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Path Optimisation of Electric Vehicles for Collection and Delivery based on Intelligent Waste Bins

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Abstract

This paper proposes a dynamic electric vehicle path optimization method for intelligent garbage collection and transportation systems to address the increasing uncertainty of urban household waste and the carbon emissions caused by vehicles in traditional garbage collection and transportation processes. With the goal of minimizing total cost and maximizing garbage collection and transportation, adjust the soft time window in a timely manner based on whether the amount of garbage generated by the intelligent garbage bin reaches the collection and transportation threshold. Taking into account the position of the garbage bin to be cleared, the position of the garbage collection and transportation vehicle, the amount of electricity, and the loading capacity, dynamically adjust the vehicle path. Due to the fact that genetic algorithms require a long time to converge to an acceptable solution, this paper uses greedy genetic algorithms to comprehensively utilize their advantages in local search and global search capabilities to achieve faster convergence solutions. The research results indicate that compared with traditional static garbage collection and transportation modes, dynamic garbage collection and transportation schemes can reduce total costs and increase garbage collection and transportation volume, and reasonable planning of the path of electric collection and transportation vehicles can effectively reduce carbon emissions. Finally, the effectiveness and efficiency of the algorithm were verified through comparative analysis of numerical examples.

Keywords

Smart Bins; Dynamic Demand; Electric Vehicles; Path Optimisation; Greed Genetic Algorithm.

1. Introduction

With the accelerated development of urbanisation, the amount of rubbish in China is also increasing, in order to actively respond to the national environmental policy, in the construction of urban waste collection and transportation system and path optimisation process, the carbon emission factor should be taken into account, the use of new energy vehicles for collection and transportation. Many companies in China have already used smart bins for rubbish collection, such as "TuoNiu townew", "EKO", "Nasdaq NSD" and so on. Intelligent bins rely on sensors, big data, Internet of Things and other technologies to sense the rubbish situation, when the bins need to be emptied to remind the relevant personnel to deal with the rubbish in a timely manner, effectively solving the uncertainty of the amount of rubbish and traffic congestion brought about by the path of the planning problem. It also adopts a sealed design with multiple segregation areas for waste classification, which reduces odour and secondary pollution caused by waste distribution.

Currently, many scholars have studied the problem of urban waste collection and transportation system.Seyed Emadedin Hashemi designed a sustainable energy-saving and

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emission-reducing reverse logistics network for urban waste collection, and established a fuzzy multi-objective optimisation model to protect the environment and the health of the population [1]. Ooi Jun Keat et al. established a new multi-objective mixed-integer linear programming method to optimise seven conventional waste disposal facilities. conventional waste disposal facilities to examine the extent of emission reduction in MSW management systems [2]. Gutierrez et al. selected the bins to be collected by analysing the data from the sensors and calculated the paths for optimal travelling distances [3]. In terms of research methodology, Vinay Yadav et al. designed a multi-objective brainstorming optimisation algorithm based on ranked clustering method and bi-directional mutation, which helps the health sector to improve the economic and environmental benefits [4]. Hu Zhineng modified the parameters and learning strategy to design multi-objective particle swarm optimisation algorithm which combines optimistic and pessimistic approaches to solve and provide the Pareto optimal solution respectively [5]. Pehlivanoglu Y implements ACO in genetic algorithm to generate suboptimal paths and proposes initial population enhancement method to accelerate the convergence process and solve the path planning problem [6].

2. Methodology

2.1. Problem Description and Modelling

In this paper, we consider a dynamic waste collection model with multiple smart bins. The initial amount of rubbish in each smart bin is randomly generated. The rubbish in the smart bin increases over time and when the rubbish in the bin exceeds the threshold set for cleaning, an alarm is issued to tell the rubbish collection vehicle, which needs to plan a path and clean up the rubbish after receiving the alarm. The amount of rubbish in each smart bin increases at each time period is fixed and the trash in the bin is cleaned when it exceeds the threshold value. In this paper, a waste recycling centre with power switching, parking and compression processing is used, while multiple purely electric waste recycling vehicles work in the waste recycling centre. In this paper, a planning period T is set in which all the smart bins are visited and cleaned, and the overall task of waste recycling is carried out with the objective function of minimising the total cost consumption of the overall task of waste recycling and maximising the number of wastes to be cleaned.

2.1.1. Model Assumptions and Parameter Definitions

In order to solve the above problem, let's assume the conditions from our side.

Assumption 1: All the vehicles involved in the rubbish collection task have the same parameters.

Assumption 2: The amount of rubbish in each smart bin follows a uniform distribution.

Assumption 3: The power consumption per unit distance of the vehicle is related to the weight of the loaded rubbish.

Assumption 4: The amount of rubbish generated per unit time is fixed in all smart bins.

Assumption 5: If the residual current of the vehicle is not enough to travel to the next smart bin location during the rubbish collection process, it returns to the rubbish collection centre for a power change, which takes a negligible amount of time.

