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Dynamic Uncertainty Study of Multi-Center Location and Route Optimization for Medicine Logistics Company

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Abstract: Multi-center location of pharmaceutical logistics is the focus of pharmaceutical logistics research, and the dynamic uncertainty of pharmaceutical logistics multi-center location is a difficult point of research. In order to reduce the risk and cost of multi-enterprise, multi-category, large-volume, high-efficiency, and nationwide centralized medicine distribution, this study explores the best solution for planning medicine delivery for the medicine logistics. In this paper, based on the idea of big data, comprehensive consideration is given to uncertainties in center location, medicine type, medicine chemical characteristics, cost of medicine quality control (refrigeration and monitoring costs), delivery timeliness, and other factors. On this basis, a multi-center location- and route-optimization model for a medicine logistics company under dynamic uncertainty is constructed. The accuracy of the algorithm is improved by hybridizing the fuzzy C-means algorithm, sequential quadratic programming algorithm, and variable neighborhood search algorithm to combine the advantages of each. Finally, the model and the algorithm are verified through multi-enterprise, multi-category, high-volume, high-efficiency, and nationwide centralized medicine distribution cases, and various combinations of the three algorithms and several rival algorithms are compared and analyzed. Compared with rival algorithms, this hybrid algorithm has higher accuracy in solving multi-center location path optimization problem under the dynamic uncertainty in pharmaceutical logistics.

Keywords: uncertainty; medicine distribution; FCM-SQP-VNS hybrid algorithm

MSC: 37M10

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1. Introduction

The location of pharmaceutical logistics centers has become an important research direction due to the stringent service requirements, strict timeliness standards, and difficulty in quality control in pharmaceutical logistics. At present, the following phenomena exist in the pharmaceutical logistics industry: (1) uncertain disasters always affect the location of pharmaceutical logistics centers; (2) multi-enterprise, multi-category, multi-specification, high-volume, high-efficiency, nationwide centralized medicine distribution has become the trend of pharmaceutical logistics development. However, there are few studies in the pharmaceutical logistics literature involving multi-enterprise, multi-class, and multi-specification drug distribution. The paper addresses the problem of multi-enterprise, multi-category, large-volume, high-efficiency, and nationwide centralized medicine distribution. In order to reduce the risk and cost of multi-enterprise, multi-category, high-volume, high-efficiency, and nationwide centralized medicine distribution, comprehensive consideration is given to uncertainties in center location, medicine type, medicine chemical characteristics, cost of medicine quality control (refrigeration and monitoring costs), delivery timeliness, and other factors to design a multi-center location- and route-optimization plan under dynamic uncertainty. An FCM-SQP-VNS hybrid algorithm is designed.

Current research in pharmaceutical logistics has focused on static problems [1–4], with less attention to dynamic problems and situations affected by uncertainty.

In addition, most studies have addressed single-dimensional rather than multi-dimensional problems [3,5]. There is a lack of studies investigating the national-scale, multi-category, high-volume, and high-efficiency centralized distribution of medicines. Additionally, there is no comprehensive consideration of factors such as the uncertainties in center location, medicine type, medicine chemical characteristics, costs of medicine quality control, delivery timeliness, and other factors in studies on multi-center location and route optimization for pharmaceutical logistics enterprises.

Based on the idea of big data, this paper designs a multi-center location- and route-optimization plan under dynamic uncertainty by considering uncertainty factors such as center location, medicine type, medicine chemical characteristics, cost of medicine quality control (refrigeration and monitoring costs), delivery timeliness, and other factors. We design an FCM-SQP-VNS hybrid algorithm. The accuracy of the algorithm is improved by combining the respective advantages of the fuzzy C-means (FCM) algorithm, sequential quadratic programming (SQP) algorithm, and variable neighborhood search (VNS) algorithm. Finally, the model and algorithm are verified through multi-enterprise, multi-category, high-volume, high-efficiency, and nationwide centralized medicine distribution cases, and various combinations of the three algorithms and several rival algorithms are compared and analyzed. It is proved that the model and algorithm are effective and feasible.

