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Retraction

Retracted: A Supply Chain Model Based on Data-Driven Demand Uncertainty under the Influence of Carbon Tax Policy

Mobile Information Systems

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] L. Chen, J. Zhao, J. Zhao, F. Li, and Y. Yang, "A Supply Chain Model Based on Data-Driven Demand Uncertainty under the Influence of Carbon Tax Policy," *Mobile Information Systems*, vol. 2022, Article ID 5960949, 10 pages, 2022.

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Research Article

A Supply Chain Model Based on Data-Driven Demand Uncertainty under the Influence of Carbon Tax Policy

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The era of digital economy has spawned new factors of production represented by big data. Data-driven sustainable growth and innovative development is the main line of enterprise digital transformation. In view of the uncertainty of supply chain demand, the optimization of supply chain management under the influence of carbon tax policy is studied from the low-carbon perspective. By introducing the fuzzy theory and a membership function to describe the need for uncertainty, a supply chain optimization model considering the influence of carbon emissions is constructed. Carbon tax policy is regarded as the constraint condition of external production. In the case of fuzzy cost changes, the optimization decision of enterprise supply chain management under carbon tax policy is explored. A trapezoidal fuzzy number is used to determine model fuzziness, and the trapezoidal fuzzy number combined with a genetic algorithm is used to solve the model. Furthermore, taking a certain enterprise as an example, the validity of the model is verified by the mathematical programming model method, considering the data driven and taking the data as the means of production.

1. Introduction

One of the key points of the 14th Five-Year Plan is to seize the opportunity of the fourth industrial revolution and accelerate the digital transformation of the whole industry and society by taking advantage of the rapid development of digital economy and digital technology. The key to the success of enterprise digital transformation is the digital transformation of its supply chain. In today's world, economic development has provided people with great wealth, but the consumption of energy and all sorts of waste emissions have also occurred. Especially in recent years, with global warming, higher temperatures are becoming a serious threat to the environment, as they can cause ice to melt, thus raising the sea level. There may even be a larger number of natural disasters, threatening people's lives and negatively affecting the economy. Therefore, it is an important research direction to consider low carbon in the context of digital transformation of the supply chain.

Some scholars have studied the influence of low-carbon policies on supply chains. Li et al. studied the optimization of the supply chain network of automobile manufacturing enterprises from the perspective of carbon trading to coordinate government carbon policy and consumers' low-carbon preferences [1]. Under a carbon trading policy, Wang built a low-carbon emission reduction model, studied the direct impact of a low-carbon emission policy on the emission reduction in supply chain enterprises, and concluded that the government should reward low-emission enterprises with low-intensity policies to enhance the pressure faced by the high-emission enterprises [2]. Cheng et al. with their model of supply chain emission reduction under the coimplementation of the carbon tax and carbon trading policies studied the influence of these two policies on each link of the supply chain, including bidding, product capacity, and other aspects in the supply chain. Finally, the feasibility of the model has verified through example calculations [3]. Moreover, Dresner wanted to reduce the proportion of carbon emissions faced in family life and proposed relevant methods to solve such problems for people, hoping that people could actively participate in energy conservation and emission reduction and reduce the influence of national emission reduction policies on them [4]. According to the response of the carbon tax system to people at different levels in the country, the Bureau finally concluded that the impact of the carbon tax system on high-income people was lower than that on low-income people [5].

Some scholars used robust optimization to study and establish multiobjective robust fuzzy optimization models. For example, Li studied mainly a green and low-carbon Internet design concept and direction of supply chain management and constructed a multiobjective robust fuzzy optimization model in a fuzzy environment [6]. Boronoos et al. used the robust linear precision optimization decision analysis method to construct and design a robust linear decision analysis model to realize supply chain diversification without high certainty [7].

Some scholars studied the optimization of supply chain networks based on a genetic algorithm (GA). For example, Yuan et al. studied the path optimization problem under different carbon emission policies, used the disaster adaptive heritage algorithm to solve this problem, and analysed an example for the multimodal transport network to achieve the requirement of reducing costs and carbon emissions [8]. Based on a GA, Wang controlled the multistage inventory complex system at each node of the supply chain to minimize the cost of the supply chain and ensure the safety of the inventory [9]. Huo studied such problems in a closed-loop network of fresh products. With the goal of minimizing costs and maximizing social benefits, he established a network model and solved it with an improved GA [10]. To cope with the design and planning issue of a comprehensive closed-loop supply chain network, Hamed et al. develop an extended model, which is multiechelon, multiproduct, and multiperiod in a mixed integer linear programming framework. The proposed model is solved by CPLEX optimization software and by a developed genetic algorithm, and the results prove the acceptable performances of the developed genetic algorithm [11].

