[1]Canni Lin

[2]Zhengting Liu

Optimization of the "Last Kilometer" Delivery Path at SF Fenglin Jiayuan Branch

Journal of Electrical Systems

Abstract: - The "last kilometer" logistics delivery is the main difficulty of the rapid development of e-commerce. To address this issue, this study proposed an optimization strategy for the "last kilometer" biopharmaceutical delivery path at the SF Fenglin Jiayuan branch based on an improved sparrow search algorithm. Firstly, a biopharmaceutical cold chain "last kilometer" delivery path optimization model based on an improved sparrow search algorithm was established. Secondly, the optimization results of the biopharmaceutical cold chain delivery path based on the improved sparrow search algorithm were tested. In the test results, when iterating 258, the improved algorithm tended to stabilize at a distance length of around 900. The search results showed a clearer and more orderly delivery route. Meanwhile, its ability to find optimal solutions was improved by 30.7% compared to the sparrow search algorithm. As a result, the proposed optimization strategy achieves significant results in improving distribution efficiency and optimizing distribution paths. This provides a new and effective solution for solving the "last kilometer" logistics delivery problem.

Keywords: SF; Fenglin Jiayuan branch; The last kilometer; Delivery path; Biopharmaceuticals

INTRODUCTION

In today's logistics industry, especially in biopharmaceutical distribution, there are extremely high requirements for distribution efficiency, safety, and timeliness [1-2]. Due to their unique properties, biopharmaceuticals need to maintain a constant temperature environment throughout the entire delivery process to ensure that their quality and efficacy are not affected [3-4]. Therefore, for SF, how to optimize the "last kilometer" biopharmaceutical cold chain delivery path of its business points not only involves customer satisfaction, but also directly relates to the safety and effectiveness of the drugs. As an important node of SF, the Fenglin Jiayuan branch of SF undertakes a large number of biopharmaceutical delivery tasks. However, traditional distribution path planning methods often struggle to achieve optimal distribution results in the face of complex urban transportation networks, variable weather conditions, and strict temperature control requirements. Therefore, it is particularly important to find a more efficient and intelligent Delivery Path Optimization (DPO). Sparrow Search Algorithm (SSA), as an emerging swarm intelligence optimization method, has the advantages of fast search speed and strong global search ability. SSA has been successfully applied in multiple fields. For example, Yang et al. applied SSA in multi-agent systems and proposed an improved elastic dynamic event triggering mechanism based on sampled data with auxiliary dynamic variables, verifying its effectiveness [5]. For example, Guo Feng et al. applied SSA to the electricity market, using SSA to simulate the prediction and anti-prediction behavior of sparrow populations. SSA has a good optimization effect, which is very similar to the electricity consumption behavior of various industries [6]. However, when applying SSA directly to the cold chain DPO of biopharmaceuticals, there may be some challenges, such as adjusting algorithm parameters and handling constraint conditions. Therefore, this study proposes an IDSSA-based "last kilometer" biopharmaceutical cold chain DPO for SF Fenglin Jiayuan branch. This optimization path takes into account that the variables in the cold chain DPO of biopharmaceuticals are usually discrete. The SSA that is originally suitable for continuous optimization problems is discretized to form an Improved Discrete Sparrow Search Algorithm (IDSSA). This

[1] [1]* The Schoole Of Nature Science，Trinity College Dublin , D02 PN40, Dublin, Ireland. Email:Trinity_Cannilin@126.Com

[2]THE SCHOOLE OF NATURE SCIENCE，TRINITY COLLEGE DUBLIN , D02 PN40, DUBLIN, IRELAND.

paper aims to provide some reference and inspiration for the biopharmaceutical cold chain DPO of SF and the entire logistics industry.

1. Optimization of the "last kilometer" delivery path for biopharmaceuticals

1.1 Optimization of cold chain delivery paths for biopharmaceuticals based on improved sparrow search algorithm

The inspiration for SSA comes from the behavior of sparrows in search of food and anti-predation [7-8]. SSA has high efficiency and accuracy in solving optimization problems by simulating the behavior strategies of sparrows such as foraging, clustering, jumping, and evasion. In the sparrow population, discoverers will prioritize obtaining food source information and search for food transmission direction information for the entire population, with a wider search range than followers [9-10]. The position update in the search of each generation of discoverers is represented by equation (1).

$$X_{ij}^{t+1}=\begin{cases} X_{ij}^{t}\cdot\exp(-\frac{i}{\sigma\cdot t_{\max}}) & if \quad R_2<ST \\ X_{ij}^{t}+Q\cdot L & if \quad R_2\geq ST \end{cases} \tag{1}$$