2. Literature Review

2.1. Research on Traditional Logistics and Cold Chain Logistics

Logistical network planning on a rational, scientific basis can reduce logistical costs, improve service levels and capital use efficiency, and realize automation, informatization, and efficiency of logistics. These benefits have attracted the attention of researchers in China and abroad. Logistical cost factors, such as carbon emissions, cargo damage, transportation time, center location, and transportation costs, have been intensively studied. Researchers in both traditional logistics and cold chain logistics typically take the minimum total cost as the objective function and use heuristic algorithms to solve the minimization problem. The emergence of logistics distribution centers has become a popular phenomenon in the global economic process over the past decades [6]. Kim et al. [7] employed an analytic hierarchy process to analyze the hierarchal structure of determinants for selecting the location of a regional logistics distribution centers. Tomáš [8] considered those locations in Bratislava—the capital of the Slovak Republic—which were designated, or suitable for the establishment of urban logistics centers. These locations were afterwards evaluated in a real-world case study employing methods of mathematical programming (linear programming), the nearest neighbor method, and the Clarke–Wright method. Yen [9] modeled the center locations and designed adaptive genetic algorithms based on the current state of ASEAN logistics networks and the characteristics of hub-based networks with taking the total cost minimization as the optimization objective. Lin [10] constructed a vehicle routing optimization model to minimize carbon emissions by logistics enterprises, and used an improved genetic algorithm to solve the model with reduced time complexity. Peng et al. [11] constructed a robust location–path optimization model for emergency resources that was capable of reducing the overall logistical cost. Bao and Zhang [12] constructed a joint distribution route optimization model that comprehensively considered the time window, carbon emission cost, cargo damage cost, and other factors to improve the delivery timeliness and reduce the overall cost. Qin et al. [5] constructed a path optimization model to minimize the cost of customer satisfaction and thereby reduce the overall service cost. Chen et al. [13] by comprehensively considering the constraints of a customer soft time window, mobile battery capacity, and charging vehicle mileage, constructed a mathematical programming model that reduced the overall cost. Huang and Yang [14] incorporated the capacity limits of distribution centers, fixed costs, transportation costs, and time penalty costs into a mathematical programming model to improve the delivery timeliness and reduce the overall cost. Li and Zhou's [15] multi-objective location model for distribution centers comprehensively considered factors including carbon emissions, customer satisfaction, construction costs, and operating costs, and was demonstrated to reduce the overall carbon emissions and costs of logistics and improve customer satisfaction. Xu et al. [16] designed an improved wolf pack algorithm to solve a logistics distribution center model. The algorithm was demonstrated to be more robust than other intelligent algorithms. Yong et al. [17] considering the influence of the COVID-19 pandemic, constructed a location model for an e-commerce logistics center. Using an improved particle swarm algorithm to solve the model was found to enhance computational efficiency and positioning accuracy. Yu et al. [18] constructed a vehicle path model based on data from real-world problems, which was solved by an improved ant colony algorithm. The algorithm successfully improved the timeliness and accuracy of the calculations.

The research content of traditional logistics and cold chain logistics is rich and the theory is mature. Medicine logistics is characterized by stringent service requirements, strict timeliness standards, and difficulty of quality control. Therefore, traditional logistics and cold chain logistics solutions such as those investigated in the above studies are usually inadequate for medicine distribution.

2.2. Medicine Logistics Research

Medicine logistics has attracted much research attention in its own right. Multi-cost, reverse, flexible, multi-objective pharmaceutical logistics has become an important object of research. Chen et al. [19] comprehensively considered factors such as distance and time, and used a weighting method based on a membership function to obtain a plan for medical center location and allocation. Zhou et al. [1] constructed a location–inventory model for a national strategic reserve blood bank, with consideration of distance, time, and inventory, to optimize the layout of the blood bank and enhance its ability to respond to sudden disasters. Zhou [20] comprehensively considered the costs of transportation, distribution, operation, land occupation, storage, damage, and other factors to construct a model for cost minimization in medicine logistics. Wang and Huang [21] constructed a model specifically to minimize the costs associated with drug expiration by incorporating recovery point costs, processing center costs, operating costs, transportation costs, recovery costs, sales revenue, and subsidy revenue. The model reduced the overall cost of recycling. Cao and Lin [2] constructed a medicine reverse-supply-chain model to improve the recovery rate of expired drugs. Sabouhi et al. [22] comprehensively considered volume discounts and the risk of interruption in medicine delivery to construct a flexible supply chain model that improved the overall robustness of medicine distribution against risk. Similarly, Lawrence [23] used the Bayesian network method to construct a medicine delivery model improving the robustness of medicine distribution. Hamdan and Diabat [3] constructed a dual-objective robust optimization model to improve the timeliness of blood distribution and reduce unnecessary casualties. According to Pereira [4], reverse logistics is also important in the pharmaceutical sector to help reduce medication exposure to other people and the environment. The absence of reverse logistics for household waste medicine could lead to serious environmental and public health challenges [24].

The above studies mostly focused on static problems. Less attention has been paid to dynamic problems and situations affected by uncertainty. In addition, most studies have addressed single-dimensional rather than multi-dimensional problems. No study has investigated the national-scale, multi-category, high-volume, and high-efficiency centralized distribution of medicines. Nor have factors such as the uncertainties in center location, medicine type, medicine chemical characteristics, costs of medicine quality control, delivery timeliness, and other factors been comprehensively considered in any study of the multi-center location and route optimization of a medicine logistics company.

3. Mathematical Model

3.1. Research Method

The study is applied and quantitative. In this paper the data are based on the National Medicine Centralized Procurement Document and tender results. Pharmaceutical companies are randomly selected in different regions and different types of medicines. The travel time on each road section for each vehicle is based on real-time road condition data from Auto Navi Map. The objective is to plan the best solution for medicine delivery with the least risk and cost. In this paper, based on the idea of big data, comprehensive consideration is given to uncertainties in center location, medicine type, medicine chemical characteristics, cost of medicine quality control (refrigeration and monitoring costs), delivery timeliness, and other factors. On this basis, a multi-center location- and route-optimization model for a medicine logistics company under dynamic uncertainty is constructed. The FCM-SQP-VNS hybrid algorithm is designed. The algorithm in this paper is developed in C++ language, and its testing and running are carried out in an environment with a 2.5 GB CPU, 8 GB memory, and the Windows 10 operating system. The model and algorithm are verified through multi-enterprise, multi-category, high-volume, high-efficiency, and nationwide centralized medicine distribution cases, and various combinations of the three algorithms and several rival algorithms are compared and analyzed. It is proved that the model and algorithm are effective and feasible.

