Optimization of the Milk-run route for inbound logistics of auto parts under low-carbon economy

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Abstract
Greenhouse gas emissions have brought serious negative impacts on human beings and organisms, so energy saving and emission reduction have been recognized by more and more people. Traditional Milk-run model seldom considers the factors of energy saving and emission reduction, and its routing optimization cannot meet the current needs of low-carbon economic development. On the basis of traditional Vehicle Routing Problem research, considering the fixed cost, time penalty cost, energy consumption cost and carbon emission cost of vehicles, the Milk-run model of distribution routing considering carbon emissions under time window constraints is studied. Then the improved ant colony algorithm is used to solve the constructed model. Finally, the order and related data of a company are used to verify the validity and practicality of the model and algorithm. Compared to the scanning method, the results show that not only the total journey distance has been shortened but also the total cost and cost of carbon emissions have been reduced. The optimization of distribution routing considering carbon emissions can reduce the distribution cost of logistics enterprises, respond to the call of low-carbon development in China and help to achieve a win-win situation of social and economic benefits.

Keywords
Ant colony algorithm, carbon emissions, Milk-run, vehicle routing problem (VRP)

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Introduction
In recent years, the competition among automobile manufacturers has been becoming more and more fierce in China. In order to reduce the cost and improve the competitiveness, an increasing number of automobile manufacturing enterprises put ‘lean production’ into practice. Simultaneously, they also benefit from an efficient logistics system as ‘third profit source’. According to statistics, the inbound logistics accounts for 70% of the total logistics costs of automotive enterprises, and reasonable vehicle path planning is the key to the operation management on inbound logistics. The transportation route optimized by Milk-run mode can effectively reduce the transportation cost. However, traditional logistics and distribution pay more attention to economic costs, ignoring the carbon emissions of vehicles, and the concept is inconsistent with low-carbon development. Therefore, the exploration of the optimization of logistics and distribution routes based on the low-carbon concept has a strong practical significance.

The Milk-run problem is a kind of vehicle routing problem (VRP). Scholars have conducted extensive research on it from different perspectives since the first proposition of this issue was put by Dantzig and Rams in 1959.\textsuperscript{1} These scholars are Gutierrez et al.,\textsuperscript{2} Errico et al.,\textsuperscript{3} Xuping et al.,\textsuperscript{4} Yaming et al.,\textsuperscript{5} Sacramento et al.,\textsuperscript{6} Belgin et al.,\textsuperscript{7} Fink et al.,\textsuperscript{8} Li et al.,\textsuperscript{9} Xue et al.,\textsuperscript{10} Timo,\textsuperscript{11} Wang et al.,\textsuperscript{12} Hoogeboom et al.,\textsuperscript{13} Rostami et al.,\textsuperscript{14} Uit het Broek et al.,\textsuperscript{15} Hoogeboom et al.,\textsuperscript{13} Dumez et al.,\textsuperscript{16} Zhang et al.,\textsuperscript{17} Pessoa et al.,\textsuperscript{18} and so on. However, most of

