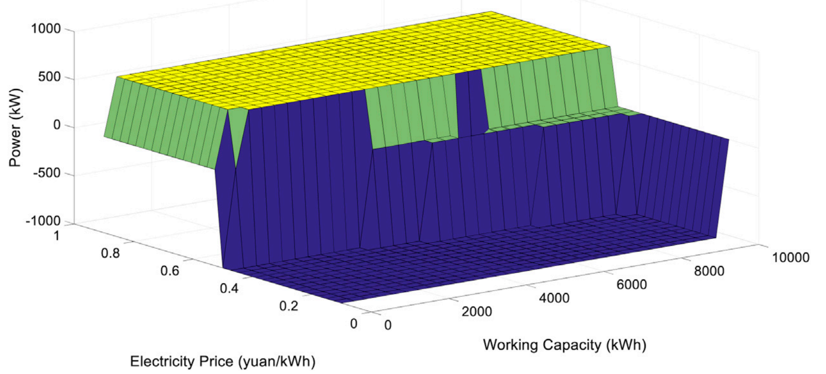


**FIGURE 4 |** Control surface of wind-power HESS.

capacity is high, the wind power-HESS is equivalent to a call option of the electricity market price. When the system's working capacity is low, it is equivalent to a put option. When the working capacity is between zero and its maximum, the wind power-HESS is equivalent to a saddle option (a compound option with calls and puts) of the electricity market price.

**Figure 4** shows the optimal generating, storing, and discharging strategies of the HESS under various power prices and system capacities. The joint distribution of power price and working capacity decides the operator's optimal generating, storing, and discharging decision. When the power price is low, the operator will be willing to purchase extra electricity from the spot market for storage after completing the overabundant wind power storage as long as the system has not fully loaded. When the electricity price increases to a threshold, the optimal choice changes to convert stored hydrogen into electric energy and sell it for profit. The boundary area in **Figure 4** shows that when the working capacity of the wind-power HESS is zero, even if the electricity price is high, it is still impossible to convert hydrogen energy for on-grid sales. Similarly, when the wind-power HESS works at full load, the decision-maker will not purchase low-cost electricity for storage, even if the electricity market price is meager.

Besides, when the electricity price fluctuates to its long-term average level, the decision-maker may not buy additional power to charge the energy storage system if its working capacity is already high. It depends on the power price trend and the variable cost of producing and storing hydrogen energy.

**Figure 5** shows the changes in power price and the working capacity with time and the corresponding operation strategies.

(1) *Price Volatility*. We assume that the wind-power HESS was working at full load initially. The simulation results have captured the electricity price fluctuation during different hours. The seasonal effect is much smaller than the intraday fluctuation, although we set the electricity price to repeat the first rising then falling twice a year. The trend of electricity price is shown in **Figure 5A**.
(2) *Change of Working Capacity*. **Figure 5B** describes the changes in working capacity during the operation. Within a day, as the electricity price rises high enough for the on-grid sales to compensate for the operating cost, the operator will always

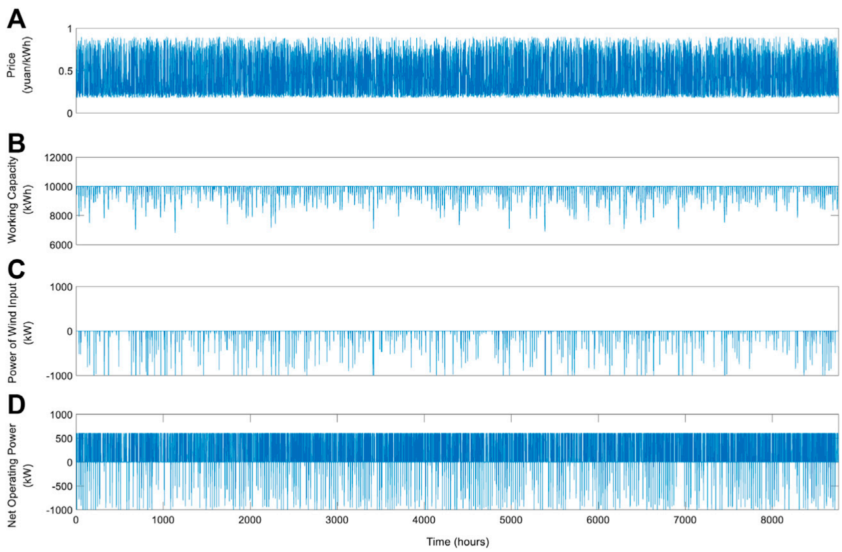


**FIGURE 5 |** Working capacity and operational strategy changing with electricity prices.

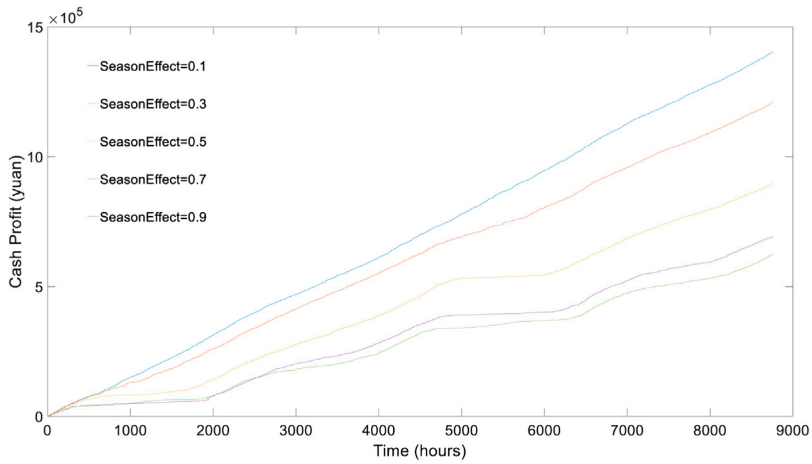


**FIGURE 6 |** Total cash flows with different seasonal factors of electricity price (for one year).

convert hydrogen energy to output electric power for sales. During that time, the energy storage system's working capacity keeps declining. Starting from the intraday peak, the price of electricity begins to decrease. When it drops to a certain level, the operator begins to purchase additional electricity to input the system and transform it into hydrogen to store. During this period, the operator waits until the power price rises for on-grid sales. However, when the electricity price falls to the bottom, it's difficult to recover the operating cost of on-grid sales. When the electricity price reaches the peak, it is too expensive to buy additional electricity to produce hydrogen for subsequent discharging. In the above two states of nature, the system will only take in the zero-cost wind power and slowly reach saturation. Figure 5B shows that the system maintains more than 60% of energy at work and it reaches the full load frequently, which implies that the charging frequency is higher than the discharging frequency or energy storage speed is quicker than the discharging speed. This difference is mainly because the wind-power HESS must first absorb surplus wind power during the storage phase, which is the system's principal primary function. Surplus wind power carries no procurement cost. As long as the unit energy storage cost is lower than the output electricity price, the storage system will always consume electric energy and transform it into hydrogen energy. When the wind-power HESS starts to discharge continuously, the discharged power is the absolute operating power. To sum up, when the system starts storing energy, the excess wind power consumed is

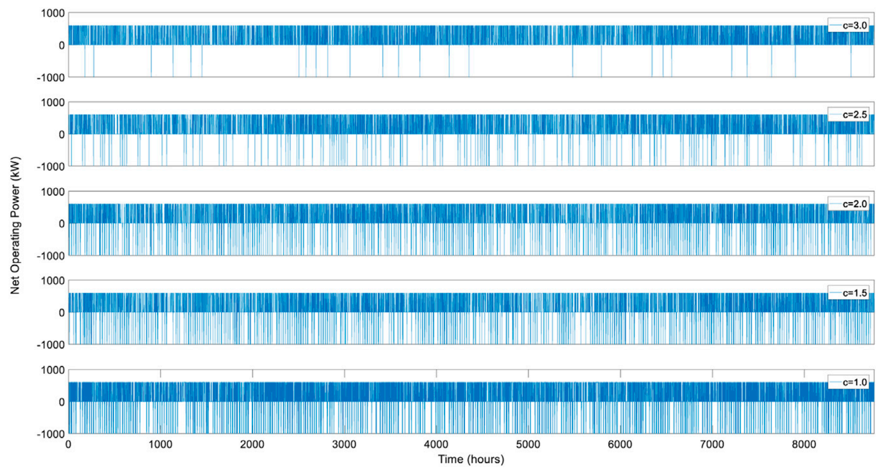


**FIGURE 7 |** The impact of the operation costs on decision-making in wind-power HESS..

superimposed, increasing the energy storage velocity and the working capacity rapidly. Thus the wind-power HESS can quickly reach the full load.

(3) *Energy Storage and Discharge Strategies*. **Figure 5C** shows the system's operating power of wind absorbing, while **Figure 5D** describes the net operating power without surplus wind power. Comparing these two figures, we find that the HSEE system can timely digest surplus wind power to reduce capacitance loss from discharging. The operating strategy in **Figures 5C,D** varies consistently with the change of capacity in **Figure 5B**. The operator repeats a loop of releasing energy for sale (being bullish on electricity price), no operation (maintaining value), energy storage (being bearish on electricity price), and waiting for appreciation. The circulatory strategy accords with those above-mentioned three real options.

## Sensitivity Analysis

### Seasonal Parameter of Electricity Price, β

There is no seasonal effect when the seasonal fluctuation rate of electricity price, β, equals 0. As β increases, the seasonal fluctuation of the electricity price will increase gradually. We assume that the values of β are equal to 0.1 (which is the base scenario), 0.3, 0.5, 0.7, and 0.9, respectively; repeat the simulation procedures and summarize the results in **Figure 6**.

As shown in **Figure 6**, with the seasonal fluctuation of electricity market price increases, the accumulated cash flow of the wind-power HESS gradually decreases so that operators' profit decreases. Under different β values, the overall upward trend of the system's accumulated cash flows is approximately the same.

When $\beta = 0.9$, the seasonal fluctuation of the electricity price is the strongest among the five scenarios, which means it takes the longest time for the price to return to its long-term average because the intraday fluctuations are superimposed with a large seasonal deviation. Therefore, operators have to face a lot of time to idle the system and wait for the price to fluctuate to the other side of the long-term average. A shorter operational window period leaves less room for the wind-power HESS to earn profits across time. Therefore, the accrued cash flow is the least when $\beta = 0.9$. Nevertheless, considering zero-cost excess wind power consumption, the annual accumulated cash flow is still positive in this case. As β decreases, the mean-reverting speed of electricity price rises gradually, and the real-time value of the wind-power HESS increases accordingly. It's the intraday volatility instead of β that decides the opportunity to exercise the real options. The power sector's marketization reform is conducive to improve the value of wind-power HESS and promote the industrialization of hydrogen energy storages. Marketization reform will increase the ultra-short-term price jumps or spikes in electricity prices and iron out the seasonal effects using electricity derivatives such as futures, options, and swaps.

### Unit Operating Cost of the System, c.

**Figure 7** shows the simulation results of net operating power without surplus wind power when c is equal to 1.0 (which is the base scenario), 1.5, 2.0, 2.5, and 3.0, respectively. The time of zero operating power ($u = 0$) will be prolonged as c increases because the increasing operating cost reduces profit margin, leaving little space for operators to exercise options. That is, the time for operators not to execute storage operation is prolonged. It implies that technological breakthroughs are essential to reduce the system's operating cost and further stimulate operators' enthusiasm for the system.

### Subsidies, *Sub*

**Figure 8** shows the change in the value of wind-power HESS when the subsidy parameter, *Sub,* is equal to 0, 20%, 40%, 60%, 80%, and 100% of investment (which is the base scenario). Subsidies can significantly improve the economy of energy storage systems. In the absence of subsidy (*Sub* = 0), which is the worst case and severe crackdown on operators' investment enthusiasm, the value of wind-power HESS will be 87% of that when initial investment is 100% subsidized. Therefore, it is still necessary for the government to subsidize enterprises to promote investment in energy storage system projects until notable technological innovations come.

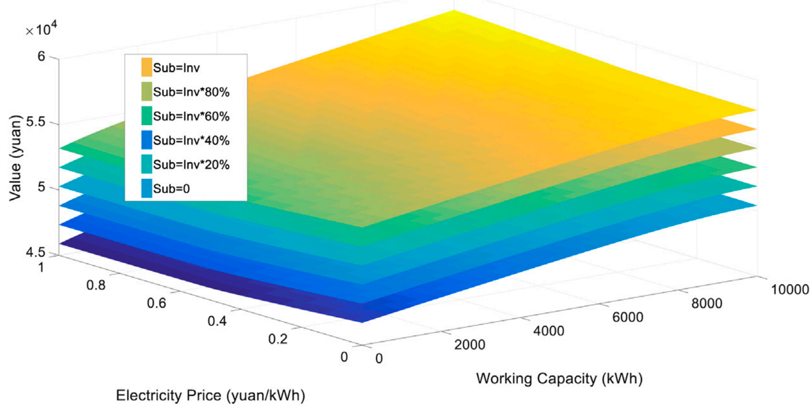


**FIGURE 8 |** The impact of the subsidy changes on value surface.

## CONCLUSION

This article comprehensively evaluates the investment value of the wind-power HESS from three aspects: resource utilization, emission reduction, and economic value.

First of all, the intermittence and fluctuation of wind power generation decrease the power system's stability, causing great losses due to wind power casted away off-grid. Since the wind-power HESS can dynamically absorb the excess power and convert it into hydrogen energy for storage and timely release on-grid, it effectively makes up for the instability of wind power generation. According to our scenario hypothesis, China's curtailed wind power is as high as 16.9 billion kWh per year. The installment of the wind-power HESS can absorb the surplus wind power and equivalently save 21.9–32.85 million tons of standard coal consumption per year. The coal consumption saving can reduce pollutant emissions (such as $CO_2$, $SO_2$, $NO_x$, and PM) by 3.31–4.97 million tons per year and save the environmental cost by 286.6–429.8 million yuan annually.

Secondly, operational flexibilities will increase the economic value of the wind-power HESS. We established a real option valuation model to capture the value of flexibilities and discuss the influence of factors (including price fluctuation, investment cost, unit operation cost, operation efficiency, and subsidies) on the project's value with a dynamic programming method. Specifically, the wind-power HESS can be regarded as a call option, put option, and saddle option according to the electricity price and storage workload. To maximize the system's value, operators need to make reasonable operational strategies according to the power price and the storage system's workload. Overall, operators should store energy when the electricity market price is low and discharge energy when the electricity market price climbs high.

Finally, the sensitivity analysis of the valuation model's critical parameters shows that (1) the less significant the seasonal fluctuation of electricity price, the better the HESS's economy. To some extent, the marketization of electricity industry will enhance energy storage's potential benefits and further promote its industrialization. (2) The lower the unit operating cost is, the more frequent charging and discharging operators perform. Therefore, it is necessary to encourage investment in the technological breakthroughs of wind-power HESS to reduce the system's operating cost. (3) The subsidy level has a meaningful influence on the value of wind-power HESS. The development of energy storage technology also relies on incentive policies (such as subsidies and tax incentives).

## 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

QX participated in methodology, writing-reviewing, and editing. ZW performed conceptualization, establishing the framework, and supervision. YZ conducted simulation and writing original draft preparation. All authors contributed to the article and approved the submitted version.

## FUNDING

This research was supported by the National Natural Science Foundation of China (grant no. 71904111), the Humanities and Social Sciences Program of Chinese Ministry of Education (grant nos. 19YJCZH106 and 20YJCZH201), and the Research Startup Fund of China University of Petroleum Beijing (grant no. ZX20200110).

## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2021.629136/full#supplementary-material.

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**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.

frontiers in Energy Research

REVIEW
published: 10 March 2021
doi: 10.3389/fenrg.2021.638105

# Identifying and Regulating the Environmental Risks in the Development and Utilization of Natural Gas as a Low-Carbon Energy Source

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In response to climate change and energy transition, natural gas has been rapidly developed as a relatively low-carbon energy source by many countries. However, there remain environmental risks at different stages in the entire process from exploitation to utilization. Firstly, this article identifies various environmental risks and benefits of natural gas along the entire industry chain from upstream exploitation and midstream transportation to downstream utilization. It is found that, during upstream exploitation, hydraulic fracturing has the worst environmental impact. During the midstream storage and transportation stage, methane leakage is the biggest environmental risk. In the downstream combustion and utilization stage, the risk to environment is less than other energy sources, although there are some greenhouse gas effects and water pollution issues. Thus, this article puts forward some policy recommendations for different stages from exploitation to utilization. In the upstream stage, especially hydraulic fracturing activity, we suggest strengthening environmental assessment management, improving policy standards, creating a water quality monitoring plan, and promoting the innovation of key technologies. In terms of the midstream, besides pipeline laying and site selection, we focus on monitoring the system, including leak detection, quality management of engineering materials, and risk identification and management. When it comes to the downstream, we encourage the application of advanced technologies to improve thermal efficiency and reduce emissions, such as gas-fired related technologies, natural gas recycling technologies, distributed energy technologies, and green and low-carbon service technologies.

