OPTIMIZATION OF THE WORKSTATION-DRIVEN INBOUND LOGISTICS MODE FOR AUTOMOBILE PARTS SUPPLY

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ABSTRACT: The optimization of inbound logistics plays a vital role in reducing the logistics cost and improving the logistics efficiency. This paper proposes a new workstation-driven inbound logistics mode to optimize the traditional inbound logistics for automobile parts supply. For the purpose of minimizing inbound logistics costs, an optimization mathematical model is established adopting the proposed new inbound logistics mode. Then, a double-population adaptive genetic algorithm (DPAGA) method is developed to solve the optimization model. Finally, a case study of one automobile manufacturing enterprise is presented to demonstrate the feasibility and validity of the proposed model. This study offers reference model and algorithm for the optimization of the inbound logistics mode for automobile manufacturing enterprises, which will improve their management performance of inbound logistics.

KEYWORDS: workstation-driven, inbound logistics, optimization model, genetic algorithm

1 INTRODUCTION

With the rapid development of economy and increase of car ownership, the automotive industry in China is given more development space and market opportunities, but it also faces more serious challenges(Yu and Lu, 2017). The diversification of the market and automobile products have been raising higher requirements for automobile manufacturing enterprises. In order to adapt to such diversification, automobile manufacturing enterprises must make further plans for automobile logistics. Automobile logistics can be divided into the components inbound logistics, production logistics and vehicle logistics (Hui and Chen, 2011; Tang and Liu, 2015). The inbound logistic activities involve a great number of suppliers and thousands of components and parts, so the management of inbound logistics is very complicated. Therefore, working out an inbound logistics management mode that is suitable for the present situation of the auto industry in China has a great practical significance. On the one hand, selecting the inbound logistics mode is the fundamental guarantee for the efficient and low-cost operation of automobile logistics. The essence of the inbound logistics mode is to integrate and coordinate the internal and external resources of an enterprise. essence of the inbound logistics mode is to integrate and coordinate the internal and external resources of an enterprise. On the other hand, the inbound logistics mode has become the main way to settle the conflicts between key operational areas and node enterprises in the automobile supply chain (Warkentin et al., 2001; Wong et al., 2013).

Regarding the definition of inbound logistics, Michael Porter believes that: inbound logistics is an important activity of material supply between the supplier and the assembler and the important guarantee for enterprises' continuous and stable production and operation. In Porter's value chain model, inbound logistics is one of the five major value-added activities. The components inbound logistics in an automobile manufacturing enterprise mainly uses the milk run and cross-docking of third party logistics. Milk run is a kind operation mode by which the manufacturers can use the same freight vehicles to collect goods from multiple suppliers. At the fixed time every day, from the manufacturing facility or distribution centre, the trucks pick up goods from each supplier and return, along the designed route (Huang et al., 2010; Hosseini et al., 2014). The milk run can most economically achieve the components transportation requirements of Just In Time (JIT), that is, small batch and high frequency. On the other hand, in the cross-docking mode, the third party logistics works with the assembly plant to accomplish the JIT delivery. The third party logistics picks up goods from the upstream suppliers by the milk-run mode, and deliver the components to the warehouse of the assembly plant production line (Wen et al., 2009; Wen and Liu, 2013).
The inbound logistics problem has attracted the wide attention of scholars and practitioners. Fakhrzad and Esfahani, (2014) proposed a cross-docking network model to determine how many trucks should be assigned to each link and how each link should be routed. Ma et al., (2011) studied a new cargo transportation problem in the cross-docking network considering the trade-offs between transportation costs, inventory and time scheduling requirements. Shi and Liu (2013) built a simulation model which integrated the operations of milk run and cross-docking based on practical research data, and proposed an optimization algorithm that uses sequential bifurcation and response surface methodology (SB-RSM) to analyze the theory of the simulation experiments. Through simulation, Kum et al., (2010) examined the decisions in moving freight between inbound and outbound trailers in cross-docking, which involved the direct and indirect handling of pallets, number of open receiving doors, door layout, size of cross dock and freight mix. Apte and Viswanthan (2000) regarded the cross-docking system as one of the most important ways to decrease transportation costs. Boysen and Fliedner (2010) proposed a classification of deterministic truck scheduling at cross-docking terminals. Li et al., (2014) summarized the characteristics of the milk-run mode practiced by a number of Chinese enterprises, and proposed the milk-run supply logistics mode based on 3PL for the complex manufacturing industry. Zhou and Hu (2015) studied a multi-item supply chain composed of a manufacturer and multiple suppliers, consolidated with milk run. Korytkowski and Karkoszka (2016) examined the efficiency, interactions and impacts of a milk-run operator on a typical assembly line, and developed a discrete-event simulation model to evaluate the interactions between the milk-run operator and the workstation assembly line. Hosseini et al., (2014) developed a novel integer programming model for the transportation problem in a consolidated network where a set of vehicles are used to transport goods from suppliers to their corresponding customers via three transportation systems: direct shipment, shipment through cross docking and milk run. Shi et al., (2013) developed a solution framework based on discrete-event simulation and enhanced robust design technology to address a multi-response optimization problem inherent in the logistics management.