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these studies consider how to reduce the total cost of distribution from the view of economy. With the national attention to ecological civilization construction, energy conservation and emission reduction, some scholars consider low-carbon factors (Li et al., Wang et al., Liu et al., Balamurugan et al., Yu et al., Guo et al., Chen et al., Wang et al., Zhang et al., Wu et al., Abdollahi et al., Qiu et al., Abdi et al., Alkaabneh et al., Andelmin and Bartolini, Norouzi et al., Ashlineh and Pishvaea, Basso et al., Niu et al., Bravo et al., Bruglieri et al., etc.). Guo et al. built the distribution route optimization model for fresh food e-commerce and verified the effectiveness of the model by using genetic algorithm (GA) and particle swarm optimization algorithm (PSO). Chen et al. proposed the multi-compartment vehicle routing problem with time window arising in fresh food e-commerce by considering carbon emission. Wang et al. established the model of low-carbon cold chain logistics route optimization, and the change of distribution path under different carbon taxes and its influence on total distribution cost was discussed. Wu et al. constructed the green vehicle route model with the goal of minimum travel distance and carbon emissions. The multiobjective evolutionary algorithm was used to solve this problem, and a set of Pareto’s optimal solutions was obtained. Qiu et al. constructed the model of distribution route pollution under carbon emission, and the model was proved to be effective in reducing carbon emissions and distribution costs of logistics enterprises. Norouzi et al. constructed a path optimization model with the shortest path and minimum total carbon emission cost by considering the road condition, air resistance and vehicle load, and an improved PSO algorithm was designed. For minimizing the total cost of distribution, Wang et al. established an optimal model and algorithm of cold and multi-temperature co-assignment under random demand. Unlike the above study which did not consider customer delivery time factors, Niu et al. established a mathematical model of the green open vehicle route problem with a time window on the basis of the integrated model emission model, and a mixed taboo search algorithm was designed to solve it. Compared with the closed vehicle path problem, the total cost of opening vehicle path problem would be reduced. Ge et al. established a multi-vehicle path model with a time window considering carbon emission factors and designed a hybrid GA. There are also some scholars who have studied the Milk-run problem (Mao et al., Xiong et al., Wu et al., Ranjbaran et al., Ranjbaran et al., Wang et al., Wang et al., Baran, Güner et al., Bocewicz et al.). Mao et al. proposed a new logistics method for VRP by embedding the progress-lane into it. Xiong et al. constructed a mixed Milk-run logistics model involved second-level suppliers. Wu et al. studied the multi-factory Milk-run problem under uncertain demand by taking the actual situation of China’s automobile industry into account. By taking account of delivery time windows and returning empty pallets from assembly-plants backwards to suppliers, Ranjbaran et al. constructed a mathematical model to minimize total transportation costs. Bocewicz et al. presented a solution to a milk-run vehicle routing and scheduling problem subject to fuzzy pick-up and delivery transportation time constraints.

To sum up, though a lot of progress has been made in VRP, it is rare to be considered about the customer’s time window requirements based on the low-carbon background. Some scholars have studied the problem of path optimization in a low-carbon economy, but the fuel consumption model is too simple and idealistic (Wang, 2018) or too complex (Niu, 2018; Li, 2019) to implement easily. On the basis of the above scholar’s fuel consumption calculation model, this paper designs a fuel consumption function with vehicle load as an independent variable and builds a corresponding path optimization model by considering about the carbon emission cost and customer’s time window requirements. Ant colony algorithm is widely used in combinatorial optimization problems such as traveling salesman and vehicle routing optimization because of its positive feedback mechanism, parallel search and distributed computing. Traditional ant colony algorithm has some problems such as easy convergence to local optimal solution and slow convergence speed. So, an improved ant colony algorithm is proposed for the improvement of the global search capability of the algorithm, which takes the total cost of distribution into account in the transfer probability. The validity of the model is also verified by testing for a case study.

**Basic assumptions and symbol descriptions**

**Basic assumptions**

Based on the background of the problem and the objective of the study, the following assumptions are made:
1. A distribution centre takes goods from multiple suppliers and the site of the distribution centre and the supplier is determined.
2. The vehicle departing from the distribution centre will return to the starting point after delivery. The delivery mode is as shown in Figure 1.
3. The delivery quantity for each supplier is fixed and will not exceed the vehicle’s capacity.
4. The operation cost of each vehicle consists of fixed cost and variable cost. The fixed cost is known, and the variable transportation cost is a linear function of driving distance.
5. The goods for each supplier are distributed by the same vehicle and they are not split into several deliveries.
6. If the delivery time doesn’t meet the customer’s requirements on time window, the carrier will be punished.
7. The vehicle runs at a uniform speed.