**Keywords: life cycle assessment, environmental risks, different stages, control measures, natural gas**

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***Edited by:***
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***Specialty section:***
*This article was submitted to Sustainable Energy Systems and Policies, a section of the journal Frontiers in Energy Research*

***Received:*** *05 December 2020*
***Accepted:*** *19 January 2021*
***Published:*** *10 March 2021*

***Citation:***
*Fu J, Liu Y and Sun F (2021) Identifying and Regulating the Environmental Risks in the Development and Utilization of Natural Gas as a Low-Carbon Energy Source. Front. Energy Res. 9:638105. doi: 10.3389/fenrg.2021.638105*

## 1 INTRODUCTION

As a result of actual or predicted effects of climate change and the ongoing energy transition, natural gas has become a favored energy source, due to its relatively clean combustion, during the transition from fossil fuels to fully renewable energy by the governments of various countries. As a result, natural gas, rich in reserves, is the cleanest and fastest growing fossil fuel and accounts for nearly one-third of global energy demand growth and nearly one-quarter of power generation (World Energy Agency, 2020). Data from the Organization of Petroleum Exporting Countries (OPEC) show that the world's proven natural gas reserves were 188 trillion cubic meters (OPEC, 2019). According to BP's *World Energy Statistics Review 2020* (BP, 2020), the global average annual growth rate in natural gas consumption was 2.6% over the past ten years. In 2019, global natural gas consumption increased by 78 billion cubic meters, a year-on-year increase of 2%. Its growth rate is faster than that of oil (0.3% per year) and coal (average −0.1% per year). It is estimated that, by 2040, natural gas usage will surpass coal and approach oil (when converted to tons of oil equivalent) and will be the only fossil fuel energy source competing against renewable energy. Natural gas is significantly cleaner and has less greenhouse effect than coal and oil energy sources, based on carbon dioxide emission in the combustion and utilization stages. According to the United States Energy Information Administration (EIA) estimates, the carbon dioxide emissions of one million Btu of calorific value produced by natural gas combustion are 53.97 kg, whereas the combustion of various types of coal emits 95.35 kg of carbon dioxide on average, gasoline emits 71.30 kg, and petroleum coke emits 102.1 kg (EIA United States Energy Information Administration, 2018). Although the carbon dioxide emissions of natural gas in the combustion and utilization stage are much lower than other fossil energy sources, natural gas still has certain environmental risks in other stages of the industrial chain from exploration and production to utilization (Kondash et al., 2017). Therefore, it is necessary to conduct a comprehensive assessment of these environmental risks, given the expanding consumption of natural gas.

Natural gas is a fossil fuel mainly composed of methane, which is usually divided into conventional and unconventional natural gas. Conventional natural gas is found either as just a gas phase or as a gas cap over an oil reservoir. Unconventional gas reservoirs are mainly shale, tight sandstone, coal, and hydrate. Different reservoir types need different technologies for recovery of gas, and different technologies bring different environment risks. Depending on the transportation mechanism, natural gas can be divided into pipeline, compressed, and liquefied natural gas.

Many studies have focused on the environmental risks along the natural gas industrial chain. Published research mainly focuses on water resources and greenhouse gases. For example, a number of studies have conducted extensive research on water pollution caused by hydraulic fracturing activities during natural gas development. Gagnon et al. (2016) reviewed the literature on the impacts of hydraulic fracturing on water quality and focused on regulatory frameworks. Rodriguez et al. (2020) evaluated the impact of hydraulic fracturing on groundwater quality in the Permian Basin, West Texas. Yazdan et al. (2020) conducted a review of the impacts of wastewater disposal in the hydraulic fracturing industry in the United States. Some studies conducted research on the amount of greenhouse gas emissions in natural gas development. For example, Crow et al. (2019) assessed the potential impact of greenhouse gas emissions from natural gas production by combining the estimates of $CO_2$ and methane emissions with a dynamic, technoeconomic model of gas supply. MacKinnon et al. (2018) studied natural gas emission in the context of greenhouse gas mitigation and air quality improvement. In addition, other studies have specifically studied the leakage risk and response technology of methane in one point of the industry chain. For example, Moortgat et al. (2018) focused on gas leakage into the air causing pollution in the upstream stage; McCabe et al. (2015) observed the leakage to the greenhouse effect in the middle stage; Xu and Lin (2019) focused on the relationship between natural gas consumption and $CO_2$ emission in the downstream stage. However, there is very little research on other types of environmental impacts, such as that on soil ecology or wildlife, in the development and utilization of natural gas.

Secondly, the published research has been mostly aimed at a given stage of the chain. Studies have focused on the environmental risks from upstream exploitation and production of natural gas. For example, Kondash et al. (2017), Gallegos et al. (2015), and Thacker et al. (2015) studied water treatment issues related to unconventional oil, gas exploration, and hydraulic fracturing activities in the upstream stage. Wang et al. (2020) focused on short-term mechanism coupling shear stress and hydraulic fracturing in an experimental simulation triggered by hydraulic fracturing and found that short-term hydraulic fracturing was less likely to cause rock mass instability or earthquake, but the long-term fluid injection could increase the pore pressure and change the *in situ* stress field in a large area to induce an earthquake. Mohan et al. (2013) and Brittingham et al. (2014) studied the ecological risks of natural gas development to wildlife, aquatic resources, and their habitats. Some studies have also conducted studies on other aspects of the natural gas industry. For example, Ou and Yuan (2019) conducted a life cycle analysis of greenhouse gas emissions on liquefied natural gas (LNG) and compressed natural gas (CNG) in heavy-duty trucks. Yuan et al. (2019) estimated the venting and fugitive leaks from natural gas supply chains and found that promoting natural gas vehicles is effective at helping to reduce greenhouse gas emissions from road transportation. However, there is still a lack of integrated analysis of the potential risks of natural gas utilization over the entire industry chain.

The purpose of this article is therefore to systematically analyze various environmental risks at different stages of the entire natural gas industry chain and recommend regulatory policies to deal with these environmental risks. The novel aspects of this article are mainly twofold: one is to cover the most environmental risks related to natural gas all around the world, not just the water pollution and greenhouse gas emissions that current scholars are mostly concerned about in one country; the other is to cover the entire natural gas industry chain, rather than just focusing on the environmental risks at a specific stage.

## 2 RESEARCH FRAMEWORKS

This article presents a systematic review of the environmental risks from exploitation of natural gas resources along the industry chain. Generally, the entire industry chain of natural gas can be divided into three major stages: upstream, midstream, and downstream. The upstream industry is mainly engaged in the exploration for and development of different types of gas resources, such as conventional natural gas, coalbed methane, shale gas, and other tight gas. The midstream industry mainly provides natural gas transportation, storage, vaporization, and liquefaction services, including pipeline network transportation,

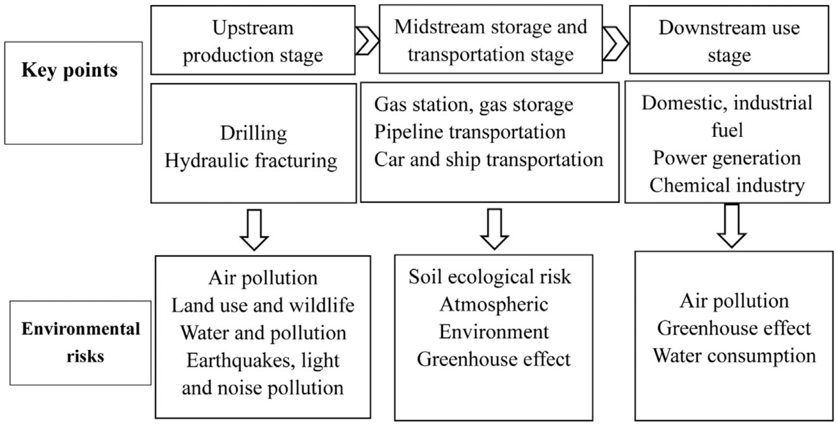


**FIGURE 1 |** Environmental risks from natural gas utilization throughout the industry chain.

gas storage facilities, gasification, and tank truck transportation. Downstream industries mainly involve the delivery of natural gas to the end user for different purposes, including domestic gas, industrial fuel, natural gas power generation, natural gas chemical industry, and different types of transportation. Since different technologies, equipment, and processes are used in different stages, the potential environmental risks are also different; then, we recognize the main points of environmental risks in the following (see **Figure 1**).

## 3 POTENTIAL ENVIRONMENTAL RISKS IN THE UPSTREAM PRODUCTION STAGE

In the upstream extraction stage of natural gas, the main types of activities carried out include seismic exploration, drilling, workover, gas field gathering and on-site transportation, and natural gas purification (Dong et al., 2003). Conventional natural gas mostly exists in highly porous and permeable reservoirs, and standard vertical wells are easy to produce (see **Figure 2**). However, unconventional natural gas is mostly found in low-permeability rocks, and it is relatively difficult to produce. It is often necessary to develop and adopt novel technologies, such as horizontal drilling and formation stimulation. Hydraulic fracturing is currently the commonly used formation stimulation technology for gas in rocks with low porosity and permeability. In hydraulic fracturing operations, the fracturing fluid is pumped carefully under controlled high pressure, and the sand mixed with the fracturing fluid flows in to support the fractures generated. Afterward, sealing wells is necessary to prevent natural gas, fracturing fluids, chemicals, and produced water from leaking into the groundwater supply (Union of Concerned Scientists, 2020). Therefore, the entire upstream process may cause air, water, light, and noise pollution; affect

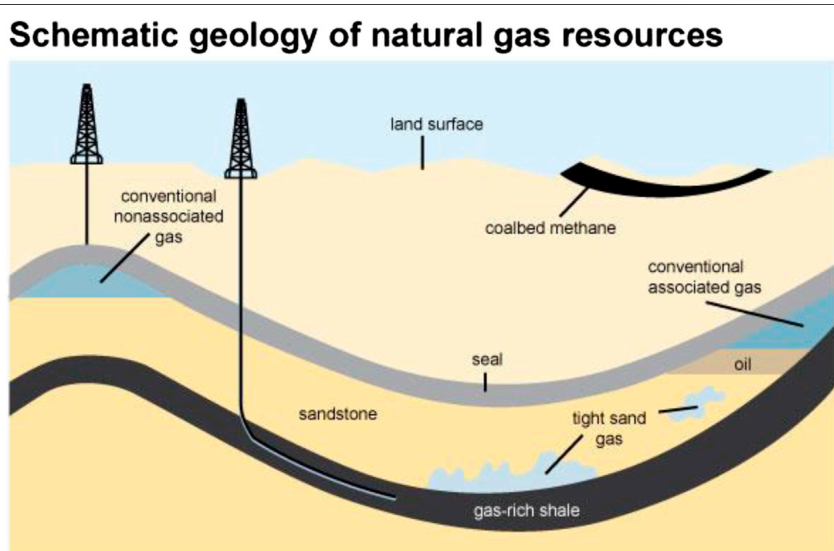


**FIGURE 2 |** Schematic geology of natural resources.

land use, wildlife activities, and water use; and even induce earthquakes (source: adopted from United States Geological Survey Factsheet 0113–01 (public domain)).

## 3.1 Air Pollution

The air pollutants produced during natural gas extraction mainly include construction dust, fuel exhaust gas, blast burning exhaust gas, leakage of methane, and pipeline cleaning exhaust gas (Yuan and Yang, 2019). Many studies show that the concentration of these harmful air pollutants increase in some areas during the drilling and production process (CEPAARB, 2012). Adverse health conditions can arise in some people when exposed to high levels of air pollutants, including respiratory symptoms, cardiovascular disease, and cancer (EPA Environmental Protection Agency, 2013b). Furthermore, the extent of the pollution and its impact on the environment are related to the distance from the development zone. It has been found that residents who lived within half a mile radius from gas wells were affected more severely than those who lived further away (McKenzie et al., 2012).

The main component of natural gas is methane ($CH_4$), whose content is generally greater than 60% (in most cases it is more than 99%), and highly variable amounts of $C_2H_6$, $C_3H_8$, $C_4H_{10}$, $CO_2$, $N_2$, $H_2S$, and trace inert gases (Milkov et al., 2005). Therefore, methane emission caused by natural gas leakage is usually the most abundant pollutant. According to estimates by the United States Environmental Protection Agency in 2017, natural gas, other petroleum systems, and abandoned gas wells accounted for approximately 32% of total United States methane emissions and approximately 4% of total United States greenhouse gas emissions (EPA, 2017). Greenhouse gas refers to any gas that absorbs and releases infrared radiation and exists in the atmosphere and mainly includes $CO_2$, $CH_4$, $N_2O$, $HFC_S$, $PFC_S$, and $SF_6$ (Breidenich et al., 1998). Untreated emitted methane will have some impact on global warming. It is known that the greenhouse effect of every cubic meter of methane leakage is nine times greater than the products of methane combustion (IPCC Intergovernmental Panel on Climate Change, 2007). However, there is still some controversy about the rate of methane leakage. Allen et al. (2013) systematically collected information on methane leakage from shale gas production in the United States, and they found that, under good conditions, methane emissions accounted for about 0.5% of the natural gas extracted. McCabe et al. (2015) believed that the leakage reported from the entire natural gas system ignored the emissions generated during well completion and production. The quantification of methane leakage is still an ongoing issue (Brandt et al., 2014). Although the impact of methane leakage is large, some technological improvements can greatly help reduce methane leakage. For example, green completion technology can reduce methane emissions by 90% during drilling activities and the total wellhead emissions by 81% (Mackay and Stone, 2013). Taking this a step further, the installation of leak-proof components in a well can help the natural gas sector reduce methane emissions by 31–44 $M_tCO_{2e}$ every year in China (Brink et al., 2013).

Besides methane, there is still a small volume of other emissions from natural gas production. VOC, PM, and $SO_2$ emissions in production are less than 1% of that in industrial emissions, and $NO_x$ emissions account for 2.9–4.8% of that in industrial emissions (Litovitz et al., 2013), but even this small-scale pollution discharge will have an impact on local or regional air quality. The concentration of harmful air pollutants increases in some areas during the drilling process, and although this impact may be short-term, it can still cause harmful effects on health and environment (Witherspoon, 2012).

In summary, in this stage, natural gas emissions are relatively small, but, limited by the current technology, there is a certain risk of leakage. The main outcome from natural gas leakage (methane) is to increase greenhouse gas emission, which will contribute to global warming, while a small volume of other gases is harmful to human health. Therefore, the key to the problem is to improve technology to reduce the risk of gas leakage.

## 3.2 Land Use and Wildlife

The environmental impacts caused by the large-scale production of natural gas mainly include occupation of land resources, destruction of surface landforms and vegetation, change in surface runoff, and increase in soil erosion. It may also affect wildlife habitat, biodiversity, and local ecosystem balance in general (Yuan and Yang, 2019). During the drilling process, construction and land disturbance can change land use, damage or destroy local ecosystems, cause erosion, and destroy wildlife habitats and migration patterns. The hydraulic fracturing process will directly occupy the land, destroy animal habitats, and cause the fragmentation of the ecosystem. Well sites and dirt roads will also increase soil erosion and affect the flow and properties of rivers (Granoff et al., 2015). Taking coal-bed methane (CBM) as an example, a single CBM well covers an area of about 1,000–3,500 $m^2$ during the construction period and a permanent area of about $600–25{,}00^2$ during the mining period (Huang et al., 2018). Chen et al. (2017) studied the potential impact of flowback water from hydraulic fracturing on agricultural soil quality and found that soil enzyme activities were sensitive to the composition of flowback water. Mohan et al. (2013) compared the microbial ecology of prefracture water (fracturing raw water and fracturing fluid) and produced water at multiple time points in a natural gas well in southwestern Pennsylvania and found that the biodiversity is gradually declining.

In summary, the construction process will cause serious ecological damage to land, vegetation, and streams, which will affect the ecological environment of animals and plants, and affect the development of biodiversity. Especially for hydraulic fracturing activities, the fracturing fluid will directly affect the structure of the microbial community and break the original ecological balance. Thus, it is very necessary to reduce the frequency of human activities in the production process.

## 3.3 Water Pollution

Water consumption for unconventional natural gas development is relatively larger than that of conventional natural gas (EPA Environmental Protection Agency, 2013a). The growth of hydraulic fracturing and its use of large amounts of water per well may strain local ground and surface water supplies, especially in water-scarce areas. Water consumption for hydraulic fracturing may vary depending on the local geology, as well as construction and hydraulic fracturing processes (Gagnon et al., 2016). Unlike other energy-related water extraction methods, where water usually returns to rivers and lakes, most of the water used for unconventional natural gas development is not recyclable. When a well continues to operate or is additionally fractured later in its life cycle to maintain well pressure and natural gas production, an additional large volume of water is required (Breitling Oil and Gas, 2012). At the same time, gas gathering stations, living areas, and site greening also require water resources. The more complex the reservoir conditions are and the greater the burial depth is, the more difficult it is to increase production and the greater the volume of water resources used becomes (Yuan and Yang, 2019).

Water pollution is mainly caused by gas pollutants including methane and volatile organic compounds, drilling fluid, fracturing fluid pollutants, equipment leakage, and improper handling during development (Shonkoff et al., 2014). The drilling fluid and hydraulic fracturing fluid contains a lot of chemical components, including acids (especially hydrochloric acid), fungicides, scale removers, and friction reducers (Wang et al., 2014). If the drilling and other activities are not handled properly and under inadequate supervision, it may cause fracturing fluid leakage in the vertical well section (Mordick, 2014). In other laterals, fracturing fluid can also enter groundwater along abandoned wells, improperly sealed and improperly constructed wells, and induced cracks or cesspits, and this can affect local water quality (Vidic et al., 2013). Many companies in the United States, China, and other places use wastewater recharge in the shale gas industry (wastewater recharge rate is close to 100%), and this wastewater recharge method will disrupt the water recycling and cause aquifer pollution (Freyman, 2014).

Pollution of drinking water sources will affect biological health and bring about a series of ecological and environmental impacts (Rahm and Riha, 2014). Depending on the geological structure of the rock formation, the fracturing fluid contains 20%–80% of the flowback wastewater within a few weeks after fracturing (Zammerilli et al., 2014). The harmful substances in wastewater can be in high enough concentrations to not only kill microorganisms but also induce negative effects on human health if consumed (Colborn et al., 2011).

In summary, in the process of natural gas extraction, the activities need consume large water and cause water pollution to some extent. Due to the fracturing activities' need of adding some extra chemical substance, the improper dealing of technology and management would bring great water pollution. If drinking water is corroded, it will also affect microorganisms and human health. Thus, improving the technology of gas extraction, especially that of fracturing activities, is the key point to protect water resources.

