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INTEGRATED OPTIMIZATION OF VEHICLE ROUTING OF AUTOMOTIVE PARTS INBOUND LOGISTICS

Wu, Q.[*,**,***]; Su, J. F.[****]; Xuan, J.[*****,#] & Lei, S.[*]

[*] College of Management Science and Engineering, Chongqing Technology and Business University, Chongqing, China

[**] Chongqing Research Center for Industrialization and Informatization Integration and Logistics Information Technology Application, Chongqing, China

[***] Postdoctoral Research Station of Changzufeiyue (CZFY) Technology Co., Ltd, Chongqing 402360, China

[****] International College, Krirk University, Bangkok 10220, Thailand

[*****] College of Foreign Languages, Chongqing Technology and Business University, Chongqing 400067, China

E-Mail: xuanjing8045@163.com ([#] Corresponding author)

Abstract

This paper makes a systematic analysis of the automotive inbound logistics, and integrates the automotive inbound logistics system and the production system by rationalizing the three main links of the logistics, taking the theory of value chain increment as the guide, and using the idea of station marshalling driving. This paper integrated and optimized three main links of inbound logistics, constructed the optimization mode of automotive inbound logistics driven by station feeding marshalling and its supporting system. In the Work-Station Marshalling-Driven Automotive Inbound Logistics Mode, we construct a mathematical model and design a hybrid genetic algorithm that combines a local search algorithm and a genetic algorithm. And at the end the validity and practicality of this research is demonstrated by real-life examples.

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Key Words: Inbound Logistics, Station Grouping, Hybrid Genetic Algorithm (HGA), Automotive Logistics, Logistics Mode

1. INTRODUCTION

In the automotive industry, parts logistics encompasses the complete supply chain process, from supplier delivery to the final presentation of parts on the Original Equipment Manufacturer (OEM) production line. This process can be classified into three categories: external inbound logistics, which deals with the transportation of parts from the supplier's plant to the OEM's facility; in-house logistics, which manages all activities from goods receipt to assembly.

Chinese Original Equipment Manufacturers (OEMs) in the automotive industry predominantly utilize Third-Party Logistics (TPL), Vendor Management Inventory (VMI), and Milk-run logistics modes to manage the transportation, storage, processing, and distribution of parts until they are delivered to the assembly stations of the OEM production line. However, several issues exist with China's inbound logistics model, including: (1) Inadequate logistics planning and overall plant design. (2) Inconsistent in-plant and out-of-plant logistics.

This paper rationalises the inbound logistics system under the guidance of value chain value-added theory. The author uses the idea of station marshalling to systematically optimize and integrate the inbound logistics system with the production system, and constructs a Work-Station Marshalling-Driven Automotive Inbound Logistics Mode (WSMDM). In this inbound logistics and distribution model, we have developed a mathematical model for the integrated optimization of vehicle paths and storage capacity driven by station marshalling and designed a hybrid genetic algorithm (HGA) combining genetic algorithm (GA) and local search (LS) algorithm to solve the mathematical model.

Our contributions are: (1) A comprehensive and holistic problem formulation with a high level of detail. (2) Methodologically, we construct an effective WSMDM that improves the efficiency of logistics distribution and allows for solving real-world instances. (3) To improve the efficiency of the model solution, we designed the HGA. (4) Numerically, we validated the model at an automotive plant based on a real-world case study.

2. LITERATURE REVIEW

Numerous scholars have extensively researched inbound logistics modes. Tellini et al. [1] and Nemoto et al. [2] have improved the milk-run operation system and its performance, as well as reduced its time and logistics cost, through the logistics mode of milk run based on real cases. Chargui et al. [3] have further studied the PI-hub mode and deemed it as an effective strategy to enhance responsiveness and reduce costs. De Maio and Laganà [4] have optimized inventory and routing simultaneously in the VMI mode to decrease logistics cost. Huang et al. [5] and Borgström et al. [6] have proposed the utilization of modern information technology, such as the Internet of Things, or the development of advanced solutions to enhance the service efficiency of the TPL model. The aforementioned logistics research has tackled different logistics problems through various modes, and yielded significant results.

