Research Article
Multi-Period Multi-Product Supply Chain Network Design in the Competitive Environment

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This paper studies a supply chain network design model with price competition. The supply chain provides multiple products for a market area in multiple periods. The model considers the location of manufacturers and retailers and assumes a probabilistic customer behavior based on an attraction function depending on both the location and the quality of the retailers. We aim to design the supply chain under the capacity constraint and maximize the supply chain profit in the competitive environment. The problem is formulated as a mixed integer nonlinear programming model. To solve the problem, we propose two heuristic algorithms—Simulated Annealing Search (SA) and Particle Swarm Optimization (PSO)—and numerically demonstrate the effectiveness of the proposed algorithms. Through the sensitivity analysis, we give some management insights.

1. Introduction

With the development of economy globalization, enterprises are forced to align themselves with supply chains (SCs) rather than work as independent entities. The integration of different parties in the supply network and the control of material flow for the entire supply chain network play crucial roles in the performance and competitiveness of the supply chain. With the intensification of global market competition, designing an optimal supply chain network has become one of the important strategic goals of many enterprises [1].

There have been many studies in the area of the supply chain network design. Supply chain network design (SCND) specifies the physical structure of the supply chain, which has a great influence on the whole performance of the supply chain. Competitive SCND (CSCND) considers the effect of competitive market on the supply chain network structure to improve the future competitiveness of the supply chain [2]. There are few studies focusing on CSCND in the literature. In the supply chain context, there are three kinds of competitions: (a) competition between enterprises at a certain level in a particular supply chain, (b) competition between enterprises at different levels of a specific supply chain, and (c) competition between rival supply chains [3]. The analysis and research on the multiperiod and multi-product competitive supply chain are limited. The supply chain network design makes decisions at different supply chain tiers, from the strategic level (about the features of the facility, such as size, type, and location) to the tactical level (about transportation and inventory). This paper studies the strategic and tactical decisions of the dynamic SCND issue with price sensitive demand. As an operational decision, price is a key decision that plays two major roles in the supply chain: it has an impact on the unit revenue for each product, and, by establishing the price-demand function of each product in each customer area, it can influence the desired network facilities and their capacities to meet demand. Moreover, in previous works [4–8], price is all about a single level of a fairly simplified network, and it only takes into account one period of location decisions. Furthermore,
researchers supposed that price and location decisions are at the same planning level and remain the same. These assumptions do not apply to real supply chains, and the purpose of this article is to consider price decisions in the integrated model of SCND, which also captures many aspects related to real applications.

In the current competitive, complex, and volatile economic situation, many parameters such as supply and potential market demand are subject to change. However, in some cases, such as running into turbulent market conditions, it may be essential to consider the possibility of making multiperiod adjustments in the supply chain decisions. Furthermore, with the diversification of the product and the growth of customer demand, it is particularly important to consider multiperiod multiproduct to make SCND decisions effectively. In addition, under competitive conditions, customer patronage behavior must also be considered because the market share captured by the facilities depends on it. We presume inelastic demand and utilize the attraction demand function on the customer behavior model. As proposed by Huff [9, 10], the probability of customers visiting each facility is directly connected with the attractiveness of the facility and contrary to the attractiveness of other facilities. Here, we suppose that distance and quality of retailers are the key factors affecting the market share of rivals. Therefore, retailers can better serve customers with a better service quality level. High service quality can result in more frequent customers’ patronage behavior [11, 12].

In this study, an optimization model is presented to solve the problem of multiperiod, multiproduct, and capacitated supply chain network design considering the competitive environment between supply chain network members. A mixed integer nonlinear programming (MINLP) formulation is used to deal with this problem. To make the model realistic, consideration needs to be given to various aspects of the supply chain, such as multiple planning periods, locations of the production facilities and retailers, and retailers’ quality, as well as capacity constraints for production, transportation, and inventory. Two heuristic algorithms, namely, Simulated Annealing Search (SA) and Particle Swarm Optimization (PSO), are developed. This paper aims to solve a location-allocation and pricing problem to optimize the objective of a supply chain network by considering multiple periods, multiple products, and retailer’s quality level.

The main contributions of this paper are as follows:

1. A novel dynamic SCND problem is presented, in which a retailer’s demand depends on all retailers’ price decisions. This research considers multiple products over multiple periods to integrate location, quantity, quality, and price decisions.

2. We consider not only the competition among the retailer level but also the competition among the manufacturer level.

3. A mixed integer nonlinear programming model is proposed to characterize the multiperiod multiproduct supply chain network design problem considering competition, where topological designing decisions and selections of product types are modeled by 0-1 variables and operation decisions at all time periods are modeled by continuous variables.

4. Two heuristic algorithms are recommended in order to acquire feasible solutions within a reasonable computational time, and the data sets of small, medium, and large groups are compared.

5. The influence of the demand sensitivity of retailers’ prices and the distance sensitive parameter are analyzed.

The rest of the article is structured as follows. Section 2 reviews the relevant literature. Section 3 presents the problem description, assumptions, notations, and mathematical model formulas for the basic model. Section 4 introduces two heuristic solution methodologies to solve several randomly generated examples. In Section 5, the sensitivity analysis is studied and several management enlightenment are given on this basis. Finally, conclusions are drawn in Section 6.