## 3.4 Earthquakes, Light Pollution, and Noise Pollution

The recharge of wastewater during hydraulic fracturing will put pressure on geological faults and may induce earthquakes. High-pressure injection to dispose hydraulic fracturing wastewater can cause major earthquakes in the United States (National Research Council, 2013). Van der Elst et al. (2013) found that at least half of the 4.5 or larger earthquakes on the Richter scale that hit the United States mainland in the past decade occurred in areas with potential injection-induced seismic activity. Amini and Eberhardt (2019) investigated the influence of the tectonic stress regime on the magnitude of induced seismicity related to hydraulic fracturing practices through a series of numerical simulations and found that thrust faulting stress regimes are more susceptible to larger induced seismicity than strike-slip stress regimes. The latest research showed that short-term hydraulic fracturing was less likely to cause rock mass instability or earthquakes, but the long-term fluid injection could increase the pore pressure and change the *in situ* stress field in a large area, thereby inducing an earthquake (Wang et al., 2020). Furthermore, Villa and Singh (2020) reached the same conclusion through a detailed analysis of 17 major hydraulic fracturing sites in the United States. They found that the incidence of earthquakes depends on the amount of water injected from horizontal injection wells; disposal injection wells; and the geological, hydrological, and geophysical environment near the drilling site. Burton and Nadelhoffer (2013) also showed that the effects of hydraulic fracturing could increase erosion and subsidence. If free methane and other gases reach a sufficient volume, they may cause an explosion and bring about a minor earth tremor (Airgas, 2013). According to Stark et al. (2014), frequent construction activities and bright lights at night bring intensive noise and light pollution, which directly affect the local environment and its ecosystem and affect the daily lives of local residents (Brittingham et al., 2014). Li et al. (2019) analyzed the effects of different gas wells exploitation on the concentrations of heavy metals in the soil and found that although the exploitation of shale gas mining had no obvious influence on the concentrations of heavy metals in the soil around the well field, the wells pose potential heavy metal pollution because of the high content of Cd in the soil before exploitation.

In summary, these frequent human activities directly affect the local environment, and the hydraulic fracturing activity even has deep, albeit mostly minor, geological impact.

## 3.5 Summary for This Section

Through this literature review, we found that in the upstream phase, the impact on land use, wildlife activities, and water use can be great due to the frequent human construction activity. Natural gas emissions are relatively small in the production process, but there is a certain risk of leakage. Gas leakage will increase the greenhouse effect. Work on quantification of methane leakage is still ongoing, and there is no consensus at present. However, there is no doubt that improvements in technology to reduce the risk of gas leakage will be of benefit. In terms of specific activities, many environmental risks are caused by hydraulic fracturing activities, such as minor earthquakes and water pollution. As for water consumption and pollution, the hydraulic fracturing process consumes the most water (see **Figure 3**) and the combination of hydraulic fracturing and horizontal drilling produces a large amount of wastewater (called "produced water") (Clark et al., 2013).

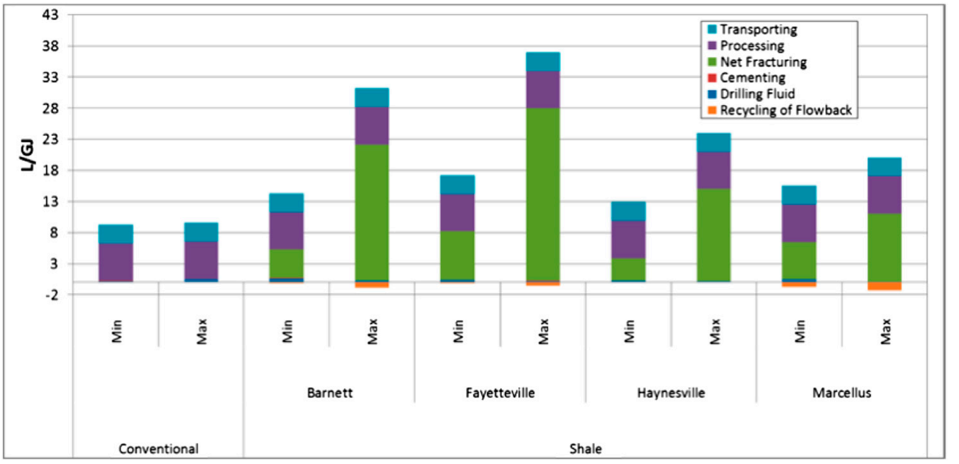


**FIGURE 3 |** Water consumption for conventional and shale gas production by life cycle stage, accounting for use of recycled flowback water in hydraulic fracturing. Min and max scenarios show the extent of variability in water consumption by key processes (Silva et al., 2017).

Fortunately, improvements in technology, such as membrane technology (membrane distillation, forward osmosis, membrane bioreactor, and pervaporation) and advanced oxidation processes (ozone oxidation, Fenton, and photocatalysis) can help to a degree with treatment of such water (Silva, 2017).

## 4 POTENTIAL ENVIRONMENTAL RISKS IN THE MIDSTREAM STORAGE AND TRANSPORTATION STAGE

Natural gas is normally presented in one of three states: gaseous natural gas (PNG), compressed natural gas (CNG), and liquid natural gas (LNG). Transportation is generally carried out by pipelines. Trains and ships are used as an effective supplementary method to transport CNG and LNG by land or sea (Zhao et al., 2015).

The natural gas pipeline system is mainly composed of gas gathering pipelines, dry gas transmission pipelines, domestic gas distribution pipelines, and related gas transmission (compression) fields and stations. The equipment and devices used start at the wellhead of the gas field, collect the gas, purify and transport it through the main pipeline, and then distribute it to the users through the gas distribution network (**Figure 4**) (Li, 2014).

### 4.1 Soil Ecological Risk

Most pipelines are buried underground, traverse a wide area and complex terrain. Xu et al. (2014) and others believe that the soil and vegetation damage caused by the excavation of pipe trenches during the construction process is more serious than the pollution

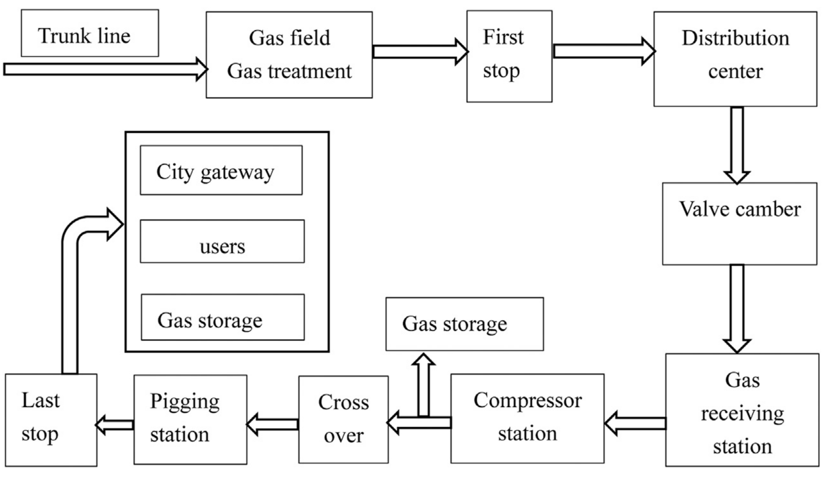


**FIGURE 4 |** The overall process of the natural gas gathering and transportation pipeline system (Li, 2014).

impact produced after the pipeline is put into operation. During the pipeline construction process, the rolling of machinery and vehicles will disturb the soil; destroy the natural vegetation near the pipeline; discharge more waste water, waste gas, and waste residue; and produce more waste soil and rock. The layout of infrastructure such as pipelines and roads under construction destroys 2.9–3.6 ha of habitat and may even block rivers and cause ecosystem fragmentation (Brittingham et al., 2014). Tens of thousands of gallons of chemical additives per well are transported by trucks to well pads for storage. If not managed properly, these chemicals may leak or overflow from inappropriate storage containers or during transportation. Drilling mud, diesel, and other liquids can also spill on the surface (Wiseman, 2013). Yazdan et al. (2020) pointed out that in the process of wastewater transportation, land resources may be polluted due to pipeline breaks.

## 4.2 Atmospheric Environment

Luo et al. (2008) found that process units such as stations, pipe sections, and shut-off valve chambers in natural gas pipeline facilities can lead to environmental risks. When the critical mass of natural gas production sites is greater than 1t, it is a major hazard to install actions (Zhong et al., 2017). Due to the nature of some of the components in the gas transported, such as hydrogen sulfide, condensate oil and gas field water, the potential danger to the environment is substantial. For sulfur-containing natural gas pipelines, hazardous substances include hydrogen sulfide and sulfur dioxide. For the purification of natural gas pipelines, the main hazard is methane. For natural gas pipelines, the risks for accidents are leakage, explosion, and fire (Zhong et al., 2017). It is generally believed that leakage has little effect on water and soil because natural gas has low toxicity and is a gas at room temperature (He, 2009). However, Zhong et al. (2017) noted that it is difficult to conduct daily inspections of pipelines, and the pipelines are vulnerable to corrosion and breaks leading to leaks. Once the integrity of the pipeline is compromised, gas will leak and spread quickly in large quantities in a short period of time, which is likely to cause major accidents such as explosions and poisoning, causing heavy losses of lives and damage to property and even resulting in serious environmental pollution. Yuan et al. (2019) concluded that methane leakage during transportation accounts for 42–86% of the total methane leakage in the total supply chain and is the single largest cause of leakage.

## 4.3 Greenhouse Effect

$CH_4$ and $CO_2$ are both greenhouse gases and are usually present in natural gas albeit in widely varying concentrations. Therefore, the leakage of natural gas during transportation can release a large amount of $CH_4$ and $CO_2$ into the atmosphere, further enhancing the greenhouse effect. Studies have shown that there is serious leakage in natural gas transportation. Bylin et al. (2009) found that methane emissions from natural gas distribution pipelines account for 32% of the industry's total $CH_4$ emissions in the United States. 5.3–10.8% of the natural gas that flows through the United Kingdom's natural gas pipelines leaks each year (McKenzie, 2010). The impact on the greenhouse effect depends on the amount of gas leakage. McKenzie (2010) used data from the United Nations Intergovernmental Panel on Climate Change to study the problem of natural gas leakage. It was found that when the natural gas leakage rate reaches 2.8%, the greenhouse effect it brings will offset the advantages from not using fossil fuels such as oil and coal. Other studies suggest substantial gas leakage. The United States Environmental Protection Agency (EPA) estimated that methane leakage from natural gas systems doubled during 2011. The EPA's estimate of methane content shows that natural gas network leaks and emissions between production wells and the local distribution network comprised approximately 570 billion cubic feet in 2009, equivalent to 2.4% of the total United States natural gas production. Recent studies in the United States have shown that the leakage and combustion emissions of natural gas processing and distribution systems are serious (ICF International, 2014). Other studies have shown that solving the problem of natural gas leakage can effectively slow down the greenhouse effect. Alvarez et al. (2012) found that if the "well-to-wheel" leakage is reduced to an effective natural gas leakage rate of 1.6%, CNG fuel vehicles will immediately lead to climate benefits over time. Cooper and Balcombe (2019) adopted IPCC AR5 LCIA methodology to calculate the impacts on climate change using global warming potential (GWP) $CO_2$ equivalences and found that LNG exhibits a lower GWP (17–21%) than diesel, and thus using natural gas as an alternative energy source can reduce the greenhouse effect.

## 4.4 Summary for This Section

On the whole, gas collection, laying of pipelines and final delivery of gas to user departments and gas storage can bring about environmental risks to the soil ecology and the atmosphere due to the greenhouse effect. The construction of pipelines and roads can cause soil, vegetation damage and habitat loss. In the transportation process of chemical additives, the leakage of the chemicals can cause soil pollution. In general, gas leakage is a risk and can be difficult to manage, leading to air pollution, potential explosion, and increase of the greenhouse effect. Although it is difficult to conduct daily inspections of pipelines, this study has concluded that the leakage in natural gas transportation is a serious issue. If we want to use natural gas as an alternative energy source to reduce the greenhouse effect, the leakage must be minimized. Thus, at this stage, the key point is to control gas leakage.

# 5 POTENTIAL ENVIRONMENTAL RISKS IN THE DOWNSTREAM STAGE

The use of natural gas downstream can be roughly divided into two categories: chemical raw material and fuel. As for chemical raw materials, it is mainly used to make synthetic ammonia and urea, and the pollutants from the production process are mainly $CO_2$, waste liquid, etc., which is relatively an ideal and economical production method (Wang et al., 1995). In terms of global natural gas utilization, industrial fuel accounts for 40%, power generation accounts for 37%, domestic gas accounts for 21%, and transportation stations account for 2%. The development of natural gas usage in a typical country is typically driven initially by industrial and domestic gas consumption and subsequently by power generation. At this stage, the main environmental impact is increased air pollution, greenhouse effect, and water consumption. Considering the different technology in power plant, carbon dioxide emissions produced by burning natural gas in existing power plants in the United States are equivalent to 42–63% of those from coal (Lattanzio, 2015) for an equivalent amount of energy produced. Mackay and Stone (2013) found that, for natural gas to have lower life cycle emissions than new coal plants over short time frames of 20 years or less, methane losses must be kept below 3.2 percent, and low emissions depend on using new technology.

## 5.1 Air Pollution

The use of natural gas will produce NOx, $CO_2$, $CH_4$, etc., but it causes little air pollution. The burning of natural gas does produce NOx, but the content is lower than that of combustion products from gasoline and diesel for automobiles. Using natural gas can improve air quality. Analysis by the United States Department of Energy suggests that every 10,000 United States households that use natural gas instead of coal can avoid emitting 1,900 tons of NOx, 3,900 tons of $SO_2$, and 5,200 tons of particulate matter per year (National Renewable Energy Laboratory, 1999). The reduction of these air pollutants can alleviate health conditions such as asthma, bronchitis, lung cancer, and heart disease for thousands of Americans (Witherspoon, 2012). Che et al. (2017) found that $CO_2$ emissions from gas-fired power generation and heating are close to 1/2 of that of coal-fired power generation and heating. $CH_4$ emissions are less than 1/3 of coal-fired emissions, and $N_2O$ emissions are less than 1/10 of coal-fired emissions. In the transportation and residential areas, the use of natural gas has greatly reduced $CO_2$, $CH_4$, and $N_2O$ emissions. Sathaye et al. (2011) and others also found that, compared with coal power generation, natural gas power generation can significantly reduce the emission of air pollutants. Compared to other fossil fuels, the amount of sulfur, mercury, and particulates produced by natural gas combustion is also negligible **(Table 1)**.

## 5.2 Greenhouse Effect

Research studies have not yet resulted in a clear and consistent view on the magnitude of the greenhouse effect brought about by the use of natural gas. Some studies believe that replacing traditional energy sources with natural gas can significantly reduce greenhouse gas emissions. Fulton et al. (2011) used the latest emission factor from the EPA's 2011 upward revisions, through top-down life-cycle analysis, and found that the greenhouse gas emissions from natural gas power generation are 47% lower than those of coal-fired power generation. Afsah and Salcito (2012), according to the environmental assessment method, used short-term price elasticity changes and the substitution relationship between natural gas and other energy sources and found that the replacement of coal by shale gas in the United States power sector has reduced carbon dioxide emissions by 35–50% in recent years. From 2008 to 2012, fossil fuel in the United States power sector fell by 13% based on the supply model of cost-optimal mix technologies (Logan et al., 2013). Expanding natural gas power generation capacity is the cheapest way to advance the use of low-carbon energy technologies in the next ten years (Lee et al., 2012). Yuan and Yang (2019) also found that the $CH_4$ emissions from CBM are relatively small and will not significantly increase the total emissions of greenhouse gas and that replacing coal with CBM can also offset some greenhouse gas emissions. In the field of transportation, natural gas buses have low greenhouse gas emissions, which can make the greenhouse gas emission reduction potential reach 13.31% (Wang, 2015).

However, other studies have shown that the large supply of natural gas could cause an increase in overall energy consumption in the absence of strict policy implementation, which may increase greenhouse gas emissions that offset the reduction in net greenhouse gas emissions by switching from coal to gas (McJeon et al., 2014). Perhaps the actual situation is more complicated. Ravindra et al. (2006) evaluated various standard air pollutants (SPM, $PM_{10}$, CO, $SO_2$, and $NO_x$), benzene, toluene, xylene (BTX) and the concentration of polycyclic aromatic hydrocarbons (PAHs) before and after the implementation of CNG in Delhi, India, and found that the concentration of PAHs, $SO_2$, and CO showed a downward trend, while the level of $NO_x$ was higher than before CNG was implemented, and the concentrations of SPM, $PM_{10}$, and BTX did not change significantly after CNG was implemented. That is to say, the greenhouse effect brought about by CNG applications is uncertain.

## 5.3 Water Consumption

Research by Jenner and Lamadrid (2013) found that coal and natural gas demand roughly the same water consumption during the production and processing stages, but water consumption during the combustion and power generation stages is significantly lower than that of coal. Meldrum et al. (2013) found that in the process of power generation, natural gas life cycle water consumption is 220–1,000 L per thousand kilowatt-hours of electricity, while coal consumption is 1,500–2,500 L. Clark et al. (2013) found that when natural gas is used as a transportation fuel, its water consumption is significantly lower than other transportation fuels. Compared with the operation of a power plant, the water consumption of fuel has little impact. Natural gas needs to be compressed first when used as a car fuel tank, and electricity consumption during the compression process consumes an additional 0.6–0.8 L of water. Macknick et al. (2011) pointed out that among all power plants that use circulating cooling, natural gas power plants consume the least water, which is a little more than half of the most water-efficient coal-fired power plants. When the same cooling technology is used, it is less than 1/3 of the water consumption of nuclear power plants. In summary, during the use of natural gas, a small amount of water is consumed, and the amount of water consumed depends on the type of usage.

