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Research Article

A Joint Optimization Model considering the Product User's Risk Preference for Supply System Disruption

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Logistics distribution is the terminal link that connects the manufacturer and product user and determines the efficiency of the manufacturer's service. Therefore, the disruption risk of the joint system is an essential factor affecting the product user experience. In this paper, while considering the product user's supply disruption risk preference (PUSDRP), a biobjective integer nonlinear programming (INLP) model with subjective cost-utility is proposed to solve the manufacturer's combined location routing inventory problem (CLRIP). According to the user's time satisfaction requirement, a routing change selection framework (RCSF) is designed based on the bounded rational behavior of the user. Additionally, the Lagrange Relaxation and Modified Genetic Algorithm (LR-MGA) is proposed. The LR method relaxes the model, and the MGA finds a compromise solution. The experimental results show that the biobjective cost-utility model proposed in this paper is effective and efficient. The RCSF based on user behavior is superior to the traditional expected utility theory model. The compromise solution provides a better solution for the manufacturer order allocation delivery combinatorial optimization problem. The compromise solution not only reduces the manufacturer's total operating cost but also improves the user's subjective utility. To improve the stability of cooperation between manufacturers and users, the behavior decision-making method urges manufacturers to consider product users' supply disruption risk preferences (PUSDRPs) in attempting to optimize economic benefits for the long term. This paper uses behavior decision-making methods to expand the ideas of the CLRIP joint system.

1. Introduction

1.1. Background. Many countries were hindered by the global COVID-19 pandemic. Uncertainty leads to supply disruption and cost increases, thus further burdening the global supply chain. The fourth wave Delta variant has caused a backlog of orders and transportation delays in many regions, thereby creating new obstacles to the recovery of the global supply chain. The global circulation of raw materials, parts, and consumer goods is also threatened. Further, emergencies, such as the natural disasters in China and Germany in 2021 and the network attacks against major ports in South Africa, led to more serious supply chain disruptions and pushed the global supply chain to collapse. According to the prediction of medical experts at home and abroad, the end of the epidemic is basically impossible this autumn. Currently, many countries and regions in the world are facing a high risk of imported cases. Countries have strengthened epidemic prevention and control measures, including border controls, curfews, closures, and strict controls of personnel flow, thereby further stagnating international trade and disrupting the global supply chain.

Supply chain disruption may lead to short-term operation damage and enterprise profit decline, which may lead to a sharp decline in market share or even the bankruptcy of enterprises, thereby irreparably damaging the long-term

performance of enterprises [1–3]. Therefore, the uncertain optimization of supply chain networks has practical significance for enterprises.

As the CLRIP integrates three levels, namely, strategy, military, and operation, the CLRIP has been widely used to solve the problem of supply chain integration optimization [4–7]. Enterprises need more coordinated system networks when facing disruption and hope to resist disruption, reduce costs, and improve efficiency by optimizing strategies [8–10]. Therefore, the joint optimization of location, routing, and inventory in discrete networks has become a hotspot for scholars and managers [11, 12].

1.2. Motivations. First, before COVID-19, supply chains had never been similarly tested in modern history. Since the beginning of 2020, port closures or delays have occurred in many parts of the world, and frequent extreme weather and chip and labor shortages have disrupted global supply chains and affected industries. 'One ship' is difficult to obtain, and DHL predicts that global supply chain disruption may continue until 2022. Scholars and decision-makers hope to respond quickly to disruptions and reduce losses. Therefore, more attention is given to the uncertain optimization of discrete networks. It is hoped that the research results of this paper can curb the further disruption of the supply chain and provide a reference for enterprises to make anti-disruption decisions.

Second, because of the epidemic, KFC had no chickens to fry in 2021. Behind this are the shortages of slaughterhouse workers and chicken stock caused by the shortage of the poultry supply throughout the year, and the global supply chain is deeply affected.

Third, uncertain factors, such as supply disruption, have affected the experience of product users. Product users also pay more attention to alternative options when choosing products. The bounded rationality and subjective behavior of product users in uncertain environments is risk preference. Consumers' risk attitude affects the integrated optimization of enterprise location, routing, and inventory. Therefore, this paper attempts to use quantitative methods to measure risk preferences to help manufacturers find a compromise solution between minimizing economic investment costs and maximizing product user utility.

Finally, product users want to obtain maximum satisfaction from products. Manufacturers expect to obtain maximum benefits from the investment. Participants know that investment is risky and are faced with balancing risks and benefits. How should manufacturers and consumers make decisions? The utility is the equilibrium point of the relationship between risk and benefit and is the equilibrium index of risk and benefit. Therefore, this paper uses a utility function to analyze product users' risk preferences to help manufacturers use the benefits of a product user routing change selection framework to absorb or reduce the loss caused by disruption.

1.3. Contribution. First, this paper finds that interruptions and product users' risk preferences importantly affect the uncertainty optimization of discrete networks. This paper contributes to the cost-utility biobjective integer nonlinear programming model to accurately describe the integrated location routing inventory optimization problem in discrete networks and quantify the subjective risk preference of product users. The model used in this paper helps manufacturers predict the choice preference of product users for disruption response schemes and optimize the biobjectives of minimizing economic cost input and maximizing product user utility. Additionally, the model can quantify more complex uncertainty scenarios (such as the transport of hazardous or contaminated goods), especially for businesses that need to consider user risk preferences.

Second, in this paper, we find that the CLRIP considering disruption and risk preference is NP-hard, and even small-scale examples have difficulty finding exact solutions. This paper contributes an LR-MGA algorithm. The LR algorithm relaxes the constraint conditions to simplify the model, and the MGA algorithm finds the compromise solution between the biobjective functions. The example experiment proves the effectiveness and efficiency of the LR-MGA algorithm proposed in this paper. The compromise solution provides a better solution for the manufacturer CLRIP.

Third, this paper finds that an increase in customer experience imposes higher requirements for supply chain efficiency. This paper presents a routing change selection framework that considers disruption and product user risk preferences. The framework helps manufacturers explore more strategic and effective delivery schemes for product users. Additionally, the behavior decision method used in this paper extends the theoretical connotation of the uncertain optimization of discrete networks.

1.4. Structure. This paper is organized as follows. Section 2 reviews the literature and identifies the research gap. Section 3 describes the location routing inventory problem in discrete networks and provides the necessary definition of the cost-utility uncertainty optimization model for supply disruption risk and product users' subjective risk preference. This section describes a biobjective linear integer programming model with the objective function of minimizing the total cost of the manufacturer and maximizing the subjective utility of the product users. Section 4 introduces the implementation of the LR-MGA algorithm. Section 5 presents an example verification and comparative analysis. Based on randomly generated examples, a series of experiments and comparisons are completed to verify the effectiveness and efficiency of the LR-MGA algorithm. Section 6 gives the conclusions and insights.

2. Literature Review

2.1. Subject Locking. To accurately find the study focus and hotspot of research on the CLRIP under disruption risk, this paper uses CiteSpace visualization software to sort 1798 pieces of literature based on the WoS database [13]. CiteSpace draws a cluster network (in Figure 1) to determine the study focus. Figure 1 reports that supply disruption

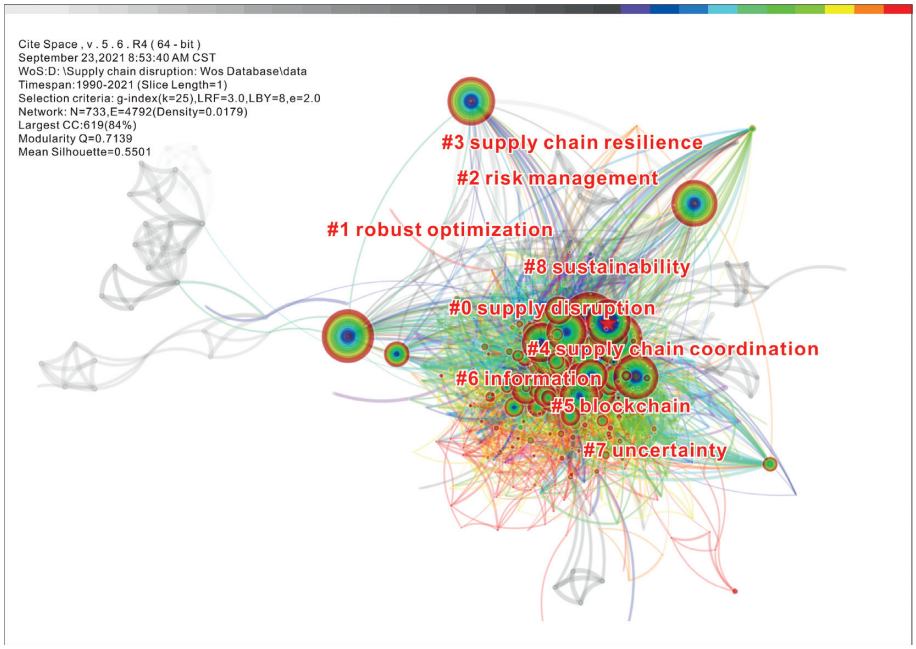

Figure 1: Cluster network of the CLRIP under disruption risk.