Other scholars studied the optimization methods of supply chain networks under uncertain conditions from different perspectives. For example, Zhang et al. established a multiobjective closed-loop supply chain network planning model with fuzzy parameters to solve the problem of sustainable closed-loop supply chain network design under uncertain conditions, minimize the cost and environmental impact, and maximize the social impact [12]. Jia used stochastic and fuzzy programming to transform the uncertain model into a deterministic programming model and combined the hierarchical, ε–constraint, and weighted ideal point methods to solve numerical examples [13]. Moreover, Zhang built a three-tier supply chain consisting of factories, distribution centres, and retailers to minimize costs and carbon emissions. The theory of integrated stochastic programming and fuzzy mathematical programming uses the hierarchical, weighted ideal point, constraint, and weighted ideal point methods to solve a multiobjective model [14].

By sorting out the above relevant documents, most of the research on supply chains can be seen as being based on research on traditional supply chains, without the addition of low-carbon elements and lacking mathematical planning, to study the optimization mode of low-carbon supply chains. Considering the low carbon factor in the design of enterprise supply chain, on the one hand, the sustainable development of enterprises can be ensured, and on the other hand, it can make a contribution to environmental problems. For carbon limitation in the supply chain, a large number of scholars established supply chain optimization models based on game theory and network flow models. Supply chain optimization model methods mainly include queuing theory model, game theory model, network flow model, and mathematical programming model. Queuing theory model is suitable for enterprises in a stable state to optimize resource allocation and improve production efficiency. The game theory model is suitable for the equilibrium adjustment when the behavior of the research object interacts with each other. The network flow model is suitable for studying supply chain regulation to coordinate supply chain layout. The mathematical programming model is suitable for realizing the objective function of the network supply chain. The research in this paper is the requirement of network structure supply chain considering low-carbon factors to achieve the goal of minimum cost. Based on the applicability analysis of the above model, it is found that the mathematical programming model is the most suitable. Because a mathematical programming model can well describe and solve the realistic environment with complex and highly specific supply chain management activities and can truly embody and reflect the actual circumstances of the enterprise supply chain, and the model of the mathematical programming method for the problems in terms of enterprise supply chain management and optimization solution to the model is more credible.

The theoretical contributions of this paper are as follows:

(1) The research of this paper will provide ideas for the supply chain optimization model considering carbon tax policy and the uncertain environment under the digital background and establish a three-level supply chain system composed of product suppliers, retailers, and customers

(2) Based on the carbon tax policy, quantitative research is the main research method assisted by qualitative analysis under the environment of uncertain demand

The practical value of this study is mainly as follows:

(1) This paper solves the problem of supply quantity uncertainty of enterprises in the supply chain through fuzzy planning theory.

(2) The implementation of a low-carbon supply chain studied in this paper will bring positive impacts to enterprises. It can not only enable enterprises to better achieve sustainable development but also enable enterprises to increase initiative and options in the supply chain.

(3) The research of this paper responds to the green and sustainable development advocated by the country and contributes to the environmental issues that the country comprehensively concerns.

2. Model Establishment

2.1. Problem Description. With the suppliers, retailers, and customers of a three-stage supply chain as the research objects, product suppliers and retailers need to pay transportation costs, so they generate corresponding carbon emissions. At the same time, they can also pay the carbon tax and retailers can sell their products to customers. The retailer is responsible for transportation once the customer pays the transportation cost. At the same time, corresponding carbon emissions are generated and retailers have to bear the cost of the carbon tax. From the overall interests of the supply chain, its information, capital and logistics aspects should be adjusted to minimize such costs under the condition of the normal operation of each supply chain link. At present, there are three kinds of carbon tax functions, namely, linear carbon tax function, exponential carbon tax function, and segmented carbon tax function. Three different carbon tax functions are applicable to industries with different carbon emission characteristics. The linear carbon tax function is widely used, and the government also sets a certain linear tax rate for carbon emissions. In the enterprise, the linear carbon tax function is not only easy to understand and accept but also very suitable for modeling and theoretical research. Therefore, this paper selects the linear carbon tax function from the perspective of representativeness and easy modeling. The structural model of the supply chain is shown in Figure 1.

