Research Article

Design and Application of Genetic Algorithm Based on Signal Game and Newsboy Model for Optimizing Supply Chain

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Reasonable communication and cooperation between enterprises are helpful for the efficient operation of a supply chain. To explore the maximum utility of an entire supply chain, we propose a supplier-manufacturer-seller supply-chain game decision-making model. We use the model as the fitness function of a genetic algorithm that calculates the optimal solution and optimizes the total utility parameters. We analyze the theoretical and practical properties of the supply-chain optimization process and implement it in MATLAB, which provides quantitative support and useful references for making business decisions and optimally managing a supply chain.

1. Introduction

With the increasingly fierce competition in the global market, competition is no longer limited to enterprises but is increasingly between rival supply chains [1]. An efficient supply chain responds more quickly to market demand, gives wider visibility for production, plans orders better, reduces enterprise operating costs and risks, and avoids inefficient revenue and expenses [2, 3]. Therefore, enterprises are concerned about improving the operating efficiency of their supply chain.

Scholars generally believe that improving supply-chain efficiency is mainly achieved through the competition and cooperation between upstream and downstream enterprises acting under the influence of market demand [4, 5]. Game theory (including cooperative games and noncooperative games) is recognized as one of the best methods to study supply chains, especially the competition and cooperation between members of a supply chain [6, 7] (e.g., the newsboy model, Stackelberg game model, bargaining model, or signal game model [8, 9]). Roy et al. [10] established a function of expected average cost for supply chains to obtain the optimal order quantity for suppliers, manufacturers, and retailers by balancing the inventory cost and shortage cost in the framework of the newsboy model. Pakseresht et al. [11] put forward the optimized configuration of green supply chain by analyzing the Stackelberg game, which involves the optimal selection of suppliers, manufacturers, assembly plants, distribution centers, and retailers. Matsui [12] discussed the optimal time for a manufacturer to bargain with a retailer in a dual-channel supply chain composed of a manufacturer and a retailer. Shao et al. [13] established a supplier-selection model with an embedded game in which the firm signals its supplier choice through price based on two mechanisms: signaling and disclosure.

In addition, optimizing a supply chain is essentially an overall planning problem, so many scholars put forward optimal models with intelligent algorithms to solve it. For example, genetic algorithms (GAs) in supply-chain optimization are a hot research topic. Radhakrishnan et al. [14] used GAs to optimize supply-chain inventory with lead times and predicted the optimal stock levels to be maintained to minimize the total supply-chain cost. Istokovic et al. [15] presented a simulation-optimization approach that combines a discrete event simulation and a GA to solve the batching and batch scheduling problem in a hybrid flow shop. Pirnagh et al. [16] analyzed the bi-objective closed-loop supply-chain problem with shortage and all unit discount; they use the nondominated sorting GA II and multiobjective particle swarm optimization to optimize the
supply chain. In other works, Shi et al. [17] established a
dynamic scheduling model for the flexible job-shop
scheduling problem with fuzzy delivery time and then solved
the model with an improved immune GA. The results shed
light on the flexible job-shop scheduling problem in real-
world scenarios. Finally, Amjad et al. [18] proposed a four-
layered GA and implemented it with adaptive parameters of
population initialization and operator probabilities to in-
telligently manage intensification and diversification.

The existing literature shows that scholars have explored
the fair and reasonable distribution of income between
objects and the maximum incentive of the supply chain by
building a mathematical model of the game, which provides
a decision-making basis for balancing the income between
supply chain objects and improving the overall efficiency of
the supply chain. However, most of the research focuses on
the optimization problems at one phase of the supply chain,
such as production plan, inventory management, procure-
ment decision-making, or pricing strategy, and lack of a
more systematic analysis framework. In other words, the
game relationship between members of the supply chain and
the optimal decision-making need to be further explored
from a systematic perspective. For supply-chain optimiza-
tion, most scholars use intelligent algorithms (such as GAs
or particle swarm optimization) to optimize the design from
the perspective of overall planning, which provides ideas for
studying the overall optimization of a supply chain. This
paper studies supply-chain optimization from the per-
sonpective of agent behavior decision. The purpose of supply-
chain optimization is to find a decision-making scheme to
promote coordination between members in the supply chain
and achieve the maximum total utility under conditions of
constraint or limited resources. With that in mind and based
on the analysis of a typical supply-chain model, this paper
proposes a GA optimization for a supply chain based on a
signal game and the newsboy model by combining the game
model and intelligent algorithms. We also iterate the GA
through numerical simulation to implement the optimal-
decision solution for the agent to maximize supply-chain
utility.