(clustering #0) is a study focus of research on the CLRIP under disruption risk. Figure 2 shows the color legend corresponding to time. CiteSpace draws a history of the appearance of the keyword "supply disruption" from 1990 to 2021 (Figure 3). Figure 3 shows that supply disruption is always the critical factor of the CLRIP under disruption risk.

CiteSpace analyzes the 1798 pieces of literature and draws Figures 1–3. The data report shows that supply disruption is the key influencing factor of CLRIP optimization. Figure 1 shows the study topic and hotspot of the CLRIP under disruption risk. Figure 3 dynamically shows that supply disruption has always fundamentally affected the CLRIP with respect to disruption risk.

2.2. Literature Review. Disruption risk is the deviation of any subsystem or parts (raw materials) from the original plan in moving from the starting point to the demand point [14–17]. Supply disruption analysis is of great practical significance to the system decision of the CLRIP. Scholars pay more attention to logistics disruption and supplier disruption [18, 19], among which supplier disruption and transportation disruption caused by external environmental factors are the most serious [20, 21]. Some scholars considered whether the supplier is regular or disrupted. Supply disruption is described as a fixed probability in a single period and is abstracted as a continuous Markov process in a multiperiod. Meyer first assumed that the demand and production capacity were determined and proposed the inventory production decision when the supply was disrupted [22]. Tomlin designed a strategy of replacing inventory with capacity flexibility under supply disruption and compared the disruption management strategies with and without capacity flexibility [23]. Hishamuddin found the transportation disruption caused by external environmental

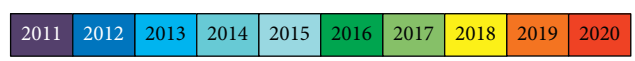

Figure 2: Color legend corresponding to time.

factors, designed a two-stage series, production-inventory restoration model with a recovery time window, determined the optimal order quantity and production quantity, and gave the restoration plan for disruption to minimize the total cost [24]. Some results show that the optimal order quantity of each supplier can provide for the supply chain network of two suppliers and one manufacturer. The production-inventory strategy is evaluated with supply disruption [25, 26]. Considering demand and supply disruption or demand and production disruption simultaneously, some scholars have studied supply chain resilience [27, 28]. Supply disruption fundamentally affects the tactical level of decision-making for the CLRIP.

Some scholars focus on stochastic supply disruption, delayed orders, rejected defective batches, and the EOQ model [29]. Liu studied the CLRIP while considering a stochastic supply disruption and the uncertainty of demand and replenishment lead times and addressed a two-phase method to solve the CLRIP by using queuing theory and integrated model technology [30]. To ensure the smooth operation of the supply chain after a major disaster, some enterprises adopt continuously holding emergency supply sources. Chakraborty studied the supply chain network with two suppliers and a retailer; the suppliers are subject to a supply disruption, and the demand is stochastic. Chakraborty uses game theory to coordinate the impact of supply chain disruption and mitigation strategies of a retailer to improve supply chain performance [31]. External disruption is one of the critical factors for the CLRIP. Because of the high disruption risk and complex externalities of the fuel

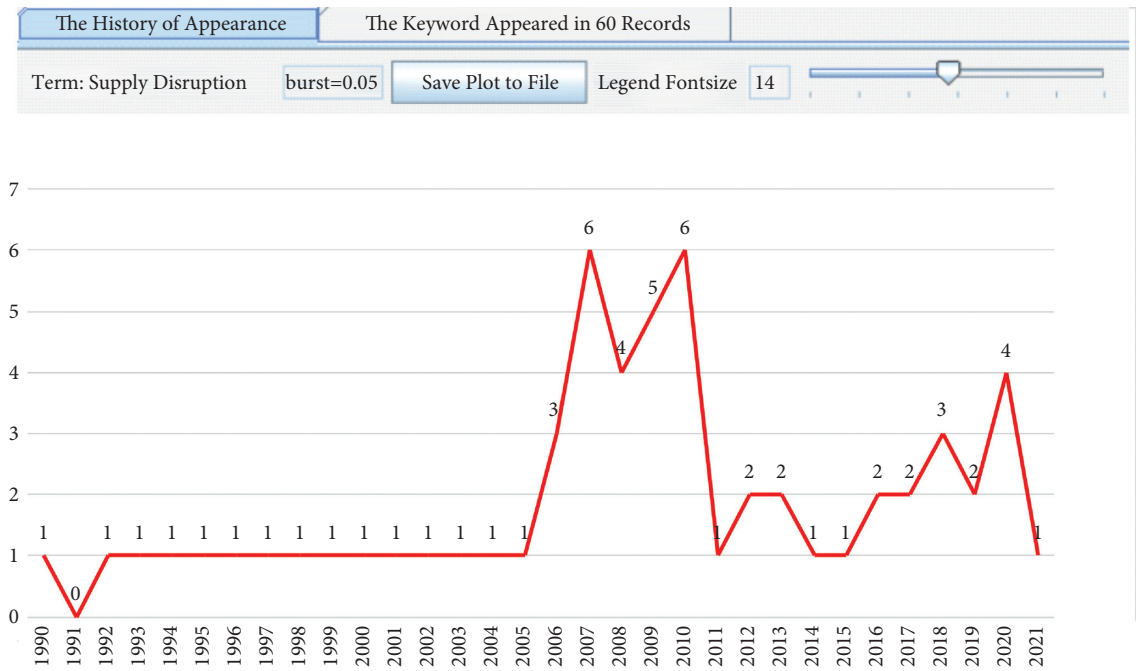

Figure 3: History of the appearance of the keyword "supply disruption."

transportation process, Pourhejaz considered the routing decision variables, designed the biobjective CLRIP model with the minimax transportation time and total system cost, and adopted a modified M-O algorithm for the CLRIP model. Research has found that the transportation time minimax can reduce the external disruption risk in the fuel logistics and improve the sustainability of the supply chain network [32]. Tavana paid attention to major public crisis incidents; emphasized the efficiency of the humanitarian logistics network before and after disasters; studied central facilities locations, predisaster inventory decisions concerning perishable goods, and postdisaster route planning for rescue vehicles according to the particularity of distribution points and effectiveness of relief materials; provided a mixed-integer linear programming (MILP) model of the CLRIP; and designed epsilon-constraint and NSGA-II algorithms for the CLRIP model. The gap analysis results show that NSGA-II outperforms other algorithms in solving small-scale examples and that RPBNSGA-II outperforms other algorithms in solving large-scale examples [5].

2.3. Literature Summary. With the continuous improvement of product users' time satisfaction, higher requirements are imposed for the efficiency of the CLRIP. The study finds that the bounded rational behavior of product users fundamentally affects the decision-making concerning CLRIPs. Consumer risk preference is the primary reference variable of the CLRIP decision system [33]. Scholars divide consumers' purchase behavior preferences after the disruption of stock into five categories: switching merchants, delaying purchases, substituting products with different specifications of the same brand, switching brands, and abandoning purchases; all these preferences are collectively referred to as product users' supply disruption risk preferences (PUSDRPs) [34]. Product users are self-adaptive individuals. The PUSDRP is a critical variable in supply chain network design. Additionally, the logical relationship between product users' purchase behavior and supply and demand fluctuation is also significant. After a disruption, consumers can perceive that retailers are out of stock. The potential losses caused by distribution networks' being out of stock include the loss of brand sales and the loss of commodity sales [35, 36]. Scholars have found that both out-of-stock brands and competitive brands will suffer losses due to supply chain disruption [37, 38]. Some scholars pay attention to retailer out-of-stock disruption and study the retailer's out-of-stock loss and the change in consumers' purchasing behavior after out-of-stock disruptions. Some scholars pay attention to supplier out-of-stock disruptions and study how to retain consumers to reduce brand sales and commodity sales [39, 40]. Reichart focused on the factor analysis of the impact of customers' risk performance on supply chain performance and thought that such factor analysis needs a set of modeling and evaluation schemes suitable for large-scale complex networks [41].

Tables 1–3 reflect the problem characteristics directly. Table 2 compares the present and earlier related studies about the CLRIP under risk. There are some current studies on the product user risk preference for the CLRIP under disruption risk (Table 3); however, there are few quantitative and subjective utility studies on user disruption risk preference. Few studies consider supply disruption and user risk preference together.

2.4. Research Gap. First, unlike the traditional integrated optimization model, this paper considers the deviation of theory from practice. Focusing on supply chain network uncertainty and product user experience, the manufacturer CLRIP integrated optimization with disruption probability

Table 1: Summary of relevant studies about CLRIP under risk.

