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The optimisation of the location of front distribution centre: A spatio-temporal joint perspective

Linlin Chen [a], Shuihua Han [a,**], Zhen Ye [b,c,e,*], Senmao Xia [d]

[a] The School of Management, Xiamen University, Fujian, 361005, China
[b] The Bartlett School, University College London (UCL), 1-19 Torrington Place, London, WC1E 7HB, UK
[c] The School of Economics, Xiamen University, Fujian, 361005, China
[d] Surrey Academy for Blockchain and Metaverse Applications & Surrey Business School, University of Surrey, Guildford, GU27XH, UK
[e] Infrastructure Systems Institute, Dept. of Civil, Environmental and Geomatic Engineering, University College London (UCL), Chadwick Building, Gower Street, London, WC1E 6BT, UK

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ABSTRACT

Front Distribution Centre (FDC) is a new terminal warehouse which is closer to customers, with its location selection being crucial for e-commerce and customer time satisfaction. We introduce in this paper a joint distribution function of demand based on time and space, which constructs two spatio-time models: spatio-time clustering model and spatio-time optimisation model. A staged clustering algorithm is designed to obtain the candidate FDCs, and an intelligent algorithm based on NSGA-II (Non-dominated Sorting Genetic Algorithm II) is applied to determine the final FDCs, in which the location selection problem is formulated as a bi-objective programming model to minimise total costs and maximise customer time satisfaction. Our results indicate that the model considering spatio-temporal joint attribute of demand performs better than the traditional spatial model. Furthermore, when compared with the k-means clustering algorithm, Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) and its improved algorithm Multi-Objective Evolutionary Algorithm based on the Adaptive Neighborhood Adjustment strategy (MOEA/D-ANA), Multi-Objective Particle Swarm Optimisation" (MOPSO) and its enhancing algorithm Competitive Multi-Objective Particle Swarm Optimiser (CMOPSO), the solving method based on staged clustering and NSGA-II absolutely performs more stable and can get a greater number of pareto-optimal solutions with higher qualities. Especially when compared with K-means clustering algorithms, it can reduce total costs by up to 38.84% and improve customer time satisfaction by up to 36.22%.

1. Introduction

As a product of community e-commerce development, front distribution centre (FDC) is a new terminal warehouse which is closer to customers (Dai et al., 2021). According to the 2021 China Fresh Food E-commerce Industry Research Report (issued by iResearch Institute), from 2018 to 2020, the scale of the real-time fresh food distribution market represented by FDC has increased from USD 1.26 billion to USD 5.24 billion, with a compound annual growth rate of 107%. FDC has expanded rapidly. For example, Alibaba Group has set up 230 front distribution centres (FDCs) (freshHEMA) in two years (Huang and Shi, 2021). However, inappropriate location selection of FDC leads to higher operation costs and lower efficiency, and even large loss (Huang and Shi, 2021). Many studies have pointed out that an appropriate location is decisive for minimizing inventory holding and transportation cost (Holzapfel et al., 2023; Yazdekhasti et al., 2022). Therefore, selecting appropriate FDC location with the optimal demand allocation plays an essential role in an effective supply chain system (Chen and Tsai, 2016; Xuan and Chi, 2020), but so far, there is still limited research on the location selection of FDC. To address this issue, this paper proposed a FDC location selection method from spatio-temporal perspective.

Different from the traditional warehouse, the order response speed of the FDC is faster because its delivery distance is shorter (Huang and Shi, 2021), and this characteristic directly affects its customer time satisfaction, which mainly refers to the satisfaction with delivery time in this paper (Ma et al., 2006). However, same as other instant delivery

* Corresponding author. Zhen Ye, The Bartlett School, University College London (UCL), 1-19 Torrington Place, London, WC1E 7HB, UK
** Co-Corresponding author. Shuihua Han, The School of Management, Xiamen University, Fujian, 361005, China.
E-mail addresses: chenlinlin@stu.xmu.edu.cn (L. Chen), hansh@xmu.edu.cn (S. Han), p.ye@ucl.ac.uk, yezhen@xmu.edu.cn (Z. Ye), s.xia@surrey.ac.uk (S. Xia).

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platforms, it is difficult for FDC to cope with the peak period of fast delivery, while the distribution resources are idle during the low peak period of orders (Yildiz and Savelsbergh, 2019). Therefore, the characteristics of demand distribution cannot be ignored. In particular, the time distribution of customer demand reflects the time information when customers place orders. In addition, Nasr et al. (2021) have demonstrated that the location-inventory-routing model is efficient, which means that considering the routing problem in advance in the location selection stage can reduce total costs effectively. Thus, this paper macroscopically considers the distribution problem, that is, from both space and time dimensions, considering which demand points are suitable for delivery by the same distribution centre.

The location of FDC is a topic which belongs to the multiple distribution centre location problem (Ge et al., 2018). Recently, location methods of multiple distribution centres can be broadly classified into two categories. One group is to assume the candidate distribution centres are known (Tnissen and Arts, 2020; Ge et al., 2018; Nasiri et al., 2014), and the other one is in a situation with unknown candidate distribution centres (Wang et al., 2020). This paper considers the latter situation more realistic due to the requirements of real life.

A key contribution of this paper is to extend the two-stage location decision method by focusing on the spatio-temporal considerations in the literature on FDC location selection problem. Specifically, in clustering stage, many studies use the K-means clustering algorithm to generate the candidate facility location (Wang et al., 2018, 2022; Shahparvari et al., 2020). However, these studies only clustered demand points based on space distance. Recently, Wang et al. (2021) have focused on customer time information and considered time windows of customers in the clustering stage. They have demonstrated that considering customer spatio-temporal information is beneficial to reducing cost and delivery time. Different from the traditional facility location problem which is business to business in Wang et al. (2021), the customer demand in FDC location problem is more stochastic and its delivery capacity is limited. Therefore, the temporal distribution function of customer demand is introduced into this study to describe customer time information. We construct a new spatio-temporal clustering model with two situations presumed, which is more in line with the operation requirements of FDC. By presenting a staged clustering algorithm of three-dimensional clustering and then two-dimensional clustering, the candidate FDCs are obtained.

Although in the planning optimisation stage, most studies focus on the optimisation of costs (You et al., 2019; Kuznietsov et al., 2017; Yong et al., 2015), all of them ignore the customer time satisfaction, which is very important in FDC operation (Ma et al., 2006). This study proposes a bi-objective optimisation model in which not only total costs, but also the customer time satisfaction that is often neglected can now be considered, which we refer to as the spatio-temporal optimisation model. Our optimisation model ensures that the FDC responds to customer needs on time, which is conductive to customer retention and enterprise brand building. Finally, the Non-dominated Sorting Genetic Algorithm (NSGA-II), one of the most popular multi-objective genetic algorithms (Deb and Jain, 2012) is adopted in this study. We use it to solve the optimisation model to derive the final FDCs because of its advantages in reducing the complexity of non-inferior ranking genetic algorithms (Guo et al., 2021).

The structure of this study is organized as follows. We first review relevant literature to introduce the research and explain our thinking and contribution. Then we elaborate the methodology. Next, experiments are carried out, with the results analysed and sensitivity analysis performed. Finally, we conclude our research, its theoretical contributions, and managerial insights, as well as our limitation and future research directions.

2. Literature review

The location of FDC involves two main tasks: determining the candidate location and analysing the multiple distribution centre locations optimisation problem. This section briefly reviews the literatures in these two fields, mainly focusing on research conducted in recent years. To better introduce our contribution with a multi-objective approach, we also review the literatures on the multi-objective optimisation.

2.1. Decision of candidate location

Though the work of determining the candidate location is an important part of location selection, most studies of location selection are carried out based on the assumption of known candidate locations. Vavatsikos et al. (2022) has pointed out that site selection from candidate locations is a multiple criteria decision-making problem. Therefore, the Multi-Criteria Decision Model (MCDM) is often used to help decision making (Gul and Guneri, 2021), especially in hospital location selection (Ahin et al., 2019) and tourism location selection (Mardani et al., 2016), where there have been more mature developments. For example, Moradian et al. (2017) introduced disaster risk criteria into MCDM of hospital location selection. Popovic et al. (2019) estimated a set of criteria based on the MCDM method to select an optimal location for a tourist hotel. Besides, Liu et al. (2020) proposed a fuzzy MCDM to select suitable charging station locations. However, in many real-life location selection problems, the alternative locations are unknown (Yazdekhasti et al., 2022), so this paper carries out the research without the predetermined alternative locations, and the clustering algorithm is used to generate the alternative locations.

Clustering algorithm is a type of data mining analysis method (Ikotun et al., 2023), which has been applied in the problem of location selection and its allocation in recent years (Rajendran and Zack., 2019; Jain et al., 2022). Shahparvari et al. (2020) proposed a K-means based heuristic approach to determine potential locations. Jian (2019) proposed a new supply chain distribution centre selection method based on the clustering algorithm and the centre-of-gravity selection method. Kuznietsov et al. (2017) aimed at the logistics of a food and customer goods distributor problem, generating the initial responsibility areas based on the clustering algorithm. Shin and Kim (2016) used the clustering algorithm as well as other algorithms to design optimal locations of offshore substations. However, these studies only consider the location problem in the space dimension but ignore the time dimension. Because the FDC is a time-sensitive issue, this paper considers a spatio-temporal clustering model in the location problem.

2.2. Multiple distribution centre location optimisation

After determining the alternative location of FDC, the location selection problem can be treated like the optimisation problem of Multiple Distribution Centre Locations (MDCLs), and there is much related research on MDCLs. Some research analysed the logistic optimisation problem from upstream integration centre to multiple distribution centres (Yaghin et al., 2020; Masoud and Mason, 2016), and others focus on the logistic optimisation problem from multiple distribution centres to demand points (Memari et al., 2019; Tsao et al., 2012). Fontaine et al. (2023) have demonstrated that it is suitable to adopt 2-tier transportation strategies under the situation of higher customer density and longer distances between integration centre depots and distribution areas. Therefore, this paper constructs the optimisation model from city distribution centre to the FDCs, then to each demand point.