2. Building the Model and
Designing the Algorithm

2.1. Analysis of Typical Supply-Chain Mode. Depending on
the objectives of supply-chain management, a supply chain
can be divided into three modes: a supply chain oriented by
manufacturers, a supply chain oriented by retailers (su-
permarket chain), and a logistics service supply chain ori-
ented by 3PL (an integrated logistics supplier). This paper
argues that the supply chain oriented by manufacturers is a
whole functional network in which manufacturers are the
core enterprises in the supply chain, which can attract re-
lated firms to join the chain and connect suppliers, man-
ufacturers, sellers, and users. Under the background of
“Made in China 2025” and unlike the supply chain with
suppliers or sellers as the core, the supply chain oriented by
manufacturing firms has purchasing, manufacturing, and
sales functions, which are more representative and typical.

Therefore, this paper takes the supply chain oriented by
manufacturing firms as the research object for supply-chain
optimization.

The term “manufacturing firms” refers to the manu-
facturers who directly produce the final products for the end
consumer. The end consumer can be either the user of
capital goods or the user of laboring materials as a means
of production. The final product can be both the production
goods and the labor data in the means of production. The
upstream firms that provide raw materials or parts to
manufacturing firms belong to the category of suppliers
because their products (such as raw materials or parts) are
the subject of labor of manufacturing firms and are, by
nature, intermediate goods. Downstream of a supply chain
are found mainly distributors and retailers responsible for
the final product sales and provide after-sales services, be-
longing to the category of distributors. To sum up, the typical
supply-chain mode studied in this paper is shown in Fig-
ure 1. The characteristic of this mode is that the “chain
master” in the supply chain is the manufacturer. Different
from the general node firms, the manufacturers not only
form the bridge between suppliers and sellers but also direct,
guide, and coordinate the relationship between other node
firms so as to coordinate the development of firms in the
chain.

2.2. Construction of Game Decision-Making Model for
Supply Chain

2.2.1. The Signal Game Model between Supplier and
Manufacturer. Signal games involve two participants: the
signal sender, who sends out private information, and the
signal receiver, who makes decisions based on the infor-
mation from the sender [19]. Most of the transactions be-
tween upstream suppliers and midstream manufacturers
occur in an environment of incomplete information, which
is modeled as a signal game under incomplete information.
From the perspective of the whole process of a transaction
between raw materials, parts suppliers, and product man-
ufacturers, a series of activities such as obtaining transaction
information, determining transaction contracts, and per-
forming and supervising all consume resources. However, to
ensure the smooth progress of the transaction, the resources
initially used must produce products for the transaction to
achieve the purpose of the transaction. The transaction
process between suppliers and manufacturers is a bargaining
game based on the interests of both parties to make an
acceptable transaction price. The signal game model of the
supplier and manufacturer is to construct the utility function
of both sides under certain constraints. In this paper, the
whole signal transmission process between the supplier and
manufacturer is divided into two stages (namely, the
preparation period and transaction period), and the fol-
lowing assumptions are put forward before the game
analysis:

H1: in the preparation period, the supplier and the
manufacturer are assumed to send signals and play a
game at the same time without knowing each other's
type. Both parties in the game are signal senders and signal receivers. The behavior of suppliers and manufacturers (advertising investment behavior and consulting investment behavior) can reflect and transmit information.

H2: in the transaction period, the decision-making of suppliers and manufacturers is assumed to be affected by the signals of the preparation period, and the repeated game of bargaining is assumed to be carried out based on transaction intention.

