frontiers | Frontiers in Ecology and Evolution

TYPE Original Research
PUBLISHED 24 April 2023
DOI 10.3389/fevo.2023.1122682

OPEN ACCESS

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SPECIALTY SECTION
This article was submitted to Environmental Informatics and Remote Sensing, a section of the journal Frontiers in Ecology and Evolution

RECEIVED 13 December 2022
ACCEPTED 16 February 2023
PUBLISHED 24 April 2023

CITATION
Ding J (2023) Design of a low carbon economy model by carbon cycle optimization in supply chain.
Front. Ecol. Evol. 11:1122682.
doi: 10.3389/fevo.2023.1122682

Design of a low carbon economy model by carbon cycle optimization in supply chain

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Introduction: Concerning economic globalization, enterprises must work with the cooperative partner to obtain more profits and overall planning of the supply chain has become a new focus for enterprise development. This paper studies the joint emission reduction of the supply chain in green low-carbon economy development and achieve joint emission and economic cost reduction through the optimization of carbon emission and economic dispatch.

Methods: The paper firstly uses the multi-agent model to complete the fullcycle modeling of carbon emission and economic cost; Secondly, the simulated annealing-adaptive chaos-particle swarm optimization (SAACPSO) method is used to optimize various parameters in the model to achieve emission and cost reduction

Results: The results show that after the optimization, the economic cost is reduced by 0.07 and the carbon emission is also reduced by 0.16; Finally, the practical test of the model is conducted with the collected data from the local company. The results show that the multi-objective optimization model of a joint enterprise supply chain is significantly better than single optimization in terms of emission reduction.

Discussion: It provides new ideas for a green economy and technical support for the global planning of supply chain integration.

KEYWORDS

carbon emission reduction, supply chain carbon optimization, economy dispatch, PSO optimization, economic development

1. Introduction

With the deterioration of the environment, the greenhouse effect has become an important issue that hinders sustainable economic development. Balancing economic development and environmental protection has become an important issue for all countries across the world (Golpîra and Javanmardan, 2022) "Carbon peaking" and "carbon neutrality" have emerged, and various countries have responded to develop low-carbon economies. At present, the main sources of carbon emissions are developing countries, which have a late start in carbon trading, backward industrial structure, and insufficient linkage between various links, resulting in more unnecessary carbon emissions in their trading process (Eslamipoor, 2023). Therefore, promoting research and development (R&D) in low carbon technology innovation in developing countries is vital to achieving a low carbon economy. While some new low-carbon emission reduction technologies require continuous large-scale investment, which leads to high costs. This requires the government to mobilize enterprises by providing them with subsidies for R&D and to guide their investment toward the optimal level that can be achieved. According to the experience of developed countries, government carbon subsidy policy has a great influence in promoting enterprises to conduct R&D and promote emission reduction technologies (Chen et al., 2018).

In addition to strengthening government subsidies and supervision, enterprises should also fully combine their own characteristics to actively adjust their strategies to achieve low-carbon economic development. In today's globalized economy, the development of each enterprise does not rely on its own, but needs more cooperation through a large number of supply chain enterprises. How optimize each part of the supply chain to realize the maximum economy and minimum carbon emission simultaneously is the final goal (Tully and Winer, 2014). Each enterprise in the supply chain is interdependent. It is a chain structure that integrates business flow, logistics, capital flow, and information flow. It integrates procurement, manufacturing, and distribution, and creates value for the end customer. Therefore, it is essential to optimize each link in the supply chain through smarter means. With the continuous development of computer science, complete deductive reasoning of the carbon emission process through mathematical modeling has become possible (Heiskanen et al., 2010). Using artificial intelligence techniques to quantify the various links in the supply chain using supervised, semi-supervised and unsupervised learning (Fritzke, 1994; Le et al., 2013) methods to form intelligent models makes it possible to save energy and reduce emissions. In the economic scheduling process of low-carbon development of an enterprise's multiple supply chains, the overall process is shown in Figure 1, and it can be seen that the process can be abstracted as a regression problem based on multi-source data fusion, with the ultimate purpose of achieving low-cost while minimizing carbon emissions. Therefore, supervised learning using a large amount of historical data to achieve an artificial intelligence-based (AI) classification model is a key to solving this kind of problem, which is also the current development trend of the smart economy and green economy. The optimization of model parameters by meta-heuristic algorithm after the model is built is the key to further improving the model performance and generalization.