Compared to the single distribution location optimisation, the optimisation of MDCLs is more beneficial to improve the efficiency of logistics systems and reduce the operational costs with growing logistics demands (Azizi and Hu, 2020). Holzapfel et al. (2023) minimised the total supply chain costs by determining the warehouses' locations, their type affiliations and capacities. Avgerinos et al. (2022) proposed a compact integer programming formulation which minimises the fixed opening costs and the connection costs per client and location. Fathi et al. (2021) considered a supply chain problem that consists of a supplier, multiple distribution centres and multiple retailers. Azizi, & Hu (2020) presented a decision-making model which took multiple distribution centres locating into account, as well as the pickup and delivery vehicle routing, and direct shipment. Most of these studies set the optimisation goal with costs minimisation. Different from the traditional MDCLs optimisation problem, the location optimisation of FDC pays more attention to customers' time satisfaction, which needs to consider goods delivery in a shorter time (Huang and Shi, 2021). Therefore, this paper constructs the bi-objective function with costs minimisation as well as customers time satisfaction maximisation (Ma et al., 2006).

2.3. Multi-objective optimisation approaches

Currently, much research has focused on the design of multi-objective solutions (Mohebalizadehgashti et al., 2020). Classical multi-objective optimisation methods include NSGA-II, multi-objective particle swarm optimisation (MOPSO) (Coello and Lechuga, 2002), and multi-objective evolutionary algorithm based on decomposition (MOEA/D) (Zhang and Li, 2007). There has been much research devoted to the improvement of algorithms. For example, Hao et al. (2020) proposed an improved NSGA-II algorithms by using the crowded distance comparison strategy. Zhang et al. (2018) extended MOPSO and put forward a Competitive Multi-Objective Particle Swarm Optimiser (CMOPSO), which has a promising convergence performance. Wang et al. (2020) studied an improved MOEA/D and proposed a decomposition Multi-Objective Evolutionary Algorithm based on the Adaptive Neighborhood Adjustment strategy (MOEA/D- ANA).

Nowadays, multi-objective methods have been applied to many areas, such as food supply chains (Mohebalizadehgashti et al., 2020), supply chain gap analysis (Jafarian et al., 2020), pricing problems (Gupta et al., 2019) and so on. NSGA-II is outstanding due to its low complexity (Guo et al., 2022; Hao et al., 2020; Shekarian et al., 2020).

3. Methodology

Fig. 1 shows the methodology framework for this research, the candidate FDCs are obtained in the clustering stage, and the final FDCs are determined in the optimisation stage.

Before construction of models, the related symbols are defined as Table 1 shown. The demand point here refers to relevant point of interest, which may be a residential area, a school and so on.

3.1. Clustering stage

In order to reduce total costs while improving customer time satisfaction, spatio-temporal clustering model is constructed in this paper. Therefore, not only geographical distribution information of demand

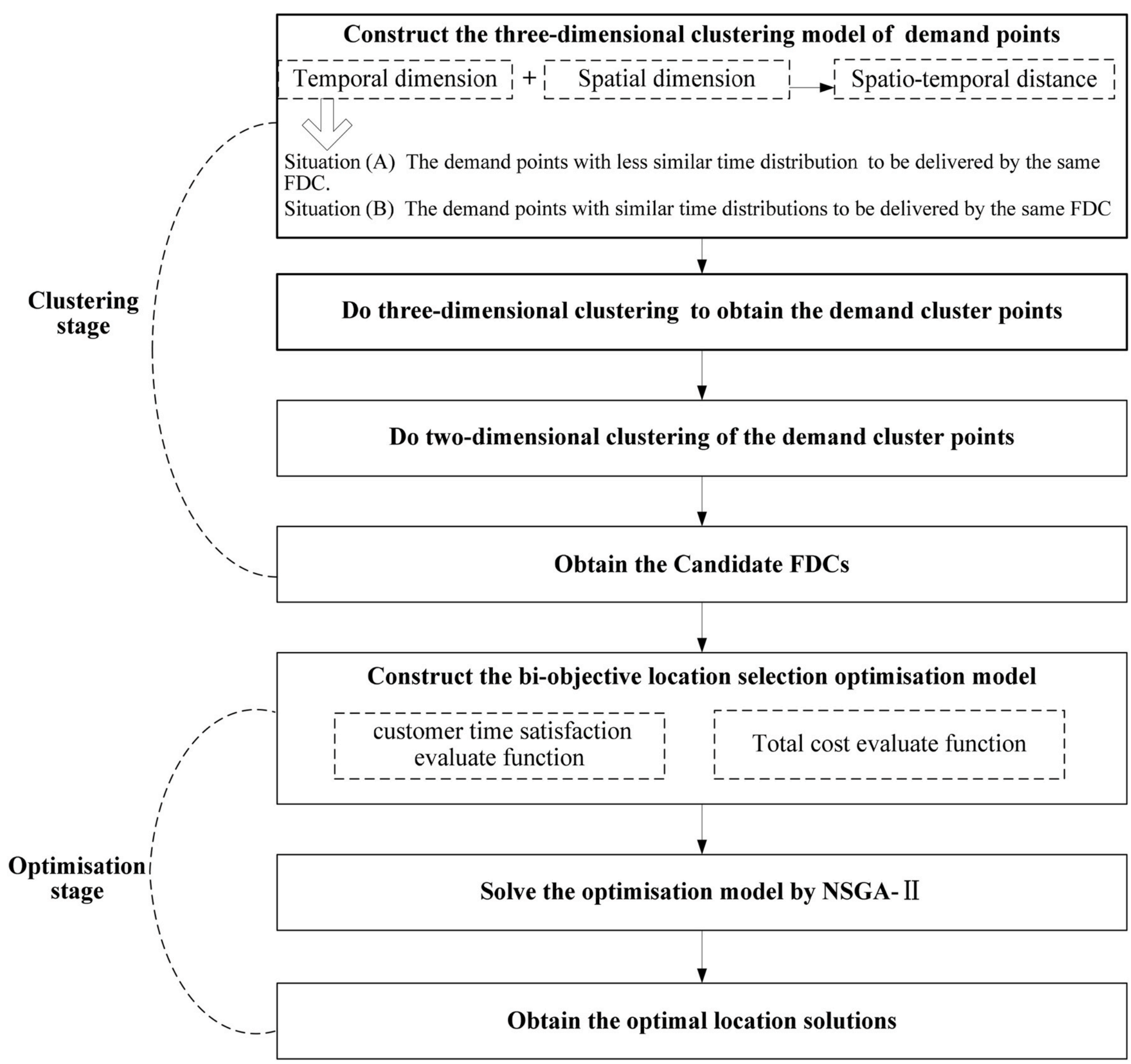


Fig. 1. Methodology framework for research.

Table 1
Indices, variables and parameters of the mathematical model.

stage	type	symbol	definition
Clustering stage	parameters	x_m	Information of demand point m, and $x_m = [lon_m, lat_m, D(T)_m]$, where (lon_m, lat_m) are longitude and latitude coordinates and $D(T)_m$ is the demand time distribution function with respect to time.
		α_m	Coefficient that controls the demand time distribution function.
		$\overline{x}_1$ and $\overline{x}_2$	Independent mean in the demand time distribution function.
		δ_1 and δ_2	Independent standard deviation in the demand time distribution function.
		R	Radius of the earth, and $R = 6,371\text{km}$.
		v	Delivery velocity from the FDC to demands.
		β	Spatio-temporal coefficient that controls the influence degree from space and time dimensions, and $\beta \in [0,1]$.
		k	Number of clusters in three-dimension clustering.
		k'	Number of clusters in two-dimension clustering.
	another variable	σ_m	Standard deviation of clusters that demand x_m wants to join, which represents the degree of dispersion, when we hope that the time lag is as longer as possible, that is we hope σ_m is bigger.
Optimisation stage	sets and indices	I	Set of DCPs, $I = \{1,2,3,...,k\}$, where k is the total number of DCPs determined in clustering stage.
		i	DCPs index, and $i \in I$.
		J	Set of candidate FDCs, $J = \{1,2,3,...,k^{'}\}$, where $k^{'}$ is the total number of the candidate FDC determined in the clustering stage.
		j	Candidate FDCs index, and $j \in J$.
		M_i	Set of demands in initial small demand cluster DCP i, $M_i = \{1,2,3,...,n_{Mi}\}$, where n_{M_i} is the total number of demands in DCP i.
		m_i	Demands index in DCP i, and $m_i \in M_i$.
	parameters	t_{jm_i}	Delivery time from FDC j to demand m_i.
		L_{m_i}	The longest waiting time that the customer m_i can accept.
		$\beta^{'}$	Positive time sensitivity coefficient in customer time satisfaction function.
		n_a	The number of final FDC.
		c_r	Fixed costs of each FDC every month, including rent and fixed operation cost.
		c_O	Unit delivery cost from city distribution centre to the FDC.
		c_1	Unit delivery cost from the FDC to demands.
		h_i	Total monthly demand of DCP i.
		d_{Oj}	Delivery distance from city distribution centre O to the FDC j.
		d_{jm_i}	Directly delivery distance from the FDC j to the demand m_i.
		γ	Probability coefficient dedicates the probability that demands in the same small demand clusters can be delivered together.
	decision Variable	$Y_{ij} = \begin{cases} 1, & \textit{demand cluster } i \textit{ is delivered by the FDC } j \\ 0, & \textit{otherwise} \end{cases}$	
	Another variable	TSP_d_{ji}	Sum of the minimum delivery distance from the FDC j to every demand point in the DCP i, which can be obtained as a traveling salesman problem.
		$TSP\_d_{jm_i}$	Delivery distance from the FDC j to demand m_i when demands in the same small demand clusters can be delivered together.