2.2. Basic Assumptions. In real life, supply chain optimization is a particularly complex process. Particularly when conducting actual modeling, it may not take into account the reality of all factors and consider only the major part of the problem. Therefore, the main problem should be considered to establish the model. Thus, this section puts forward a supply chain optimization model to consider the hypotheses and to simplify the problem when conducting convenient modeling and problem solving; this model has the following assumptions:

It is assumed that the product price is relatively fixed and does not change due to changes in time and quantity

The quantity demanded of the product is assumed to be vague

The amount of carbon emissions are assumed to be related only to the quantity of products in the transportation process of the retailer's procurement with suppliers and the quantity of products in the transportation process of the retailer's products to customers

The carbon tax cost is assumed to conform to the linear carbon tax function

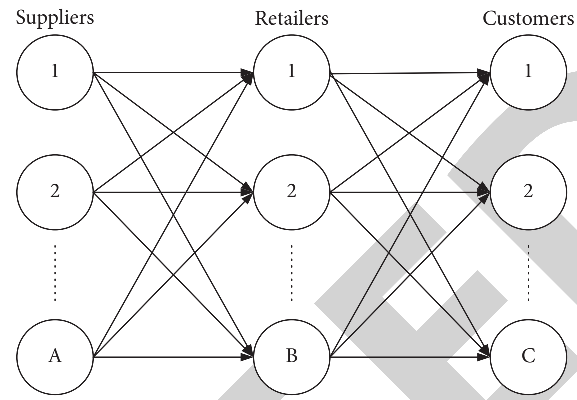

Figure 1: Supply chain structure model.

Table 1: Variable parameter definitions.

Variable parameters	Definition
G_1	The amount of carbon emitted per unit of product that a retailer buys from a supplier
G_2	The amount of carbon emitted per unit of product that a retailer sells to a customer
V	The lowest tolerance of a retailer's profit
P	The unit price of a product that a retailer sells to a customer
E	Unit carbon tax
W	The maximum quantity of the product that the supplier can provide
M	The maximum volume of a retailer's inventory
h_1	The distance between the retailer and the supplier
h_2	The distance between the retailer and the customer
f	The maximum volume of a single shipment
O_s	The transportation cost per unit of distance
O_c	Fixed costs incurred per shipment
O_r	The disposal cost per unit of returned product
β	Vague requirements for products
l	The cost per unit of surplus product
K	The cost per unit of the out-of-stock product
O_1	The storage cost per unit of product
O_2	The storage cost per unit of returned product
Nr	The number of returned products to be disposed of
O_t	The cost of purchasing a unit's product from a supplier
N_t	The quantity of products purchased from suppliers by retailers

2.3. Variable Parameter Definitions. When we use a mathematical model to study problems, we need to define various variable parameters, which are shown in Table 1.

2.4. Model Construction. In the case of carbon tax costs, the demand for products is ambiguous.

When $(Nr + Nt) < \beta$, supply is less than demand, it leads to out-of-stock products. At this time, the total product cost consists of the procurement, transportation, out-of-stock product, returned product, inventory, and carbon tax costs.

At this point, the total cost is as follows:

$$C = Nt \times Ot + \frac{Nt}{f}\left[Oc + (h_1 + h_2) \times Os\right] + k(\beta - Nt - Nr) + Or \times Nr + (O_1 \times \beta + O_2 \times Nr) + e(G_1 + G_2). \tag{1}$$

When $(Nr + Nt) > \beta$, supply is greater than demand, which leads to a product surplus. At this time, the total product cost consists of the procurement, transportation, surplus product, returned product, inventory, and carbon tax costs.

At this point, the total cost is as follows:

$$C = Nt \times Ot + \frac{Nt}{f}\left[Oc + (h_1 + h_2) \times Os\right] + l(Nt + Nr - \beta) + Or \times Nr + (O_1 \times \beta + O_2 \times Nr) + e(G_1 + G_2). \tag{2}$$

Define a function, $y(\partial), \partial = Nr + Nt - \beta$, such that if $\partial > 0, y_1(\partial) = 0, y_2(\partial) = 1$; if $\partial = 0, y_1(\partial) = y_2(\partial) = 1/2$; and if $\partial < 0, y_2(\partial) = 0, y_1(\partial) = 1n$.

In the case of carbon tax costs, the demand for products is ambiguous. The supply chain optimization model is constructed as follows:

$$\begin{cases} \min C = Nt \times Ot + \frac{Nt}{f}\left[Oc + (h_1 + h_2) \times Os\right] \\ +y_1(Nt + Nr - \beta) \times l \\ + y_2(\beta - Nt - Nr) \times k + Or \times Nr \\ +(O_1 \times \beta + O_2 \times Nr) + e(G_1 + G_2) \\ S.T. O < Nt < W\ Nr + Nt < M\ p \times (Nt + Nr) - C \geq v. \end{cases} \tag{3}$$

The objective function, according to the supply chain, to minimize the cost contains six parts. The first part of the objective function is the purchase cost for retailers purchasing from the supplier. The second part of the objective function is the cost of transportation for retailers when shipping products back to suppliers. The third part of the objective function is the excess or shortage of products. The fourth part of the objective function is the cost of returning products. The fifth part of the objective function is the storage costs of products. Finally, the sixth part of the objective function is the carbon tax costs generated by carbon emissions.

Constraint condition 1 means that the quantity of products purchased by retailers is within the volume range of suppliers and is a nonnegative continuous variable.