The external factors mainly considered in the modeling process include the policies of relevant government subsidies and department regulations. Internal factors mainly include supply chain deployment, including personnel deployment and product transportation. Efficient economic dispatch and low-carbon development can be achieved through joint analysis of internal and external factors (Rezaee et al., 2017). There are many factors involved in the establishment of the model. How to quantify these contents and determine the optimization of its internal parameters to achieve an efficient allocation of each link is the focus of research on the establishment of a low-carbon economy smart model.

Therefore, this paper investigates the cooperation strategy and economic scheduling model of supply chain enterprises. After completing the modeling of enterprise economic scheduling and carbon emission by the multi-agent method, the model optimization is completed by meta-heuristic algorithm to improve the enterprise supply chain management and achieve the win-win situation of reducing carbon emission and lowering economic cost. The specific contributions of this paper can be concluded as follows.

(1) In this paper, the multi-agent method is used to improve the traditional carbon emission model to achieve the establishment of the model with the optimization goal of enterprise carbon emissions and economic scheduling.
(2) The optimization of model parameters was achieved based on the SA-ACPSO method, and results showed that the model performance was substantially optimized.
(3) After the optimization of the model, a practical test was also conducted, and the results showed that the model can optimize the carbon emission and economic scheduling of the operation of the enterprise, to reduce the operating cost and reduce carbon emission at the same time. Results showed that the economic operating cost was reduced by 0.07 and carbon emission was reduced by 0.16 after the optimization.

The remainder of the investigation is organized as follows. In section 2, the related works for the carbon emission reduction and model construction methods are introduced, section 3 introduces the methods used, section 4 describes the experiment and result analysis of model optimization, where the model application is also discussed. In section 5, we discuss the result and the notice that should be paid in the enterprise development and carbon concerning the supply chain.

2. Related works

2.1. Research on carbon cooperative emission reduction

Concerning low carbon economy, it is vital to ensure the low carbon emission of the supply chain for its future market development and supply chain green schedule. However, low carbon scheduling is not easily achieved by itself and requires the cooperative efforts of several enterprises and sectors. Ji et al. (2017) studied the online to offline (O2O) supply chain in a low-carbon environment and found that the government is the key. Liu et al. (2021) explored the possibility of cooperative emission reduction in agricultural supply chains through game theory and found that the environment can be protected when a centralized supply chain is established. Li et al. (2021) investigated the joint emission reduction problem of government

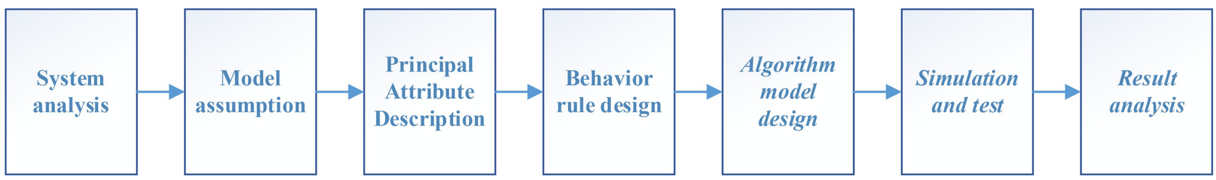

FIGURE 1
The framework for the construction of the economic dispatch model.

subsidies and supply chains under the cap-and-trade mechanism. Three mathematical models considering green technology investment and two types of subsidies were developed. It was found that government subsidies do not guarantee the total amount of carbon emission reduction by firms. Compared to subsidies based on the cost of green investments, subsidies based on emission reductions have greater emission reductions, but also larger total carbon emissions. Fang et al. (2012) compared the effects of two types of emission reduction subsidies, product innovation subsidies, and R&D subsidies, on the profits and social welfare levels of supply chain firms. Product innovation subsidies were found to be more likely to motivate firms to invest in R&D and enhance total social welfare. Both government subsidies are found to lead to supply chain coordination, especially for low-carbon technology subsidy policies. Peng et al. (2018) investigated the impact of cap-and-trade policies on supplier and manufacturer supply chain systems. They considered the impact of uncertainty on manufacturers' production capacity to improve system performance. Sun et al. (2020) studied the transfer of carbon emissions between suppliers and manufacturers and considered the lag time of green technology and consumer green awareness. Chen et al. (2018) indigenized emission reduction subsidies into a research joint venture and derived an equilibrium strategy for the level of innovation effort and cost-sharing rate.