**Parameters and variables**

The parameters and variables used in the model are described as follows:

1. \( N \) — Node set of distribution network, \( N = \{ i | i = 0, 1, 2, \ldots, n \} \), where \( i = 0 \) represents the distribution centre, \( i = 1, 2, \ldots, n \) represents the pick-up point (supplier).
2. \( U \) — The set of truck, \( U = \{ u | u = 1, 2, \ldots, p \} \), \( p \) is the total number of vehicles.
3. \( q_i \) — Delivery from supplier \( i \).
4. \( AT_i \) — The truck’s arrival time to supplier \( i \).
5. \( d_{ij} \) — The distance between supplier \( i \) and \( j \).
6. \( T_j \) — The time from supplier \( j \) to supplier \( i \).
7. \( Q_u \) — The load of the vehicle \( u \).
8. \( Q \) — The maximum load of the vehicle.
9. \( ET_i \) — The earliest pickup time allowed by supplier \( i \).
10. \( LT_i \) — The latest pick up time allowed by supplier \( i \).
11. \( c_i \) — Fixed cost of the truck \( u \).
12. \( c_1 \) — Penalty cost of per unit time when the truck arrives earlier than supplier’s agreed time.
13. \( c_2 \) — Penalty cost of per unit time when the truck arrives later than supplier’s agreed time.
14. \( c_3 \) — The fuel consumption cost per unit load.
15. \( c_4 \) — The carbon emissions cost per unit load.
16. \( \rho(Q_u) \) — The linear function of \( Q_u \) for fuel consumption, \( \rho(Q_u) = \rho_0 + (\rho^* - \rho_0) \cdot \frac{Q_u}{Q} \).
17. \( \rho^* \) — The fuel consumption per kilometer, \( L/km \).
18. \( \rho_0 \) — The fuel consumption per kilometer when trucks run in no-load case, \( L/km \).
19. \( f_i \) — The fuel density, \( t/L \).
20. \( f_2 \) — The carbon dioxide emissions factor, \( t/L \).
21. \( TT_i \) — Unloading time at supplier \( i \).
22. \( T_0 \) — The vehicle’s starting time from distribution centre.

23. \( z \) — The total distribution cost.

**Model formulation and ant colony algorithm solution**

In this part, we first build a path optimization model considering carbon emissions and time window constraints and then propose an ant colony algorithm program.

**Model formulation**

1. The fixed cost of vehicle

\[
C_k = \sum_{u=1}^{p} c_u \tag{1}
\]

2. The time penalty cost

\[
C_f = c_1^1 \sum_{i=1}^{n} \max \{ [ET_i - AT_i], 0 \}
+ c_2^1 \sum_{i=1}^{n} \max \{ [AT_i - LT_i + TT_i], 0 \} \tag{2}
\]

3. The fuel consumption cost

\[
C_n = \sum_{u=1}^{p} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{iju} \left[ c_3 (d_{ij}^2 \rho(Q_u)^* f_i) \right] \tag{3}
\]

4. The carbon emissions cost

\[
C_p = \sum_{u=1}^{p} \sum_{i=0}^{n} \sum_{j=0}^{n} x_{iju} \left[ c_4 (d_{ij}^2 \rho(Q_u)^* f_i) \right] \tag{4}
\]

5. The total distribution cost

\[
\min z = C_k + C_f + C_n + C_p \tag{5}
\]
Formula (5) is the objective function, indicating that the total distribution cost is minimized; Formula (1) is the fixed cost of the vehicle, including the vehicle’s abrasion and the salary for the driver. Formula (2) is the time penalty cost when the delivery vehicle does not meet the time window requirements. Formula (3) is the fuel consumption cost related to the vehicle’s driving distance and the carrying load. Formula (4) is the carbon emissions cost related to fuel consumption and travel distance by the vehicle.

The meaning of each constraint is as follows:

Formula (6) indicates that all vehicles depart from the distribution centre and return to it after distribution.

Formula (7) indicates that each supplier has only one vehicle to use.