To improve the inbound logistics performance and minimize its total transportation cost, this paper proposes a hybrid programming model to study the inbound logistics mode driven by the workstation distribution. As solving this mode is NP-hard an efficient hybrid genetic algorithm (GA) is developed. The rest of the paper is structured as follows. In Section 2, we describe the inbound logistics mode driven by the workstation distribution and define the problem. Then, we present the hybrid programming model in detail in Section 3. Next, we develop a double-population adaptive genetic algorithm (DPAGA) to solve the model in Section 4. In Section 5, we use a real case to show the validity of the proposed model and method. Finally, the conclusions are drawn in Section 6.

2 INBOUND LOGISTICS MODE DRIVEN BY THE WORKSTATION DISTRIBUTION

Facing the intense market competition, assembly plants are undertaking production tasks beyond their planning capacity, and they need to produce a variety of automobiles on multiple platforms at the same time. However, limited by the physical conditions of the factories, the traditional batch distribution logistics model cannot effectively solve the problem, because the traditional logistics mode are based on batch supply and batch delivery, which will lead to huge inventory of parts in the inbound logistics process. In this case, the JIT and zero inventory logistics mode of assembly plants will transfer the risks of inventory and supply to the suppliers, making it difficult to optimize and reduce the parts inventory costs and activity costs in DC warehouses and materials handling areas. Recently, JV and domestic automakers in China have stepped into a price war as products have been more and more homogenized. The whole automobile supply chain endogenously calls for lower prices, and the extent of price reduction is far beyond than the normal optimization and cost saving. Therefore, assembly plants need a new logistics mode to sharply reduce the logistics costs of supply chain. To this end, this paper presents a workstation-centred material distribution mode for general assembly workshops (Figure 1). The workstation-centred distribution mode is an active distribution mode driven by workstation. In this mode, the workstation logistics department and the suppliers (or third party logistics) need to forecast the workstation demands and time according to the production plan and bill of material (BOM) so as to actively deliver the materials on time to the workstation. The mode designs uniform inbound logistics, and systematically solves the delivery and operation problems caused by the inconsistent logistics modes, when a single supplier tries to supply parts for multiple auto models of different assembly plants. This mode may lay a solid
foundation for the stable supply and continuous optimization of logistics costs, and also effectively enhance the service ability of unit production logistics.

In this mode, the logistics service provider reasonably plans the vehicles’ pickup line, volume and time according to assembly plants’ daily rolling plans and locked production queue information, in combination with the information on the marshalling requirement of each station section. It can efficiently deliver the parts variety and quantity requirements of each time zone to the cross-docking centre. The cross-docking centre carries out cross-docking operations quickly according to the marshalling requirements of each section at the same station, and then sorts the parts by variety and quantity. Through the feeding and distribution information system, it can achieve refined feeding and distribution management, and make vehicles deliver the exact varieties and quantities of parts to the corresponding feed ports of assembly plants at the right time. This mode can control the inbound logistics inventory to a minimum. The line location, the material control area and the cross-docking centre can all hold inventory for 2-4 hours; the short-range suppliers hold 0.5-1 day’s inventory, and the remote suppliers hold 3 days’ inventory in VMI warehouses. Thus, the whole inventory level of inbound logistics is greatly reduced, and the inventory holding costs, space costs and operating costs are also reduced.