3.2. Problem Formulation

In accordance with the requirements of the *National Medicine Centralized Procurement Document*, medicine suppliers in China distribute drugs from medicine logistics centers to medical institutions based on the volume and time requirements of medical institutions. The amount of each medicine possessed by each supplier, the delivery cities, and the distribution volume of each medicine in each city are known. For transportation from medicine manufacturers to medicine logistics centers, and from logistics centers to cities, a variety of vehicles are available. The available medicine logistics centers are known, and the cost of monitoring for transportation by each type of vehicle is known. The probability of future disasters for each candidate medicine logistics center is also known.

To reduce the cost of medicine distribution for logistics companies, this paper addresses the problem of multi-enterprise, multi-type, large-volume, high-efficiency, and nationwide centralized medicine distribution. Comprehensive consideration is given to uncertainties in center location, medicine type, medicine chemical characteristics, cost of medicine quality control (refrigeration and monitoring costs), delivery timeliness, and other factors to design a multi-center location- and route-optimization plan under dynamic uncertainty. The schematic diagram of the medicine logistics network is shown in Figure 1.

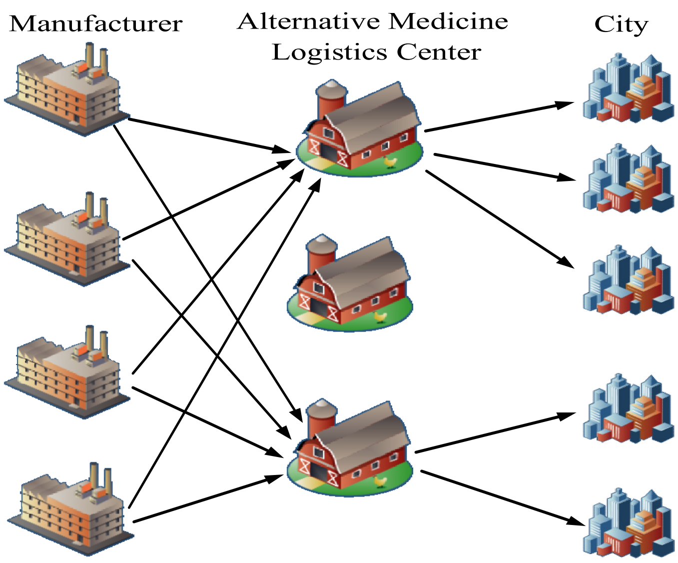

Figure 1. Schematic diagram of medicine logistics network.

3.3. Notation and Decision Variables

(1) Notation

h: a pharmaceutical manufacturer, $h = 1, \ldots, H$;
j: an alternative medicine logistics center, $j = 1, \ldots, J$;
i: a city participating in centralized medicine procurement, $i = 1, \ldots, I$;
n: the type of medicine, $n = 1, \ldots, N$;
k: the type of vehicle used for medicine transportation, $k = 1, \ldots, K$;
c_{k0}: the environmental monitoring cost per unit time by vehicle type k;
c_1: the environmental monitoring cost per cubic meter of inventory per day;
q_{in}^h: the amount of the nth medicine delivered to city i produced by pharmaceutical manufacturer h;
w_{jn}^h: the amount of the nth medicine delivered to medicine logistics center j produced by pharmaceutical manufacturer h;
b_{khn}: the refrigeration cost per unit volume per unit time for the nth medicine produced by pharmaceutical manufacturer h transported by vehicle type k;
ω_{hn}: the unit penalty cost of the nth medicine produced by pharmaceutical manufacturer h that does not arrive on time;
o_{hn}: the weight per cubic meter of the nth medicine produced by pharmaceutical manufacturer h;
s_{hn}: the weight of each box of the nth medicine produced by pharmaceutical manufacturer h;
t_{khjn}: the travel time from pharmaceutical manufacturer h to medicine logistics center j using vehicle type k to deliver the nth medicine;
t_{kjihn}: the travel time from medicine logistics center j to city i to transport the nth medicine produced by pharmaceutical manufacturer h by vehicle type k;
Q_n^h: the total distribution amount of the nth medicine produced by pharmaceutical manufacturer h;
V_j: the medicine logistics center j storage space;
l: the area around the alternative medicine logistics center;
y: year;
d_{jl}: the average distance between the alternative medicine logistics center j and surrounding area l;
p_j: the predicted probability of future disasters for the alternative medicine logistics center j, $j = 1, \ldots, J$;
p_{jl}: the predicted probability of future disasters in the area around the alternative medicine logistics center j, $l = 1, \ldots, L$;
P_j: the predicted probability of future disasters for the alternative medicine logistics center j.

(2) Decision variables

X_{khjn}: If a medicine logistics company chooses the kth type of transportation vehicles to deliver nth type of medicines from the pharmaceutical manufacturer h to the medicine logistics center j, then $X_{khjn} = 1$; otherwise, $X_{khjn} = 0$; Y_{kjihn}: If a medicine logistics company chooses the kth type of transportation vehicles to deliver the nth medicine produced by pharmaceutical manufacturer h from the medicine logistics center j to the city i, then, $Y_{kjihn} = 1$; otherwise, $Y_{kjihn} = 0$; G_{jn}^h: If a medicine logistics company chooses medicine logistics center j to deliver the nth medicine produced by pharmaceutical manufacturer h, then $G_{jn}^h = 1$; otherwise, $G_{jn}^h = 0$.

