The Impact of GA Optimization Model Under the Constraint of Maximum Inventory on the Logistics Cost Control of Automotive Parts Production in the Factory

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The logistics of parts entering the factory is an important component of the cost source for manufacturing plants. How to efficiently transport is the key for its enterprises to achieve low-cost control. To address this issue, this study proposed a path planning model based on an improved genetic algorithm. Firstly, a circular distribution model suitable for component transportation logistics is selected, and then constraints such as maximum inventory at the line edge are introduced for design. The basic design of the genetic algorithm is also carried out. Subsequently, three neighborhood structures are introduced for optimization to address the convergence speed and other issues of the algorithm. In response to the demand fluctuation phenomenon in practical applications, a new coding design is carried out. To verify the impact of the model on inbound logistics costs, simulation experiments are conducted on the MATLAB platform. The results showed that the designed algorithm had an average decrease of 14% in total mileage compared to single objective nonlinear models and collaborative network models, while the total cost had decreased by 26.58%. In summary, the improved genetic algorithm model designed in this study has a positive impact on the cost control of inbound logistics.

Povzetek: Raziskava uvaja izboljšan genetski algoritem za optimizacijo poti vhodne logistike avtomobilskih delov, kar zmanjša skupne stroške za 26,58%.

1 Introduction

The continuous increase in sales in the automotive industry has driven the rapid development of automotive enterprises. At the same time, competition among enterprises is gradually intensifying. To achieve high profit and benefits as much as possible, cost control naturally becomes an important component of enterprise development. Among them, the inbound logistics cost (ILC) is the key to the entire logistics cost system, which is closely related to the transportation mode of automotive components. Moreover, the production methods of manufacturers also affect the operation of transportation modes. In the context of manufacturing, the concept of just-in-time production serves as a benchmark for the timely delivery of the correct quantity of components at the optimal time, with a particular focus on reducing inventory levels. Therefore, transportation is usually carried out in a high-frequency and small quantity form [1]. The circular distribution model (CDM) precisely meets this demand and is therefore the most widely used transportation model at present. How to achieve the lowest cost transportation and inventory under relevant distribution modes are closely related to the planning of transportation routes [2]. Therefore, the control of ILC is essentially a problem of path planning. Common path planning methods include genetic algorithm (GA), Dijkstra algorithm, A* algorithm, and random road-map algorithm. As a new type of heuristic algorithm, GA starts searching from the initial solution space and is easier to obtain the global optimal solution compared to traditional single point search. The updated method that only relies on the fitness function also enhances its adaptability, which is relatively common and mature in existing research [3]. Therefore, a simulation design is conducted for inbound logistics path planning (LPP) based on an improved genetic algorithm (IGA). The innovation of the research lies in the constraint on the maximum inventory of the manufacturing center and the introduction of neighborhood structure to optimize the encoding of GA. Considering the problem of demand fluctuations in actual situations, further optimization design has been carried out. The study is divided into four parts. Part 1 introduces the current research status of ILC control. Part 2 has designed a GA-based path planning model. Part 3 conducts simulation experiments on the model. Part 4 summarizes the experimental results.

2 Literature review

The path planning and design for inbound logistics is currently a popular research topic, and its impact on the environment and costs should not be underestimated. Muoz Villamizar et al. optimized the daily delivery service launched by companies such as Amazon to address the increased transportation costs and carbon emissions associated with fast shipping. It used a discrete event simulation model and was validated with Mexican retailers, where fast shipping resulted in a 15% and 68% increase in carbon dioxide emissions and costs, respectively [4]. Wang et al. believed that the rise of the cruise market has increased demand for the cruise construction industry, but it was a complex heavy industry that may have negative impacts on the environment. Therefore, through the just in time logistics strategy, two logistics system models were established to study the optimal inbound logistics modes for three different routes. Their models helped cruise ship construction companies control costs and achieved sustainable development [5]. Santos et al. explored cooperation between shippers and carriers to improve the efficiency of transportation networks and reduce empty operations, and developed a dual layered vehicle routing problem and selective return model. At the upper level of the model, shippers chose the lowest cost delivery route and incentive measures, while at the lower level, carriers decided which incentives to accept and which return trips to choose. This double-layer approach could increase collaborative benefits more than non-cooperative methods [6]. Darvishi et al. used the textile industry as an example and used a mixed integer nonlinear model to handle procurement and production decisions under multiple cycles, products, and transportation modes. To address this model, an effective multi-stage algorithm was developed and a powerful two-stage stochastic programming method was designed using possibility programming to fuzzify it. Finally, numerical research on the clothing industry has confirmed the effectiveness of the model and solutions [7].

Coindreau et al. optimized the cross platform multi-modal logistics problem of a large European automobile manufacturer and integrated it into a mixed integer linear programming model, taking into account loading constraints and loading scheduling. By conducting numerous computational experiments in real scenarios, this integration method could reduce inventory losses by an average of 40% [8]. Kundra et al. proposed a quantum inspired path planning model combining the firefly algorithm with the cuckoo search strategy, introducing the Levy flight attribute to avoid premature convergence and stagnation in the model. Their path planning method had a certain optimization effect [9]. Ntakolia et al. addressed the multi-objective path planning problem of unmanned surface vehicles (USVs) by employing an ant colony optimization algorithm, a fuzzy reasoning system, and advanced algorithms. They then compared and evaluated various methods. The algorithm that combined fuzzy reasoning had better performance, while the algorithm that combined root mean square error converged faster [10]. Sun et al. proposed a GA-based path planning method for collecting seabed observation data from multiple USVs. This method could simultaneously solve multiple traveling salesman problems and obstacle avoidance problems, combining special search methods and IGA to achieve global path optimization and task load balancing, with excellent path planning effects [11]. A summary of the related works is shown in Table 1.

Table 1: Related works summary table

Source	Method	Major technology	Relative to the limitations of research method
Muoz-Villamizar et al.	Discrete event simulation	Express shipping	Inventory constraints are not considered
Wang et al.	Just-in-time logistics strategy	Optimize the inbound logistics mode	Not optimized for line side inventory
Santos et al.	Double-deck vehicle routing problem model	The shipper works with the carrier	Focus on non-path planning
Darvishi et al.	Mixed integer nonlinear model	Optimize purchasing and production decisions	It does not target the inbound logistics of auto parts
Coindreau et al.	Mixed integer linear programming	Automotive manufacturer logistics optimization	Demand fluctuations are not taken into account
Kundra et al.	Quantum heuristic algorithm	Path planning	Not specifically for inbound logistics
Ntakolia et al.	Ant colony optimization algorithm	Path planning for unmanned surface vehicles	Inventory constraints are not considered
Sun et al.	Data collection	Solve the problem of multiple travel agents	Focus on data collection

In summary, path planning is closely related to logistics cost control. This study utilizes a mature GA for inbound LPP and introduces neighborhood structure optimization in coding to enhance the application performance of the model in the face of uncontrollable factors and achieve better cost control effects.