Compared with the traditional inbound logistics mode, the workstation-driven mode has the following advantages. First, in the traditional mode, the picking section only picks up the materials, and marshalling is completed in the warehouse. Now, in the workstation-driven mode, the parts are picked up and marshalling is performed according to the workstation demands in the picking section. This new mode can change the moving vehicles into mobile warehouses with real-time inventory information, which can further reduce the inventory of inbound logistics. Second, the new mode can reconstruct the DC warehouse inside the original factory. The functions of the material handling zone in the factory are changing from “large-scale delivery and secondary sorting” to “distribution according to the workstation section demands and fast-in and fast-out inventory”. It can make the material requirements of the workstation sections on the production line match the pre-marshalling of workstation sections in the control zone, which effectively improves the feeding efficiency. Third, the new mode selects a warehouse at a suitable location around the cluster area of assembly plants as the cross-docking warehouse, which will be responsible for carrying out the milk run and sorting materials into new groups with station location information according to the needs of assembly plants. Then, the parts will be delivered by vehicles to each assembly plant to achieve distribution at the fixed-point and with the fixed quantity and fixed-marshalling. This can improve the unloading and feeding efficiency.

3 WORKSTATION-DRIVEN INBOUND LOGISTICS OPTIMIZATION MODEL

This section constructs the optimization model for inbound logistics of auto parts from the
3.1 Problem description

Suppose there are \(k\) transportation vehicles between \(N\) suppliers and the cross dock, and the milk run mode is used to deliver materials. There are \(k'\) transportation tools between the cross dock and the OEMs, and there are \(n\) workstations and \(m\) groups of workstations. The transportation tools deliver materials according to the order and demand of workstations. It is required to reasonably arrange the distribution paths under the given time constraints and inventory constraints so that the total distribution cost is minimized. This model is intended to achieve the minimum total delivery cost, which is composed of three parts: the milk run picking cost, the cross-docking cost and the delivery cost between the cross dock and each assembly plant.

3.2 Notations

In this paper, the notations used for the problem are listed below:

- \(N\): number of suppliers
- \(V\): the set of suppliers
- \(K\): the set of vehicles
- \(k\): number of transportation vehicles between suppliers and the cross-docking
- \(d_{ij}\): the distance between supplier \(i\) and \(j\)
- \(\alpha\): unit cost of transportation between suppliers and the cross-docking
- \(f_k\): fixed cost of inbound vehicle \(k\)
- \(x_{ijk}\): 1, if vehicle \(k\) go through between supplier \(i\) and \(j\); 0, otherwise
- \(\beta\): unit inventory costs of suppliers
- \(\rho_k\): the unit pickup volume of vehicle \(k\) from supplier \(i\)
- \(y_{ik}\): 1, if vehicle \(k\) is assigned to supplier \(i\); 0, otherwise
- \(\sigma\): unit cost of cross-docking
- \(\gamma_{ijk}\): 1, if cross-docking between workstation \(i'\) and \(j\); 0, otherwise
- \(V'\): the set of workstations
- \(K'\): the set of transportation tools between the cross-docking and the main engine plants
- \(k'\): number of transportation tools between the cross-docking and the main engine plants
- \(\alpha'\): unit cost of transportation between suppliers and the cross-docking
- \(f_{k'}\): fixed cost of transportation tool \(k'\)
- \(x_{ijk'}\): 1, if transportation tool \(k'\) go through between workstation \(i'\) and \(j'\); 0, otherwise
- \(\beta'\): unit inventory costs of material supermarket

\(\rho_{k':}\) the unit pickup volume of transportation tool \(k'\) to workstation \(i'\)

\(y_{ij'}: 1,\) if transportation tool \(k'\) is assigned to workstation \(i'\); 0, otherwise

\(Q_k: \) the volume limit of vehicle \(k\)

\(s: \) the highest level of inventory of supplier

\(Q'_k: \) the volume limit of transportation tool \(k'\)

\(S': \) the highest level of inventory of material supermarket

\(\omega_{ij'}: \) the match relationship between workstation \(i'\) and material supermarket \(m\)