## 5.4 Summary for This Section

In summary, the burning of natural gas downstream generates less emission of pollutants and causes little pollution compared with coal and gasoline. Thus, it can improve the air quality if it replaces coal or gasoline consumption. However, the greenhouse effect accompanied by the usage of gas is hard to establish. The varying degrees of impact depends on different usages and the different technologies adopted. Generally speaking, natural gas can reduce greenhouse gas effects in the power generation sector. However, there is no doubt that reducing greenhouse gases requires speeding up adoption of new technology. For water consumption, natural gas requires less water in power generation stages and as a transportation fuel than coal. We expect that the more advanced the production technology, the less water will be consumed in the gas consumption process.

In terms of the entire life cycle of natural gas from extraction to using, some environmental risks exist at every stage. In the upstream phase, some toxic gas in the air may influence the health of both wildlife and human beings who live nearby; in the middle stage, the leakage of gas may cause explosion; in the downstream stage, the burning of gas will generate some pollution, but that will have less impact than that of coal and gasoline, and the pollution will vary depending on the type of usage. At every stage, regular human activities, such as drilling, hydraulic fracturing, and pipe laying, will cause some impact to land use, soil, wildlife, and the ecosystem as a whole. With regard to water consumption and pollution, there is a huge negative impact in the upstream phase and a more positive influence in other stages. The extent of the impact depends on the specific utilization, working activities, and the adoption of technology, especially for hydraulic fracturing. However, the biggest controversy is whether natural gas can reduce the greenhouse effect compared to other source of energy. The biggest uncertainty in this regard is the scale of gas leakage. Thus, making efforts to control and reduce the level of leakage of natural gas will enhance the environmental quality.

# 6 KEY MEASURES AND POLICY RECOMMENDATIONS FOR ENVIRONMENTAL RISK MANAGEMENT AND CONTROL

## 6.1 Focus on the Upstream Hydraulic Fracturing Activity

Firstly, strengthen environmental assessment management. Establish environmental assessment procedures for pre-, mid-, and posthydraulic fracturing; fracturing operations; and wastewater treatment. The environmental impact assessment of natural gas exploitation can prevent environmental pollution and ecological damage (Wu et al., 2018). The advancement of monitoring technologies and data-analysis technologies in the digital era make this task more practical and efficient. The comprehensive policies, regulations, and standards of the United States have played a guiding role in the environmental assessment work by other countries. During project preparation, design, and approval, monitor the integrity comprehensively, monitor environmental indicators in real time, and conduct environmental risk emergency management in advance.

Secondly, improve policy standards. Formulate strict environmental supervision policies, especially clarify the treatment standards for wastewater reinjection, wastewater treatment, and fracturing fluid composition for hydraulic fracturing. It is necessary to learn from the mature regulatory systems of the United States and Canada to improve the well spacing and casing integrity standards during the oil well construction process (Gagnon et al., 2016). Develop sensible well spacing, and limit the distance to houses, buildings, etc. Enact strict casing integrity regulations to prevent oil, gas, and water from migrating from one formation to another, thereby ensuring the safety of the surrounding ground and surface water.

Thirdly, make a water quality monitoring plan specifically for hydraulic fracturing. The United States Environmental Protection Agency (2015) pointed out that the lack of data and related chemical information collected before and during hydraulic fracturing operations will reduce the ability to identify hydraulic fracturing contaminated areas. It is vital to make a plan for water quality monitoring. Determine water quality monitoring standards, including monitoring time, location, and the number of detections. Identify potential pollutants, determine the priority of pollutant hazards test chemical composition, and make a list of water quality analytes. Based on the water quality monitoring data, formulate a regional water quality supervision plan.

Fourthly, promote the innovation of key technologies. Further improve green drilling and completion technologies, efficient drilling technologies, and recycling technologies to reduce environmental pollution from drilling activities. Promote technological breakthroughs in the direction of waterless fracturing technology, key oil production engineering technologies, and intelligent gas production technologies. Government subsidies and financial support will quickly promote the development and application of technology substitution.

## 6.2 Improve Natural Gas Storage and Transportation Monitoring System in the Midstream Stage

Firstly, in the process of natural gas storage and transportation, pipeline laying and storage site selection should be as far away as possible from environmentally sensitive areas and residential areas, and an environmental assessment should be prepared with in-depth demonstrations of specific construction and environmental risks.

Secondly, strengthen the leak detection of methane and volatile organic compounds, and then take effective measures to prevent and manage risks. Continuously improve monitoring technology of methane emissions. There are already some technologies that can help us monitor the leakage of natural gas pipelines, such as infrared imaging technology, olfactory sensor leak detection technology, schlieren imaging technology, gas detection method, and distributed optical fiber acoustic sensor detection method.

Thirdly, strengthen the quality control of engineering materials. Pipeline gas engineering is usually constructed based on its expected service life. The quality of engineering pipes and equipment has a direct impact on the service life of the project. The main reason for leakage of natural gas is defects in the pipe equipment (Peng et al., 2013). Therefore, the entire process of manufacturing pipe equipment, from design, model selection, bidding, quality inspection, procurement, and transportation to construction, requires a sound quality assurance system.

In addition, urban gas has the closest connection to the residents. In order to reduce the hazardous consequences,

**TABLE 1 |** Various emissions from coal and natural gas power generation.

| Pollutants ($g/kWh_e$) | Hard coal | | Natural gas | |
|---|---|---|---|---|
| | Best performance | Worst performance | Best performance | Worst performance |
| $NO_X$ | 0.5 | 4.5 | <0.5 | <0.5 |
| $SO_2$ | <0.5 | 27 | <0.5 | <0.5 |
| $PM_{2.5}$ | <0.5 | 1.85 | ~0 | ~0 |
| NMVOC | <0.5 | 0.2 | 0.25 | 0.25 |

*Source:* Sathaye et al. (2011).
*Note: $PM_{2.5}$ refers to particulate matter with an aerodynamic equivalent diameter of 2.5 μ or less. The higher the particulate concentration in the air, the more serious the air pollution. NMVOC is nonmethane volatile organic compounds.*

frequency and impact of accidental gas fires and explosions caused by the rupture of urban gas pipelines, the risk identification and management of urban gas pipelines should be strengthened. This should include design, construction, daily maintenance, and strict control of the aging and connection of pipes. Strengthen safety training and guidance, and prepare accident emergency plans in advance.

## 6.3 Promote More Environmentally Friendly Downstream Natural Gas Utilization Technologies

It is shown that gas utilization is more efficient than coal-fired equipment. Gas-fired power plants have a thermal efficiency of more than 10%, and cogeneration and distributed energy have a thermal efficiency of more than 20% (He, 2016). Compared with ordinary coal-fired units and "ultra-low emission" units, gas-fired power plants have obvious advantages in terms of reduced emissions. Among them, smoke and dust can be reduced by 14–80%, $SO_2$ can be reduced by 100%, and $CO_2$ can be reduced by 45–62% (Shen et al., 2016). Therefore, it is recommended to promote the application of advanced technology. One is to promote the technologies, such as gas-fired cogeneration, the combination of refrigeration, heating and power generation, and gas-fired air-conditioning technologies, actively to stimulate urban gas consumption and gradually replace traditional energy sources. The second is to vigorously develop technologies to reduce consumption and improve energy efficiency in the use of natural gas, and give priority to supporting natural gas recycling, distributed energy technologies, and green and low-carbon service technologies.

# 7 CONCLUSION

After systematically reviewing the studies on the whole life cycle of the upper, middle, and lower stages of the natural gas industry chain, we focused on identifying environmental risks such as air pollution, land use, water use, ecological impact, and greenhouse effect at various stages. There are some conclusions that can help us carry out more targeted work.

Firstly, although there are environmental risks in the natural gas production and supply process, they can be reduced through technologies and measures. Secondly, the usage of natural gas is accompanied by the release of greenhouse gases. However, compared with traditional energy sources such as coal, environmental pollution, the greenhouse effect, and the ecological impact of natural gas are much smaller. Thirdly, through this literature review and identification of various environment risks, we identify the key activities at different stages. During upstream exploitation, hydraulic fracturing has the worst environmental impact. In the midstream storage and transportation stage, methane leakage is the biggest environmental risk. In the downstream combustion and utilization stage, different application technologies will produce different resource consumption and emissions.

Therefore, this article puts forward some policy recommendations for different stages. In the upstream stage, for hydraulic fracturing activities in particular, we suggest strengthening environmental assessment management, improving policy standards, making a water quality monitoring plan, and promoting the innovation of key technologies. In terms of the midstream, besides pipeline laying and site selection, we focus on monitoring the system, including leak detection, quality management of engineering materials, and risk identification and management. When it comes to downstream, we encourage the application of advanced technologies to improve thermal efficiency and reduce emissions, such as gas-fired related technologies, natural gas recycling technologies, distributed energy technologies, and green and low-carbon service technologies.

# AUTHOR CONTRIBUTIONS

The authors confirm being the sole contributors of this work and have approved it for publication.

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**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.

frontiers in Energy Research

ORIGINAL RESEARCH
published: 24 March 2021
doi: 10.3389/fenrg.2021.628321

# Accounting and Management of Natural Resource Consumption Based on Input-Output Method: A Global Bibliometric Analysis

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OPEN ACCESS

***Edited by:***
*Fan Tong,*
*Lawrence Berkeley National Laboratory, United States*

***Reviewed by:***
*Bo Zhang,*
*China University of Mining and Technology, Beijing, China*
*Yuwei Qin,*
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***Specialty section:***
*This article was submitted to Sustainable Energy Systems and Policies, a section of the journal Frontiers in Energy Research*

***Received:*** *11 November 2020*
***Accepted:*** *26 February 2021*
***Published:*** *24 March 2021*

***Citation:***
*Wang S, Tang X, Zhang B and Wang W (2021) Accounting and Management of Natural Resource Consumption Based on Input-Output Method: A Global Bibliometric Analysis.*
*Front. Energy Res. 9:628321.*
*doi: 10.3389/fenrg.2021.628321*

Resources and environment management have always been a research hotspot. In the context of sustainable development and environmental governance, scholars and policy makers have been increasing their research efforts on natural resource utilization and its environmental impact. By using the Web of Science Core Collection database, this article applies the bibliometric method to accomplish a systematic review about studies on accounting and management of natural resource consumption based on input-output method. The results indicate that both in terms of the quantity and quality of academic achievements and international cooperation, China is in high academic position and has made great contributions to the development in this research field. While energy and water account for a large proportion of the study objects, more attention is paid on the other kinds of natural resources, such as land, metal, and ocean. International trade is an eternal hot topic in this field. With the continuous progress of the multi-regional input-output model, the importance and feasibility in the analysis of sub-national level or region in the global supply chain gradually emerged. Combining input-output model with other methods can obtain more comprehensive and accurate results for scientific decision-making. Meanwhile, the uncertainty and limitations inherent in such models clearly need further attention.

**Keywords: natural resource consumption, bibliometric analysis, co-occurrence network analysis, social network analysis, input-output analysis**

## INTRODUCTION

Natural resources are the important material basis of social stability and economic development. In recent decades, global resource extraction has risen to about 80–90 billion tons a year. Historical trends suggest that this number could double to 190 billion tons a year by 2060 (International Resource Panel, 2019). Resource consumption has brought unprecedented harm to the ecology environment. Climate changes such as melting glaciers, water pollution and ecosystem degradation have caused widespread concern about health and sustainable development (Lenzen et al., 2012). This resource-intensive development route is causing a rethink.

In September 2015, the 193-member states of the United Nations put forward 17 Sustainable Development Goals (SDGs) at the Sustainable Development Summit, aiming at completely solving the development problems (United Nation-UN, 2015). In September 2020, President Xi announced

China's decision to become carbon neutral by 2060 at the 75th general debate of the United Nations General Assembly (Xinhuanet.com, 2020). This is the first long-term climate goal of China to limit carbon dioxide emissions to zero. That means China is not only under pressure to transition to a low-carbon energy system, but also need to use negative emission technologies such as carbon capture utilization and storage (CCUS) (Mallapaty, 2020). However, this systemic shift has increased the demand for other types of resources, such as copper and nickel (Li et al., 2020). This low-carbon transition complicates the economic system's demand for natural resources, which in turn makes integrated management more difficult. Globalization also leads to an increasing geospatial separation of supply and demand (Wiedmann and Lenzen, 2018). Therefore, it is necessary to consider the relationship systematically and comprehensively among natural resources, economic development, and low-carbon transition.

Input-output analysis (IOA) is a top-down economic technique developed by Leontief in the 1930s. It uses departmental currency transaction data to explain the complex interdependencies between different sectors of the economy (Leontief, 1970; Munksgaard et al., 2005). Compared with the bottom-up approach, this method can fully reflect the economic exchanges between industries without arbitrary boundaries (Suh et al., 2004; Lenzen, 2008). By calculating direct and indirect impact, Input-output method captures the environmental impacts generated over the entire supply chain from the perspective of consumer or producer. This can reflect the environmental impacts outsourcing through trade (Wiedmann and Lenzen, 2018). Therefore, the research on resource accounting and management based on Input-output method is of great significance to sustainable development. Because of the diversity of research perspective, scope and methods, the results vary greatly.

Bibliometrics is a mature literature analysis and information mining technology, which uses the law of research publication to explore the research status and development history (Van Raan, 2005). Xie et al. (2018) used bibliometric analysis to characterize the literatures related to Input-output analysis between 1990 and 2017, pointing out the most influential works and authors, and the emerging studies. Hawkins et al. (2015) surveyed the published articles regarding Environmentally Extended Input-output (EEIO) analysis for China in peer-reviewed journals and provided a quantitative overview of literatures. Zhong et al. (2016) reviewed research progress on natural resource accounting for the period of 1995–2014 through the methods of bibliometric analysis and social network. Previous reviews have focused on either method of Input-output or topic of resource consumption, concentrating on the patterns of these articles rather than content and conclusions. A comprehensive overview in natural resource consumption and management based on Input-output method is currently lacking. The evolution of both topic and methods needs to be further analyzed.

This systematic literature review serves to investigate this research gap by analyzing the research evolution of natural resource consumption and management based on Input-output method. It cannot only have a grasp of this field in terms of structure, but also provide empirical evidence and theoretical support for the recent resource management policies in terms of content. The rest of the article is structured as follows. Bibliometric analysis method and data are described in Part 2. An in-depth review of the patterns in this field is given in Part 3. Part 4 presents the discussion, while the conclusion drawn from the study is provided in Part 5.

## DATA AND METHODOLOGY

### Methodology

Bibliometric analysis is a quantitative analysis method using various external characteristics of academic publications (Van Raan, 2005). Based on statistical and mathematical methods, this method cannot only investigate the distribution characteristics and numerical laws of the bottom layer, but also reveal research hotspots and future trends (Du et al., 2015; Hu et al., 2015). Bibliometrics has become an important basis and component of library and information science. Meanwhile, word frequency analysis, citation analysis, and occurrence analysis have been widely used in empirical research (Hawkins et al., 2015; Zhong et al., 2016; Xie et al., 2018). Bibliographic coupling (Kessler, 1963) and co-citation analysis (Marshakova, 1973; Small, 1973) are primary methods of probing the frontiers of research by tracing their roots back several decades.

Bibliometric analysis can present the external characteristics of academic achievements in the form of a knowledge graph. According to different purposes, the items are selected from the literature data as nodes on the knowledge graph, and the links between the items are shown as edges (Van Eck and Waltman, 2014). In this paper, VOSviewer is selected as the visualization software of the knowledge graph. In this software, items and links' properties are described by the node weight and edge weight, called weights and strength, respectively. By calculation, items are grouped into different clusters, shown in the same color. In general, the closer the items are, the more relevant they are.

In the co-authorship analysis, the links between nations, institutions or authors represent the cooperative relationship, while the link strength stands for the number of collaborative publications. In co-citation analysis, the links between journals or publications appear as the citation of the same literature, and the link strength means the number of common citations. Links between publications in bibliographic coupling analysis act for the sharing of one or more citations, and link strength symbolizes the number of shared references for both publications. In co-occurrence analysis, the links between keywords denote the co-occurrence of the keywords, and the link strength illustrates the number of publications in which the keywords appear simultaneously (Van Eck and Waltman, 2010).

### Data Source

The aim of this article is to review the literatures of natural resource consumption and management based on Input-output method. Referring to the retrieval methods of existing articles, the search criteria include three parts: resource type, Input-output, and usage (Jin et al., 2019). The retrieval formula is

[Topic = ("Input Output Analysis" OR "Input Output Model" OR "Input Output Table" OR "Input Output Method" OR "Input Output Framework" OR "IO analysis" OR "IO Model" OR "IO table" OR "IO technique*" OR "IO framework" OR "IO method") AND Topic = ("fossil fuel*" OR "natural gas" OR coal OR oil OR energy OR water OR freshwater OR wastewater OR land OR wood OR biomass OR metal OR mineral OR material OR "natural resource") AND Topic = (footprint OR use OR consumption OR withdrawal OR demand OR requirement OR extraction)]. A total of 1,977 peer-reviewed articles in English from 2000 to 2020 (as of July 9, 2020) were retrieved from the Web of Science Core Collection (SCI-Expanded, CPCI-S, CCR-Expanded, IC.). Articles that are not within the scope of this study are excluded, such as those applied in control systems, inventory management, biochemistry, computer science, oncology, etc. Therefore, after data cleaning, 1,824 references were finally determined. Each document contains information such as title, author, organization, abstract, keywords, and citations.