3 Application of GA based on line edge maximum inventory constraint in ILC control

Automobile parts manufacturers not only need to control the cost of the product itself, but also need to exercise certain control over external costs such as inbound logistics. This study proposes a cost control model based on IGA. Firstly, the inbound logistics model is selected and introduced to design constraints on inventory and transportation costs, and GA is introduced to solve the model. To address the shortcomings of the algorithm, neighborhood structure is introduced for optimization, and further design improvements are made to address the unstable demand for component products.

3.1 Analysis and solution design of ILC control model under constraint conditions

Entering the factory logistics planning is one of the basic requirements for just in time production of automotive parts, aiming to evenly distribute parts to the production line according to certain criteria and time windows. It is the foundation for maintaining production stability and the initial component of the entire supply chain logistics. Common inbound logistics include three modes: supplier direct delivery, Milk Run (MR), and joint delivery. Among them, the high-frequency and small batch characteristics of CDM are consistent with the material demand pattern of automobile manufacturers, and therefore have been widely used, as shown in Figure 1.

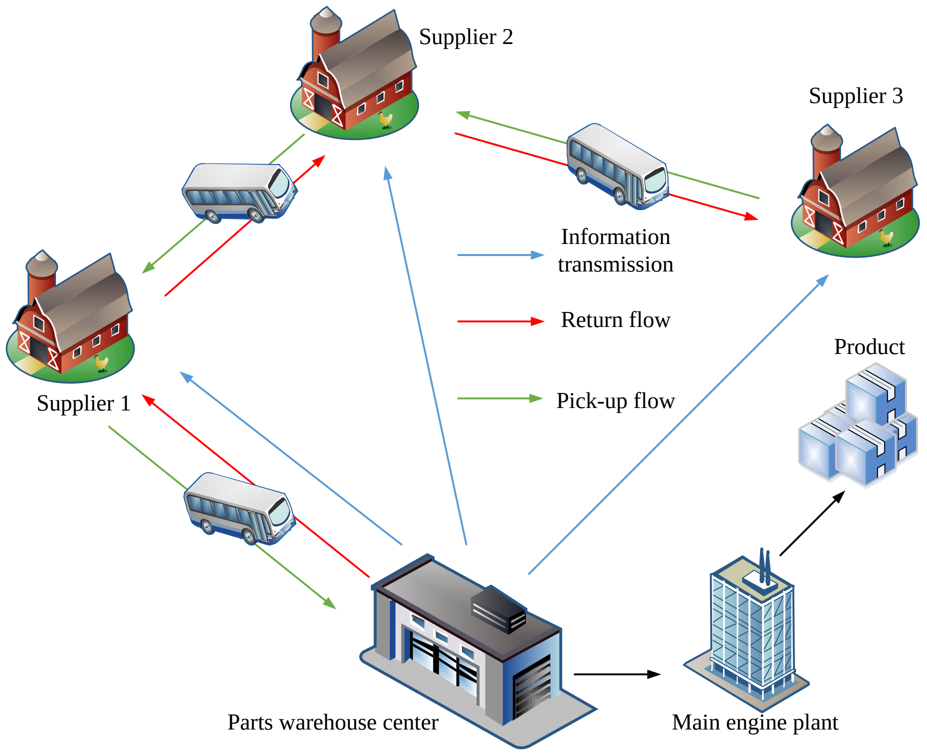


Figure 1: Visualization of milk run mode

The cost of inbound logistics includes four parts: ordering, management, inventory, and transportation, with inventory and transportation accounting for about 85% of the total cost. ILC should be optimized for these two parts. Vehicle path planning is the core of inbound delivery, aimed at achieving goals with appropriate quantities and paths at the lowest cost [12]. At the same time, MR needs to meet the supplier's inventory level at the automotive factory. The basis of this constraint is to assume that the consumption of components on the production line is linear, and an increase in the number of pick-up times will reduce the supplier's inventory on the production line. When the inventory of the manufacturing plant's production line is low, the high-frequency and small quantity mode of MR can be achieved. Therefore, this study introduces the maximum line edge inventory to forcibly reduce the single transportation volume of suppliers, as shown in Figure 2.

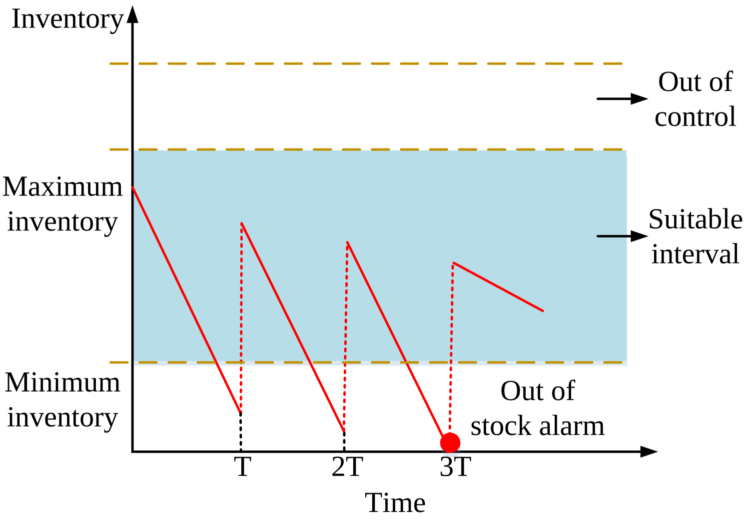


Figure 2: Schematic diagram of product inventory changes

Secondly, to ensure a smooth pick-up process, it is necessary to constrain the independent paths of each supplier. When the total transportation volume is greater than the single vehicle loading capacity, it is necessary to increase the pickup frequency, as shown in equation (1).