According to the above study, it is not difficult to find that in the current low carbon research of enterprises, from the supply chain of enterprises and market product sales, multi-faceted efforts to achieve carbon reduction and environmental protection in the whole cycle of enterprises is the current consensus reached by the academic and business sectors.

2.2. The research on the carbon reduction model and optimization

In the theoretical research, the scientists established the relevant theoretical model fundamentally by analyzing the low-carbon behavior of enterprises in an all-around way. Du et al. (2015) analyzed the possibility of coordination and cooperation between manufacturers and suppliers to reduce emissions under aggregate control and emissions trading policies. Huang et al. (2016) proposed a game model with multiple suppliers. They apply GA (generic algorithm) to maximize the profit of each party and minimize the manufacturer's carbon emissions. For the emission reduction strategy, by constructing a cooperative emission reduction revenue allocation scheme, Wang et al. (2019) gave the emission reduction revenue allocation coefficients and the initial revenue allocation matrix of each subject in the region to improve the cooperation of entities in emission reduction. In addition, the role of carbon cap-and-trade policies is also discussed. For more complex engineering problems, intuitive representation through multi-Agent modeling approaches has become a focus of current research. Multi-Agent approaches have a wide range of applications (Ajitha et al., 2009), which include the stock markets prediction and epidemics spread model, and the range can be expected from small model simulations to large decision support systems. Models are based on a set of idealized assumptions designed to capture the most salient features of the system (Musa et al., 2015). Also, methods based on multi-objective regression and parameter optimization have important applications in low carbon emission reduction models, and such problems are ultimately accomplished by multi-objective optimization regression using machine learning (Wang and Chen, 2020), deep learning (Lee and Shin, 2019) and statistical learning methods to form appropriate carbon cycle models and optimize their parameters have become the focus of research in such work. As a class of multi-objective regression problems, how to improve the parameter generalization and complete the corresponding parameter modification to enhance the model capability becomes the focus. In the current research on model parameter optimization, the use of metaheuristic algorithms, i.e., GA methods, PSO, and other methods have some advantages in the optimization of model parameters due to their simplicity and low computational load. Soumaya et al. (2021) collected the speech of Parkinson's patients, Alzheimer's disease, and depression patients by processing the speech signals into a dataset and optimized the important parameters of support vector machines using genetic algorithms with recognition accuracy 91.18%. Wang et al. (2022) used PSO to improve SVM (support vector machine) parameters based on grid search and K-fold crossover and did prediction on the heart disease standard dataset of UCI and got 84.04% accuracy. Through the above research, it can be found that for the emission reduction analysis based on supply chain scheduling, the optimization of the model is generally completed by considering environmental factors, supply chain factors, and the market behavior of related enterprises to achieve efficient economic scheduling and carbon emission reduction of the supply chain. The multi-agent method is used to realize the modeling of observable data, quantify, and confirm these parameters, and through an intelligent algorithm optimization model, transform it into a traditional multi-objective regression model for parameter optimization, to efficiently complete the win-win of enterprise economic scheduling and carbon emission reduction.

3. The economic dispatch model construction using the supply chain information

3.1. Multi-agent model establishment

The basic model used in the modeling process of this paper is based on the multi-agent supply chain enterprise carbon emission model, which is a system model that follows the multi-agent-based model framework shown in Figure 2 and is completed with improvements based on the existing standing model[1] (Cucuzzella, 2017). The SA-ACPSO method in Section 3.2 is used for optimization to complete the final use of the model. If building the model, the main factors concerned can be abstracted into two goals, namely, the lowest cost and the lowest carbon emissions. The objective function can be expressed as

$$F(t) = \min \sum_{t=1}^{T} \left(F_1(t) + F_2(t) + F_3(t) + F_4(t) \right) \quad (1)$$