Constraint condition 2 indicates that the total amount of purchased and returned products cannot exceed the maximum warehouse storage capacity.

Constraint condition 3 indicates that the retailer can obtain the lowest expected profit.

3. Model Solution

3.1. Fuzzy Set Theory. The first step is to solve the trapezoidal fuzzy number by using the fuzzy statistics method. The trapezoidal fuzzy variable is a quad composed of certain numbers $(t_1, t_2, t_3, t_4), t_4 > t_3 > t_2 > t_1$, the relational function of which is shown in Figures 2–4. The numerical formula is as follows:

$$y = \begin{cases} \frac{U\text{-}t_1}{t_2 - t_1}, & t_1 < U < t_2, \\ 1, & t_2 < U < t_3 \\ \frac{U\text{-}t_4}{t_3 - t_4}, & t_3 < U < t_4 \\ 0, & \text{other.} \end{cases} \tag{4}$$

The aim of using the fuzzy statistical method is to find out whether the elements in a region, W, belong to a collection of certain judgements. In view of its different elements, this collection has different ranges, but they are all within a fuzzy set, the element is a constant, the collection is changed, and we need to perform countless calculations to obtain the frequency.

The calculation steps are as follows.

In the third step, with the increase in the total number of calculation statistics, the membership frequency slowly begins to stabilize, and then, the membership value can be obtained.

In the fourth step, after the membership value is obtained, the trapezoidal fuzzy number is transformed into a definite number.

3.2. GA. The supply chain model is solved by a GA, which is derived from Darwin's biological evolution process and is a method that is used to find the optimal solution by simulating the natural evolution process.

3.2.1. Genetic Coding. The number of selected features comprises a combination of genes. To reduce the number of combinations, the image is divided into blocks and each fragment is regarded as a gene for the calculation of the optimal combination of genes. The number of each gene is calculated experimentally.

A GA cannot deal directly with the parameters of the problem space; genes must be converted to chromosomes or individuals composed of a certain structure, called the transformation work code, and the evaluation code strategy always uses the following three norms.

First, in the completeness norm, all points (candidates) in the problem space can be represented by points (chromosomes) in the GA space.

Second, for the soundness norm, the spatial chromosome can respond to candidate hazards in all spaces.

Third, the nonredundancy norm is a one-to-one correspondence between chromosomes and candidates.

In the coding of the GA, the solving process uses a real number coding method.

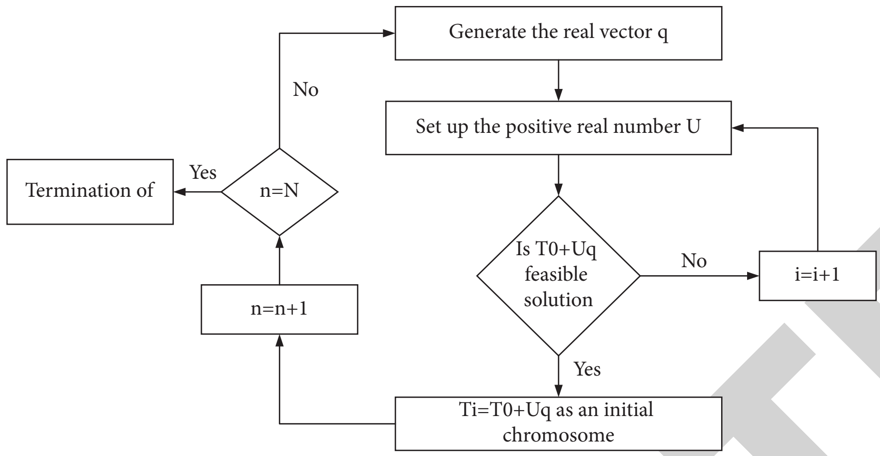

Figure 2: Generation of the initial population.

For function optimization problems, the real number coding method is generally adopted.

The advantages of real number coding are as follows: it can be used to represent numbers with a large range and search a large range and is suitable for problems requiring precision. This coding method is not only very efficient but also not very complicated. Moreover, this coding method can be combined with other algorithms to solve problems with complex constraints.

The model uses the real number coding method, using the real number vector $T = (t_1, t_2)$ for chromosomes and n for numbers.

3.2.2. Generating the Initial Population. The initial population is randomly generated.

Therefore, let us start with an arbitrary solution, T0. Just as with the initial chromosome, the remaining chromosomes are generated by repeating the following process from 1 to $n - 1$.

The first step is to generate arbitrarily a real number vector, q.

The second step is to establish a positive real number, U. If $T_0 + U_q$ is a viable solution to the problem, then Ti←$T0 + Uq$, as an initial chromosome ($i = 1, \ldots, n - 1$), and $I \leftarrow I + 1$; then, return to the previous step, or otherwise, go to the last step.