2. Literature Review

2.1. Single-Product Competitive SCND. Despite the grand significance of market competition in the current environment which compels supply chain integrators to ameliorate or redesign their networks, most of the literature did not take into account the competitive factors in the network design stage. Rezapour and Farahani [13] studied a bilevel centralized single-product supply chain equilibrium model with competition from rival supply chains, taking into account deterministic price-dependent demand. Rezapour et al. [14] researched the sequential game of deterministic demand for a single product between two competing supply chains. Based on the Stackelberg strategy, a leader of a new chain is expected to determine the location of its distributor and retailer after the new retailer of the existing chain is determined to maximize its profit. Rezapour and Farahani [15] presented a bilevel model to design a new entry chain in competition with a single product in the existing supply chain. After the outer part of the model determined the network structure, it predicted the market variable price and service-level competition under the elastic demand of random price and service level. Rezapour et al. [16] proposed a bilevel model for a Stackelberg game, describing the competition between two single-product SCs in which demand was elastic in terms of retail price and distance. Fallah et al. [17] studied single-product competition between two closed-loop supply chains with stochastic demand in simultaneous and Stackelberg competition, respectively. The competitive factors were the retail price of new products and the price of recycled second-hand products. Rezapour et al. [18] presented a bilevel closed-loop single-period supply chain model operating in a competitive environment where price depended on demand. Both SCs offered new products to the same market, and the new SC had internal competition between new products and remanufactured products. Fahimi et al. [19] researched the simultaneous entry of two
SCs into the market to compete for the continuous attractiveness of distribution center to maximize its market share and minimize cost. Both SCs produced the same product. Based on the mixed integer nonlinear programming model, they presented a two-stage algorithm. Rezapour et al. [20] studied the impact of disruption on supply chain competitiveness. The potential demand in the market was related to the retail price. Anderson and Bao [21] investigated the price competitions among at least two SCs in the case of different integration structures. They offered similar products to the same market, and the demand function was linear. Finally, the influence of the price level on the objective function was analyzed. From what has been discussed above, it can be found that most of the above-mentioned literature research studies concerning the competitive supply chain decisions are about single-product single-period decisions; furthermore, many do not consider the strategic decision but presume that the structure of the supply chain is established and known in advance, or think of the strategic decision only and neglect the tactical and/or operational decisions.

The majority of studies in SCND suppose that the supply chain has a specific market share. Moreover, the articles on competitive markets reveal that a corporation’s demand can be critically dependent on some operational competitive decisions such as retail prices. As an operational competitive factor, the retail price is a principal factor influencing customers’ consumption behaviors in the highly competitive markets, such as electronic products, food and clothing, automobiles, and air tickets in the field of transportation. Saghaeeian and Ramezanian [3] established a bilevel programming model for the Stackelberg game between supply chains with probabilistic linear demand, in which the entrant was the leader and the existing one was the follower. The paper also studied facility location (strategic decisions), production, flow (tactical decisions), and pricing decisions (operational decisions) in the leader-follower supply chain of multiproduct competition. Therefore, modeling a competitive SCND problem with the retail price as a competition factor seems necessary and motivates us to fill the gap. The study develops a model of the SCND competition problem in which strategic, tactical, and operational competitive factors are taken into account.

2.2. Multiperiod and Multiproduct. As far as we know, almost all of the existing research about competitive SCND focus on single period and single product under deterministic conditions. Some research, such as Melo et al. [22], Correia et al. [23], Badri et al. [24], and Melo et al. [25], has solved multiperiod models for designing and redesigning supply chains with more than three layers, and the location decisions are made by involving at least two layers. Canel et al. [26] hypothesized that facilities can be opened, closed, and reopened multiple times within a planning horizon of an uncapacitated, two-layer, and multiproduct supply chain. Zeballos et al. [27] presented a planning approach to solve a closed-loop supply chain with multiple periods and products. Finally, multistage stochastic programming and mixed integer linear programming (MILP) methods were used to optimize the network. Kalaitzidou et al. [28] adopted the MILP method to model a multiproduct, multilayer, and multiperiod closed-loop supply chain network design. They employed a standard branch-and-bound approach to obtain the global optimum of the model. Pasandideh et al. [29] studied a biobjective optimization problem of a multiproduct, multiperiod, and three-level hierarchical supply chain network. Nondominated sorting genetic algorithm (NSGA-II) was used to solve the deterministic mixed-integer nonlinear programming model. Tosarkani and Amin [30] studied the establishment and application of fully fuzzy programming (FFP) method to determine the possible upper, middle, and lower profit ranges of a multicomponent, multiproduct, and multiperiod battery closed-loop supply chain in the case of inaccurate information. Moreover, the problem was extended to multiobjective considering green factors. Jindal and Sangwan [31] adopted a fuzzy MILP method to optimize a multiproduct, multichannel capacitated closed-loop supply chain with several uncertain parameters such as demand of products. Talaei et al. [32] presented a multiobjective MILP model to study the facility location/allocation problem in a multiproduct closed-loop green supply chain network, so as to minimize the total cost of the network. The proposed model was optimized with $\varepsilon$-constraint. Dai [33] established a multiproduct, multilayer, and multiobjective supply chain network model in a fuzzy environment. A fuzzy multiobjective decision-making (MODM) method was used to address the problem by minimizing the total cost, carbon dioxide, and risks of the network. Pazhani et al. [34] studied a dual-objective model for a multiperiod multiproduct closed-loop supply chain. The two objectives of this model were to minimize the total costs and maximize the service efficiency of the warehouses and mixed facilities. Ramezani et al. [35] proposed a multiobjective model of a multiproduct, multiperiod, and closed-loop supply chain network. A fuzzy planning method was utilized to maximize profit and quality and minimize delivery time. Keshavarz Ghorabaee et al. [36] established a green supplier evaluation model for a multiproduct, multiperiod, and closed-loop supply chain network integration, and developed a mathematical model in an uncertain environment. However, it should be noted that most articles in this area have proposed the cost minimization model; the profit-maximization SCND with multiple periods and multiple products is still seldom studied in the literature.