3.4. Components of the Optimization Model under Dynamic Uncertainty

This paper uses the above notation, parameters and decision variables. Comprehensive consideration is given to uncertainties in center location, medicine type, medicine chemical characteristics, cost of medicine quality control (refrigeration and monitoring costs), delivery timeliness, and other factors. On this basis, a linear programming model is constructed.

(1) Medicine quality control cost

The cost of medicine quality control includes two parts: the cost of medicine refrigeration and the cost of medicine storage environment monitoring.

1. The refrigeration cost consists mainly of the cost of refrigeration during medicine distribution. It is directly proportional to the transportation time and volume of the medicine, and is expressed as:

$$f_1 = \sum_{j=1}^{J}\sum_{h=1}^{H}\sum_{n=1}^{N}\left(\sum_{k=1}^{K}\left\lceil\frac{w_{jn}^{h}}{o_{hn}}\right\rceil b_{khn}X_{khjn}t_{khjn} + \sum_{k=1}^{K}\sum_{i=1}^{I}\left\lceil\frac{q_{in}^{h}}{o_{hn}}\right\rceil b_{khn}Y_{kjihn}t_{kjihn}\right)(1+P_j)G_{jn}^{h} \tag{1}$$

2. Environmental monitoring cost of medicine storage

The cost of environmental monitoring of medicine storage consists of two main parts, associated with the costs of environmental monitoring of medicine transportation and that of medicine inventory. The first part is directly proportional to the time and volume of medicine transportation. The second is directly proportional to the storage time and volume of medicines. The combined cost is expressed as:

$$f_2 = \sum_{j=1}^{J}\sum_{h=1}^{H}\sum_{n=1}^{N}\left[\sum_{k=1}^{K}c_{k0}\left\lceil\frac{w_{jn}^{h}}{o_{hn}}\right\rceil X_{khjn}t_{khjn} + \sum_{i=1}^{I}\sum_{k=1}^{K}c_{k0}\left\lceil\frac{q_{in}^{h}}{o_{hn}}\right\rceil Y_{kjihn}t_{kjihn} + c_1\left\lceil\frac{w_{jn}^{h}}{o_{hn}}\right\rceil t_{n}^{h}\right](1+P_j)G_{jn}^{h} \tag{2}$$

(2) Satisfaction cost of medicine delivery time

The main component of the medicine delivery time is the transportation time from the medicine logistics center to the target city. To accord with the delivery time requirements for centralized medicine procurement (response within 12 h, delivery within 24 h) and the penalty policy, the delivery time is set to a maximum of 24 h, beyond which penalties will be imposed. The time cost of medicine delivery is expressed as:

$$f_3 = \sum_{j=1}^{J}\sum_{h=1}^{H}\sum_{i=1}^{I}\sum_{n=1}^{N}\left(\omega_{hn}\left\lceil\frac{q_{in}^{h}}{s_{hn}}\right\rceil \max\left\{Y_{kjihn}t_{kjihn}-24,0\right\}\right)(1+P_j)G_{jn}^{h} \tag{3}$$

According to the above definitions, under dynamic uncertainty, the route optimization model for medicine logistics multi-center location selection is expressed as:

$$\begin{aligned} F &= \min\{f_1+f_2+f_3\} \\ &= \min\sum_{j=1}^{J}\sum_{h=1}^{H}\sum_{n=1}^{N}\left\{\sum_{k=1}^{K}\left\lceil\frac{w_{jn}^{h}}{o_{hn}}\right\rceil(b_{khn}+c_{k0})X_{khjn}t_{khjn}\right. \\ &+\sum_{k=1}^{K}\sum_{i=1}^{I}\left\lceil\frac{q_{in}^{h}}{o_{hn}}\right\rceil(b_{khn}+c_{k0})Y_{kjihn}t_{kjihn}+c_1\left\lceil\frac{w_{jn}^{h}}{o_{hn}}\right\rceil t_{n}^{h} \\ &\left.+\sum_{i=1}^{I}\left(\omega_{hn}\left\lceil\frac{q_{in}^{h}}{s_{hn}}\right\rceil\max\left\{Y_{kjihn}t_{kjihn}-24,0\right\}\right)\right\}(1+P_j)G_{jn}^{h} \end{aligned} \tag{4}$$

s.t.