Based on these assumptions, the two-stage signaling game between the supplier and manufacturer proceeds as follows: (1) in the preparation period, the signal sent by the supplier to the manufacturer is the level of investment in advertising, $a_1 (a_1 \in [0, 1])$, and the signal sent by the manufacturer to the supplier is the level of investment in consultation, $b_2 (b_2 \in [0, 1])$. (2) During the transaction period, the signal sent by the supplier to the manufacturer is the price of raw materials and parts, $p_1$, and the signal sent by the manufacturer to the supplier is the purchase quantity of raw materials and parts, $q_2$. The type of supplier is measured by enterprise quality $\eta (\eta \in [0, 1])$, which is a concept of supply capability, raw material supply, and parts quality. The type of manufacturer is measured by its demand for raw materials and parts, $\varepsilon (\varepsilon \in [0, 1])$, which is determined by its production capacity and market demand.

The utility function of the supplier is

$$U_1(a_1, p_1, b_2, q_2) = p_1 q_2 - \frac{1}{2} \mu^{-1} a_1^{\eta} + b_2 \varepsilon. \quad (1)$$

The utility function of the manufacturer is

$$U_2(a_1, p_1, b_2, q_2) = q_2 \eta + a_1 \epsilon b_2 - b_2 - p_1 q_2 - (\varepsilon - q_2)^2. \quad (2)$$

The quantity $(1/2)\mu^{-1} a_1^{\eta}$ is the advertising cost of different quality types of raw materials and parts suppliers in the same level of advertising investment, where $\mu$ is the perceived coefficient of advertising investment. The product $q_2 \eta$ refers to the actual usage or perceived benefits of the type-$\varepsilon$ manufacturer when the quantity of raw materials and parts is $q_2$ (raw materials and parts products are supplied by type-$\eta$ supplier). The quantity $(\varepsilon - q_2)^2$ refers to the use loss due to shortage or surplus of the type-$\varepsilon$ manufacturer when the manufacturer’s purchase quantity of raw materials and parts is $q_2$. To fully explain the influence of these four signals, this paper does not consider how other factors in the market affect the utility function of suppliers and manufacturers, such as the promotion of brand value brought by the increase of market share, the possible future benefits brought by the manufacturer’s recommended value, or the opportunity cost that the manufacturer pays for its search in the preparation before the transaction.

2.2.2. Newsboy Model of Seller’s Optimal Decision under Manufacturer’s Lead. The newsboy model is a mathematical model in which the manager decides the optimal order quantity when facing a stochastic demand [20]. The model is simple, straightforward, and practical and has been widely used in the research of supply-chain management and optimization [21, 22]. In the supplier-manufacturer-seller supply chain, the seller considers both cost and profit in the process of ordering products from the manufacturer [23]. The seller must balance the reduction of residual risk and the realization of revenue, then determine the seller’s optimal order quantity, and price the product at the critical point. Therefore, the newsboy model is more appropriate to analyze the game between the manufacturer and seller. In a downstream supply chain with the manufacturer as lead, the seller can find the optimal order quantity and price according to the market demand. In other words, the goal of this part is to build the newsboy model for an optimal seller decision of sellers under the manufacturer’s lead.

This paper assumes that the product’s market demand is a random variable related to the product pricing, and the product manufacturer has unlimited capacity. In the face of stochastic market demand, the seller determines the product’s order quantity and sales price to maximize its profit. In other words, this is a market dominated by product...
manufacturers, who have an advantage in information. The model is a static noncooperative game model, and each decision-maker can only make a decision once. There are two ways to describe the stochastic demand function: the additive form and the multiplicative form. In either case, demand includes a deterministic part $D(p)$ (a decreasing function of $p$) and a random variable $\delta$. In this paper, we use the multiplication form to describe the market demand, that is, $R D(p, \delta) = D(p)\delta$. For convenience, Table 1 shows the notation and definitions for the model.

Next, to make the newsboy model mathematically solvable (i.e., not deviating seriously from the actual situation), this paper proposes four hypotheses and explains the rationality of each.

**H1:** the random variable $\delta_1$ is independent of $p_3$, and $E[\delta_1] = 1$, so $E[R\delta_1] = D_1(p_3)$. The hypothesis shows that the overall trend of the seller's demand is determined by the product's price, but the real demand is controlled by a random variable $\delta_3$ that obeys a certain distribution.