In equation (1), X_{ij}^{t} represents the position information of sparrow i in the jth dimension. t represents iteration. $t_{\max}$ represents the maximum iteration. Q represents a random number and follows a standard normal distribution. L represents the identity matrix of dimensions. The position update of followers is represented by equation (2).

$$X_{ij}^{t+1}=\begin{cases} Q\cdot\exp(-\frac{X_{worst}-X_{ij}^{t}}{i^2}) & if \quad i<\frac{n}{2} \\ X_{p}^{t+1}+\left|X_{ij}^{t}-X_{p}^{t+1}\right|\cdot A^{+}\cdot L & otherwise \end{cases} \tag{2}$$

In equation (2), X_{worst} represents the worst sparrow in the current global situation. X_{p}^{t+1} is the optimal position obtained by the discoverer at $(t+1)$th iteration. A represents a matrix with randomly selected internal elements between 1 and -1 and a size of 1×J. The position update of the vigilante is represented by equation (3).

$$X_{ij}^{t+1}=\begin{cases} X_{best}^{t}+\alpha\left|X_{ij}^{t}-X_{best}^{t}\right| & if \quad f_i>f_g \\ X_{ij}^{t}+k\cdot(\frac{X_{ij}^{t}-X_{worst}^{t}}{f_i-f_w+\varepsilon}) & if \quad f_i=f_g \end{cases} \tag{3}$$

In equation (3), X_{best}^{t} is the best sparrow in the current population. f_i represents the current fitness of sparrow i. f_g represents the optimal and worst fitness values in the current population. α represents a normally distributed random number. k represents the step size control parameter. ε represents a very small constant. In the cold chain logistics of biopharmaceuticals, there are large-scale DPO problems and a wide distribution of customers. It needs to meet the complex requirements of strict time window restrictions. Therefore, IDSSA is proposed by improving SSA, introducing new search strategies, and combining other optimization algorithms to improve the algorithmic performance and stability. Figure 1 shows the specific design of IDSSA.

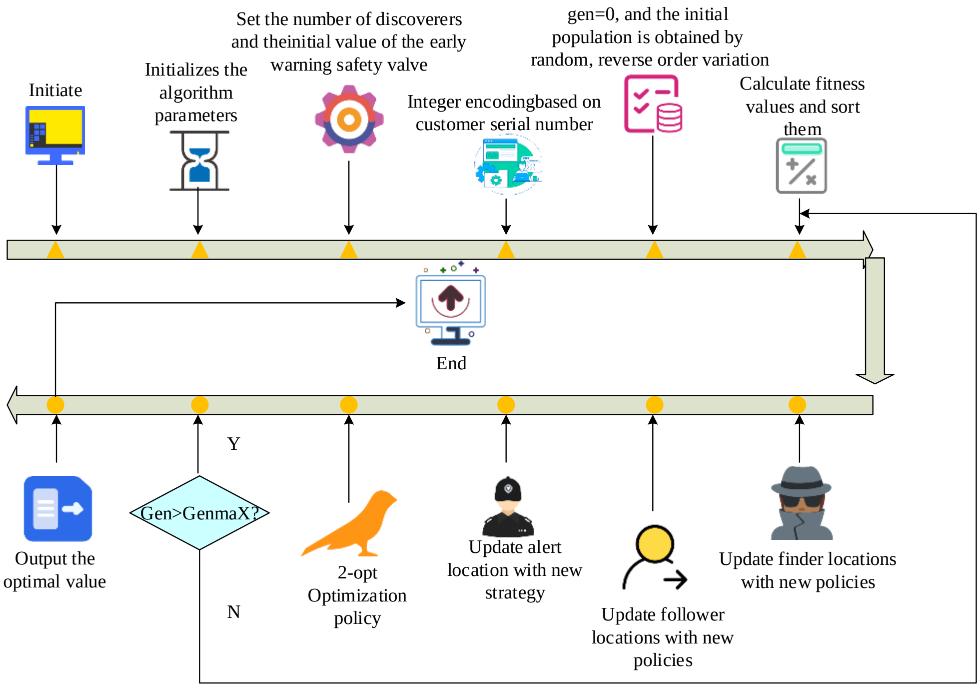


Figure 1 Design process of IDSSA

In Figure 1, a simple and intuitive integer arrangement encoding method is adopted to address the characteristics of the DPO problem in pharmaceutical cold chain logistics. Specifically, each sparrow individual is composed of customer numbers, which directly reflect the order in which each vehicle visits customers [11]. To better represent the role of distribution centers in distribution, this study codes distribution centers as 0 and uses them as the starting and ending points of the path. It is assumed that there are 8 customers, numbered 1, 2,..., 8. The distribution center code is 0. A possible sparrow individual code is [1,2,5,3,6,4,0,0,0]. Due to the existence of multiple distribution centers, there are multiple zeros, which actually contain information about multiple distribution vehicles. When decoding, the consecutive 0 is first used as separators. The encoding is divided into several subsequences, each representing the delivery path of a vehicle, excluding the starting 0s. By removing the 0 at the end of each subsequence as the ending point, the delivery path for each vehicle is obtained.