1 https://github.com/LantaoYu/MARL-Papers

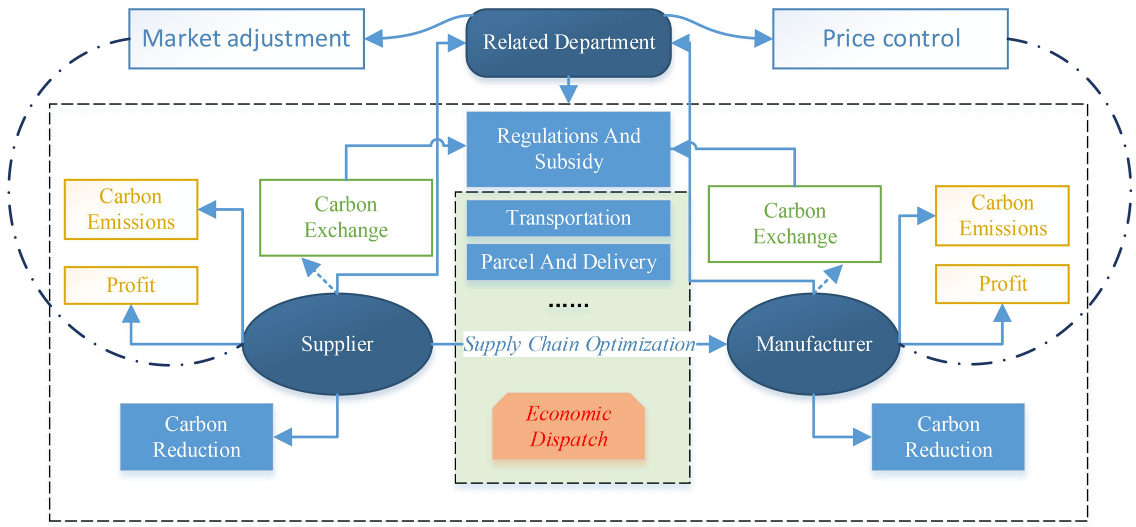

FIGURE 2
The dispatch in the low-carbon economy.

$$F_{EP}(t) = \min \sum_{i=1}^{r} \left(\sum_{k=1}^{M} C_k \left(\sum_{i=1}^{N} r_{ik} P_i(t) + ar_{grikl} Q_{buy}(t) \right) \right) \quad (2)$$

In the lowest cost objective function, there are four terms, which correspond to the transportation costs and production scheduling costs at the relevant suppliers and manufacturers in Figure 2, while the latter carbon emission function is a further refinement of the carbon emission-related coefficients, including factors such as fuel consumption in transportation and production carbon emissions. Taking $F_2(t)$ in production scheduling as an example, it is calculated as shown in Eq. (3).

$$F_2(t) = \sum_{i=1}^{n} k_i P_i^t \quad (3)$$

where k indicates the specific link of the product in the supply chain, P indicates its corresponding equipment consumption parameters, and n is the total number of equipment links. Through intelligent scheduling, reducing carbon emissions and costs can be achieved, so the optimization of carbon emission function also considered the optimization of equipment consumption parameters. On this basis, the impact of environmental factors and policy-oriented factors on the model should be considered. It can be found that the established model has a large number of parameters and its own adjustment ability is not strong, so it is urgent to introduce intelligent optimization methods to complete the optimization of the model.

3.2. Model optimization using SA-ACPSO

Considering machine learning and deep learning, the model itself often falls into the problem of locally optimal solutions, which also occurs in multi-agent-based modeling. In the process of model building, if the initial values are not selected properly, the algorithm will converge to the local extremes, which greatly reduces the prediction performance of the model. The commonly used method for the model optimization is the meta-heuristic algorithm like the GA and PSO (Agushaka et al., 2022a). Some scientists proposed the new metaheuristic method based the classic ones (Agushaka et al., 2022b). The SA-ACPSO method is an improvement of the traditional PSO method, which is shown in algorithm 1 (Qian et al., 2009).