Milk-run has been extensively studied by scholars in the field of path optimization. They have developed various mathematical models and algorithms to efficiently solve pickup problems under different constraints. For instance, Bocewicz et al. [7, 8] proposed algorithms and models for vehicle path and scheduling, while Ranjbaran et al. [9] developed a mathematical model and heuristic algorithms for optimizing auto-part milk-run logistics network. Mao et al. [10] proposed a new approach by integrating process-lanes (P-LANE) into milk-run routing problem to minimize total production and inbound logistics cost. Although the existing studies provide valuable guidance for milk-run in the automobile industry, they often focus on optimizing individual links and may not guarantee overall optimality. Few studies have approached milk-run from the perspective of the entire incoming logistics system.

Efficient scheduling of inbound logistics is crucial to streamline the goods pickup process. Wang and Chen [11] developed a time-indexed integer linear programming model and a column generation-based algorithm to optimize delivery schedules for capable trucks. Yue et al. [12] focused on workshop scheduling arrangements to ensure line work flexibility.

Many scholars have researched logistics and distribution model studies and solution algorithms by integrating transportation paths with other problems for optimization. Zhou and Zhao [13] developed a multi-objective decomposition evolutionary algorithm (MOEA/D-DFMB) to solve the squeeze material scheduling problem based on a two-level logistics network of a modern hybrid model assembly line. Lv and Sun [14] proposed a unified framework that simultaneously considers the location inventory routing problem (LIRP) in automotive parts supply logistics. Straka et al. [15] improved efficiency of manufacturing logistics by using computer simulation. Pekarcikova et al. [16] conducted simulation testing of the e-kanban to increase the efficiency of logistics processes.

Previous studies have mainly focused on optimizing various aspects of logistics distribution, such as pickup link, vehicle path optimization. However, there has been a lack of research on the overall logistics integration optimization from parts factory to assembly line stations. To address this gap, we proposed a mixed logistics model and used the concept of station grouping to integrate the material inbound, handling and pick-up segments into a single system. Our goal is to achieve optimization of the overall logistics system.

3. INTEGRATED OPTIMIZATION MODEL OF INBOUND LOGISTICS VEHICLE ROUTING AND STORAGE CAPACITY

3.1 Inbound logistics mode design

In guarantee the main characteristic of the research question, highlights the key factors, and not lose the general at the same time, make the following assumptions:

1) The production plan and assembly process remain stable, with the production line following a predetermined production plan and body queue order.

2) As safety inventory is established, uncertainties such as traffic delays, and vehicle breakdowns during the distribution process are not taken into account.

3) The time of vehicle marshalling adjustment in the cycle pickup process is linearly correlated with the pickup batch.

The Work-Station-Marshalling-Driven Automotive Inbound Logistics Mode is shown in Fig. 1.

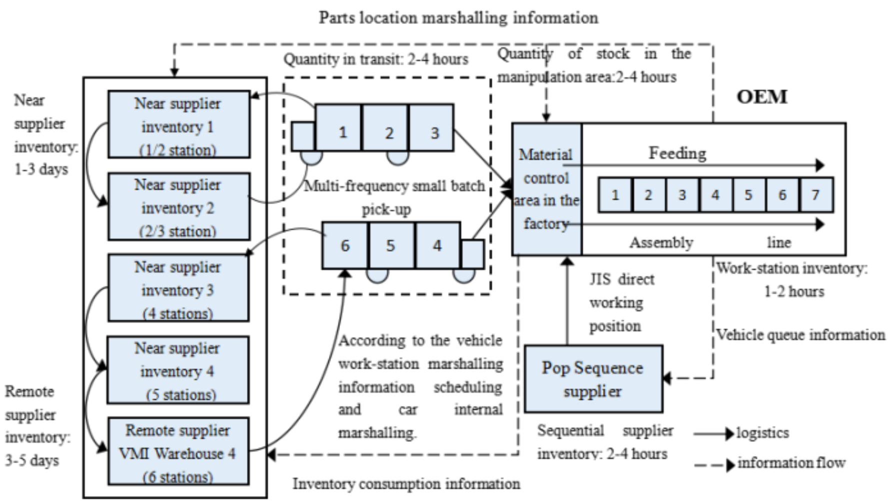

Figure 1: Inbound logistics operation mode based on station marshalling.