Author	MP	DT	MC	LC	Risk	Object	Model	SM
Ying and Mingyao (2015) [42]	—	Deterministic	—	√	Stochastic disruption	—	MIP	Metaheuristic
Zhao and Ke (2017) [43]	—	Deterministic	—	√	Stochastic disruption	Bi-o	MINLP	TOPSIS
Rayat et al. (2017) [44]	—	Variable	—	—	Stochastic disruption	Bi-o	MINLP	Metaheuristic
Bozorgi and Ali (2017) [45]	√	Stochastic	√	√	Supply disruption	Bi-o	MINLP	AMOSA
Pourhejazy et al. (2019) [32]	—	Deterministic	—	—	Stochastic disruption	Muti-o	MINLP	Metaheuristic
Tavana et al. (2018) [5]	√	Stochastic	√	√	Humanitarian supply chain	Muti-o	MILP	RPBNSGA-II
Vahdani 2017 [46]	√	Variable	√	√	Supply disruption	Muti-o	MIP	Metaheuristic
Tomlin (2006) [23]	—	Variable	—	√	Supply disruption	One-o	Mip	Tailored hybrid GA
Hishamuddin et al. (2013) [24]	√	Stochastic	—	√	Supply disruption	One-o	MILP	Proposed heuristic
Liu et al. (2020) [30]	—	Uncertainties	—	√	Supply disruption	One-o	MILP	GA
Current study	√	Stochastic	√	√	Supply disruption	Bi-o	MILP	Proposed heuristic

MP: multiperiod; DT: demand type; MC: multicommodity; LC: limited capacity; SM: solution method.

Table 2: Comparing the present study with earlier related studies.

Author	MP	DT	MC	LC	Risk	Object	Model	SM
Rayat et al. (2017) [44]	—	Variable	—	—	Stochastic disruption	Bi-o	MINLP	Metaheuristic
Pourhejazy et al. (2019) [32]	—	Deterministic	—	—	Stochastic disruption	Muti-o	MINLP	Metaheuristic
Ying and Holweg (2015) [41]	—	Deterministic	—	√	Stochastic disruption	—	MIP	Metaheuristic
Current study	√	Stochastic	√	√	Supply disruption	Bi-o	MILP	LR-MGA

MP: multiperiod; DT: demand type; MC: multicommodity; LC: limited capacity; SM: solution method.

Table 3: A summary of relevant studies about CLRIP based on product user risk preference.

Author	QS	SU	Focus
Gruen et al. (2008) [37]	—	—	(i) To define risk preference (ii) To divide risk preference into five types
Apurba et al. (2020) [33]	√	—	(i) To propose an NLIP model to integrate the LIP (ii) To locate the facility based on the customer risk preference (iii) To adopt a metaheuristic algorithm to solve the problem
Gruen (2002) [36]	—	—	(i) To study the retail supply disruption (ii) To analyze the impact of the customer preference
Andreas and Holweg (2007) [41]	—	—	(i) To focus on the factor analysis of risk preference on supply chain performance (ii) To find out factor analysis needs a set of models and evaluation scheme
Current study	√	√	(i) To design the subject utility maximize object function (ii) To integrate the disruption probability to CLRIP model

QS: quantitative study; SU: subjective utility.

ensures that the delivery procedure can achieve management optimization.

Second, unlike the existing combined network optimization research, our research divides the combined system into location, routing, and inventory according to the circulation link. The network optimization problem is transformed into a traditional CLRIP problem, which is conducive to the expansion of the method.

Third, unlike conventional uncertainty research methods, this paper focuses on the subjective behavior characteristics of product users and quantifies the risk preference of product users. The subjective utility function is used to evaluate the impact of risk attitude on discrete network optimization.

Finally, unlike the traditional expected utility theory model, this paper considers the bounded rationality and subjectivity of product users and proposes a routing change selection framework for product users. Compared to traditional expected utility theory, this framework is significantly better in evaluating utility value and preference.

3. Problem Description and Symbol Explanation

3.1. Assumption.

A joint network is composed of the manufacturer and product user $V_c = \{1, 2, \ldots, j\}$

The number of $V_{\mathrm{DC}} = \{1, 2, \ldots, i\}$ in the manufacturer warehouse is limited

The possible capacity levels for each warehouse are known

The manufacturer provides one or more than one product type

The manufacturer has the ability to ensure the quantity of product user orders through inventory control

Each product user could be assigned to only one warehouse

Each vehicle has a maximum capacity

Each vehicle could be assigned to only one route

The manufacturer's total cost includes fixed warehouse cost, fixed vehicle cost, and the variable routing cost

3.2. Problem Description. Manufacturers allocate and distribute orders according to product user demand after product users send order requests to the manufacturers. To meet the demands of users, manufacturers allocate their products to warehouses near users in advance to enhance the flexibility of manufacturers to respond to user orders. This paper fully considers PUSDRPs to solve this problem from the perspective of manufacturers and optimizes the order allocation and logistics distribution to maximize product user utility and minimize operation costs. The supply chain system is shown in Figure 4.

Manufacturers face the antinomy problem when making inventory decisions. On the one hand, manufacturer inventory deployment, which is usually 20%–40% of the manufacturer's total assets, is very expensive. On the other hand, because warehouse capacity is limited, manufacturers do not have unlimited inventory. Therefore, in order allocations, the order delivery time may be affected.

When a product user places an order demand according to his or her own business activities, the manufacturer allocates the order that can meet the demand; that is, the distribution warehouse is allocated, and the routing is selected according to the product user order quantity. For a batch of user orders accepted by the manufacturer, we assume that the utility of the PUSDRP is closely related to the joint system, and the manufacturer can ensure the quantity of product user orders through inventory control. Assuming that the number of $V_{\mathrm{DC}} = \{1, 2, \ldots, i\}$ in the manufacturer warehouse is limited, a joint system is composed of the manufacturer and product user $V_c = \{1, 2, \ldots, j\}$.

The problem to be solved in this paper is to optimize the manufacturer operating cost and product user utility in the joint system by considering the product user disruption risk preference. The manufacturer distributes the products to customers by using $i\,(1 \le i \le K)$ warehouses. When the manufacturer meets customer demand d_j, the transportation time from warehouse i to product user j directly affects the joint system service. The direct utility of this process to meet the product user demand is recorded as e_g_i from manufacturer to warehouse. Product user indirect utility e_t_{ij} is generated when the manufacturer transports the product to user j. Each selected warehouse i will indirectly give utility e_e_i to the product user.

3.3. Symbol Explanation. The symbols, variables, and objective functions used in this study are described in Tables 4–7.

3.4. Biobjective Model of the Joint CLRIP System. Increasing brand awareness is a great incentive for manufacturers to obtain many user orders. Additionally, decision-makers are also faced with the problem of order allocation and logistics distribution of the CLRIP for joint systems.

The manufacturer distribution cost includes the fixed warehouse cost, the fixed vehicle cost, and the variable transportation cost. From the perspective of the demand objectives of the joint system, the manufacturer's operation cost and the product user's subjective utility are expressed as two objective functions, which are the main design objectives of joint system optimization. The purpose of this paper is to find the optimal warehouse quantity, allocate users to warehouses, minimize the cost of opening warehouses, and maximize user utility.

$$Z_1 = Z_1 = \min \sum_{i \in V_{DC}} f w_i y_i + \sum_{h \in H} \sum_{i \in V_{\mathrm{DC}}} \sum_{j \in V_C} f v_h x_{ij}^h + \sum_{i \in V_{\mathrm{DC}}} \sum_{j \in V_C} c_{ij} x_{ij}, \tag{1}$$

$$\text{s.t.} \sum_{h \in H} \sum_{i \in V_{\mathrm{DC}}} x_{ij}^h = 1, \quad j \in V_C, \tag{2}$$

$$\sum_{h \in H} \sum_{i \in V_{DC}} x_{ij}^h = \sum_{h \in H} \sum_{i \in V_{DC}} x_{ji}^h, \quad j \in V_C, \tag{3}$$

$$\sum_{j \in V_C} x_{ij} q_j \le q_i y_i. \quad i \in V_{\mathrm{DC}}, \tag{4}$$

$$\sum_{i \in V_{DC}} x_{ij} = 1, \quad j \in V_C, \tag{5}$$

$$x_{ij}^h + \sum_{h' \in H, h' \ne h} \sum_{i' \in V_{DC}, i' \ne i} x_{ii'}^{h'} \le 2, \quad i \in V_{\mathrm{DC}}, j \in V_C, i \ne j, h \in H, \tag{6}$$

$$\sum_{i \in V_{DC}} \sum_{j \in V_C} x_{ij}^h \le x_{ij}, \quad h \in H, \tag{7}$$

$$u_{ij}^h \ge 0, \quad (i, j) \in E, h \in H, \tag{8}$$

$$x_{ij}^h \in \{0, 1\}, \quad (i, j) \in E, h \in H, \tag{9}$$

$$x_{ij} \in \{0, 1\}, \quad i \in V_{\mathrm{DC}}, j \in V_C, \tag{10}$$

$$y_i \in \{0, 1\}, \quad i \in V_{\mathrm{DC}}, \tag{11}$$

$$\sum_{i \in V_{DC}} f_{ij} - \sum_{i \in V_{DC}} f_{ji} = q_j, \quad j \in V_C, \tag{12}$$

$$f_{ij} \le Q_h x_{ij}^h, \quad i \in V_{\mathrm{DC}}, j \in V_C, i \ne j, \tag{13}$$

$$f_{ij} \le \sum_{h \in H} \left(Q_h - q_j\right) x_{ij}^h, \quad i \in V_{\mathrm{DC}}, j \in V_C, \tag{14}$$

$$f_{ij} \ge q_i \sum_{h \in H} x_{ij}^h, \quad i \in V_{\mathrm{DC}}, j \in V_C. \tag{15}$$