\(M: \) the set of material supermarkets

3.3 Optimization model

\[
\begin{align*}
\min z_1 &= \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \alpha f_k d_{ij} x_{ijk} + \sum_{i \in V} \sum_{j \in V} \beta \rho_k y_{ik} \\
\min z_2 &= \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \sigma f_{k'} y_{ij'k'} \\
\min z_3 &= \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \sum_{k' \in K} \alpha' f_{k'} x_{ijk'} + \sum_{i \in V} \sum_{j \in V} \beta' \rho_{k'} y_{ik'} \\
\text{s.t.} & \quad \sum_{i \in V} x_{ijk} - \sum_{j \in V} x_{ijk} = 0 \quad (1) \\
& \quad \sum_{i \in V} \sum_{j \in V} x_{ijk} \geq 1 \quad (2) \\
& \quad \sum_{i \in V} x_{ijk} = \sum_{i \in V} x_{ijk} = 1 \quad (3) \\
& \quad \sum_{i \in V} x_{ijk} = y_{jk} \quad (4) \\
& \quad \sum_{i \in V} x_{ijk} = y_{ik} \quad (5) \\
& \quad \sum_{i \in V} y_{ik} = 1 \quad (6) \\
& \quad \sum_{i \in V} \sum_{j \in V} x_{ijk} \leq Q_k \quad (7) \\
& \quad \sum_{i \in V} \sum_{j \in V} x_{ijk} \leq S \quad (8) \\
& \quad \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} x_{ijk} \geq 1 \quad (9) \\
& \quad \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} x_{ijk} = 1 \quad (10) \\
& \quad \sum_{i \in V} x_{ijk'} = \sum_{j \in V} x_{ijk'} \quad (11) \\
& \quad \sum_{i \in V} x_{ijk'} = y_{jk'} \quad (12) \\
& \quad \sum_{i \in V} x_{ijk'} = y_{ik'} \quad (13) \\
& \quad \sum_{i \in V} y_{ik'} = 1 \quad (14) \\
& \quad \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \rho_{k'} y_{ik'} \leq Q'_k \quad (15) \\
& \quad \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} \rho_{k'} y_{ik'} \leq S' \quad (16)
\end{align*}
\]
\[
\sum_{m \in M} \varepsilon_{im} = 1 \quad (17)
\]
\[
\sum_{k \in K} \delta_{mk} = 1 \quad (18)
\]
\[
\sum_{m \in M} \mu_{mk} = \delta_{mk} \quad (19)
\]
\[
\sum_{m \in M} f_k \cdot \varepsilon_{im} \leq V_i \quad (20)
\]

In this model, the objective 1 represents the minimum of milk run delivery cost between suppliers and cross-docking, the objective 2 represents the minimum of cross-docking operation cost, and the objective 3 represents the minimum of the delivery cost between cross-docking and each assembly plants by milk run. Formula (1) ensures that the number of suppliers going out i is equal to the number of suppliers i coming in; Formula (2) guarantees that each supplier is traversed; Formula (3) ensures that the transport vehicle departs from the origin and eventually returns to it; Formulas (4)-(6) ensure that supplier i chooses the unique path k; Formula (7) ensures that the total load on path k does not exceed the load limit of the vehicle; Formula (9) ensures that the sum of the materials picked by all suppliers does not exceed a certain value; Formulas (10)-(16) are the constraints on the circulation of materials between the cross dock and assembly plants, with no details given here; Formula (17) guarantees that one workstation group corresponds to one material supermarket; Formula (18) guarantees that one workstation group is delivered to by one tool; Formula (19) ensures that every workstation is serviced and only supplied to by a material supermarket; and Formula (20) ensures that the storage space required by all workstations does not exceed the volume limit of the material supermarkets.