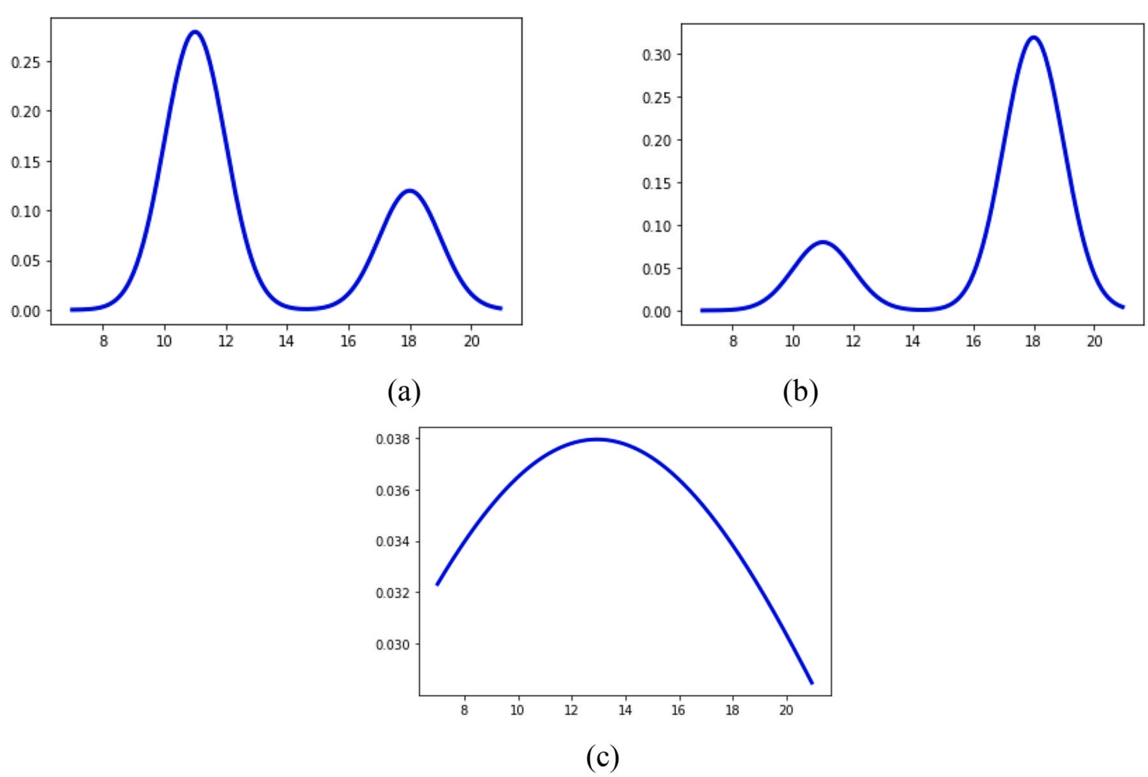


Fig. 2. Time distribution function.

points needs to be known, but also time distribution information of demand points is required. In this section, demand time distribution function is discussed at first, then the distance function in three-dimension clustering model is constructed based on the time distribution information and geographical distribution information. Finally, a staged clustering algorithm of three-dimensional clustering and then two-dimensional clustering is designed to obtain candidate FDCs.

3.1.1. Demand time distribution function

Usually shopping time is concentrated around 11:00 a.m. and 18:00 p.m. (Guidotti et al., 2018), so this paper supposes that the demand time distribution function is a bimodal distribution, which is shown as formula (1), and can also be turned into a unimodal distribution, like normal distribution and skewness distribution, by adjusting its parameters.

$$D(T)_m = \alpha_m * \frac{e^{-\frac{(x_1-\bar{x}_1)^2}{2\delta_1^2}}}{\sqrt{2\pi}\delta_1} + (1-\alpha_m) * \frac{e^{-\frac{(x_2-\bar{x}_2)^2}{2\delta_2^2}}}{\sqrt{2\pi}\delta_2} \tag{1}$$

For example, when $\bar{x}_1 = 11$, $\bar{x}_2 = 18$, $\delta_1 = 1$ and $\delta_2 = 12$, the different symbol α_m generates a different time distribution (Fig. 2), where (a) indicates that the order in this demand point usually occurs around 11:00 a.m., and (b) represents that the order in this demand point often occurs around 18:00 p.m. Furthermore, the probability of (a) occurring at around 18:00 p.m. is higher than the probability of (b) occurring at around 11:00 a.m. In another situation, when $\bar{x}_1 = 11$, $\bar{x}_2 = 18$, $\delta_1 = 10$ and $\delta_2 = 1$, the time distribution is a unimodal distribution, which is shown as Fig. 1 (c).

According to the research by Guidotti et al.(2018), we set $\bar{x}_1 = 11$, $\bar{x}_2 = 18$, $\delta_1 = 1$ and $\delta_2 = 12$ in this paper, and simulate the different characteristics of each demand point by randomly generating the corresponding parameter α_m of the bimodal distribution. For example, if the order occurred time is often around 11:00 a.m., it may be full-time family members who are responsible for the purchase (Fig. 2 (a)), and if it is concentrated at around 18:00 p.m. (Fig. 2 (b)), it is mostly workers who are not at home during the day.

3.1.2. Distance function in three-dimensional clustering model

Different from the traditional Euclidean distance in k-means cluster, the spatio-temporal joint distance is proposed in this paper.

According to the actual goal of operation, it can be divided into two application: situation (A) to reduce later stage delivery costs, arranging the demand points with similar time distributions to be delivered together, so as to realise the strategy of putting together orders; situation (B) to reduce the delivery pressure, arranging the demand points with less similar time distribution to be delivered by the same FDC, so as to reduce the total number of delivery clerks in each FDC. Therefore, the spatio-temporal joint distance has two expressions, and the detail formulations are as follows:

$$Td_{m,m'} = [\alpha_m \times \bar{x}_1 + (1-\alpha_m) \times \bar{x}_2] - [\alpha_{m'} \times \bar{x}_1 + (1-\alpha_{m'}) \times \bar{x}_2] \tag{2}$$

$$Sd_{m,m'} = R \times arc\cos\left(C_{m,m'}\right) \times pi/180$$
$$where\ \ C_{m,m'} = \cos(lat_m) \times \cos(lat_{m'}) \times \cos(lon_m - lon_{m'}) + \sin(lat_m) \times \sin(lat_{m'}) \tag{3}$$

$$D_{m,m'} = \sqrt{Sd_{m,m'}{}^2 + \left(Td_{m,m'} \times v \times \beta\right)^2}$$
$$\text{or} \quad D_{m,m'} = Sd_{m,m'} - \beta\sigma_m \tag{4}$$

Based on formula (1), formula (2) indicates the time lag of order between two points, and formula (3) indicates the space distance between two points. Formula (4) represents the spatio-temporal joint distance that replaces the traditional Euclidean distance in three-dimensional clustering. When the application situation is (A), $D_{m,m'} = \sqrt{Sd_{m,m'}{}^2 + (Td_{m,m'} \times v \times \beta)^2}$, it means that we hope the time lag between demands is as short as possible. While application situation is (B), $D_{m,m'} = Sd_{m,m'} - \beta\sigma_m$, it makes the demand time distribution of points in the same cluster the more dispersed, the better.

3.1.3. Staged clustering algorithm

The basic idea is to take demand points that are needed to be delivered by the same FDC as a whole, then do the second clustering of it to obtain the candidate FDCs. The specific algorithm flow is shown in Fig. 3:

The K-means clustering algorithm is an iterative algorithm of clustering analysis, which can divide the population into several groups according to the distance between points. The three-dimensional clustering algorithm is designed based on the principle of K-means. A three-dimensional coordinate system is established in space, the x-o-y axis represents the geographic information of each point, and the z-axis represents the time information. The space distance is calculated by formula (3) and the time lag is calculated by formula (2), and then the spatio-temporal distance is defined, which is used in the three-dimension clustering stage to get the initial small demand clusters, where the number of demand points in each initial small clusters are limited to n, k and are defined as the number of clusters in three-dimension clustering, with $totalD$ being the total number of demands. The cluster centres of these initial small demand clusters are named demand cluster points (DCPs), which are used as the representative of these demands.

Through preliminary three-dimensional clustering, we have obtained the DCPs in three-dimensional space. Then the problem that these

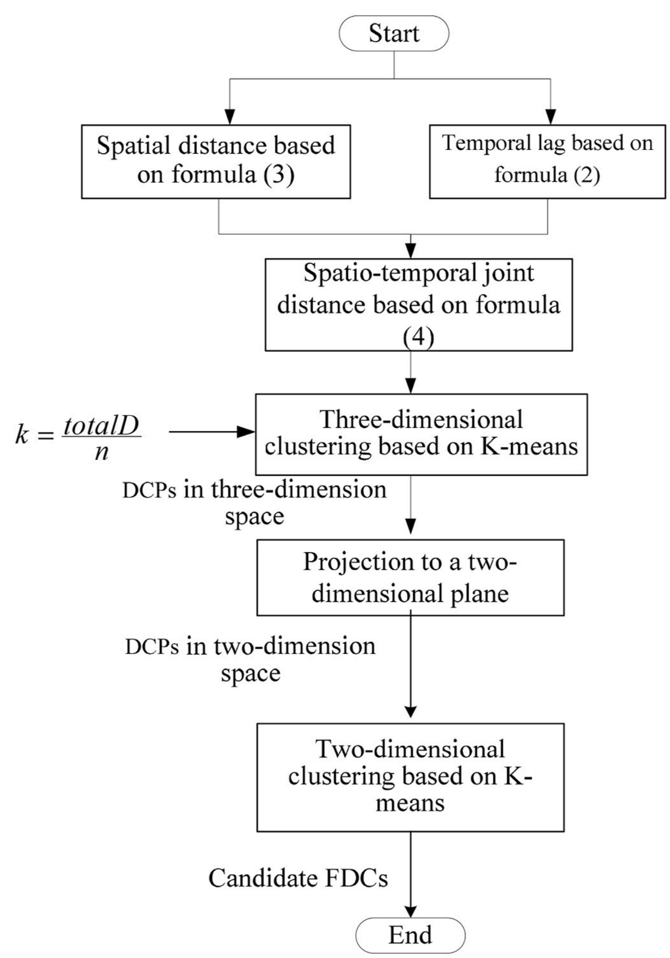


Fig. 3. Staged clustering algorithm flow.

DCPs should be covered by which FDC is considered. That is only a problem in space dimension, so we reduce the dimensionality of the DCPs in the three-dimensional space to the two-dimensional space, eliminating the time information. Through projecting to the x-o-y plane, the DCPs in the two-dimensional space are obtained. After that, the traditional k-means clustering algorithm is used to do secondary clustering of these DCPs to get k' cluster centres, that is, to derive the candidate FDCs.

3.2. Optimisation stage

3.2.1. Optimisation model

This paper builds the spatio-temporal optimisation model with the goal of improving customer time satisfaction and reducing total costs. To simplify the model, these assumptions are made below:

(1) Each demand point can only be delivered by one FDC, and the transfer of goods between the FDCs is not considered.
(2) The maximum supply capacity of the city distribution centre and the FDCs can always meet all current corresponding needs.
(3) Within the service range of the FDCs, the demand time distribution of each demand point is predictable.