$$\sum_{i=1}^{I}q_{in}^{h} \le Q_{n}^{h}, h\in H, n\in N \tag{5}$$

$$\sum_{h=1}^{H}\sum_{n=1}^{N}\sum_{k=1}^{K}\left\lceil\frac{w_{jn}^{h}}{o_{hn}}\right\rceil X_{khjn} < V_j \tag{6}$$

$$\sum_{h=1}^{H}\sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{i=1}^{I}\left\lceil\frac{q_{in}^{h}}{o_{hn}}\right\rceil Y_{kjihn} < V_j \tag{7}$$

$$\sum_{j=1}^{J} w_{jn}^{h} G_{jn}^{h} \geq \sum_{i=1}^{I} q_{in}^{h}, h \in H, n \in N \tag{8}$$

$$\sum_{k=1}^{K} \sum_{j=1}^{J} X_{khjn} \geq 1, h \in H, n \in N \tag{9}$$

$$\sum_{k=1}^{K} \sum_{j=1}^{J} Y_{kjihn} \leq 1, i \in I, h \in H, n \in N \tag{10}$$

$$X_{khjn}, Y_{kjihn}, G_{jn}^{h} \in \{0,1\}, \forall k, h, j, i, n \tag{11}$$

Constraint condition (5) indicates that the total amount of each medicine delivered by the medicine supplier is greater than or equal to the sum of the amount of medicines delivered to each city; constraint condition (6) indicates that the volume of medicines distributed from pharmaceutical manufacturers to the medicine logistics center is smaller than the storage space of the medicine logistics center; constraint condition (7) indicates that the storage space of the medicine logistics center is larger than the demand space for the distribution of medicines; constraint condition (8) indicates that the delivery volume of medicines is not less than the demand of the city; constraint condition (9) indicates that a pharmaceutical manufacturer can choose multiple medicine logistics centers; constraint condition (10) indicates that a city only chooses a medicine logistics center for distribution; constraint condition (11) indicates decision variables.

3.5. Comprehensive Prediction Model of Future Disasters for Medicine Logistics Centers

(1) The prediction model of future disasters in the medicine logistics centers and surrounding areas

In order to improve the safety of the medicine logistics center site selection and drug distribution routes and reduce the impact of sudden disasters on pharmaceutical distribution, this paper uses the ratio of the number of major sudden disasters occurring in the local area within 20 years to the selected period 20 as the predicted probability of future major disasters in the area based on the idea of big data. The probability model of future disasters in the medicine logistics center and surrounding areas is established as follows:

$$p_j = \sum_{y=2001}^{2020} \frac{j_y}{20}, \; p_{jl} = \sum_{y=2001}^{2020} \frac{l_y}{20} \tag{12}$$

(2) Comprehensive prediction model of future disasters for medicine logistics centers

In order to avoid the impact of sudden disasters on the medicine logistics center, it is necessary to fully consider the probability of disasters affecting the location of the alternative medicine logistics center and the surrounding area before selecting the location of the medicine logistics center. Generally, the farther the medicine logistics center is from the source of risk, the smaller the probability of the medicine logistics center suffering from disasters, otherwise, the greater the probability of suffering disasters. The expression is:

$$P_j = p_j + \sum_{l=1}^{L} p_{jl} e^{-\theta d_{jl}} \tag{13}$$

Among them, d_{jl} is the distance between the candidate medicine logistics center j and the surrounding area l, and θ is the distance sensitivity coefficient, with a value of $0 < \theta < 1$ [25,26]. If θ is large, the impact of the surrounding area on the alternative logistics center will be particularly small; if θ is small, the impact of the surrounding area on the alternative logistics center will be particularly large. In order to reflect the impact of the surrounding area on the alternative logistics center, this paper combines the horizontal earthquake influence coefficient and takes $\theta = 0.01$.

4. FCM-SQP-VSN Hybrid Algorithm

4.1. Problem Analysis

The model is a strategic location–allocation problem, and its solution has been proved to be NP-hard. There are many ways to solve such problems, including the ant colony algorithm, particle swarm optimization algorithm, tabu search algorithm, VNS algorithm, and others. However, these methods are often affected by issues such as poor initial solution quality, slow search speed, and low global search capability when solving complex site-selection problem models, leading to low accuracy.

4.2. Solution Approaches

VNS is a heuristic algorithm for solving optimization problems. It has shown outstanding performance in terms of simplicity, speed, humanity, and innovation, and has been applied to solve many combinatorial optimization problems [27–29]. The selection of the initial solution in VNS has a direct impact on the optimal solution, computing time, and number of iteration steps. If the initial solution is selected well, the time and the number of iteration steps required to obtain the global optimal solution will be reduced [30–32].

Studies have shown that the use of the FCM algorithm in combination with VNS can improve the initial solution and calculation efficiency [33–35]. Furthermore, the larger the solution neighborhood, the higher the number of feasible solutions in the neighborhood, and the longer the local search time. In this context, SQP is recognized as one of the best algorithms for medium and small-scale nonlinear programming problems. It has good local convergence and high super-linear convergence speed [36–38]. To improve the accuracy of the local optimal solution search, this paper integrates the SQP algorithm into the VNS algorithm. To further improve the local search ability of the algorithm, multiple points in the neighborhood are selected simultaneously as the starting point, the SQP algorithm is run in parallel, and the optimal local solution is compared with the existing optimal solution. This not only improves the initial solution selection and maintains the advantage of the SQP algorithm in solving local optimal solutions but also exploits the characteristics of the global convergence of the VNS algorithm [39–41] (Algorithm 1).

Algorithm 1. Algorithm Design.