This study introduces a discoverer proportion adaptive strategy to improve SSA. Firstly, half of the population individuals are generated using a random initialization method to ensure the diversity of the initial population. Then, reverse mutation is performed on the remaining half of the population individuals. In mutation operations, it is necessary to sort the fitness values of the randomly generated population of individuals. After sorting, the top 50% of individuals with good fitness values are retained as excellent representatives in the population. For the remaining 50% of individuals, this study adjusts using a reverse mutation strategy to produce individuals with better fitness. When evaluating the strengths and weaknesses of sparrows, this study uses a fitness function as a measure. The design of this fitness function is directly related to the optimization objective of the problem model, which is to reduce the sum of distribution comprehensive cost F [12]. Therefore, a fitness function corresponding to F is constructed, which is the reciprocal f of F, represented by equation (4).

$$f = \frac{1}{F} \quad (4)$$

In SSA, the update strategy of discoverers is optimized and redefined. When searching for safe environments, to extensively search for food sources, discoverers will move around on a large scale. Therefore, in practical operation, two customer points are randomly selected in the study. The elements on one customer point are inserted into the position before the other customer point. The order of the remaining elements is then adjusted to generate a new search location. When encountering hazardous factors, to maintain safety, the discoverer will take small movements. At this point, two customer points are randomly selected and the elements on them are exchanged, while the remaining unselected elements remain unchanged, generating a new search location. Secondly, the fitness of the newly generated search location is evaluated and compared with the fitness of the original location. If the fitness of the new location is better, then the discoverer's position is updated to the new location. Otherwise, its original position remains unchanged.

In SSA, the updating strategy for followers is redefined. When the fitness is poor, follower X randomly selects customer point i and element ei. The corresponding positional element ew is found in the global worst Xw. The above process was repeated to form an elemental ring. The selected elements in X are retained, the remaining elements are deleted, and the unselected elements in Xw are filled, resulting in Xnew1. Similar operations are performed on Xw, resulting in Xnew2. Finally, Xnew1 and Xnew2 are evaluated. The position with higher fitness is selected as the updated position. When the fitness is good, follower X randomly selects a set of elements E. The corresponding position of E is found in the optimal discoverer Xbest, forming Eb. The unselected elements in X and Eb are retained, while the selected elements E and Eb are removed. The elements in Eb are inserted back into X in the order of Eb, resulting in Xnew1, and similarly, inserting back into E results in Xnew2. Xnew1 and Xnew2 are evaluated. The position with higher fitness is selected as the updated position. Figure 2 shows the specific operation of updating followers with good fitness.

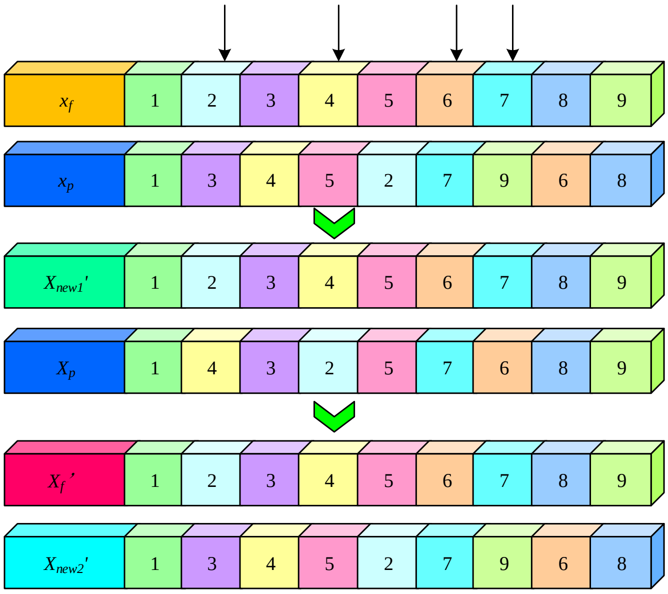


Figure 2 Specific operations for updating followers with good fitness

In SSA, this study redefines the updating strategy of vigilance. When the fitness value of the vigilante exceeds the global optimal fitness, it discovers a more optimal solution. When the fitness values of both are the same, the environment is no longer beneficial to the vigilante and may face resource depletion or potential threats. At this point, the vigilante adopts an avoidance strategy and seeks a new environment by approaching other individuals. In terms of specific operations, the vigilance randomly selects three customer points and deletes them from their current positions, retaining the remaining elements to form a new partial solution Xnew. Subsequently, the deleted points are rearranged and inserted back into Xnew according to a certain strategy, generating five new solutions. After evaluating these new solutions through fitness functions, the optimal one becomes the new position for the vigilance.