The third step is to generate a random number from (0, U), replace U with this random number, and return to the previous step until N times (a predetermined positive integer). If T0+Uq is still not a viable solution to the problem, then return to the first step, all the way to T0+Uq, as long as it works.

The structure of the initial population is shown in Figure 2.

3.2.3. Construction of the Fitness Function. In the GA, the next search information can be obtained by using the objective function value.

The evaluation of the individual fitness function is shown in Figure 3.

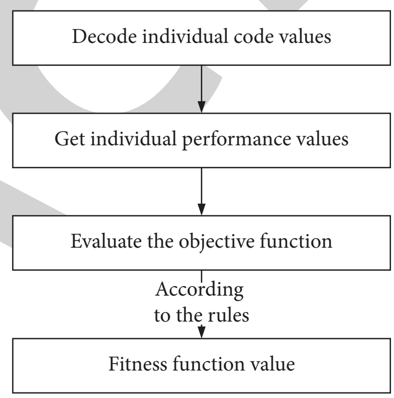

Figure 3: Evaluating the individual fitness function.

3.2.4. Selection of an Operation. In this paper, roulette is used to confirm the survival and elimination of chromosome I according to its probability of being selected and the upper limit of military size. Roulette is a proportional selection strategy. New chromosomes are selected according to a specific probability, which is proportional to fitness.

The steps of the roulette method are shown in Figure 4.

The calculation steps of the roulette method are as follows.

The first step is to compute Ti, which is the cumulative probability of Ji.

The second step is to generate a random number from 0 to 1.

In the third step, if the number in Step 2 is less than Ji, then Ti is chosen; otherwise, Pi is chosen.

In the fourth step, the second and third steps are repeated to generate a population to prepare for the next selection of good populations.

In the fifth step, if no offspring are found to be best, then a random member of the offspring population is selected.

3.2.5. Conducting Cross-Operations. A single point crossing method is used in this model. The method selects a crossover point in the gene composed of each chromosome, randomly

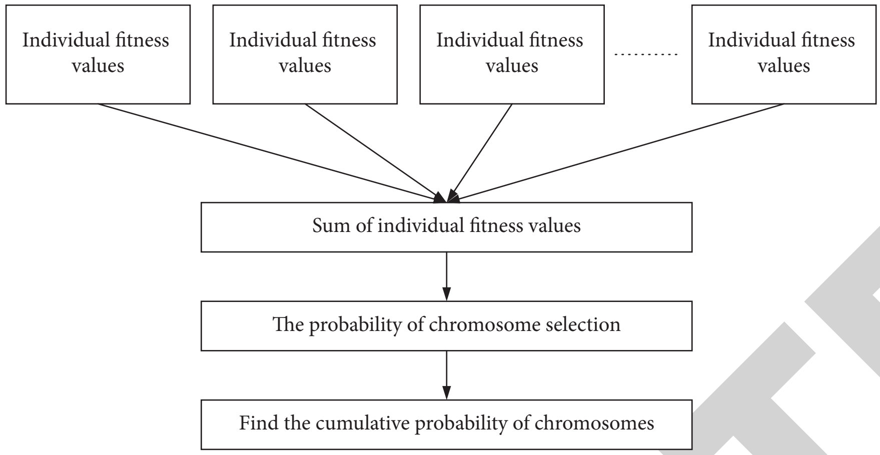

Figure 4: Roulette method steps.

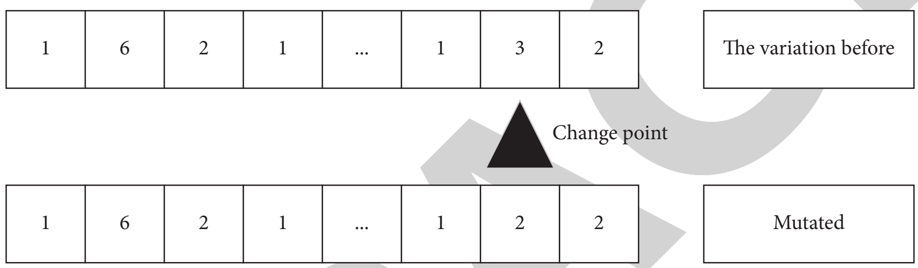

Figure 5: Mutation process.

