Mixed Integer Programming Model Based on Data Algorithms in Sustainable Supply Chain Management

Shaobin Dong[1]*, Aihua Li[2]
Faculty of Business, Huaiyin Institute of Technology, Huai'an, 223001, China[1]
Faculty of Electronic and Information Engineering, Huaiyin Institute of Technology, Huai'an, 223001, China[2]

***Abstract*—With the deepening of globalization and increasing demands for environmental sustainability, modern supply chains are faced with increasingly complex management challenges. To reduce management costs and enhance efficiency, an experimental approach is proposed based on a Mixed Integer Programming Model, integrating heuristic algorithms with adaptive genetic algorithms. The objective is to improve both the efficiency and sustainability of supply chain management. Initially, the selection of suppliers within the supply chain is analyzed. Subsequently, heuristic algorithms and genetic algorithms are jointly employed to design, generate, and optimize initial solutions. Results indicate that during initial runs on training and validation sets, the fitness values of the research method reached as high as 99.67 and 96.77 at the 22nd and 68th iterations, respectively. Moreover, on the training set with a dataset size of 112, the accuracy of the research method was 98.56%, significantly outperforming other algorithms. With the system running five times, the time consumed for supplier selection and successful order allocation was merely 0.654s and 0.643s, respectively. In practical application analysis, when the system iterated 99 times, the research method incurred the minimum total cost of 962,700 yuan. These findings demonstrate that the research method effectively minimizes supply chain management costs while maximizing efficiency, offering practical strategies for optimizing and sustainably developing supply chain management.**

Keywords*—*Mixed Integer Programming Model; sustainable; supply chain management; heuristic algorithm; adaptive genetic algorithm

I. Introduction

As environmental issues and social responsibilities become increasingly prominent, enterprises must consider not only economic benefits but also the long-term impacts of their operations on the environment and society. Sustainable supply chain management has become an integral part of corporate strategies, demanding that companies maintain supply chain efficiency and cost advantages while also considering environmental protection and social responsibility [1-2]. The complexity of supply chain management arises primarily from multi-stage coordination and the handling of numerous decision variables [3]. Against this backdrop, traditional supply chain management approaches often prove inadequate when faced with growing market demand fluctuations and environmental sustainability requirements, necessitating reevaluation and optimization [4]. Therefore, leveraging modern technologies and algorithms to enhance the flexibility and adaptability of supply chains while achieving environmental and social sustainability goals has become a pressing issue. Data algorithms, particularly Mixed Integer Programming Models, offer new solutions for supply chain management due to their efficiency and precision in addressing complex decision-making problems [5]. These models effectively integrate and coordinate various elements within the supply chain, such as supplier selection, product manufacturing, and finished product consumption, while considering factors like time, resources, and environmental impact. However, relying solely on Mixed Integer Programming Models is insufficient to address all complexities of supply chain issues, especially in large-scale problem-solving and real-time decision optimization. To better address these challenges, the experiment incorporates heuristic algorithms and adaptive genetic algorithms (GA) to jointly enhance the Mixed Integer Programming Model, aiming for a more comprehensive and profound resolution of optimization issues in supply chain management. The aspiration is to provide new perspectives and methods for sustainable supply chain management, assisting enterprises in pursuing efficiency while also achieving environmental protection and social responsibility objectives.

The article is mainly divided into five sections. Section II is a literature review, which mainly analyzes and summarizes the relevant research at home and abroad. Section III is the research method, which analyzes the selection problem of the supply chain in supply chain management, and then uses an interactive product order and supplier selection sorting method to generate the required initial solution. Finally, the adaptive genetic algorithm is used to optimize the supplier selection solution. Section IV is the research results, mainly analyzing the performance and application effects of the improved mixed integer programming method constructed. Section V is the conclusion, which mainly summarizes the content of the entire article and proposes current shortcomings and future research directions.

II. Related Work

In recent years, sustainable supply chain management has become a focal point of attention for both businesses and scholars. Sustainable supply chains not only emphasize traditional costs and efficiency but also involve balancing environmental protection, social responsibility, and economic benefits. Numerous scholars have undertaken summarizations of the design and management of supply chain networks. Researchers, such as Dwivedi et al., addressed the significant complexities between grain supply chain management at different levels and carbon emissions. They combined GAs with quantum GAs and metaheuristic algorithms to analyze the allocation of vehicles and the selection of order sets. The results indicated significantly reduced computation time and enhanced operational efficiency [6]. Sadeghi and the team proposed a novel closed-loop supply chain network approach based on a mixed-integer linear programming model to reduce transportation and management costs in the supply chain. The model covered both fleet transportation routes and locations and was validated through the production of Iranian automotive components, gaining full recognition from management personnel [7]. Manupati et al. introduced a monitoring system based on blockchain technology to comprehensively monitor changes in supply chain performance. Considering carbon emissions constraints, they treated product production, sales, and inventory levels as control factors. Compared to non-dominated sorting GAs, their method demonstrated better feasibility [8]. Isaloo and Paydar presented a supply chain network design based on a dual-objective mathematical programming model to enhance the flow of the entire sustainable supply chain. Through sensitivity analysis of weights, they found the optimal objective solution, validating the superiority of their model [9]. Mogale et al. proposed a data-driven supply chain network approach based on a mixed-integer linear programming model to improve the convenience of grain procurement and transportation in developing countries. The results showed a significant enhancement in grain transportation efficiency and cost reduction [10].