First, the customer time satisfaction function is constructed. The descending logarithm Sigmoid function is used to construct the customer time satisfaction function (Ma et al., 2006), as shown in formula (5), where $f(t_{jm_i})$ is a measure value that is similar to the utility, and $f(t_{jm_i}) \in (0, 1]$.

$$f(t_{jm_i}) = \begin{cases} 1, t_{jm_i} \le L_{m_i} \\ \dfrac{2e^{-\beta(t_{jm_i}-L_{m_i})}}{1+e^{-\beta(t_{jm_i}-L_{m_i})}}, t_{jm_i} > L_{m_i} \end{cases} \tag{5}$$

The objective function of the model is to improve customer time satisfaction as much as possible but simultaneously reduce total costs. The amount of demand at each demand point is used as a weight to affect overall customer time satisfaction and total costs, and the higher the total demand of the DCP, the more attention is paid to its satisfaction and costs. The detailed objective functions and constraints are as formula (6) to formula (11) shown:

$$\min\left[c_r n_a + \sum_{j\in J} c_O d_{Oj}\left(\sum_{i\in I} h_i Y_{ij}\right) + \gamma \sum_{j\in J}\sum_{i\in I} Y_{ji} c_1 h_i TSP\_d_{ji} + (1-\gamma)\sum_{j\in J}\sum_{i\in I} Y_{ji} c_1 h_i \left(2\sum_{m_i\in M_i} d_{jm_i}\right)\right] \tag{7}$$

$$\max \sum_{j\in J}\sum_{i\in I} h_i Y_{ij} \sum_{m_i\in M_i} f(t_{jm_i}) \tag{6}$$

$$\textbf{s.t.} \quad \sum_{j\in J} Y_{ij} = 1 \tag{8}$$

$$t_{jm_i} = \gamma \frac{TSP\_d_{jm_i}}{v} + (1-\gamma)\frac{d_{jm_i}}{v} \tag{9}$$

$$0 < n_a \le k' \tag{10}$$

$$Y_{ij} \in \{0, 1\}, (\forall i \in I), (j \in J) \tag{11}$$

Formula (6) is the objective function that maximizes the customer's satisfaction. When $Y_{ij} = 1$, the overall customer time satisfaction is composed of the sum of the product of the customer time satisfaction function of each DCP and its demand. Formula (7) is the objective function that minimises the total costs. The total costs are composed of fixed costs and the delivery cost from city distribution centre to FDC to demands. The distance from FDCs to demands here is divided into two types: direct delivery distance and indirect delivery distance. TSP_d_{ji} is the indirect delivery distance, which is considered in situation (A) mentioned in section 3.1.2, d_{jm_i} is the direct delivery distance, which is considered in situation (B) mentioned in section 3.1.2, and it is the same as the distance formulation in traditional location selection. In situation (A), demand time distributions in the same small demand clusters tend to be similar, there is a certain probability of delivering demands together, so $\gamma \in [0, 1]$. While in situation (B), demand time distributions in the same small demand clusters are dispersed, the case of joint delivery is not considered, so $\gamma = 0$. Constraint (8) ensures that every demand is delivered by one FDC. Constraint (9) determines the delivery time from FDC j to demand m_i, which depends on the probability coefficient γ, and the same as formula (7) $\gamma \in [0, 1]$ in situation (A), and $\gamma = 0$ in situation (B). Constraint (10) limits the range of final FDC's number. Constraint (11) represents decision variable.

3.2.2. Solving algorithm based on NSGA-II

In the optimisation part, NSGA-II is used to obtain the optimal solutions, where the greedy algorithm is embedded to find the TSP_d_{ji}. The DCPs and candidate FDCs obtained in clustering stage are the inputs in NSGA-II.

Initial population: the population size of NSGA-II is determined at first, and each individual in the population represents a delivery plan. To facilitate reading, we choose the real number to code, and the serial numbers of DCPs are used as the coding genes. Meanwhile, the range of each coding gene's values is determined based on the serial numbers of candidate FDCs, that is, the candidate FDC are numbered sequentially as $1, 2, 3, \ldots, k'$, and the value of the gene is randomly selected from $1, 2, 3, \ldots, k'$.

Non-dominant sorting and congestion calculation: following the goal of this paper that maximizes the customer time satisfaction and minimises the total costs, the optimal frontier at the stage is obtained. To calculate the TSP_d_{ji} in delivery cost, we introduce the greedy algorithm in this part, which is used in situation (A) to find the shortest path from the candidate FDC to each demand points and then back to the candidate FDC.

Combination of the populations, selection, crossover, and mutation: by duplicating the current population, the population size is expanded to 2 times of the original population size. Then the selection follows the principle of random selection. The gene fragment is selected randomly to crossover. After that, the mutation operation is to randomly change FDC. Finally, in compliance with the principle of the survival of the fittest, a new population of FDC is generated.

The stopping condition criteria: the criteria iterate multiple times until the maximum number of iterations is reached, then the Pareto optimal frontier is obtained, with each result corresponds to a solution, that is which FDC is to be chosen and the corresponding relationship between the FDCs and DCPs determined.

Table 2
Location data of the small-scale experiment.

number	X (m)	Y (m)	α	demand	number	X (m)	Y (m)	α	demand	number	X (m)	Y (m)	α	demand
0	1300	2300	0.29	40	11	3450	3100	0.55	40	22	3700	2200	0.46	50
1	1400	600	0.17	70	12	3400	2550	0.38	40	23	3900	2150	0.34	70
2	2400	1550	0.46	70	13	3500	2400	0.26	40	24	4000	2490	0.55	60
3	2500	1600	0.71	40	14	3600	2500	0.72	40	25	3990	2800	0.25	40
4	2500	2300	0.72	70	15	3250	1100	0.71	80	26	4100	2200	0.24	40
5	2750	1490	0.19	70	16	3400	1500	0.63	90	27	4250	2950	0.68	60
6	3000	1990	0.17	40	17	3450	1800	0.25	50	28	4250	1000	0.2	60
7	2400	3000	0.49	80	18	3500	1500	0.4	80	29	4300	750	0.58	40
8	2750	2750	0.49	80	19	3600	1250	0.45	50	30	4450	500	0.65	40
9	2800	3100	0.19	50	20	3650	1300	0.33	50					
10	3100	3500	0.84	60	21	3650	1600	0.55	50					

4. Results and sensitivity analysis

4.1. Results of a small-scale and a large-scale experiment

To verify the feasibility and effectiveness of the algorithm proposed in this paper and observe the influence of spatio-temporal attribute, this section first conducts a simulation analysis based on a small-scale calculation example with 31 demand locations (Hu et al., 2015). Then a large-scale example verification is carried out based on 2415 real demand points in Beijing to further verify the application of the method in this paper on real business application.

4.1.1. Small-scale experiment

Since this article does not specifically discuss demand forecasting, the simulation only randomly generates parameters and assigns corresponding demand time distributions to the 31 demand points as discussed in the literature (Hu et al., 2015). The location data are as shown in Table 2, and these data does not represent the actual values.

According to two situations (A & B) explained in section 3.1.2, this paper conducts experiments respectively, and to compare the influence of the time dimension in the demand distribution on the location selection results, we also design a control group which is the traditional location selection method that only considers problem from the space dimension. The relevant parameters of the clustering stage are set out as follows: $\gamma = 0.5$ in situation (A), $\gamma = 0$ in situation (B) and the control group, $\beta = 1$, $k = 8$, and $k^{'} = 4$, then the results of candidate FDCs obtained in clustering stage are as shown in Table 3, and the detailed discussion about the parameters will be carried out in later section.

Based on the obtained candidate FDCs, NSGA II is adopted to derive optimal solutions. To verify the advantages of NSGA II in solving the model in this research, we first compare it with five existing approaches, including staged clustering only based on K-means clustering algorithm (Ikotun et al., 2023), another well-known multi-objective algorithm MOPSO (Coello and Lechuga, 2002) and its enhancing algorithm CMOPSO (Zhang et al., 2018), and popular multi-objective evolutionary algorithms MOEA/D (Zhang and Li, 2007) and its enhancing algorithm MOEA/D-ANA (Wang et al., 2020).

Take the experiment in situation (A) as an example, the longest waiting time that the customer can accept is set to 0.5 h, the delivery cost from the city distribution centre to FDCs is 0.1 yuan/km, and the delivery fee from FDCs to demand points is 1.4 yuan/km, the fixed costs of the FDCs is 3000 yuan/month. These data are only for simulation and do not represent the actual values.

As shown in Table 4, the parameters of NSGA-II in this paper were defined after several computational experiments. The number of clusters in K-means clustering algorithms is set in turns from 1 to 4, retaining all non-inferior solutions. For fair comparisons, the parameters with the same meaning in all evolutionary algorithms take the same value, and other specific parameters of compared algorithms are set according to the original papers (Coello and Lechuga, 2002; Zhang et al., 2018; Zhang and Li, 2007; Wang et al., 2020).

We run algorithms through python 3.7. To reduce the influence of randomness, 10 independent runs are conducted based on NSGA II and other four heuristic algorithms separately. All non-inferior solutions obtained by each approach are retained, and Table 4 presents the results comparing between NSGA II and other approach:

From Table 4 above, there are 4 solutions obtained by staged clustering + NSGA II, 2 solutions obtained by K-means clustering algorithms, 1 solution obtained by staged clustering + MOPSO and staged clustering + CMOPSO, and 3 solutions obtained by staged clustering + MOEA/D and staged clustering + MOEA/D-ANA. We can find that the results obtained by staged clustering + NSGA II is completely superior to those obtained by K-means clustering algorithms, staged clustering + MOPSO and staged clustering + CMOPSO. Especially, compared with the K-means clustering algorithms, the solving method based on staged clustering and NSGA-II reduces total costs by up to 38.84% and improve customer time satisfaction by up to 36.22%. Though staged clustering + MOEA/D and staged clustering + MOEA/D-ANA show similar results, the staged clustering + NSGA II performs the best in stability as shown Table 4.

Based on NSGA II, the Pareto frontier is emerged in the iteration process, which corresponding to the solutions. Then the Pareto frontier of the last generation under different situations in Fig. 4 can be obtained after the calculation. Each node represents a potential location selection solution, and the corresponding detail information is shown in Table 5.