4 PROPOSED GENETIC ALGORITHM

The optimization model for inbound logistics driven by workstation distribution is a typical Vehicle Routing Problem (VRP) problem, which has been proved to be NP-Hard (Alipour and Alipour 2012). With the traditional optimization methods, such as the min-max boundary method, weighted sum method and \( \varepsilon \)-constraint method, etc., it is difficult to obtain the optimal solution to the NP-hard problem quickly and efficiently (Su et al., 2015). For NP-hard problems, the genetic algorithm is a common solution (Sen et al., 2017; Su et al., 2017). However, traditional genetic algorithms have problems such as the proneness to being trapped into local optima, poor local search ability and premature convergence. Therefore, in the actual application, some improvements have been made to the standard genetic algorithm. The two-population genetic algorithm and adaptive genetic algorithm are the two main improved algorithms (Liang and Leung, 2011). The former selects two different populations to evolve at the same time. Excellent individuals in different populations exchange genetic information with each other to reach a higher equilibrium state, thereby increasing the probability of skipping the local optimum. The adaptive genetic algorithm adapts itself to individual fitness. It adjusts the individual’s crossover and mutation probabilities so as to improve the slow convergence rate and poor local search ability caused by the constant crossover and mutation probability in the traditional genetic algorithm. This paper combines the two algorithms and proposes a double-population adaptive genetic algorithm (DPAGA) to solve the model. The specific steps of the algorithm are as follows.

4.1 Chromosome encoding

The genetic algorithm abstracts an object through a certain encoding mechanism into a string which is arranged in a certain order by specific symbols. In this paper, due to the constraints on the start time of the workstation group, the first process starts and the materials are prioritized. After the corresponding relationship between the vehicle distribution and the workstation group-supermarket is determined, the parts are sequentially distributed by the workstation group. Based on this, the genetic algorithm in this paper uses the two-dimensional integer coding. According to this coding rule, multiple feasible chromosomes are randomly generated, forming two initial populations.

4.2 Fitness function

The fitness function is the basis for evaluating the pros and cons of the solution set in the genetic algorithm. Individuals with high fitting values are trained preferentially. In this paper, for a chromosome group with a population of \( N \), the smaller the fitness value of the individual chromosome \( i \), the higher the individual fitness. For the proposed model, we construct the fitness function as:

\[
F = \phi \left( \sum_{i=1}^{N} \sum_{j=1}^{K} \sum_{x \in K} \alpha f_{ix} \cdot d_{ix} + \sum_{i=1}^{N} \sum_{j=1}^{K} \beta \rho_{ix} \cdot y_{ix} \right) + \varphi \sum_{i=1}^{N} \sum_{j=1}^{K} \omega y_{ij}
\]

\[
+ \theta \left( \sum_{i=1}^{N} \sum_{j=1}^{K} \sum_{x \in K} \alpha' f_{ix} \cdot x_{ix} + \sum_{i=1}^{N} \sum_{j=1}^{K} \beta' \rho_{ix} \cdot y_{ix} \right)
\]

Where \( \phi , \varphi \) and \( \theta \) are the relative importance factors of the three objectives, respectively, and \( \phi + \varphi + \theta = 1 \).
4.3 Selection operation

The algorithm uses the roulette method as the selection strategy. Firstly, the fitness value of each individual is obtained according to the fitness function, and then the roulette method is used to select the two populations. The probability that each generation of individuals will be selected into the next generation is determined according to their degree of fitness. Set $\psi_i$ as the probability of the individual $i$ being the next generation.

$$\psi_i = \frac{F(i)}{\sum_{i=1}^{n} F(i)}$$

4.4 Adaptive crossover and mutation operations

In the DPAGA algorithm, the two populations evolve independently. Different populations use different crossover and mutation operations, and communicate with each other at the right time by certain rules. The independent evolution, crossover, and mutation operations of the two populations ensure the diversity of the populations, and the exchange of excellent individuals among the populations ensures the rate of convergence to feasible solutions. To construct populations in the DPAGA algorithm, this paper mainly refers to the method proposed in the literature (Wang and Xie, 2017). Let population 1 be a probe population for local search, and new hyper-planes are provided during evolution to avoid premature convergence. Let population 2 be a developing subpopulation that is used to search for excellent individuals in a local range and retain them. For the crossover and mutation of the two populations, two-point crossing and two-point mutation operations are respectively adopted. The two-point crossing operation is to randomly select two individuals as the crossover objects from the population after the selection operation, and randomly generate two crossover points. Then, the genes at the two crossover points are exchanged, while the rest of the gene values remain unchanged. Under a two-point mutation operation, for an individual, two gene sites with different gene values are randomly generated, and then the gene values of the two sites are exchanged with their alleles.