Furthermore, many scholars have conducted analyses on the design and application of Mixed Integer Programming Models. Ahmadini and academic professionals aimed to reduce the environmental impact of pollutants emitted during the preservation and transportation of products. They proposed a green supply chain network based on a multi-project multi-objective inventory model. Simulation experiments verified the practical effectiveness of the constructed method, promoting the rapid development of the manufacturing industry [11]. Researchers, including Zhang Y, addressed the prolonged time consumption in logistics distribution within the supply chain network by proposing a method based on mixed-integer nonlinear programming. The results indicated that the constructed model effectively resolves nonlinear layout optimization issues in logistics transportation [12]. Beiki H and others, in order to tackle the sustainability of supplier selection and order allocation issues, introduced an integrated approach based on language entropy weight and multi-objective programming. The method demonstrated its effectiveness in improving the relationship between supply chain practitioners and suppliers, leading to the maximization of product profits [13]. Li C and colleagues aimed to increase the adoption rate of renewable energy generator units while reducing the complexity of operational decisions. They proposed an operational method based on the MILP-GTEP model. The study extensively explored the relationship between space and time, and the superiority of the experimentally constructed method was validated through a case study from the Texas Electricity Reliability Council, significantly reducing the difficulty of unit power generation [14]. In addressing the issue of maximizing profit extraction in open-pit mining production scheduling, Rivera Letelier O and fellow researchers presented a direct block scheduling and stage scheduling method based on mixed-integer programming modeling. Data revealed that, compared to traditional methods, the average gap during boundary cutting in the experimentally constructed method decreased from 1.52% to 0.71%, demonstrating its significant superiority [15].

In conclusion, with the advancement of globalization and technological innovation, supply chain management is facing unprecedented challenges and opportunities. Despite the availability of numerous technologies and tools to address supply chain network management issues, there are still challenges, such as balancing the computational complexity and solving efficiency of algorithms. In order to enhance the efficiency of enterprise supply chain management and reduce unnecessary time consumption, an experiment proposes a Mixed Integer Programming Model based on heuristic algorithms and adaptive GAs. This model is applied to the supply chain management of sustainable enterprises, with the expectation of promoting the development of sustainable supply chain management.

III. Heuristic Algorithm and GA Algorithm Mixed Integer Programming Model for Sustainable Supply Chain Management

Considering the complexities and variability in supply chain management, especially when facing sustainability challenges, traditional optimization methods often struggle to adapt. Therefore, the experiment introduces a Mixed Integer Programming Model based on a data-driven algorithm to enhance it. This model can not only handle problems involving a large number of decision variables and complex constraints but also flexibly adapt to the dynamic changes and diverse requirements in supply chain management.

A. *Supplier Selection in Supply Chain Management*

In order to provide a clearer description of supply chain management issues, the experiment focuses on supplier selection and product cost aspects, analyzing the management of the supply chain. The study, based on the characteristics of a three-tier supply chain with manufacturing enterprises at its core, makes assumptions about supplier selection in the three-tier supply chain management: first, within the production period of the same product order, the order will not exceed the maximum capacity of total production; second, all products in the order overlap; third, there are restrictions on the maximum capacity of the corresponding manufacturing enterprises, and so on. The operations of multi-supplier supply chain management are illustrated in Fig. 1.

The ultimate goal is to minimize the number of times a supplier is selected. The variability in supplier selection in supply chain management is defined by Eq. (1).

$$e_{jkq} \geq y_{jkq} - y_{jkq-1}, \quad \forall i \in \{1, \cdots, N\}, q \in \{1, \cdots, Q\}, j \in \{1, \cdots, M\}, k \in \{1, \cdots, K\} \tag{1}$$

In Eq. (1), y_{jkq} and e_{jkq} represent binary variables. The calculation of supplier selection is then obtained, as shown in Eq. (2).

$$\begin{cases} T_j = \sum_{k=1}^{K} \sum_{q=1}^{Q} e_{jkq} \geq 0, \forall i \in \{1, \cdots, N\}, q \in \{1, \cdots, Q\}, j \in \{1, \cdots, M\}, k \in \{1, \cdots, K\} \\ T_{total} = \sum_{j=1}^{M} T_j \geq 0, \forall j \in \{1, \cdots, M\} \end{cases} \tag{2}$$

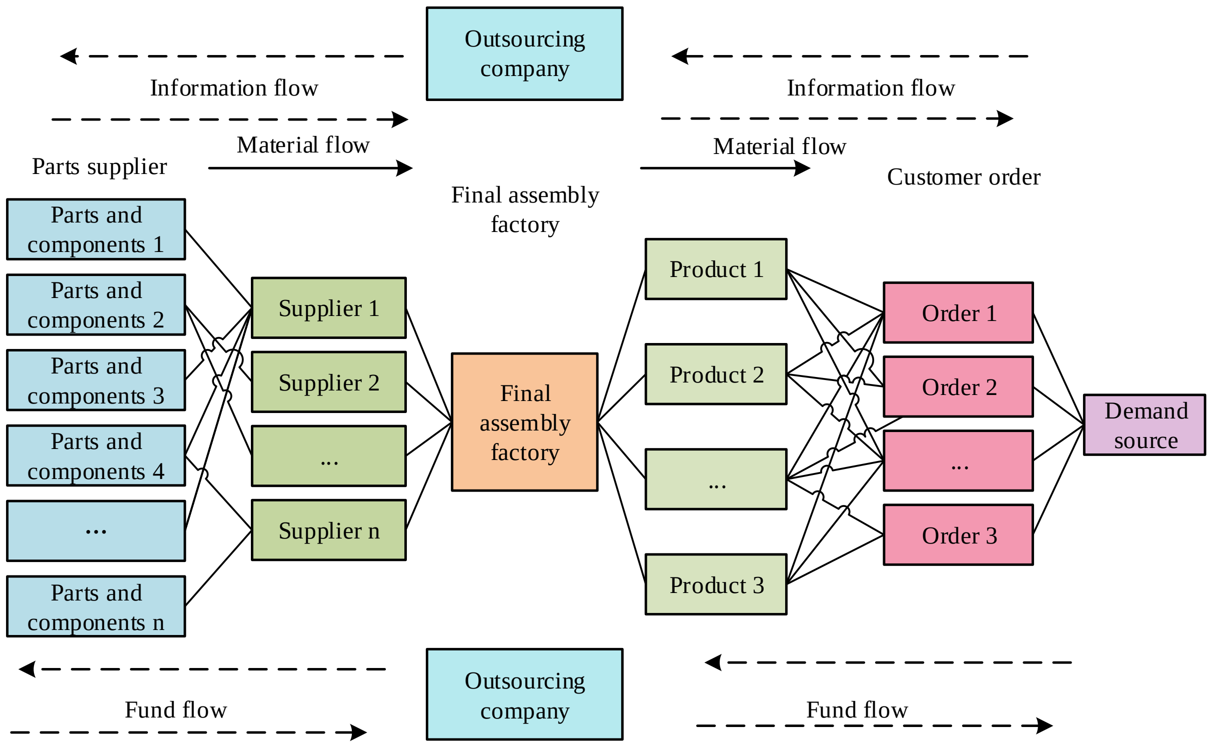


Fig. 1. Multi-supplier supply chain management operations.