Citation analysis is used to study the contributions of countries, institutions, and authors and their ways of cooperation. And the most influential authors, articles, and mainstream journals in this field are explored by this method. Keyword's co-occurrence and bibliographic coupling analysis are used to study the topic cluster composition and hot topics.

# RESULTS

## The Performances of Publications

It can be seen from **Figure 1** that the distribution and variation trend of 1,824 articles can be roughly divided into three stages. There is an increase of papers published per year from two articles in 2000 to 17 articles in 2004, with an average increase of 3.75 papers per year. From 2005 to 2014, the annual publication fluctuated from 27 articles in 2005 to 103 articles in 2014, with an average yearly increase of 8.44. Since 2015, the annual publication has multiplied to 277 articles in 2019, representing an average increase of 33.25 articles per annum.

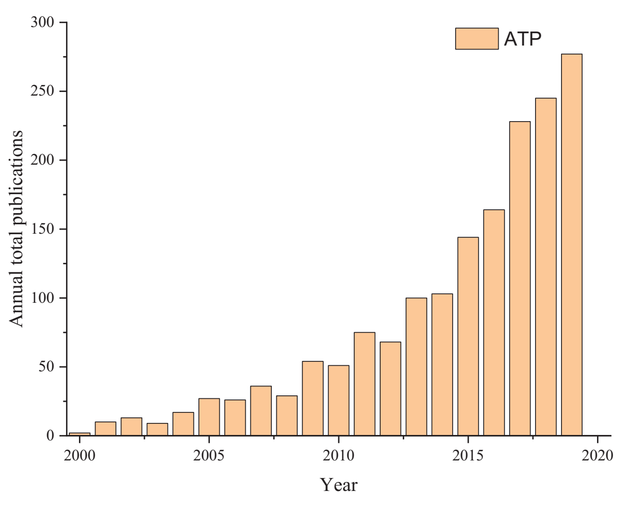


**FIGURE 1 |** The number of publications in this field from 2000 to 2019. ATP is the annual total publication.

This is roughly in sync with the formulation of the global climate-change governance system and SDGs. On June 4, 1992, the United Nations Framework Convention on Climate Change (UNFCCC) and the Convention on Biological Diversity (CBD) were adopted in Rio de Janeiro, Brazil. After that, countries began the practical exploration of market-based climate governance. However, due to the shortcomings of market mechanisms such as carbon trading, carbon compensation and carbon tax, negative externalities of the environment caused new economic inequality, ecosystem degradation, and human rights problems in the third-world countries (Xie et al., 2014). In the 21st century, the rapidly developing third-world countries have realized the importance of ecology, environment, resources, and sustainable development. In 2005, 142 countries and regions signed the Kyoto Protocol, which identified the central issue of Burden Sharing. In addition, a joint commitment to reduce greenhouse-gas emissions by 2020 is made (Kyoto Protocol, 2005). In September 2015, the member states of the United Nations proposed 17 SDGs, aiming at solving the development problems in the three dimensions of social, economy and environment, and shifting to the path to sustainable development. In December of that year, the Paris Agreement was approved to further incentive each country to make more efforts to reduce emissions through Opportunity Sharing. These milestones bear witness to academic progress within the field.

## The Contribution of Countries (regions)

Since 2000, scholars from 68 countries have made outstanding contributions to the field over the past 20 years. Among them, an in-depth analysis on 40 countries whose publication is no less than five are carried out. A total of 222 partnerships have been formed in these 40 countries, with the results shown in **Figure 2** and **Table 1**.

Although China (853 articles, 17,491 citations) started relatively late in this field, it has taken a global lead in the count of publication and citations, much higher than the United States (USA) (369 articles, 13,678 citations), the United Kingdom (UK) (181 articles, 7,396 citations), Japan (150 articles, 4,541 citations), and Australia (140 articles, 5,838 citations). However, Singapore (21 articles, 1,478 citations) and Norway (84 articles, 5,024 citations) ranked high among the 40 countries with an average of 70.38 citations per article and 59.81 citations per article.

Publications by authors from different countries can be defined as international collaborative publications. The ratio of the number of international collaborative publications to the total number of publications by a country can reflect the degree of international cooperation in this country. The ratios of United Kingdom (0.66), Netherlands (0.75), Norway (0.71), Germany (0.58), and Austria (0.85) are all greater than 0.5, indicating that these countries are more likely to conduct research in the form of international cooperation. It was followed by United States (0.49) and Australia (0.46). Although China's ratio (0.28) is smaller than those of any of the above countries, the total volume of collaborative publications is the highest in the world, with 235 collaborative publications.

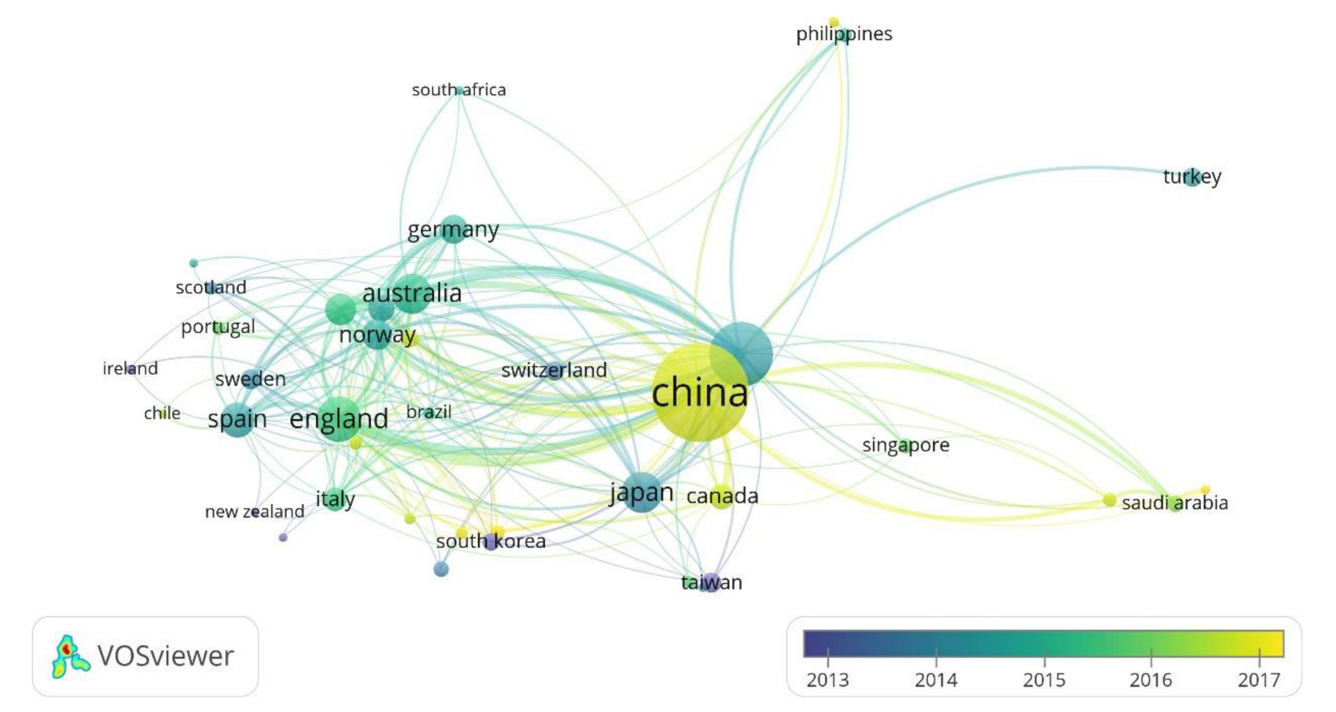


**FIGURE 2 |** Nations' collaboration. The color bar represents the average year of publication of national articles.

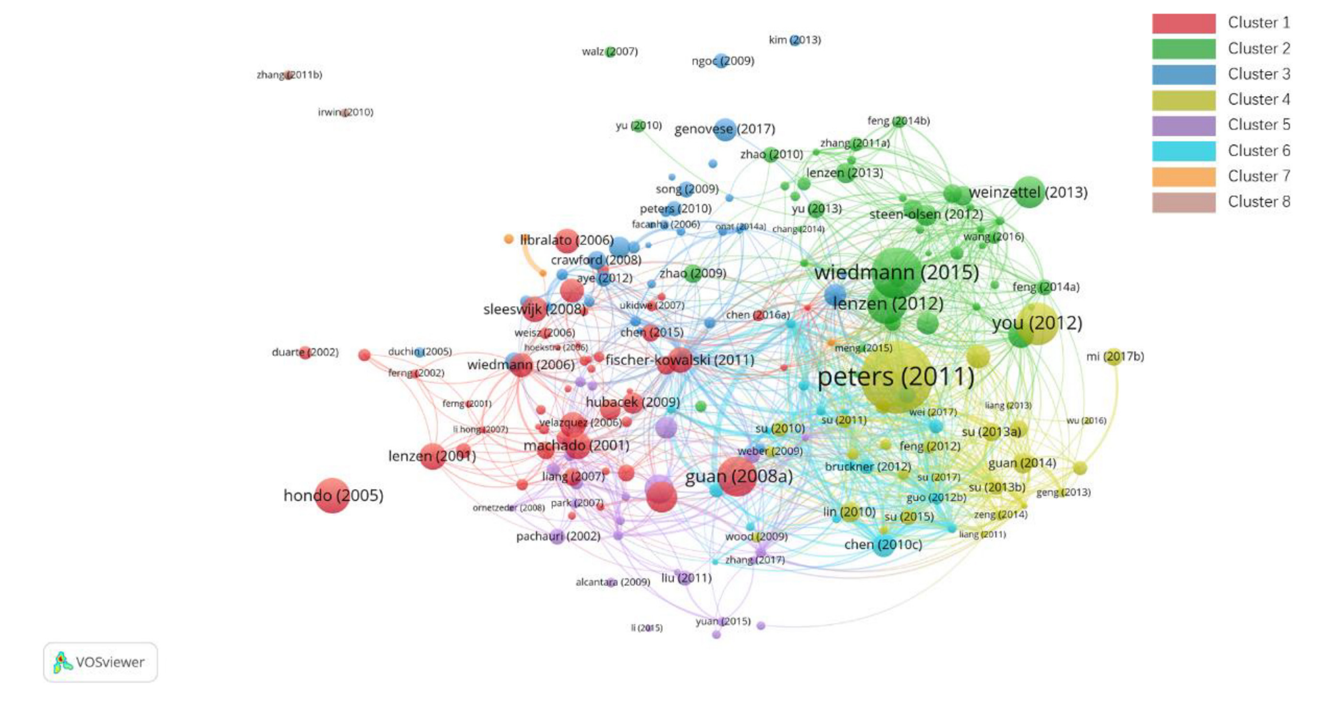


**FIGURE 3 |** Bibliographic coupling of highly cited articles.

In the global cooperative relationship, China and United States have the closest cooperative relationship in this field with 124 articles published in collaboration, accounting for 69.27% of the total in United States and 52.77% in China. The number of cooperative articles between China and United Kingdom came second, with 71 articles jointly published, accounting for 5.90% of the total, 59.66% for United Kingdom and 59.66% for China. After that, United Kingdom and

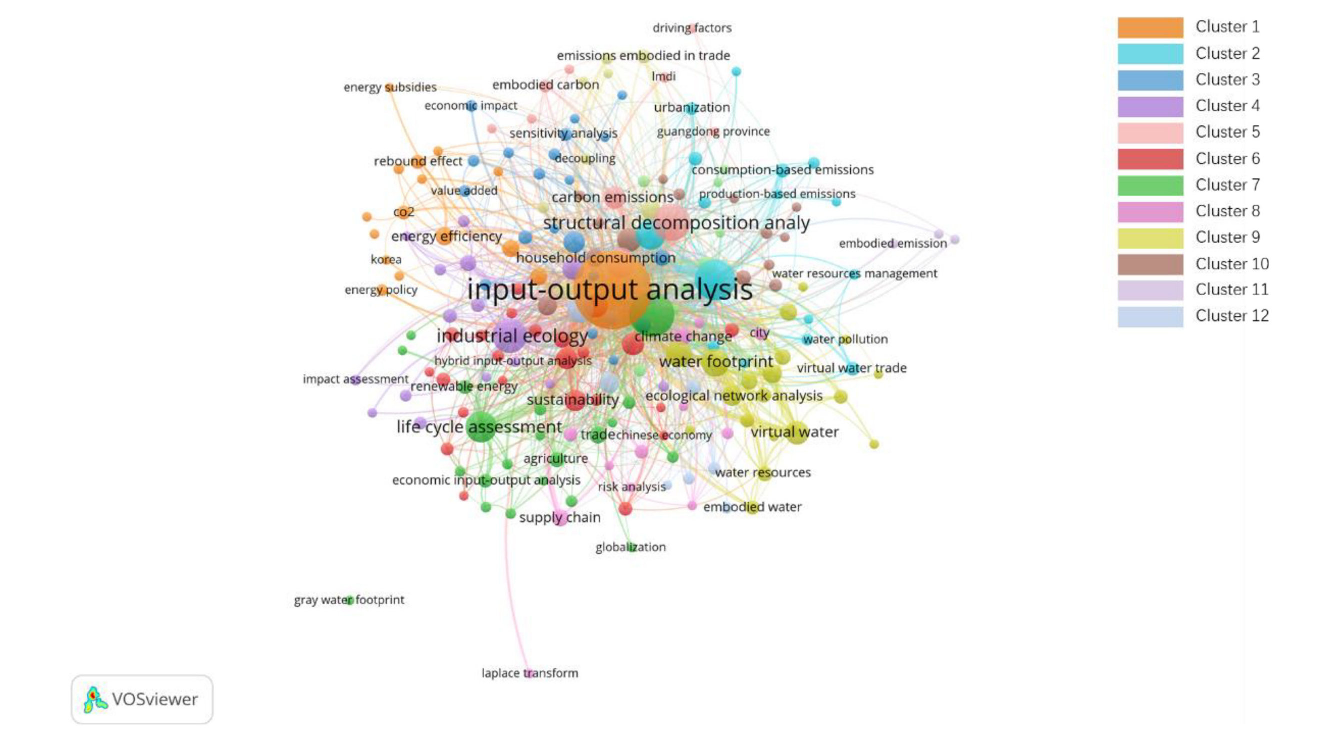


**FIGURE 4 |** Distribution of keywords in co-occurrence relation.

United States jointly published 47 articles, accounting for 3.91% of the total volume of articles published by 40 countries. China has become an indispensable part of this field and is playing an important role in promoting research progress in this field. The performances of institutions and authors are shown in **Supplementary Material**.

## The Performances of Journals

The main carriers of academic achievements are articles and journals. The 1,824 target papers are from 259 journals. Forty-three journals with no less than five publications in 20 years are analyzed in depth. The specific results are shown in **Tables 2**, **3**.

There are 79.89% of the total papers in this field published in 15 journals as shown in **Table 2**. And the citations of these papers account for 87.80% of the total. The distribution of high-level achievements in this field is relatively concentrated. *Ecological Economics* (115 articles, 6,846 citations) is the most influential journal with the most citations. *Energy Policy* (133 articles, 5,833 citations), *Journal of Cleaner Production* (290 articles and 5,490 citations), *Applied Energy* (115 articles, 3,822 citations), and *Journal of Industrial Ecology* (125 articles, 3,584 citations) followed closely. Among the 15 journals, *The Global Environmental Change* with the highest impact factor (10 articles, 1,261 citations) ranked 9th in terms of publication. Journals such as *Environmental Science and Pollution Research* (26 articles, 78 citations), *Environmental Pollution* (5 articles, 76 citations), *Earths Future* (9 articles, 84 citations), and *Environmental Research Letters* (18 articles, 612 citations) have published more articles in recent years. This indicates that these journals begin to pay more attention to this research field. *Journal of Cleaner Production* (290 articles, 5,490 citations), *Science of the Total Environment* (46 articles, 902 citations), and *Resources Conservation and Recycling* (58 articles, 647 citations) all have high publication and citation. And their year of average publication is also recent. This shows that these three journals not only have high influence, but also have been active in the academic forefront.

## The Characteristics of Publications

Among 1,824 selected articles, 211 articles have been cited more than 60 times. The bibliographic coupling analysis was carried out, and the evolution path of the topic was explored. The specific results are shown in **Supplementary Tables A, B**.