3.2 Parameters and variables

Table I: Notions and description.

Set	Description
N_0	Set of material control areas, $N_0 = \{1\}$
Ns	Set of suppliers, $Ns = \{2, 3, ..., n+1\}$
N	Combination of nodes, $N = N_0 \cup N_s$
V	Vehicle type set, $V = \{1, 2, ..., n_v\}$
K	Set of vehicles, $K = \{1, 2, ..., n_k\}$
P	Set of parts, $P = \{1, 2, ..., n_p\}$
M	Set of parts grouping, $M = \{1, 2, ..., n_m\}$
C_m	Part set in part group m, $C_m \in M$
S_i	Parts set supplied, $i \in N_s$ by suppliers, $S_i \in M$
B	Set of pick-up batches, $B = \{1, 2, ..., n_b\}$
A	Parts group covers an area set, $a_m \in A$, $m \in M$
Parameters	
d_{ij}	The distance between node i and node j
u_c	The unit cost of distance coefficient
t_{ij}	Driving time from node i to node j
Q_v	Maximum loading capacity of vehicle type V

Set	Description
q_{im}	The volume of part m supplied at supplier i in a group
f_v	Fixed service cost of model v
μ	Inventory cost per unit of goods per unit of time
τ	Unit batch loading time
h	Unit unloading time of goods in material control area
c_u	Management cost per unit area of material control area
η	The calculation coefficient of the required floor area for the internal arrangement of parts and components
δ_1	The base time of the group adjustment time in the cycle pick-up process
σ_1	The calculated coefficient of the marshalling adjustment time in the cyclic pick-up process
δ_2	The benchmark time of the parts arranging and adjusting time in the material control area
σ_2	Calculation coefficient of grouping adjustment time in material control area of parts
ε	Calculation coefficient of total area of material control area
ω	The waiting cost per unit time of a unit batch of parts when the vehicle arrives at the material control area in advance
n_b	The number of parts and components that have been assembled during the cycle pickup process
T_s	Safety stock maintenance time
b_s	Spare parts quantity of safety stock
T_D	The delivery time of the parts group from the material control area to the line edge
T_H	Time length of a planning cycle
O_{ipm}	Supplier-parts-group mapping relationship
Decision variable	
x_{ijk}	Vehicle k is 1 from node i to node j; otherwise 0
y_{ik}	Supplier i is assigned to vehicle k
z_b	When the pick-up batch is b, it is 1; otherwise 0.
w_v	When the selected model is v, it is 1; otherwise 0.
u_i	When the Process of marshalling, $i \in M$ completes the process of circular pickup, the group is 1; otherwise 0

The relevant variables and parameters in the mathematical model are shown in Table I. In particular, the distance unit is meters (m), the unit of cost and expense is yuan, the unit of time is minutes (min), and the unit of area is square meters (m^2).

3.3 Calculation of main parameters of the model

Because the parts in the same process group may belong to different suppliers, when the access order of multiple suppliers in the same process group is not continuous during milk-run, it is necessary to adjust the position of the assembly to realize the part grouping, and the adjustment time increases with the increase of the access order difference. For any part $p \in P$, $p \in S_i$ and $p \in C_m$, when vehicle K visits supplier I, the marshalling adjustment time at I can be calculated as follows:

$$t_{kip} = \begin{cases} 0, \text{Vehicle } k \text{ accesses belong to } C_m \\ \delta_1(1+\sigma_1)^H, \text{Supplier } i \text{ and parts suppliers belonging to } C_m \text{ is } H \end{cases} \tag{1}$$

As each supplier can only be visited by one vehicle, parts from the same station group may be collected by different vehicles. Consequently, the station code of these parts must be adjusted once all vehicles arrive at the distribution centre. The time required to adjust the unit station grouping is determined by the level of dispersion of the parts, which is based on the number of trucks used to collect the parts from the same station grouping. To calculate the adjustment time for an incomplete process group *M*, use the following formula:

$$t_m = \delta_2(1+\sigma_2)^{k'} \tag{2}$$

where, k' is the number of pickup vehicles for parts in group *M*.