(1) Run the FCM algorithm to obtain the initial solution $x = [x_1, x_2, \cdots, x_c]$, with neighborhood structure $N_k(x)$, $k = 1, 2, \cdots, k_{\max}$, where $k_{\max}$ is the largest neighborhood;
(2) Let k = 1;
(3) Randomly select a solution $x'_1, x'_2, \cdots, x'_m$ in the neighborhood of x;
(4) Using $x'_1, x'_2, \cdots, x'_m$ as the initial solution, run multiple SQP algorithms in parallel, obtain the local optimal solution $x''_1, x''_2, \cdots, x''_m$, choose the best solution as x'';
(5) If $F(x'') < F(x')$, let $x = x''$, go to (2); otherwise, let $k = k + 1$;
(6) If $k \leq k_{\max}$ go to (3);
(7) If the termination rule is met, output the result and end the calculation.

4.3. Time Complexity Analysis

The time complexity of the FCM-SQP-VNS hybrid algorithm includes three parts, which are the time consumed by FCM, SQP and VNS, respectively. In practical applications, the time complexity of the FCM algorithm is 0 (N), the time complexity of the SQP algorithm is 0(N^2), and the time complexity of the VNS algorithm is 0 (kN). The time complexity of SQP-VNS algorithm is 0 (kN^2), and the time complexity of the FCM-SQP-VNS hybrid algorithm is 0 (kN^2 + N). The accuracy of the algorithm has been improved.

5. Case Study and Results

5.1. Case Study

To meet the demand for medicines delivery, a third-party medicine logistics company undertakes the centralized distribution of three medicines: flurbiprofen ester (injection), amoxicillin (oral regular-release dosage form), and cefuroxime (oral regular-release dosage form), denoted 1, 2, and 3, respectively. The companies and medicines are shown in Table 1, and the parameter values are shown in Table 2. The medicine logistics company comprehensively considers the uncertainties in center location, medicine type, medicine chemical characteristics, cost of medicine quality control, and medicine delivery timeliness, and seeks multi-center location and route optimization plans.

Table 1. Companies and medicines.

No.	Enterprise Name	No.	Medicine Name	Specifications	Number
12	Beijing Ted	1	Flurbiprofen ester	50 mg/5 mL	516.41×10^4
13	Shiyao Group	2	Amoxicillin	250 mg	5614.6×10^4
14	Chengdu Times	3	Cefuroxime	250 mg	3351.59×10^4

Table 2. Parameter values.

Parameter	Value	Parameter	Value
Q_1^{12}	258,205 g	Q_2^{13}	14,036,500 g
Q_3^{14}	8,378,975 g	ω_{11}	20 ¥
ω_{22}	0.2 ¥	ω_{33}	1 ¥
b_{1hn}	3 ¥/h	b_{2hn}	2.5 ¥/h
b_{3hn}	2 ¥/h	t_1^1	30 day
c_{10}	2 ¥/h	t_2^2	30 day
c_{20}	1.5 ¥/h	t_3^3	30 day
c_{30}	1 ¥/h	c_1	2 ¥/h
s_{11}	50 mg	o_{11}	2 kg/m^3
s_{22}	250 mg	o_{22}	50 kg/m^3
s_{33}	250 mg	o_{33}	30 kg/m^3
v_1	70 km/h	v_2	90 km/h
v_3	80 km/h	P_1	0.17
P_2	0.15	P_3	0.18
P_4	0.21	P_5	0.19
P_6	0.19	P_7	0.20
P_8	0.18	P_9	0.18
P_{10}	0.16	P_{11}	0.17

The algorithm in this paper is developed in C++ language, and its testing and running are carried out in an environment with a 2.5 GB CPU, 8 GB memory, and the Windows 10 operating system. With respect to parameters, $m = 2$, $\varepsilon = 0.001$, $\theta = 0.01$, $V_j = 5000$ m^3, $k_{\max} = 20$, the neighborhood radius difference is 50 km, and the travel time on each road section for each vehicle is based on real-time road condition data from Auto Navi Map. The distribution of medicines in each city is shown in Table 3. Default values are used for other parameters. The calculation results of the program are rounded to the nearest whole number. The results of the operation are shown in Table 4, and the optimized medicine delivery route is visualized in Figure 2.

Table 3. Medicine delivery volume in each city (10^4).

No.	Name	Medicine Name and No.		
		1	2	3
		Flurbiprofen Ester	Amoxicillin	Cefuroxime
		q_{i1}^{12}	q_{i2}^{13}	q_{i3}^{14}
1	Shanghai	54,355 g	2,753,775 g	2,193,800 g
2	Beijing	53,230 g	203,850 g	3,069,250 g
3	Tianjin	41,785 g	229,175 g	598,475 g
4	Chongqing	4820 g	190,350 g	47,750 g
5	Shenzhen	21,915 g	1,588,475 g	785,425 g
6	Dalian	3805 g	1,073,025 g	140,775 g
7	Shenyang	19,185 g	709,275 g	204,375 g
8	Xi'an	11,360 g	215,300 g	29,275 g
9	Guangzhou	39,025 g	1,227,700 g	901,325 g
10	Chengdu	4055 g	5,539,525 g	378,800 g
11	Xiamen	4670 g	306,050 g	29,725 g

Table 4. Optimal solution for medicine logistics.