Function (1) is an object function z_1 which represents the total minimization cost of the CLRIP system, and the

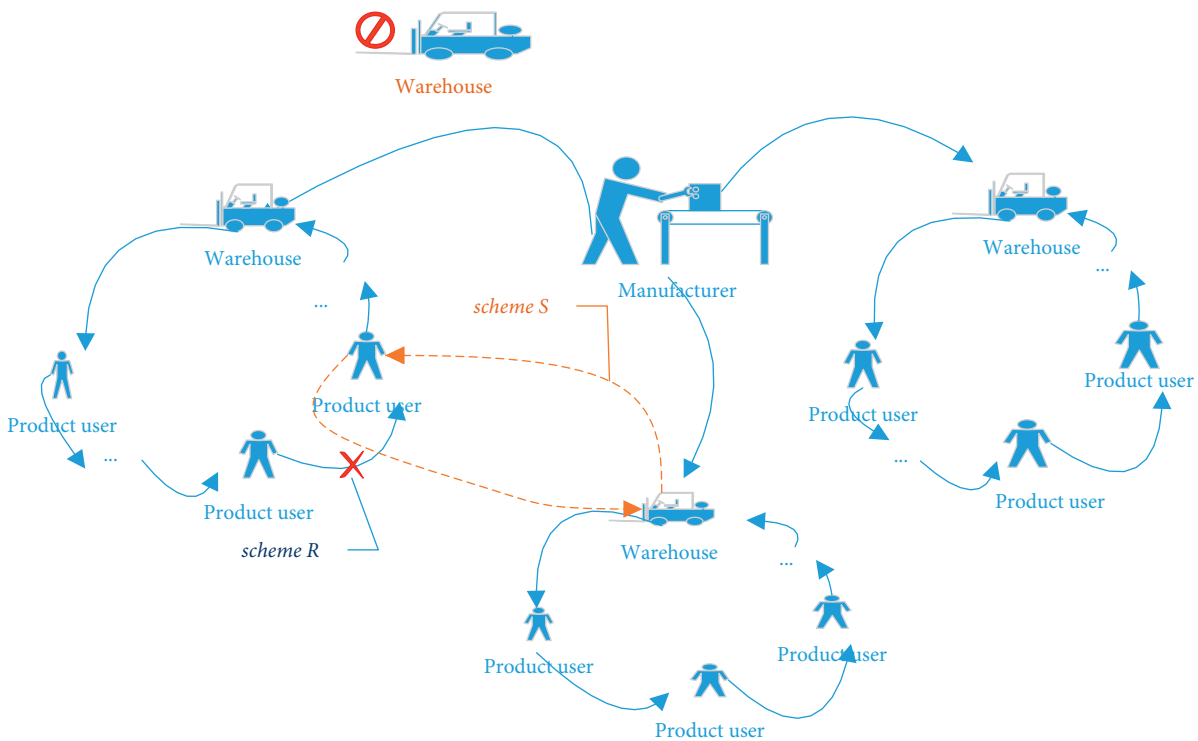

Figure 4: Product user service supply chain system based on the CLRIP.

manufacturer's total cost includes the fixed warehouse cost, the fixed vehicle cost, and the variable routing cost.

Constraint (2) ensures that each product user can only be assigned once. Constraint (3) ensures that the departure of each vehicle from each node is possible only after its entering them. Constraint (4) ensures that the manufacturer warehouse facilities' service capacity is sufficient to meet the demands of product users. Constraints (5) and (10) ensure that each product user accepts only one warehouse order allocation. Constraints (6) and (7) are routing constraints. Constraint (8) guarantees the total load limit of the vehicle. Constrains (9)–(11) assign 0-1 decision variables for users to open the warehouse. Constraint (12) guarantees the warehouse capacity limit. Constraint (13) guarantees the vehicle load does not exceed the vehicle capacity limit. Constraints (14) and (15) ensure that a load of the vehicle can meet the orders of the product users.

To simplify the joint system optimization problem in this paper, the vehicle problem in the distribution process is simplified. Only the cost of serving all users' demands and the inherent cost of operating the warehouse are considered; the latter cost, including the transportation and warehouse costs, is a variable cost.

The total cost $C_{ij} = \sum_{i\in V_{DC}}\sum_{j\in V_C} c_{ij}x_{ij} + \sum_{i\in V_{DC}} fw_i y_i$ from warehouse i to user j, where $\sum_{i\in V_{DC}}\sum_{j\in V_C} c_{ij}x_{ij}$ is the total variable transportation cost and $\sum_{i\in V_{DC}} fw_i y_i$ is the fixed warehouse cost related to the process from warehouse i to user j. To simplify y object function Z_1 into function (16),

$$Z_1 = \min \sum_{i\in V_{DC}} \sum_{j\in V_C} c_{ij}x_{ij} + \sum_{i\in V_{DC}} fw_i y_i. \tag{16}$$

Function (17) is the object function Z_2 which represents the maximization of user utility. For the CLRIP under disruption risk, user utility, which is essential, is the main optimization objective of this paper. $\sum_{i\in V_{DC}}\sum_{j\in V_c} e\_t_{ij}x_{ij}$ represents the direct utility of transportation to meet the demands of users, and $\sum_{i\in V_{DC}}(e\_g_i + e\_e_i)y_i$ represents the indirect utility of manufacturer to warehouse and warehouse to the user.

$$Z_2 = \max \sum_{i\in V_{DC}} \sum_{j\in V_C} e\_t_{ij}x_{ij} + \sum_{i\in V_{DC}} (e\_g_i + e\_e_i)y_i, \tag{17}$$

$$\text{s.t.} \sum_{i\in V_{DC}} x_{ij} = 1, \quad \forall j \in V_C, \tag{18}$$

$$\sum_{j\in V_C} d_j x_{ij} \le q_i y_i, \quad \forall i \in V_{DC}, \tag{19}$$

$$\sum_{j\in V_C} x_{ij} \le n_i y_i, \quad \forall i \in V_{DC}, \tag{20}$$

$$x_{ij} = \begin{cases} 1, \\ 0, \end{cases}, \quad i \in V_{DC}, j \in V_C, \tag{21}$$

$$y_i = \begin{cases} 1, \\ 0, \end{cases}, \quad i \in V_{DC}. \tag{22}$$

Constraints (18) and (21) ensure that each user accepts only one warehouse order allocation. Formulas (19) and (20) ensure that the manufacturer warehouse facilities' service capacity is sufficient to meet the demands of product users. Constraints (21) and (22) assign 0-1 decision variables for users to open warehouses.

Table 4: Set description.

No.	Set	Explanation
1	$J = \{1, 2, \ldots, J^{\max}\}\partial$	The number of users, any user $j \in J$
2	$K = \{1, 2, \ldots, K^{\max}\}$	The number of open warehouses, any open warehouse $k \in K$
3	$V_{\mathrm{DC}} = \{1, 2, \ldots, i\}$	The potential warehouse node
4	$V_{\mathrm{C}} = \{1, 2, \ldots, j\}$	Product user node
5	$H = \{1, 2, \ldots, H^{\max}\}$	The vehicle set, any vehicle $h \in H$
6	$E = \{e^1, e^2, \ldots, e^{\max}\}$	The set of arcs, any arc $e \in E$
7	f_{ij}	The total load of the vehicle driving on the arc $(i, j) \in E$, which is the set of variables u_{ij}^h with respect to H

Table 5: Variable parameter description.

No.	Variable parameter	Explanation
8	q_i	The storage volume $i \in V_{\mathrm{DC}}$ of warehouse i
9	n_i	The number of users served by warehouse i in one order cycle, $i \in V_{\mathrm{DC}}$
10	Q_h	The vehicle capacity
11	fv_h	The fixed dispatching cost of the vehicle
12	u_{ij}^h	The total load of vehicle access node i to node j
13	c_{ij}	The variable cost generated by the transportation process and warehouse operation process from warehouse i to user j
14	fw_i	The fixed cost incurred by warehouse i
15	d_j	The demand of user j
16	e_t_{ij}	Product user utility that is satisfied by transportation from warehouse i to user $j$when the demand is met d_j directly
17	e_g_i	Product user utility generated by the manufacture transport product to each warehouse directly
18	e_e_i	Product user utility generated by the transport between each warehouse i and product user indirectly

Table 6: Decision variable description.