$$\begin{cases} \sum_{i \in G} x_{ijk} = y_{ijk} & \forall j \in G, j \neq 0; \forall k \in E \\ \sum_{i \in G} x_{jik} = y_{ik} & \forall i \in G, i \neq 0; \forall k \in E \\ \sum_{k \in E} y_{ik} = 1 & i \in G, i \neq 0 \end{cases} \tag{1}$$

In equation (1), i/j represents the supplier. k represents the transportation path. x_{ijk} represents the k-th vehicle traveling from supplier i to supplier j. y_{ik} represents the completion of supply i on path k. G represents the transportation and pickup node. E represents the number of vehicles corresponding to the path. The constraint of transportation vehicles from departure to return is shown in equation (2) [13].

$$\begin{cases} \sum_{i \in G} x_{0ik} = 1 & \forall k \in E \\ \sum_{i \in G} x_{i0k} = 1 & \forall k \in E \end{cases} \tag{2}$$

In equation (2), 0 represents the component node. The minimum value of the sum of inventory cost and transportation cost is equation (3).

$$\min Z = a \sum_{i \in G} \sum_{j \in G} \sum_{k \in E} f_k d_{ij} x_{ijk} + b \sum_{i \in G} \sum_{k \in E} p_{ik} y_{ik} \tag{3}$$

In equation (3), a/b are unit distance freight and unit inventory cost, respectively. f_k represents the pickup frequency of the corresponding path. d_{ij} represents the distance between two suppliers. p_{ik} represents the loading volume of the route supplier. The above constraints on vehicle path planning need to be implemented in a computer through algorithms. Modern heuristic algorithms are easier to obtain global optimal solutions when solving problems for complex scene models. Therefore, a more mature GA is chosen to solve the model. GA is a random search algorithm based on biological evolution simulation, with higher advantages in large-scale combinatorial optimization problems due to its genetic operator and parallelism. Firstly, the problem must be encoded, an initial cluster generated according to the rules, the quality of the solution evaluated based on fitness values, and the solution updated using selection and crossover operators, with the process repeated continuously until the iteration completion condition is met. Among them, encoding is to transform the solution space into a search space that the algorithm can recognize, which determines the performance of GA. The selection of a population, also known as the replication process, is based on the individual's fitness value for selection. Individuals with higher fitness values have a higher probability of inheritance. This study introduces the roulette wheel selection method, where the probability of individual selection is directly proportional to the fitness value, as shown in equation (4).

$$P_{X_i} = f(X_i) / \left(f(X_i) + f(X_1) + f(X_2) + \ldots + f(X_n) \right) \tag{4}$$

In equation (4), P_{X_i} represents the probability of an individual being selected. $f(X)$ represents the fitness value of each individual. Individuals are considered as a part of a sector in a disk, and if the random selection process stops in which sector, the individual is selected. Each sector represents the prefix and probability of an individual, which are directly proportional to the selection probability, as shown in equation (5).

$$Q_j = \sum_{i=1}^{j} f(X_j) \tag{5}$$

In equation (5), Q_j represents the prefix and probability of the individual. Crossover operator is a simulation of mating recombination in biological evolution. OX crossover operator is introduced in this study. OX crossover operator is an ordered crossover method widely used in GA, which is especially suitable for solving problems involving sequence or path planning. The OX crossover operator is capable of maintaining the path order of optimal individuals within the parent chromosome, which facilitates the algorithm's rapid convergence towards optimal solutions. The reason for choosing the OX crossover operator is that it can maintain the efficiency of path continuity in the path planning problem, while avoiding the generation of illegitimate offspring chromosomes. The OX crossover operator is shown in Figure 3.

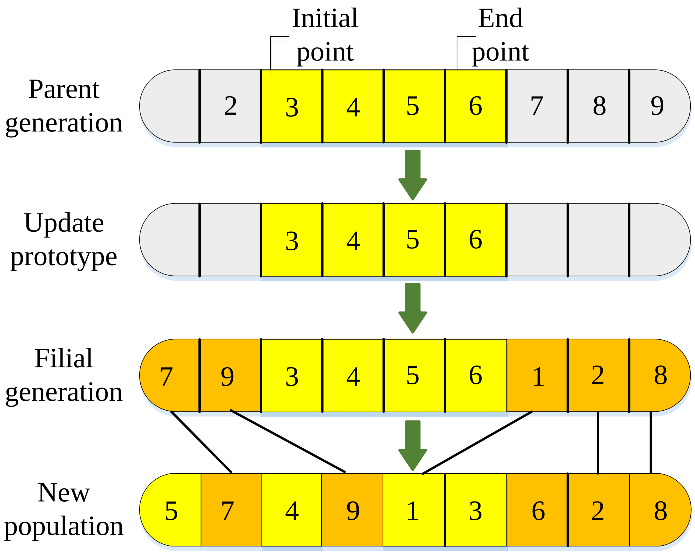


Figure 3: Operation flow of OX crossover operator

Firstly, it is necessary to randomly generate a starting position in the parent generation and generate offspring based on this, and generate a new population in order according to the gene position of the offspring in another parent generation. The mutation operator is designed to simulate the process of gene mutation, ensuring that individuals exhibit variation according to predefined rules, maintaining population diversity, and preventing the phenomenon of rapid convergence due to local optimization. There is no overlap between nodes in the incoming logistics of auto-parts. The study chooses exchange mutation as the mutation technology [14]. Swap mutation operator is a simple and effective mutation method, which is realized by randomly swapping two gene locations in chromosomes. In the path planning problem, this mutation operator can simulate the small adjustment of the route in the real world, which helps the algorithm to jump out of the local optimal solution and find the global optimal solution. The swap mutation operator is chosen because it is simple and easy to implement, and can increase the diversity of the population and avoid premature convergence while maintaining the search efficiency of the algorithm. In the above steps, corresponding control parameters need to be selected to achieve better global optimal solution results.