PSO algorithm
1. Coding and random particles generation
2. Fitness calculation of each particle
3. The particles replicate according to fitness
If the condition is met, it will be terminated. Otherwise, go back to step 2

The specific algorithm flow is shown below, first defining the number of particles in the particle swarm and their corresponding characteristic parameters.

$$P_j = \left[C_j \varepsilon_j \sigma_j \right] j = 1,2,..,Q \quad (4)$$

Performing random initialization of the particles after the definition is complete. Then let the particles be updated. Each particle in the kth iteration is defined by three characters (1) the position in the search space $P_j(k)$; (2) the best position during iterations 1 ~ k, $P_{jbest}(k)$; (3) the flight speed $V_j(k)$.

Furthermore, the global optimal position of the whole particle swarm is defined as $P_{jbest}(k)$, then each particle is iteratively updated during the flight as a function of the velocity V_j and the position P_j is defined. The process for the PSO update can be expressed as follows:

$$a(k) = (a_{\max} - a_{\min}) \left(\frac{k}{K} \right)^2 + a_{\min} \quad (5)$$

$$c_1(\mathrm{k}) = (C_{1\max} - C_{1\min})\left(\frac{k}{K}^2\right) + c_{1\min} \tag{6}$$

$$c_2(k) = (C_{2\min} - C_{2\max})\left(\frac{k}{K}^2\right) + c_{2\max} \tag{7}$$

$$v(k+1) = \alpha(k)v_j(k) + c_1(k)r_1\left[P_j(k) - P_{jbest}(k)\right] + c_2(k)r_2\left[P_j(k) - P_{gbest}(k)\right] \tag{8}$$

$$P_j(k+1) = P_j(k) + v_j(k+1) \tag{9}$$

where $\alpha(k)$ is the inertial variable, $c_1(k)$ and $c_2(k)$ are the acceleration factors representing the self-cognitive and social-cognitive parameters, respectively, r_1 and r_2 are the two random variables randomly distributed between 0 and 1, and K is the maximum iterations. It should be noticed that the speed and position of the particles are determined by the optimal position of the individual P_{jbest} and the global optimal position of the whole particle population P_{gbest}. To better increase the population diversity and improve the probability of the global solution can be achieved by introducing the simulated annealing operator SA, which can probabilistically avoid the local optimal solution and converge to the global optimal solution. In this paper, a chaos factor is added to the SA-ACPSO algorithm (Narayanan et al., 2020), which is calculated as shown in Eq. (10).

$$z_{n+1} = \mu z_n(1 - z_n), n = 0,1,2\ldots \tag{10}$$

The chaotic state regulation of the model is accomplished through the control variable μ. The chaotic algorithm is shown in the *Chaos Algorithm*.

Chaos algorithm
1. Select an initial value in the interval [0,1] and substitute it into the Eq. (10) for iteration
2. Generate chaotic random sequence $Z = a_1, a_2, a_3 \ldots$
3. Then, the optimization variable X is obtained by mapping $Z \to x : x = a + (b - a)$
4. $x \in [a,b]$

The overall process of model parameter optimization through the SA-ACPSO method is shown in Figure 3.

First, initialize the parameters, then randomly generate the particle velocity and position, and then evaluate the particle fitness. When the fitness is less than the average value of the objective function at the moment, update the particle position, otherwise record the individuals with poor fitness. After updating the particle speed and position, judge whether the particle is in the definition domain. If not, judge whether the maximum number of iterations is reached. If not, return to step 3. If the maximum number of iterations is reached, the output is the current optimal value.