Finally, this study introduces the classic 2-opt optimization strategy to enhance the local development capability of SSA in solving the DPO of biopharmaceutical cold chain logistics. 2-opt can perform local optimization on the current solution, improving the quality of the solution by swapping two nodes or edges in the path. This further improves the algorithmic efficiency and accuracy in searching for the optimal path.

1.2 Construction of an optimization model for the "last kilometer" delivery path of biopharmaceutical cold chain

Biopharmaceuticals refer to the use of multidisciplinary principles to extract or manufacture from living organisms for prevention, treatment, and diagnosis [13]. In supply chain management, "last kilometer" delivery affects drug safety, efficacy, and timely patient medication. However, the existing cold chain distribution methods are not applicable to pharmaceutical cold chains. Due to the small size and high value of biopharmaceuticals, it is necessary to consider both the load capacity and the compartment volume [14]. Logistics companies have diverse delivery fleets. It is necessary to choose vehicle models reasonably based on needs to balance cost and efficiency. In addition, real-time changes in road conditions and peak traffic congestion can affect driving speed and transportation time, thereby threatening drug quality and customer satisfaction [15]. A comprehensive model is proposed to address these issues, taking into account multiple vehicle types, speed time segmented functions, and drug volume limitations. Based on the IDSSA optimization of delivery routes and vehicle scheduling proposed in the previous section, the lowest cost transportation plan is designed. This can ensure the safety, efficiency, and timeliness of biopharmaceuticals in the "last kilometer" delivery.

In the actual distribution of cold chain logistics, the driving speed of vehicles is often influenced by various complex factors [16]. The changes in road traffic conditions are influenced by various unforeseeable and dynamic factors such as weather conditions and road construction. To accurately simulate and analyze these impacts, this study uses the Baidu Map traffic data platform to quantitatively analyze the actual road traffic conditions [17]. Firstly, this study employs a piecewise function approach. According to the data provided by Baidu Maps, the actual average speed during each time period is recorded. It is assumed that the speed during each time period is constant [18]. However, in actual delivery, vehicles traveling from one customer point to another may cross multiple time periods, resulting in changes in driving speed. Therefore, research is conducted on two scenarios: driving at the same speed during a single time period and driving at multiple speeds during multiple time periods. Based on this, the travel time between customers is accurately calculated.

When driving at the same speed during a single time period, if the distance between two customers is relatively short and the vehicle departs earlier, the delivery task from the starting point to the destination will be completed completely within the same time period. In this case, vehicles do not need to travel across different time periods, ensuring a constant driving speed. The departure time of the vehicle from customer a is set as t_a. The time of arrival at customer b is t_b. This time period is h. Firstly, the research needs to determine the time period in which the vehicle is located based on t_a of a, and then determine the allowed vehicle speed within that time period. Due to being in the same time period throughout the journey, vehicles will travel at a constant speed $v1$. The time t_1 required for the vehicle to travel the entire distance at the allowed speed during the current time period is represented by equation (5).

$$t_1 = \frac{d_{ab}}{v_1} \quad (5)$$

The time t when the vehicle arrives at customer point b is represented by equation (6).

$$t = t_a + t_1 \quad (6)$$

At this point, the travel time t_{ab} of the vehicle from a to b is represented by equation (7).

$$t_{ab} = \frac{d_{ab}}{v_1} \quad (7)$$

In multiple time and speed driving scenarios, the vehicle's speed on the actual path is not constant. When the distance between two customers is relatively long or vehicle’s departure time is late, it may occur that the vehicle needs to cross multiple different time periods during the journey to the next customer point. This type of crossing will result in multiple changes in the vehicle's speed to adapt to the specified speed limit or optimal driving speed during each time period. Figure 3 is a schematic diagram of vehicle driving during multiple time periods.

