Low Carbon Vehicle Routing Optimization with Multi-Energy and Multi-Vehicle Types under Traffic Restriction Conditions

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Abstract. Aiming at the problem of automobile exhaust pollution and the measures of urban traffic restriction, this paper introduces the traffic restriction conditions into the vehicle path problem. Firstly, the speed characteristic models of different road conditions are established. Then, aiming to minimize the total cost such as carbon emission and distribution cost in the distribution process, a multi-energy and multi-vehicle hybrid vehicle path optimization model is constructed under traffic restrictions. Finally, an improved adaptive genetic algorithm is proposed based on the idea of simulated annealing. The effectiveness of the model and algorithm is verified by simulation experiments and examples.

1. Introduction
Many cities in China have taken measures to restrict the driving sections of freight vehicles. Moreover, new energy vehicles are used in logistics distribution. Electric and fuel vehicles will coexist in urban distribution for a long time. Therefore, how to arrange the low-carbon distribution route is one of the important problems in logistics distribution under the condition of traffic restriction.

At present, the optimization of low-carbon distribution path has been studied by many scholars. Xiao et al.[1]constructed the optimization model of cold chain low-carbon logistics distribution path with comprehensive total cost minimization; Hou et al.[2]studied the optimization of multi-vehicle distribution path under the environment of carbon trading; Chen et al.[3]established the integer programming model of distribution vehicle path optimization and proposed the multi-chromosome genetic algorithm. Wang et al.[4]established the distribution path optimization model with the lowest carbon emission, and applied ant colony algorithm to optimize the path. The above studies assume that the energy consumption and carbon emission of vehicles are related to the distribution path, ignoring the influence of different road conditions. In addition, many studies fail to consider the scenarios where distribution vehicles contain various types of energy vehicles. And there is little research on the optimization of distribution vehicle paths under traffic restrictions.

Therefore, this paper constructs the multi-energy and multi-vehicle hybrid vehicle path optimization model under traffic restriction with the goal of minimizing the total cost of carbon emission and distribution costs. To solve this problem, an improved adaptive genetic algorithm based on simulated annealing is proposed.

2. Model establishment

2.1. Problem description
The distribution centre (DC) has electric vehicles and fuel vehicles with different rated load. DC arranges vehicles for distribution according to the demand of each customer. Starting from DC, vehicles will be distributed one by one according to the planned route and expected distribution time window of each customer, and finally return to DC. A customer is delivered by one vehicle. The total demand for products shall not exceed the maximum load of vehicles, and the driving distance of electric vehicles shall not exceed their maximum driving range of the electric vehicle. Moreover, fuel vehicles are forbidden to enter the time-limited area in the control period, and heavy vehicles are forbidden to enter the load restricted area. This problem needs to arrange the distribution routes of each vehicle to minimize the total cost of carbon emission and distribution costs.

2.2. Model analysis

2.2.1. Analysis of vehicle speed. Based on the existing theoretical results[5] and combined with the actual monitoring data of China’s vehicle condition information system platform, this paper established the vehicle speed model at different periods and different weather conditions. The driving speed at different periods and weather conditions is

\[ v_S \zeta = \sum S \cdot (1 - \zeta_{con}) \]

where \( v_S \) is the average technical speed of the vehicle, and \( \zeta \) is the influence rate of vehicle speed in different weather conditions and periods.

2.2.2. Fuel consumption and carbon emission measurement of fuel vehicles. Based on the working principle of the vehicle engine, the fuel consumption \( \hat{F}_{ij}^k \) of type \( k \) fuel vehicles from the customer \( i \) to \( j \) is calculated:

\[
\hat{F}_{ij}^k = \left[ \xi' (\tilde{w}^k + \tilde{w}_s^k) + \xi (S_v)^2 \right] \cdot d_{ij},
\]

where \( \tilde{w}^k \) is the self-weight of type \( k \) fuel vehicle; \( \tilde{w}_s^k \) is the load of type \( k \) fuel vehicle from customer \( i \) to \( j \); \( \xi \) is the traction coefficient of fuel vehicle; \( A \) is the windward area of vehicles; \( \rho \) is the density of the air; \( d_{ij} \) is the distance from customer \( i \) to \( j \); \( \xi' \) is a parameter, usually \([0.09, 0.2]\).

