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Research on Route Optimization of Multi-compartment Classified Collection and Transportation of Domestic Waste under Uncertain Environment

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Abstract. In the process of urbanization, the effective classified collection and transportation of domestic waste is crucial for the realization of circular economy, among which multi-compartment vehicles capable of handling multiple types of waste simultaneously show great application potential. However, two tough problems are often encountered in practical scheduling: fluctuations in vehicle speed caused by the complex urban road conditions, and the difficulty in predicting the waste generation amount in advance. To address these uncertain factors, this research focuses on the route optimization problem of classified collection and transportation. We attempt to introduce a new type of equipment—vehicles with flexibly adjustable compartment ratios, and on this basis, construct a scheduling model based on chance-constrained programming, aiming to improve the overall efficiency of collection and transportation by dynamically adjusting compartment configurations. Simulation experiments show that in areas with large fluctuations in waste generation, this flexible compartment design can help sanitation enterprises effectively reduce operational costs; meanwhile, if the differences in vehicle speed at different time periods are fully considered in route planning, vehicles can better avoid traffic congestion, thereby reducing carbon emissions during transportation. It is hoped that these findings can provide some practical references for the complex and changeable sanitation scheduling work in reality.

Keywords: Multi-compartment Vehicle Routing Problem, time dependence, demand splitability, genetic algorithm

1. Introduction

With the deepening of urbanization in China, the generation of domestic waste has been increasing continuously. Data from the National Bureau of Statistics shows that 259 million tons of domestic waste were collected and transported nationwide in 2024. Faced with such a huge amount of waste, the implementation of effective classified collection and transportation is not only an important way to realize resource recycling, but also directly related to the level of urban environmental governance [1,2]. However, we have observed that traditional collection and transportation methods often suffer from inadequate classification and low vehicle loading rates. Studies have pointed out that the cost of the collection and transportation link can even account for more than 60% of the entire waste treatment chain [3], leaving enormous room for efficiency improvement.

To solve this problem, Multi-compartment Vehicles (MCV) have become a solution attracting much attention. Such vehicles are equipped with multiple independent compartments inside, which can load different types of waste at the same time. This can not only prevent the waste sorted at the front end from being mixed again during transportation, but also is expected to significantly reduce transportation costs [4,5]. However, in practical urban applications, we have found another tricky problem: traffic conditions change in real time, and traffic congestion during peak hours will seriously affect vehicle driving speed [6,7]. Therefore, how to plan efficient and low-carbon routes for MCVs in a dynamically changing road network has become a key research direction in the field of intelligent sanitation [8,9].

At present, the academic community has conducted many discussions on the Multi-compartment Vehicle Routing Problem (MCVRP), but most studies still assume that the road network is static and the compartment size is fixed. To be more in line with the complex actual situation, this paper explores a more flexible solution: the use of flexible multi-compartment vehicles with adjustable compartment partitions. On this basis, we construct a low-carbon route optimization model (GFMCVRP) aiming at minimizing the total cost. For this model, an improved genetic algorithm is designed for solution, and the feasibility and superiority of the proposed model and algorithm are verified through the test and analysis of multiple groups of numerical examples.

2. Establishment of the GFMCVRP model

2.1. Problem description

In the urban domestic waste collection and transportation system, there is a fixed garbage transfer station responsible for the unified collection and transportation of several waste generation nodes with known geographical locations. The transfer station is equipped with several homogeneous flexible multi-compartment waste collection and transportation vehicles, which are installed with movable partition boards inside and can adjust the volume of each sub-compartment in advance according to the actual collection and transportation tasks of different types of waste. All vehicles depart from the transfer station with no load and drive in a road network environment considering the time-varying characteristics of urban road traffic congestion. The driving speed of vehicles changes dynamically with the departure time and the traffic operation status of road sections. The fuel consumption and carbon emission level of vehicles during the collection and transportation process are depicted by the CMEM micro energy consumption model, which indicates that energy consumption has a nonlinear relationship with vehicle driving speed and real-time load.

