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Enhancing Logistics Optimization:
A Double-Layer Site-Selection Model Approach

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ABSTRACT

With the expansion of the logistics network, enterprise logistics distribution faces increasing challenges, including high transportation costs, low distribution efficiency, and unstable distribution networks. To address these issues, this study focuses on optimizing enterprise logistics distribution using a double-layer (DL) model. In this paper, we propose a DL model for optimizing enterprise logistics distribution. The DL model is designed to find the optimal solution using the particle swarm optimization (PSO) algorithm. By leveraging location data from the region, the DL model evaluates and compares alternative distribution centers to determine the most efficient distribution strategy. The results demonstrate that the DL site selection model developed in this study effectively addresses the tasks of logistics center location and distribution optimization among alternative distribution centers. Comparison tests reveal that the distribution path proposed by the DL model is more accessible and cost-effective compared to alternative approaches.

KEYWORDS

Double Layer Model, Logistics Enterprises, Path Planning, PSO

With the incessant evolution of technology, the logistics industry is undergoing profound transformations and innovations. The advent of novel technologies has opened expansive vistas and opportunities for the evolution of the logistics sector. Notably, the expeditious advancement of the Internet of things (IoT) technology has furnished more comprehensive data support and intelligent solutions for logistics management. IoT technology connects diverse physical devices to the Internet, facilitating seamless interconnection and information dissemination among these devices. Through the implementation of IoT technology, logistics companies can attain real-time monitoring and management across transportation vehicles, goods, and personnel (Tsai & Wang, 2019; Xu et al., 2023). This not only enhances the efficiency of logistics transportation but also ensures the safety and stability of goods, thereby providing logistics companies with more dependable and efficient

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operational methodologies. Simultaneously, the integration of artificial intelligence (AI) technology has found widespread application in the logistics industry. Overall, the progression of IoT and AI technologies will usher in more innovation and breakthroughs for the logistics industry, propelling its advancement toward intelligence and digitization (Ślusarczyk et al., 2020; Xu et al., 2022).

AI technology can adeptly process and analyze vast volumes of data, furnishing logistics enterprises with more precise and efficacious decision support. Through the implementation of AI technology, logistics enterprises can actualize intelligent prediction and scheduling of goods, optimizing capacity utilization and resource allocation in the transportation process (Li et al., 2020; Woschank et al., 2020). Additionally, emerging technologies like drones and autonomous driving extend the horizons for the logistics industry. Drones enable swift transportation of goods, significantly enhancing the efficiency of logistics distribution, while autonomous driving technology facilitates self-directed control and management of vehicles, thereby improving the safety and stability of transportation. Technological advancement in the logistics industry is profound, exerting extensive impact and inducing transformative changes. With the continual emergence and integration of novel technologies, the logistics industry is poised for accelerated and efficient development. Consequently, logistics enterprises must promptly seize the opportunities presented by technological development, incessantly undertaking technological upgrades and innovations to meet customer demands and enhance enterprise competitiveness (Oleśków-Szłapka et al., 2019).

The paramount objective of employing emergent technologies is to expedite the delivery of goods to the customer, making the meticulous selection of the distribution center's optimal location a primary concern in alignment with the company's strategy. In the logistics and distribution industry, the decision of selecting a central location holds pivotal importance (Zdravković et al., 2022). This choice significantly impacts the operational efficiency and cost of the logistics network. The selection of a location should be informed by various factors, including the origin and destination of goods, the number and distribution of customers, transportation costs, accessibility to transportation and logistics facilities, among others. An optimal central location should aim to minimize the transportation distance and time, thereby enhancing efficiency and reducing costs, while also ensuring the reliability and flexibility of the supply chain (Shamout et al., 2022; Yang et al., 2022; Chen et al., 1998). Consequently, when making decisions regarding a central location, logistics companies should meticulously consider various factors, carefully weighing the pros and cons to guarantee the selection of the optimal central location and attain a competitive advantage. Therefore, this article introduces the digital learning (DL) model in game theory for the location study of logistics distribution centers, aiming to achieve location optimization. Contributions are as follows:

1. Develop a DL site selection model tailored to the requirements of distribution center site selection, where the overarching goal is to minimize costs at the upper level and maximize satisfaction at the lower level.
2. Utilize the particle swarming optimization (PSO) method to solve the DL site selection model and identify the optimal location for distribution centers.
3. Analyze the strengths and weaknesses of various site selection locations, assessing the computational efficiency of different solution methods through model calculations.