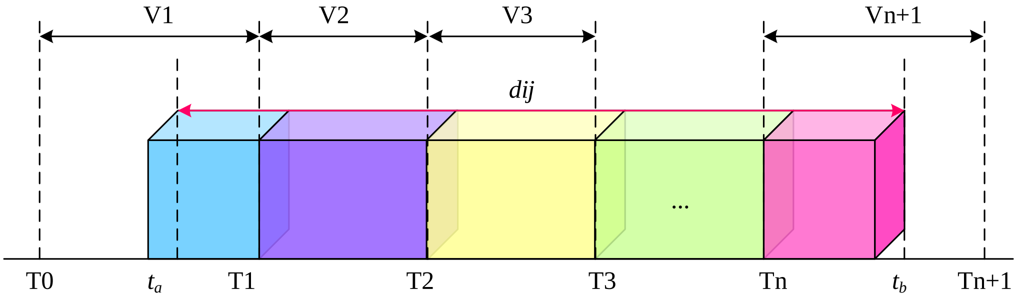


Figure 3 Schematic diagram of vehicle driving in multiple time periods

In Figure 3, when a vehicle departs from the previous customer point, if the departure time happens to be within the $[T_0, T_1]$ time period, the vehicle will travel at the corresponding speed of that time period. As the vehicle travels, if it crosses different time periods, its driving speed will also change accordingly. Assuming that the vehicle needs to cross two or more time periods throughout the entire driving process, the speed change will correspond to the time period. When the vehicle travels from a to b, if this distance needs to cross two different time periods, the total distance can be recorded as d_{ab}. Furthermore, assuming that during these two time periods, the vehicle travels distances d_1 and d_2, respectively. The corresponding driving speeds are $v3$ and $v4$. At this point, vehicle's travel time t_{ab} from a to b is represented by equation (8).

$$t_{ab} = (T_1 - t_a) + \frac{d_4}{v_4} \quad (8)$$

When a vehicle departs from a to b during $[T_0, T_1]$, the driving speed may vary due to differences in road traffic conditions during different time periods. If this driving route spans more than one time period, vehicle's total driving time t from the starting customer to the target customer needs to be calculated and accumulated based on the actual average speed during each time period. This processing method can more accurately reflect the time consumption in actual delivery, thereby optimizing the path and time arrangement of pharmaceutical cold chain logistics distribution. The DPO model for the biopharmaceutical cold chain's last kilometer is designed with fixed cost C_1, transportation cost C_2, biopharmaceutical loss cost C_3, refrigeration cost C_4, carbon emission cost C_5, and penalty cost JJ, represented by equation (9).

$$\min F = C_1 + C_2 + C_3 + C_4 + C_5 + C_6 \quad (9)$$

2. Testing of cold chain delivery path results for biopharmaceuticals based on improved sparrow search algorithm

This study selected the Bays29 problem with a scale of 29 from the traveling salesman problem library as a benchmark test to evaluate the improved design algorithm's effectiveness in solving discrete optimization problems. The original SSA and IDSSA's performance in solving this problem was compared and analyzed. Figure 4 shows the convergence curves of the two algorithms.

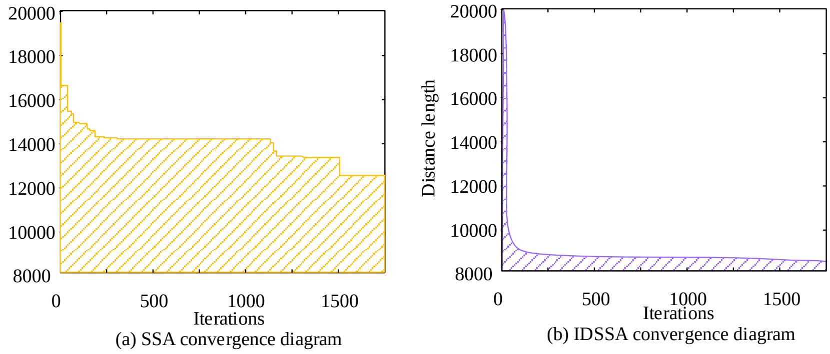


Figure 4 Convergence curves of two algorithms

Figure 4 (a) shows the convergence curve of SSA. After 1500 iterations, the convergence curve of SSA gradually stabilized, with a corresponding distance length of 1300, indicating that SSA had lower efficiency and slower convergence speed in the solving process. Figure 4 (b) shows the convergence curve of IDSSA. As iterations increased, the convergence speed of IDSSA was significantly faster than SSA. When the iteration was only 258, the distance length of IDSSA tended to stabilize at around 900, demonstrating the efficient convergence and superior performance of IDSSA. Figure 5 shows the optimal path's comparison between two algorithms.