3.2 Optimization GA design for the logistics model of automotive parts recycling in factories

By studying CDM based on line edge inventory constraints and GA, the GA model based on MR can be further solved. Firstly, the description of the path planning solution consists of two codes: one is a description of the frequency of supplier replenishment, and the other is a description of the route, both of which are real number codes. The constraints of the model are also tailored to these two parts. The maximum inventory level at the production line and the preparation time for a single supply are related to the frequency of replenishment. The vehicle's own load capacity is related to route planning, and the former is also limited by the single vehicle's load capacity [15]. There are two necessary conditions to satisfy the inventory constraint at the line edge. Firstly, the single replenishment quantity cannot exceed the difference between the maximum and minimum inventory, and the maximum inventory for pickup is shown in equation (6).

$$\sum_{i \in G, i \neq 0} p_{ik} y_{ik} \leq S \quad \forall k \in E \tag{6}$$

In equation (6), S represents the highest inventory level. Secondly, the replenishment interval should not be less than the preparation time for a single supply. The constraints of route planning must be implemented using coding. This involves first inputting chromosome segments and subsequently introducing penalty functions. When the corresponding chromosome violates the restriction condition, punishment is required, which is to reduce the fitness value, as shown in equation (7) [16].

$$\min Z = a\sum_{i\in G}\sum_{j\in G}\sum_{k\in E} f_k d_{ij} x_{ijk} + b\sum_{i\in G}\sum_{k\in E} p_{ik} y_{ik} + M\sum_{k\in E}\max\left(\sum_{i\in G}\sum_{k\in E} p_{ik} y_{ik} - S, 0\right) \quad (7)$$

In equation (7), $M\sum_{k\in E}\max\left(\sum_{i\in G}\sum_{k\in E} p_{ik} y_{ik} - S, 0\right)$ represents the penalty value, and M is an appropriately large integer. Regarding the selection of fitness function, fitness function has different definitions for different problems, therefore it is a variation of the objective function, as shown in equation (8).

$$F_k = r\frac{Z'}{Z_k} \quad (8)$$

In equation (8), F_k represents the fitness value of the chromosome. Z' represents the transportation cost of the initial optimal chromosome. Z_k represents the transportation cost. r represents a constant. The initial cluster of suppliers is randomly selected. Supplier $s = \{1, 2, ..., u\}$ needs to meet the conditions shown in equation (9).

$$\begin{cases} \sum_{i=1}^{s-1} p_{ik} y_{ik} \le V_k \\ \sum_{i=1}^{s} p_{ik} y_{ik} > V_k \end{cases} \quad (9)$$

The control parameters of GA include population size N, crossover probability P_c, and mutation probability P_m. The population size is related to the convergence speed of the model. Small scale can easily lead to local optima, while conversely, it can lead to slow convergence. A higher probability of crossover can lead to better genetic crossover effects, but it may also disrupt the better individuals, leading to a randomization process. Conversely, it may result in individuals directly entering the next generation. Therefore, the crossover probability is usually within the range of [0.4,0.8], while the mutation probability is less than 0.2 [17]. However, setting only the crossover and mutation probabilities of the algorithm can easily lead to local optima, so optimization strategies are needed to ensure the inheritance of excellent individuals. This study introduces three neighborhood structures for improvement, namely the 2-OPT structure, part shuffle structure, and random insert structure, as shown in Figure 4.

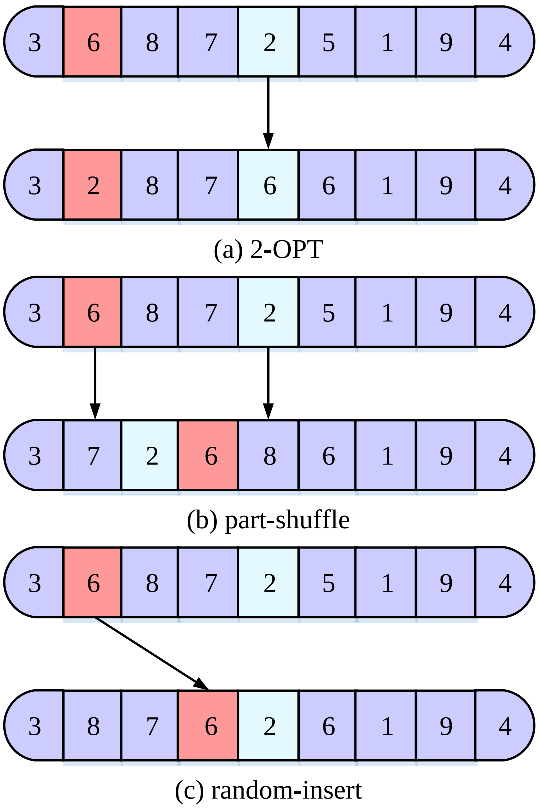


Figure 4: Three kinds of neighborhood optimization structures

The 2-OPT operator originates from the two-path switching structure in the path switching + depth first search algorithm, and has a significant advantage in path planning. The part shuffle structure aims to enhance population diversity by randomly selecting two gene loci and shuffling them. The random insert structure also requires randomly selecting two gene loci, then inserting one into the other, and performing lateral movement on the remaining gene loci [18]. The above design is aimed at the situation of stable demand. However, it is difficult to meet the requirement of stable demand under real conditions. The demand for automotive components fluctuates around 1.5-2 times, so optimization should also be carried out in this area. The objective function of path optimization under demand fluctuations is shown in equation (9).

$$\min Z = a\sum_{i\in G}\sum_{j\in G}\sum_{k\in E} f_k d_{ij} x_{ijk} + b\sum_{i\in G}\sum_{k\in E} p_{ik} y_{ik} + \sum_{k=1}^{m}\sum_{s=u+1}^{w} \lambda_s f_k \quad (10)$$

In equation (10), m represents the total number of paths, and λ_s represents the single transportation cost of vehicle s. The vehicle load constraint is equation (11).

$$\sum_{i=0}^{n} q_i^s y_{iks} W_i \leq W^s, \forall k \in K, \forall s \in S \quad (11)$$

In equation (11), K / S represent the set of paths and the set of vehicles, respectively. W_i represents the unit weight of the component. W^s represents the maximum load capacity of the vehicle. q_i^s represents the single pickup volume of the vehicle at the supplier's location. The maximum inventory constraint at the edge of the line is equation (12).

$$\left(y_{iks} / f_{ks}\right) Q_i \leq E_{\max}^i - E_{\max}^i \quad (12)$$

In equation (12), Q_i represents the daily supply of supplier i. $E_{\max}^i / E_{\max}^i$ represent the maximum and minimum inventory of the warehouse, respectively. The time constraints of the model are shown in equation (13).

$$\begin{cases} x_{ij}^{ks}\left(S_{lea,i}^{k} + S_{ij}^{k}\right) = S_{rea,i}^{k} \\ T_i^{f+1} - T_i^{f} \geq 12 \end{cases} \quad (13)$$

In equation (13), x_{ij}^{ks} represents whether path k vehicle s is from supplier i to supplier j. $S_{lea,i}^{k} / S_{rea,i}^{k}$ are the time when vehicle k leaves and reaches supplier i. S_{ij}^{k} represents the travel time between suppliers. T_i^f represents the time of supplier i's f supply. In summary, the GA model requires three encoding segments. Compared to the original encoding for replenishment frequency and path planning, the encoding for the vehicle model has been added, as shown in Figure 5.