The remainder of the article is organized as follows. Section 2 introduces related works for the site selection problem. Section 3 discusses the double layer model and its solution process. Section 4 illustrates the results of the experiment. Section 5 explores the development trends for logistics enterprises and site selection. The conclusion is presented at the end of the article.

RELATED WORKS

Following the elucidation of the significance of path planning for logistics enterprises, this article undertakes an exhaustive examination of the extant research on distribution center location selection and the application of the two-layer model. This provides a pertinent research foundation for the subsequent analysis presented in this article.

Distribution Center Site Selection Study

Logistics distribution center site selection models are classified into three primary types: (1) continuous models; (2) discrete models; and (3) expert consultation methods.

The continuous model approach to site selection posits that the distribution center's alternative location can be chosen freely, unencumbered by the constraints of intricate terrains and landscapes like rivers, lakes, and mountains. A principal method within this category encompasses the center of gravity (Boyacı & Şişman, 2022). While the continuous model demonstrates flexibility and finds widespread use, real-world applications often encounter challenges. For instance, the center of gravity method may propose new distribution centers in unsuitable areas due to complex topography, leading to high costs for establishing new distribution centers. Decision-makers, after considering various factors, may need to discard initially identified optimal solutions, thereby contributing to wasted time. Brimberg and Mehrez (1994) were pioneers in formulating the site selection problem at a single location, known as the Weber problem. Weber's mathematical model aimed to minimize the distance from the new warehouse to each customer, marking the initiation of site selection theory research. Building upon previous literature, the Weber problem has been enhanced, utilizing the circularity principle to correct the initially chosen distribution center location and achieve an extremely small sum of distances.

Contrarily, the discrete model approach to site selection posits that the location of a distribution center is discontinuous. Decision-makers identify a limited number of alternative addresses suitable for a new distribution center based on local information and site visits. Discrete models are formulated to minimize model costs, similar to the Weiszfeld method. Prominent discrete models include the Kuehn-Hamburger model (Kuehn & Hamburger, 1963), the Baumol-Wolfe model (Baumol & Wolfe, 1958), and the Elson model (Roehlen et al., 2022). Aikens (1985) developed nine distinct mathematical models based on various objectives and costs, providing solutions to various siting problems, including dynamic regularization and the 0-1 model.

While the continuous model and discrete model provide some guidance, persistent issues like high model complexity and limited solutions remain. Consequently, further research is imperative for the location selection of distribution centers, aiming to enhance the accuracy and practicality of these models. Potential research directions include, but are not limited to: optimizing existing models to address practical application challenges; developing new site selection models that consider a broader array of factors and constraints; and integrating expert consultation methods by incorporating expert knowledge and experience to enhance the model's reliability and applicability.

In summary, comprehensive and in-depth research is essential for the location selection of distribution centers to propel the advancement of this field and tackle challenges in practical applications.

Application of DL Model

The DL planning model has gained widespread utilization in siting studies due to its comprehensive consideration of the interests of all parties. The DL objective model holds distinct advantages for models with intricate paths and multifaceted analysis requirements. Building upon the analysis of electric vehicle location issues, Current et al. (1985) asserted that many location problems fundamentally entail multiobjective optimization challenges. They introduced four essential location optimization goals: (1) cost minimization; (2) demand orientation; (3) profit maximization; and (4) environmental impact reduction. Hodgson and Rosing (1992) formulated a multiobjective siting optimization model aimed at maximizing intercepted user traffic and minimizing the sum of distances between the demand generation point and the charging station. Wang and Wang (2010) delved into the charging station siting problem using a coverage-based approach, weighing economic considerations like cost-effectiveness. They developed a multiobjective siting model that minimized construction costs while maximizing the coverage of people, applying it to a real case in Taiwan. Wei et al. (2016) introduced a spatiotemporal demand coverage method, utilizing a spatiotemporal distribution path tool for analyzing periodic interactions between user demand, electric cabs, and charging stations. They established a multiobjective siting model maximizing the service levels of electric cabs and charging stations, employing electric cab data for arithmetic analysis. Taniguchi (2009) applied a DL planning model to study the siting problem of public infrastructure like distribution centers. In comparison to earlier models, the DL planning model incorporates a more extensive array of factors influencing site selection, demonstrating increased complexity. The addresses selected are more accurate and realistic, accompanied by comprehensive basic information. While computationally intensive, the DL planning model, historically challenging to solve, has become more manageable with the advent of modern software like Matlab and Lingo (Wang et al., 2022).