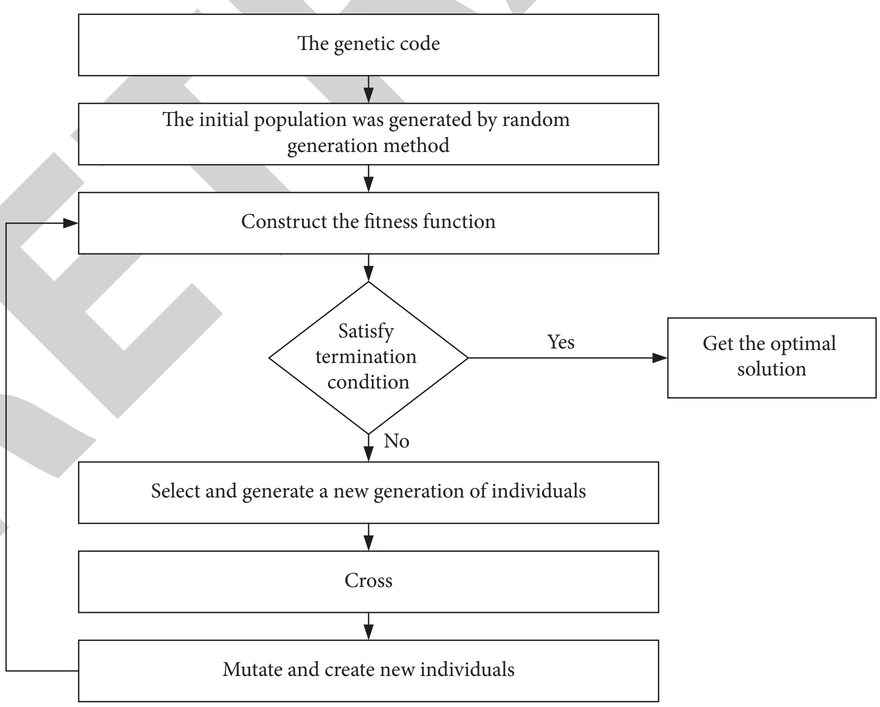

Figure 6: GA.

selects two individuals as parents, and randomly sets up chromosomes at the crossover point to produce two new individuals.

3.2.6. Conducting the Mutation Operation. There is little possibility of changing the specific position or specific position value of the personal password string during the

Table 2: Parameter values.

Variable parameters	Definition	Value
G_1	The amount of carbon emitted per unit of product that a retailer buys from a supplier	5.25
G_2	The amount of carbon emitted per unit of product that a retailer sells to a customer	3
v	The lowest tolerance of a retailer's profit	202,000
P	The unit price of a product that a retailer sells to a customer	3,000
W	The maximum quantity of the product that the supplier can provide	270
M	The maximum volume of a retailer's inventory	280
h_1	The distance between the retailer and supplier	186
h_2	The distance between the retailer and customer	47
F	The maximum volume of a single shipment	75
O_s	The transportation cost per unit of distance	15
O_c	The fixed costs incurred per shipment	50
O_r	The disposal cost per unit of returned product	10
L	The cost per unit of surplus product	20
K	The cost per unit of the out-of-stock product	60
O_1	The storage cost per unit of product	15
O_2	The storage cost per unit of returned product	10
O_t	The cost of purchasing a unit of product from a supplier	2,260