The basic assumptions are as follows: (1) The collection and transportation vehicles equipped at the garbage transfer station are homogeneous and sufficient in quantity. (2) Each waste node must be served by exactly one collection and transportation vehicle. (3) The number, location and waste generation amount of waste nodes are known, and the waste generation amount is regarded as an uncertain variable following a normal distribution. (4) Movable partition boards are installed inside the collection and transportation vehicles, which can adjust the sub-compartment space according to the volume proportion of different types of waste, and the influence of the volume occupied by the partition boards themselves on the effective volume of the vehicle is ignored.

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2.2. Notation

The optimization model constructed in this paper involves the following key sets and parameters. Let the set of all nodes be $N = \{0,1,2,...,n,n+1\}$, where both 0 and n+1 represent the same garbage transfer station; $N' = \{1,2,...,n\}$ is the set of waste collection nodes; $K = \{1,2,...,k\}$ is the set of collection and transportation vehicles. The decision variables in the model include: x_{ijk} which takes the value of 1 if vehicle k travels from node i to node j, and 0 otherwise; V_{pk} is the volume allocation of vehicle k for loading the p-th type of waste; u_{ik} is the visiting order; t_{ik} is the departure time. The definitions of relevant parameters are as follows: the total load capacity of the vehicle is Q; q_{ip} and ρ_p represent the generation amount and density of the p-th type of waste at node i, respectively. The driving time of the vehicle at time t is depicted by the function $T_{ij}(t)$, and the maximum working hour limit is T_{max} . f_0 is the fixed startup cost per vehicle, C_v is the maintenance cost per unit distance, and C_f and C_c represent the fuel unit price and carbon emission tax price, respectively. In addition, S_i is the operation time, d_{ij} is the shortest distance between nodes, and M is a sufficiently large positive number.

2.3. Time-dependent function and carbon emission calculation method

To describe the actual collection and transportation scenario more accurately, research on the Time-dependent Vehicle Routing Problem (TDVRP) has been deepening continuously, and research on continuous time-dependent functions has become increasingly abundant. This paper draws on the continuous improvement method in Reference [9]: the advance speed adjustment between constant speed sections is realized by introducing an acceleration mechanism.

The CMEM (Comprehensive Modal Emission Model) micro energy consumption model used in this paper was first proposed by Barth et al. [10]. This model comprehensively considers the comprehensive influence of various factors such as vehicle driving speed, vehicle real-time load, road environment and vehicle attributes on fuel consumption. Bektaş et al. [11] first incorporated the CMEM measurement model into the research field of the green vehicle routing problem, and the specific calculation formula of its fuel consumption is as follows, including three items: engine internal consumption, work done against rolling resistance and work done against air resistance:

$$F_{ijk} = \xi \sum_{s \in S} (k_{eng} N_e V_e \frac{d_s}{v_s} + \frac{1}{\eta}(W_{curb} + \omega_{ik}) g C_r d_s + \frac{1}{2\eta} \rho C_d A v_s^2 d_s) \tag{1}$$

Where: F_{ijk} is the fuel consumption of vehicle k on road section (i,j); ξ is the fuel consumption conversion coefficient; S is the set of constant speed sub-sections divided from road section (i,j), and s is a specific sub-section in set S ; d_s is the driving distance of the vehicle in sub-section s , where the sum of the distances of each sub-section satisfies $\sum_{s \in S} d_s = d_{ij}$; v_s is the driving speed of the vehicle in sub-section s ; k_{eng} is the engine friction coefficient; N_e is the engine speed; V_e is the engine displacement; W_{curb} is the curb weight of the vehicle; ω_{ik} is the vehicle load; η is the power transmission efficiency of the engine; g is the gravitational acceleration; C_r is the vehicle tire rolling resistance coefficient; ρ is the air density; C_d is the air resistance coefficient; A is the windward area.