The control area is mainly composed of four parts: the area of the parts of the completed marshalling the staging area, marshalling adjustment area, safety inventory storage area and auxiliary function area (standard small parts area, temporary storage area, channel, personnel office/rest area and equipment storage/charging area). Among of them:

Formula for the area of parts storage area with completed marshalling:

$$A_1 = \sum_{m\in M} u_m a_m z_b b \tag{3}$$

Formula for calculating the area of the marshalling adjustment area:

$$A_2 = (1+\sigma_2)^{k'} \sum_{m\in M} (1-u_m) a_m z_b b \tag{4}$$

Formula for calculating the area of safety stock storage area:

$$A_3 = \sum_{m\in M} u_m a_m z_b b_s \tag{5}$$

Approximate formula for calculating the area of control area:

$$A_{MH} = (A_1 + A_2 + A_3)(1+\varepsilon) \tag{6}$$

Let $t_{max} = \max\{t_{ki0}\}, \forall k \in K$ denote the time of milk-run link. In a planning period, the number of milk-run is:

$$\overline{\lambda} = T_H / t_{max} \tag{7}$$

3.4 Mathematical model

According to the above analysis, the integrated optimization model of inbound logistics vehicle routing and storage capacity based on station grouping can be expressed as follows:

$$\begin{aligned} minF = {} & \overline{\lambda} \sum_{i\in N}\sum_{j\in N}\sum_{k\in K} d_{ij} u_c x_{ijk} + \sum_{v\in V}\sum_{k\in K} f_v w_v x_{1jk} \\ & + \overline{\lambda} \sum_{k\in K}\left(\sum_{l\in N_s} x_{ilk} z_b b \sum_{h\in S_l} q_h \omega (t_{max} - t_{ki0})\right) + c_u A_{MH} \end{aligned} \tag{8}$$

$$\sum_{k\in K} y_{ik} \le 1, \forall i \in N_s \tag{9}$$

$$\sum_{i\in N}\sum_{m\in S_i} y_{ik} q_{im} z_b b \le Q_v, v \in V \tag{10}$$

$$\sum_{i\in N}\sum_{m\in S_i} x_{ijk} q_{im} z_b b - \sum_{i\in N}\sum_{m\in S_i} x_{jik} q_{im} z_b b = \sum_{m\in S_i} z_b b\, q_{im}, \forall i \in N_s, k \in K \tag{11}$$

$$\sum_{i\in N}\sum_{j\in N} x_{ijk} t_{ij} + \sum_{i\in N_s}\sum_{p\in S_i} t_{kip} + \sum_{i\in N}\sum_{m\in S_I} y_{ik} q_{im} z_b bh + \sum_{m=1}^{n_m - n_b} t_m + T_D \le T_S,\ \forall k \in K \tag{12}$$