In Eq. (2), T_j represents the number of times supplier j is selected, and T_{total} represents the total number of times all suppliers are selected. T_j must be above zero. In the process of supply chain management selection, these are positive integers. Considering the entire production stage, the optimization of the supplier selection frequency in the supply chain management process is achieved, and the objective function $\min_{total}$ of this mathematical model is obtained. However, selecting product suppliers to meet production orders is a highly complex problem that requires consideration of constraints on supplier selection [16]. To some extent, reducing the number of supplier selections must ensure that different products in the total production orders are supplied by at least one supplier, and the corresponding constraint is expressed in Eq. (3).

$$\begin{cases} \sum_{k=1}^{K}\sum_{j=1}^{M}\sum_{i=1}^{N} y_{ijk} \geq 1, \forall i \in \{1,\cdots,N\}, j \in \{1,\cdots,M\}, k \in \{1,\cdots,K\} \\ \sum_{j=1}^{M}\sum_{i=1}^{N} y_{ijk} \leq 1, \forall i \in \{1,\cdots,N\}, j \in \{1,\cdots,M\}, k \in \{1,\cdots,K\} \\ \sum_{j=1}^{M} B_{is} \geq \sum_{i=1}^{N} A_{is}, \forall i \in \{1,\cdots,N\}, j \in \{1,\cdots,M\}, s \in \{1,\cdots,S\} \end{cases} \tag{3}$$

In Eq. (3), y_{ijk} and B_{is} are both binary variables. Their values are 1 when the supplier can complete the corresponding task. These constraints reflect the main attributes of supply chain management, optimizing the experimental process.

B. *Initial Solution Generation Method for Supplier Selection in Supply Chain Management Based on Heuristic Algorithms*

The experimental method employs an interactive approach to generate the required initial solutions by ordering product orders and selecting supplier rankings. Initially, orders are selected and sorted according to certain patterns in the interactive process of product orders and supplier ranking [17]. To assess the fulfillment rate of suppliers for products in the k th batch, assume the relationship between supplier j and products corresponds to B_{js}, and the relationship between order i and products corresponds to A_{is}. If the products in the orders cannot be produced by the corresponding suppliers, the decision variable $B_{js}=0$. Otherwise, if production by the supplier is possible, the corresponding pointer variable $B_{js}=1$. Simultaneously, if the number of component types in products from different orders is S_i, including product s, then the corresponding pointer variable $A_{is}=1$, otherwise, $A_{is}=0$. Based on the parameters and principles mentioned above, for a product supplier M, the calculation of the fulfillment rate for the corresponding supplier's product orders is given by Eq. (4).

$$f_{ijk} = \frac{\sum_{s=1}^{S} B_{js} A_{is}}{\sum_{s=1}^{S} A_{is}},$$
$$\forall i \in \{1,\cdots,N\}, j \in \{1,\cdots,M\}, s \in \{1,\cdots,S\} \ldots \tag{4}$$

In Eq. (4), the multiplication of B_{js} and A_{is} represents the common product relationship between suppliers and orders. It can be observed that the maximum value of the fulfillment rate of products in the orders does not exceed 1. When $f_j = 1$, indicating a value of 1, all the required products for customers in the supply chain product orders can be provided by that supplier. The enterprise can freely choose suppliers in the process of management and sales. The experiment sets the supply rate of supplier j as f_{ijk} to represent the extent to which the product supplier can meet the demands of a set of customer orders. The calculation is cyclically performed on the order pool within the same batch [18-19]. By cumulatively adding the fulfillment rates of products related to suppliers in all orders, the fulfillment rate f_{jk} of the supplier providing the required products in the k th batch is obtained, as shown in Eq. (5).

$$f_{jk} = \sum_{i=1}^{N} f_{ijk} \tag{5}$$

In Eq. (5), f_j has a value range of [0, n]. After selecting the supplier with the highest product fulfilment rate, it is necessary to decide how to allocate the required quantity of these products to the corresponding suppliers. This requires an appropriate production sequence to reduce the number of supplier transports (i.e., product order selection strategy). To avoid orders being repeatedly assigned while ensuring a complete order is in a corresponding set of orders awaiting production, the supplier's set of orders awaiting production is designated as OA, with specific calculations outlined in Eq. (6).

$$OA = \left\{ O_i \middle| f_{ij} > 1, \forall j \in \{1, \cdots, M\}, i \in \{1, \cdots, N\} \right\} \tag{6}$$

In Eq. (6), OA represents the set of orders awaiting production. Additionally, due to various constraints and limitations on supplier production capacities, the production of ordered products by relevant suppliers may be significantly insufficient. To describe these constraints, the experiment introduces a new set of supplier production orders, assuming this order set is OW. The total demand value for orders in this set will not exceed the total production capacity of the factory, as detailed in Eq. (7).

$$OW = \left\{ Oi \middle| f_{ij} > 0, and \quad I_{is} \le L, \forall j \in \{1, \cdots, M\}, s \in \{1, \cdots, S\} \right\} \tag{7}$$

By comprehensively calculating the above equations, a specific method for arranging and managing supplier orders in the Kth batch is obtained. Furthermore, a feasible solution to the problem of selecting multiple suppliers in supply chain management is achieved by fixing the orders of suppliers one by one in priority order.

In Fig. 2, by analyzing the correspondence between suppliers and orders, the priority mechanism for selecting suppliers and orders is clarified. A heuristic algorithm for solving the multi supplier selection problem was developed based on this mechanism. The main process of supplier and order selection for each round of the algorithm is shown in the figure above. This heuristic algorithm can efficiently obtain an initial solution to the studied problem.