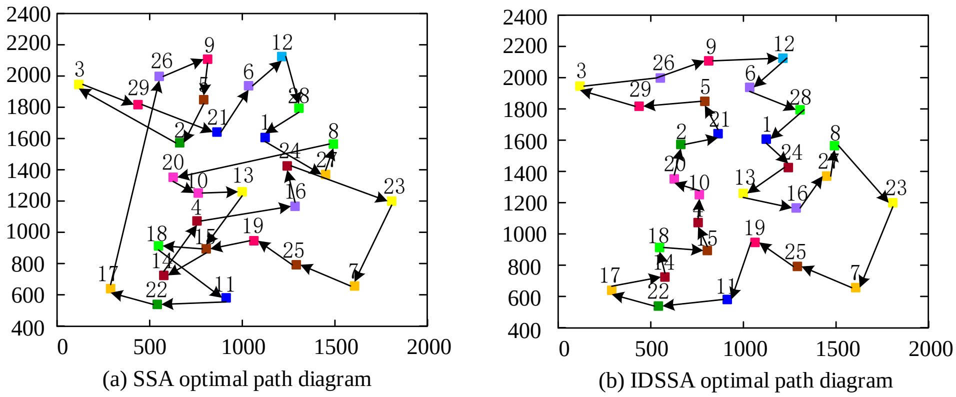
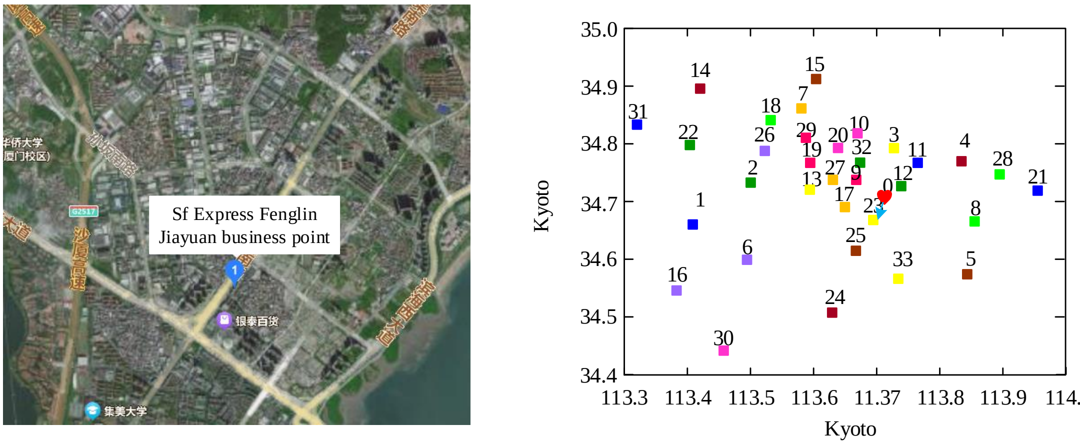


Figure 5 Comparison of optimal paths between two algorithms

Figure 5 (a) shows the optimal path diagram of SSA. The optimization route of SSA presented a relatively chaotic state in the initial stage. This indicated that SSA encountered difficulties in the search process, making it difficult to quickly jump out of the local optimal solution. Therefore, SSA failed to find the global optimal solution in the later stage of iteration. Figure 5 (b) shows the optimal path diagram of IDSSA. Compared to SSA, IDSSA's search resulted in a clearer and more orderly optimal route, demonstrating a significant improvement in search efficiency and optimal solution finding ability. The optimal search ability of IDSSA was improved by 30.7% compared to SSA, indicating the effectiveness and advantages of IDSSA in discrete optimization problems.

The Fenglin Jiayuan branch of SF in Xiamen was selected as the specific research object. The constructed biopharmaceutical logistics DPO model was applied to the branch. A geographical location and customer location distribution map of SF Fenglin Jiayuan branch were provided to more intuitively display the research object and its environment in Figure 5.



(a) Geographic satellite map of Fenglin Jiayuan business location

(b) Customer coordinates scatter

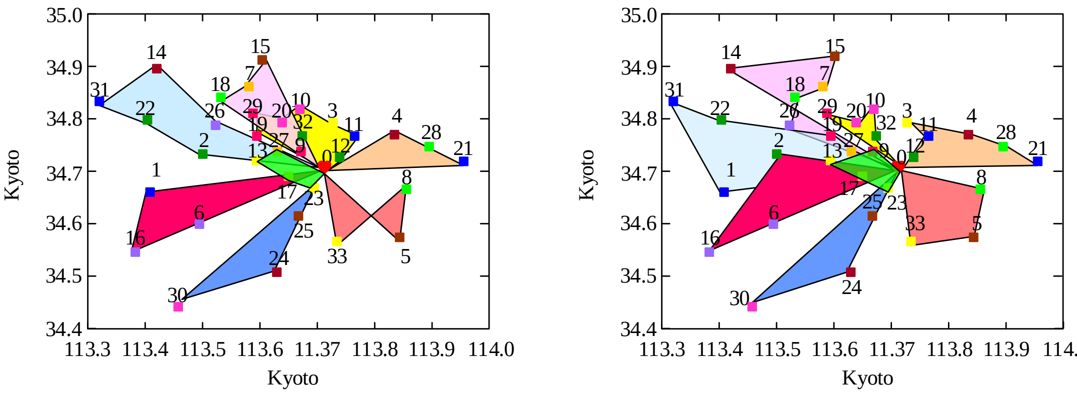
Figure 6 Geographical location and customer location distribution of SF Fenglin Jiayuan branch