The top 10 cited articles are mainly from countries such as Australia, Norway, and China. "Growth in Emission Transfers Via International Trade From 1990 to 2008" published in *Proceedings of the national academy of the united states of America* (PNAS) in 2011 has a great influence, with 655 citations (Peters et al., 2011). This paper calculates trade-related carbon emissions of 113 countries and regions between 1990 and 2008. It was found that emission's transfers through international trade tended to exceed emission's reductions by importing countries. "The Material Footprint of Nations," also from PNAS, ranked second with a cumulative 468 citations (Wiedmann et al., 2013). This paper focuses on natural resources, including fossil energy, metal minerals, non-metallic minerals, and biomass energy. And this paper conducts a quantitative analysis of the natural resource footprint and its drivers in 186 countries in 2008 from a

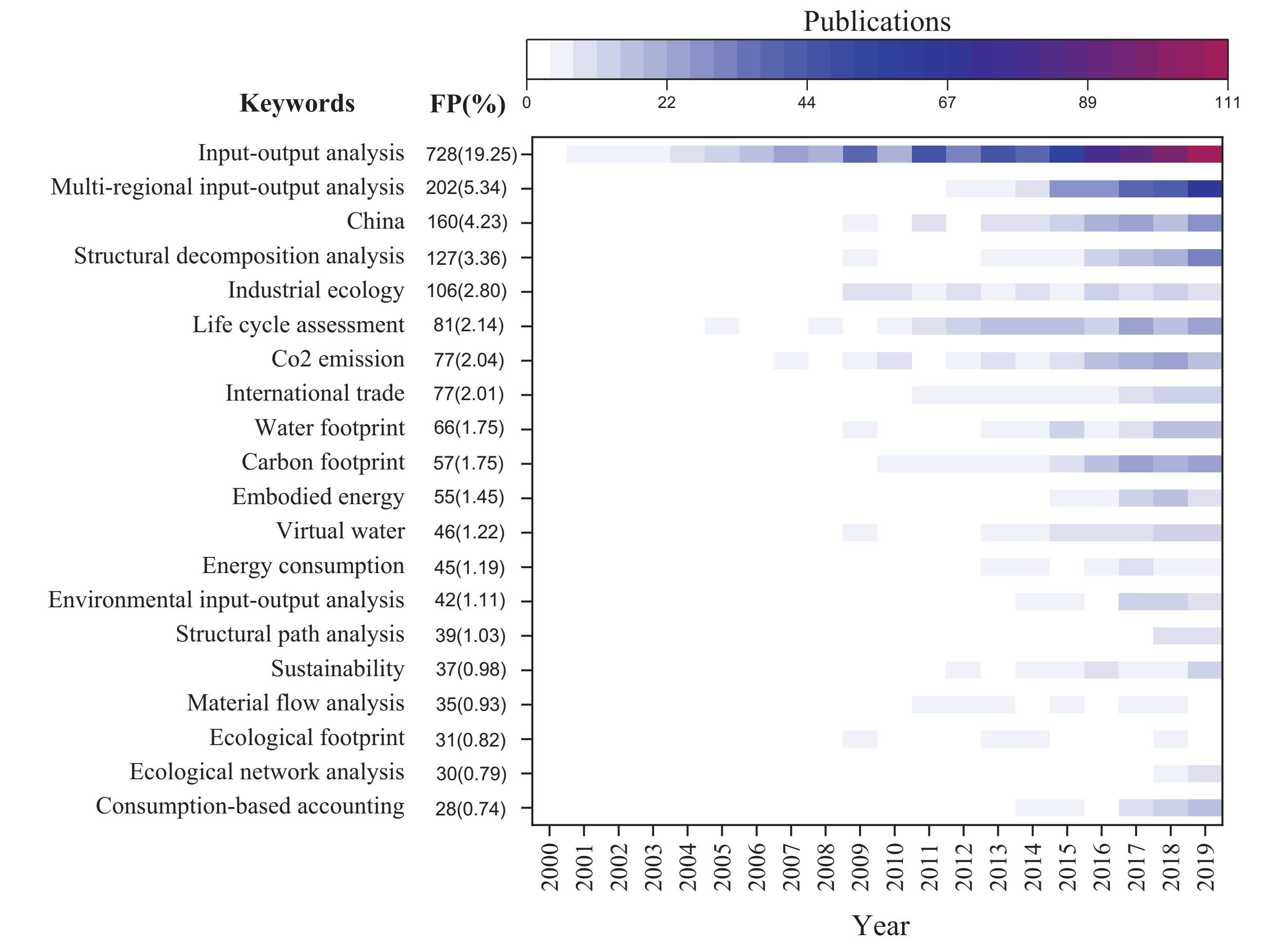


**FIGURE 5 |** Frequency distribution of research topics. The color bar represents publications per year of keywords.

consumption-based perspective. The results show that the use of non-domestic natural resources in developed countries is about three times the volume of physical trade. A paper published in the *Global Environmental Change* in 2013, "Affluence Drives the Global Displacement of Land Use" ranked sixth with a cumulative 287 citations (Weinzettel et al., 2013). This paper tracks the land and ocean footprints of 113 countries in the global supply chain based on the GTAP database. It found that high-income countries require more biologically productive land per capita than low-income countries, with a one-third increase in a country's land and ocean footprint per capita for each doubling of per capita income. The above three articles all carry out accounting analysis on natural resource consumption and transfer embodied in international trade from a global perspective, while other highly cited literatures mainly focus on a single country.

Bibliographic coupling occurs when two documents share one or more citations, indicating that the content expressed by these documents is about the same topic (Boyack and Klavans, 2010). The more references the two articles share, the more similar the content will be. According to the differences in shared citations, the 211 articles were divided into eight clusters (**Figure 3**). According to the scope of research objects, eight clusters are divided into two categories. One is the research on carbon emissions from fossil fuel's consumption; The other one is the research on natural resources, including energy, water, and land.

Cluster 1, represented by Lenzen and Murray (2001); Hondo (2005), and Guan et al. (2008) calculate and analyze the energy and related carbon emissions embodied in international trade. Since then, research has evolved in two directions. One is a change of topic. Cluster 5, represented by Weber and Matthews (2008); Baiocchi et al. (2010), and Liu et al. (2011), further analyzes the impact of household consumption patterns on carbon emissions from a micro perspective. Cluster 8 and Cluster 7 study the inter-sectoral economic dependence and vulnerability to shocks among technical facilities from a macro perspective through Input-output. The other one is a shift in methodology. Cluster 3, represented by Tukker and Jansen (2006); Wiedmann et al. (2011), and Genovese et al. (2017), started to compare and analyze the carbon emission results related to energy consumption calculated by top-down Input-output method and bottom-up life cycle analysis, and built an improved integration model from various aspects.

**TABLE 1 |** Top 10 countries (regions) in cumulative publication.

| Country | TP (%) | TC (%) | Avg. pub. year | Num. co-countries | Num. co-publication (%) | RA |
|---|---|---|---|---|---|---|
| China | 853 (31.65%) | 17491 (21.73%) | 2016.73 | 31 | 235 (19.53%) | 0.28 |
| United States | 369 (13.69%) | 13678 (16.99%) | 2014.33 | 32 | 179 (14.88) | 0.49 |
| United Kingdom | 181 (6.72%) | 7396 (9.19%) | 2015.44 | 26 | 119 (9.89%) | 0.66 |
| Japan | 150 (5.57%) | 4541 (5.64%) | 2014.05 | 17 | 55.5 (4.61%) | 0.37 |
| Australia | 140 (5.19%) | 5838 (7.25%) | 2015.08 | 19 | 64.5 (5.36%) | 0.46 |
| Spain | 110 (4.08%) | 2672 (3.32%) | 2014.40 | 21 | 39.5 (3.28%) | 0.36 |
| Netherlands | 87 (3.23%) | 3152 (3.92%) | 2015.34 | 22 | 65.5 (5.44%) | 0.75 |
| Norway | 84 (3.12%) | 5024 (6.24%) | 2014.63 | 18 | 60 (4.99%) | 0.71 |
| Germany | 73 (2.71%) | 3050 (3.79%) | 2014.77 | 15 | 42.5 (3.53%) | 0.58 |
| Austria | 67 (2.49%) | 3179 (3.95%) | 2014.55 | 18 | 57 (4.74%) | 0.85 |

*TP is the cumulative total publication; TP% is the proportion of cumulative total publication; TC is the cumulative cited times; TC% is the proportion of cumulative citations; Avg. pub. Year is the average publication year; Num. Co -countries is the number of cooperative countries; Num. Co-publication refers to the number of international collaborative publications; RA is the ratio of the number of international collaborative publications in a country to its total number of publications, the same as below.*

Around 2010, the research focuses gradually shifted from the environmental impact to other kinds of natural resources such as energy, water, land, and minerals, primarily represented by literature such as Chen and Chen (2010); Chen and Zhang (2010), and Bruckner et al. (2012). Since then, with the improvement of the Multi-regional Input-output database, the research mainly focuses on the consumption and management of natural resources in countries and even cities from the perspective of the global supply chain.

## The Features of Keywords

Keywords are the epitome of the article, which can let readers understand the key content of article in a short time (Xia et al., 2017). There were 3,879 keywords in 1,824 articles. In order to increase the effectiveness of keyword analysis, this paper first preprocesses the original data and unifies the keywords with similar meanings into one expression form. For example, Input-output analysis is used to represent Input-output models, Input-output modeling, and other similarly keywords. After that, 195 keywords that appeared no less than five times were analyzed deeply.

From the perspective of occurrence frequency, there is no doubt that "Input-output analysis" is the keyword with the most occurrences (**Figures 4**, **5**). "Multi-regional Input-output analysis" and "China" ranked second and third, respectively. The current research in this field has turned to the discussion of interregional issues, and the research object has been inclined to China. "Structural decomposition analysis" and "Life cycle assessment" rank fourth and sixth, respectively. It shows that many articles in this field combine the above two methods with Input-output. **Table 4** shows the 20 most-recent keywords in terms of publication per annum. Energy-water nexus, energy transition and trade inequality have gradually become hot topics. System optimization, driver factors analysis and complex

**TABLE 2 |** Top 15 cited journals.

| Journal name | IF (2019) | TP (%) | TC (%) | TC/TP |
|---|---|---|---|---|
| Ecological Economics | 4.482 | 115 (7.61) | 6846 (15.47) | 59.53 |
| Energy Policy | 5.042 | 133 (8.80) | 5833 (13.18) | 43.86 |
| Journal of Cleaner Production | 7.246 | 290 (19.18) | 5490 (12.41) | 18.93 |
| Applied Energy | 8.848 | 115 (7.61) | 3822 (8.66) | 33.32 |
| Journal of Industrial Ecology | 6.539 | 125 (8.27) | 3584 (8.10) | 28.67 |
| Environmental Science and Technology | 7.864 | 69 (4.56) | 3298 (7.45) | 47.80 |
| Energy | 6.082 | 72 (4.76) | 2081 (4.70) | 28.90 |
| Proceedings of the National Academy of Sciences of the United States of America | 9.412 | 5 (0.33) | 1364 (3.08) | 272.80 |
| Global Environmental Change | 10.466 | 10 (0.66) | 1261 (2.85) | 126.10 |
| Ecological Modelling | 2.497 | 33 (2.18) | 1092 (2.47) | 33.09 |
| Ecological Indicators | 4.229 | 38 (2.51) | 1080 (2.44) | 28.42 |
| Science of the Total Environment | 6.551 | 46 (3.04) | 902 (2.04) | 19.61 |
| International Journal of Life Cycle Assessment | 4.307 | 27 (1.79) | 850 (1.92) | 31.48 |
| Resources Conservation and Recycling | 8.086 | 58 (3.84) | 647 (1.46) | 11.16 |
| Sustainability | 2.576 | 72 (4.76) | 644 (1.46) | 8.94 |

**TABLE 3 |** The top 10 journals with more recent publication years on average.

| Journal name | IF (2019) | TP (%) | TC (%) | Avg. citations |
|---|---|---|---|---|
| Environmental Science and Pollution Research | 3.056 | 26 (1.72) | 78 (0.18) | 3.00 |
| Environmental Pollution | 6.792 | 5 (0.33) | 76 (0.17) | 15.20 |
| Sustainable Production and Consumption | 3.660 | 5 (0.33) | 10 (0.02) | 2.00 |
| Earths Future | 6.141 | 9 (0.60) | 84 (0.19) | 9.33 |
| Fresenius Environmental Bulletin | 0.553 | 8 (0.53) | 20 (0.05) | 2.50 |
| Science of the Total Environment | 6.551 | 46 (3.04) | 902 (2.04) | 19.61 |
| Journal of Cleaner Production | 7.246 | 290 (19.18) | 5490 (12.41) | 18.93 |
| Sustainability | 2.576 | 72 (4.76) | 644 (1.46) | 8.94 |
| Resources Conservation and Recycling | 8.086 | 58 (3.84) | 647 (1.46) | 11.16 |
| Environmental Research Letters | 6.096 | 18 (1.19) | 612 (1.38) | 34.00 |

**TABLE 4 |** Research frontier distribution.

| Keywords | FP (%) | Avg. pub. year | Keywords | FP (%) | Avg. pub. year |
|---|---|---|---|---|---|
| LMDI | 7 (0.19%) | 2018.57 | Final demand | 7 (0.19%) | 2018.14 |
| Energy-water nexus | 10 (0.26%) | 2018.40 | Construction sector | 8 (0.21%) | 2018.13 |
| Driving factors | 5 (0.13%) | 2018.40 | Guangdong province | 6 (0.16%) | 2018.00 |
| Energy conservation | 5 (0.13%) | 2018.40 | Optimization | 6 (0.16%) | 2018.00 |
| Energy transition | 5 (0.13%) | 2018.40 | Production-based emissions | 6 (0.16%) | 2018.00 |
| $SO_2$ emissions | 5 (0.13%) | 2018.40 | Carbon footprints | 5 (0.13%) | 2018.00 |
| Water-energy nexus | 14 (0.37%) | 2018.21 | Urban agglomeration | 7 (0.19%) | 2017.86 |
| Interprovincial trade | 5 (0.13%) | 2018.20 | Complex network | 12 (0.32%) | 2017.83 |
| Linkage analysis | 5 (0.13%) | 2018.20 | Consumption-based emissions | 13 (0.34%) | 2017.69 |
| Trade imbalance | 6 (0.16%) | 2018.17 | Gray water footprint | 5 (0.13%) | 2017.60 |

networks are the new research methods in this field. However, the frequencies of occurrence and co-occurrence of the above keywords are still small, indicating that there are still large academic gaps worth studying.

Through the classification of the meanings of keywords, it is found that among 195 keywords, 48 keywords were research objects, and 57 keywords were research methods, while the remaining 92 keywords included research background and other expressions.

The object includes a single kind of resources and resource nexus. In terms of a single type of resources, the pollutants emitted by fossil energy consumption have been studied the most, among which carbon dioxide emission and sulfur dioxide emission had a larger proportion of single pollutant types. Then there is the study of primary energy and renewable-energy consumption, in which coal, electricity, and biomass energy subcategories are studied more. The next is the study of water, which gray water footprint and water pollution research more. More and more attention has been paid in the study on the consumption of land metals and other materials. The other type of research focuses on the nexus of multiple resources, which is mainly energy-water nexus, water-energy nexus, and energy-water-food nexus at present. The essential metaphor of these nexuses is the synergy between them. The implementation of single resource-saving actions in resource-intensive industries would effectively promote the synergistic other resource-conservation effects (Bleischwitz et al., 2018; Tang et al., 2018).

In terms of research methods, Input-output analysis extends and refines the model itself, such as Multi-Region Input-output model, Physical Input-output model, and other Extended Input-output. On the other hand, it is actively applied in combination with other models, such as hybrid life cycle analysis and economy-wide material flow analysis. In addition, structural decomposition analysis (SDA), structural path analysis (SPA), network analysis, data envelopment analysis (DEA), computable general equilibrium (CGE), and multi-objective optimization methods are also widely used in this field.

In other aspects, there are many case studies in China, Australia, South Korea, and other countries, including cities and city agglomeration. The construction industry, electric vehicle and electric power industry are also highly focused. International trade, inter-provincial trade, global supply chain, climate change, sustainable development, industrial structure reform, and energy transition are the frequent research background.

# DISCUSSION

## Improvement of Research Method

The uncertainty of Input-output analysis has been mentioned many times in the selected articles. First, the Input-output model itself has many uncertainties and limitations, including the process of data investigation, model coordination and balance, and the assumption of departmental homogeneity in order to maintain the stability of technical and economic links between departments (Hawkins et al., 2007; Lenzen, 2008; Weber, 2008). Secondly, the single regional Input-output model assumes that the production technologies of imported goods and services are the same as those of the economy surveyed. However, this assumption is not consistent with reality. In order to reduce the uncertainty caused by this assumption, the multi-regional Input-output model is built with other uncertainties, such as the sectoral division system of multiple regions, the currency exchange rate, and the treatment of other regions in the world (Weber, 2008). At the same time, Input-output tables from different scientific research institutions and databases also have different results due to different data sources and calculation methods (Hoekstra et al., 2014). So, the uncertainty and limitations inherent in such models clearly need further attention from the research community, which needs to improve the availability and quality of data. There is also a need for more in-depth evaluation of the data results and model programming estimates for each country (Wiedmann, 2009; Tukker et al., 2018).

Jumping out of the Input-output model itself, it is found that Input-output model is widely combined with others to establish an integrated model. In the process of accounting, it can be found that Input-output is often combined with life cycle analysis (LCA) or material flow analysis (MFA). Different from the top-down macroscopical characteristics of Input-output method, life cycle evaluation can provide microscopic data with the bottom-up paradigm, while material flow analysis can track the flow and stock of materials, which are complementary to Input-output method from distinct perspectives (Hertwich et al., 2000; Ayres and Ayres, 2002; Fischer-Kowalski et al., 2011; Beylot et al., 2020). Nevertheless, due to the initial "pure sector" hypothesis of Input-Output model, the data collected through LCA or MFA must be merged into the unified sector (Sleeswijk et al., 2008; Kondo et al., 2012; Wang et al., 2021). In the aspect of driving factor analysis, structural decomposition method (SDA) and LMDI and measurement methods are used in some researches. However, in the decomposition process, SDA will produce a non-unique problem of decomposition results, leading to great differences among the decomposition results and reducing the accuracy and reliability of the conclusions (Peters et al., 2007; Guan et al., 2008; Lenzeiy et al., 2012; Liang et al., 2013). LMDI can overcome the cross-term problem, but it cannot analyze the resource consumption effect related to trading or demand. Therefore, some articles combine SDA and LMDI to analyze the driving factors (Wang and Yang, 2015; Román-Collado and Colinet, 2018). Most researches adopt structural path analysis (SPA) and network analysis. SPA is a step-by-step path analysis method, which can decompose the effect to each production layer from the perspective of consumption along the supply chain (Hong et al., 2016). In network analysis, the connection between individuals can be expressed through the set of nodes and edges. Compared with SPA, network analysis theory can capture the information of the transmission sectors in the supply chain (Liang et al., 2017). Therefore, some articles combine SPA and network analysis methods to analyze the path of resource consumption in the supply chain (Feng et al., 2019). In the aspect of natural resource management, Input-output model is also combined with multi-objective optimization, data envelopment analysis, computable general equilibrium model and other methods to explore the integrated management mode and path (Jin et al., 2017; Tang et al., 2018). In addition, there are also literatures that combine Input-output with GIS for spatial analysis, system dynamics for dynamic simulation, etc.