Studies pertaining to the distribution center location and DL model reveal an increasing complexity of the DL model in tandem with enhanced computational power, leading to improved solution accuracy and broader application scope. Consequently, optimizing and arranging distribution centers in enterprise logistics distribution emerges as the optimal solution for addressing these challenges through the establishment of a multilayer model.

MODEL DESIGN OF DISTRIBUTION CENTER ESTABLISHMENT BASED ON SITE SELECTION MODEL

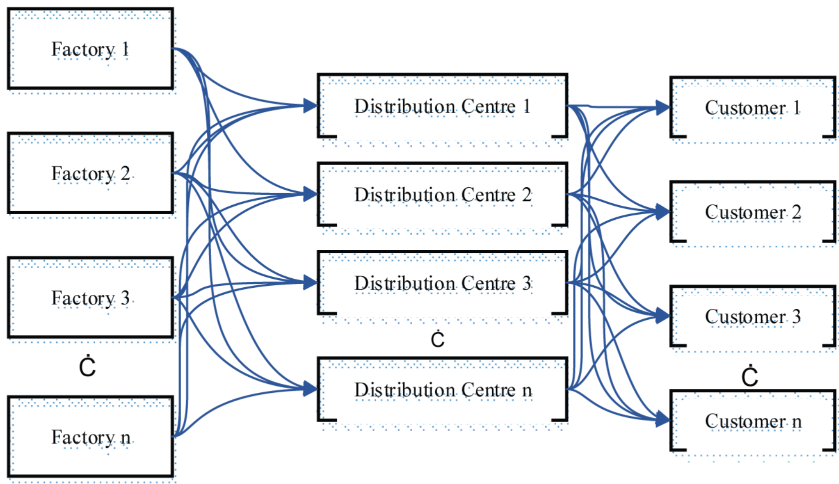
To guarantee high-precision location selection for distribution centers while mitigating model complexity and accounting for practical application speed, a classic double-layer mathematical model was employed for the planning research of distribution centers. The subsequent chapter will provide a comprehensive explanation of the specific methods employed, elucidating the detailed process of solving the model through classic metaheuristic algorithms.

Basic Mathematical Model of DL Planning

The distribution center location problem is conceptualized as a multiobjective optimization challenge, aiming to maximize benefits and efficiency by formulating optimized mathematical models across various locations (Khudhair et al., 2020). This article adopts a perspective that treats the distribution center location problem as a master-slave game, wherein the location decision-maker serves as the leader making the initial decision, while taking into account customer responses. In this game scenario, the customer, as the follower, responds differently based on the decision-maker's choices. The leader influences the customer's distribution cost through the pricing and quality of distribution services, subsequently impacting the customer's choice of supplier. However, the leader cannot dictate the customer's independent choice, as the customer selects an efficient and cost-effective logistics service provider based on their own needs, comparing services and prices across different suppliers (AbdulRahman et al., 2020). The illustrative depiction of a typical distribution system problem is presented in Figure 1.

In contrast to traditional models, the DL planning model incorporates a two-level structure. In the upper-level model, the site selection decision-maker opts for a suitable location to establish a distribution center within a specific region, targeting the lowest total cost (comprising transportation cost, distribution cost, fixed cost, and warehouse management cost) under a predetermined investment

Figure 1. Distribution Center System



budget. Simultaneously, in the lower level, the customer aims to solve the distribution from each distribution center to the customer, striving for the lowest total cost, typically the cost borne by the consumer for logistics and distribution services. The model encompasses the game dynamics between the location decision-maker and the customer, considering the interests of both parties and aligning with real-world scenarios (Zou et al., 2021).

The upper and lower decision-makers independently control their respective decision variables x and y.