Figure 6 (a) shows the geographical satellite map of SF Fenglin Jiayuan branch. Figure 6 (b) shows the scatter plot of customer coordinates. Red love is the distribution center of the SF Fenglin Jiayuan branch. Numbers 1 to 33 represent the biopharmaceutical delivery customers of SF Fenglin Jiayuan branch. In Table 1, this study used the Baidu Map transportation big data platform to obtain average traffic speed data for various time periods. This could improve the delivery efficiency of biopharmaceutical express delivery, ensuring that biopharmaceuticals could be delivered to customers more quickly.

Table 1 Average speed of each time period

Time period	Speed($km \cdot h^{-1}$)
[7:00,9:00)	40.8
[9:00,11:00)	33.5
[11:00,13:00)	34.9
[13:00,15:00)	30.7
[15:00,17:00)	27.2
[17:00,19:00)	28.4
[19:00,20:00)	33.6

The effectiveness of the research model in dealing with this speed variability was tested. The improved algorithm was used to solve the problem in both time-varying and constant velocity states. At a constant speed, this experiment selected the highest average speed recorded in Table 1, 40.8km/h, as the constant speed throughout the entire journey. Under these conditions, the solution was repeated 10 times to obtain stable experimental results. Figure 7 shows the research model's vehicle route map at different speed states.



(a) The road map of the vehicle under the condition of time varying speed

(b) The road map of the vehicle at constant speed

Figure 7 Vehicle route map of the research model at different speeds

Figure 7 (a) shows the vehicle route map under the condition of time-varying speed. In this state, by applying IDSSA-based cold chain delivery path method for biopharmaceuticals, 8 vehicles were effectively used for delivery. The optimal paths for each vehicle were determined, which were distribution center → 5 → 8 → 33, distribution center → 25 → 24 → 30, distribution center → 6 → 16 → 1, distribution center → 23 → 17 → 13 → 27, distribution center → 2 → 22 → 31 → 14 → 26, distribution center → 9 → 18 → 7 → 15 → 32, distribution center → 12 → 11 → 3 → 10 → 20 → 29 → 19, distribution center → 4 → 28 → 21. Figure 7 (b) shows the vehicle route map at a constant speed. The optimal path for 8 vehicles was from the distribution center → 8 → 5 → 33, distribution center → 25 → 24 → 30, distribution center → 6 → 16 → 2, distribution center → 17 → 1 → 31 → 22 → 19 → 27, distribution center → 26 → 18 → 7 → 15 → 14, distribution center → 25 → 13 → 9, distribution center → 32 → 10 → 20 → 29, distribution center → 12 → 3 → 11 → 4 → 28 → 21. In summary, the biopharmaceutical cold chain delivery path method based on IDSSA can adapt well to time-varying and uniform speed conditions. By adjusting the delivery path in real-time, it is possible to ensure that biopharmaceuticals are delivered to customers in the best possible condition.

3. Conclusion

This study adopted a biopharmaceutical DPO strategy based on IDSSA to improve the efficiency of the last kilometer delivery of biopharmaceuticals. This research strategy was tested. When the iteration reached 258 times, the delivery path distance of IDSSA stabilized at around 900, which fully demonstrated the efficient convergence and excellent performance of IDSSA. Under time-varying speed conditions, IDSSA could flexibly allocate 8 delivery vehicles and plan the optimal delivery path for each vehicle. For example, the path of vehicle 1 was distribution center → 5 → 8 → 33, the path of vehicle 2 was distribution center → 25 → 24 → 30, and so on. This indicated that the optimization strategy could ensure the timeliness of biopharmaceuticals during transportation. By reducing unnecessary driving distance, transportation cost was reduced, thereby improving overall delivery efficiency. Under constant speed conditions, nodes' order changed in some paths. For example, the path of vehicle 1 became distribution center → 8 → 5 → 33, and the path of vehicle 6 became distribution center → 6 → 16 → 2, etc. This change further demonstrated the flexibility and adaptability of IDSSA under different speed conditions. In summary, the biopharmaceutical cold chain DPO method based on IDSSA can flexibly adjust the delivery path under time-varying and uniform speed conditions. Meanwhile, this method can ensure that biopharmaceuticals are delivered to customers in the best condition, thereby improving the efficiency of "last kilometer" delivery. Future research requires in-depth exploration in areas such as real-time performance, multi-objective optimization, application of big data and artificial intelligence technology, and cross disciplinary cooperation and communication. It is hoped to promote innovation and development of cold chain DPO methods for biopharmaceuticals.