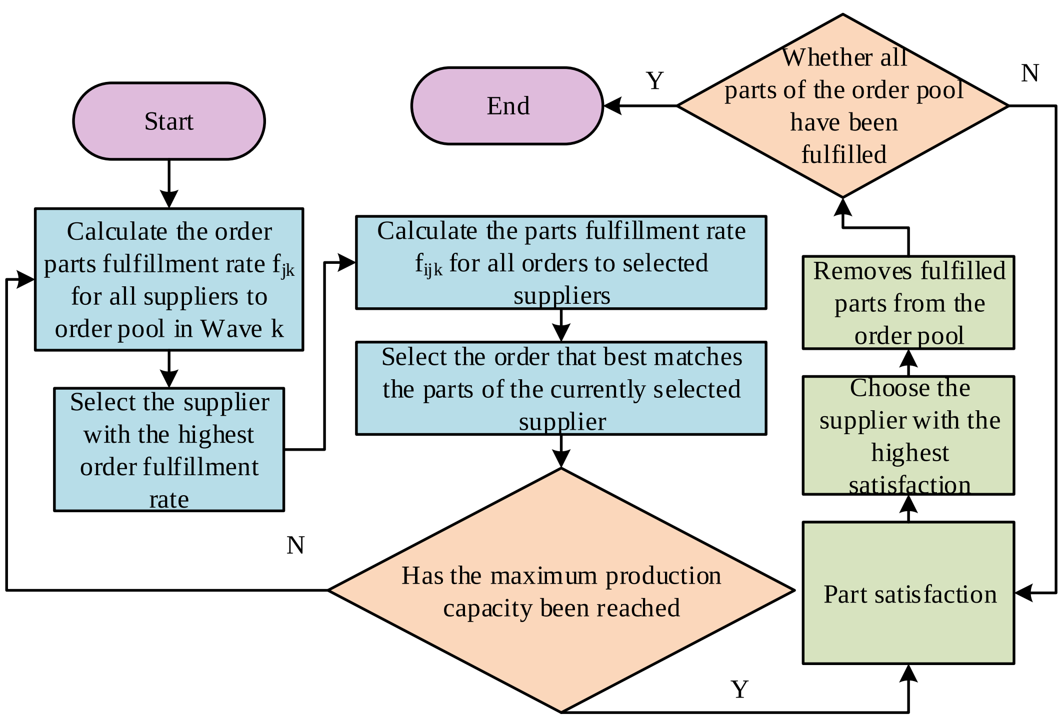


Fig. 2. Supplier and order selection method in Wave k.

C. Optimization of Feasible Solutions for Supply Chain Supplier Selection Management Based on Adaptive GA

An initial feasible solution is obtained by decoupling the relationship between supplier management and order products. Subsequently, a local search is applied to the feasible solution to obtain an initial population. Iterative updates are performed using a Genetic Algorithm (GA) to generate various order production sequences. In each GA iteration, suppliers for each order group are sorted based on specific constraints, and this sorting is used as the fitness indicator for individuals in the population. After multiple iterations, a cost-optimized selection solution is finally obtained. The solution process of GA is illustrated in Fig. 3.

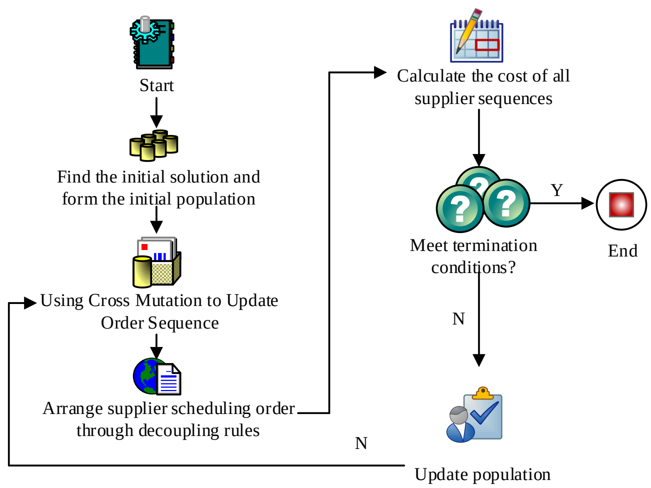


Fig. 3. The whole process of initial solution optimization.

It is important to note that the management and selection problem involving multiple suppliers is, in fact, an NP-hard problem. Due to the high complexity of this problem, experiments result in numerous initial feasible solutions using heuristic algorithms. To preserve the characteristics of these initial feasible solutions to the maximum extent, the experiment introduces a simulated annealing algorithm to expand the search neighborhood of initial feasible solutions. The initial temperature is set as T_0, and the objective function values of the obtained initial feasible solutions are calculated. The generation process of new solutions is illustrated in Fig. 4.

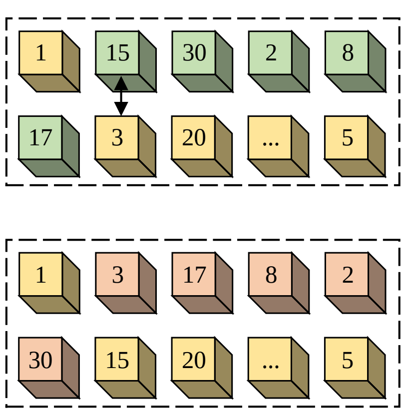


Fig. 4. Value generation method of new solution.

New solutions are evaluated using the Metropolis criterion in the simulated annealing algorithm. When the fitness of the new solution is higher than that of the original solution, the retention probability is 1. For lower fitness, acceptance is probabilistic. The mathematical formula for the Metropolis criterion is shown in Eq. (8).

$$p=\begin{cases} 1 & if \quad E(x_{new})<E(x_{new})' \\ \exp\left(-\dfrac{E(x_{new})-E(x_{new})'}{T}\right) & if \quad E(x_{new})\geq E(x_{new})' \end{cases} \tag{8}$$

In Eq. (8), p represents the probability of accepting the new feasible solution. E represents the internal energy corresponding to each state. T represents the current temperature of the system. The experiment adopts an exponential cooling annealing strategy, and the decay function is shown in Eq. (9).

$$T_{n+1}=CT_n \tag{9}$$

In Eq. (9), T represents a constant less than 1. n represents the index of a state. Subsequently, the experiment employs a roulette wheel method to select outstanding individuals and uses a two-point crossover method for individual crossover operations. After randomly generating a crossover probability, two individuals are randomly selected from the population. If the random number is less than the crossover probability, a crossover operation is performed: determining two crossover points, exchanging and repairing the corresponding chromosome segments, and generating two new individuals. The process of crossover operation is illustrated in Fig. 5.