The carbon emission \( \hat{E}_{ij}^k \) of type \( k \) fuel car from customer \( i \) to \( j \) is calculated:

\[
\hat{E}_{ij}^k = \hat{F}_{ij}^k \cdot \left( \xi_{cov} + \xi_{emi} \right),
\]

where \( \xi_{cov} \) and \( \xi_{emi} \) represent the fuel conversion coefficient and carbon emission coefficient of fuel vehicles.

2.2.3. Measurement of electric vehicle power consumption and carbon emission. Based on the electric vehicle power consumption model in literature[6], the electric power consumption \( \hat{F}_{ij}^k \) of type \( k \) electric vehicle from customer \( i \) to \( j \) is calculated:

\[
\hat{F}_{ij}^k = \left[ \tilde{w}^k + \zeta' \cdot \tilde{w}_s^k + \xi (S_v)^2 \right] \cdot d_{ij},
\]

where \( \tilde{w}^k \) is the self-weight of type \( k \) electric vehicle; \( \tilde{w}_s^k \) is the load of type \( k \) electric vehicle from customer \( i \) to \( j \); \( \zeta' \) and \( \xi \) are parameters. The carbon emissions of electric vehicles are only generated in the power production process. Carbon emission \( \hat{E}_{ij}^k \) from customer \( i \) to \( j \) of type \( k \) electric vehicle is expressed as:

\[
\hat{E}_{ij}^k = \hat{F}_{ij}^k \cdot \xi_{cov} \cdot \xi_{emi} ^k,
\]
where $\hat{\theta}$ is the proportion of thermal power generation in the whole power grid; $\zeta_{\text{cov}}$ is the carbon emission coefficient per unit of power generation.

2.3. Mathematical model

2.3.1. Carbon emission cost. Carbon emission cost $C_1$ can be expressed as:

$$C_1 = \hat{p} \left( \sum_{k=1}^{l} \sum_{i=0}^{N} \sum_{j=0}^{N} \tilde{E}_{ij}^k \cdot x_{ij}^k + \sum_{k=1}^{l} \sum_{i=0}^{N} \sum_{j=0}^{N} \tilde{E}_{ij}^k \cdot x_{ij}^k \right),$$  \hspace{1cm} (5)

where $\hat{p}$ is the trading price per unit of carbon emission; $k = \{1, 2, \ldots, l, l+1, \ldots, K\}$, $l$ represents fuel vehicles, and $l+1 \sim K$ represents electric vehicles; $N$ is the number of customers; $x_{ij}^k$ is the decision variable. When $k$ cars are distributing from customer $i$ to $j$, $x_{ij}^k=1$; otherwise, $x_{ij}^k=0$.

2.3.2. Distribution costs. Distribution costs contain vehicle transportation cost $C_2$ and time window penalty cost $C_3$. $C_2$ is expressed as:

$$C_2 = \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} c^k \cdot x_{ij}^0 + \sum_{k=1}^{l} \sum_{i=0}^{N} \sum_{j=0}^{N} \tilde{c}^k \cdot \tilde{E}_{ij}^k \cdot x_{ij}^k + \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} c^k \cdot \tilde{E}_{ij}^k \cdot x_{ij}^k,$$  \hspace{1cm} (6)

where $c^k$ is the operating cost of vehicles; $\tilde{c}^k$ is the driving cost of unit energy consumption of $k$ vehicle; $x_{ij}^0=1$ means $k$ vehicle completes the task between the DC and the customer $j$.

Time window penalty cost $C_3$ can be expressed as:

$$C_3 = \begin{cases} M & 0 < t_{ik} < t_{ik}^l \text{ or } t_{ik}^h \leq t_{ik} < t_{ik}^l \\ \alpha_c \cdot (t_{ik}^l - t_{ik}^l) & t_{ik}^l \leq t_{ik} < t_{ik}^l \\ \beta_c \cdot (t_{ik}^h - t_{ik}^h) & t_{ik}^h < t_{ik} \leq t_{ik}^h \\ 0 & t_{ik}^h \leq t_{ik} \leq t_{ik}^h \end{cases},$$  \hspace{1cm} (7)

where $M$ is a large positive number; $t_{ik}$ represents the time when the $k$ distribution vehicle arrives at the customer $i$; $\alpha_c < 0$, $\beta_c > 0$ are parameters, and their values depend on customer demand for delivery time.