### Limitation and Future Work

Since this paper only selects the Web of Science Core Collection as the basic database, and the research scope is limited to the peer-reviewed English journal articles related to the search terms, the coverage of selected literature is incomplete. At the same time, in the process of citation analysis, co-authorship analysis, bibliographic coupling analysis and keyword co-occurrence analysis, initial thresholds are set on the research objects. And some researches with novel topics but few publications are also kicked out of the research scope. Moreover, due to the time lag in the creation, publication, and citation of academic achievements, there should be a delay in the definition of academic hot topics in this paper. Bibliometrics analysis mainly uses the external feature information of the article to carry out structural analysis. It would be better to combine the method of meta-analysis to further analyze the specific data results of resource consumption from various analytical perspectives.

## CONCLUSION

This study provides a review of current developments and hot topics about natural resource consumption and environment management based on Input-output research. Word frequency analysis, bibliographic coupling, and co-citation analysis are conducted to discover the evolution pattern of the research frontiers.

The results show that academic research in this field is increasing rapidly due to the ever-growing focus on sustainable development. While China is playing the role of the world's manufacturer, its demand for natural resources is soaring both at home and abroad. Although China started later, it has taken a global lead in citations and international cooperation. The distribution of high-level achievements in this field is relatively concentrated. Journals like *Ecological Economics*, *Energy Policy*, *Journal of Cleaner Production*, *Science of the Total Environment*, and *Resources Conservation and Recycling* are mainstream journals, from which is easier to track the academic frontiers. Depending on the topic, the literatures can be divided into two categories. One is the research on pollutant emissions related to fossil fuel's consumption. The other one is the research on natural resources, including energy, water, and land. With the development of the Multi-regional Input-output database, the research topic is gradually focusing on the sub-national and regional natural resources consumption accounting and management in the global supply chain. Methods such as LCA, MFA, SDA, SPA, network analysis, DEA, CGE and multi-objective optimization are also widely used in this field, which are combined with Input-output. The integration of these methods can obtain more comprehensive and accurate results for scientific decision-making.

## DATA AVAILABILITY STATEMENT

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

## AUTHOR CONTRIBUTIONS

SW: conceptualization, methodology, software, writing – original draft, and writing – review and editing. XT: conceptualization, funding acquisition, writing – review and editing, project administration, and supervision. BZ: conceptualization, software, and writing – review and editing. WW: software, writing – original draft, and funding acquisition. All authors contributed to the article and approved the submitted version.

## FUNDING

We appreciate the National Natural Science Foundation of China (71673297), Science Foundation of China University of Petroleum, Beijing (ZX20200109 and 2462020YXZZ041), and Soft Science Research Foundation of Zhejiang Province (2019C25G2020667) for sponsoring this research.

## SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2021.628321/full#supplementary-material

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**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.

frontiers in Energy Research

ORIGINAL RESEARCH
published: 09 June 2021
doi: 10.3389/fenrg.2021.633528

# An Explanation of Energy Return on Investment From an Entropy Perspective

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OPEN ACCESS

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**Reviewed by:**
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*Hongbo Duan, University of Chinese Academy of Sciences, China*

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**Specialty section:**
*This article was submitted to Sustainable Energy Systems and Policies, a section of the journal Frontiers in Energy Research*

**Received:** 25 November 2020
**Accepted:** 13 April 2021
**Published:** 09 June 2021

**Citation:**
*Hu Y, Chen Y, Tang S, Feng L and Huang C (2021) An Explanation of Energy Return on Investment From an Entropy Perspective. Front. Energy Res. 9:633528. doi: 10.3389/fenrg.2021.633528*

Low-carbon energy transformation is a major trend in world energy development, and measures to mitigate carbon emissions can vary substantially in terms of the energy they require. A common method of evaluating energy use in energy resource exploitation is energy return on investment (EROI). One of the criticisms of EROI concerns uncertainty regarding the input and output factors for the calculation. To make the issue clear, we interpret EROI in terms of entropy, which is the most basic concept in physics. We consider an energy resource exploitation system to be a kind of dissipative structure and construct a basic entropy analysis framework for an energy resource exploitation system. We then derive the relationship between EROI and entropy change. The theory of EROI is consistent with the basic requirement for a dissipative structure, which is that the total entropy change must be negative. EROI is a method of using entropy theory to evaluate energy resource exploitation. It is inappropriate and unnecessary to quantify all factors as energy units as the input and output factors are multidimensional while energy is a one-dimensional standard. Future development of the EROI method should be guided by entropy theory. A series of EROI related indicators will increase its application and policy significance.

**Keywords: EROI, net energy, entropy, dissipative structure, energy resource exploitation**

## INTRODUCTION

Energy return on investment (EROI) is a method of calculating the energy returned to the economy and society compared to the energy required to obtain that energy and, thus, to measure the net energy produced for society (Odum, 1973; Mulder and Hagens, 2008; Hall, 2011; Hall et al., 2014). The concept of net energy was first proposed by Odum in 1973, and EROI has been the subject of research for over 40 years (Hall et al., 2014; Xu et al., 2016).

One of the criticisms of EROI concerns uncertainty regarding the input and output factors for the calculation. This is because it is difficult to determine accurate and reasonable input and output factors for energy exploitation activities (Mulder and Hagens, 2008; Hall et al., 2009; Murphy et al., 2011). Input factors include direct energy, non-energy resources (e.g., land, water, time, labor), and embodied energy (e.g., energy consumed by infrastructure construction and material production), while output factors include direct energy output, coproducts, and externalities (e.g., carbon emissions, soil erosion, ground and water pollution, loss of habitat, job creation, maintenance of rural communities). In most studies, the calculation is based on standard EROI, which only includes direct and indirect energy and material inputs and outputs. However, standard EROI is highly inaccurate for some energy sources, such as shale gas, biomass energy, and solar energy (Chen et al., 2020). If the input and output factors are not determined strictly, EROI will be one-sided and misleading. Research on EROI calculation and input and output factors is important, otherwise EROI will not be useful for policy.

Research on EROI focuses on the economic process of energy resource exploitation. As early as 1971, Georgescu-Roegen observed that "the economic process is a process of entropy, wealth is a kind of exploitation system, which is produced in the circulation process of the low-entropy resource consumption as the beginning and the discharge of equal high entropy waste to the environment as the end" (Georgescu-Rogen, 1971). Tsuchida (1991) regards entropy as the value of energy, because entropy is a good representation of value change for humans and because the natural law that the consumption of resources indicates that the consumption process is the process of value creation and entropy production. The focus of EROI on the economic process of energy resource exploitation follows the basic laws of nature. As one of the most fundamental theories of physics, entropy theory has the potential to deepen our understanding of EROI and resolve the criticisms levied against it as a method.

In the EROI calculation, what is the basis of the decision which input and output factors should be included in the accounting system? We discuss this issue from the perspective of entropy. We use the concept of entropy under the assumption of a thermodynamically open economy to analyze energy resource exploitation activity and explore the EROI method from an entropy perspective. Ultimately, this paper is to promote further application of EROI theory and method. The article's organizational framework is structed as follows. Section 2 presents the basic theory of EROI and entropy and explains EROI theory from an entropy perspective. Section 3 constructs an analytical diagram for energy resources exploitation and explains EROI method from an entropy perspective. Section 4 discusses the process and result of explanation. Finally, Section 5 summarizes the paper.

## THE THEORY OF EROI FROM AN ENTROPY PERSPECTIVE

### Net Energy Theory and EROI

From an industrial perspective, the general pattern of any energy resource exploitation is that workers use a variety of equipment, materials, and resources and consume a certain amount of energy when extracting the energy resource from nature. Then, the resource is ultimately transformed into secondary and final energy products to meet human demands. The net energy is the amount of energy left over from the gross energy extracted (and processed and delivered) from a primary energy source after the energy needed to sustain extraction, processing and delivery processes has been subtracted (Carbajales-Dale et al., 2014). The recommended method of calculating net energy is EROI (Gilliland, 1975). As **Figure 1** shows, EROI focuses on the input and output of energy and the process of energy circulation. To ensure that energy resource exploitation can provide net energy for the development of society, the energy output must be greater than the energy input (Chen et al., 2017a).

The true value of energy to society is the net energy, which is the energy output minus the energy input (Odum, 1973), and social and economic development is based on this net energy surplus (Gilliland, 1975). Each increment in EROI allows more and more work to be done. The energy needs of human beings can be represented as a pyramid (**Figure 2**). More complex social activities require more energy and, hence, higher EROI from the energy system (Lambert et al., 2014).

### Development of the Concept of Entropy

The theory of entropy originates from thermodynamics, where it represents a state function for measuring the degree of disorder in a system. Entropy was first proposed by Clausius in 1865 and was defined as the "quotient of heat-temperature." The term was used to describe energy in transformation and the direction of that transformation within a system (He and He, 2006). Later, in 1877, Boltzmann proposed a formula, known as the Boltzmann entropy formula, that linked entropy to the microscopic state of a system and the degree of chaos of molecular motion (He and He, 2006). In 1948, Shannon connected entropy to information as a quantitative measure of the uncertainty of information source signals (Shannon, 2014). In 1967, Prigogine first proposed a theory of dissipative structures and explained this as an open system at a nonlinear region far from equilibrium that will undergo mutation (Prigogine and Lefever, 1973).

In 1971, Georgescu-Rogen studied the relationship between thermodynamics and the economic process and claimed that the economic process was a process of entropy. The link between entropy and economics was explored in more depth in 1976 by Atsushi Tsuchida, who proposed that what an economic system consumes is not energy or material itself, but the diffusion capacity that is useful for mankind (Xue, 1994). Both production and consumption within an economy can be seen as a kind of consumption of resource diffusion capacity that can be measured using entropy (Tsuchida, 1991; Yu, 1992). In 1980, Rifkin and Howard published *Entropy: A New World View*. Although it was controversial, the book established a world view based on the law of entropy generation, which has had a profound impact on the system of value judgments in normative economics (Qian, 1990; Zhang, 2006). Since then, debates on entropy and how it should be applied in economics have persisted.

Developments in the theory of entropy and its implementation in engineering have greatly improved society. Clausius first proposed the concept of entropy when he was analyzing the efficiency of heat engines and exploring energy conversion optimization. The scientific beauty of thermodynamic concepts such as energy, exergy, and entropy have been essential in human scientific endeavors, from the development of combustion technology to advancing our understanding of the final frontiers of our universe [perhaps best illustrated by the late Stephen Hawking's (1976) work on black holes].

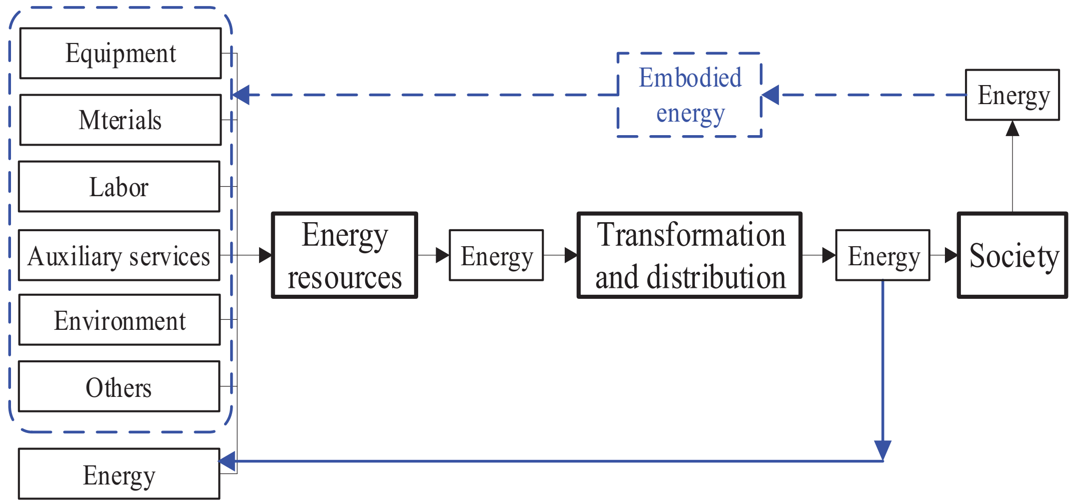


**FIGURE 1 |** Energy resource exploitation from a material perspective.

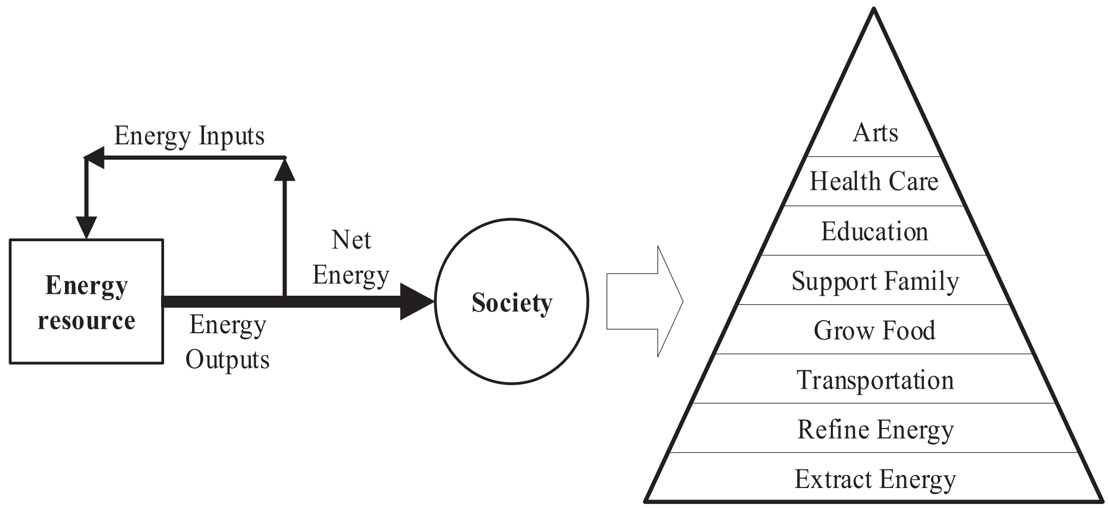


**FIGURE 2 |** Net energy and pyramid of energetic needs.

Thermodynamic ideas have been used extensively to devise alternative accounts of economics by drawing analogies with physical or natural processes, such as energy usage. It is easy to argue that the transition intermediary of entropy from a thermodynamic system to a social economic system is the correspondence of energy and economic value orientation (Yu, 1992).

The operation of an economic system is a process of transforming nature into value for society, and it may be argued that such transformations mirror energy transformations in the sphere of thermodynamic engineering. However, one must be aware that such analogs are indirect and can be contested (Hammond, 2004). The economic value assigned to a product by the market is different from energetic value in physics. Nevertheless, such metaphors are still useful for illustrative purposes (Van Gool, 1987; Hammond, 2007). From this perspective, the dissipative structure theory and other thermodynamic analogs can be used to explain the significance of entropy to the social economic system, both micro- and macroscopically. This theoretical background renders these methods suitable for further exploration of EROI.

## Connecting EROI Theory and Entropy

The exploitation of energy resources can be regarded as a social-economic-natural complex ecosystem consisting of human activities, physical environments, resource flows, and social culture (Ma and Wang, 1984; Wang and Ouyang, 2012). This ecosystem constantly exchanges energy, material, and information with the outside world. It consumes energy, materials, and labor and produces energy products while discharging waste materials and energy into the environment. Therefore, this energy exploitation system can be regarded as an open thermodynamic system involving entropy change, which we can analyze using dissipative structure theory (Wu, 1991; Shi and Hu, 2004; Sun and Li, 2004; Xu et al., 2004).

As **Figure 3** shows, any societal economic system is a subsystem of a broader ecosystem, and of which (primary) energy resources are natural components. Thus, an energy resource exploitation system represents the intersection of the subsystem and the wider ecosystem. According to dissipative structure theory, a dissipative structure system is an open system in a state that is far from equilibrium. It exchanges energy and materials with the outside world, thus producing a state of order in time and space or function out of chaos when the external conditions reach a certain threshold (Prigogine, 1967; Shi and Hu, 2004).

It can be assumed that the energy resource exploitation system is a dissipative structure by virtue of the fact that it has the four characteristics of a dissipative structure (Wu, 1995; Shi and Hu, 2004; Xu et al., 2004; Chu, 2005). (1) An energy resource exploitation is an open system, as its normal functioning depends on a continuous exchange of energy, material, and information with an external environment. (2) It is a system that is far from equilibrium, as various factors, including technical progress, the discoveries of new areas for exploitation, production declines, or changes in exploitation policies, continuously disrupt the equilibrium of the system. (3) The energy resource system consists of nonlinear interaction mechanisms, as each subsystem or element of the system promotes as well as restricts other elements, generating positive feedback that upsets the equilibrium state and negative feedback that restricts growth. (4) The system is also subject to fluctuations; the advantages, disadvantages, and disequilibrium of the system generate increasing instability and disorder until mutation occurs over a critical point if one or more factors (such as production, price, or policy) change.