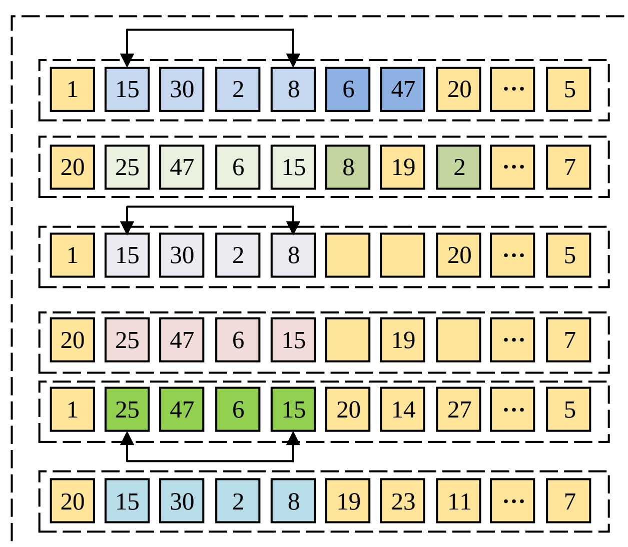


Fig. 5. The whole process of crossover operator calculation.

Similar to the crossover operation, the mutation method selected is two-point mutation. With a certain probability, two points are randomly generated, and natural numbers in the individual are exchanged to obtain a completely new order sequence. The calculation process of the mutation operator is illustrated in Fig. 6.

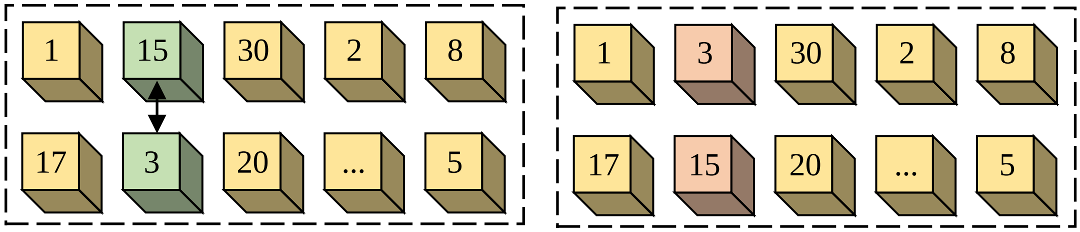


Fig. 6. The whole calculation process of mutation operator.

Based on the decoupling relationship, the order sequence is transformed into a supplier sequence, thereby determining the selection frequency of each supplier. The calculation method of the fitness function is shown in Eq. (10).

$$fitness\_F(x) = \frac{C}{T_{total}}, T_{total} > 0 \tag{10}$$

In Eq. (10), T_{total} represents the total cost of supplier selection. T_{total} represents a positive real number. After successfully obtaining the value of the fitness function, the experiment, to prevent the calculation process from falling into a local optimal solution, further establishes a Genetic Algorithm based on Invasive Weed Optimization (IWO) for adaptive large neighborhood search. In this algorithm, when the cumulative value of random numbers can disrupt the population, the larger the numerical value, the more severe the disruption. The relevant calculation is shown in Eq. (11).

$$\partial = \frac{\sum \lambda - C}{\sum 2\lambda} \tag{11}$$

In Eq. (11), λ represents the cumulative value of random numbers. C represents a constant. ∂ represents the proportion of individual disruption. It is observed that the range of ∂ is [0, 1/2). By controlling the numerical value of C, the degree of individual disruption is controlled. Based on the degree of disruption, the number of individuals to be destroyed in the population is calculated, and inappropriate individuals are randomly removed from the population. Additionally, based on the fitness of individuals, supplier management is ranked, and the optimal individual is selected, forming the final seed individual for the next round of optimization.

IV. Results

In order to validate the superior performance of the constructed method, three existing methods were chosen for comparison with the proposed approach in the context of sustainable pharmaceutical supply chain networks. These methods include the Improved Hybrid Multi-Objective Heuristic Algorithm (IHMOH) based on an improved mixed multi-objective heuristic algorithm, the Supply Chain Closed-Loop Management Method (MINLP) based on a mixed-integer nonlinear programming model, and the Two-Stage Integrated Method for Green Supply Chain Supplier Selection and Order Allocation (FAHP-MILP) based on fuzzy analytic hierarchy process and multi-objective mixed integer linear programming [20-22]. To ensure fairness and reasonableness in the experimental setup, all models shared identical simulation environment parameters, as detailed in Table I.

TABLE I. SETTINGS OF RELATED PARAMETERS

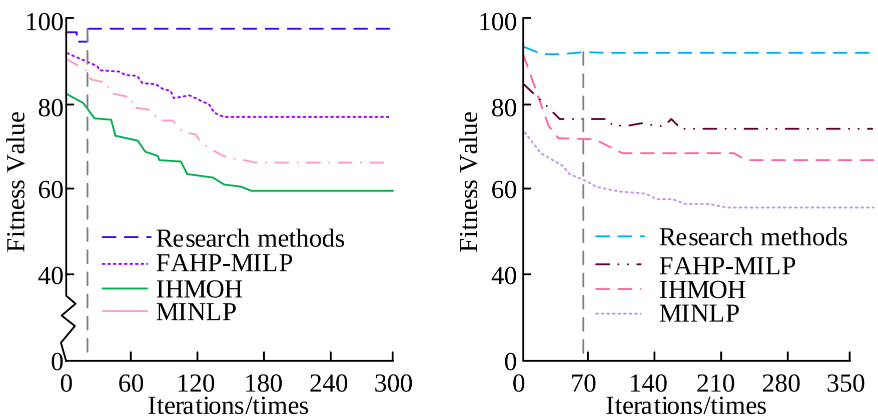
Project	Choice
Graphics card	NVIDIA RTX2080Ti
Graphics card memory	32G
Fresh products	50
Crossover rate	0.7
Mutation rate	0.1
Operating system	Ubuntu18.04
Network architecture	Pytorch v1.2.0
Optimizer	Adam
Programming software	Vscode2017 Anaconda3
CUDA	Cuda 11.0 with cudnn

The selected dataset for the experiment is from the supply chain management system of a well-known company in the United States, and a total of 10000 valid data points were obtained. Before applying the dataset to the model, the following preprocessing steps were performed on all data: data cleaning to remove incomplete or erroneous records; Standardization processing to eliminate the influence of different dimensions; Outlier detection and processing to ensure the reliability of the dataset. These steps are crucial for improving the predictive accuracy of the model. After data preprocessing to remove redundant data, 8000 valid data were obtained, and 80% of the total dataset was randomly selected as the validation set; another 20% is used as the training set. Firstly, the fitness values of the four algorithms were compared when performing tasks on the two datasets, as illustrated in Fig. 7.