According to the goals of operation, managers can choose any potential solutions above. Comparing the location selection results under different situations, the results in situation (A) are the best. Though the results in situation (B) is worse, the delivery pressure under this situation is lower. To further analyse the characteristic of FDC delivery under different situations and illustrate the impact of spatio-temporal attributes on the location results, we take the solutions with the largest number of FDC under each situation as an example (bold highlighted solutions in Table 5) and draw the location selection results of the FDCs as shown below.

As shown in Fig. 5, the results obtained in situation (A) and situation (B) are very different, while the results obtained in situation (B) and control group are more like. That is because the coefficient β we set here is relatively large. Combining the data in Table 2, many points that seem close in the space dimension are far away in the time dimension, so they are not allocated in the same small demand clusters, resulting in not being covered by the same FDC, such as points 10 and 11. The impact of

Table 3
FDC coordinates information under different situations.

group	1	2	3	4
Situation (A)	(3433.53, 1838.97)	(3112.67, 2650.00)	(2200.00, 1295.00)	(3850.00, 1985.00)
Situation (B)	(2768.75, 1530.83)	(1400.00, 600.00)	(1300.00, 2300.00)	(3399.72, 2199.44)
Control group	(2331.25, 2693.75)	(3783.34, 1166.67)	(3742.23, 2533.78)	(2031.25, 1128.75)

Table 4
The results comparison between NSGA II and other approach in the literature in situation (A).

Approach	Reference	Relative parameters settings	Number of solutions	cost	satisfaction	Number of occurrences in 10 times experiments
staged clustering + NSGA II	This paper	Population size: 100 maximum iteration algebra: 200 crossover rate: 1 mutation rate: 0.3	4	44021.80 45829.20 46318.40 49192.60	29845.20 29871.60 29883.80 29885.00	10 10 10 10
staged clustering	Ikotun et al. (2023)	K = 1, 2, 3, 4	2	67121.16 71976.91	21909.35 21909.39	–
staged clustering + MOPSO	Coello and Lechuga (2002)	population size: 100 maximum iteration algebra: 200 archive size: 300 inertia factor: 0.4 local velocity factor: 0.1 global velocity factor: 0.1 divisions for the adaptive grid: 30	1	46563.60	29875.50	1
staged clustering + CMOPSO	Zhang et al. (2018)	population size: 100 maximum iteration algebra: 200 archive size: 300 inertia factor: 0.4 local velocity factor: 0.1 global velocity factor: 0.1 divisions for the adaptive grid: 30 Number of elite particles to selected: 10	1	46397.60	29882.70	1
staged clustering + MOEA/D	Zhang and Li (2007)	population size:100 maximum iteration algebra: 200 mutation rate: 0.3 neighborhood size: 10	3	44021.80 45829.20 46318.40	29845.20 29871.60 29883.80	10 6 3
staged clustering + MOEA/D-ANA	Wang et al. (2020)	population size: 100 maximum iteration algebra: 200 mutation rate: 0.3 neighborhood size: [5,30]	3	44021.80 45829.20 46318.40	29845.20 29871.60 29883.80	9 6 1

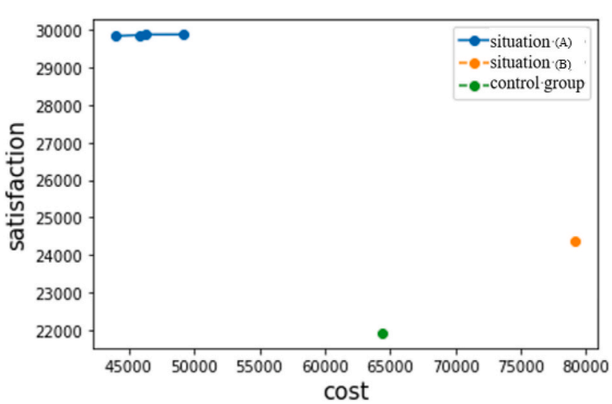


Fig. 4. Pareto frontier of the last generation under different situations.

the β on the location selection results will be discussed in detail in the subsequent sensitivity analysis part.

4.1.2. Large-scale experiment

To verify the applicability of the models and methods proposed in this paper in large-scale examples, especially in real life, we take the actual data of residential areas in Xicheng District of Beijing, China as an example for further verification. The latitude and longitude information of 2415 demand points are collected, and part of the coordinate information are as shown in Table 6. Because the emphasis of this paper is to discuss the spatio-temporal attribute of demands, in this experiment, the total demand of each demand point is assumed to be the same, which can be standardised as a unit, and no longer appear in Table 6.

The parameters in clustering stage are set as follows: $\gamma = 0.5$, $\beta = 1$, k is 483 and k' is 10. To observe the clustering situation under different situations, the three-dimensional clustering results are drawn as shown in Fig. 6.

As shown in Fig. 6, we can find that in situation (B), demand points are more concentrated from the spatial dimension, and more dispersed from the time dimension, which is consistent with our situation definition, indicating that the staged clustering algorithm we proposed in this paper is appropriate.

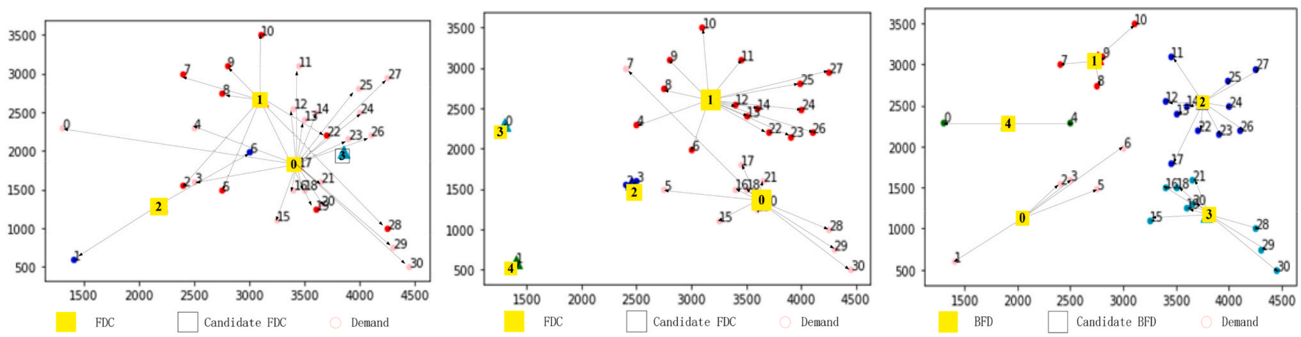
The parameters in optimisation stage of this instance are set as follows: the population size in NSGA-II is 200, the maximum iteration algebra is 300, the crossover rate is 1, and the mutation rate is 0.3. The longest waiting time that the customer can accept is set 0.5 h, the delivery cost from city distribution centre to FDCs is 0.1 yuan/km, the delivery cost from FDCs to demand points is 1.4 yuan/km, and the fixed costs of FDCs is 3000 yuan/month.

As in the previous section 4.1.1, the pareto frontiers of the last generation in different situations are shown in Fig. 7.

From Fig. 7, we can find that in this instance, situation (A) has the minimum costs, and control group has the maximum satisfaction.

Table 5
The location selection solution under different situations.

Situation (A)				Situation (B)			Control group		
Solution No.	Cost	Satisfaction	The number of FDC	Cost	Satisfaction	The number of FDC	Cost	Satisfaction	The number of FDC
1	44021.80	29845.20	1	**79096.70**	**24384.40**	**4**	**64357.00**	**21910.00**	**4**
2	45829.20	29871.60	2						
3	46318.40	29883.80	2						
4	**49192.60**	**29885.00**	**3**						

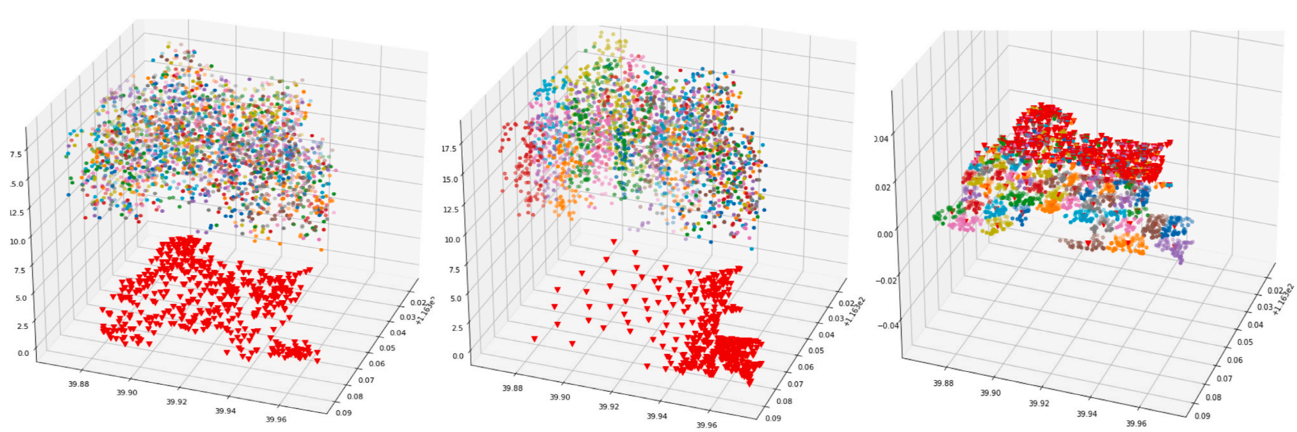


(a) situation (A) (b) situation(B) (c) control group

Fig. 5. Location selection results under different situations.

Table 6
Part of the coordinate information.