**H2:** the seller’s decision variable $p_3$ changes only in the interval $[c_3, p_t]$, where $p_t$ is the maximum retail price asked by the sellers for the products. It is impossible for the seller to sell the product at a price lower than the purchase cost, so $p_3 \geq c_3$. At the same time, to prevent product prices from getting out of control, the government often gives guidance prices and limits product prices to a reasonable range, so we assign an upper limit of $p_3$, and the maximum price is $p_t$.

**H3:** the price elasticity $\theta_3$ of $D_3$ is a monotonic function of $p_3$, that is, $\partial \theta_3 / \partial p_3 > 0$. According to the definition of price elasticity, it can be expressed as $\theta_3 = (\partial \theta_3 / \partial p_3) / (D_3/p_3))$. This hypothesis shows that an increase in seller’s product price reduces the expected demand, making it easier to lose customers.

**H4:** $\delta_1$ is well-distributed within $[1 - \varphi_3, 1 + \varphi_3]$, where $\varphi_3 \in [0, 1]$. This hypothesis shows that the market demand of sellers is uniformly distributed in $[(1 - \varphi_3)D_3, (1 + \varphi_3)D_3]$.

Based on these four assumptions and the decision-making analysis of the newsboy model, we construct the expected utility function of the retailer. The expected utility function is

$$U_3(p_3, q_3) = p_3E\delta_3[q_3 \wedge D_3(p_3)\delta_3] - c_3q_3. \quad (3)$$

For a given marginal cost (manufacturer’s price), the seller is faced with a newsboy pricing problem. Therefore, the expected utility function of the seller can be modified as follows:

$$U_3(p_3, q_3) = p_3\left\{\int_0^{D_3/p_3} t f_{\delta_3}(t)dt + q_3\int_{D_3/p_3}^{\infty} f_{\delta_3}(t)dt\right\} - c_3q_3. \quad (4)$$

### 2.2.3. Total Utility Function for Supplier-Manufacturer-Seller Supply Chain

The utility functions for suppliers, manufacturers, and sellers are combined to construct the total utility function for a supplier-manufacturer-seller supply chain by analyzing the signal game between suppliers and manufacturers and the newsboy decision-making of sellers under the manufacturer’s lead. We propose herein a group utility function as a total utility function. To ensure that all decision-makers (suppliers, manufacturers, and sellers) can measure the utility of each element in a given decision set, we set the range of individual utilities, which is the element utility value of suppliers, manufacturers, and sellers, to be between 0 and 1 (calculation standard is the ratio of the actual utility value to the possible maximum utility value).

The range from 0 to 1 represents the utility level from low to high. The total utility function $V(a_1, p_1, b_2, q_2, p_3, q_3)$ is

$$V(a_1, p_1, b_2, q_2, p_3, q_3) = \omega_1 \cdot U_1 + \omega_2 \cdot U_2 + \omega_3 \cdot U_3$$

$$= \omega_1 \cdot \left(p_1 \cdot q_2 - \frac{1}{2}\mu^{-1}a^n + b_2 \cdot \epsilon\right)$$

$$+ \omega_2 \cdot \left[q_2 \cdot \eta + a_1 \cdot \epsilon b_2 - b_2 - p_1 \cdot q_2 - (\epsilon - q_2)^2\right]$$

$$+ \omega_3 \cdot p_3\left\{\int_0^{D_3/p_3} t \cdot f_{\delta_3}(t)dt + q_3\int_{D_3/p_3}^{\infty} f_{\delta_3}(t)dt\right\} - c_3q_3, \quad (5)$$

s.t. $a_1, p_1, b_2, q_2, p_3, q_3 \in [0, 1], \quad (6)$

where $\omega_1$, $\omega_2$, and $\omega_3$ are the contribution weights of suppliers, manufacturers, and sellers, respectively, to the total utility of the supply chain. Note that $\omega_1 + \omega_2 + \omega_3 = 1$ and $\omega_1, \omega_2, \omega_3 \in [0, 1]$. 