Medicine (n)	Medicine Supplier (h)	Vehicle (k)	Logistics Center (j)	w_{j1}^{12}	w_{j2}^{13}	w_{j3}^{14}	Vehicle (k)	City (i)	Cost
1 2 3	12 13 14	3	1	54,355 g	2,753,775 g	2,193,800 g	2	1	119,452 ¥
		3	2	118,005 g	2,215,325 g	4,012,875 g	2	2 3 6 7	
		3	10	20,235 g	5,945,175 g	455,825 g	2	4 8 10	
		3	11	65,610 g	3,122,225 g	1,716,475 g	2	5 9 11	

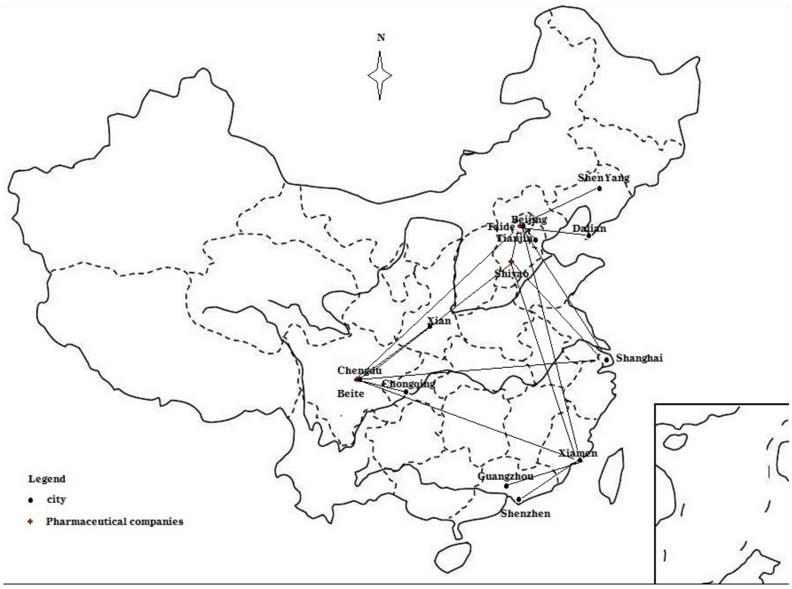

Figure 2. Diagram of optimized medicine distribution path.

5.2. FCM-SQP-VSN Algorithm Analysis

The timeliness and accuracy of the FCM-SQP-VSN hybrid algorithm designed in this paper are first compared with those of the VNS algorithm and SQP-VSN algorithm. Each algorithm's parameter settings are shown in Table 5. The programs are run 20 times, and the results are shown in Table 6 (calculation times are rounded).

Table 5. Parameter settings.

Algorithm Name	Parameter
VNS	The initial solution is randomly selected; neighborhood radius difference: 50 km, maximum number of iterations: 50, number of neighborhood steps per iteration: 100.
SQP-VSN	The initial solution is randomly selected; neighborhood radius difference: 50 km, maximum number of iterations: 50, number of neighborhood steps per iteration: 100.
FCM-SQP-VSN	Weighted index: 2, threshold: 0.001, neighborhood radius difference: 50 km, maximum number of iterations: 50, neighborhood steps per iteration: 100.

Table 6. Algorithm comparison.

Algorithm Name	Average Optimal Value	Minimum Optimal Value	Optimal Number of Times	Accuracy
VNS	128,471 ¥	119,452 ¥	13	65%
SQP-VSN	126,351 ¥	119,452 ¥	13	65%
FCM-SQP-VSN	121,638 ¥	119,452 ¥	16	80%

The VSN algorithm, the SQP-VSN hybrid algorithm, and the FCM-SQP-VSN hybrid algorithm all eventually find the optimal solution to the problem, but differ with respect to the accuracy. Of the three algorithms, FCM-SQP-VSN has the highest accuracy.

Then, FCM-SQP-VSN is compared with the simulated annealing (SA) algorithm, the tabu search (TS) algorithm, and the particle swarm optimization (PSO) algorithm. Each algorithm's parameter settings are shown in Table 7. As before, the programs are run 20 times. The results are shown in Table 8 (calculation times are rounded).

Table 7. Parameter settings.

Algorithm Name	Parameter
SA	Cooling speed: 0.98, maximum number of iterations: 1000.
TS	Tabu length: 10, maximum number of iterations: 1000.
PSO	Number of particles: 20, maximum number of iterations: 1000, learning factors: both 2, inertia weight: 1.2, eps: 10^{-6}.
FCM-SQP-VSN	Weighted index: 2, threshold: 0.001, neighborhood radius difference: 50 km, maximum number of iterations: 50, neighborhood steps per iteration: 100.

Table 8. Algorithm comparison.

Algorithm Name	Average Optimal Value	Minimum Optimal Value	Optimal Number of Times	Accuracy
SA	129,841 ¥	119,452 ¥	14	70%
TS	134,292 ¥	119,452 ¥	11	55%
PSO	138,975 ¥	119,452 ¥	10	50%
FCM-SQP-VSN	121,638 ¥	119,452 ¥	16	80%

The SA, TS, and PSO algorithms each eventually find the optimal solution to the problem, but differ with respect to the accuracy. Again, the FCM-SQP-VSN hybrid algorithm has the highest accuracy.

Finally, to further demonstrate the effectiveness of the FCM-SQP-VSN hybrid algorithm, Cplex software is used to solve the problem, with the program likewise run 20 times. The results are shown in Table 9 (calculation times are rounded).

Table 9. Algorithm comparison.