The mathematical model for the upper-level planning by modeling is shown in Equation 1.

$$U : \min_x F(x, y) \text{ s.t. } G(x, y) \leq 0 \tag{1}$$

The mathematical model for the lower-level planning by modeling is shown in Equation 2.

$$L : \max_y f(x, y) \text{ s.t. } g(x, y) \leq 0 \tag{2}$$

$y = y(x)$ can be obtained by solving the lower model. U and the L form a DL programming model. F is the upper objective function. x is the variable controlled by the upper layer, and the constraint on the variable x The constraints on the variables are $G; f$ is the lower objective function. y idoes the lower-level control the variable level, and the constraint on the variable is y. The constraint on the variable is g. Moreover, the relationship between the variables controlled by the lower level and the variables controlled by the upper level can be characterized by the reaction function (i.e., $y = y(x)$).

In this article, the upper-level and lower-level functions are established per the specified requirements. The decision-making department of the logistics enterprise is tasked with selecting the optimal solution, determining the most suitable location to establish the distribution center to minimize the total cost. The upper-level objective function is formulated accordingly in Equation 3 to reflect this goal.

$$\min F = \sum_i \sum_j c_{ij} x_{ij} + \sum_j \sum_k p_{jk} w_{jk} + \sum_j f_j Z_j + \sum_i \sum_j g_j x_{ij} \tag{3}$$

Equation 3 consists of four parts: (1) total distribution cost; (2) total transportation cost; (3) total cost of establishing the distribution center; and (4) storage management cost of the distribution center. The customer wants prompt delivery of the goods; thus, optimizing for higher satisfaction with time efficiency is crucial. Additionally, customers often want to pay lower costs. Thus, the lower-level objective function is shown in Equations 4 and 5.

$$\max S = \frac{1}{\sum_i \sum_j x_{ij}} \sum_i \sum_j x_{ij} s_{ij} \tag{4}$$

$$\min T = \sum_i \sum_j H_{ij} x_{ij} \tag{5}$$

where S represents satisfaction and T denotes cost. Once the objective function is established, corresponding constraints must be introduced. These constraints primarily encompass inbound and outbound balance constraints of distribution centers, supply capacity constraints, capacity constraints, distribution center constraints, and investment constraints. Additionally, for Equation 4, it is imperative to ensure that s_{ij} is maximized to achieve the highest possible satisfaction, thus concluding the construction of the DL site selection model (Ringe et al., 2020).

PSO-Based Model Solving and Optimization

PSO is a population intelligence-based optimization algorithm that emulates the behavior of a population of organisms, guiding a swarm of particles toward the optimal solution by continuously updating the velocity and position of each particle. In PSO, particles represent potential solutions, with each particle's position signifying a point in the feasible solution space, and its velocity indicating the search direction and speed of the solution. PSO is advantageous in that it does not require information about the gradient of the solution function, making it suitable for tackling nonlinear, nonconvex, and high-dimensional optimization problems (Jain et al., 2022).

The application of PSO in the two-layer site selection model offers several advantages, including robust global search capability, simple and straightforward implementation, suitability for nonlinear problems, strong adaptability, and parallelism. It effectively enhances the optimization efficiency and performance of the model, providing an efficient solution for addressing intricate logistics allocation challenges. The PSO algorithm is widely employed for its rapid convergence and ability to search for a global optimal solution, particularly in problems like function optimization. For the given objective function, the process of searching for the solution can be described in the following steps.

Step 1: Determine the objective function and Constraints. In a DL optimization model, upper- and lower-level problems usually exist. The objective function of the upper level depends on the solution of the lower level. Thus, the objective function and constraints of the two layers need to be defined separately.

Step 2: Initialize the Position and Velocity. Suppose the particle swam has n particles, where each particle has m dimensions, representing each particle as an m-dimensional vector. Initially, the positions and velocities of the particle swarm can be generated randomly or according to certain laws.

Step 3: Calculate the Fitness. Based on the upper objective function, each particle's fitness at the current position can be calculated. If constraints exist, it is also necessary to check whether each particle satisfies the constraints.

Step 4: Update the Velocity and Position. The equations for updating the velocity and position of the particle swarm are shown in Equations 6 and 7.

$$v_{ij}\left(t+1\right)=\omega v_{ij}\left(t\right)+c_1 r_1\left(p_{ij}-x_{ij}\left(t\right)\right)+c_2 r_2\left(g_{ij}-x_{ij}\left(t\right)\right) \tag{6}$$

$$x_{ij}\left(t+1\right)=x_{ij}\left(t\right)+v_{ij}\left(t+1\right) \tag{7}$$

where $v_{ij}(t)$ denotes the velocity, $x_{ij}(t)$ denotes the position o, p_{ij} denotes the historical optimal position, and g_{ij} denotes the global optimal position and searches around the global optimal position. ω, c_1, and c_2 are the inertia factor, individual learning factor, and social learning factor, respectively. r_1 and r_2 are random numbers between [0,1].