$$\sum_{i\in N} x_{ijk} = y_{jk}, \forall j \in N_s, k \in K \tag{13}$$

$$\sum_{i \in N} x_{ijk} = y_{ik}, \forall i \in N_s, k \in K \tag{14}$$

$$\sum_{b \in B} Z_b \leq 1 \tag{15}$$

$$\sum_{v \in V} w_v \leq 1 \tag{16}$$

$$x_{ijk} \in \{0, 1\}, \forall i, j \in N, k \in K \tag{17}$$

$$y_{ik} \in \{0, 1\}, \forall i, j \in N_s, k \in K \tag{18}$$

$$z_b \in \{0, 1\}, \forall b \in B \tag{19}$$

$$w_v \in \{0, 1\}, \forall v \in V \tag{20}$$

$$u_i \in \{0, 1\}, \forall i \in M \tag{21}$$

The objective function, represented by Eq. (8), seeks to minimize the total cost incurred by the vehicle routing, fixed service, parts arrival waiting, and management in the control area within the planning period. Eq. (9) stipulates that each customer can only be accessed by a single vehicle, while Eq. (10) imposes a limit on the loading capacity of each vehicle, which cannot exceed the rated volume. Traffic balance in the network is ensured by Eqs. (11) and (12) sets a limit on the total time taken for a trip, including vehicle driving time, marshalling adjustment time at the supplier, parts unloading time in the control area, and delivery time for incomplete marshalling parts to the line edge. Eqs. (13) and (14) express the relationship between two variables, while Eq. (15) specifies the constraint for vehicle pick-up batches. Eq. (16) sets a constraint on the type of vehicle to be used. The variable range is defined by Eqs. (17) to (21).

4. DESIGN OF SOLVING ALGORITHM

The vehicle routing problem is known to be NP-hard, and the integration optimization problem for vehicle routing and storage capacity in inbound logistics, based on work-station marshalling, is further complicated by the need to consider work-station marshalling, vehicle type selection, and pickup batch. As a result, the solution space for this problem is highly complex, and solving the model becomes challenging. To address this issue, we propose a hybrid genetic algorithm (HGA) that combines the superior global search ability of genetic algorithms (GA) with the better local search feature of the local search (LS) mechanism. This approach is designed to effectively solve the problem.

4.1 Principle and process of HGA

To achieve both global and local optimization, the designed hybrid genetic algorithm (HGA) utilizes the population-based genetic operation of the genetic algorithm and educates the newly generated individuals using local search (LS) in the evolution process of the GA. The HGA is thus able to simultaneously consider both global and local search. In addition, we also consider the impact of gene fork and gene mutation probability on genetic evolution behaviour and performance during the evolution process. Following the adaptive mutation and crossover mechanism proposed by Xue et al. [17], we increase the mutation probability and crossover probability when the fitness of different individuals in the population tends towards consistency or local optimization. Conversely, we reduce the mutation probability and crossover probability when the fitness of individuals in the population is dispersed.

4.2 Chromosomal coding design

It is crucial for the heuristic algorithm based on genetic algorithm to code the solution of the problem [18, 19]. The effectiveness of the coding scheme in this step will directly affect the efficiency and complexity of the algorithm. According to the typical characteristics of the problem, a real number code with three layers of chromosome strings was designed to characterize the solution of the problem.

4.3 The population initialization

Because the solution space of the problem is highly complex, generating the initial population purely randomly will affect the overall evolutionary search efficiency of the algorithm. Therefore, in order to make the initial population can better cover the solution space of the problem, so as to better guide the evolutionary search process, a simple and efficient initial population construction algorithm (IPCA) is designed.

4.4 Cross operation design

In this paper, two-point crossover operation based on chromosome gene position is used. Considering the different vehicle types and pickup batches of different individuals, in order to ensure the relative effectiveness of the solution, the crossover operation only acts on the path layer. During the operation, two gene loci were randomly selected, the genes between the two gene loci were exchanged between the two parental individuals to obtain two offspring, and the integrity of the gene was checked and adjusted according to the composition of the gene. The crossover diagram is shown in Fig. 2.

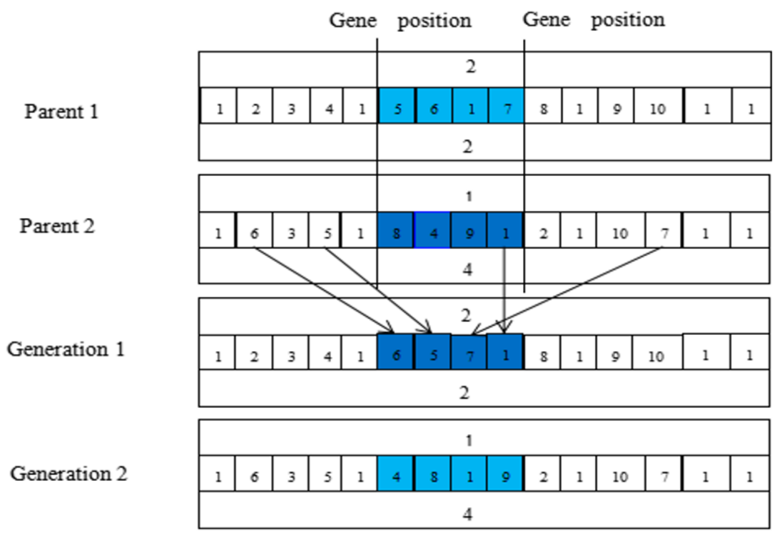

Figure 2: Chart of crossover operation.