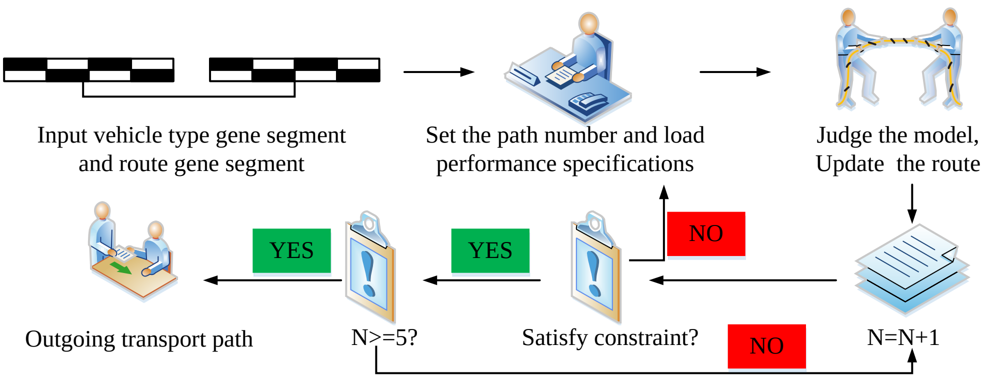


Figure 5: Constraint coding process

In Figure 5, the vehicle model code and route code are shown in equation (14).

$$\begin{cases} C = \begin{bmatrix} 1 & 1 & 3 & 2 & 1 \end{bmatrix} \\ N' = \begin{bmatrix} 3 & 2 & 5 & 1 & 4 \end{bmatrix} \\ G = 1 \end{cases} \quad (14)$$

In equation (14), $C/N^{'}$ are the vehicle model code and route code, respectively. The parameter settings include route code, loading capacity, carriage length, and pickup frequency. Based on the selection of constraints and optimization strategies, the final IGA operation process is Figure 6.

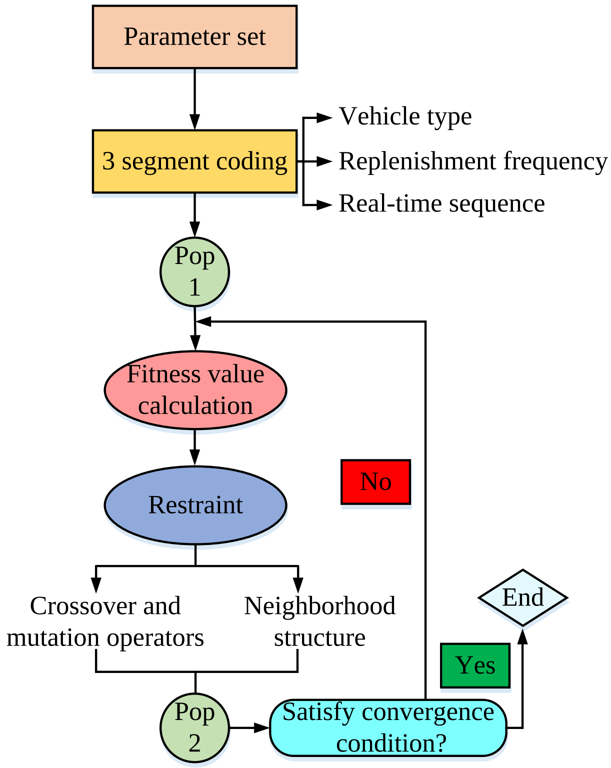


Figure 6: Process of improving GA algorithm

From Figure 6, the designed IGA mainly includes: coding, fitness calculation, and cross variation. Meanwhile, neighborhood structure and corresponding constraint conditions are added for optimization to further enhance path planning performance. At run time, the population needs to be initialized before each individual is encoded using real number encoding. The fitness value of each individual is calculated, and individuals are selected for crossover and mutation operations in accordance with their respective fitness values. Fitness values are calculated for the new individuals generated by crossover and mutation operations, and according to the fitness values, a new population is formed. The fitness value of an individual who violates a constraint condition is reduced by the penalty function to ensure that all individuals in the population meet the problem constraint. After iteration, the individual with the highest fitness value is selected from the current population as the final optimal path planning scheme.

4 Performance analysis and simulation experiment of an inbound lpp model based on IGA

To verify the performance of IGA-based ILC control, this study first conducted experiments on the performance of IGA itself. Subsequently, the model was applied to a cost control model, which simulated the process of inbound LPP based on demand fluctuations and demand stability. In addition, other models were introduced to enable a comparison of the final cost control effect.