2.3. Quality Level. In addition, the important factor that affects competitive SCND is the patronizing behavior of customers. In a deterministic model, the entire customer demand is served by the facility closest to it, whereas in a probabilistic model, the demand is divided according to the attractiveness of the existing facilities. Generally, the attraction function is dependent on the distance between the customer and the facility and other features of the facility that identify its quality [37, 38]. According to Huff [9, 10], the probability of a customer visiting each facility was proportional to the attractiveness of the facility and inversely
proportional to the attractiveness of other facilities. Rezapour et al. [14] developed a SCND model in which retailers’ locations are discrete and customers’ behavior is probabilistic based on an attraction function that is dependent on both the distance and the quality level of retailers. Fahimi et al. [19] presented a nonconvex MINLP model considering the simultaneous competitive SCND problem of different structures, as well as the continuous attractiveness levels of the distribution centers, in order to maximize their market shares and minimize their costs.

The abovementioned studies are summarized with respect to some important characteristics in Table 1.

3. Problem Definition

The overall structure of the presented supply chain network is shown in Figure 1. The paper designs a multiperiod and multiproduct SC network composed of several manufacturers, several retailers, and a market with inelastic customer demand. The customer’s patronizing behavior in market is probabilistic and depends on the attraction function, namely, the Huff gravity rule model. The supply chain wants to determine the optimal locations of the manufacturers, retailers, their allocations, cycle inventory, prices, and equilibrium attractiveness of the opened retailers, thus maximizing its revenue.

The assumptions used to develop the presented model are stated as follows:

(i) The required number of facilities to be established in each stage is known
(ii) The probabilistic behavior of consumers creates different demands for the retailers
(iii) The capacity of required facilities and cost parameters related to them are definite
(iv) Multiple products are manufactured, distributed, and retailed
(v) There is no flow between facilities of the same stage
(vi) Shortage is not possible and there is no discount
(vii) The freight of different product units may be different

3.1. Notation

3.1.1. Sets

\( \text{LC}^M \), \( \text{LC}^R \): the set of potential locations \( j \) of manufacturers and retailers (\( j \in \text{LC}^M, j \in \text{LC}^R \))

\( I \): the set of required manufacturers \( i (i \in I) \)

\( K \): the set of required retailers \( k (k \in K) \)

\( N \): the set of products \( n (n \in N) \)

\( T \): the set of time periods \( t (t \in T) \)

3.1.2. Parameters

\( C^M_j \): the fixed cost for establishing a manufacturer at potential location \( j \in \text{LC}^M \)

\( p_{nkt} \): the price of the product \( n \in N \) the manufacturer \( i \in I \) sells to the retailer \( k \in K \) at time period \( t \in T \)

\( x_{nkt} \): the quantity of the product \( n \in N \) manufactured in the manufacturer \( i \in I \) at time period \( t \in T \)

3.1.3. Decision Variables

\( x_{nkt} \): the minimum allowable quality level for retailers

\( q_{\text{min}} \): the maximum allowable quality level for retailers

\( C^R_j \): the fixed cost for establishing a retailer at potential location \( j \in \text{LC}^R \)

\( F_{\text{cm}} \): the fixed cost for setting up the production line of the product \( n \in N \) in the manufacturer \( i \in I \) at time period \( t \in T \)

\( V_{\text{cm}} \): the variable cost for the manufacturing product \( n \in N \) in the manufacturer \( i \in I \) at time period \( t \in T \)

\( I_{\text{cm}} \): the inventory cost for the manufacturing product \( n \in N \) in the manufacturer \( i \in I \) at time period \( t \in T \)

\( R_{\text{cm}} \): the purchasing cost of raw material in the manufacturer \( i \in I \) at time period \( t \in T \)

\( IC_{\text{mk}} \): the inventory cost of the product \( n \in N \) in the retailer \( k \in K \) at time period \( t \in T \)

\( TC_{\text{mk}} \): the transportation cost of one unit of the product \( n \in N \) between the manufacturer \( i \in I \) and the retailer \( k \in K \)

\( TC_{\text{mk}} \): the transportation cost of one unit of the product \( n \in N \) between the retailer \( k \in K \) and the customer

\( CP_{\text{mk}} \): the capacity of the manufacturer \( i \in I \) for the manufacturing product \( n \in N \) at time period \( t \in T \)

\( CP_{\text{mk}} \): the capacity of the retailer \( k \in K \) for the selling product \( n \in N \) at time period \( t \in T \)

\( \text{INV}_{\text{mk}} \): the inventory capacity for the product \( n \in N \) in the retailer \( k \in K \) at time period \( t \in T \)

\( \text{DEM}_{\text{mk}} \): the demand for the product \( n \in N \) for the customer at time period \( t \in T \)

\( TR_{\text{mk}} \): the capacity of transportation between the manufacturer \( i \in I \) and the retailer \( k \in K \) at time period \( t \in T \)

\( a_{\text{nk}} \): the potential demand of the product \( n \in N \) for the retailer \( k \in K \) at time period \( t \in T \)

\( \delta \): the demand sensitivity of each retailer’s own price

\( \gamma \): the demand sensitivity of the rival retailers’ price

\( \beta \): the distance sensitivity of attraction function

\( c \): the cost-of-unit increase in the quality of retailers

\( s \): the distance between the market and retailer \( k \in K \)
Table 1: Studies on the supply chain network design.