Number	Longitude	Latitude	α	Time focus	Number	Longitude	Latitude	α	Time focus
1	116.38750	39.97132	0.29	15.93629	20	116.37740	39.96120	0.45	14.87742
2	116.36480	39.96453	0.17	16.78777	21	116.37650	39.96514	0.33	15.68747
3	116.36660	39.96174	0.46	14.74774	22	116.37690	39.96933	0.55	14.12138
4	116.36780	39.96533	0.71	13.00200	23	116.37660	39.97062	0.46	14.76248
5	116.3860	39.97117	0.72	12.97563	24	116.37710	39.96806	0.34	15.61161
6	116.37580	39.97084	0.19	16.66819	25	116.37660	39.97013	0.55	14.17224
7	116.37660	39.96322	0.17	16.82624	26	116.37160	39.96505	0.25	16.22592
8	116.36450	39.96354	0.49	14.54783	27	116.36840	39.96323	0.24	16.31529
9	116.37730	39.96794	0.49	14.57897	28	116.37830	39.96597	0.68	13.24337
10	116.37320	39.96304	0.19	16.65481	29	116.37780	39.96600	0.20	16.57527
11	116.37140	39.96541	0.84	12.08999	30	116.37400	39.96209	0.58	13.95146
12	116.37880	39.96728	0.55	14.13220	31	116.37680	39.96607	0.65	13.42617
13	116.37840	39.96210	0.38	15.32852	32	116.37200	39.96180	0.99	11.04044
14	116.36450	39.96310	0.26	16.15298	33	116.37410	39.96231	0.24	16.28978
15	116.37140	39.96573	0.72	12.98876	34	116.37710	39.96788	0.15	16.94156
16	116.37320	39.96291	0.71	12.99747	35	116.37020	39.96482	0.77	12.58498
17	116.37330	39.96374	0.63	13.56998	36	116.37660	39.96926	0.14	17.02448
18	116.37320	39.96308	0.25	16.24826	37	116.37300	39.96179	0.78	12.57407
19	116.37410	39.96187	0.40	15.23451	38	116.37260	39.96374	0.82	12.27416



(a) situation (A) (b) situation (B) (c) control group

Fig. 6. The three-dimensional clustering results under different situations.

Though the results in situation (B) appear to be the worst, the delivery pressure under this situation is generally the smallest. This is because under this situation, the time for customers of the same FDCs to place orders is relatively scattered, which alleviates the situation of the imbalance between supply and demand.

4.2. Sensitivity analysis

In the next section, we conduct sensitivity analyses by changing the relevant parameters in the model, to investigate the effect of each parameter on location selection results under different situations. The sensitivity analysis is carried out based on the data of the small-scale experiment.

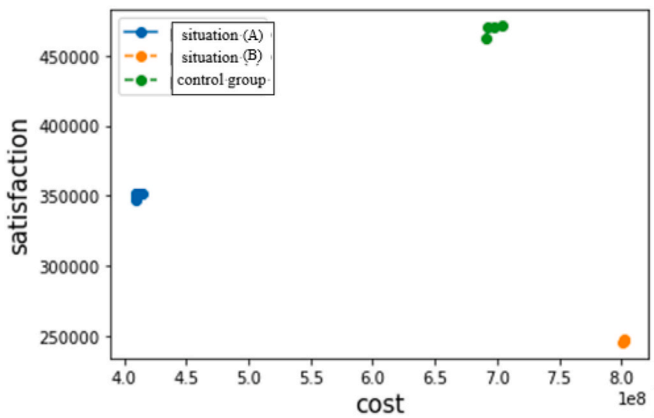


Fig. 7. Pareto frontier of the last generation under different situations.

4.2.1. *Sensitivity analysis on the spatio-temporal coefficient*

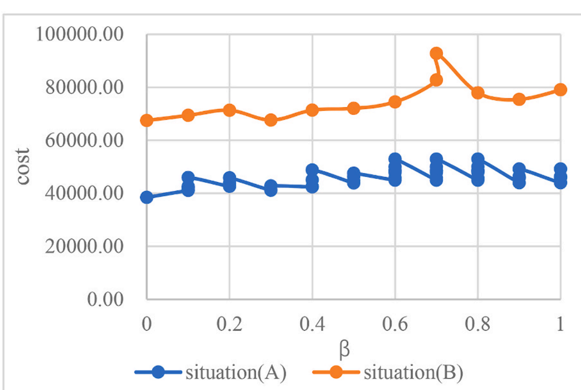
In the previous section 4.1, we allocated $\beta = 1$ to expand the impact of time attribute on location selection to facilitate the comparison of results. In this section, we conduct a sensitivity analysis to examine how the spatio-temporal coefficient β that controls the degree of influence from time and space dimensions on clustering affects the location selection results. Fig. 8 indicates that the coefficient β has little effect on costs but has a skipping effect on customer time satisfaction. When the value of β is relatively small, the time lag between points has little impact on clustering, and when β is relatively large, the space distance has little impact on clustering. Therefore, choosing a proper β can comprehensively consider the problem from the spatio-temporal dimension, and help managers to make a more reasonable decision to reduce the costs and improve the customer time satisfaction.

4.2.2. *Sensitivity analysis on the number of clusters in three-dimension clustering*

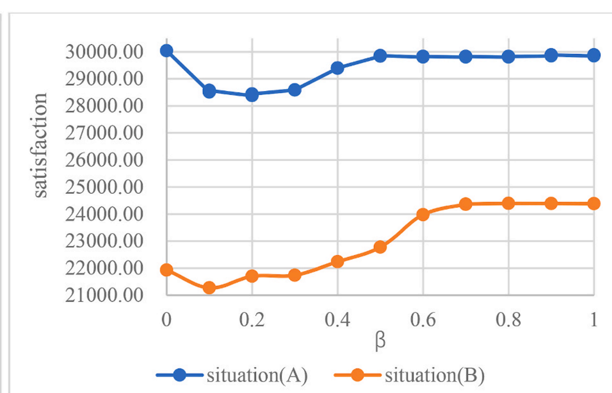
In this section, we conduct a sensitivity analysis to examine how the clustering parameter k affects the results of location selection. The parameter k controls the number of small demand clusters, the larger the k, the less the demand points in the small demand clusters. Fig. 9 indicates that the impact of k on total costs and customer time satisfaction is different under different situations. In situation (A), the bigger the k, the higher the customer time satisfaction, but the higher the costs as well, and when k is relatively big, the results tend to stable. While in situation (B), there seems that the bigger the k, the higher the costs and the lower the customer time satisfaction. Therefore, in situation (A), a relatively big k is advised if managers prefer to improve customer time satisfaction, and a relatively small k is advised if managers prefer to reduce costs; in situation (B), a relatively small k is advised to reduce costs and improve customer time satisfaction.

4.2.3. *Sensitivity analysis on the number of clusters in two-dimension clustering*

In this section, we conduct a sensitivity analysis to examine how the parameter k' affects the overall customer time satisfaction and the total costs of location selection. Fig. 10 indicates that k' has little effect on satisfaction, but the costs have a downward trend with the increase of k'. Furthermore, when k' is relatively big, the location selection results tend to be stable. That is because the location selection method proposed in this paper can choose the appropriate number of FDC independently in the optimisation stage. Therefore, it is beneficial for managers to choose

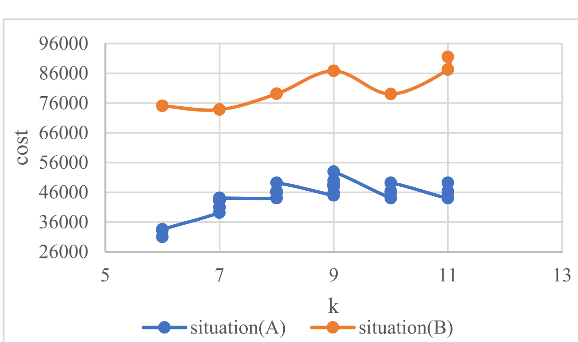


(a) the impact on costs

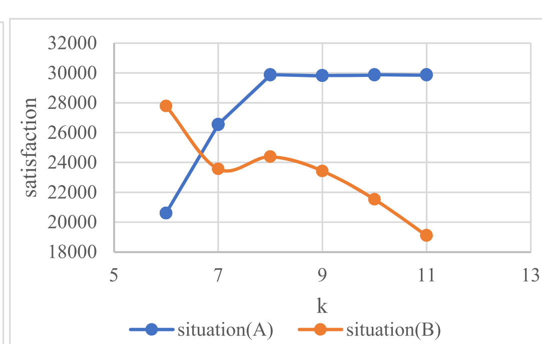


(b) the impact on satisfaction

Fig. 8. The impact of different coefficient β on results.

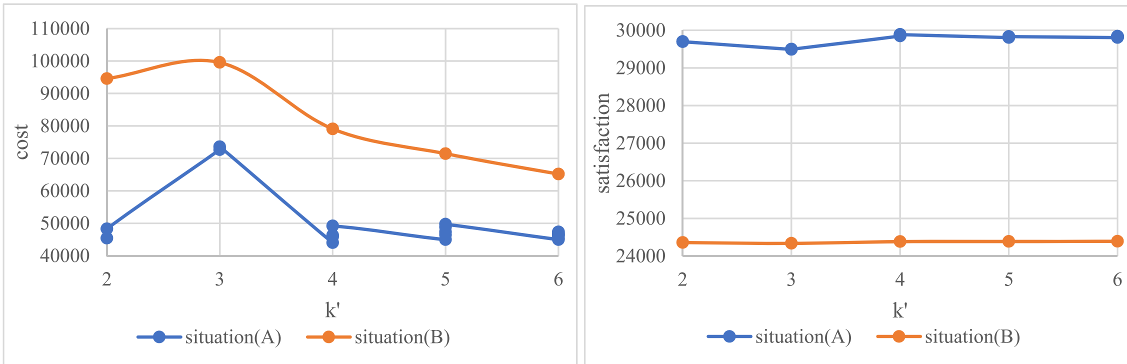


(a) the impact on costs



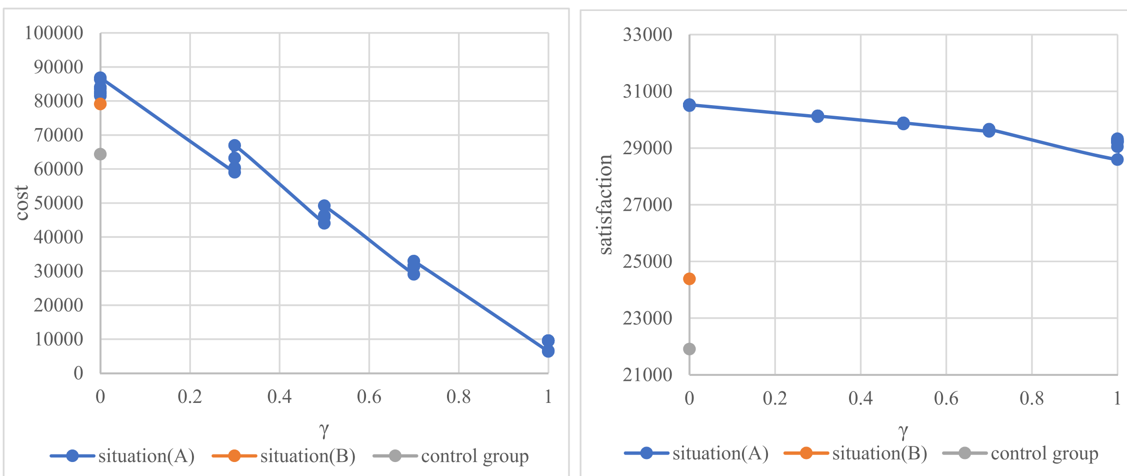
(b) the impact on satisfaction

Fig. 9. The impact of different clustering parameter k on results.