2.3.3. Model building. A multi-energy and multi-vehicle distribution route optimization model under traffic restriction is established:

$$\min Z = C_1 + C_2 + C_3$$  \hspace{1cm} (8)

s.t.  \hspace{1cm} (9)

$$\sum_{k=1}^{N} \sum_{i=0}^{N} \sum_{j=0}^{N} x_{ij}^k + \sum_{k=1}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} x_{ij}^k = 1$$

$$\sum_{j=0}^{N} x_{ij}^k = \sum_{j=0}^{N} x_{ij}^0 \leq 1, \quad k = 1, 2, \ldots, K$$

$$\sum_{i=0}^{N} x_{ij}^k - \sum_{j=0}^{N} x_{ij}^k = 0, \quad k = 1, 2, \ldots, K; r = 1, 2, \ldots, N$$

$$w_j^k \leq w_j^k - q_j \cdot x_{ij}^0 + Q^k \left( 1 - x_{ij}^0 \right), \quad k = 1, \ldots, K, i, j = 1, \ldots, N$$  \hspace{1cm} (12)
\[0 \leq w_i^k \leq Q^k, \quad k = 1, \ldots, K, i = 1, \ldots, N\]  \hspace{1cm} (13)

\[0 \leq b_j^k \leq b_{ij}^k - \hat{F}_{ij}^k \cdot x_{ij}^k + B^k(1 - x_{ij}^k), \quad k = l + 1, \ldots, K, i, j = 1, \ldots, N\]  \hspace{1cm} (14)

\[b_b^k \leq B^k, \quad k = l + 1, \ldots, K\]  \hspace{1cm} (15)

\[x_{ij}^k = 0, \quad i = 0, 1, \ldots, N; j \in R_1, k = 1, 2, \ldots K, Q^k > Q_{\text{max}}\]  \hspace{1cm} (16)

\[x_{ij}^k = 0, \quad i = 0, 1, \ldots, N; j \in R_2, k = 1, 2, \ldots l, t_{ij} \in T_{\text{no}}\]  \hspace{1cm} (17)

where formula (9) shows that each customer is served only once. Formula (10-11) shows that distribution vehicle starts from DC and returns to DC after serving the customer. Formula (12-13) is the capacity constraint of vehicles, where \(w_i^k\) is the load quality of type \(k\) vehicles when they start from the customer. \(q_i\) is the demand of the customer \(i\). \(Q^k\) is the maximum load of type \(k\) vehicle. Formula (14-15) represents the electric quantity constraint of electric vehicles, where, \(b_j^k\) represents the residual electric quantity of \(k\) vehicles at the customer \(i\). \(B^k\) is the maximum battery capacity of the type \(k\) vehicle. Formula (16) is the load restricted area prohibited by heavy vehicles, where \(R_1\) is lots of customers in the load restricted area, and \(Q_{\text{max}}\) is the maximum allowable load in the restricted area. Formula (17) indicates that fuel vehicles are banned to enter the restricted driving area during the control period, where \(R_2\) represents lots of customers in the respective control period, and \(T_{\text{no}}\) represents the restricted driving period.

3. Algorithm design
The Adaptive based Algorithm embed Simulated Annealing (AGAeSA) is proposed in this paper to handle this VRPTW problem. The main components of the algorithm are described as follows.

3.1. Coding and decoding.
The population size is assumed to be \(L\), and the \(l\) individual is expressed as \(S_l = [r_1, \ldots, r_n, \ldots, r_N]\), where \(r_n\) \((0 < r_n < 1)\) is the genetic information of an individual. \(N\) is the number of gene. In the process of chromosome decoding, the algorithm compares each gene in the chromosome, and obtains its position value in the array in order from small to large. When the value is larger than the number of customers, the value becomes 0. When there is a value of 0 adjacent to each other, the de-duplication operation is carried out to obtain the distribution routing scheme.

3.2. Fitness calculation
Fitness function \(F_l\) is constructed by simulated annealing:

\[F_l = \frac{\exp \left[ W(g) \cdot \left[1 + Z \right]^{-1} \right]}{\sum_{l=1}^{L} \exp \left[ W(g) \cdot \left[1 + Z \right]^{-1} \right]}\]  \hspace{1cm} (18)

\[W(g) = w_0 \cdot a_w \cdot g, \quad g = 1, 2, \ldots, g_{\text{max}}\]  \hspace{1cm} (19)

where \(F_l\) is the fitness of the \(l\) individual, \(l = 1, 2, \ldots, L\); \(W(g)\) is annealing temperature function; \(w_0 = g_{\text{max}}\) is the initial annealing temperature, and \(g_{\text{max}}\) is the maximum evolutionary algebra of the population; \(a_w\) is the annealing temperature coefficient.