2.4. Model establishment

In this research, the total cost of the waste collection and transportation system is mainly composed of four parts: vehicle fixed startup cost, vehicle driving maintenance cost, fuel consumption cost and carbon emission cost. The specific model is established as follows:

Objective function:

$$minZ = \sum_{j\in N\prime}\sum_{k\in K} f_0 x_{0jk} + \sum_{k\in K}\sum_{i\in N}\sum_{j\in N} c_v d_{ij} x_{ijk}$$

$$+\sum_{k\in K}\sum_{i\in N}\sum_{j\in N}(c_f + c_c\delta)F_{ijk}x_{ijk} \tag{2}$$

$$\sum_{k\in K}\sum_{j\in N, j\neq i} x_{ijk} \geq 1, \forall i \in V\prime \tag{3}$$

$$\sum_{k\in K} y_{ipk} = 1, \forall i \in V\prime, p \in P \tag{4}$$

$$\sum_{j\in N, j\neq i} x_{ijk} \geq y_{ipk}, \forall i \in V\prime, k \in K, p \in P \tag{5}$$

$$\sum_{p\in P} y_{ipk} \geq \sum_{j\in N, j\neq i} x_{ijk}, \forall i \in V\prime, k \in K \tag{6}$$

$$\sum_{i\in N} x_{ijk} = \sum_{m\in N} x_{jmk}, \forall j \in N\prime, k \in K \tag{7}$$

$$\sum_{j\in N\prime} x_{0jk} = \sum_{i\in N\prime} x_{i,n+1,k} \leq 1, \forall k \in K \tag{8}$$

$$u_{ik} - u_{jk} + Mx_{ijk} \leq M - 1, \forall i,j \in N\prime, k \in K \tag{9}$$

$$\sum_{i\in N\prime}\sum_{p\in P}\sum_{j\in N} x_{ijk} q_{ip} \leq Q \tag{10}$$

$$t_{ik} + S_i + T_{ij}(t_{ik} + S_i) - M(1 - x_{ijk}) \leq t_{jk}, \forall i,j \in N, k \in K \tag{11}$$

$$t_{n+1,k} - t_{0k} \leq T_{max} \tag{12}$$

$$x_{ijk}, y_{ipk} \in \{0,1\}, \forall i,j \in N, k \in K \tag{13}$$

$$t_{ik}, u_{ik} \geq 0, \forall i \in N, k \in K \tag{14}$$

Formula (2) is the objective function, aiming to minimize the total operational cost including vehicle startup fixed cost, driving maintenance cost, as well as fuel and carbon emission costs; Formula (3) indicates that each waste node is served at least once; Formula (4) ensures that only one vehicle is responsible for collecting each type of waste at any waste node. Formula (5) establishes the logical correlation between the route decision variable x_{ijk} and the service state variable y_{ipk} to ensure their consistency; Formula (6) is the constraint to prevent empty visits, that is, at least one type of waste must be collected when visiting waste node i ; Formula (7) ensures the flow balance of intermediate nodes, that is, the number of times a vehicle enters a node must be equal to the number of times it leaves the node; Formula (8) ensures that all activated vehicles must form a closed loop, that is, departing from the transfer station and finally returning to the transfer station; Formula (9) is the subtour elimination constraint to prevent isolated closed loops that do not pass through the transfer station in the route; Formula (10) is the vehicle load capacity constraint; Formula (11) represents the time deduction relationship between nodes, ensuring that the time when

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the vehicle arrives at the next node is later than the time when it leaves the previous node plus the operation time and dynamic driving time; Formula (12) limits the total operation time of the vehicle from leaving the depot to returning to the depot to not exceed the specified upper limit; Formulas (13) and (14) define the types and non-negative value ranges of each decision variable in the model.