No.	Decision variables	Explanation
19	$x_{ij} = \{0, 1\}$	If the user order is assigned to warehouse $x_{ij} = 1$; otherwise $x_{ij} = 0$
20	$y_i = \{0, 1\}$	If the warehouse is open as 1, otherwise 0
21	$x_{ij}^h = \{0, 1\}$	If the vehicle travels from node i to$j$, as 1, otherwise 0

Table 7: Objective function description.

No.	Decision variables	Explanation
22	Z_1	The objective function 1
23	Z_2	The objective function 2

4. Algorithm Design

Many optimization problems become NP-hard problems as the size of the problem increases. The difficulty and scale of calculation increase as the number of data increases. It is almost impossible to obtain the exact solution; it can be obtained only by using exact algorithms. In this paper, a general biobjective INLP model whose objectives are minimum economic cost and maximum utility is proposed; both objectives are difficult to attain together even in small-scale networks. To solve the problem conveniently, this paper improves the model and designs LR-MGA to approximate the objective function.

4.1. Lagrange Relaxation Method of the Biobjective Model. The LR method is a general technique that can be applied to various combinatorial optimization problems to solve specific constraints. The main idea is to relax the Lagrange factor by eliminating the problematic conditions or

transforming the factor into a function of assigning weights. Each weight represents a penalty factor that does not meet the specific conditions of the solution. The more the solutions violate the conditions, the higher the penalty coefficient. In this paper, we relax two capacity constraints for a specific problem to ensure at least one feasible solution.

Step 1: relax two constraints (the number of cases and the number of warehouses): the LR method is applied to solve the warehouse location in manufacturer order allocation to reduce the fixed cost caused by the open warehouse. The following equation ensures the demand utility generated from transportation, storage, and delivery:

$$\text{Min} \sum_{k \in V_{\text{DC\_open}}} \sum_{j \in V_C} c_{kj} x_{kj}, \tag{23}$$

$$Max \sum_{k \in V_{\text{DC\_open}}} \sum_{j \in V_C} e\_t_{kj} x_{kj}, \tag{24}$$

Equations (23) and (24) are subject to the following constraints:

$$\sum_{k \in V_{\text{DC\_open}}} x_{kj} = 1, \quad \forall j \in V_C, \tag{25}$$

$$\sum_{j \in V_C} d_j x_{kj} \le q_k, \quad \forall k \in V_{\text{DC\_open}}, \tag{26}$$

$$\sum_{j \in V_C} x_{kj} \le n_k, \quad \forall k \in V_{\text{DC\_open}}, \tag{27}$$

$$x_{kj} = \begin{cases} 1, \\ 0, \end{cases}, \quad k \in V_{\text{DC\_open}}, j \in V_C. \tag{28}$$

Constraints (25) and (28) ensure that each user is assigned to only one warehouse, and constraint (28) defines a binary decision variable. Constraints (26) and (27) guarantee capacity boundary constraints.

The number of experimental cases in a single warehouse and the number of users that the manufacturer can serve. The number of cases and users defined by the Lagrange factor in the model are as follows: $(\lambda_k \ge 0) \in R, (\varphi_k \ge 0) \in R, \forall k \in V_{\text{DC\_open}}$.

LR1: manufacturer cost minimization is function:

$$Min \sum_{k \in V_{\text{DC\_open}}} \sum_{j \in V_C} c_{kj} x_{kj} + \sum_{k \in V_{\text{DC\_open}}} \lambda_k \left(\sum_{j \in V_C} d_j x_{kj} - q_k \right) + \sum_{k \in V_{\text{DC\_open}}} \varphi_k \left(\sum_{j \in V_C} x_{kj} - n_k \right). \tag{29}$$

LR2: user utility maximization is function:

$$Max \sum_{k \in V_{\text{DC\_open}}} \sum_{j \in V_C} x_{kj} e\_t_{kj} + \sum_{k \in V_{\text{DC\_open}}} \lambda_k \left(\sum_{j \in V_C} d_j x_{kj} - q_k \right) + \sum_{k \in V_{\text{DC\_open}}} \varphi_k \left(\sum_{j \in V_C} x_{kj} - n_k \right). \tag{30}$$

Both LR1 and LR2 are subject to the following limitations:

$$\sum_{k \in V_{\text{DC\_open}}} x_{kj} = 1, \quad \forall j \in V_C, \tag{31}$$

$$x_{kj} = \begin{cases} 1, \\ 0, \end{cases}, \quad k \in V_{\text{DC\_open}}, j \in V_C. \tag{32}$$

Problems (29)–(32) can be decomposed into two relaxed subproblems: LR1 and LR2. For a given multiplier $\lambda_k \in R \ge 0$, $\varphi_k \in R \ge 0$ is the optimal lower bound of the problem, thus satisfying equations (29)–(32). To solve the following subproblem for each user$\forall j \in V_C$,

LR1: minimize the total cost of the manufacturer as function:

$$\text{Min} \sum_{k \in V_{\text{DC\_open}}} x_{kj} \left(c_{kj} + d_j \lambda_k + \varphi_k \right), \tag{33}$$

LR2: maximize user utility as function:

$$\text{Max} \sum_{k \in V_{\text{DC\_open}}} x_{kj} \left(e\_t_{kj} + d_j \lambda_k + \varphi_k \right). \tag{34}$$

Suppose the time step of $\text{LB}(\varphi^t \lambda^t)$ is t. The constraints of LR1 and LR2 are as follows:

$$\sum_{k \in V_{\text{DC\_open}}} x_{kj} = 1, \quad \forall j \in V_C, \tag{35}$$

$$x_{kj} = \begin{cases} 1 \\ 0 \end{cases}, \quad k \in V_{\text{DC\_open}}, j \in V_C. \tag{36}$$

LR1 and LR2 set the following auxiliary function:

$$\text{LB}\left(\varphi^t \lambda^t\right) = \sum_{j \in V_C} \text{LB}^j \left(\varphi^t \lambda^t\right) - \sum_{k \in V_{\text{DC\_open}}} \lambda_k q_k - \sum_{k \in V_{\text{DC\_open}}} \varphi_k n_k, \tag{37}$$

Step 2: updated Lagrange factor: equations (38) and (39) can be applied to solve the minimum cost of each user order allocation. We need to update the upper bound Lagrange factor formula, and the lower bound constraint is equation (37).

At time t, the distribution of the warehouse is updated by

$$s_k^t = \sum_{j \in V_C} x_{kj}^t d_j - q_k, \tag{38}$$

$$r_k^t = \sum_{j \in V_C} x_{kj}^t d_j - n_k. \tag{39}$$

The solution is obtained by the LR as equations (29) and (30) and constrained as equations (31) and (32).

Step 2.1: Lagrange relaxation method for a single product: in this step, we propose a Lagrange relaxation method for a single product. In this method, α is a constant in the $(0, 2]$ interval, and β^t and γ^t are scalar coefficients of the fitness function as equations (42) and (43). The updated Lagrange process starts with the Lagrange factor of the population as being 0. From equations (40) and (41), we can find that the value of λ_k increases with the increase in the number of warehouses k, and λ_k decreases if the warehouse causes excessive cost disturbance. $s_k^t > 0$ indicates that the demand exceeds the limit of warehouse capacity.

$$\lambda_k^{t+1} = \max\left(0, \lambda_k^t + \beta^t s_k^t\right), \tag{40}$$

$$\varphi_k^{t+1} = \max\left(0, \varphi_k^t + \gamma^t r_k^t\right), \tag{41}$$

$$\beta^t = \frac{\alpha\left(\mathrm{UB} - \mathrm{LB}\left(\varphi^t \lambda^t\right)\right)}{\sum_{k \in V_{\mathrm{DC\_open}}} \left(s_k^t\right)^2}, \tag{42}$$

$$\gamma^t = \frac{\alpha\left(\mathrm{UB} - \mathrm{LB}\left(\varphi^t \lambda^t\right)\right)}{\sum_{k \in V_{\mathrm{DC\_open}}} \left(r_k^t\right)^2}, \tag{43}$$

Step 3: Lagrange relaxation method for multiproduct: let $(\lambda_k^p \geq 0) \in R(\varphi_k^p \geq 0) \in R, \forall k \in V_{\mathrm{DC\_open}}$.