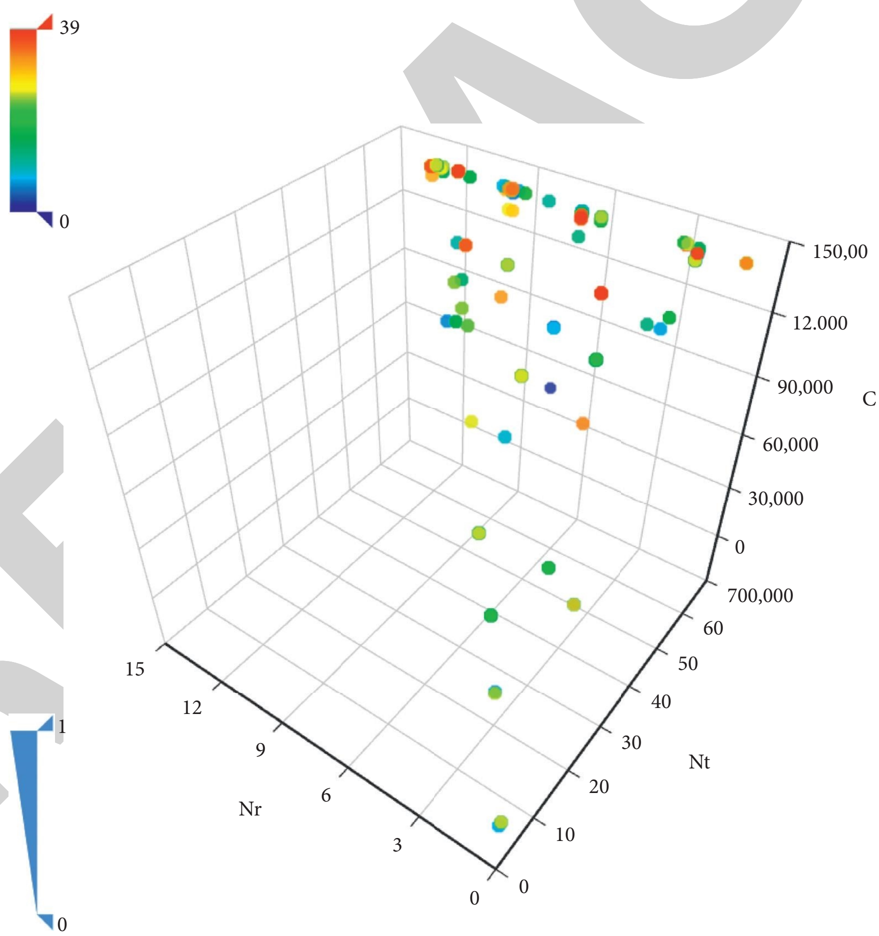

Figure 7: Images of N_t, N_r, and C.

mutation operation. Moreover, chromosomes become offspring. The variable itself is a random algorithm that generates only the auxiliary algorithm for the new individual and determines the local search capability of the GA. The optimization of the effective search space is important to prevent teams from entering, change the local areas of the search space, maintain the diversity of the population, and prevent premature phenomena.

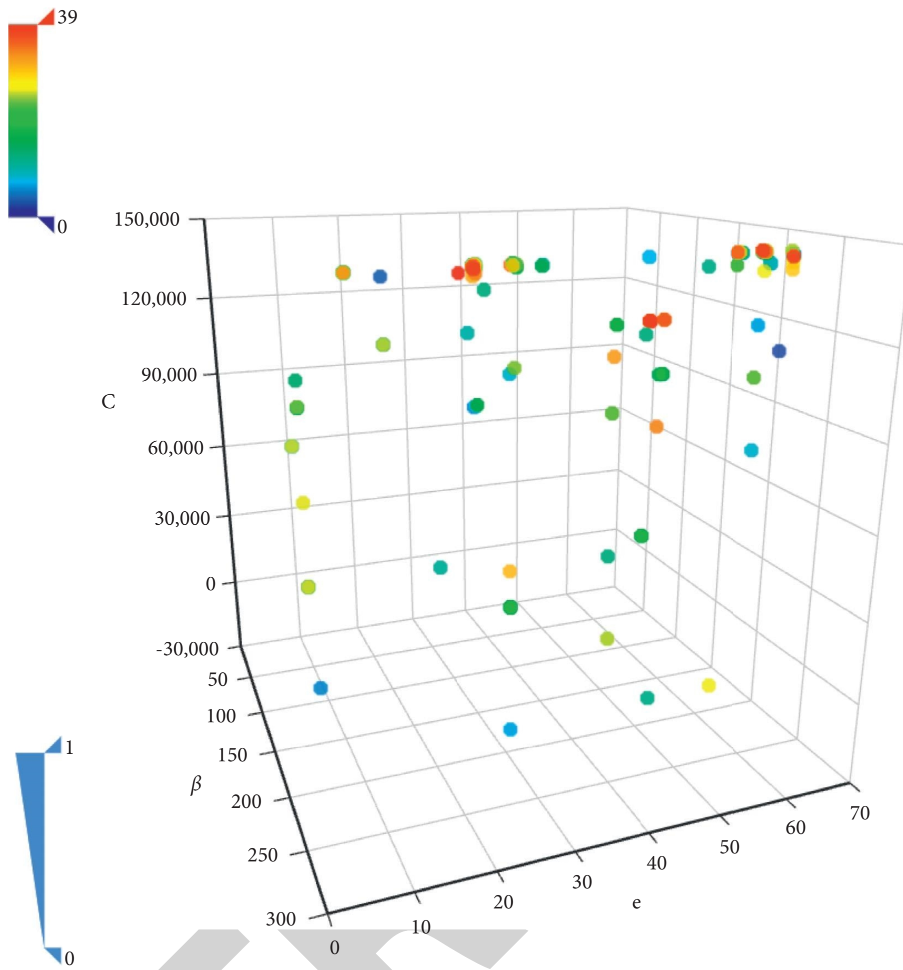

Figure 8: Images of β, E, and C.

The mutation process is shown in Figure 5.

3.2.7. Terminating the Algorithm. In this model, the maximum number of iterations is set as the termination condition. The more iterations there are, the more the population begins to converge.

Figure 6 shows the computational steps of solving the low-carbon supply chain model with uncertain demand by adopting a GA.

4. Example Analysis

To verify whether the proposed algorithm is feasible and can quickly find the optimal solution to the problem, a calculation example is specifically combined with simulation and analysis.