3. Improved genetic algorithm

This paper adopts an improved genetic algorithm to solve the constructed green collection and transportation route optimization model. This algorithm simulates the natural evolution mechanism, which can effectively handle the complex solution space with multiple constraints and nonlinearity to achieve global optimality. Natural number permutation coding is adopted, and the chromosome only contains the numbers of waste collection nodes without directly reflecting the information of the transfer station. During decoding, the chromosome sequence is restored to the actual collection and transportation route according to the capacity limit of each vehicle. To balance the quality of the initial solution and population diversity, this paper constructs the initial population by using hybrid heuristic rules based on probability selection:

(1) Seed point selection: Following the far-distance priority principle, calculate the distance from the uncollected nodes to the transfer station, and select the initial points by roulette wheel selection to cover remote nodes first and control transportation costs. (2) Subsequent node insertion: Randomly select from the optional nodes and add them to the current route in turn until the capacity limit is reached and then return to the transfer station.

In this paper, the reciprocal of the total operational cost Z of the collection and transportation system is used as the fitness evaluation index.

$$fit(i) = \frac{1}{minZ} \tag{15}$$

The design of genetic operators is as follows: (1) Selection operator: Tournament selection (scale k=3) is adopted. This method screens the parent generation through local competition between individuals, which helps maintain population diversity and prevent premature convergence. (2) Crossover operator: Order Crossover (OX) is selected. By exchanging randomly intercepted parent gene segments, the relative order between nodes can be largely retained, reducing the generation of infeasible solutions. (3) Mutation operator: Inversion mutation is adopted. Randomly select two cut-off points in the chromosome and reverse the middle segment between them. This operation principle is similar to the 2-opt local search principle, which can effectively eliminate the path crossover and detour phenomenon and enhance the global search ability of the algorithm.

After the end of each generation of evolution, the 2-opt local search strategy is introduced to fine-tune the path of the optimal individual, repair the path crossover problem caused by random operators, and further improve the convergence accuracy of the algorithm.

4. Numerical experiments

To verify the effectiveness of the algorithm, the classic Solomon instances are selected as the standard test data in this paper. Solomon instances include different types of customer spatial distribution, among which type C represents clustered distribution of customer nodes, type R represents random distribution, and type RC represents random-clustered distribution. This paper selects three instances of C101, R101 and RC101 for experiments to verify the effectiveness of the algorithm under different spatial distributions and different scales. On the basis of the Solomon

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standard instances, the vehicle capacity parameters are adjusted according to the research needs, and the demand split method proposed by Cornillier et al. [12] is adopted to expand the single demand into multi-category demand for constructing classified waste collection and transportation instances. The specific characteristics of the instances are shown in Table 1.

The algorithm parameter settings are as follows: the maximum number of iterations is 1000, the initial population size is 100, the crossover probability is 0.6, the mutation probability is 0.2, and the number of elites is 3. In view of the random characteristics of the genetic algorithm, to effectively evaluate the stability and robustness of the algorithm performance, this research runs each instance independently for 10 times, and records the optimal value, average value and standard deviation of the objective function value, driving distance and number of vehicles used. Among them, Z_{best} represents the optimal objective function value, Z_{avg} represents the average objective function value, SD_Z represents the standard deviation of the objective function value, d_{best} represents the optimal driving distance, d_{avg} represents the average driving distance, SD_d represents the standard deviation of the driving distance, N_{best} represents the optimal number of vehicles used, N_{avg} represents the average number of vehicles used, and SD_N represents the standard deviation of the number of vehicles used. The statistical results are shown in Table 2. In addition, Figure 1 shows the representative convergence curves in the instances, aiming to analyze the convergence speed, solution stability and the ability to avoid premature convergence of the algorithm under different problem scales and types.