| Author(s) and year | Multi product | Multi period | Location | Price decision | Quality level | Approach |
|--------------------|---------------|--------------|----------|----------------|---------------|----------|
| Canel et al. (2001) [26] | ✓ | ✓ | ✓ | × | × | Branch and bound dynamic programming |
| Rezapour and Farahani (2010) [13] | × | × | × | ✓ | × | LP/modified dynamic programming |
| Anderson and Bao (2010) [21] | × | × | × | ✓ | × | Game theoretic approach |
| Rezapour et al. (2011) [14] | × | × | ✓ | ✓ | × | MINLP/LINGO |
| Rezapour et al. (2011) [14] | × | × | ✓ | ✓ | × | Stackelberg model/combinatorial metaheuristic |
| Pazhani et al. (2013) [34] | ✓ | ✓ | ✓ | × | × | MILP/goal programming |
| Zeballos et al. (2014) [27] | ✓ | ✓ | ✓ | × | × | MILP/stochastic programming |
| Jindal and Sangwan (2014) [31] | ✓ | × | ✓ | × | × | MILP/fuzzy programming |
| Ramezani et al. (2014) [35] | ✓ | ✓ | ✓ | ✓ | × | MILP/fuzzy programming |
| Talaei et al. (2010) [21] | × | × | ✓ | ✓ | × | L0FPP/Cplex and LINGO |
| Rezapour et al. (2014) [16] | × | × | ✓ | ✓ | × | Stackelberg model/exact and metaheuristic |
| Fallah et al. (2015) [17] | × | × | ✓ | ✓ | × | Game theoretic approach and fuzzy programming |
| Rezapour et al. (2015) [18] | ✓ | ✓ | ✓ | × | × | Bilevel model/modified projection GAMS/LINGO |
| Kalaitzidou et al. (2015) [28] | ✓ | ✓ | ✓ | ✓ | × | MILP/CPLEX |
| Talaee et al. [32] | ✓ | × | ✓ | × | × | Robust fuzzy programming |
| Dai (2016) [33] | ✓ | × | ✓ | × | × | Fuzzy programming |
| Fahimi et al. (2017) [19] | × | × | ✓ | ✓ | × | MINLP/Lemke and Howson algorithm and modified projection |
| Rezapour et al. (2017) [20] | × | × | ✓ | ✓ | × | MINLP/CPLEX |
| Keshavarz et al. (2017) [36] | ✓ | ✓ | ✓ | ✓ | × | MINLP/fuzzy programming |
| Saghaeeian and Ramezanian (2018) [3] | ✓ | × | ✓ | ✓ | × | MINLP/hybrid genetic algorithm |

3.1.4. Dependent Variables

- $d_{nk}^t$: the demand of the product $n \in N$ in the retailer $k \in K$ at time period $t \in T$
- $MS_{nk}^t$: the market share of the product $n \in N$ captured by the retailer $k \in K$ at time period $t \in T$
- $inv_{nk}^t$: the inventory level of the product $n \in N$ in the manufacturer $i \in I$ at time period $t \in T$
- $inv_{nk}^t$: the inventory level of the product $n \in N$ in the retailer $k \in K$ at time period $t \in T$

3.2. Calculating Market Share. In attraction function models, the probability that a customer in the market visits the retailer $k$ is proportional to $q_k/g(d_k)$, where $g(d)$ is a nonnegative and increasing function of the distance between the market and the retail facility. In these papers, some forms were presented for function $g(d)$ such as $g(d) = d^\delta$ [9, 37, 39] or $g(d) = e^{d^\delta}$ [40]. Then, the total attractiveness of the open retailer for a customer is given by $\sum_k (q_k/g(d_k))$. Thus, by considering probabilistic customer utility function proposed by Huff, the probability that the customer visits facility $k$ is described as its attractiveness divided by the total attractiveness of all the retail facilities and is expressed as $q_k/g(s_k)/(\sum_k (q_k/g(s_k)))$. Now, if we define $DEM_{nt}$ as the demand, we can conclude that the market share of the retailer $k$ is the demand of market $DEM_{nt}$.
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It follows that the demand of each competing retailer is a decreasing (nondecreasing) function of its own (competitor’s) retail price. In the expression, $a_{nkt}$ is the market base for retailer $k$ and $\delta$ is the demand sensitivity of each of its own prices and $\gamma$ is the demand sensitivity coefficient of the rival retailers. There is a hypothesis that retailers simultaneously decide their retail prices to maximize their profit given the competitors’ pricing strategies.

To explore the relationship between $\delta$ and $\gamma$, we simplify some parameters and assume that rival retailer produces the product at cost $c_{nkt}$ and sells it at price $p_{nkt}$. Thus, the $k$th retailer’s profit for product $n$ at period $t$ is as follows:

$$
\pi_{nkt} = (p_{nkt} - c_{nkt}) \cdot d_{nkt} = (p_{nkt} - c_{nkt}) \cdot \left( a_{nkt} - \delta p_{nkt} + \gamma \sum_{l=1}^{K} p_{nl} \right).
$$

Then, the equilibrium of the competition is characterized by

$$
\bar{d}_{nkt} = \frac{a_{nkt} - \delta p_{nkt} + \gamma \sum_{l=1}^{K} p_{nl}}{2 \cdot \delta + \gamma \cdot (1 - K)}, \quad \forall k \in K.
$$

Proof. Differentiate this profit function over the retail price $p_{nkt}$ for the first-order condition. We will have

$$
\frac{\partial \pi_{nkt}}{\partial p_{nkt}} = d_{nkt} + (p_{nkt} - c_{nkt}) \frac{\partial d_{nkt}}{\partial p_{nkt}} = a_{nkt} - 2 \cdot \delta \cdot p_{nkt} + \gamma \cdot \sum_{l=1}^{K} p_{nl} + \delta \cdot c_{nkt}.
$$