Formula (8) indicates that the total weight does not exceed the maximum load of the vehicle.

Formula (9) indicates that the vehicle must leave the supplier after finished pickup.

Formula (10) represents the running time during which the vehicle travels from the node $i$ to the supplier $j$.

Formula (11) and formula (12) represent integer constraints.

**Improved ant colony solution algorithm**

**Parameters and meaning of ant colony algorithm**

1. $B_i(t)$—The number of ants at time $t$ on supplier $i$.
2. $m$—The total quantity of ants, $m = \sum_{i=1}^{n} B_i(t)$.
3. $Q$—The total pheromones released.
4. $\rho$—The volatilization rate of pheromones.
5. $\tau_{ij}$—The pheromone concentration on edge $(i, j)$.
6. $\eta_{ij}$—The visibility on edge $(i, j)$, $\eta_{ij} = \frac{1}{z}$ (the reciprocal of distribution costs).
7. $D_{ij}$—Distance between suppliers $i$ and $j$.
8. $p^k_{ij}(t)$—Represents the probability of ant $k$’s crawling from supplier $i$ to $j$ at time $t$.
9. $k$—The ant’s number.
10. $\alpha$—The information heuristic factor.
11. $\beta$—The expected heuristic factor.
12. $tabu_k$—The search tabu table, indicating the vendors that the ant $k (k = 1, 2, \ldots, m)$ visited.

The optimizing steps of improved ant colony algorithm

**Path construction for ant colony.** Let $B_i(t)(i = 1, 2, \ldots, n)$ be the number of ants at supplier $i$ at time $t$, so $m = \sum B_i(t)$ (where $m$ is the total number of ants).

It is assumed that the pheromone strength of each path is equal at the initial time, that is, $\tau_{ij}(0) = c$ (is a constant). The ant colony algorithm used in this paper is improved on the basis of the basic ant colony algorithm to improve the global search ability and solving ability of the algorithm. The specific improvement is reflected in the calculation of the probability of ant colony transfer, taking into account the total cost ($z$), then $\eta_{ij} = \frac{1}{z}$. It can be seen that the smaller the total cost, the greater the probability of ants choosing the next customer point. Let $p^k_{ij}(t)$ represent the probability of ants from supplier $i$ to $j$ at time $t$, such as Formula (13):

$$p^k_{ij}(t) = \begin{cases} \frac{\tau_{ij}(t)^{\alpha}}{\sum_{s \in allowed} \tau_{ij}(t)^{\alpha}, j \in allowed} \frac{1}{z}^{\beta}, & j \in allowed \\ 0, & others \end{cases}$$

![Figure 2. The procedure of the ant colony algorithm.](image-url)
Inside, $\frac{1}{2}$ indicates the total distribution cost. The smaller the total cost of distribution, the greater the probability of transfer. *tabu* records all the suppliers that ant $k$ has passed in the current cycle.

*Updating of pheromones.* Over time, the new pheromones add up and the old ones evaporate, $\rho$ indicates the rate of pheromone volatilization, $\rho \in (0, 1)$. When all ants complete a cycle, the pheromones on each path are adjusted as follows:

$$\tau_{ij}(t + n) = (1 - \rho)\tau_{ij}(t) + \Delta\tau_{ij}(t)$$  \hspace{1cm} (14)

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{n} \Delta\tau_{ij}^{k}(t)$$  \hspace{1cm} (15)

$\Delta\tau_{ij}(t)$ represents the pheromone increment on the path $(i, j)$ during this distribution. At the beginning, $\Delta\tau_{ij}(0) = 0$. $\Delta\tau_{ij}^{k}$ represents the amount of pheromones released by the ant $k$ on the path $(i, j)$ during the distribution process, and its value depends on the performance of the ant.

$$\Delta\tau_{ij} = \begin{cases} \frac{Q}{\sum_{k} L_{k}} & \text{if the ant } k \text{ passes through edge in this tour from } i \text{ to } j \\ 0, & \text{others} \end{cases}$$  \hspace{1cm} (16)

Among them, $Q$ is a constant, $L_{k}$ represents the pheromone strength and represents the length of the loop formed by the distribution of the $k$ ant.