2.3. GA Optimization of Supply Chain Based on Game Decision-Making Model

2.3.1. Design of Optimization by Genetic Algorithm. Based on the objective optimization function of a supply chain (i.e., the maximum total utility function), we use a GA to optimize a supply chain. A GA is a computational model based on biological evolution that simulates the evolutionary process of natural selection and the genetic mechanism to search for the optimal solution in an evolutionary process. Therefore, a GA is suitable for the supply-chain game and the optimization problem studied herein. The GA mathematically transforms the solution of the problem into a computer simulation process of chromosome and gene crossover and mutation in biological evolution and transforms the objective function of the problem into the fitness function as the search information in the GA. Based on a signal game and newsboy model, we set as a fitness function for the supply chain the total utility function of supplier-manufacturer-seller and use the GA to find the optimal solution for the supply chain's total utility. Figure 2 shows the basic procedure of a GA.

The implementation of the GA for supply-chain optimization includes determining coding schemes, establishing fitness functions, designing genetic operators, and selecting control parameters.

(1) Determine Coding Scheme. In the game decision-making model for a supply chain, the goal of suppliers, manufacturers, and sellers is to maximize their interests, which is affected by a variety of parameters in the game process. From the game results and the total utility function of the supply chain, we obtain six main optimization parameters, \( a_1, p_1, b_2, q_2, p_3, \) and \( q_3 \), which constitute the spatial parameters of the optimization problem for the objective function. Therefore, the game problem among members in the supply chain becomes an optimization problem for a multiparameter.

To optimize a supplier-manufacturer-seller supply chain, we select the GA coding scheme as the coding structure of multiparameter mapping. The basic idea is that the six optimization parameters are encoded to get the substring, and then, these substrings are connected into a complete chromosome. The range of each parameter is related to the actual order of magnitude of the problem, which belongs to the abstraction of the actual problem. In this paper, the GA based on the game decision-making model for supply chain uses 42-bit coding; each parameter has 7 bits.

### Table 1: Notation and definitions for the newsboy model.

| Variable notation | Variable meaning |
|-------------------|------------------|
| \( c_3 \)         | Seller’s marginal cost of products |
| \( P_3 \)         | Seller’s product pricing |
| \( q_3 \)         | Seller’s order quantity |
| \( D_3 \)         | Determination part of seller’s product demand, which can also be expressed as \( D_3(p_3) \) |
| \( \theta_3 \)     | Price elasticity of seller’s product demand |
| \( \delta_3 \)     | Stochastic part of seller’s product demand |
| \( \phi_3 \)       | Consumer demand coefficient for products; the larger the coefficient, the smaller the consumer demand |
| \( f_{RD_3}(t) \)  | Density function of a random variable \( \delta_3 \) |
| \( RD_3 \)        | Seller’s demand function for products, where \( RD_3 = D_3 \cdot \delta_3 \) |
| \( U_3(p_3, q_3) \) | Seller’s expected utility function |

(2) Establishing the Fitness Function. Fitness refers to the individual’s ability to adapt to the environment. The fitness function in GAs is also called the evaluation function and is used to judge an individual’s advantages and disadvantages in the group and evaluate according to the objective function of the problem. The GA uses the fitness function to evaluate the quality of an individual (solution) and as the basis for subsequent genetic operation. The design of a fitness function satisfies the following conditions: (i) single valued, continuous, nonnegative, and maximized; (ii) a whole consistency; (iii) less computation complexity; (iv) high universality. The design of the fitness function is mainly based on the objective function of maximizing the total utility function with the game relationship of members in the supply chain. In this paper, the objective function of the utility maximization for the supply chain is taken as the fitness function of the GA. The fitness function is

\[
F' = V(a_1, p_1, b_2, q_2, p_3, q_3) = \omega_1U_1 + \omega_2U_2 + \omega_3U_3. \tag{7}
\]

In addition, to ensure that the fitness function is non-negative, the following transformation is made:

\[
F = F', \\
F' > 0, \\
F = 10^{-6}, \\
F' \leq 0. \tag{8}
\]
(3) Designing Genetic Operators and Selecting Control Parameters.