In light of the problems that the fixed crossover and mutation probabilities may lead to premature convergence and local optimum, this paper adopts the adaptive selection method to optimize the crossover and mutation probabilities of the two populations. When the two chromosomes perform crossover operations, their fitness values are compared. When the larger fitness value is less than or equal to the average fitness value of the population, the crossover probability increases adaptively; otherwise, it decreases adaptively. On the other hand, when the fitness value of the chromosome performing the mutation operation is less than or equal to the population average fitness value, the mutation probability increases adaptively; otherwise, it decreases adaptively. In this way, the individuals in each generation have different crossover and mutation probabilities, and achieve adaptive crossover and mutation. The adaptive crossover probability and mutation probability are:

$$P_c = \begin{cases} 
\frac{f_{\text{max}} - f}{f_{\text{max}} - f_{\text{min}}} (p_{c_{\text{max}}} - p_{c_{\text{min}}}), & f > \bar{f} \\
\frac{f_{\text{max}} - f_{\text{min}}}{f_{\text{max}} - f_{\text{min}}} (p_{c_{\text{max}}} - p_{c_{\text{min}}}), & f \leq \bar{f} 
\end{cases}$$

$$P_m = \begin{cases} 
\frac{f_{\text{max}} - f'}{f_{\text{max}} - f_{\text{min}}} (p_{m_{\text{max}}} - p_{m_{\text{min}}}), & f' > \bar{f} \\
\frac{f_{\text{max}} - f_{\text{min}}}{f_{\text{max}} - f_{\text{min}}} (p_{m_{\text{max}}} - p_{m_{\text{min}}}), & f' \leq \bar{f} 
\end{cases}$$

Where, $P_c$ and $P_m$ are the crossover and mutation probabilities, respectively. $p_{c_{\text{max}}}$ and $p_{c_{\text{min}}}$ are the maximum and minimum crossover probabilities, respectively. $p_{m_{\text{max}}}$ and $p_{m_{\text{min}}}$ are the maximum and minimum mutation probabilities, respectively. $f_{\text{max}}$, $f_{\text{min}}$ and $\bar{f}$ are respectively the maximum, minimum and average fitness value of the population. $f$ is the higher fitness value of the two crossover individuals. $f'$ is the fitness value of the mutated individual.

4.5 Migration operation

After the two populations are selected, crossed, and mutated to produce a new next-generation population, a random number $\text{num}$ is generated, and the optimal solutions in the two populations are obtained, respectively. Then, they are crossed over with $\text{num}$ chromosomes and enter each other’s population and achieve inter-population exchange of genetic information among excellent individuals, by breaking the balance within the population and avoiding local optimal solutions.

5 CASE STUDY

In order to verify the practicability of the optimization model proposed in this paper, it is applied to solve the actual logistics problems of automobile company $C$. Take the power component assembly line in a car assembly workshop for example. There are 60 work stations in the workshop, 5 material supermarkets and 8 suppliers, and the 60 workstations are divided into 6 groups.
according to production requirements. The survey data necessary for the case are shown in Table 1. The method proposed in this paper is applied to solve the inbound logistics optimization problem in this case. Let the initial population of the genetic algorithm be 200 and the maximum number of genetic iterations be 100. For the fitness function, there are $\phi=0.5$, $\varphi=0.2$ and $\theta=0.3$. The calculation results of the DPAGA algorithm are shown in Figure 1 and Table 2-3.