*Calculation steps of ant colony algorithm*

1. Parameter initialization. Initialize the parameters such as $m, \alpha, \beta, \rho$ and $Q$. Let $T_{0} = 6.5$ and the amount of information on each path at the initial moment be constant, i.e. $\tau_{ij}(t) = C(C$ is a constant) and $\Delta\tau_{ij}(0) = 0$.

2. All ants set off from the distribution centre and updated the tabu table for each ant, marking the first node as the point visited by the ant.

3. Determine whether the time window requirements and vehicle load limits are met when the vehicle is being distributed. If not, go to (2), otherwise, go to (4).

**Table 1.** Related data of distribution centre and supplier.

| Number | X coordinate(km) | Y coordinate(km) | Demand(t) | The prescribed time window | Service time (h) |
|--------|------------------|------------------|-----------|---------------------------|-----------------|
| 0      | 35               | 35               | 0         | [9.5,10.7]                | 0.25            |
| 1      | 41               | 49               | 1.7       | [6.5,7.7]                 | 0.25            |
| 2      | 35               | 17               | 1.6       | [8.0,9.2]                 | 0.25            |
| 3      | 55               | 45               | 0.5       | [11.5,12.7]               | 0.25            |
| 4      | 47               | 20               | 1.4       | [12.5,13.7]               | 0.25            |
| 5      | 15               | 30               | 0.9       | [9.3,10.5]                | 0.25            |
| 6      | 25               | 30               | 1.5       | [10.2,11.4]               | 0.25            |
| 7      | 20               | 50               | 0.7       | [7.7,8.9]                 | 0.25            |
| 8      | 10               | 43               | 0.5       | [8.7,9.9]                 | 0.25            |
| 9      | 57               | 60               | 1.6       | [12.1,13.3]               | 0.25            |
| 10     | 30               | 60               | 0.6       | [11.7,12.9]               | 0.25            |
| 11     | 20               | 65               | 0.6       | [10.4,11.6]               | 0.25            |
| 12     | 50               | 35               | 1.9       | [7.3,8.5]                 | 0.25            |
| 13     | 30               | 25               | 2.3       | [11.0,12.2]               | 0.25            |
| 14     | 15               | 10               | 2         | [8.9,2]                  | 0.25            |
| 15     | 30               | 5                | 1.8       | [9.3,10.7]               | 0.25            |

Note: data from an automobile third party logistics company in Shanghai, China. (Due to the need of confidentiality, the company name is anonymous).

**Table 2.** Distribution routes and load rates.

| Truck number | Distribution routes | Load ratio |
|--------------|--------------------|------------|
| 1            | (0.13,65.0)        | 94.0%      |
| 2            | (0.12,42.0)        | 98.0%      |
| 3            | (0.78,14,15.0)     | 100.0%     |
| 4            | (0.1,3,9,10,11.0)  | 100.0%     |

**Figure 3.** Spatial distribution and demand of suppliers and distribution centre.
4. According to the random state transfer rule, each ant $k$ should be transferred to the next supplier $j$, while $j$ is placed in the taboo table of ant $k$. The cycle won’t stop until all ants complete the distribution of $n$ suppliers.

5. Calculate the distribution route length and cost of each ant, and record the current optimal cost, route length and distribution sequence.

6. Update the pheromones on each side according to formulae (14), (15) and (16).

7. For the sides $(i, j)$, set $\Delta \tau_{ij} = 0$, $\text{iter} = \text{iter} + 1$.

8. Judge whether $\text{iter}$ reaches $\text{iter}_{\text{max}}$, if $\text{iter} \leq \text{iter}_{\text{max}}$, then go to (2). Otherwise, go to (9).