(i) Design of genetic operators: the task of GA is to apply, according to their adaptability to the environment, certain operations to individuals in the initial population formed by the coding to do the optimization. The genetic operation mainly includes three basic genetic operators: selection operator, crossover operator, and mutation operator. The searching ability of the GA is mainly determined by the selection operator and the crossover operator, whereas the mutation operator ensures that the algorithm searches every solution in the problem-solution space so that the algorithm offers global optimization. According to the behavior strategy characteristics of suppliers, manufacturers, and sellers, the selection operator is determined by the fitness proportion method, the crossover operator is a single-point crossover operator, and the mutation operator is a basic bit mutation operator.

(ii) Control parameters: in establishing the structure of GAs, it is necessary to determine their control parameters. The main parameters include population size \( N \), crossover probability \( P_c \), and mutation probability \( P_m \). The crossover probability and mutation probability are set to \( P_c = 0.6 \) and \( P_m = 0.005 \), the population size is set to \( N = 4 \) to simplify the calculation, and the genetic evolution algebra is set to 100.

The fitness function established in this paper has strong convergence and can optimize the supply chain. In the process of supply-chain optimization for specific examples, combined with the characteristics of a supplier-manufacturer-seller supply chain and based on the actual situation of a specific supply chain, the fixed parameters (control parameters) in the fitness function are assigned, and then, the optimal solution of the total utility of the supply chain and the six optimal parameters of the optimal utility are obtained by using the GA.

2.3.2. Description of Optimization Genetic Algorithm Process.

The six optimization parameters of the group-selection strategy of members in the supply chain constitute the fitness-function parameters. To be easy to grasp, these parameters are set to be discrete, so this algorithm belongs to the combinatorial optimization problem. The optimization process of the algorithm is implemented in MATLAB6.5 by using the GA toolbox. The optimization process is as follows:

Step 1: the group size \( N = 4 \) is determined, and \( N \) possible solutions \( X_i(k) \) \((1 \leq i \leq 4)\) are generated at random. Each possible solution is composed of six parameters.

Step 2: for each individual \( X_i(k) \), the fitness \( F(X_i(k)) \) is calculated by using the formula for the total utility function of the supply chain (see formulas (5) and (7)).

Step 3: according to selection rules in the roulette, the survival probability of each individual \( X_i(k) \) is calculated. The selection operator \( p_i(k) = (F(X_i(k))/\sum_{i=1}^{n} (FX_i(k))) \), and a random selector is designed to generate the breeding individuals \( X_i(k) \) by using a random method according to \( p_i(k) \).

Step 4: two mating individuals \( X_1(k) \) and \( X_2(k) \) are selected and combined into two next-generation individuals \( X_1(k+1) \) and \( X_2(k+1) \) according to the rule of single-point crossover and basic position variation until \( N \) next-generation individuals are formed.

Step 5: repeat steps 2–4 until the end condition of the program is met (reaching the end \( K \)).

3. Simulation Example

3.1. Example and Parameter Setting. This example assumes that a supply chain oriented by manufacturing firms consists of three members and one market, including supplier A, manufacturer B, seller C, and target market M, that is, \( N = 4 \). Table 2 shows the relevant fixed parameters of the example. In addition, \( D_3 \) is a monotonically decreasing function of \( p_3 \), so the demand function of seller C for products affected by price in target market M is expressed as \( D_3 = 1 - 0.6p_3 \). The demand for final products in target market M is evenly distributed in the interval \([ (1 - \varphi_3)D_3, (1 + \varphi_3)D_3] \). The random variable \( \delta_3 \) follows the distribution of the density function \( f_{\delta_3}(t) \), which is expressed as

\[
f_{\delta_3}(t) = \begin{cases}
1, & t \in [1 - \varphi_3, 1 + \varphi_3] \\
0, & \text{otherwise}.
\end{cases}
\]

Based on these parameter settings, when combined with the actual situation, the range of optimization variables is set, as shown in Table 3.

Before the optimization operation uses the GA of the supply chain, we must input the fixed parameter values in the mode so that the algorithm can be used in the game optimization process between different agents in the supply chain. In a word, through the setting of the relevant fixed parameters (see Table 2) and the setting of the optimal parameter range (see Table 3), the GA of the supply-chain game model is iterated and runs many times in MATLAB6.5, producing the final optimal solution.