Step 5: Update the Historical Optimal Position and Global Optimal Position. Each particle will record its own historical optimal position p_i, and the global optimal position g is the optimal value of all particles' historical optimal positions.

Step 6. Determine Whether the End Condition is Met. The stopping conditions of the particle swarm algorithm can be set according to the actual situation, such as reaching the maximum number of iterations, reaching a certain accuracy of the objective function value, and not changing the objective function value for several consecutive iterations.

Step 7. If not stopping, return to step 3. Recalculate the fitness of each particle. Repeat steps 4, 5, and 6.

The objective function of the upper-level problem relies on the solution of the lower-level problem. Following the elucidation of the upper level, the lower-level model can be addressed through the subsequent steps. This involves initializing the feasible solution of the model, calculating particle fitness, and updating particle velocity and position. Simultaneously, the global optimal solution is employed to optimize the model. Based on this foundation, iterative processes are conducted to attain the optimal solution for the DL model.

EXPERIMENT RESULT AND ANALYSIS

The authors conducted an analysis of the location selection for logistics distribution centers in the region, utilizing the two-layer site selection model established in Chapter 3. Collaborative efforts with local logistics enterprises were undertaken to procure relevant data, facilitating the computation and validation of the model. The data collection primarily focused on pertinent information regarding the location of logistics centers in the local area over the past five years, encompassing freight volume, distribution distance, center cost, and other relevant details. A total of five express logistics centers were included in the data collection to finalize the model construction. The specific results obtained are as follows.

Costing of Different Distribution Centers

In their experiments, the authors performed calculations based on the upper layer cost function of the proposed DL model. The results obtained are shown in Figure 2. In Figure 2, the authors utilized the established DL model and modeled it based on cost and satisfaction. They compared the logistics cost calculation for each location center after optimizing its final cost. The figure reveals substantial cost variations for different customers across different logistics centers, with the highest cost observed at customer 3 in distribution center 1, significantly surpassing the costs at other distribution centers. To provide a clearer depiction of the costs for each distribution center, the authors computed the sum of costs for the five primary customers, and the results are presented in Figure 3.

Figure 3 underscores the remarkable cost efficiency of distribution center 2, boasting the lowest total cost among the evaluated distribution centers. In the strategic site selection process, the company

Figure 2. Cost Calculation in Different Centers

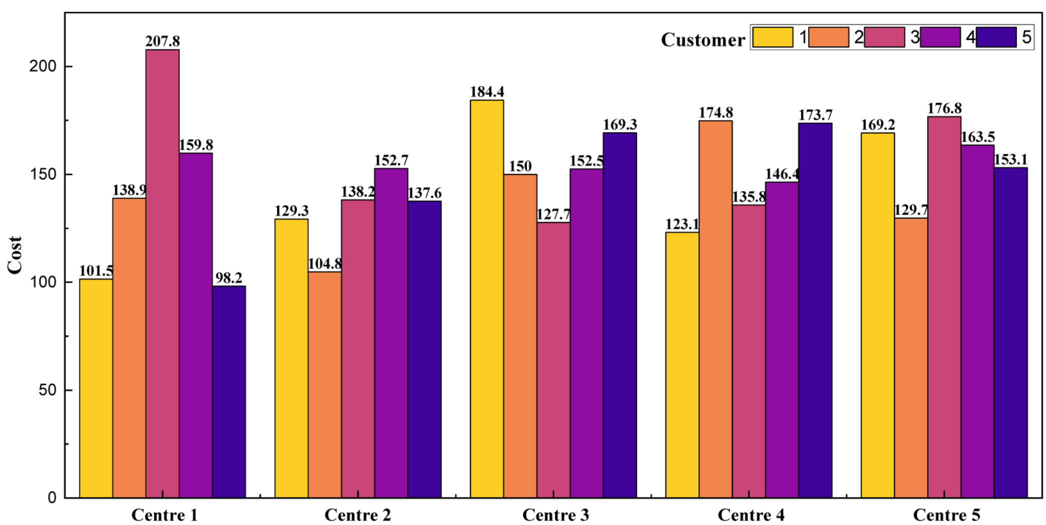
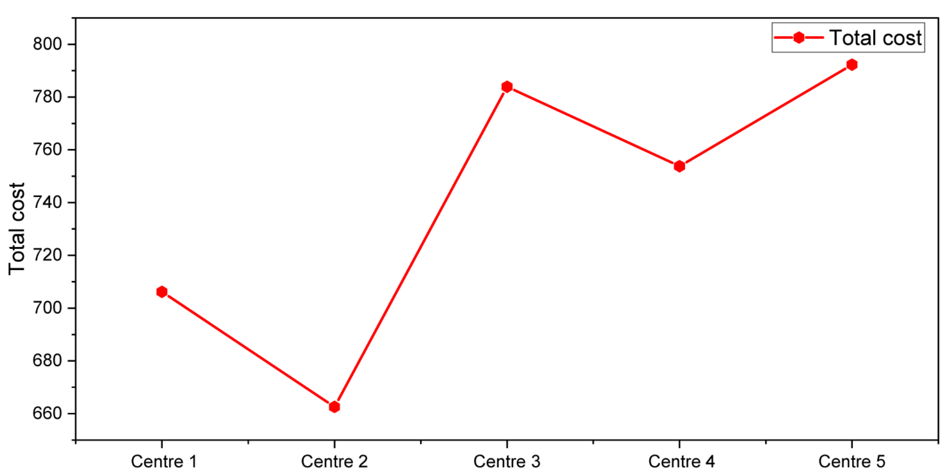