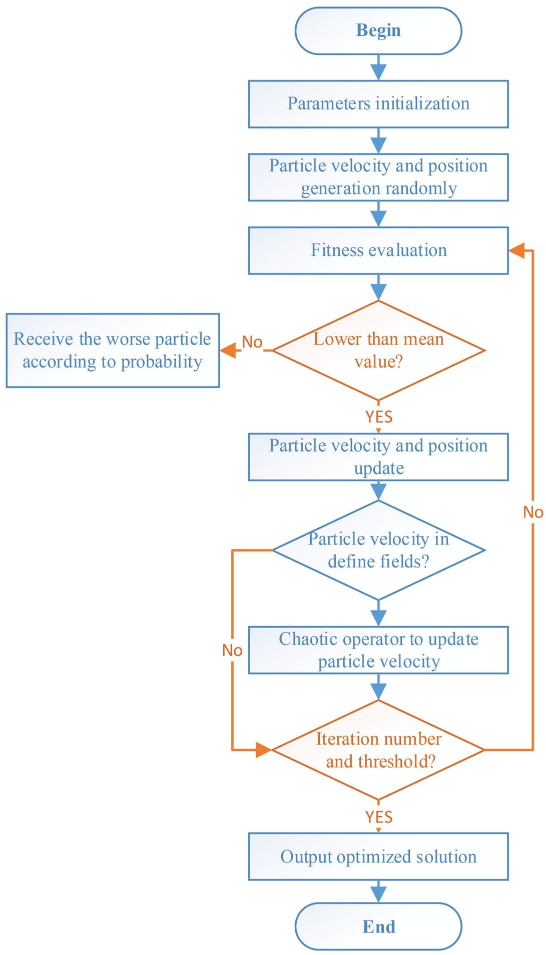

FIGURE 3
The flow chart of the model optimization using the SA-ACPSO.

4. Experiment and result analysis

4.1. The result of the economy dispatch and carbon reduction

According to the model described in section 3.1, the inputs and outputs are normalized according to the characteristics of the data at this stage when building the model in this paper. After completing the corresponding parameter optimization according to the existing low-carbon model, the effect of this paper is tested, and the results are shown in Figures 4, 5.

Figure 4 shows the economic cost effect before and after the optimization using the proposed optimization algorithm. The economic cost is reduced after the optimization of economic dispatch by this method, and the economic cost is reduced for each quarter. Similarly, for carbon emissions, after optimizing

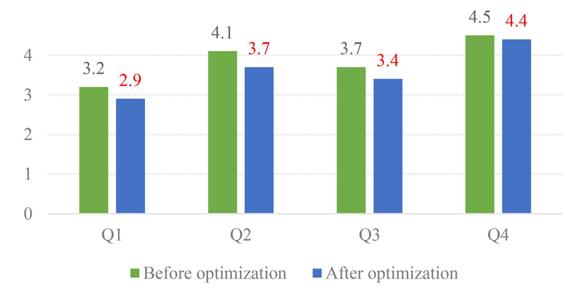

FIGURE 4
The economy cost effect before and after the model optimization.

TABLE 1 The economy cost and carbon reduction ratio.

Quarter	Economy cost reduction ratio	Carbon emissions reduction ratio
Q1	0.09	0.13
Q2	0.10	0.17
Q3	0.08	0.18
Q4	0.02	0.18

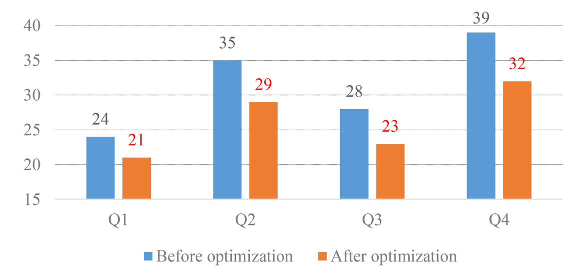

FIGURE 5
The carbon emissions before and after optimization.

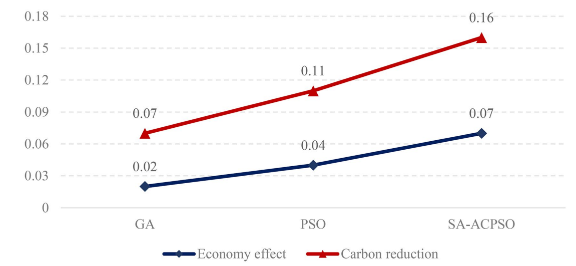

FIGURE 6
The economy effect and carbon reduction using different optimization methods.

the scheduling parameters, the results have achieved the expected effect and carbon emissions have been reduced to a certain extent.

As seen in Table 1, after the optimization of the model's scheduling, its carbon emissions and economic costs in each quarter show a trend of reduction. Amount of carbon emission reduction is more obvious, which provides a reference basis for the future green development of enterprises and their corresponding supply chain enterprises.

4.2. The comparison among different methods

To better illustrate the optimization effect, method comparison experiments were conducted in which a GA method of the same class as the PSO method was selected for comparison, the traditional PSO method without the addition of chaotic methods and annealing operators was tested, and the economic cost reduction rate and carbon emission reduction rate were compared, and the results are presented in Figure 6.