LR1: minimize the total cost of the manufacturer as function:

$$Min \sum_{k \in V_{\mathrm{DC\_open}}} \sum_{j \in V_C} c_{kj}^p x_{kj} + \sum_{k \in V_{\mathrm{DC\_open}}} \lambda_k^p \left(\sum_{j \in V_C} d_j^p x_{kj} - q_k^p \right) + \sum_{k \in V_{\mathrm{DC\_open}}} \varphi_k^p \left(\sum_{j \in V_C} x_{kj} - n_k^p \right). \tag{44}$$

LR2: maximize the user utility as function:

$$Max \sum_{k \in V_{\mathrm{DC\_open}}} \sum_{j \in V_C} x_{kj} e_{\_}^p t_{kj} + \sum_{k \in V_{\mathrm{DC\_open}}} \lambda_k^p \left(\sum_{j \in V_C} d_k^p x_{kj} - q_k^p \right) + \sum_{k \in V_{\mathrm{DC\_open}}} \varphi_k^p \left(\sum_{j \in V_C} x_{kj} - n_k^p \right). \tag{45}$$

Constraints of LR1 and LR2 are

$$\sum_{k \in V_{\mathrm{DC\_open}}} x_{kj} = 1, \quad \forall j \in V_C, \tag{46}$$

$$x_{kj} = \begin{cases} 1 \\ 0 \end{cases}, \quad k \in V_{\mathrm{DC\_open}}, j \in V_C. \tag{47}$$

The problem constraints are relaxed and used to allocate each customer order with the lowest cost to obtain the LB function. To obtain an excellent updated Lagrange multiplier factor, we need to determine an upper bound. We will use a feasible solution based on the product user warehouse allocation evaluation utility. However, the calculation of the lower bound of allocation will likely result in some loss of accuracy in capacity calculation, especially for a multiproduct problem. To obtain the best upper bound (for example, the lowest cost), we need to establish a good method for reallocating user orders when warehouse capacity overflows.

For the order allocation problem of a single product, the allocation is based on the decreasing utility of product user demand. When the product user demand capacity constraint violates the warehouse capacity, the product user order is assigned to the next lowest cost solution. However, when multiple products are allocated, each product has a certain demand utility for each user and is constrained by the warehouse capacity. Therefore, different solutions ensure the utility value of user satisfaction.

4.2. Basic Design Idea of LR-MGA. This paper designs a biobjective solving framework for the joint optimization of order allocation and distribution problems. The framework uses LR-MGA to generate a set of compromise solutions during order allocation and routing. This phase determines the warehouse's location-allocation strategy and routing planning.

To simplify the calculation, the manufacturer uses the LR method to optimize the location allocation, thereby ensuring only the lowest essential economic cost and ignoring the solution of each warehouse location. The method is suitable for users with biobjective allocation. This paper extends the Lagrange Relaxation Model in three aspects: (1) by relaxing the two capacity constraints, (2) by evaluating the robustness of each candidate location solution according to the manufacturer cost and user utility through optimal allocation, and (3) by identifying a robust compromise solution for facility location and then further exploring the possibility of multiobjective optimization. The possible trends of compromise solutions to joint optimization problems are shown in Figures 5–7.

Figure 5 shows the process of decision-making equilibrium before the facility location and the trend chart of the cost target and utility target obtained by each decision scheme. When manufacturers consider the risk preference for disruption of the user supply system, opening more warehouses can significantly shorten the delivery time and

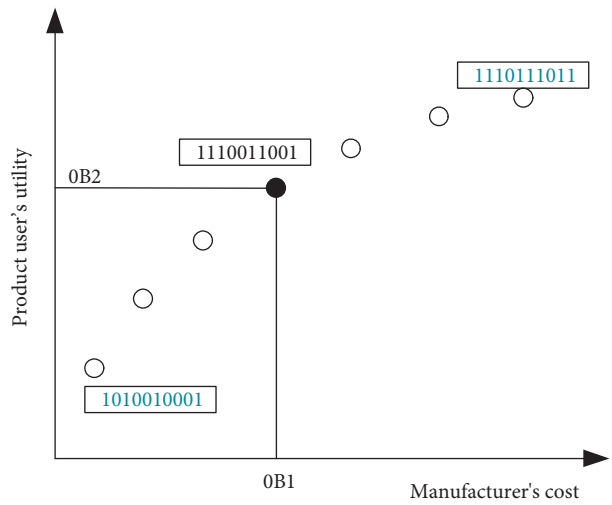

Figure 5: The idea of the compromise solution.

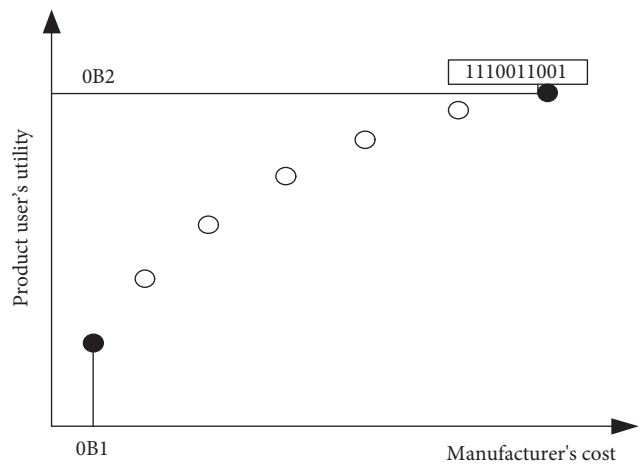

Figure 6: The process of the compromise solution.

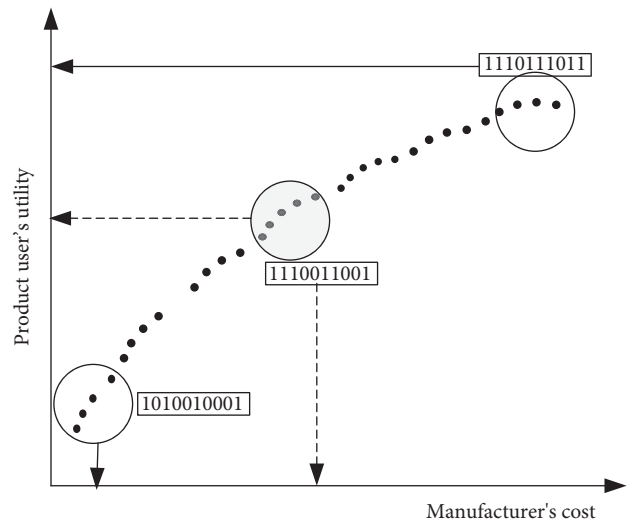

Figure 7: The compromise solution.

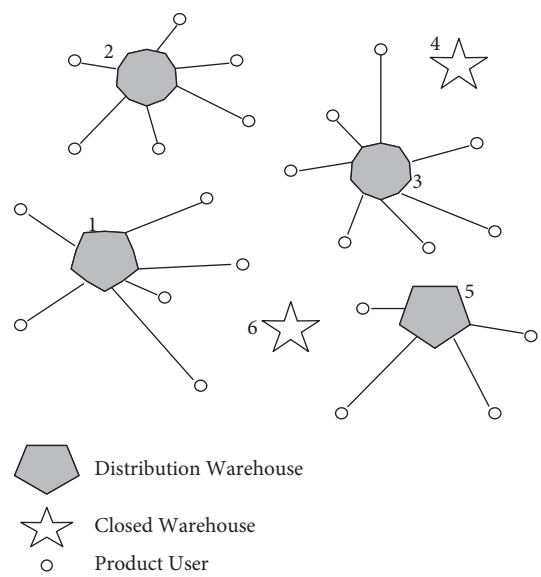

Figure 8: Solutions under cost-based allocation.

improve the subjective utility of users, but the cost will increase.

The binary string in Figure 6 shows the opening and closing of warehouse facilities (1 represents an open warehouse and 0 represents a closed warehouse). For example, strings 1110011001 indicate that warehouse facilities 1, 2, 3, 6, 7, and 10 are open and that facilities 4, 5, 8, and 9 are closed. The idea and process shown in Figures 5 and 6 jointly generate the compromise solution decision-making shown in Figure 7.

Figure 7 shows that, in biobjective optimization, when the manufacturer achieves the optimal economic cost, product user allocation can be realized. That is, the manufacturer can obtain the range compromise solution at each stage. The purpose of this paper is to propose a multi-objective optimization method that enables manufacturers to explore a more strategic and effective distribution scheme for users according to the predetermined location of warehouse facilities.

In this paper, the genetic algorithm is used to solve a joint optimization problem of a joint system considering the PUSDRP. The objective function is used as an index, and the process is as follows:

Step 1: select an open warehouse. According to the constraints, the chromosome is divided into several gene segments, and each gene segment represents a warehouse

Step 2: select product users to serve. Assign the selected users to the warehouse

Step 3: calculate the warehouse selection cost in the order allocation process

Step 4: calculate the transportation cost in the distribution process

Step 5: calculate the joint total cost of order allocation and distribution

In Figure 8, users are assigned to different warehouses after an open warehouse combination is selected, thus leading to a trend between manufacturer cost and user utility. As shown in Figure 6, for example, 111010 stands for warehouses Nos. 1–6, among which warehouses Nos. 1, 2, 3, and 5 are open. From the perspective of minimizing the manufacturer cost, as shown in Figure 8, the transportation cost caused by routing will decrease as much as possible based on the cost allocation. The warehouse will distribute products to users according to the standard of a low routing cost as much as possible at the cost of prolonging the delivery time of user orders and reducing utility.

However, based on the distribution of supply disruption risk preference, as shown in Figure 9 considering the PUSDRP, if the delivery time is reduced as much as possible, a warehouse with a short delivery time will select as much as possible to improve product user utility, but the manufacturing cost will increase.