9. The minimum cost, the length of the path and the distribution sequence of this calculation are output.

The procedure of ant colony algorithm is shown in Figure 2.

**Case analysis**

**Basic data**

A company distributes goods for 15 suppliers around a city, the data about distribution centres and suppliers are shown in Table 1, where serial number 0 represents distribution centres and serial numbers 1 to 15 represent suppliers.

Other parameters are: (1) The capacity of the vehicle is five tons; (2) The fixed cost is 300 yuan; (3) The unit fuel consumption cost is 6000 yuan per ton; (4) The unit carbon emission cost is 200 yuan per ton; (5) The penalty cost of arriving earlier than the time window is 10 yuan/h; (6) The penalty cost of arriving later than the time window is 20 yuan/h; (7) Diesel fuel density is 0.00084 tons per litre; (8) Diesel fuel CO$_2$ emission factor is 0.00264 L/km; (9) The vehicle fuel consumption is 0.24 L/km; (10) The vehicle load is 0.15 L/km and vehicle speed is 50 km/h.

The spatial distribution of suppliers is shown in Figure 3. The numbers in brackets are supplier number and it’s demand, the triangle in the figure is distribution centre, and the dot is supplier node.

**Model solving**

In this paper, MATLAB is used to solve the mathematical model of considering carbon emissions under time window constraints. The parameters of the ant system are $m = 12, Q = 100, \alpha = 2, \beta = 5, \rho = 0.5$ and $\text{iter}_{\text{max}} = 100$. The result of the solution is shown in Table 2. The relationship between the number of iterations and cost is shown in Figure 4, and the result diagram is shown in Figure 5.

**Table 3. Comparative analysis of optimization results.**

| Project                   | Total distance (km) | Total cost (¥)   | Time cost (¥)   | Energy cost (¥) | Carbon emission cost (¥) | Fixed cost (¥) | Average load ratio (%) |
|---------------------------|---------------------|------------------|-----------------|-----------------|--------------------------|----------------|------------------------|
| Scanning method           | 355.7               | 2169.2312        | 312.5612        | 322.7036        | 33.9664                  | 1500           | 79.20                  |
| Ant colony algorithm      | 339.2               | 1866.4892        | 327.6226        | 314.0851        | 24.7815                  | 1200           | 98.00                  |
| Relative ratio            | $-4.6\%$            | $-14.0\%$        | $4.8\%$         | $-2.7\%$        | $-27.0\%$                | $-20.0\%$      | $23.7\%$               |
In order to prove the advantages of the ant colony algorithm in considering carbon emissions under time window constraints, we compare them by scanning method, as shown in Table 3.

It can be seen from the table that the time cost increases by 4.8% compared to the scanning method for the reason that the ant colony algorithm comprehensively considers the total distribution cost. However, the total journey distance is shortened by 4.6%, and the total cost is reduced by 14.0%. Specifically, the fixed cost is reduced by 20.0%, the energy consumption cost reduced by 2.7% and the cost of carbon emissions was reduced by 27.0%. In addition, the average loading ratio increased by 23.7%.

Conclusion

The research of VRP in low-carbon environment has very important practical significance for today’s logistics enterprises to comply with the trend of energy saving and emission reduction and also helps to promote the realization of resource-saving and environment-friendly sustainable development social goals in China. This paper constructs a path optimization model including fixed cost, time-constrained cost, fuel consumption cost, carbon emission cost of distribution vehicles and designs an improved ant colony algorithm to solve the problem. Finally, using the example of logistics company to verify the effectiveness of the model and the algorithm. Results show that the model can not only reduce the total distribution cost of logistics enterprises but also take into account the economic and social benefits. Moreover, the algorithm has a good convergence. It should be pointed out that when constructing the carbon emission path optimization model under the constraints of the time window, the factors affecting the carbon emissions such as the real-time status of the road and the speed of the vehicle can be considered in the future research to make the model more realistic.

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