3.3. Crossover operation
The crossover probability between two paired individuals is:
\[ p_c = \begin{cases} k_1' - (k_1' - k_2') \frac{(F' - \bar{F})}{F_{\text{max}} - \bar{F}} & F' \geq \bar{F} \\ k_1' & F' < \bar{F} \end{cases} \]  

where \( F_{\text{max}} \) is the maximum fitness in the current population; \( \bar{F} \) represents the average fitness of the population; \( F' \) represents the higher fitness value among paired individuals; \( k_1 \) and \( k_2 \) represent cross parameters. The algorithm uses arithmetic crossover to realize crossover operation.

3.4. Mutation operation
The mutation probability \( p_{l,m} \) of the \( l \) individual is defined as:

\[ p_{l,m} = \begin{cases} k_3' - (k_3' - k_4') \frac{(F_l - \bar{F})}{F_{\text{max}} - \bar{F}} & F_l \geq \bar{F} \\ k_3' & F_l < \bar{F} \end{cases} \]

where \( F_l \) is the fitness of the \( l \) individual; \( k_3 \) and \( k_4 \) are the variation parameters. The algorithm is implemented by Gauss mutation.

4. Algorithmic simulation and analysis
4.1. Standard test function results and analysis
In order to verify the performance of the proposed AGAeSA algorithm in global optimization, the standard test functions (Generalized Rastrigin and Sphere Model) are used to test the convergence and global optimization ability of the algorithm. The results of AGAHC (Adaptive Genetic Algorithm with Hill Climbing), AGA (Adaptive Genetic Algorithm) and ACO (Ant Colony Optimization Algorithm) were compared and analyzed. The test results are shown in Table 1 and Table 2.

| Population size | Number of iterations | AGA | AGAHC | ACO | AGAeSA |
|-----------------|----------------------|-----|-------|-----|--------|
| 30              | 1000                 | 2.3176 | 0.6457 | 0.5794 | 0 |
|                 | 2000                 | 0.9165 | 0.2136 | 0.3547 | 0 |
| 60              | 1000                 | 1.2671 | 0.1152 | 0.3794 | 0 |
|                 | 2000                 | 0.2753 | 0.0428 | 0.1743 | 0 |
| 90              | 1000                 | 0.4697 | 0.0089 | 0.0197 | 0 |
|                 | 2000                 | 0.0029 | 4.5761e-04 | 0.0072 | 0 |

Table 2. Test results of the Generalized Rastrigin function.

| Population size | Number of iterations | AGA | AGAHC | ACO | AGAeSA |
|-----------------|----------------------|-----|-------|-----|--------|
| 30              | 1000                 | 5.6238 | 5.7921 | 3.7824 | 0 |
|                 | 2000                 | 4.2315 | 4.1294 | 3.1493 | 0 |
| 60              | 1000                 | 5.1489 | 4.5923 | 2.8541 | 0 |
|                 | 2000                 | 4.2134 | 3.9742 | 1.0574 | 0 |
| 90              | 1000                 | 4.3706 | 4.1824 | 2.9074 | 0 |
|                 | 2000                 | 3.2821 | 2.4118 | 1.2873 | 0 |

By comparing the results of 10 repeated tests, we can see that for the test functions Generalized Rastrigin and Sphere Model, AGAeSA has found the global minimum point, and each optimization converges to the global minimum point. Thus, AGAeSA algorithm has better global convergence performance and accuracy.
4.2. Example experiments and analysis
A logistics distribution company has a number of small, medium and heavy fuel vehicles and electric vehicles, providing distribution services for 30 demand points. The location coordinates of each customer are randomly generated in the area with a side length of 50 kilometers, and the coordinates of distribution centre are (18.70, 15.29). The demand and service time window of each customer are shown in Table 3. The distribution parameters of various types of vehicles are shown in Table 4. Traffic is restricted during the control period, which is from 8:00 to 9:00 in the morning and from 18:00 to 19:00 in the evening. For large tonnage vehicle control zoning, tonnage limit is 3 tons. Time window penalty factors are $\alpha_c = -10$ and $\beta_c = -0.05$; The transaction price of carbon emissions is 55 yuan/ton. The electricity price is 0.53 yuan/kW·h. The fuel price is 6.5 yuan / liter. The population size of AGAeSA is $L = 200$. The maximum number of iterations is $g_{\text{max}} = 2000$. The annealing temperature coefficient is $\omega_a = 0.99$. The parameters are $k_1 = 0.85$, $k_2 = 0.6$, $k_3 = 0.1$ and $k_4 = 0.05$.