Fig. 7(a) depicts the changes in fitness values of the four algorithms on the training set. As the number of system iterations increases, the fitness values of all four algorithms exhibit a rapid and fluctuating trend. At the commencement of the system operation, the fitness value of the research method undergoes a slight variation. Subsequently, at the 22nd iteration, the research method attains its maximum fitness value, maintaining a stable state thereafter with a numerical value as high as 99.67. In contrast, the fitness values of the FAHP-MILP, IHMOH, and MINLP algorithms start stabilizing only after a higher number of iterations, reaching stability at the 157th, 178th, and 176th iterations, respectively, with corresponding values of 81.23, 62.23, and 68.84. Fig. 7(b) illustrates the changes in fitness values of the four algorithms on the validation set. The research method achieves its optimal fitness value of 96.77 after 68 iterations, while the fitness values of the other three methods continue to decrease and remain consistently lower than that of the research method. These results indicate that the research method consistently maintains a higher fitness value, emphasizing its faster convergence speed and higher computational efficiency. Given the varying product categories supplied by different vendors and their differing accuracy in product selection during the management process, the experiment proceeds to compare the accuracy of vendor selection. Specific results are presented in Fig. 8.

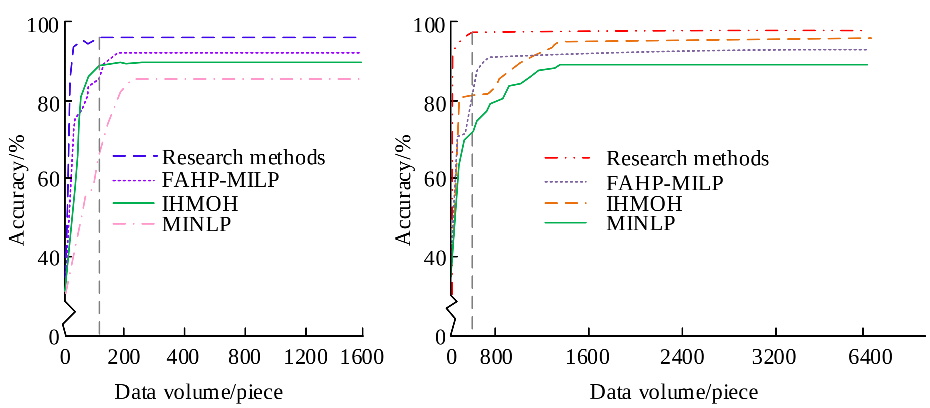
Fig. 8(a) displays the vendor accuracy obtained by different methods on the training set. It is observed that as the data volume increases, the accuracy of all four algorithms shows varying degrees of improvement. When the data volume is 112, the research method achieves the maximum accuracy at 98.56%, significantly higher than the accuracy of the other three methods. Fig. 8(b) shows the accuracy of different algorithms in selecting vendors on the validation set. When the accuracy of the experimentally constructed method reaches its maximum value at a data volume of 402, the corresponding accuracy is 98.33%. Additionally, at data volumes of 789, 1544, and 1502, the accuracy of vendor selection for the FAHP-MILP, IHMOH, and MINLP algorithms is 90.15%, 96.32%, and 89.36%, respectively. In summary, the research method exhibits the highest accuracy in vendor selection and can be applied in the development process of green enterprises. Subsequently, the four methods were applied to the training set for a comparative analysis of computation time. The entire experiment was conducted in five cycles, and the specific results for supplier selection time (Supplier option-T1) and successful order allocation time (Order allocation -T2) are presented in Fig. 9.

In Fig. 9 (a)–(d), different research methods and algorithms, namely the research method, FAHP-MILP algorithm, IHMOH algorithm, and MINLP algorithm, were employed. It can be observed that, in the five parallel experiments designed, the research method exhibited significantly less time consumption for adapting to suppliers compared to the other three algorithms. The minimum time for T1 was 0.654s, and for T2, it was 0.643s. This indicates that the research method, while running the supply chain system, has a more agile decision speed and lower time consumption in selecting suppliers. However, the system, despite having faster operational efficiency, also requires an analysis of the overall cost expenditure. To analyze the overall cost expenditure during the operation of the supply chain management system, the experiment proceeded by selecting the data source company as the product supplier and applying the four methods to two datasets. The analysis focused on the variation in supply chain management costs as the data volume increased, as shown in Fig. 10.



(a) Training set (b) Validation set

Fig. 7. Comparison of fitness values on the two data sets.



(a) Training set (b) Validation set

Fig. 8. Accuracy of supplier selection.

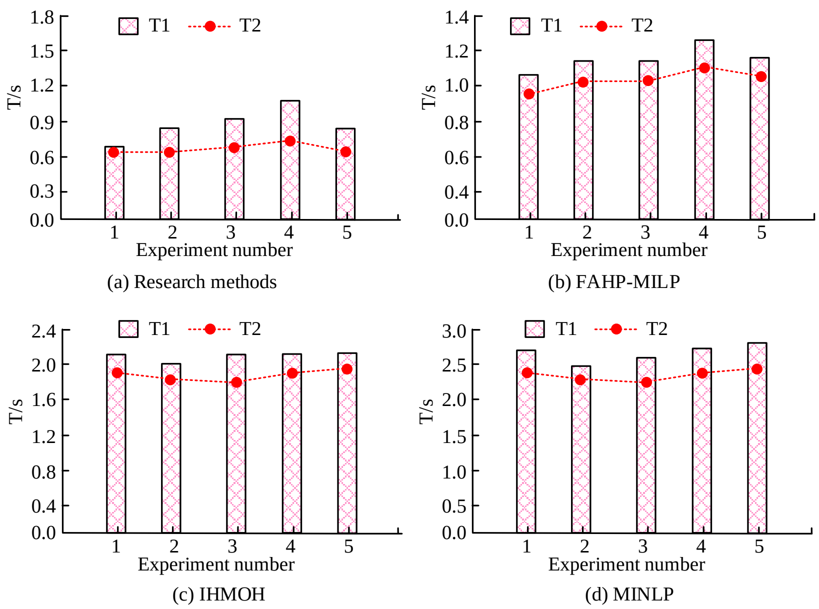


Fig. 9. Comparison of the operation time of the four algorithms on the two data sets.