<table>
<thead>
<tr>
<th>Route</th>
<th>Distance</th>
<th>Frequency</th>
<th>Total Distance</th>
<th>Loading rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-2-1-0</td>
<td>95.55</td>
<td>2</td>
<td>191.1</td>
<td>79%</td>
</tr>
<tr>
<td>0-7-3-0</td>
<td>86.85</td>
<td>2</td>
<td>173.8</td>
<td>96%</td>
</tr>
<tr>
<td>0-6-8-5-0</td>
<td>166.54</td>
<td>1</td>
<td>164.54</td>
<td>91%</td>
</tr>
<tr>
<td>0-2-4-0</td>
<td>60.53</td>
<td>2</td>
<td>121.06</td>
<td>92%</td>
</tr>
<tr>
<td>0-5-3-0</td>
<td>93.42</td>
<td>10</td>
<td>280.26</td>
<td>87%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td><strong>12</strong></td>
<td><strong>930.76</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Route</th>
<th>Distance</th>
<th>Frequency</th>
<th>Total Distance</th>
<th>Loading rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-4-5-7-0</td>
<td>97.72</td>
<td>2</td>
<td>195.44</td>
<td>71%</td>
</tr>
<tr>
<td>0-5-2-1-0</td>
<td>101.04</td>
<td>1</td>
<td>101.04</td>
<td>73%</td>
</tr>
<tr>
<td>0-4-6-0</td>
<td>123.31</td>
<td>2</td>
<td>246.62</td>
<td>80%</td>
</tr>
<tr>
<td>0-3-7-8-0</td>
<td>189.77</td>
<td>1</td>
<td>189.77</td>
<td>79%</td>
</tr>
<tr>
<td>0-6-0</td>
<td>39.84</td>
<td>4</td>
<td>159.36</td>
<td>81%</td>
</tr>
<tr>
<td>0-2-6-0</td>
<td>124.41</td>
<td>2</td>
<td>248.82</td>
<td>83%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td><strong>12</strong></td>
<td><strong>1141.05</strong></td>
</tr>
</tbody>
</table>

Table 3. Comparison between DPAGA Algorithm Results and Manual Schedule Results – workstation

<table>
<thead>
<tr>
<th>Route</th>
<th>Distance</th>
<th>Frequency</th>
<th>Total Distance</th>
<th>Loading rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>PAGA 0-1-3-4-6-0</td>
<td>5</td>
<td>2</td>
<td>10</td>
<td>95%</td>
</tr>
<tr>
<td>Algorithm 0-2-4-5-0</td>
<td>4</td>
<td>3</td>
<td>12</td>
<td>93%</td>
</tr>
<tr>
<td>Calculation 0-6-3-2-0</td>
<td>4</td>
<td>2</td>
<td>8</td>
<td>97%</td>
</tr>
<tr>
<td>Results 0-1-5-0</td>
<td>3</td>
<td>4</td>
<td>12</td>
<td>94%</td>
</tr>
</tbody>
</table>
As seen in the distance of each path and its operating frequency in the Table 2, the total distance of the Manual Schedule Routes is 1141.05, while the total distance of the DPAGA Algorithm Schedule Routes is 781.38. The DPAGA Algorithm saves 18.4% distance than the Manual Schedule method, and the transportation frequency saves 4 times. Meanwhile, the loading rate of vehicles also get a significant improvement. This shows that the DPAGA algorithm's calculation result is much better than the Manual Schedule results.

As seen in the table 3, we can get that the the DPAGA algorithm can get the much better route than the Manual Schedule method. Based on the above results and discussions, we can finally achieve the conclusion that the proposed workstation-driven inbound logistics mode and the DPAGA algorithm can deliver the materials to the workstations to improve the delivery accuracy. Using this new inbound logistics mode and algorithm, the automobile manufacturing company's logistics department more reasonably arrange the quantity of material storage and delivery route, effectively reducing the inbound logistics cost.

6 CONCLUSIONS

In this paper, we have proposed a new workstation-driven inbound logistics mode. The proposed logistics mode is a workstation-oriented and active delivery mode, which is different from the other existing logistics modes. The workstation-driven inbound logistics mode is suitable for the material distribution in manufacturing assembly workshops with small batches, multiple batches, and high material turnover rates, and it is particularly suitable for the parts distribution in automobile assembly shops. An optimization model is presented to minimize the delivery cost and cross-docking cost. To solve this NP-hard problem efficiently, a DPAGA algorithm is then proposed. Finally, a case study is conducted to test the performance of the developed algorithm, which is shown that the DPAGA algorithm is much more effective than the Manual Schedule method. In this logistics mode, the supply chain optimization based on direct delivery, the storage area allocation of the storage area distribution method, and the development of the material distribution information system will be one direction of the future research.

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8 REFERENCES

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