The second order-condition of the profit function is

$$
\frac{\partial^2 \pi_{nkt}}{\partial p_{nkt}^2} = -2 \cdot \delta < 0,
$$

which means there is a unique maximum $\bar{p}_{nkt}$. Setting the first-order derivative equal to zero, we have

$$
\delta \cdot p_{nkt} = \frac{1}{2} \cdot a_{nkt} + \frac{\gamma}{2} \sum_{l=1}^{K} p_{nl} + \delta \cdot \frac{c_{nkt}}{2}, \quad \forall k \in K.
$$
The total revenue of the retailer is equal to the unit price multiplied by the demand of the retailer, namely, the sales of the retailer to market. The total profit incurred by the retailer is equal to the total revenue minus various costs (including retailers location costs, inventory costs, purchase of products costs, total transportation costs, and retailer quality cost). The profit of retailer \( k \) is presented as follows:

\[
\begin{align*}
z_k &= \sum_n \sum_i P_{nkt}d_{nkt} - \sum_{k \in LC^R} \sum_i C_{ji}^R y_{ji}^R - \sum_n \sum_i IC_{nkt} \text{inv}_{nkt} \\
& \quad - \sum_n \sum_i \sum_{j \in LC^M} P_{nkt} y_{nkt} - \sum_n \sum_i TC_{nkt} d_{nkt} - \sum_k c (q_k - q_{\text{min}}) y_{kj}^R \\
& \quad + \sum_{k \in LC^R} IC_{nkt} \text{inv}_{nkt} - \sum_n \sum_i RC_{nit} - \sum_n \sum_k \sum_{j \in LC^M} TC_{nkt} y_{nkt}^R - \sum_n \sum_k \sum_{j \in LC^M} IC_{nkt} y_{nkt}^R \\
& \quad - \sum_n \sum_k TC_{nkt} \text{inv}_{nkt} - \sum_n \sum_i \sum_k TC_{nkt} \text{inv}_{nkt} - \sum_n \sum_k \sum_{j \in LC^M} IC_{nkt} y_{nkt}^R \\
& \quad + \sum_{k \in LC^M} IC_{nkt} \text{inv}_{nkt} - \sum_n \sum_k \sum_{j \in LC^M} IC_{nkt} \text{inv}_{nkt} - \sum_n \sum_k IC_{nkt} \text{inv}_{nkt} - \sum_n \sum_k IC_{nkt} \text{inv}_{nkt} \\
& \quad + \sum_{k \in LC^M} IC_{nkt} \text{inv}_{nkt} - \sum_n \sum_k IC_{nkt} \text{inv}_{nkt}
\end{align*}
\]

(13)

The total profit of the supply chain is the sum of all manufacturers’ profits plus the sum of all retailers’ profits. We can express the profit for the supply chain, to be maximized, as

\[
\begin{align*}
\text{max } z &= \sum_i z_i + \sum_k z_k = \sum_n \sum_i P_{nkt}d_{nkt} \\
& \quad - \sum_i \sum_{j \in LC^M} C_{ji}^M y_{ji}^M - \sum_n \sum_i (FC_{nit} y_{nit} \\
& \quad + VC_{nit} \text{inv}_{nit} + IC_{nit} \text{inv}_{nit}) - \sum_i RC_{nit} \\
& \quad - \sum_n \sum_k \sum_{j \in LC^M} TC_{nkt} \text{inv}_{nkt} - \sum_n \sum_k \sum_{j \in LC^M} IC_{nkt} y_{nkt}^R \\
& \quad - \sum_n \sum_k \sum_{j \in LC^M} TC_{nkt} y_{nkt}^R - \sum_n \sum_k \sum_{j \in LC^M} IC_{nkt} y_{nkt}^R \\
& \quad + \sum_{k \in LC^M} IC_{nkt} \text{inv}_{nkt} - \sum_n \sum_k \sum_{j \in LC^M} IC_{nkt} \text{inv}_{nkt} - \sum_n \sum_k IC_{nkt} \text{inv}_{nkt} - \sum_n \sum_k IC_{nkt} \text{inv}_{nkt} \\
& \quad + \sum_{k \in LC^M} IC_{nkt} \text{inv}_{nkt} - \sum_n \sum_k IC_{nkt} \text{inv}_{nkt}
\end{align*}
\]

(14)

s.t.

\[
x_{nit} \leq CP_{nit} y_{nit}, \quad \forall n \in N, \forall i \in I, \forall t \in T, \\
\text{inv}_{nit} = \text{inv}_{nit(t-1)} + x_{nit} - \sum_k x_{nkt}, \quad \forall n \in N, \forall i \in I, \forall t \in T, \\
\text{inv}_{nit} \leq \text{INV}_{nit}, \quad \forall n \in N, \forall i \in I, \forall t \in T, \\
y_{nit} \geq y_{nit(t-1)}, \quad \forall n \in N, \forall i \in I, \forall t \in T, \\
d_{nkt} \leq CP_{nkt}, \quad \forall n \in N, \forall k \in K, \forall t \in T, \\
\text{inv}_{nkt} = \text{inv}_{nkt(t-1)} + \sum_i x_{nkt} - d_{nkt}, \quad \forall n \in N, \forall k \in K, \forall t \in T, \\
\text{inv}_{nkt} \leq \text{INV}_{nkt}, \quad \forall n \in N, \forall k \in K, \forall t \in T, \\
\sum_k d_{nkt} \leq DEM_{nt}, \quad \forall n \in N, \forall t \in T, \\
\sum_n x_{nkt} \leq TR_{k_t}, \quad \forall i \in I, \forall k \in K, \forall t \in T.
\]

(15) (16) (17) (18) (19) (20) (21) (22) (23)

The first term of the objective function is the total revenue from the demand captured by retailers. The second, third, fourth, and fifth terms are the various costs associated with the manufacturer. The sixth, seventh, and eighth terms are the various costs associated with the retailer. The last term is the construction cost of retailers whose qualities are to be determined.