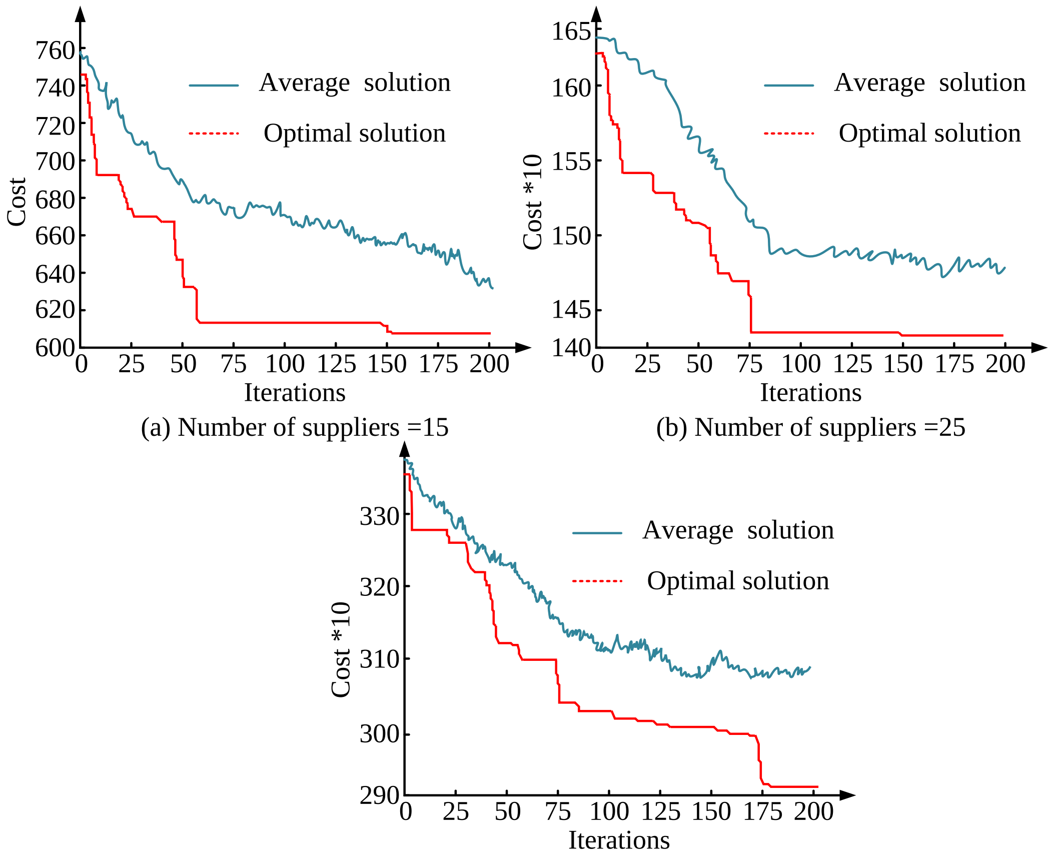
4.1 Optimization performance verification experiment and comparative analysis of IGA

This study first conducted experimental verification on the performance of IGA. Table 1 shows the experimental environment and algorithm parameters.

Table 1: Selection of experimental environment and algorithm parameters

Name	Experimental environment/Parameters
Operating system	Window 10
RAM	4GB
GPU	NVIDA Ge Force GTX 1080 Ti
Simulation platform	Matlab R2018a
Maximum capacity of a single transport W^s	15 tons
Maximum inventory $E^i_{\max}$	20 tons
Maximum single pickup time T	8h
Pop size N	200
Max iterations	200
Para.ftemperature	500
Para.etemperature	0.06
Crossover probability P_c	0.6
Mutation probability P_m	0.2

To explore the optimization performance of IGA under different numbers of nodes, i.e. the number of suppliers, this study selected the conditions of 15/25/50 suppliers for experiments, and the results are shown in Figure 7.



(a) Number of suppliers =15

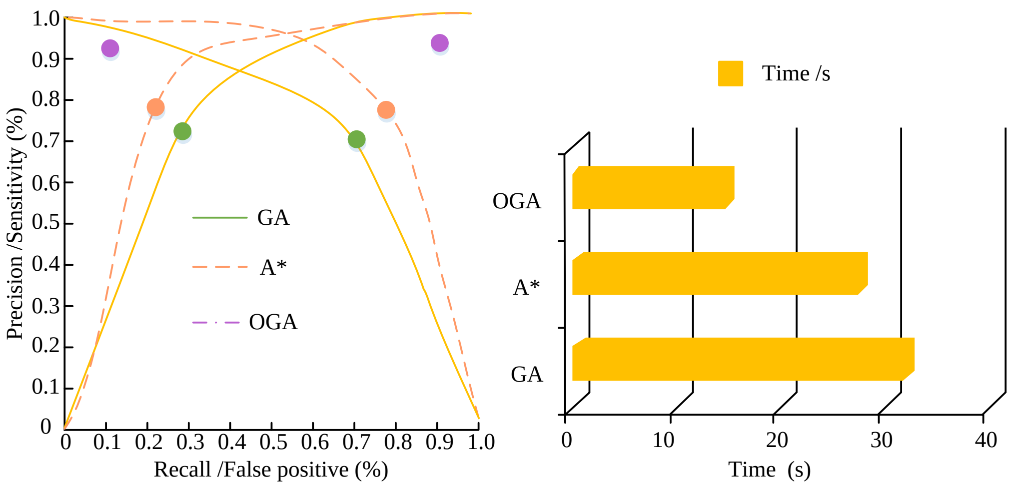
(b) Number of suppliers =25

(c) Number of suppliers =50

Figure 7: IGA performance with different number of suppliers

In Figure 7, the smaller the number of nodes, the lower the cost value of the model solution and the fewer iterations. In the optimal solution curve of Figure 7 (a), the model gradually begins to converge around the 55th iteration, with a final convergence value of 601.23, which is 19.48% lower than the initial optimal solution. The difference between the average solution and the optimal solution gradually increases with the iteration of the optimal solution, and at the beginning of convergence, the difference between the two curves reaches 8.97%.

When the number of nodes increases to 25, the initial convergence number of the model is 75, and the final convergence value is 1404.58, a decrease of 14.31% compared to the initial value. The average solution is also consistent with the previous trend, but the convergence performance is more pronounced. When the number of nodes increases to 50, the convergence frequency of the model is about 175, and the final convergence value is 2911.45, which is a decrease of 14.32% compared to the initial value. In summary, IGA has a better global optimization effect. This study further compares it with un-optimized GA and the more common path optimization A* algorithm under the condition of 25 nodes, as shown in Figure 8.



(a) Comparison of PR/ROC curves of each algorithm (b) Comparison of time complexity of each model

Figure 8: Performance comparison of different algorithms

Figure 8 (a) shows the PR and ROC curves of each algorithm. The performance of the un-optimized GA is the worst, with accuracy and recall corresponding to the PR curve balance point of 72.14% and 71.59%, respectively, while the A* algorithm reaches 79.98% and 81.46%, respectively. The accuracy and recall corresponding to the PR curve equilibrium point of the proposed IGA algorithm are 95.37% and 96.71%, respectively, with an average improvement of 19.31% and 20.19%. The trend of ROC variation for each algorithm is also the same. The sensitivity and false positive probability of IGA are 93.88% and 7.63%, respectively. The false positive rate is the misjudgment rate of the algorithm, which is on average 15.41% lower than the other two algorithms, and the sensitivity is on average 18.97% higher than the other two algorithms. Figure 8 (b) shows the runtime of each algorithm. The runtime of IGA, A* algorithm, and un-optimized GA are 12.14s, 28.97s, and 32.59s, respectively. Therefore, the average duration of IGA is 56.94% lower than other algorithms. In summary, the proposed IGA has the best performance.