| Number | Demand (ton) | Service time window | Demand (ton) | Service time window |
|--------|--------------|---------------------|--------------|---------------------|
| 1      | 0.57         | (7:00,8:30,15:45,19:30) | 16 | 0.52 | (17:00,19:00,23:30,24:00) |
| 2      | 0.35         | (8:00,10:30,12:40,14:50) | 17 | 0.41 | (15:30,18:30,21:00,22:00) |
| 3      | 0.38         | (5:00,7:50,9:50,10:50) | 18 | 0.63 | (2:30,4:30,18:20,20:00) |
| 4      | 0.51         | (9:00,10:30,17:50,19:30) | 19 | 0.35 | (3:30,5:00,13:30,15:30) |
| 5      | 0.48         | (6:30,8:30,12:50,14:30) | 20 | 0.51 | (6:30,8:30,12:50,14:30) |
| 6      | 0.32         | (10:00,11:00,17:00,20:00) | 21 | 0.13 | (3:00,6:00,19:00,20:30) |
| 7      | 0.13         | (17:00,19:00,23:30,24:00) | 22 | 0.13 | (8:30,10:00,14:45,16:00) |
| 8      | 0.25         | (15:30,18:30,21:00,22:00) | 23 | 0.28 | (15:00,17:00,21:45,24:00) |
| 9      | 0.31         | (2:30,4:30,18:20,20:00) | 24 | 0.33 | (5:00,7:50,9:50,10:50) |
| 10     | 0.42         | (3:30,5:00,13:30,15:30) | 25 | 0.43 | (9:00,10:30,17:50,19:30) |
| 11     | 0.13         | (3:00,6:00,19:00,20:30) | 26 | 0.33 | (6:30,8:30,12:50,14:30) |
| 12     | 0.48         | (8:30,10:00,14:45,16:00) | 27 | 0.25 | (10:00,11:00,17:00,20:00) |
| 13     | 0.58         | (15:00,17:00,21:45,24:00) | 28 | 0.41 | (17:00,19:00,23:30,24:00) |
| 14     | 0.41         | (11:00,19:00,22:00,23:30) | 29 | 0.42 | (6:30,8:30,12:50,14:30) |
| 15     | 0.39         | (12:30,18:45,20:30,24:00) | 30 | 0.13 | (3:00,6:00,19:00,20:30) |

| Vehicle type   | Departure cost (yuan/time) | Empty vehicle weight (tons) | Maximum Load Weight (tons) | Maximum range (km) |
|----------------|----------------------------|-----------------------------|----------------------------|-------------------|
| Small Fuel Vehicle | 150                       | 1.8                         | 1.2                       | —                 |
| Medium-sized Fuel Vehicle | 230                   | 2.7                         | 3                         | —                 |
| Large Fuel Vehicle     | 270                       | 3.5                         | 5                         | —                 |
| Electric Vehicle         | 220                       | 1.5                         | 2                         | 200               |

The simulation results of the algorithm in different restricted areas are shown in Figure 1 and Figure 2. In Figure 1, the distribution centre arranges one large, medium and small fuel vehicle and one electric vehicle respectively. The distribution route of each vehicle is shown in...
Figure 1, and the cost of distribution is 1735.46 yuan. In order to further discuss the influence of the size of the restricted area on urban distribution vehicle routing, the simulation expands the restricted area. Under this condition, the DC arranges one medium-sized fuel vehicle, three small fuel vehicles and two electric vehicles for distribution. The distribution route of each vehicle is shown in Figure 2 and the cost of distribution is 2469.77 yuan. It can be seen that with the expansion of urban traffic restriction areas, the number of large-scale fuel vehicles has decreased due to more restriction measures, the number of electric vehicles has increased accordingly, and the total cost of logistics has also increased.

5. Conclusion
Considering the influence of road conditions on energy consumption and carbon emissions, a multi-energy and multi-vehicle hybrid vehicle routing optimization model under traffic restriction is constructed, and an adaptive hybrid genetic algorithm is developed. Compared with the existing methods, the rationality of the model and the effectiveness of the algorithm are verified.

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