Table 1. Instance characteristics table

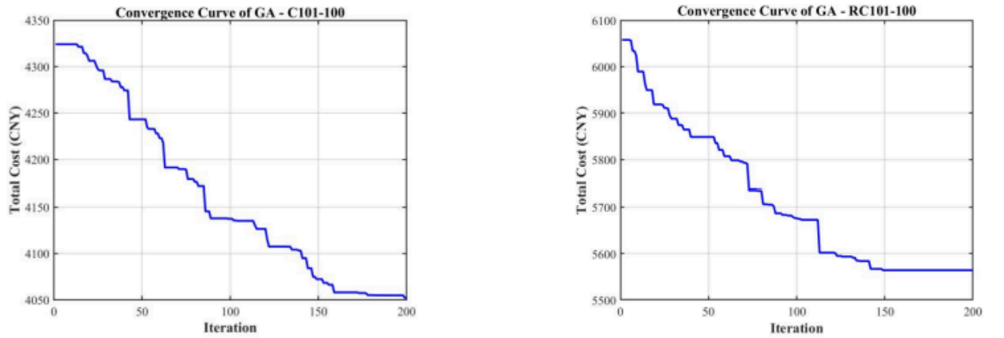
Instance	Number of Waste Nodes	Load Capacity of Each Vehicle Compartment
C101-25	25	(50,50,50)
R101-25	25	(50,50,50)
C101-25	25	(50,50,50)
R101-50	50	(60,60,60)
RC101-50	50	(60,60,60)
C101-50	50	(60,60,60)
C101-100	100	(100,100,100)
R101-100	100	(100,100,100)
RC101-100	100	(100,100,100)

Table 2. Calculation results table

Instance	Z_{best}	Z_{avg}	d_{best}	d_{avg}	N_{best}	N_{avg}
C101-25	1882.05	1918.91	249.80	263.92	4	4
R101-25	3713.67	3771.59	739.45	762.54	6	6
RC101-25	1839.03	1877.70	233.40	248.16	4	4
C101-50	3197.82	3284.73	391.92	426.55	7	7
R101-50	4753.67	4894.57	1011.80	1067.69	7	7
RC101-50	3133.11	3190.46	366.38	390.18	7	7

Table 2. (continued)

C101-100	4052.45	4116.75	567.36	593.81	8	8
R101-100	6598.46	6845.56	1460.11	1558.57	9	9
RC101-100	5443.59	5661.64	1122.96	1207.15	8	8



(a) Convergence Curve of Instance (b) Convergence Curve of Instance

Figure 1. Convergence curves

In all test instances, the deviation between Z_{best} and Z_{avg} remains at a low level. For example, the average deviation of the 25-node instances is only about 1.9%; even in the large-scale complex instances with 100 nodes, such as R101-100, the deviation does not exceed 3.7%. This objectively confirms that the algorithm has excellent robustness and anti-interference ability when dealing with high-dimensional decision-making problems. Moreover, the optimal number of vehicles N_{best} and the average number of vehicles N_{avg} of each instance show a high degree of consistency in 10 runs. This indicates that under the deterministic capacity constraint, the algorithm can stably determine the optimal scale, which greatly reduces the instability of the scheduling scheme.

5. Conclusions

This paper studies the route optimization problem of domestic waste classified collection and transportation under the background of urbanization and waste classification, and the core conclusions obtained are as follows:

(1) Model construction and optimization objective: Aiming at the classification constraints and time-varying road network characteristics in waste collection and transportation, this paper constructs a low-carbon route optimization model based on flexible multi-compartments (GFMCVRP), aiming to minimize the total operational cost including vehicle fixed cost, driving maintenance cost, fuel consumption and carbon emission cost.

(2) Algorithm effectiveness and stability: An improved genetic algorithm is adopted for solution, and numerical experiments show that the algorithm has significant solution stability. In the tests with the scale of 25 to 100 nodes, the deviation between the optimal objective value and the average value is very low (about 1.9% for 25 nodes and about 3.7% for 100 nodes), and the algorithm can stably determine the optimal fleet size.

(3) Convergence performance: The convergence curves verify that the algorithm has a strong global search ability and the ability to jump out of local optimum, and can maintain good convergence accuracy and steady state in the late stage of iteration.

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(4) Practical application value: Experimental results show that flexibly adjusting the proportion of flexible compartments and considering time dependence to avoid traffic congestion can significantly improve the collection and transportation efficiency, reduce operational costs and cut carbon emissions, providing scientific decision support for vehicle scheduling in complex and dynamic environments.

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