4.2 Practical application analysis of path planning model based on IGA in ILC control

This study embedded IGA into the factory LPP model and selected 38 suppliers near a certain company for experiments. The transportation of automotive parts is a box truck with a load capacity of 28 tons and a loading volume of 12.6m*2.5m*2.5m. The experimental results are shown in Figure 9.

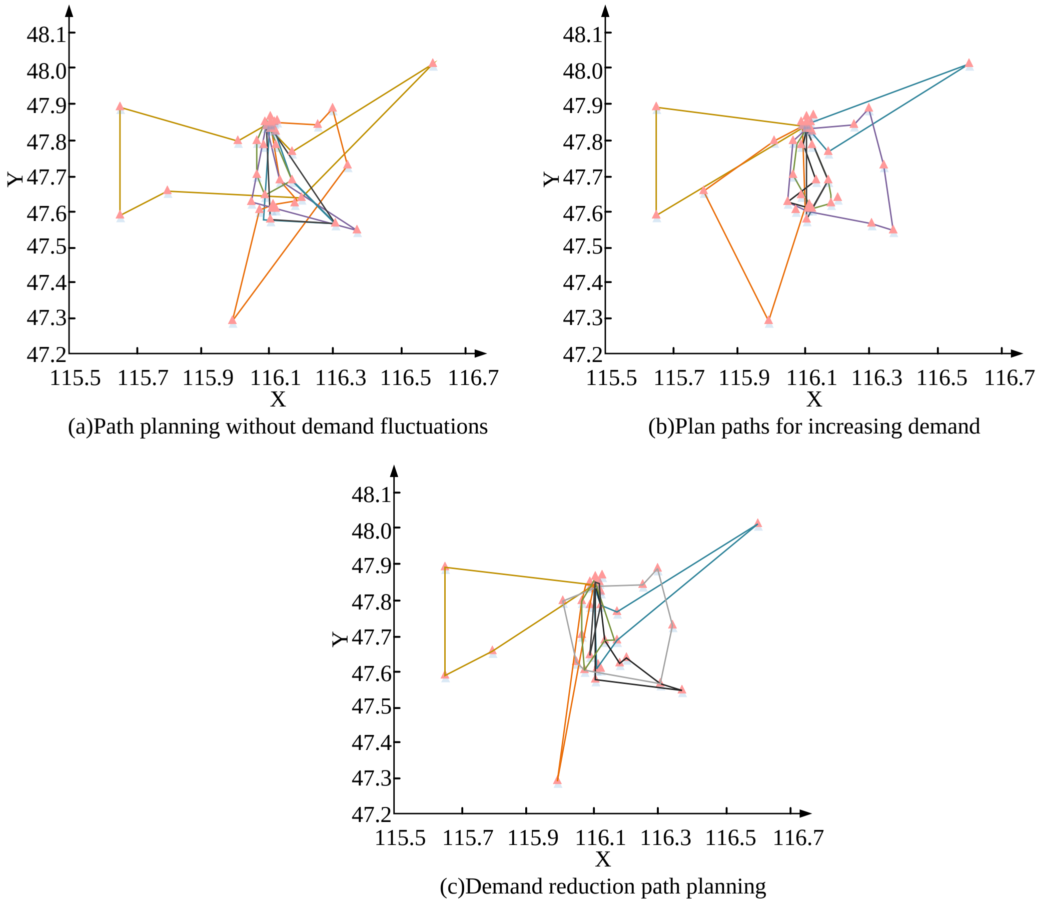


Figure 9: Visualization of path planning under different requirements

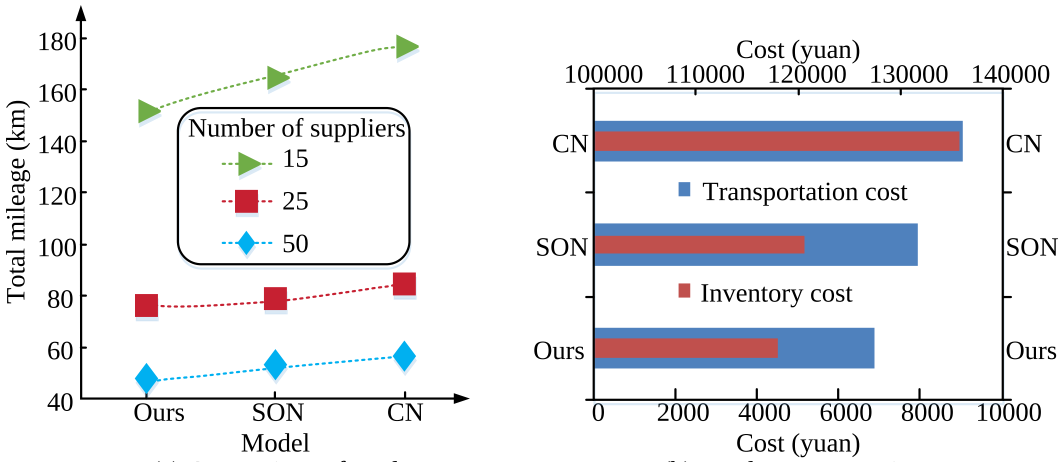
All path planning results in Figure 9 are 7 paths. Figure 9 (a) shows a visual diagram of path planning with stable demand. The number of nodes passing through each path is 6/8/7/2/7/6/2, and in the 15-day transportation time, the frequency is 20/23/5/10/15/30/10, respectively. Figure 9 (b) shows a visual diagram of path planning after increasing demand. The number of nodes passing through each path is 5/4/9/8/2/8/2, and the frequency of each path is 7/8/12/11/2/14/3. Figure 9 (c) shows a visual diagram of path planning after demand reduction. The number of nodes passing through each path is 3/2/9/7/3/6/8, and the frequency of each path is 2/3/14/9/2/7/10. When the demand is stable, each path passes through nodes more evenly and frequently. When demand increases, each path passing through the nodes needs to be adjusted accordingly. The corresponding frequency is higher for routes with more nodes. When the demand decreases, the route also changes according to the changes in demand for each node. Table 2 shows the specific cost control results obtained from the path before and after demand changes.