Constraints (15) and (19) show the capacity constraints of manufacturers and retailers, respectively. Constraints (16) and (17) are the inventory constraints of products in manufacturers. Constraints (20) and (21) are the inventory constraints of products in retailers. Constraint (18) shows that if a production line is built in a time period, it can be operational after that time period. Constraint (22) shows the supply of retailers to the market is less than or equal to the market demand. Constraints of transportation amounts between different echelon of the supply chain network are expressed in equations (23) and (24). Constraint (25) indicates that the quantities of products provided by the retailer cannot exceed the market share occupied by the retailer when there are competitors in the market. Constraints (26) to (29) indicate the limitations on the allocation of potential locations for the establishment of required facilities at different levels. Constraints (26) and (28) mean that for a potential candidate location, the required facility is selected at most once. Constraints (27) and (29) mean that for a required facility, it can only be selected by a potential candidate location. It is worth noting that there is no initial inventory at all stages (i.e., \( \text{inv}_{nit} = 0, \text{inv}_{nkt} = 0 \)).

4. Solution Approach

In recent decades, heuristic methods have been proposed as effective tools for solving complicated problems such as NP-hard and NP-complete issues. In the study, location, quantity, quality, and price decisions should be made for a comprehensive SCND problem during a multiperiod horizon. Therefore, the optimization problem is complicated and involves nonconvex and nonlinear factors. To solve this problem, we use two heuristic
algorithms, Simulating Annealing (SA) and Particle Swarm Optimization (PSO), to find the approximate optimal solution.

4.1. Simulated Annealing (SA). The first algorithm is based on the Simulated Annealing procedure. Proposed by Kirkpatrick [41], SA is a local search-based metaheuristic method which can avoid falling into local optimal values and is still widely used as a powerful optimization tool [42]. Figure 2 shows the flowchart of the proposed SA algorithm. The algorithm mainly follows these four steps:

1. Initial state: we set the baseline, which can be randomly extracted from the solution space. The solution is the initial energy \(E_0\) figured out from the objective function to be optimized. The initial temperature \(T_0\) is generally chosen at a higher value.

2. Iterations: at each iteration of the algorithm, calculate the difference between the objective function corresponding to the new solution. This change leads to a change in energy. If the change \(\Delta E\) is negative (that is, the energy of the system decreases), the solution is generated by changing the current solution. If not, accept it with a given probability \(p(\Delta E)\) as the new current solution. \(p(\Delta E) = \exp(-\Delta E/T)\).

3. Temperature variation: in the existing theory of temperature variation, we prefer the approach of iterations to keep the temperature constant. After a certain number of iterations, the system reaches thermodynamic equilibrium and the system temperature decreases according to the criterion of this decline: \(T_{i+1} = \alpha T_i\). After several tests, we set \(\alpha\) to 0.99.

4. Stopping condition: if the temperature drops to a preset temperature threshold or the system becomes stable, the algorithm stops.

Here, we employ the SA algorithm for finding a feasible approximate optimal solution for the problem. The solution space can be defined by a set of constraints consisting of binary and continuous variables. When the binary decisions are made, the problem becomes relatively simple, so it can be easily solved using commercial solvers. In the SA algorithm, we search on the set of candidate manufacturers’ and retailers’ status (i.e., \(Y_{ij}\) and \(Y_{kj}\) variable domain). After determining each binary solution in the feasible space of variables, we fix them to obtain the optimal objective function values and \(Q\) corresponding to the new solution. If an update position and its \(P_{best}\) is better than the current solution, we accept it as the new current solution. \(\Delta E\) is the difference between the objective function values and \(T\) is the current temperature. The adopted termination condition of this algorithm is to reach the terminal temperature. The pseudocode of SA is given in Table 2.

4.2. Particle Swarm Optimization (PSO). The second algorithm is based on the Particle Swarm Optimization procedure. The PSO algorithm was explored by Eberhart and Kennedy [43] as a population-based search approach. Kadadevaramath et al. [44] applied the PSO method to optimally align procurement, production, and transportation in a three-layer supply chain network. The PSO method is suitable for solving such complex problems and may effectively obtain approximate optimal solutions [45–48]. This approach is based on the social behavior of bird flocking or fish schooling when they exchange information with each other for seeking food. Figure 3 shows the flowchart of the proposed PSO algorithm. The algorithm flow is as follows:

1. First, we set the maximum number of iterations, the particle swarm size, the maximum velocity of the particle, and the position information as the whole search space.

2. We randomly generate the velocity and position of each particle, whose range is specified in the constraint.

3. The particles of population are substituted into the objective function expression (5) to acquire the optimal solution \(P_{best}\) of each particle and the optimal solution \(G_{best}\) of the population. The fitness function is defined, and the individual extreme value is the optimal solution found for each particle. The global value found from these optimal solutions is called the global optimal solution.

4. Use the Inertia Weight Method to update the velocity and position of particles.

5. Substitute the updated particle position into the constraints. Judge whether the updated position satisfies the requirements of the restriction conditions. If any particle is out of range, it is updated again until all particles satisfy the constraints.

6. The objective function value of the particle is compared with the updated particle position and its optimal value \(P_{best}\). If the result is better than the \(P_{best}\), it is replaced with the objective function value of the updated particle position.

7. Compare the numerical values of \(P_{best}\) and \(G_{best}\). If the particle’s optimal value is better than \(G_{best}\), the particle’s optimal value replaces \(G_{best}\).