References

[1] Salem H, Elsoud F A, Magdy A, Magdy, A, Heshmat, D, Soliman, A. A. Wissa, K. Spectroscopic Methods for Analysis of Nano Drug Distribution System. Nano Biomedicine and Engineering, 2020, 12(2):167-177.

[2] Fang T, Wang Q, Li W. Distribution and Drug Resistance Analysis of 2287 Strains of Pathogenic Bacteria in Children's Blood Culture. MOLECULAR AND CELLULAR BIOLOGY, 2023, 13(1):24-31.

[3] Hui Z, Zhijun H U, Xiaolong P. Clinical Distribution and Drug Resistance Changes of Staphylococcus Aureus in a Hospital from 2016 to 2020. Medicine and health, 2021, 3(7):247-250.

[4] Guo S, Li K, Chen Y. Unraveling the drug distribution in brain enabled by MALDI MS imaging with laser-assisted chemical transfer. Acta Pharmacologica Sinica, 2022, 12(4):2120-2126.

[5] Yang Y, Siyu M A, Dawei L I. Modified dynamic event-triggered scaled formation control for multi-agent systems via a sparrow search algorithm based co-design algorithm. Frontiers of Information Technology & Electronic Engineering, 2024, 25(2):197-213.

[6] Guo-Feng Fan, Li Y, Xin-Yan Zhang. Short-term load forecasting based on a generalized regression neural network optimized by an improved sparrow search algorithm using the empirical wavelet decomposition method. Energy Science And Engineering, 2023, 11(7):2444-2468.

[7] Meng K, Chen C, Xin B. MSSSA:a multi-strategy enhanced sparrow search algorithm for global optimization. Frontiers in information and electronic engineering, 2022, 23(12):1828-1847.

[8] Fan Y, Sui T, Peng K, Sang Y, Huang F. Study on load monitoring and demand side management strategy based on Elman neural network optimized by sparrow search algorithm. Circuit world, 2023, 49(1):56-66.

[9] Rohith B C, Nelson M. Artificial Intelligence Based Credit Card Fraud Detection for Online Transactions Optimized with Sparrow Search Algorithm. International Journal of Performability Engineering, 2023, 19(9):624-632.

[10] Hui X, Guangbin C, Shengxiu Z. Hypersonic reentry trajectory optimization by using improved sparrow search algorithm and control parametrization method. Advances in Space Research: The Official Journal of the Committee on Space Research, 2022, 69(6):2512-2524.

[11] Chen J, Li X, Xu J, Wang Y. Deployment for NOMA-UAV Base Stations Based on Hybrid Sparrow Search Algorithm. IEEE Transactions on Aerospace and Electronic Systems, 2023, 59(5):6138-6149.

[12] Gharehchopogh F S, Namazi M, Ebrahimi L, et al. Advances in sparrow search algorithm: a comprehensive survey. Archives of Computational Methods in Engineering, 2023, 30(1): 427-455.

[13] Walther R, Zelikin A N. Chemical (neo) glycosylation of biological drugs. Advanced Drug Delivery Reviews, 2021, 171(2): 62-76.

[14] Ahtiainen H K, Kallio M M, Airaksinen M. Safety, time and cost evaluation of automated and semi-automated drug distribution systems in hospitals: a systematic review. European Journal of Hospital Pharmacy, 2020, 27(5): 253-262.

[15] Huizing L R S, McDuffie J, Cuyckens F. Quantitative mass spectrometry imaging to study drug distribution in the intestine following oral dosing. Analytical Chemistry, 2021, 93(4): 2144-2151.

[16] Kumar D. Analysis of issues of generic medicine supply chain using fuzzy AHP: a Pilot study of Indian public drug distribution scheme. International Journal of Pharmaceutical and Healthcare Marketing, 2021, 15(1): 18-42.

[17] Shearer J, Castro J L, Lawson A D G. Rings in clinical trials and drugs: present and future. Journal of Medicinal Chemistry, 2022, 65(13): 8699-8712.

[18] Angın M, Ali S I A. Analysis of factors affecting road traffic accidents in North Cyprus[J]. Engineering, Technology & Applied Science Research, 2021, 11(6): 7938-7943.

ABOUT THE AUTHOR

Canni Lin:The Schoole of Nature Science，Trinity College Dublin , D02 PN40, Dublin, Ireland

E-mail: trinity_cannilin@126.com

Zhengting Liu:The Schoole of Nature Science，Trinity College Dublin , D02 PN40, Dublin, Ireland

E-mail: dtclzt@gmail.com