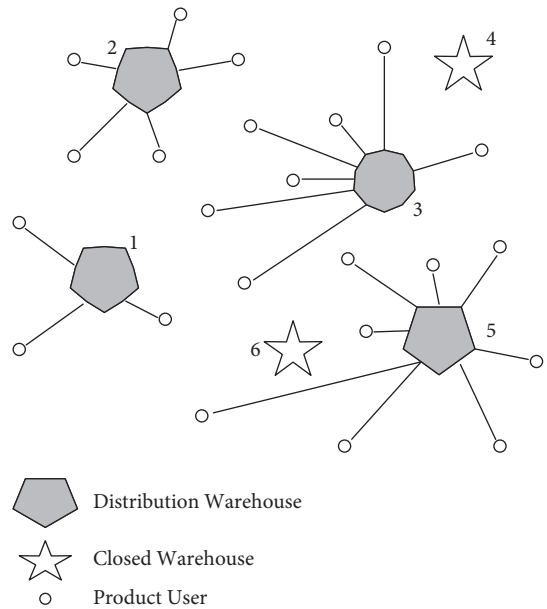

Figure 9: Solutions under preference-based allocation.

5. Discussion and Numerical Experiment

5.1. Analysis Process and Influencing Factors of Route Selection. In this paper, we consider that warehouse allocation and route selection are closely related to order allocation in joint optimization, which considers the disruption risk preference of product users for joint systems.

In logistics distribution, the manufacturer cannot determine the perfect delivery time first due to the uncertainty of the distribution network. Therefore, delivery time is regarded as a random variable. Product user delay time preference will significantly affect product user subjective utility. For a given path scheme, there is a probability distribution and the delivery time of users. The manufacturer seeks a distribution scheme that meets product user preferences to improve product user utility. Product user utility is the joint utility expectation of maximizing order allocation and logistics distribution. This paper proposes a joint optimization idea that considers the disruption risk preference of the user supply system.

5.2. Numerical Experiment Analysis

5.2.1. User Preferences. The fundamental problem of user routing risk preference is to choose the most desired routing subjectively from two alternative routes R and S. The specific situation is divided into two hypotheses, which are described as Q1 and Q2 questionnaires (the investigators have the knowledge reserve and rational conditions and fully understand the setting of the experiment scene). Generally, when placing an order, the interviewees must choose two routes R and S in the questionnaire, and the delivery time of each route is the same. The alternative path diagram is shown in Figure 10.

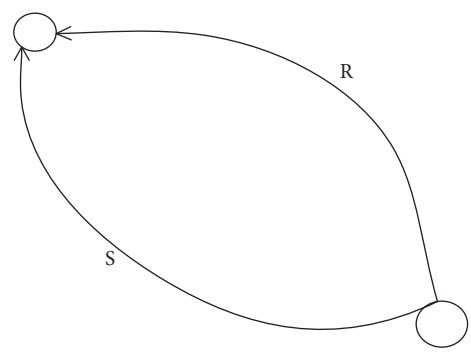

Figure 10: The schematic diagram of alternate routes R and S.

$Q1$: the delivery time on both routes may be reduced due to improved transportation conditions. Let $(t_1, p\%; t_2, q\%)$ represent that there is $p\%$ possibility of saving t_1 time when the order is fulfilled and there is $q\%$ possibility of saving t_2 time when the order is fulfilled. Then, there is a $1 - p\% - q\%$ possibility that there is no decrease in the delivery time. For the interviewed users, the selection of characteristic parameters is shown in Table 8. In Table 8, disruption response scheme sets are denoted as R and S under $Q1$. In set R, (30, 50%; 50, 10%) means that there is a 50% possibility of decreasing the delivery time by 30 when the order is fulfilled and a 10% possibility of decreasing the delivery time by 50 when the order is fulfilled. Then, there is a $1 - 50\% - 10\% = 40\%$ possibility that there is no decrease in the delivery time.

$Q2$: the delivery time on the two routes may increase due to traffic congestion. Let $(t_1, p\%; t_2, q\%)$ represent that there is a $p\%$ possibility of increasing t_1 time when the order is fulfilled and there is a $q\%$ possibility of increasing t_2 time when the order is fulfilled. Then, there is a $1 - p\% - q\%$ possibility that there is no increase in the delivery time. For the interviewed users, the selection of characteristic parameters is shown in Table 9. In Table 9, disruption response scheme sets are denoted as R and S under$Q2$. In set R, (30, 40%; 50, 10%) means that there is a 40% possibility of increasing the delivery time by 30 when the order is fulfilled and there is a 10% possibility of increasing the delivery time by 50 when the order is fulfilled. Then, there is a $1 - 40\% - 10\% = 50\%$ possibility that there is no increase in the delivery time.

Table 8: The routing risk preference of Question Q1.

	Disruption response scheme R			Disruption response scheme S		
	Parameter setting	Size	Percentage	Parameter setting	Size	Percentage
1	(30, 50%; 50, 10%)	258	0.47	(65, 10%; 75, 10%)	585	0.83
2	(30, 50%; 50, 30%)	314	0.56	(65, 10%; 75, 15%)	530	0.76
3	(30, 50%; 50, 25%)	243	0.44	(65, 10%; 75, 65%)	600	0.85
4	(30, 50%; 50, 35%)	230	0.41	(65, 10%; 75, 35%)	614	0.88
5	(30, 50%; 50, 45%)	237	0.42	(65, 10%; 75, 45%)	606	0.86
6	(30, 50%; 50, 55%)	243	0.44	(65, 10%; 75, 55%)	600	0.85
7	(30, 50%; 50, 65%)	261	0.47	(65, 10%; 75, 65%)	582	0.83
8	(30, 50%; 50, 75%)	273	0.48	(65, 10%; 75, 75%)	570	0.82
9	(30, 25%; 50, 30%)	282	0.50	(65, 15%; 75, 15%)	561	0.80
10	(30, 45%; 50, 30%)	302	0.54	(65, 35%; 75, 15%)	542	0.77
11	(30, 50%; 50, 30%)	290	0.51	(65, 40%; 75, 15%)	554	0.79
12	(30, 55%; 50, 30%)	273	0.48	(65, 45%; 75, 15%)	570	0.82
13	(30, 60%; 50, 30%)	266	0.47	(65, 50%; 75, 15%)	578	0.83
14	(30, 65%; 50, 30%)	264	0.47	(65, 55%; 75, 15%)	579	0.83
15	(30, 70%; 50, 30%)	245	0.44	(65, 60%; 75, 15%)	599	0.85
16	(30, 7 5%; 50, 30%)	228	0.41	(65, 65%; 75, 15%)	615	0.88
17	(30, 80%; 50, 30%)	195	0.35	(65, 70%; 75, 15%)	648	0.92
18	(30, 85%; 50, 30%)	164	0.29	(65, 75%; 75, 15%)	680	0.97
19	(30, 30%; 50, 30%)	290	0.51	(65, 75%; 75, 15%)	554	0.79
20	(30, 35%; 50, 30%)	360	0.65	(65, 65%; 75, 15%)	483	0.68

The estimated values based on the expected utility theory are shown in Table 10. According to Tables 8 and 9, the comprehensive parameter estimation statistics table for the two strategies is obtained. When considering only the user's risk preference for disruption, the utility value and the probability that both strategies will be adopted show a gradual change, and the risk neutrality is a relatively balanced value.

5.2.2. Parameter Estimation Based on Experimental Data. Parameter estimation is performed according to the previous experimental data statistics on user preferences. For convenience, the following symbols are defined in this section:

$(\Delta x_i^+, p_i)$ is the utility increased by probability p_i because of Δx_i^+

$(\Delta x_{-i}^-, p_{-i})$ is the utility loss obtained from the probability p_{-i} because of Δx_{-i}^-

$U(R) = \sum_{i=1}^{n} \varphi(\Delta x_i^+)\pi^+(p_i) + \sum_{j=-m}^{j=0} \varphi(\Delta x_j^-)\pi^-(p_j)$is the expected value of the user utility-related characteristic parameter sequence $(\Delta x_m^-, p_{-m}; \ldots; \Delta x_1^+, p_1; \ldots; \Delta x_n^+, p_n)$, where $\Delta x_{-m}^- \leq \cdots \leq 0 \leq \Delta x_1^+ \leq \cdots \leq \Delta x_n^+$

$R\%$ is the probability of choosing the disruption response scheme Rin test scenario i

$U(R_i)$ is the utility of Rin scenario i

$U(S_i)$ is the utility of disruption response scheme S in test scenario i

$P(R_i > S_i) = 1/1 + \exp(U(S_i) - U(R_i))$: the probability that R is more effective than S in scenario i

This paper can predict product user respondents' preference for a disruption response scheme selection by using the values of the reevaluation parameters mentioned above, as shown in Table 11. The tuning parameters are shown in Table 12.