8. Repeat (2) to (7) until the stopping criteria is satisfied or the set number of iterations is reached.

The particles in the PSO method are generated randomly and each particle represents a possible solution to the presented problem. Each particle knows not only its previous optimal experience but also the global optimal experience of the entire population. Based on the information received, every particle updates its speed and position to search for the best status, as shown in the following expressions:
The velocity updating formula of the particle is shown in equation (30), where parameter $v_{mt}$ denotes the current velocity of particle $m$ and $\omega$ is the inertia factor that influences the local and global exploitation abilities of the method. Parameters $c_1$ and $c_2$ are weights affecting the social and cognitive factors, respectively. Parameters $r_1$ and $r_2$ represent two independent random numbers evenly distributed between 0 and 1. Vector $P_{ib}$ represents the individual optimal solution of the particle and vector $P_{gb}$ represents the global optimal solution of all the particles in the population. Equation (31) shows the new position of the particle, which is related to the updated velocity. Expressions (32) and (33) give the upper and lower bounds of the particle’s speed and position, respectively. When all particles undergo the updating process, the whole population will eventually approach the optimal fitness function. The PSO method has been diffusely used to obtain the desired result because of its simplicity and fast convergence features. The pseudocode of PSO is given in Table 3.

\[
\begin{align*}
v_{m+1} &= \omega \cdot v_m + c_1 \cdot r_1 \cdot (P_{ib} - x_m) + c_2 \cdot r_2 \cdot (P_{gb} - x_m), \\
x_{m+1} &= x_m + v_{m+1},
\end{align*}
\]

(30)  
(31)  
(32)  
(33)
over a normal interval. The fixed cost of establishing a manufacturer and a retailer at a potential location are generated from a uniform distribution over an interval [80, 200] and [60, 150], respectively. The fixed cost of setting up the production line of the product $n$ in the manufacturer $i$ at time period $t$ is uniformly drawn from the interval [10, 75]. The variable cost and inventory cost for manufacturing the product $n$ in the manufacturer $i$ at time period $t$ are uniformly drawn from the interval [1, 20] and [10, 26], respectively. The purchasing cost of the raw material in the manufacturer $i$ at time period $t$ is uniformly created from the interval [10, 50]. The inventory cost of the product $n$ in the retailer $k$ at time period $t$ is uniformly drawn from the interval [1, 25]. The transportation cost of one unit of the product $n$ between the manufacturer $i$ and retailer $k$ is uniformly drawn from the interval [2, 20]. The transportation cost of one unit of the product $n$ between the retailer $k$ and customer is uniformly drawn from the interval [2, 15]. The capacities of the manufacturer $i$ and retailer $k$ for product $n$ at time period $t$ are generated from a uniform distribution over intervals [170, 400] and [150, 400], respectively. The capacities of transportation between the manufacturer $i$ and retailer $k$ and between the retailer $k$ and customer at time period $t$ are generated from a uniform distribution over intervals [265, 300] and [250, 300], respectively. Although the majority of parameters in the data sets are created randomly, we manage to make the intervals of the drawn data as realistic as possible. Using these numerical values, we can obtain the locations, the equilibrium retail prices, the equilibrium quantities, the quality level, and the demand of the supply chain in the market dependent on the price sensitivity parameter.

Regarding the six examples in Table 4, the optimal results provided by the proposed algorithms, including the SA, are compared with PSO. The best objective function values and computation times are presented in Table 5. From Table 5, it can be concluded that the proposed SA algorithm outperforms PSO. As could be seen in the table and Figure 4, in terms of the processing time, the SA algorithm presents the near-optimal solutions with a shorter computation time than PSO in all instances. Moreover, Figure 5 shows the

![Flowchart of the proposed PSO](image-url)
objective values for all instances with SA and PSO. SA also produces a better solution than PSO. Finally, these results show that the proposed SA algorithm for solving the network design problem of the supply chain considering locations, shipments, price, and quality performs more appropriately and can converge to reasonable solutions in a sensible amount of CPU time. To evaluate the performance of the developed algorithms, the relative percentage deviation is used to evaluate the efficiency of SA and PSO. This measure is obtained as (solution values obtained by SA-PSO)/PSO. Table 5 indicates that there exists a miniscule gap between optimal solutions of the two proposed heuristic algorithms so that, in the majority of small groups, the gaps between the solution approaches tend to reach zero. In the medium-scale and large-scale problems, however, the gaps become more substantial. The calculation results and process also show that the advantages of the simulated annealing algorithm are simple, universal, robust, and suitable for parallel processing and can be used to solve complex nonlinear optimization problems.

5.2. Sensitivity Analysis. We investigate the influences of the price sensitivity parameters δ and γ with the SA algorithm. First, we research how the objective function value in Example P11 (the SC has three available manufacturers, three candidate retailers, two types of products, and two periods) changes as the demand sensitivity parameter δ of each retailer’s own price increases from 0.8 to 3 in Figure 6, and we
set \( \gamma = 0.2 \). It can be seen from the curve that the profit of the SC decreases with the price sensitivity parameter and finally trends to flat. In general, the self-price sensitivity parameter \( \delta \) appears to have a passive influence on the profit of the supply chain. When the self-price parameter \( \delta \) reaches a specific point, the SC earns less from locating some facilities than it costs to locate them; therefore, the optimal structure of the SC requires the elimination of these facilities. Through canceling some facilities, the SC’s revenue in the market reduces or disappears totally, resulting in a sudden sharp decline in SC’s profit. The larger the self-price sensitivity, the thinner the supply chain network. This means that supply chain managers must have a better understanding of the self-price sensitivity parameter to determine whether to open or close facilities to maximize the profit.