Through the simulation study of mobile phone retailers, relevant online market statistics are queried on the network, referring to the relevant papers published on the network and the statistics and analysis of network-related second-hand consultation and are combined with the actual situation to obtain the required data parameters in the model for the analysis of mobile phone retailers. The body of this calculation example is a three-level supply chain system, which consists of the retailer as the leading factor, as well as suppliers and customers. The goal is to minimize costs for retailers under the constraints of carbon tax costs and obtain a certain profit to minimize the total cost. Let us denote the quantity demanded for the product as a trapezoidal fuzzy number:

$$\lambda = (250, 265, 275, 285). \quad (5)$$

Therefore, it can be seen that the customer's most likely demand quantity is between 265 and 275, at which time the membership function value is 1. The number of customer requirements must not be less than 250 or higher than 285; that is, the membership function value is 0.

The other parameters are shown in Table 2.

Based on the above data, the fuzzy programming model in Section 3 is solved. The parameters used in the algorithm are as follows: 36 chromosomes constitute a population; that is, the size of the population, and a trapezoid is used to select chromosomes on the rotating wheel. When $G = 0.05$, a fuzzy number is used to determine the fuzzy model. The cycle number of the GA is 600. When the fuzzy simulation is used to process the fuzzy objective function, it is necessary to determine the horizontal cutoff set of the fuzzy requirements, which is set to [250, 285].

Second, the above data are added to the optimization model of a low-carbon supply chain network under uncertain conditions in Section 3 to solve the model, and the optimal solution of which is obtained: Nt = 64, and Nr = 12. The corresponding total cost is as follows:

$$C = Nt \times Ot + \frac{Nt}{f}\left[Oc + \left(h_1 + h_2\right) \times Os\right] + l\left(Nt + Nr - \beta\right) + Or \times Nr + \left(O_1 \times \beta + O_2 \times Nr\right) + e\left(G_1 + G_2\right). \quad (6)$$

Here, $C = 148{,}598.61$, and the images of quantity Nt of products purchased by retailers from suppliers, quantity Nr of returned products to be processed, and total cost C in the iterative process of model solving are presented in Figure 7. The images of fuzzy demand β of products, unit carbon tax E, and total cost C are shown in Figure 8.

Second, through an analysis of calculation examples, it is found that the carbon tax changes within the range of 0 to 62.38 yuan/ton, which does not change the decision-making process of supply chain enterprises. In general, carbon emissions decrease gradually with an increase in the carbon tax rate, but the total cost increases linearly with an increase in the carbon tax rate. It can be seen that the higher the carbon tax rate is, the greater the significance of carbon emission reduction and supply reduction. Only by formulating an appropriate carbon tax rate can supply chain enterprises actively cooperate with low-carbon restrictions and reduce emissions. Moreover, by doing so, the government's low-carbon policy can be successfully implemented, ultimately realizing the possibility of long-term social development and economic harmony. Otherwise, such a policy will not only fail to achieve emission reduction but also lead to environmental problems.

5. Conclusions

In this paper, an uncertain supply chain optimization model with low carbon demand is studied under the background of digitization. The main innovations are as follows:

(1) In the environment of uncertain demand, construct a three-level low-carbon supply chain network, establish a multiobjective fuzzy programming model with the goal of minimizing total cost and carbon emissions, and analyze the carbon emissions in the process of procurement and transportation, so as to find a balance between economic benefits and environmental protection.

(2) The carbon emissions generated in the conventional production and transportation process are increased. The corresponding mathematical model is established and optimized for analysis.

The theoretical contributions and practical values of this study are as follows:

(1) *Theoretical Contribution*. This paper found the deficiencies of existing literature on the low-carbon supply chain model and put forward a supply chain optimization model considering carbon tax policy and uncertain environment in the context of digitization; it confirms the research method that quantitative is the main and qualitative is the auxiliary in the uncertain environment of carbon tax policy and demand

(2) *Practical Value*. This paper uses fuzzy programming theory to avoid supply chain uncertainty; low carbon supply chain provides support for the sustainable development of enterprises; it also provides response support for the national green and sustainable development policy

However, there are still some limitations in this paper. The deficiencies and prospects of this paper are as follows:

(1) In the case of an uncertain environment, in addition to fuzzy cases, it may also be random cases. Therefore, randomness can be taken into account in future studies.

(2) In real life, supply chains of different industries have different dominant nodal enterprises, and the relationship and number of nodal enterprises in the supply chain are also different. In this paper, only suppliers are considered in the third dominant position. Therefore, dominant positions in suppliers or intermediate companies can be considered in future studies.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

J. Z. and J. Z. contributed to the writing of the first draft of this study, model building, case analysis, and analysis of relevant experimental results; F.L. contributed to the concept, method design, research work, and experimental analysis; L.C. contributed to the background research of this study and put forward constructive suggestions for revision. L.C. and Y.Y. helped to analyze and make important suggestions for the framework of this article and to make some modifications to the original draft. All authors have read and agreed to the published version of the manuscript.

Acknowledgments

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