3.2. Operating Results and Analysis of Optimization. After 100 generations of genetic evolution, the optimal individual is (decimal representation) \( x = 0.877 0.934 0.373 0.087 0.253 0.560 \) and the optimal fitness is (decimal representation) \( F = 0.72976 \). Figures 3 and 4 show the optimized emulation results.

The optimized results of the simulation (see Figures 3 and 4) show that, under the total optimal utility of the supply chain, the supplier’s level of investment in advertising and the price level of raw materials and parts are higher, whereas the manufacturer’s consulting investment level for intermediate products (raw materials and parts) and the level of the manufacturer’s purchasing quantity for intermediate
Table 2: Setting of relevant fixed parameters.

| Parameter name                                              | Parameter notation | Parameter range   | Example parameter value |
|--------------------------------------------------------------|--------------------|-------------------|-------------------------|
| Perceived coefficient of supplier’s advertising investment  | $\mu$              | [0, 1]            | 0.8                     |
| Supplier’s quality type                                     | $\eta$             | [0, 1]            | 0.7                     |
| Manufacturer’s demand type                                  | $\varepsilon$      | [0, 1]            | 0.9                     |
| Seller’s marginal cost of products                          | $c_3$              | [0, $p_3$]        | 0.3                     |
| Consumer demand coefficient for products                    | $\varphi_3$        | [0, 1]            | 0.5                     |
| Supplier’s contribution weight for total utility            | $\omega_1$         | [0, 1]            | 0.35                    |
| Manufacturer’s contribution weight for total utility        | $\omega_2$         | [0, 1]            | 0.45                    |
| Seller’s contribution weight for total utility              | $\omega_3$         | [0, 1]            | 0.2                     |

Table 3: Range of optimization parameters.

| Parameter name                                              | Parameter notation | Parameter range   |
|--------------------------------------------------------------|--------------------|-------------------|
| Supplier’s investment level in advertising                   | $a_1$              | [0, 1]            |
| Supplier’s price level of raw materials and parts            | $p_1$              | [0, 1]            |
| Manufacturer’s consulting investment level for raw materials and parts | $b_2$              | [0, 1]            |
| Manufacturer’s purchasing quantity for raw materials and parts | $q_2$              | [0, 1]            |
| Seller’s order quantity                                     | $q_3$              | [0, 1]            |
| Seller’s pricing                                            | $p_3$              | [0.3, 1]          |

Figure 3: Trajectory of evolutionary process over 100 iterations.

Figure 4: Variation of evolutionary individual optimal and evolutionary processes.
products (raw materials and parts) are not high. The results show that the supplier should invest in more advertising to let manufacturers know their advantages. The results also show that manufacturers are willing to pay high prices for high-quality raw materials and parts, so suppliers should try to improve the quality of raw materials and parts rather than reduce prices. In addition, under the optimal solution, the seller’s product order quantity is small, and the product pricing is at an intermediate level, which is indicative of relatively stable market demand for the product. Therefore, given a slight demand fluctuation (less demand risk), the seller can maintain a low level of product order quantity, thus reducing the seller’s inventory management cost and reducing the product backlog.

4. Conclusions

Manufacturer-oriented supply-chain optimization is currently the emphasis of research worldwide, although the complex factors affecting the decision-making of supply-chain businesses make the research more complicated. Making some basic assumptions, this paper studies the “supplier-manufacturer-seller” game decision-making model of a supply chain, which is based on a signal game and the newsboy model. We furthermore design a GA optimization method based on the game decision-making model of supply chains. The selection, crossover, mutation, and other operations in GA make this approach adaptable for all kinds of actors to the environment is gradually improved. Suppliers, manufacturers, and sellers constantly modify their behavior to act in a way that maximizes the total utility to the supply chain. In general, GA optimization based on the game decision-making model of supply chains provides a quantitative support tool for signal selection, transaction decisions, and for setting the pricing strategy of business members.

However, we only describe the implementation process for using a GA to optimize the supply chain based on the game decision-making model but do not conduct in-depth research on the theoretical aspects of GAs, such as proving algorithm convergence, estimating algorithm convergence speed, preventing premature mechanisms, or setting the crossover probability, mutation probability, and other genetic parameters. In other words, the algorithm proposed herein may be further optimized and is thus expected to be improved in future research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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