Figure 3. Total Cost for Different Centers



made a judicious decision to utilize the same address for operating a secondary distribution center dedicated to logistics warehousing. This approach not only showcases a meticulous cost-effective strategy but also attests to the organization's adept handling of logistics management. The emphasis on a shared address for dual functionality underscores the company's commitment to optimizing resources and enhancing overall operational efficiency, contributing to a competitive edge in the logistics distribution landscape.

Satisfaction Calculation for Different Distribution Centers

After completing the estimation of distribution costs based on the upper model data, the authors analyzed the satisfaction of different centers. The results are shown in Figure 4.

Satisfaction, an important objective function of the lower model, can be found in Figure 4. Its distribution is more dispersed, with satisfaction rarely exceeding 90%. Therefore, the authors calculate the average satisfaction rate of customers under different distribution centers to achieve a fairer judgment. The average satisfaction rates of different distribution centers are shown in Figure 5.

Figure 5 illustrates the average satisfaction rates for various distribution centers. Notably, distribution center 2 maintains the highest satisfaction level, validating the high precision of the proposed model. Conversely, distribution center 5 exhibits equally high satisfaction levels, yet its associated costs are elevated. This highlights the effectiveness of the DL model in achieving the target alignment of multiple demands, where a balance between satisfaction and cost optimization is crucial.

Comparison of Different Site Selection Models

After the site selection was completed, the authors conducted a comparative analysis of the total cost and satisfaction level of distribution center 2 under different models. The results are shown in Figure 6.

In comparing different models, the authors chose the classical transportation planning method, the Capacitated Facility Location Problem method, and the Baumol-Wolfe method for comparison. These methods can solve linear and nonlinear problems and have wide applications in path optimization. The comparison experiments found that while different models can accurately identify the distribution center 2, their final calculation results deviate greatly. Notably, the model proposed can be found to have the smallest deviation from the real results.