Entropy change ($dS$) of an open system in time (dt) is the sum of two parts: the internal entropy change ($d_iS$) produced by the processes inside the system and the external entropy flow ($d_eS$) resulting from the exchange of energy and materials with the outside world, as shown in **Figure 3**. It is important to note that a low-entropy resource (e.g., petroleum, construction materials, process water) consumed within the energy resource exploitation system comes from the social economic system and results in entropy production $d_iS$ (i.e., $d_iS > 0$). The energy produced within the energy resource exploitation system is also a low-entropy resource (e.g., crude oil, natural gas, coal, electricity), which originates from the natural environment and is mainly consumed within the social economic system rather than the energy resource exploitation system. Furthermore, the low-entropy resource corresponding to the system's energy production flows into the energy resource exploitation system, which means that the potential for entropy production flows into the energy resource exploitation system, so $d_eS$ is negative (i.e.,$d_eS < 0$). Conversely, the low-entropy resource corresponding to the energy investment from the social economic system is consumed within the energy resource exploitation system, so $d_iS$ is positive. According to dissipative structure theory, the basic requirement of a dissipative structure is a total entropy change that is non-positive ($dS \leq 0$). This means that the entropy production in the system is not greater than the negative entropy production flowing into the system ($d_iS \leq \left|d_e\,S\right|$).

From the perspective of entropy, the focus of the energy resource exploitation system is on the quantity and the direction of the flow of entropy, because the system has a particular purpose, namely to provide energy for the development of society. This corresponds to the issue of input and output or cost and benefit in economics. Both dissipative structure theory and EROI focus on the input and output of energy by considering issues of quantity and quality, and both require that the output is not less than the input.

Energy can be explained by entropy. However, entropy is more than an explanation of energy. Processes such as carbon emission and water consumption are also important issues for energy

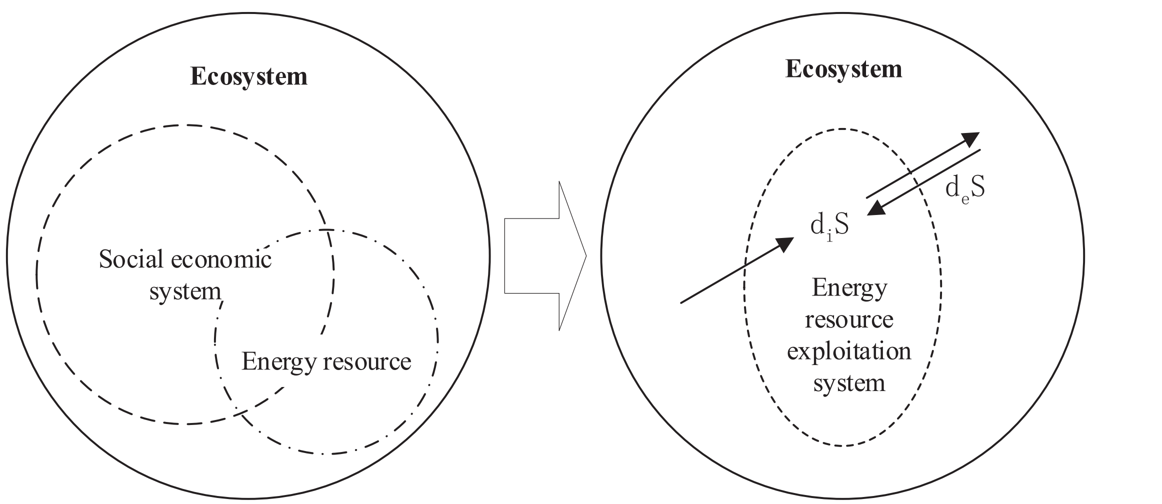


**FIGURE 3 |** An energy resource exploitation system and its dissipative structure.

resource exploitation. These issues can be explained by entropy, whereas it can be controversial to explain carbon emission or water consumption in terms of energy. The concept of entropy is broader than energy. In terms of energy production, EROI is consistent with dissipative structure theory, while entropy gives a more profound and general explanation.

## THE EROI METHOD FROM AN ENTROPY PERSPECTIVE

### Basic Formula

The basic formula of dissipative structure theory is as follows:

$$dS = d_iS + d_eS \tag{1}$$

where $dS$ is the total entropy change in time $dt$, $d_iS$ is the internal entropy change, and $d_eS$ is the external entropy flow.

The conventional equation for calculating EROI is as follows (Mulder and Hagens, 2008):

$$EROI = \frac{\sum_{i=1}^{n} E_i^O}{\sum_{j=1}^{m} E_j^I} \tag{2}$$

where $E_i^O$ is the energy production (outputs), and $E_j^I$ is the energy invested (inputs).

In general, different forms of energy are converted into heat equivalents and expressed in calorific values. Taking energy quality into consideration, the equation may be rewritten as follows (Cleveland, 1992; Murphy et al., 2011; Hu et al., 2014):

$$EROI = \frac{\sum_{i=1}^{n} \lambda_i E_i^O}{\sum_{j=1}^{m} \lambda_j E_j^I} \tag{3}$$

where λ is the energy quality factor. Depending on one's perspective, energy quality can have different meanings, such as emergy, exergy, and price (Gao et al., 2011).

### Connecting the EROI Method and Entropy

We construct an analytical diagram based on the Carnot heat engine to discuss the relationship between entropy and EROI, as shown in **Figure 4**. The heat of the non-energy substance and the energy initially invested in the energy resource exploitation system is $Q_1$, and the entropy is $S_1$. When the substance and the energy invested is consumed, the waste heat and the heat contained in the waste material is $Q_2$, and the entropy is $S_2$. The useful work produced for exploiting the energy resource is $W_1$. The heat contained in the energy products is $Q_3$, and the entropy is $S_3$. When the energy products are transferred to the social economic system and consumed, the useful work produced for humans is $W_2$, the waste heat and heat contained in the waste material is $Q_4$, and the entropy is$S_4$. The term ER in **Figure 4** designates the energy resource. The heat contained in substances (e.g., equipment, raw material) can be interpreted as "embodied energy" that is consumed for producing the non-energy substance. The waste heat and waste material are discharged into the natural environment. The useful work serves the social economic system and can be used to meet human needs.

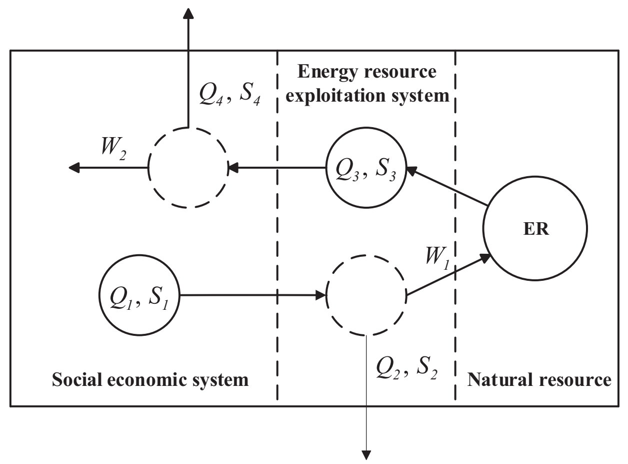


**FIGURE 4 |** An energy resource exploitation system from an entropy perspective.

The dissipative structure theory formula is in the form of a differential, as shown in formula (1); therefore, it can be assumed that

$$d_iS = f_1{'}(t)dt \tag{4}$$

$$d_eS = f_2{'}(t)dt \tag{5}$$

In time $t$, the accumulative total internal entropy production $IS$ and the accumulative total external entropy flow $ES$ are as follows:

$$IS = \int_a^b f_1{'}(t)dt = S_2 - S_1 \tag{6}$$

$$ES = \int_c^d f_2{'}(t)dt = -(S_4 - S_3) \tag{7}$$

where $a$ and $b$ are the beginning and end states of the factors invested and consumed in the energy resource exploitation system, respectively, and $c$ and $d$ are, respectively, the beginning and end states of the energy products produced by the energy resource exploitation system and consumed in the economic system of society. The total entropy change $\Delta S$ of the energy resource exploitation system is as follows:

$$\Delta S = IS + ES \tag{8}$$

which is calculated as follows:

$$\Delta S = (S_2 - S_1) + [-(S_4 - S_3)] \tag{9}$$

If the absolute temperature of the ecosystem is $T$ ($T > 0$), then both sides of Eq. 9 are multiplied by $T$:

$$T\Delta S = T(S_2 - S_1) + T(S_3 - S_4) \tag{10}$$

According to Clausius's entropy formula

$$dS = \frac{\delta Q}{T} \tag{11}$$

Then Eq. 10 becomes

$$T\Delta S = (Q_1 - Q_2) + (Q_4 - Q_3) \tag{12}$$

According to the first law of thermodynamics,

$$Q_1 = Q_2 + W_1 \tag{13}$$

$$Q_3 = Q_4 + W_2 \tag{14}$$

Substituting Eqs. 13, 14) into Eq. 12, then

$$T\Delta S = W_1 - W_2 \tag{15}$$

Equation 15 shows that entropy can indeed indicate the useful value that is available for humans. In addition, the most basic function of the energy resource exploitation system is to provide the necessary energy for the development of a social economic system. More specifically, the useful value invested in the energy resource exploitation system by humans must be used to gain more useful value (i.e., it is required that $W_2 \geq W_1$). This is consistent with the basic requirement of the dissipative structure theory that $\Delta S \leq 0$. If we assume that the ratio of useful value to total energy (direct energy and embodied energy) is α, then

$$W_1 = Q_1\alpha_1 \tag{16}$$

$$W_2 = Q_3\alpha_2 \tag{17}$$

Substituting Eqs 16, 17 into Eq. 15, then

$$T\Delta S = \alpha_1 Q_1 - \alpha_2 Q_3 \tag{18}$$

We can simplify Eq. 3 of the EROI calculation as follows:

$$EROI = \frac{\lambda_O E_O}{\lambda_I E_I} \tag{19}$$

where $E_O$ is the energy output, $E_I$ is the energy input, $\lambda_O$ is the energy quality factor of the energy output, and $\lambda_I$ is the energy quality factor of the energy input. If energy quality is taken to mean useful value, that is, the energy quality factor λ is the ratio of useful value to total energy, then

$$\lambda_O = \alpha_2 \tag{20}$$

$$\lambda_I = \alpha_1 \tag{21}$$

Furthermore, it is obvious that

$$E_I = Q_1 \tag{22}$$

$$E_O = Q_3 \tag{23}$$

Substituting Eqs. 20–23 into Eq. 19, then

$$EROI = \frac{\alpha_2 Q_3}{\alpha_1 Q_1} \tag{24}$$

If both sides of Eq. 24 are multiplied by $\alpha_1 Q_1$ ($\alpha_1 Q_1 > 0$), then

$$\alpha_2 Q_3 = EROI \cdot \alpha_1 Q_1 \tag{25}$$

Substituting Eq. 25 into Eq. 18, then

$$T\Delta S = \alpha_1 Q_1 - EROI \cdot \alpha_1 Q_1 \tag{26}$$

If both sides of Eq. 26 are divided by $\alpha_1 Q_1$, then

$$EROI = -\frac{\Delta S}{\Delta S_1} + 1 \tag{27}$$

$$EROI = \frac{-\Delta S + \Delta S_1}{\Delta S_1} \tag{28}$$

where $\Delta S_1 = \frac{W_1}{T}$ indicates the environmental entropy change of the useful work dissipated in the form of heat.

Under the assumption that the energy quality factor is the ratio of useful value to total energy, it can be seen that net energy and $\Delta S$ are almost the same thing. This assumption implies that the use value measured by entropy is presented by energy. Entropy has a more general significance, but it can appear more abstract and less comprehensible. Furthermore, entropy change is more difficult to quantify than EROI, which is more intuitive as an indicator. There are strong connections between entropy and EROI in an open thermodynamic economy. While EROI analysis may appear to be a more concrete approach, entropy is a more holistic approach, albeit at the expense of tractability.

## DISCUSSION

Thermodynamic concepts may be used to theoretically connect EROI and entropy within an economy if the basic assumption that economic properties metaphorically correspond to thermodynamic factors is accepted. Since the days of Georgescu-Rogen (1971), biophysical and ecological economists have long argued that entropy, exergy, and other thermodynamic properties are meaningful indicators within economies.

The classical criticism of these ideas revolves around the fact that there are no direct links between thermodynamic properties and various economic values within a complex economy, as discussed by Kovalev (2016). Söllner (1997) and Slesser (1978) independently argued that thermodynamics can – via proper use of metaphors and analogs – lead to new insights primarily regarding the absolute limits of economies. Examples of such limits include the finiteness of fossil fuels and other planetary boundaries that are important to consider for the long-term planning of interactions between mankind and nature (Hammond, 2004; Hammond and Winnett, 2006; Haberl et al., 2014; Hall et al., 2014).

Some common input and output factors are summarized in **Table 1**. It is obvious that there are major differences between the various factors when it comes to ease of measurement and use. This may potentially explain why most EROI studies only cover direct energy inputs, embodied energy inputs, and direct energy outputs (Hall et al., 2014; Chen et al., 2017b). Though the concept of entropy is broader than energy, it cannot

**TABLE 1 |** Common input and output factors for EROI analyses.

| No. | Input factors | | No. | Output factors | |
|---|---|---|---|---|---|
| 1 | Direct energy | | 1 | Direct energy | |
| 2 | Embodied energy | Material | 2 | Coproducts | |
| | | Equipment | | | |
| | | Infrastructure | | | |
| | | ...... | | | |
| 3 | Resource | Land | 3 | Social consequences | Jobs |
| | | Water | | | Maintenance of rural communities |
| | | ...... | | | ...... |
| 4 | Labor and technology | | | | |
| 5 | Ecological service (Environmental) | Carbon emissions | | | |
| | | Habitat | | | |
| | | ...... | | | |
| 6 | Auxiliary services | | | | |
| 7 | Time | | | | |

measure all the factors listed in **Table 1** using a single unit. The factors are multidimensional, whereas energy is a one-dimensional standard. This demonstrates the deficiency of trying to uniformly quantify the various input and output factors as simple energy units.

For EROI to accurately measure net energy, it is necessary to calculate all energy input and output factors as correctly as possible. However, this is quintessentially the same as the argument that to maximize economic benefits, economic evaluation methods for energy resource exploitation use economic benefits as a sole criterion and leave out other non-economic factors such as energy efficiency, environmental impacts, which has been criticized by EROI scholars (Hu, 2013; Chen et al., 2017b). The various kinds of input and output factors listed in **Table 1** cannot be fully represented by net energy alone. This implies that EROI does not account for the importance of other factors, such as land, water, labor, and technology. Energy is the most basic and indispensable resource for the development of human society, but that does not mean as long as there is enough energy, it can produce, renew or restore other input factors correspondingly. For example, less than one square mile of the 296 square miles of land that has been disturbed by tar sands development in Alberta of Canada has been certified as reclaimed. Struzik (2014), it is almost impossible to recreate a wetland that takes thousands of years to form. Although the land petroleum industry has reclaimed may look good in newspaper, magazine, and television advertisements, it is not the original wetland-rich landscape that was dominated by forest and shrubby fens. In theory, the calculation of EROI should include all kinds of factors, as energy resource exploitation entails even more input and output factors than those listed in **Table 1**. However, we must recognize the limitations of EROI, and future EROI research should acknowledge this rather than attempting to quantify and compare all kinds of input and output factors as energy units.

## CONCLUSION

Essentially, EROI is a method of using entropy theory to evaluate energy resource exploitation. An energy resource exploitation system acts as a bridge between a social system and natural energy resources. It can be considered a dissipative structure system as it has the characteristics of being an open system that is far from a state of equilibrium state and that entails nonlinear interaction mechanisms and continuous fluctuation. In terms of energy resource exploitation activities, both EROI and entropy theory focus on the input and output of useful value and on a comparative analysis from a physical point of view. In an EROI analysis, net energy is the real contribution of an energy resource exploitation system, whereas net energy is representative of the total entropy change in the entropy analysis. Entropy has a more general significance, as it can also explain processes such as carbon emission and water consumption. However, it may appear more abstract, less comprehensible, and more difficult to quantify than energy. The focus of EROI is the flow of energy in energy resource exploitation. Thus, EROI is essentially a method of applying entropy theory from an energy perspective.

It is inappropriate and unnecessary to quantify all factors as energy units. The input and output factors involved in energy resource exploitation are multidimensional, whereas energy is a one-dimensional standard. Recognizing this limitation can advance research on the EROI methodology. Future development of the EROI method should be guided by entropy theory. Juxtaposing some important factors with energy or focusing on the use value of energy may be promising new research directions. For example, Huang et al. (2019) have come up with EROC and EROW, and Chen et al. (2020) have proposed ExEROI.

Energy return on investment leads to the loss of many meaningful information because of the data is aggregated into a simple ratio (González-López, 2021), but EROI is not useless for policy. EROI is a method to reveal the law of energy flow in energy exploitation activities. After establishing a series of EROI related indicators, the application and policy significance of EROI will increase. Along with net present value (NPV), EROI should be considered when evaluating the feasibility of energy resource exploitation projects. Physical indicators, such as EROC and EROW, should be further developed, especially against a background of low-carbon energy transformation. Further research is required on methods such as EROI, EROC, and EROW, as they can play an important role in optimizing the path of energy substitution. Although we establish a useful framework for energy resource exploitation, it does simplify some details. For instance, it does not distinguish between feedstock and processing energy. However, this study mainly focuses on theory and method analysis. Future research on the topic should include case studies. Another avenue for further study would be to address how the standard EROI method and related auxiliary indexes could be improved.

## 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 authors.

## AUTHOR CONTRIBUTIONS

YH: methodology and funding acquisition. YC: conceptualization, methodology, and writing – original draft. ST: methodology and funding acquisition. LF: supervision. CH: methodology. All authors contributed to the article and approved the submitted version.


## FUNDING

This study was supported by the Doctors Start Funding Projects (No. BS201902) of Shandong Technology and Business University, the National Natural Science Foundation of China (No. 72004122/71874202/71874201/71903114), the National Social Science Fund of China (No. 15BJY052), and by the STandUP for Energy Research Initiative. Science and Technology of Sinopec Group Foundation (No. P18055-2).


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