We then research how the objective function value in Example P11 changes as the demand sensitivity parameter \( \gamma \) of rival retailers’ prices increases from 0.05 to 4 in Figure 7, and we set \( \delta = 2 \). As shown in Figure 7, the profit of the SC increases with the rival price sensitivity parameter \( \gamma \) initially; however, after reaching the maximum, it sharply decreases with any further increase of \( \gamma \). We can conclude that increasing the rival price coefficient first increases the profit. When \( \gamma < \delta/K - 1 \), we have positive profit; however, when the coefficient becomes higher, to prevent negative profit, the structure of the supply chain will be transformed by removing some facility locations. Because of this, at some point within the parameter, a sudden decrease can be seen. This shows that \( \delta/(K - 1) \) is a crucial point for the rival price sensitivity parameter in supply chain decision-making. As the parameter moves closer to \( \delta/(K - 1) \) from the right side, additional potential paths develop and, consequently, more new facility locations are selected in the supply chain. As it approaches \( \delta/(K - 1) \) from the left side, the structure will contract through the deterioration of some paths and shutting some facilities down. In this problem, the demand sensitivity of rival retailers’ prices is a vital parameter in market competition. The analysis indicates how this parameter affects the network configuration of the SC in a competitive market. It is worth noting that the maximum profit does not appear on \( \gamma = 0 \). Even if there is little horizontal competition among the rival retailers, it can result in relatively high equilibrium retail prices in the network.

Finally, we investigate the effect of the attractive function’s sensitivity parameter \( \beta \) on the solution by Example P11. The retailer’s unit cost of improving product quality is set at 8. Candidate retailers have minimum and maximum permissible quality levels of 1 and 30, respectively. We assume \( g(s) = s^\beta \) and set \( \beta = 1 \). According to the calculation results, Retailer 1 and Retailer 2 have been selected from three candidate locations for establishing the retailers. But Retailer 1 in the network is closer to the demand point than Retailer 2. In Figure 8, we analyze the impact of on retailer qualities. When it is small, the quality of Retailer 1 increases first, and the optimal flows assigned to Retailer 1 and Retailer 2 have relatively high quality. When the value is relatively large, the overall quality of Retailer 1 is higher than that of Retailer 2, and Retailer 1 becomes the most attractive rival in the market and can easily acquire most of the market demand. In these circumstances, Retailer 1 does not necessarily have a higher quality since his proximity makes it attractive enough. Therefore, as shown in Figure 8, when the value is large, the quality of the retailer is lower compared with that when it is small. As shown in Figure 9, the flow assigned to the retailer increases with \( \beta \), and the flow for Retailer 1 is generally larger than that for Retailer 2. By increasing the value of the parameter, the importance of distance in the attraction functions increases, the contribution of Retailer 1 to the market share increases and the assigned flow to its paths increases. Therefore, closer retailers can capture more demand.

5.3. Managerial Insight. In this paper, the sensitivity analysis about the three parameters obtain some management insights that are not provided in previous studies. For example, Keshavarz and Ghorabaee et al. [36] put forward the model based on supply chain cost minimization as the optimization goal, without considering the impact of price competition between retailers on the flow of retailers to the market, and the impact of distance between the retailers and the market on its market share. Fahimi et al. [19] considered the quality level of retailers, but did not carry out sensitivity analysis on distance parameters, nor did they consider the influence of linear demand function and price sensitive parameters. Based on this model, we conclude that the SC must carefully formulate strategies to enter into competition and adjust its own competitiveness. Experimental analysis indicates how the important parameters of a competitive market affect the network structure of the supply chain. On the one hand, with the increase of the self-price sensitivity parameter within a certain range, the profit of the SC tends to decline and the profit will monotonically drop to zero or even negative. The price sensitivity is a crucial factor in the market, which enables the supply chain to make an adequate balance between products flowing to the market and retail prices. Higher price sensitivity results in a sparser supply chain network and less activation of potential paths to allocate products to the market. In contrast, lower price sensitivity results in a denser supply chain network by
opening more facilities and activating more potential paths. This indicates that SC managers need to know more about the self-price sensitivity parameter so that they know whether to open or close facilities of the supply chain to maximize their profits.

On the other hand, the rival price sensitivity parameter is also a vital factor in the market’s competition. With the increase of the rival price sensitivity parameter, the profit first increases to a certain value and then decreases sharply. We also discover a critical point of the parameter for SC design decisions. As the parameter moves towards this threshold from the right side, more potential paths will be activated, so more new facilities will be set up in the network. As it moves towards this threshold from the left side, the network will shrink by inactivating some paths and shutting down some facilities. Finally, through the analysis of distance-sensitive parameters, we draw the conclusion that closer retail facilities can capture more market demand.

6. Conclusion

In this study, we developed a multiperiod, multiproduct, and multilayer supply chain network design (SCND) in the context of competition. A mixed integer nonlinear programming mathematical model has been developed for maximization of the total profit of the supply chain to make decisions of location, product flows, prices, quality level, and so on. In order to solve this problem, we propose two heuristic algorithms and the results verify that simulated annealing is more efficient than particle swarm optimization in terms of both solution quality and CPU times. Some numerical examples are given to illustrate the procedure of the presented approaches. The results indicate that the methods can effectively and feasibly solve the proposed SCND problem and can determine optimal decisions. Moreover, the sensitivity analysis helps us to explore the impact of changing area of retailers’ demand by changing parameters $\delta$ and $\gamma$ in the model; the influence of distance-sensitive parameter $\beta$ is also analyzed. On the basis of this analysis, some management inspirations are obtained.

Finally, this article can be extended in other ways. In further research, we can consider the robustness of the model, the closed-loop design, or the integration of environmental factors into the competitive supply chain network design. The uncertainty of other parameters of the model such as the demand of the market can be considered as fuzzy programming problems in future studies. In addition, the model of this study does not take into account multiple markets and their locations, which can be used as decision variables in future research. To deal with such problems, other metaheuristic algorithms or combinatorial metaheuristic algorithms can be extended instead of the general metaheuristics.

Data Availability

The numerical study 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.

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