In this paper, the average reduction ratio is selected to illustrate the comparison process, i.e., the data from Q1-Q4 are averaged for comparison. The comparison results in Figure 6 show that the GA method performs an average in model optimization, while PSO is slightly better, but both are lower than the method proposed. It can also be seen that the optimization of carbon emissions is better than the optimization of economic costs for all types of methods. The problem of higher carbon emissions persists in the whole cycle of the supply chain, which needs to be further explored and illustrated in future research.

4.3. Model test and application

To test the effectiveness of the optimization model proposed, the test was conducted based on historical data of the relevant companies in the region and compared with their historical economic costs and carbon emissions, etc. The framework for the model test is shown in Figure 7.

The historical data are first inputted according to the model requirements, and the optimized model is used to optimize the economic dispatch and carbon emission reduction, and the obtained data are uploaded to the enterprise expert panel for evaluation, and the contemporaneous historical data are provided for reference. To illustrate the role of the proposed method more accurately in the joint emission reduction of enterprises, i.e., multi-objective cooperation and full-cycle optimization, we give the emission reduction effects of enterprises under different cooperation scenarios during the testing process as shown in Figure 8.

It can be found that the reduction effect is not obvious when they only reduce emissions individually, and although there is a certain reduction of carbon emissions in each quarter, it is not as good as the joint reduction effect. This is because after the optimization of model parameters, through the control and optimization of global variables, all industries form a unified whole in the whole cycle. The multi-directional scheduling of the upstream and downstream industrial supply chain has better fulfilled the

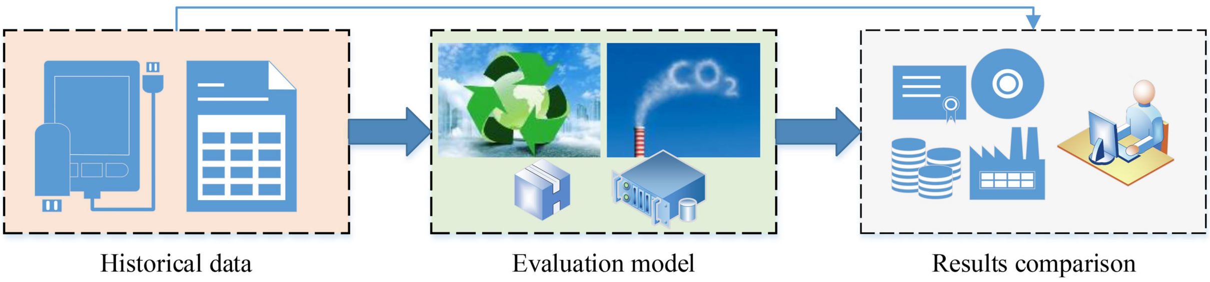

FIGURE 7
The framework for the economy dispatch application test.

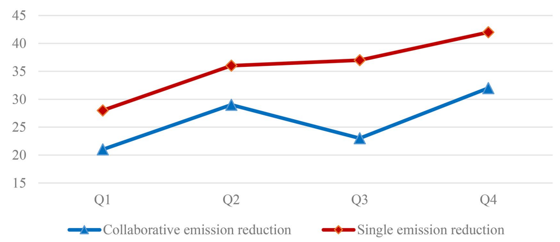

FIGURE 8
The carbon reduction in the different emission ways in the test data.

low-carbon emission target, providing a reference model for more enterprises' green development.

5. Discussion

5.1. Model performance analysis

At present, there are many factors involved in carbon emissions and enterprise supply chain scheduling. It is difficult to fully quantify them to achieve parameter optimization and complete strategy optimization through a neural network or machine learning. First of all, the influence factors of parameter selection on the enterprise are unknown (Dhiman and Kumar, 2017). On the other hand, because many parameters in the neural network are difficult to explain, it is difficult to apply them in practice. Therefore, this paper selects the multi-agent method, which is widely used in complex system modeling. To optimize the relationship between each link in the model promotion model, this paper uses the SA-ACPSO method to optimize accordingly. The SA-ACPSO algorithm mentioned in this paper combines the simulated annealing operator and the mixed pure perturbation based on PSO and makes particles increase their randomness and ergodicity through chaotic mapping, which can improve the ability of the algorithm itself to avoid local convergence, which is, improve the global convergence performance (Singamaneni et al., 2022). In order to better conform to and adapt to the characteristics of the multi-objective and multi-constraint of the economy scheduling problem, the inertia weight of particles will be adjusted before scheduling, which can enable the algorithm to expand the search scope at the initial stage. The optimization can also improve the accuracy of solution seeking at the later stage of solution seeking, optimize the solution seeking efficiency.