Table 2: Specific cost control results of path planning before and after demand changes

Path	Index	Demand stabilization	Rising demand	Demand reduction
1	Total time(h)	2.11	1.59	2.98
	Loading rate(%)	92.51	98.75	68.96
2	Total time(h)	1.46	3.52	0.82
	Loading rate(%)	91.16	66.25	85.97
3	Total time(h)	5.82	1.76	0.63
	Loading rate(%)	98.56	97.17	82.64
4	Total time(h)	1.92	2.83	2.81

	Loading rate(%)	58.49	94.20	85.89
5	Total time(h)	3.96	2.86	3.57
	Loading rate(%)	99.67	73.42	68.73
6	Total time(h)	0.47	0.56	2.47
	Loading rate(%)	99.89	90.14	85.34
7	Total time(h)	0.12	3.11	1.52
	Loading rate(%)	71.46	76.17	95.38
Total cost(yuan)	399781.96	169185.35	136905.20	

The data in Table 2 represent the total value of 15-day transportation. Under stable demand, the average time taken for each path is 2.27 hours, and the average loading rate is 87.39%. Its frequency is at most twice a day, and at least once every three days. The total cost of MR under the total transportation days reaches 399781.96 yuan, which is 20.34% less than the simple direct delivery form. The total mileage is 1748 kilometers, a relative decrease of 53.54%. After the increase in demand, the average time for each path is 2.32 hours, the average loading rate is 85.17%, the total cost is 169185.35 yuan with a relative decrease of 23.25%, and the total transportation mileage decreases by 64.32%. When the demand decreases, the average time for each path is hours, the average loading rate is %, the total cost is 136905.20 yuan with a relative decrease of 21.42%, and the total transportation mileage is 46.95%. The research method has a significant effect on the control of ILC. This study further introduces the Single Objective Nonlinearity (SON) model proposed by J Wang et al. and the Collaborative Network (CN) model proposed by MJ Santos et al. for comparative experiments, as shown in Figure 10.



(a) Comparison of total mileage of different nodes

(b) Total cost comparison of each model

Figure 10: Comparison of cost control effects of various route planning models on warehousing logistics

Figure 10 (a) shows the total mileage of path planning for each model under different numbers of suppliers. When the number of suppliers is 15, the mileage of the research model, SON, and CN are 45.9km, 53.29km, and 58.25km, respectively. The total mileage of the research method decreases by 21.51% compared to the SON and CN models, respectively. As the number of suppliers increases, the mileage continues to rise. The total mileage of the research model is 76.51km and 153.01km when the number is 25 and 50, which is on average 8.39% and 12.10% lower than the other two models. Figure 10 (b) shows the average transportation cost and average inventory cost for each model. The average cost of the two research models is 589.83 yuan and 118100.74 yuan, respectively, which are lower than the other models by 23.35% and 29.84%. Comparing the IGA model with the traditional SON and CN, ANOVA tests are used to evaluate the differences in cost-effectiveness between the different models. If the test results are P<0.01, indicating that the IGA model has a statistically significant cost control advantage. The validity of the research method is further confirmed by comparison with baseline models and testing with real-world data sets. The results show that the average cost of IGA model is 169185.35 yuan, while the average cost of SON model and CN model is 198000 yuan and 213000 yuan respectively. The P-value of T-test is 0.005, which is much lower than the significance level of 0.05. By applying the IGA model to a real-world case study of 38 suppliers, the study collects key metrics such as shipping miles, load rates, and total costs over a 15-day period. Compared to the baseline model, the load rate of the IGA model reaches 92.51%, while the baseline model is only 85.67%, and the total cost is reduced by 26.58%. In the actual case test, the IGA model shows good adaptability and cost control effect under the three conditions of stable demand, increasing demand and decreasing demand. Especially in the case of 20% increase in demand, the IGA model successfully controls the cost at 169185.35 yuan, which is 23.25% lower than the baseline model. In summary, the path planning model based on IGA has the best control effect on ILC of automotive components.

5 Discussion

The path planning model based on proposed IGA has been deeply analyzed and optimized for the cost control problem of automotive component inbound logistics. Compared to the research of A Muoz Villamizar et al., the study not only focuses on cost and environmental impacts, but also specifically introduces the constraint of maximum inventory at the line edge, which has not been fully considered in the optimization of fast shipping services. Although MJ Santos et al. proposed a cooperation model between shippers and carriers, their focus is on establishing cooperation mechanisms rather than path planning itself. In contrast, research methods focus on optimizing path planning through IGA to achieve cost control. Darvishi F et al. applied mixed integer nonlinear models in the textile industry, while their research focused on the specific industry of automotive components. They improved GA to solve practical inbound logistics problems, which has higher specificity and practicality in industry applications. The innovation of the research lies in the targeted improvement of GA, which introduces three neighborhood structures that effectively enhance the global search ability and quality of the algorithm. Special consideration is also given to the phenomenon of demand fluctuations in practical applications, and the algorithm is re-coded and designed to better adapt to the uncertainty in actual production. The study provides a new cost control strategy for automotive component manufacturers, which helps companies gain advantages in fierce market competition.

6 Conclusion

A LPP model based on IGA was proposed to address the cost issue of logistics for automotive parts entering the factory. Firstly, the distribution mode was designed, and constraints such as maximum inventory at the line edge were introduced for optimization. GA was used to solve the model. In response to the problem of easily falling into local optima in the initial algorithm, neighborhood structures and other improvements have been introduced. To verify the reliability of the model, experimental analysis was first conducted on IGA. The results showed that the convergence times of the model were 55/75/175 respectively when the number of nodes was 15/25/50. In comparison with the initial algorithm and A* algorithm, the PR curve and ROC curve of the research algorithm were superior to the other two models. Among them, the accuracy and recall corresponding to the equilibrium point increased by an average of 19.31% and 20.19%. The average runtime of the algorithm was 56.94% lower than the other algorithms. The experimental analysis of the overall model was conducted based on demand stability and demand fluctuations. There were 7 paths in all three cases, corresponding to a total frequency mean of 17, 5, and 4 times, respectively. When the demand was stable, the average time taken for each path was 2.27 hours, and the total cost was reduced by 20.34% compared to the simple direct delivery form. After the increase in demand, the total cost decreased by 23.25%. When the demand decreased, the total cost was 136905.20 yuan with a relative decrease of 21.42%. In the comparative experiment between the SON model and the CN model, the total mileage of the designed algorithm decreased by an average of 14% and the total cost decreased by 26.58% under three different node numbers. Therefore, the research method has the best control effect on ILC. However, this study did not take into account the limitation of driver time, and in the future, time window constraints should be added for solving to further enhance the practical applicability of the model.

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