(a) the impact on costs (b) the impact on satisfaction

Fig. 10. The impact of different clustering parameter k' on results.



(a) the impact on costs (b) the impact on satisfaction

Fig. 11. The impact of different coefficient γ on results.

a relatively large value of k' according to the budget.

4.2.4. *Sensitivity analysis on the probability coefficient*

In the previous section 3.2.1, we have explained that in situation (B) $\gamma = 0$. In this section, the sensitivity analysis is for situation (A), which examines how the probability coefficient γ that controls the probability of successfully delivering the order together in the same small demand cluster affects the overall customer time satisfaction and the total costs of location selection. Fig. 11 indicates that in situation (A), the larger the γ, the smaller the costs of location selection, but the lower the customer time satisfaction. Furthermore, even though when $\gamma = 0$, the results in situation (A) are no worse than the results of control group that without considering the time attribute, which means that although demand forecasts may be biased, the results obtained by the location selection method proposed in this paper for situation (A) is not bad. Therefore, it is reasonable to consider the spatio-temporal attribute in location selection. In addition, because the value of coefficient γ in situation (A) depends on the accuracy of demand forecasting, the more accurate the demand forecast, the higher the probability of simultaneous delivery of demand points in a small demand cluster.

5. Discussion

This paper considers the actual delivery route that from city distribution centre to FDCs to each demand point, rather than the straight-line distance between FDCs and demand points. Due to the time sensitive nature of FDC, the spatio-temporal attribute of demand point is especially focused. Without assuming the FDCs is known, this paper designs a staged clustering algorithm of three-dimensional clustering and then two-dimensional clustering to generate the candidate FDCs, considering the spatio-temporal joint distance. And then a bi-objective spatio-temporal optimisation model is constructed to determine the final FDCs, where an intelligent algorithm based on NSGA-II is designed and applied.

This study provides several contributions to the location problem of FDC, which are discussed in the following sections from key aspects of the theory and practice.

5.1. *Theoretical contributions*

This paper proposes a location selection approach based on a two-stage decision method, so the main theoretical contributions can also be summarized from these two aspects:

In clustering stage, a spatio-temporal clustering model is constructed to obtain the candidate FDCs instead of assuming candidate FDCs is known, and a staged clustering algorithm of three-dimensional clustering and then two-dimensional clustering is designed to solve the clustering model. Traditional research of location selection only considers the demand points from space dimension (Jian, 2019; Kuznietsov et al., 2017; Shin, and Kim, 2016), while the time attribute of demand distribution reflects the customer consumption habit, which is very important in instant delivery. This paper introduces the time dimension of demand into location selection problem, considering the spatio-temporal distance. This provides a new aspect for research on the demand in the location selection research, which paves the way for considering customer time satisfaction. In addition, the staged clustering algorithm can also provide a reference for the solution of location problems focusing on other multi-dimensional attributes. It is not limited to space attribute and time attribute, but may also be other attributes, such as shopping types. For example, gathering demand points with similar shopping types can optimise types of goods in the FDC effectively, which also provides benefit to reduce the operation costs.

In optimisation stage, a spatio-temporal optimisation model is formulated to determine the final FDCs. The operation process from the city distribution centre to FDCs then to demand points is considered, which provides a more complete modeling idea. The spatio-temporal optimisation model in this paper is a bi-objective optimisation model. Most of traditional location selection modeling only pay attention to reduce the operation costs (Holzapfel et al., 2023; Avgerinos et al., 2022; Fathi et al., 2021), this paper not only tries best to reduce total costs but also focuses on improving the customers satisfaction that is of essential importance nowadays.

5.2. *Managerial insights*

Based on upon experiments and sensitive analysis of two-stage location decision method, we have derived two directions of managerial insights in this section: response to different operation situation in clustering stage and manage operation goals in optimisation stage.

5.2.1. *Clustering stage: response to different demand distribution*

In real life, demand usually mismatches the supply in the peak period, it is hard to result in all-win outcome (Zhong et al., 2023). To overcome this challenge, we can imagine a location selection strategy, considering the spatio-temporal joint dimension of demand. The clustering model is constructed according to the different demand distribution. When demand is relatively small (maybe office building), the clustering model is constructed based on situation (A), which means that arranging the demand points with similar time distributions to be delivered together, so that it can increase the probability of placing orders together and improve the efficiency of delivery. When demand is relatively large (maybe residential), the clustering model can often be built based on situation (B), which indicates that the demand points with different distribution characteristics can be covered by the same FDC. It is because the delivery capacity is limited and the probability of placing orders together within each demand point is very high, there is no need to delivery orders together between different demand points.

Our numerical results suggest that the spatio-temporal joint dimension of demand plays an important role in location selection problem, in situation (A), it makes the costs the lowest, while in situation (B), the delivery pressure is generally the lowest. Then the problem that delivery staffs are often idle during off peak periods but overwork during peak periods can be alleviated.

5.2.2. *Optimisation stage: operation goals management*

Because of the fierce market competition nowadays, retaining customers is a constant challenge. Zihayat et al. (2021) have pointed out that marketers need to improve customer satisfaction to retain customers. However, the customer satisfaction is usually ignored in location selection (Holzapfel et al., 2023; Avgerinos et al., 2022), which goes against the sustainable development of business. Especially, in the operation of FDC, customers have strong bargaining power to choose their service providers due to the digital transformation of business (Zihayat et al., 2021). Therefore, it is important to take the customer satisfaction into account in FDC location selection. By constructing the spatio-temporal multi-objective optimisation model and designing the corresponding solving algorithm, a series of optimal results can be obtained. A manager is able to choose an appropriate solution according to the real-life operation goals, where both operation costs and customer time satisfaction can be considered.

Our numerical experiments have shown that the optimisation algorithm based on NSGA-II performs better than MOPSO (Coello and Lechuga, 2002), CMOPSO (Zhang et al., 2018), MOEA/D (Zhang and Li, 2007), MOEA/D-ANA (Wang et al., 2020) and simple K-means clustering algorithm (Ikotun et al., 2023), which could achieve a greater number of Pareto-optimal solutions with higher qualities. In particular, compared with K-means clustering algorithm, the customer time satisfaction can be improved by up to 36.22% when costs are declined by up to 38.84%. Besides, the algorithm stability of NSGA-II is also the best. This finding suggests that our approach can provide support for the location decision of FDC, and at the same time, it can also provide certain guidance for the delivery arrangement of FDC. In addition, our sensitivity analysis also provides some important insights. For example, decision maker can improve customer time satisfaction by increasing the number of three-dimension clusters. In conclude, in the FDC management, improving customer time satisfaction is conducive to building corporate brands, making it easier to retain customers. Managers need to consider the customer satisfaction in their operation goals, which has also been emphasized by Ashill et al. (2022), they presented that customer satisfaction is one of the most important measures of project success.

5.3. *Limitation and future research*

At the same time, there are several limitations and future research directions of our study should be highlighted. First, the discussion of demand time distribution is restricted by data sources. This paper assumes that the demand time distribution is a bimodal distribution according to a reference (Guidotti et al., 2018) and no further verification work has been done. In the future research, we can collect a large amount of user order data to grasp the demand time distribution characteristics more specifically and focus on the prediction aspects of demand time distribution. Although the daily needs of users are not fixed, the probability coefficient can be used to abstract the time distribution function of each demand point. In addition, future studies can incorporate more demand information, such as detailed order time and the category of the product purchased to further refine the research.

Second, the optimisation algorithm based on NSGA-II has not been improved further in this paper. Though this paper adopts the NSGA-II to simplify the solving process, the attention has not been paid to how to further improve the solving speed of NSGA-II. Therefore, we can try improving its solving efficiency in the future study and making more comparisons between improved NSGA-II and other optimisation algorithms like simulated annealing algorithm and so on.

Third, the measurement of customer time satisfaction levels will become more complicated when customer needs are heterogeneous. Therefore, future works can take customer heterogeneity into account to improve the application of location selection method, and how to measure the heterogeneity of customer time satisfaction is one of our focuses of future research.

Data availability

Data attached with the submission

Acknowledgment

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References

Ahin, T.S., Ocak, S., Top, M., 2019. Analytic hierarchy process for hospital site selection. Health Pol. Technol. 8 (1), 42–50.

Ashill, N., Williams, P., Khan, M.S., Naumann, E., 2022. Dynamic and ordinary capabilities: a project management perspective. IEEE Trans. Eng. Manag. 69 (5), 2173–2186.

Avgerinos, L., Mourtos, L., Zois, G., 2022. Multi-type facility location in printing and parcel delivery services. Ann. Oper. Res. 309, 365–393.

Azizi, V., Hu, G.P., 2020. Multi-product pickup and delivery supply chain design with location-routing and direct shipment. Int. J. Prod. Econ. 226, 107648.

Chen, L.F., Tsai, C.T., 2016. Data mining framework based on rough set theory to improve location selection decisions: a case study of a restaurant chain. Tourism Manag. 53, 197–206.

Coello, C.C.A., Lechuga, M., 2002. MOPSO: a proposal for multiple objective particle swarm optimisation. Proceedings of the IEEE congress on evolutionary computation 1051–1056.

Dai, B., Chen, H.X., Li, Y.A., Zhang, Y.D., Wang, X.Q., Deng, Y.M., 2021. Inventory replenishment planning of a distribution system with storage capacity constraints and multi-channel order fulfilment? Omega-International Journal of Management Science 102, 102356.

Deb, K., Jain, H., 2012. Handling Many-Objective Problems Using an Improved NSGA-II Procedure. IEEE Congress on Evolutionary Computation. IEEE, pp. 1–8.