5.2. Inspiration from supply chain emission reduction

The industrialization has accelerated the pace of economic development, but it has also brought about an environmental crisis and resource shortage. To solve the "greenhouse effect" in the environmental crisis, a low-carbon economy is the best solution, in which the government plays an indispensable role and needs to actively guide enterprises to make energy-saving and sustainable development of the circular economy as the new development goal in the future (Chung et al., 2013). A low carbon economy can reduce carbon emissions to the lowest possible level or zero in production and life, and maximize ecological and economic benefits, which can be equated with the concept of Green (De Giovanni, 2014). The low-carbon supply chain advocates the concept of low or even zero emissions and promotes the green concept in the whole closed loop of raw material procurement-design-production-delivery-support of the company, to achieve the maximum sustainable development with the minimum environmental sacrifice (Ahmad et al., 2022). The internal and external influences of the supply chain jointly affect the emission reduction behavior of supply chain companies. For suppliers, regardless of the external environment, reducing the cost is a core, so it is necessary to make both or more parties reduce the cost of emission reduction through cooperation. For manufacturers, are more influenced by external factors (carbon regulation, market preferences for low carbon) and need to cooperate to reduce carbon abatement costs in addition to cooperating to better exploit carbon regulation and market preferences to avoid penalties. Under different scenarios, the choice of strategies will vary under different preferences of firms. When the market preference for low carbon is strong and government subsidies are strong, the abatement full cooperation strategy is optimal if firms focus more on low carbon, and the abatement technology and knowledge sharing strategy is optimal if firms focus more on profit. If the market's low carbon preference is general and the government's emission reduction subsidy is moderate, if the cooperation coefficient is found, the complete cooperation strategy for emission reduction is optimal. When the market is not low carbon biased and the government does not have low carbon subsidies, the emission reduction technology and knowledge-sharing strategy are optimal. Therefore, subsidies and policies of relevant government departments cannot fundamentally solve the problem of optimal scheduling and carbon emissions in all links of the supply chain, and enterprises need to be reformed from within by more intelligent means to achieve efficient operation.

6. Conclusion

As required by the low carbon economy development, we give an integrated method for the supply chain. This paper researches the problem of emission reduction optimization and efficient economic dispatch of enterprise supply chain in the context of low-carbon economy and proposes an SA-ACPSO method to optimize the model built based on multi-Agent method, which reduces carbon emissions by 0.16 and economic costs by 0.07, helping enterprises to reduce carbon emissions and corresponding operating costs. In the comparison of optimization methods, the SA-ACPSO method in this paper is significantly better than the GA method and single PSO method, which greatly improves the model performance. In the actual test, this paper analyzes the historical data of enterprises and finds that the joint emission reduction performance is significantly better after the integrated management of the supply chain. From the these results we can draw that the optimization for supply chain using the AI-based methods can greatly reduce the human work and improve the efficiency. The new ideas for the carbon-neutral can be got from the research,

However, the relationship considered in this study is relatively simple, and the competition relationship and environmental impact in supply chain enterprises is not considered, which often makes the model more complex and should be considered in the future. At the same time, it is the future research focus and direction to form corresponding model paradigms for specific industries to help them achieve win-win results in economic development and carbon emission reduction.

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.

Ethics statement

This study was approved by the Faculty of Business, Monash University. The participants provided written informed consent to participate in this study.

Author contributions

JD contribution lies in the writing of the first draft, data analysis and sorting experimental ideas and method design.

Acknowledgments

The author would like to thank the reviewers whose comments and suggestions helped improve this manuscript.

Conflict of interest

The author declares 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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