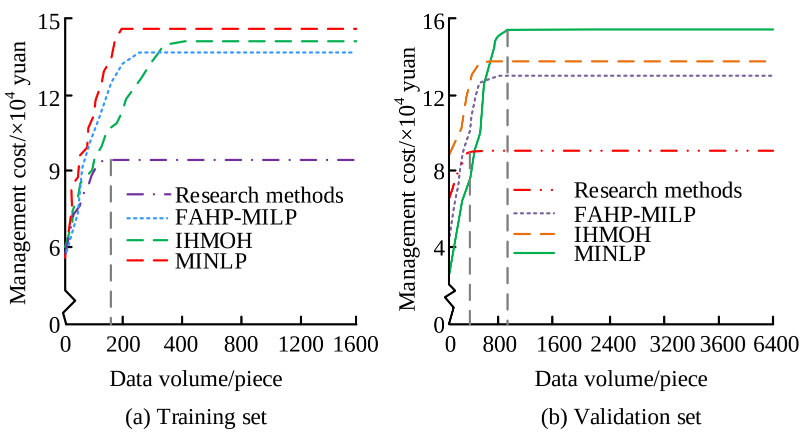


Fig. 10. Changes in supply chain management costs under different algorithm operations.

Fig. 10 (a) depicts the variation in supply chain management costs on the training set. When the data volume reached 191, the research method exhibited the minimum management cost, valued at 97.6 thousand yuan. When the data volume reached 268, the FAHP-MILP algorithm's management cost reached its minimum, with a value as high as 135.8 thousand yuan. Fig. 10 (b) illustrates the variation in supply chain management costs when the four methods were applied to the validation set. As the data volume increased to 392, the research method had the minimum management cost at 92.3 thousand yuan. The supply chain management costs of the other three methods were significantly higher, especially when the data volume reached 908, where the MINLP algorithm incurred a very high cost of 158.9 thousand yuan. In summary, the research method demonstrated better cost-effectiveness in handling complex supply chain problems and effectively controlling supply chain management costs. Finally, the four algorithms were applied to the closed-loop supply chain network of a sustainable agricultural products enterprise. This enterprise, a large company in the United States, initiated the implementation of a green closed-loop supply chain network in response to national policies in August 2020. The study selected 50 examples of fresh products owned by the enterprise for closed-loop supply chain network optimization, and the total cost results are shown in Fig. 11.

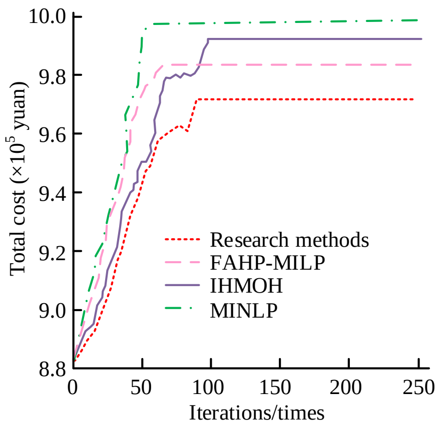


Fig. 11. Total cost under different algorithm operations.

From Fig. 11, it can be observed that the FAHP-MILP algorithm, IHMOH algorithm, and MINLP algorithm incurred higher total costs, with corresponding maximum costs of 983.8 thousand yuan, 975.7 thousand yuan, and 998.8 thousand yuan, respectively. Additionally, when the system reached the 99th iteration, the research method had the least total cost expenditure at 962.7 thousand yuan. Comparatively, although the research method's costs were initially comparable to the IHMOH algorithm, they gradually decreased with iterations and eventually became lower than other algorithms.

V. Discussion and Conclusion

A. Discussion

A mixed integer programming model based on data algorithms has been proposed, which combines heuristic algorithms and adaptive genetic algorithms to improve the efficiency and sustainability of sustainable supply chain management. Through comprehensive analysis and optimization of supplier selection issues in the supply chain, the proposed method has demonstrated significant advantages in multiple aspects. The hybrid model proposed by the research institute effectively integrates the fast convergence characteristics of heuristic algorithms and the global search capability of genetic algorithms, improving the efficiency of solving large-scale supply chain optimization problems. At the 22nd and 68th iterations, the fitness values reached as high as 99.67 and 96.77, respectively, demonstrating the fast convergence and stability of the algorithm. This result is similar to the research findings of scholar Charles D. [18]. In addition, the research method achieved a high accuracy of 98.56% on the training set, significantly better than other existing algorithms. This result is significantly better than Goodarzian F and Ebrahim et al. [20-22]. The proposed method can maintain low management costs and high operational efficiency on both small-scale and large-scale datasets, which has important guiding significance for supply chain management practices. By minimizing supply chain management costs and maximizing efficiency, companies can meet environmental protection and social responsibility requirements while pursuing economic benefits. This is particularly important in the current context of globalization and rapid technological development.