The specific crossover operation takes the generation of filial generation 1 as an example: the position of the control region between the two gene loci (the gene loci numbered 1) is kept unchanged. After exchanging the middle fragment, the deletion genes of filial generation 1 are 5, 6, and 7, and the deletion genes are filled in according to the sequence of the positions of genes 5, 6, and 7 in the parent 2. Genetic algorithm realizes crossover operation through crossover rate. The higher the crossover rate is, the better the ability of the algorithm to open new search fields will be enhanced. However, the possibility of excellent genes being destroyed will also increase, so that the search tends to be randomized. Therefore, different crossover rates should be adopted to target individuals with different adaptive values, so as to effectively solve the above problems. Therefore, this paper adjusts the crossover rate of individuals according to the adaptation value and the evolutionary algebra, adopts the adaptive crossover probability, and adjusts it according to the following formula:

$$P_c = \begin{cases} P_{c1} - \frac{(P_{C1}-P_{C2})\left(f^{'}-f_{avg}\right)}{f_{max}-f_{avg}}, f^{'} \geq f_{avg} \\ P_{c1}, \qquad\qquad\qquad\qquad f^{'} < f_{avg} \end{cases} \tag{22}$$

where, P_c is the crossover probability, f_{avg} is the average fitness value of the current population, f_{max} is the maximum fitness value of the current population, $P_{c1} = 0.9$, $P_{c2} = 0.6$ in general.

4.5 Mutation operation design

According to the characteristics of the solution space, three mutation operators are designed respectively for the vehicle type, the vehicle path and the pickup batch.

Vehicle type mutation operator: the vehicle type which is different from the current scheme is randomly selected, and the vehicle routing is adjusted based on the loading capacity of the vehicle type to meet the vehicle loading capacity constraint.

Pickup lot mutation operator: A pickup lot that is different from the current pickup lot is randomly selected, and the vehicle path is adjusted based on the pickup lot to meet the vehicle loading capacity constraint.

Path mutation operator: The mutation operation is used to mutate the chromosome in the path layer selected according to the probability, that is, the inversion of the gene string between two different random positions in the chromosome, as shown in Fig. 3.

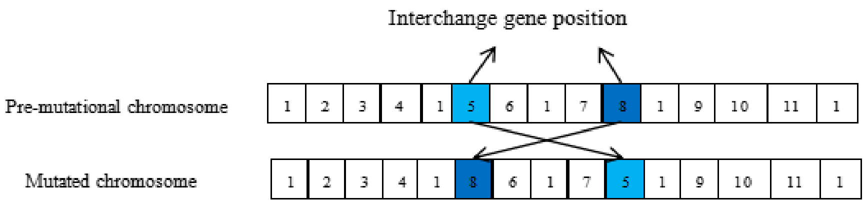

Figure 3: Routing mutation operation.

In the process of evolution, individuals with strong adaptability to the environment should have a smaller mutation probability, and the genes of such excellent individuals should be retained with a greater probability. Individuals with weak environmental adaptability and low adaptive value should have a small probability of retaining inferior genes to the next generation, and the probability of mutation of such individuals is greater than the probability of mutation of excellent genes. In order to achieve this purpose, this paper adopts the adaptive mutation probability to adjust the individual mutation rate according to the adaptation value and evolutionary algebra, and the adaptive mutation rate is adjusted according to the following equation:

$$P_c = \begin{cases} P_{m1} - \frac{(P_{m1}-P_{m2})(f_{max}-f)}{f_{max}-f_{avg}}, f^{'} \geq f_{avg} \\ P_{m1}, \qquad\qquad\qquad\qquad f^{'} < f_{avg} \end{cases} \tag{23}$$

where, P_m is the mutation probability, which is generally taken as $P_{m1} = 0.1$ and $P_{m2} = 0.001$. For any determined probability P_m, the variation probabilities of vehicle type, the vehicle path and the pickup batch are respectively p_{mv}, p_{mr} and p_{mb} ($p_{mv} + p_{mr} + p_{mb} = 1$).