Figure 4. Satisfaction of Customers Concerning Different Distribution Centers

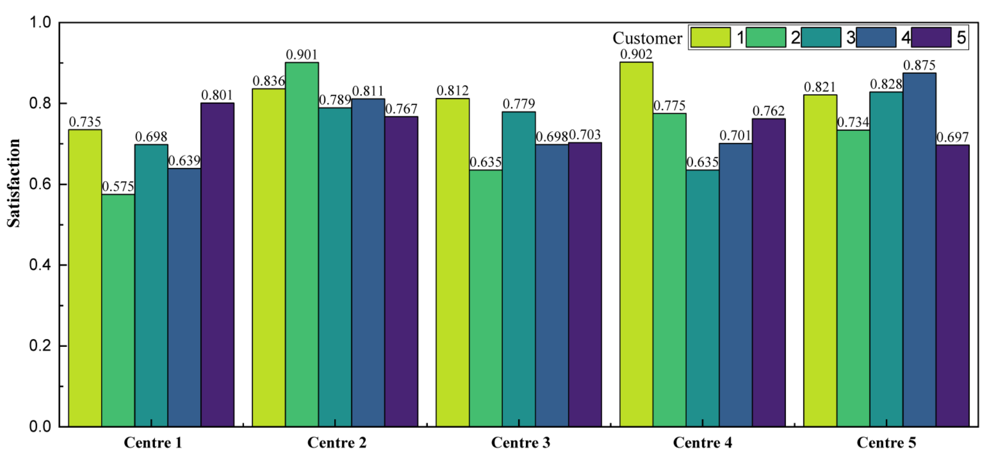


Figure 5. Result for Customer Satisfaction Concerning Different Distribution Centers

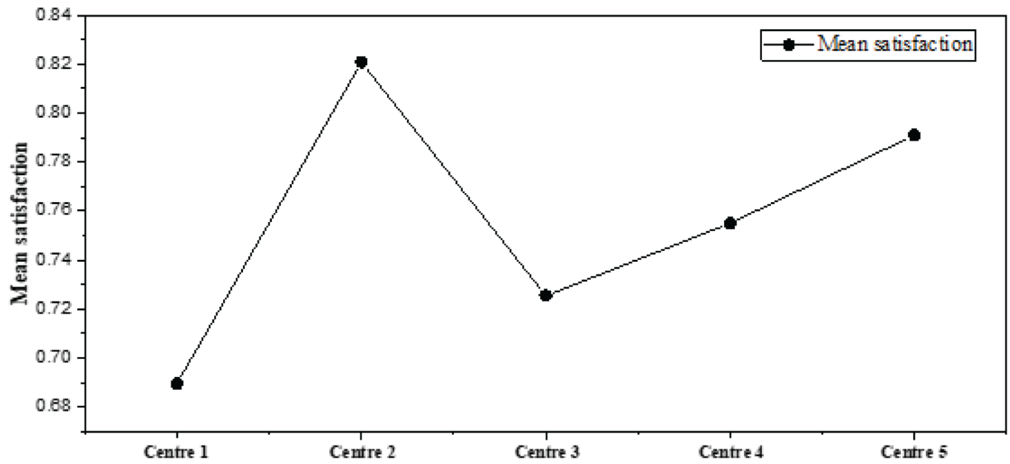


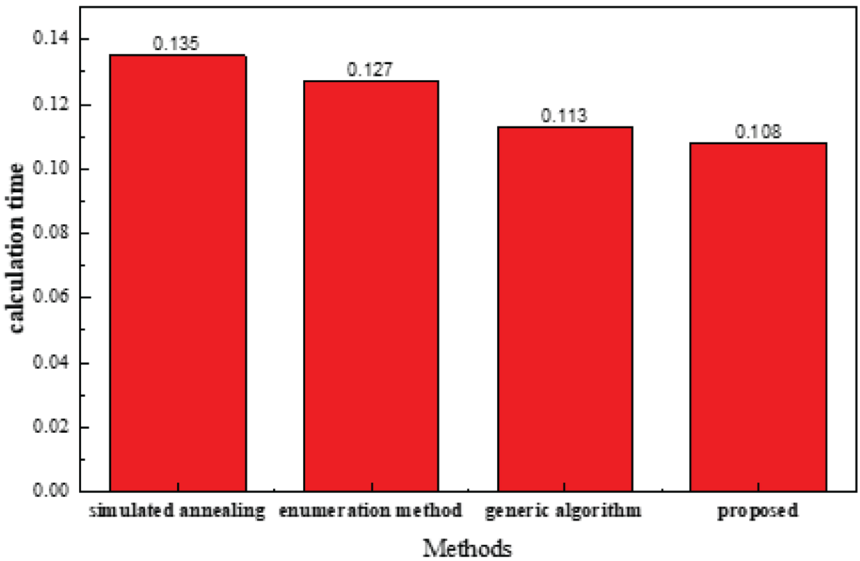
Figure 6. Comparison With Other Models

Comparison of Model Solving Under Different Methods

PSO is employed in solving the model parameters according to the constraints. However, in the solution of such problems, methods like simulated annealing, enumeration, and genetic algorithms are widely used in the optimization of model parameters. Therefore, the authors compared the solution time under different methods. The results are shown in Figure 7.