Algorithm Name	Average Optimal Value	Minimum Optimal Value	Optimal Number of Times	Accuracy
Cplex	122,517 ¥	119,452 ¥	15	75%
FCM-SQP-VSN	121,638 ¥	119,452 ¥	16	80%

We can see from Table 9 that although Cplex can obtain the global optimal solution, its accuracy is lower than the FCM-SQP-VSN hybrid algorithm.

Overall, the FCM-SQP-VSN hybrid algorithm can solve the multi-center location- and route-optimization model for a medicine logistics company under dynamic uncertainty with a relatively high accuracy compared with rival algorithms.

5.3. Results and Discussion

This paper addresses the problem of multi-enterprise, multi-category, large-volume, high-efficiency, and nationwide centralized medicine distribution. Comprehensive consideration is given to uncertainties in center location, medicine type, medicine chemical characteristics, cost of medicine quality control (refrigeration and monitoring costs), delivery timeliness, and other factors to design a multi-center location- and route-optimization plan under dynamic uncertainty. The model is a strategic location-allocation problem, and its solution has been proved to be NP-hard. There are many ways to solve such problems, including the ant colony algorithm, particle swarm optimization algorithm, tabu search algorithm, VNS algorithm, and others. However, these methods are often affected by issues such as poor initial solution quality, slow search speed, and low global search capability when solving complex site-selection problem models, leading to low accuracy.

Based on the idea of big data, this paper selects the disaster data of the candidate medicine logistics centers and their surrounding areas in the past 20 years (data from *National Bureau of Statistics of China*).

The multi-center location- and route-optimization model for a medicine logistics company under dynamic uncertainty is constructed. The FCM-SQP-VNS hybrid algorithm is designed by hybridizing the fuzzy C-means (FCM) algorithm, sequential quadratic programming (SQP) algorithm, and variable neighborhood search (VNS) algorithm to combine the advantages of each. According to the *National Medicine Centralized Procurement Document* and tender results, the pharmaceutical companies are selected in different regions and different types of medicines. The model and algorithm are verified through multi-enterprise, multi-category, high-volume, high-efficiency, and nationwide centralized medicine distribution cases. Various combinations of the three algorithms and several rival algorithms are compared and analyzed. The model can reduce the risk and cost of multi-enterprise, multi-category, large-volume, high-efficiency, and nationwide centralized medicine distribution. The FCM-SQP-VSN hybrid algorithm can solve the multi-center location- and route-optimization model for a medicine logistics company under dynamic uncertainty with higher accuracy compared with rival algorithms.

According to research results in Table 4, the farther the medicine logistics center is from the source of risk, the smaller the probability of the medicine logistics center suffering from disasters, the overall risk and cost of drug logistics are lower. Otherwise, the greater the probability of suffering disasters, the overall risk and cost of drug logistics are higher.

According to the operation results in Tables 6, 8 and 9, the FCM-SQP-VSN hybrid algorithm can solve the multi-center location- and route-optimization model for a medicine logistics company under dynamic uncertainty with higher accuracy compared with rival algorithms.

6. Conclusions and Suggestions

This paper is based on the background of the *National Medicine Centralized Procurement with Volume*, this paper addresses the problem of multi-enterprise, multi-category, large-volume, high-efficiency, and nationwide centralized medicine distribution. The multi-center location- and route-optimization model for a medicine logistics company under dynamic uncertainty is constructed. The FCM-SQP-VNS hybrid algorithm is designed. The model and algorithm are verified through multi-enterprise, multi-category, high-volume, high-efficiency, and nationwide centralized medicine distribution cases, and various combinations of the three algorithms and several rival algorithms are compared and analyzed. The FCM-SQP-VSN hybrid algorithm can solve the multi-center location- and route-optimization model for a medicine logistics company under dynamic uncertainty with a relatively high accuracy compared with rival algorithms.

In pharmaceutical logistics research, comprehensive consideration of the future risks of medicine logistics centers can reduce the overall risk and cost of medicine distribution. Using big data methods to predict the future comprehensive risks of medicine logistics centers, this paper constructed the multi-center location- and route-optimization model for a medicine logistics company under dynamic uncertainty, designed the FCM-SQP-VNS hybrid algorithm, which expanded the scope of medicine logistics research, improved the accuracy of model calculations and reduced the overall risk and cost of medicine delivery. The innovations of this paper are: (1) based on the idea of big data, the comprehensive probability model for predicting future disasters of medicine logistics centers was constructed; (2) the multi-center location- and route-optimization model for a medicine logistics company under dynamic uncertainty was constructed; (3) the FCM-SQP-VSN hybrid algorithm was designed, which was shown to improve the accuracy of the model solution compared with a variety of rival algorithms.

The main limitation of the study is that only some of the medicine logistics factors and medicine transport vehicles are considered. Comprehensive consideration of multiple medicine distribution cost factors will be the direction of the authors' next research.

The comprehensive prediction model of future disasters for medicine logistics centers is affected by various disasters, and there are still many areas to be studied to improve the predictability of the model. Two suggestions are made for future research: (1) the location of distribution centers for multi-center medicine logistics companies could be optimized; (2) the problem of dynamic and uncertain scenarios in multi-center location and route optimization for medicine logistics companies could be extended to multi-dimensional cases.

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