4.6 Adaptability evaluation

Individual fitness evaluation based on objective function and constraint penalty is adopted. The individual evaluation function is calculated as follows:

$$F_{fit} = F_0 + \alpha \sum_{k\in K} max\{0, \sum_{i\in N}\sum_{m\in S_i} y_{ik}q_{im}z_b b - Q_V\} + \beta \sum_{k\in K} max\{0, \sum_{i\in N}\sum_{j\in N} x_{ijk}t_{ij} + \sum_{i\in N_S}\sum_{m\in S_i} t_{kip} + \sum_{i\in N}\sum_{m\in S_i} y_{ik}q_{im}z_b bh + \sum_{m=1}^{n_m-n_b} t_m + T_D - T_S\} \tag{24}$$

where, F_0 is the individual objective and function value, α is the penalty coefficient for the violation of vehicle loading capacity constraint, and β is the penalty coefficient for the violation of vehicle running time.

5. EXAMPLE EXPERIMENT SIMULATION

5.1 Case description

This section focuses on the case study of the final assembly production line of a newly built car bench-marking factory belonging to Company A, as well as the logistics involved in the parts entering this factory. The first phase of Company A's new car factory has an annual design capacity of 360,000, covers four technologies, and aims to produce five models. The final assembly workshop spans 71,200 m^2, with a control area of 30,000 m^2. The usable area, excluding the office and passage areas, is 16,000 m^2, with a total of 280 stations on the main line of the OEM. This includes the first to fourth lines of interior trim, the first to second lines of chassis, and several sub-assembly lines such as the door, instrument panel, power train, and tire lines.

Table II: Process marshalling information.

Motorcycle type	Vehicle type	Effective loading volume (m^3)	Vehicle transport cost (Yuan/trip)	Increase the cost of pick-up point (Yuan/piece)
V0	4.2 m	7.5	170	30
V1	6.8 m	21.5	185	30
V2	7.6 m	24.1	200	30
V3	9.6 m	30.4	245	30
V4	12.5 m	39.6	360	30

H Logistics Company is a logistics joint venture company of an Automobile Company, and is an integrated logistics service provider of an Automobile Company, which has taken over the supply chain logistics business of an Automobile Company. The milk-run service of an Automobile Company is undertaken by H Logistics Company. The models and loading capacity parameters of H Company's circular pickup are shown in Table II. Other parameter values in the model are shown in Table III.

Table III: Parameters value of the model.

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
μ	3.5	η	2	σ_2	1.5	T_S	120
τ	8	δ_1	5	ε	2	T_D	15
h	8	σ_1	1.5	ω	5	T_H	120
C_u	7	δ_2	5	n_b	4	b_s	1

Based on the preliminary test of the algorithm, the algorithm parameters are as follows: $M_0 = 80$, $M = 120$, $p_{im} = 0.35$, $p_{mv} = 0.05$, $p_{mr} = 0.8$, $p_{mb} = 0.15$.

5.2 Results analysis

The optimization scheme obtained by the designed algorithm is shown in Table IV.

Table IV: Results of the instance (Yuan per day).

Car ID	Vehicle lines	Total cost	Vehicle transport cost	Warehouse management cost	Choose vehicle type	Pickup batches	Area of control
1	1-2-1; 1-4-1; 1-18-1	17357.1	13800	3557.1	V2 7.6 meters	2	443.6 m^2
2	1-4-3-5-1; 1-20-19-21-1						
3	1-9-7-6-8-1; 1-15-14-16-1						
4	1-11-13-12-1; 1-17-1						

The optimal results of the model operation are shown in Table V. The optimal picking batch is to pick up two batches of parts at a time, and use the 7.6 m twin wing V2 model to pick up the goods. And 20 suppliers in 9 work-station marshalling are allocated to nine picking routes of four picking vehicles, making the total cost optimal.