B. Conclusion

To optimize supply chain management and achieve the dual goals of cost efficiency and sustainability, this study proposes a supply chain management approach that integrates a Mixed Integer Programming Model with an improved GA. Firstly, by employing a supplier selection method based on heuristic algorithms, the study successfully generated initial feasible solutions. Subsequently, an optimization method based on adaptive GA was introduced to better adapt to and improve the complexity and dynamism of supply chain management. The data indicates that, on both the validation and training sets, the research method achieved maximum fitness values of 99.67 and 96.77, respectively, when the system iterated to the 68th and 22nd times. In contrast, the fitness values of other methods were significantly below 90.0. On the validation set, the accuracy of the research method reached a maximum of 98.33%. Through five parallel experiments designed, the minimum T1 time and minimum T2 value of the research method were 0.654s and 0.643s, respectively. In practical applications, when the data volume increased to 191, the research method demonstrated the minimum management cost of 97.6 thousand RMB; however, when the data volume reached 268, the FAHP-MILP algorithm exhibited the minimum management cost, reaching 135.8 thousand RMB. Additionally, when iterated to the 99th time, the research method incurred the least total cost, amounting to 962.7 thousand RMB. In summary, the research method not only reduced costs but also enhanced the flexibility and responsiveness of the supply chain. However, the experiment's choice of a single research enterprise, and factors such as supplier selection and product order allocation, which are influenced by various factors, have not been analyzed. Further application and research expansion are needed in the future.

References

[1] Lotfi R, Kargar B, Rajabzadeh M, Hesabi F, & Özceylan E. Hybrid fuzzy and data-driven robust optimization for resilience and sustainable health care supply chain with vendor-managed inventory approach. International Journal of Fuzzy Systems, 2022, 24(2): 1216-1231.

[2] Hua Wang. Research on the Influencing Factors of Block Chain Technology Adoption in Supply Chain Finance of Small and Medium-Sized Enterprises. Advanced Management Science, 2023, 12(1).

[3] Hebbi C, Mamatha H. Comprehensive Dataset Building and Recognition of Isolated Handwritten Kannada Characters Using Machine Learning Models. Artificial Intelligence and Applications, 2023, 1(3):179-190.

[4] Fakhrzad M B, Goodarzian F. A new multi-objective mathematical model for a Citrus supply chain network design: Metaheuristic algorithms. Journal of Optimization in Industrial Engineering, 2021, 14(2): 111-128.

[5] Brahami M A, Dahane M, Souier M, Sahnoun M H. Sustainable capacitated facility location/network design problem: a non-dominated sorting genetic algorithm based multiobjective approach. Annals of Operations Research, 2022, 311(2): 821-852.

[6] Dwivedi A, Jha A, Prajapati D, Sreenu N, & Pratap S. Meta-heuristic algorithms for solving the sustainable agro-food grain supply chain network design problem. Modern Supply Chain Research and Applications, 2020, 2(3): 161-177.

[7] Sadeghi A, Mina H, Bahrami N. A mixed integer linear programming model for designing a green closed-loop supply chain network considering location-routing problem. International journal of logistics systems and management, 2020, 36(2): 177-198.

[8] Manupati V K, Schoenherr T, Ramkumar M, Wagner S M, Pabba S K, & Inder Raj Singh R. A blockchain-based approach for a multi-echelon sustainable supply chain. International Journal of Production Research,

2020, 58(7): 2222-2241.

[9] Isaloo F, Paydar M M. Optimizing a robust bi-objective supply chain network considering environmental aspects: a case study in plastic injection industry. International Journal of Management Science and Engineering Management, 2020, 15(1): 26-38.

[10] Mogale D G, Ghadge A, Kumar S K, Tiwari M K. Modelling supply chain network for procurement of food grains in India. International Journal of Production Research, 2020, 58(21): 6493-6512.

[11] Ahmadini A A H, Modibbo U M, Shaikh A A, Ali I. Multi-objective optimization modelling of sustainable green supply chain in inventory and production management. Alexandria Engineering Journal, 2021, 60(6): 5129-5146.

[12] Zhang Y, Kou X, Song Z, Fan Y, Usman M, & Jagota V l. Research on logistics management layout optimization and real-time application based on nonlinear programming. Nonlinear Engineering, 2022, 10(1): 526-534.

[13] Beiki H, Mohammad Seyedhosseini S, V. Ponkratov V, Olegovna Zekiy A, & Ivanov S A. Addressing a sustainable supplier selection and order allocation problem by an integrated approach: a case of automobile manufacturing. Journal of Industrial and Production Engineering, 2021, 38(4): 239-253.

[14] Li C, Conejo A J, Liu P, Omell B P, Siirola J D, & Grossmann I E. Mixed-integer linear programming models and algorithms for generation and transmission expansion planning of power systems. European Journal of Operational Research, 2022, 297(3): 1071-1082.

[15] Rivera Letelier O, Espinoza D, Goycoolea M, Moreno E, & Muñoz G. Production scheduling for strategic open pit mine planning: a mixed-integer programming approach. Operations Research, 2020, 68(5): 1425-1444.

[16] Mokayed, H., Quan, T. Z., Alkhaled, L., & Sivakumar, V. Real-time human detection and counting system using deep learning computer vision techniques. Artificial Intelligence and Applications. 2023, 1(4): 221-229.

[17] Kumar R, Ganapathy L, Gokhale R, Tiwari M K. Quantitative approaches for the integration of production and distribution planning in the supply chain: a systematic literature review. International Journal of Production Research, 2020, 58(11): 3527-3553.

[18] Charles D. The Lead-Lag Relationship Between International Food Prices, Freight Rates, and Trinidad and Tobago's Food Inflation: A Support Vector Regression Analysis. Green and Low-Carbon Economy, 2023, 1(2): 94-103.

[19] Soleimani H, Chhetri P, Fathollahi-Fard A M, Mirzapour Al-e-Hashem S M J, & Shahparvari S. Sustainable closed-loop supply chain with energy efficiency: Lagrangian relaxation, reformulations and heuristics[J]. Annals of Operations Research, 2022, 318(1): 531-556.

[20] Goodarzian F, Hosseini-Nasab H, Fakhrzad M B. A multi-objective sustainable medicine supply chain network design using a novel hybrid multi-objective metaheuristic algorithm. International Journal of Engineering, 2020, 33(10): 1986-1995.

[21] Poursoltan L, Mohammad Seyedhosseini S, Jabbarzadeh A. A two-level closed-loop supply chain under the constract of vendor managed inventory with learning: a novel hybrid algorithm. Journal of Industrial and Production Engineering, 2021, 38(4): 254-270.

[22] Ebrahim Qazvini Z, Haji A, Mina H. A fuzzy solution approach to supplier selection and order allocation in green supply chain considering the location-routing problem[J]. Scientia Iranica, 2021, 28(1): 446-464.