5.2.3. Sensitivity Analysis. Table 11 shows a convergent estimation, thus indicating that the reassessment parameter values are more suitable for describing the choice of the disruption response scheme of product users. However, the estimation effect at $\tau = 30$ min is not as good as that in Table 10 because the initial estimation parameters are obtained according to the expected utility theory, and the estimation of expected utility is modified by considering past product user preferences.

Based on the results of the strategy set, we conduct a sensitivity analysis. To quantify from the perspective of user experience, the two objective functions of the manufacturer's economic cost and the warehouse's order allocation utility are considered at the same time as the main design objective function of optimization.

According to Tables 8 and 9, the sample set is tested in three situations. The differences in total cost, user utility, error rate, and running time of the comparison sample set used by LR, GA, and LR-MGA are shown in Table 13.

As the complexity of the algorithm increases, the operation time increases, and the error rate gradually decreases, as shown in Tables 14–16. In Table 11, the planning cost increases with the increase in utility, but utility increases slowly. Table 15 shows that the planning cost increases with the increase in utility more quickly. However, the planning cost shown in Table 16 increases most quickly with the increase in utility. The differences in cost efficiencies are well represented in different algorithmic complexities.

Table 9: The routing preference of Question $Q2$.

	Disruption response scheme R			Disruption response scheme S		
	Parameter setting	Size	Percentage	Parameter setting	Size	Percentage
1	(30, 40%; 50, 10%)	337	0.43	(65, 10%; 75, 10%)	546	0.83
2	(30, 40%; 50, 30%)	410	0.52	(65, 10%; 75, 15%)	494	0.76
3	(30, 40%; 50, 25%)	318	0.41	(65, 10%; 75, 65%)	560	0.85
4	(30, 50%; 50, 35%)	300	0.38	(65, 10%; 75, 35%)	573	0.88
5	(30, 50%; 50, 45%)	309	0.39	(65, 10%; 75, 45%)	566	0.86
6	(30, 50%; 50, 55%)	318	0.41	(65, 10%; 75, 55%)	560	0.85
7	(30, 50%; 50, 65%)	342	0.43	(65, 10%; 75, 65%)	543	0.83
8	(30, 50%; 50, 75%)	357	0.45	(65, 10%; 75, 75%)	532	0.82
9	(30, 25%; 50, 30%)	368	0.46	(65, 15%; 75, 15%)	524	0.80
10	(30, 30%; 50, 30%)	378	0.48	(65, 75%; 75, 15%)	517	0.79
11	(30, 35%; 50, 30%)	470	0.60	(65, 65%; 75, 15%)	451	0.68
12	(30, 40%; 50, 30%)	430	0.55	(65, 30%; 75, 15%)	480	0.73
13	(30, 45%; 50, 30%)	393	0.50	(65, 35%; 75, 15%)	505	0.77
14	(30, 50%; 50, 30%)	378	0.48	(65, 40%; 75, 15%)	517	0.79
15	(30, 55%; 50, 30%)	357	0.45	(65, 45%; 75, 15%)	532	0.82
16	(30, 60%; 50, 30%)	347	0.43	(65, 50%; 75, 15%)	539	0.83
17	(30, 65%; 50, 30%)	344	0.43	(65, 55%; 75, 15%)	540	0.83
18	(30, 70%; 50, 30%)	319	0.41	(65, 60%; 75, 15%)	559	0.85
19	(30, 75%; 50, 30%)	298	0.38	(65, 65%; 75, 15%)	574	0.88
20	(30, 80%; 50, 30%)	255	0.32	(65, 70%; 75, 15%)	605	0.92

Table 10: The parameter estimation.

Utility function	Relative risk aversion	R		S	
		Value	Percentage	Value	Percentage
$U(y) = e^{-ay}$	$\alpha = 0.15$	31.0914	31.10	35.7323	89.10
$U(y) = e^{-ay}$	$\alpha = 0.25$	24.7423	34.21	54.8765	61.87
$U(y) = e^{-ay}$	$\alpha = 0.50$	50.7413	50.53	58.2742	56.79
$U(y) = y$	Risk neutral	42.0432	67.34	69.4798	55.78

Table 11: The R and S parameter estimation.

τ	R		S	
	Value	Percentage	Value	Percentage
30	28.7852	32.32	61.7878	67.68
60	21.0403	39.66	37.9875	60.34
90	21.0937	44.61	31.5646	55.89
120	32.0453	48.75	35.2976	51.25

Table 12: Tuning parameters.

V_C	{1,2, . . ., 50}
V_{DC}	{1,2, . . ., 8}
d_j	U~[0, 10000]
e_e_i	U~[0, 1]
n_i	U~[0, 60]
q_i	U~[0, 200]
e_g_i	U~[0, 1]
e_t_{ij}	U~[0, 1]

Table 13: Test of algorithms.

	Situation 1	Situation 2	Situation 3
LR	√	×	×
GA	×	√	×
LR-MGA	√	√	√

Table 14: The sensitivity of costs and utilities in Situation 1.

Situation 1			
Cost ($)	Utility	Error (%)	Time (s)
1330	0.31	7.55	521.19
1401	0.31	7.00	525.86
1472	0.35	2.92	539.47
1503	0.41	2.98	542.26
1530	0.41	3.37	553.48
1635	0.43	2.56	569.20
1679	0.43	2.73	574.75

Table 15: The sensitivity of costs and utilities in Situation 2.

Situation 2			
Cost ($)	Utility	Error (%)	Time (s)
1305	0.31	6.94	563.21
1481	0.38	6.60	571.63
1493	0.45	6.34	583.31
1514	0.51	6.39	545.68
1529	0.59	5.69	569.02
1678	0.65	5.04	569.82
1732	0.68	4.18	567.11

Table 16: The sensitivity of costs and utilities in Situation 3.

Situation 3			
Cost ($)	Utility	Error (%)	Time (s)
1379	0.31	4.43	581.37
1321	0.39	4.12	590.21
1310	0.46	4.64	502.48
1506	0.53	4.67	562.97
1581	0.59	4.88	587.47
1627	0.67	4.43	588.32
1687	0.72	4.53	585.47

6. Conclusion and Managerial Insights

6.1. Main Conclusions. First, supply disruption leads to supply chain disruption. To solve the problem that the manufacturer needs to provide satisfactory distribution options for product users under the interruption scenario, this paper considered the interruption and subjective risk preference together to design the disruption response strategy of the discrete network. In this paper, the disruption probability is designed, and the cost-utility biobjective integer nonlinear programming model is given to solve the CLRIP problem of manufacturing order allocation and delivery. This model quantified the subjective risk preference of product users. Scenario 1 in Table 14 shows that the manufacturer's planned cost input increases with the increase in product user utility, but the increase in utility is slow. Scenario 2 in Table 11 shows that the planned cost input increases with the increase in utility, and the speed is faster. Scenario 3 in Table 16 shows that the planning cost input increases with the increase in utility, and the speed is the fastest.

Second, the LR-MGA algorithm is proposed in this paper. The LR algorithm relaxes constraints to simplify the model, and the MGA algorithm finds the optimal solution for the CLRIP.

This algorithm gives a compromise solution between cost minimization and utility maximization. Compromise solutions can reduce the total cost of manufacturers and enhance the subjective utility of product users. Sensitivity analysis proves that the algorithm is effective and efficient in solving discrete network integration optimization problems. The computation time and the error rate of the LR-MGA algorithm increase and decrease, respectively, with the increase in experimental complexity.

Third, to solve the problem that increasing customer satisfaction requires continuous optimization of supply chain efficiency, this paper considers the bounded rationality and subjectivity of product users and applies a behavioral decision method to design a product user RCSF. In Tables 8 and 9, the utility value and the probability that a strategy will be adopted show a gradual change trend, and the risk neutrality is a relatively balanced value. The proposed product user RCSF is obviously superior to the traditional expected utility theory model. The behavior decision method is used to solve the CLRIP integrated optimization problem, which expands the theoretical connotation of uncertain optimization of discrete networks.

6.2. Managerial Insights. Based on the above conclusions, our research has many management insights into application scenarios. Our models and methods can provide managers with solutions.

First, to improve the stability of business cooperation between manufacturers and users, manufacturers will consider PUSDRPs as much as possible in terms of the long-term economic benefits and on the premise of optimizing these benefits.

Second, the biobjective model of the joint CLRIP system can be used to quantify many uncertain practical scenarios (such as the transportation of dangerous goods and pollutants), especially for businesses with different user risk preferences.

Third, the application of algorithms in the CLRIP model can help companies transform decision-making from humanization to informationization. To solve this problem, this paper focuses on constructing a general solution framework, which needs to be extended to a specific practice.

In the future, it will be valuable to design more sophisticated algorithms to find order allocation schemes for users with different risk preferences. The IoT and blockchain have facilitated further exploration into user preferences.

Data Availability

All data generated or analyzed during this study are included in this article. The Jd warehouse logistics price.xlsx data used to support the findings of this study have been deposited in the Baidu (https://pan.baidu.com/s/1fz4M0Bjc8KJkPFSTgRXe0A(password: pm0t)) repository.

Conflicts of Interest

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

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