The cost and area optimization data before and after optimization are shown in Table V.

Table V: Comparison before and after optimization (Yuan per day).

Contrast pattern	Vehicle type	Transportation cost	Warehouse management cost	Warehouse space	Total cost
Before optimization	9.6	16240	11995.5	1666	28235.5
After optimization	7.6	13800	3557.1	443.6	17357.1
Optimization effect	—	-15 %	-70.3 %	-73.4 %	-38.5 %

Comparing the optimized data and the cost of existing logistics mode and area data, hosts, requires that all suppliers are using 9.6 m of wing truck delivery, optimized, the new logistics mode to use 7.6 m threesome wing pickup truck cycle the total cost of the optimal, the optimal pickup batches for a pickup 2 batches, including transport costs by 15 %, The storage management cost and the area occupied by the material control area in the plant have been significantly optimized, which is reduced by more than 70 % compared with the existing mode. The storage management cost has been reduced by 70.3 %, the storage area demand has been reduced by 73.4 %, and the total cost has been reduced by 38.5 %. The cost optimization effect and area optimization effect are very significant.

Under the optimal picking lot size, different picking models have a great impact on the picking and transportation cost. The 7.6 m model was calculated to be the best match for the size of the picking plots, with the lowest picking and transport costs. Because the picking lot size is the same and different models are used to pick up goods, the area of the material control area required in the factory is the same, and the storage and operating costs for parts in the same lot size are the same, so the total cost of the 7.6 m model is optimal. Under the optimal pickup batch, the optimal pickup model is a 7.6 m twin flying wing truck.

The optimal pickup model of 7.6 m twin flying wing vehicle is adopted to pick up goods. The data pairs of different pickup batches are shown in Table VI.

7.6 m in the optimal models threesome wing van pickup, different pickup volume for different transportation cost, warehouse management cost and waiting cost, can be seen from the model output data operation, when retrieving batch for two batch, the total cost to the optimum, while on the cost of transportation, a single point of batch, the more the less transportation cost.

Table VI: Comparison under different pick up batches (Yuan per day).

Picking batch	Transportation cost	Warehouse management cost	Waiting cost	Warehouse space	Total cost
1	19800	1738.2	2969.2	221.8	24507.4
2	13800	3557.1	2120.9	443.6	19478.0
3	12450	4635.3	2757.1	591.5	19842.4
4	10500	6952.9	3605.5	887.2	21058.4
5	8150	13905.9	3817.6	1774.5	25873.4

6. CONCLUSION

Through the research, we have constructed a work-station marshalling-driven automotive inbound logistics mode, and established a mathematical model for the integrated optimization of vehicle path and storage capacity under workstation grouping drive, which effectively improves the inbound logistics efficiency. Compared with the traditional inbound logistics model, this paper plans and designs the inbound logistics system for new factory parts directly in the planning stage according to the WAMSAILM idea under the ideal optimization scenario of a brand new factory, and solves the key technical problems in the optimization to study the key technical problems in achieving the optimization of inbound logistics. The idea of workstation marshalling drive is adopted to plan and design the pickup link and in-plant handling area link, and the idea of workstation marshalling drive is integrated into the grouping of pickup suppliers and the optimization of the pickup vehicle path, while the material handling area is optimized based on the workstation grouping drive and management optimization. Then, a hybrid genetic algorithm HGA with initial population construction and local search mechanism is designed to solve the model. Finally, the material feeding process, the material handling area in the host plant and the milk-run process are organically integrated into one system, and the overall goal of integrated optimization of "what is picked up and what is needed, and what is ready to be cast" is accomplished.

In future work, we will conduct an in-depth study on the following contents to effectively deal with the vehicle routing problem in the emergency rescue. (1) The application of new technologies such as the Internet of Things, artificial intelligence and big data in inbound logistics. (2) Application and improvement of the inbound logistics model under the booming trend of electric vehicles.

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