Due to the low complexity of the model itself, the calculation speed is faster on all modern computers, and the PSO method chosen is the most efficient and fastest. This better realizes the calculation and solution of the DL model.

Figure 7. Model Calculation Time With Different Solutions



DISCUSSION

The establishment of an enterprise logistics distribution center involves various factors, with construction cost, distribution cost, and customer satisfaction being crucial indicators for evaluating the center's performance. This article introduces a DL site selection model where the upper-level model optimizes the enterprise's primary concern, which is the cost issue, as an objective function. In contrast, the lower-level model achieves the objective optimization of customer satisfaction based on construction and distribution costs to derive the optimal model (Ucero et al., 2023). As an adaptable and effective decision analysis model, the DL model exhibits better moderation and scalability compared to single-tier models like Baumol-Wolfe. While a single model can handle relevant data calculations in traditional decision-making studies, its accuracy and positional deviation are significant, making direct application in actual engineering challenging (Rekik & El Alimi, 2023). Therefore, utilizing a DL structure model not only satisfies the lowest cost but also ensures maximum satisfaction, exhibiting superior independence and scalability compared to a single objective function. The PSO method, a classical optimization approach, enables the attainment of optimal solutions through relatively simple calculations, and the results outperform methods like GA and SA. Consequently, the proposed model framework holds considerable advantages in addressing such complex problems (Noorollahi et al., 2022).

The optimized DL site selection model yields dual benefits for route optimization in distribution. First, it enhances customer satisfaction and user experience by reducing delivery distance and time, improving delivery timeliness and reliability. Second, the optimized path planning minimizes transportation and labor costs, reduces fuel consumption and vehicle maintenance expenses, contributing to an overall reduction in enterprise expenditures. This improves operational efficiency and enhances cost control capabilities.

For logistics enterprises, optimizing distribution through the utilization of AI and IoT technology is paramount. The future of logistics involves increased automation, utilizing technologies like self-driving vehicles, robots, and drones to enhance distribution efficiency and reduce costs. Additionally, environmental considerations will drive the adoption of green practices, promoting the use of electric vehicles and renewable energy to reduce environmental pollution. Furthermore, with the ongoing integration of the global economy, logistics and distribution will become more globalized. Logistics enterprises will strengthen international cooperation, expand global logistics networks, and elevate the level and capacity of global logistics and distribution services.

The future trends in logistics and distribution point toward automation, intelligence, green practices, globalization, and personalization. To remain competitive, logistics enterprises must embrace technological and service innovations, continuously improving efficiency, quality, and service levels.

Beyond path optimization, the dual-layer site selection model holds broad benefits and application prospects. It can optimize the design of supply chain networks, including the location and quantity of warehousing facilities and the layout of supply centers, enhancing supply chain efficiency and flexibility. Additionally, the dual site selection model can be applied to urban planning and infrastructure construction, aiding decision-makers in planning urban development, optimizing traffic flow and resource utilization, and enhancing the quality of life and sustainability of cities.

With the ongoing advancements in data science and optimization technology, the dual-layer site selection model is poised to play an increasingly significant role in various fields, providing accurate and effective support for decision-making in complex problem scenarios.

CONCLUSION

This study tackles the optimization challenges and site selection dilemmas encountered by logistics enterprises through the introduction of a dual-layer site selection model. The model strives to minimize costs at the upper level while maximizing customer satisfaction at the lower level. Leveraging the PSO algorithm for model solving ensures that the selected optimal addresses closely align with practical site selections. Empirical testing underscores the significant improvement in customer satisfaction achieved through the proposed distribution paths, with an average satisfaction rate exceeding 80%. Comparative analysis establishes the superior performance of the dual-layer model compared to single-model approaches. Consequently, the double-layer site selection model emerges as a promising tool for providing decision support and optimization solutions in enterprise logistics distribution.

However, it is crucial to acknowledge the model's limitations, including potential complexities in implementation and data requirements. Future advancements should prioritize enhancing the model's robustness, scalability, and adaptability to diverse logistics scenarios. Integrating emerging technologies like machine learning and real-time data analytics could further elevate the model's capabilities and broaden its applications in the dynamic logistics landscape.

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CONFLICT OF INTEREST

The authors declare that they have no competing interests.

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