Fathi, M., Khakifirooz, M., Diabat, A., Chen, H.G., 2021. An integrated queuing-stochastic optimisation hybrid Genetic. Algorithm for a location-inventory supply chain network 237, 108139.

Fontaine, P., Minner, S., Schiffer, M., 2023. Smart and sustainable city logistics: design, consolidation, and regulation. Eur. J. Oper. Res. 307, 1071–1084.

Ge, H., Goetz, S., Canning, P., Perez, A., 2018. Optimal locations of fresh produce aggregation facilities in the United States with scale economies. Int. J. Prod. Econ. 197, 143–157.

Guidotti, R., Gabrielli, L., Monreale, A., Pedreschi, D., Giannotti, F., 2018. Discovering temporal regularities in retail customers' shopping behavior. EPJ Data Science 7 (1), 1–26.

Gul, M., Guneri, A.F., 2021. Hospital location selection: a systematic literature review on methodologies and applications. Math. Probl Eng., 6682958

Guo, J., Pu, Z., Du, B., Li, Y., 2021. Multi-objective optimisation of stochastic hybrid production line balancing including assembly and disassembly tasks. Int. J. Prod. Res. 60 (9), 2884–2900.

Guo, W., Jiang, P.Y., Yang, M.L., 2022. Unequal area facility layout problem-solving: a real case study on an air-conditioner production shop floor. Int. J. Prod. Res. 61 (5), 1479–1496.

Gupta, V.K., Ting, Q.U., Tiwari, M.K., 2019. Multi-period price optimisation problem for omnichannel retailers accounting for customer heterogeneity. Int. J. Prod. Econ. 212, 155–167.

Hao, J., Li, J.P., Wu, D., Sun, X.L., 2020. Portfolio optimisation of material purchase considering supply risk - a multi-objective programming model. Int. J. Prod. Econ. 230, 107803.

Holzapfel, A., Potoczki, T., Kuhn, H., 2023. Designing the breadth and depth of distribution networks in the retail trade. Int. J. Prod. Econ. 257, 108726.

Hu, W., Hou, Y., Tian, L.W., Li, Y., 2015. Selection of logistics distribution center location for SDN enterprises. J. Manag. Anal. 2 (3), 202–215.

Huang, J., Shi, X., 2023. Solving the location problem of front distribution center for omni-channel retailing. Complex Intell. Syst. 9, 2237–2248. https://doi.org/10.1007/s40747-020-00260-2.

Ikotun, A.M., Ezugwu, A.E., Abualigah, L., Abuhaija, B., Heming, J., 2023. K-means clustering algorithms: a comprehensive review, variants analysis, and advances in the era of big data. Inf. Sci. 622, 178–210.

Jafarian, A., Rabiee, M., Tavana, M., 2020. A novel multi-objective co-evolutionary approach for supply chain gap analysis with consideration of uncertainties. Int. J. Prod. Econ. 228, 107852.

Jain, A., Darbari, J.D., Kaul, A., Ramanathan, U., Jha, P.C., 2022. Facility selection model for BOPS service for an omnichannel retail chain. IEEE Trans. Eng. Manag. 69 (6), 2857–2870.

Jian, L., 2019. Optimal design of transportation distance in logistics supply chain model based on data mining algorithm. Cluster Computing-The Journal of Networks Software Tools and Applications 22 (1), S3943–S3952.

Kuznietsov, K.A., Gromov, V.A., Skorohod, V.A., 2017. Cluster-based supply chain logistics: a case study of a Ukrainian food distributor. IMA J. Manag. Math. 28 (4), 553–578.

Liu, A.J., Zhao, Y.X., Meng, X.G., Zhang, Y., 2020. A three-phase fuzzy multi-criteria decision model for charging station location of the sharing electric vehicle. Int. J. Prod. Econ. 225, 107572.

Ma, Y.F., Yang, C., Zhang, M., Hao, C.Y., 2006. Time-satisfaction-based maximal covering location problem. Chin. J. Manag. Sci. 14 (2), 45–51.

Mardani, A., Jusoh, A., Zavadskas, E.K., Kazemilari, M., Khalifah, Z., 2016. Application of multiple criteria decision making techniques in tourism and hospitality industry: a systematic review. Transform. Bus. Econ. 15 (1), 192–213.

Masoud, S.A., Mason, S.J., 2016. Integrated cost optimisation in a two-stage, automotive supply chain. Comput. Oper. Res. 67, 1–11.

Memari, A., Ahmad, R., Akbari Jokar, M., Abdul Rahim, A., 2019. A new modified firefly algorithm for optimising a supply chain network problem. Appl. Sci. Basel 9 (1), 1–12.

Mohebalizadehgashti, F., Zolfagharinia, H., Amin, S.H., 2020. Designing a green meat supply chain network: a multi-objective approach. Int. J. Prod. Econ. 219, 312–327.

Moradian, M.J., Ardalan, A., Nejati, A., Boloorani, A.D., Akbarisari, A., Rastegarfar, B., 2017. Risk criteria in hospital site selection: a systematic review. PLoS Currents 9.

Nasiri, G.R., Zolfaghari, R., Davoudpour, H., 2014. An integrated supply chain production–distribution planning with stochastic demands. Comput. Ind. Eng. 77, 35–45.

Nasr, N., Niaki, S.T.A., Hussenzadek Kashan, A., Seifbarghy, M., 2021. An efficient solution method for an agri-fresh food supply chain: hybridization of Lagrangian relaxation and genetic algorithm. Environ. Sci. Pollut. Res. https://doi.org/10.1007/s11356-021-13718-8.

Popovic, G., Stanujkic, D., Brzakovic, M., Karabasevic, D., 2019. A multiple-criteria decision-making model for the selection of a hotel location. Land Use Pol. 84, 49–58.

Rajendran, S., Zack, J., 2019. Insights on strategic air taxi network infrastructure locations using an iterative constrained clustering approach. Transport. Res. E Logist. Transport. Rev. 128 (AUG), 470–505.

Shahparvari, S., Nasirian, A., Mohammadi, A., Noori, S., Chhetri, P., 2020. A GIS-LP integrated approach for the logistics hub location problem. Comput. Ind. Eng. 146, 106488.

Shekarian, M., Nooraie, S.V.R., Parast, M.M., 2020. An examination of the impact of flexibility and agility on mitigating supply chain disruptions. Int. J. Prod. Econ. 220, 107438.

Shin, J.S., Kim, J.O., 2016. Optimal design for offshore wind farm considering inner grid layout and offshore substation location. IEEE Trans. Power Syst. 32 (3), 2041–2048.

Tnissen, D., Arts, J., 2020. The stochastic maintenance location routing allocation problem for rolling stock. Int. J. Prod. Econ. 230, 1–8.

Tsao, Y.C., Mangotra, D., Lu, J.C., Ming, D., 2012. A continuous approximation approach for the integrated facility-inventory allocation problem. Eur. J. Oper. Res. 222 (2), 216–228.

Vavatsikos, A.P., Sotiropoulou, K.F., Tzingizis, V., 2022. GIS-assisted suitability analysis combining PROMETHEE II, analytic hierarchy process and inverse distance weighting. Oper. Res. 22 (5), 5983–6006.

Wang, Y., Ma, X., Xu, M., Wang, L., Wang, Y., Liu, Y., 2015. A methodology to exploit profit allocation in logistics joint distribution network optimization. Math. Probl. Eng. https://doi.org/10.1155/2015/827021.

Wang, J., Li, Y., Cao, C., 2020. Study on location and route optimisation of distribution centre of a digital company based on clustering algorithm and ant colony algorithm method. In: 2020 9th International Conference on Industrial Technology and Management. ICITM.

Wang, P., Chen, X.J., Zhang, X.B., 2022. Research on Location of Logistics Distribution Center Based on K-Means Clustering Algorithm. Security and Communication Networks, 2546429.

Wang, Y., Sun, Y., Guan, X., Fan, J., Xu, M., Wang, H., 2021. Two-echelon multi-period location routing problem with shared transportation resource. Knowl. Base Syst. 226, 107158.

Wang, Y., Zhang, J., Assogba, K., Liu, Y., Xu, M.Z., Wang, Y.H., 2018. Collaboration and transportation resource sharing in multiple centers vehicle routing optimisation with delivery and pickup. Knowl. Base Syst. 160, 296–310.

Wang, L.P., Xu, M.N., Yu, W., Qiu, Q., Wu, F., 2020. Decomposition multi-objective evolutionary algorithm based on adaptive neighborhood adjustment strategy. IEEE Access 8, 78639–78651.

Xuan, W., Chi, T.N., 2020. New retail versus traditional retail in e-commerce: channel establishment, price competition, and customer recognition. Ann. Oper. Res. 291 (1–2), 921–937.

Yaghin, R.G., Sarlak, P., Ghareaghaji, A.A., 2020. Robust master planning of a socially responsible supply chain under fuzzy-stochastic uncertainty (a case study of clothing industry). Eng. Appl. Artif. Intell. 94 (9), 103715.

Yazdekhasti, A., Sharifzadeh, S., Ma, J., 2022. A two-echelon two-indenture warranty distribution network development and optimisation under batch-ordering inventory policy. Int. J. Prod. Econ. 249, 108508.

Yildiz, B., Savelsbergh, M., 2019. Provably high-quality solutions for the meal delivery routing problem. Transport. Sci. 53 (5), 1372–1388.

You, M., Xiao, Y., Zhang, S., Yang, P., Zhou, S., 2019. Optimal mathematical programming for the warehouse location problem with Euclidean distance linearization. Comput. Ind. Eng. 136, 70–79.

Zhang, Q., Li, H., 2007. MOEA/D: a multiobjective evolutionary algorithm based on decomposition. IEEE Trans. Evol. Comput. 11 (6), 712–731.

Zhang, X., Zheng, X., Cheng, R., Qiu, J., Jin, Y., 2018. A competitive mechanism based multi-objective particle swarm optimiser with fast convergence. Inf. Sci. 427, 63–76.

Zhong, Y., Yang, J., Zhou, Y.W., Cao, B., 2023. The role of surcharge policy on a ride-hailing service platform with long-distance drivers. Int. J. Prod. Res. (online).

Zihayat, M., Ayanso, A., Davoudi, H., Kargar, M., Mengesha, N., 2021. According to Ashill et al., (2022), customer satisfaction is one of the most important measures of project success. J. Bus. Res. 135, 112–126.