Assumption 6: The time taken by the vehicle to recycle waste in each smart bin is uniform.

Assumption 7: The amount of rubbish in each smart bin exceeds the threshold, then it needs to be cleaned.

Assumption 8: The travelling speed of the vehicle during waste collection is constant and known.

Assumption 9: The rated power consumption of the vehicle and the unloaded unit mileage power consumption are both the same and known.

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Assumption 10: The vehicle does not consume electricity during loading and unloading.

Assumption 11: If the capacity of one type of waste is full during the trip, the vehicle returns to the recycling centre to unload the waste before proceeding to the next cleaning step.

Assumption 12: There is a single flow of waste, only picking up but not delivering, and all types of waste have the same weight.

Assumption 13: The road is clear during the waste removal process, regardless of traffic jams and unforeseen circumstances such as accidents or breakdowns.

The symbols are described in Table 1 below.

Table 1. Description of symbols

Notation	Clarification
N	Bin set 1,2,...,n
O	Rubbish collection vehicle park
M	Collection of refuse collection vehicles 1,2,...,m
T	Garbage removal planning period
Z	Total cost of garbage removal during the planning period
f_0	Fixed cost of using garbage collection vehicles
f_e	Unit electricity price
f_c	The vehicle's one-time battery replacement cost, that is, regardless of the remaining power, the battery replacement cost is calculated based on the number of times.
f_l	Vehicle cost per unit distance traveled
v	vehicle speed
ta_{ik}	The time when vehicle k visits trash can i to clean up garbage
tl_{ik}	The time when vehicle k leaves trash can i after cleaning up the garbage
Q_{ik}	The amount of garbage cleaned by vehicle k in the trash can
D_{ij}	The distance between bins i and j
w_{ij}	The travel time of the garbage truck from i to j
S_i	Garbage cleaning time for trash can i
E	Vehicle energy consumption
B	Maximum capacity of electric vehicle batteries
P	vehicle power
α	vehicle acceleration
r	Motor resistance
R	tire radius
θ	slope
f_a	air resistance coefficient
f_{rl}	rolling resistance coefficient
K	Product of armature constant and magnetic flux
m	Vehicle weight
Q	Vehicle rated garbage load
f_Q	The total amount of garbage removed by vehicles during the planning period
S_e	Vehicle power consumption per unit driving distance
S_i	The time when the garbage in trash can i overflows
p_1	The cost of garbage pollution to the environment, which is the penalty cost of overflowing garbage that pollutes the environment when the garbage is full but not processed.
X_{ijk}	Decision variable, if vehicle k visits trash can i and then visits traditional trash can j, it is 1, otherwise it is 0
E_{ik}	Decision variable, if vehicle k visits trash can i and exchanges electricity, it is 1, otherwise it is 0
S_{ik}	Decision variable, 1 if the garbage in trash can i is cleaned by vehicle k, otherwise 0

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2.1.2. Objective Function

Based on the previous notation description and assumption description, the following model can be developed:

$$\min Z = f_0 \times M + f_c \times \sum_{k=1}^{M}\sum_{i=1}^{N} E_{ik} + f_l \times \sum_{k=1}^{M}\sum_{i=1}^{N}\sum_{j=1}^{N} D_{ij} \times X_{ijk} + p_1 \times \sum_{i=1}^{N}\sum_{k=1}^{M}(T_i - ta_{ik} + p_2 \times \sum_{i=1}^{N}\sum_{k=1}^{M}(ta_{ik} - S_i) \tag{1}$$

$$max\, f_Q = \sum_{k=1}^{M}\sum_{i=1}^{N} S_{ik} \times Q_{ik} \tag{2}$$

$$\sum_{k=1}^{M}\sum_{i=1}^{N}\sum_{j=1}^{N} X_{ijk} \geq 3 \ \ \forall\, i,j \ \in \ N \tag{3}$$

$$\sum_{i=1}^{N} X_{ijk} - \sum_{j=1}^{N} X_{ijk} = 0\,, \forall k \in M \tag{4}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{M} Xiok - \sum_{j=1}^{N}\sum_{k=1}^{M} Xjok = 0 \tag{5}$$

$$(tl_{ik} - ta_{ik}) + w_{ij} \leq T \ \ \forall k \in M, \forall i \in N \tag{6}$$

$$S_i \leq (tl_{ik} - ta_{ik}) \ \ \forall k \in M, \forall i \in N \tag{7}$$

$$D_{ij} \ \leq \ \frac{E}{S_e}, \forall k \in M, \forall i \in N\,, \forall i \in N \tag{8}$$

$$E_{ik} \times \left(E - S_e \times \sum_{i=1}^{N}\sum_{j=1}^{N} D_{ij} \times X_{ijk} \right) \geq 0\,, \qquad \forall k \in M, \forall i \in N \tag{9}$$

$$Q_{ik} \geq 0.7, \qquad \forall i \in N, \qquad \forall k \in M \tag{10}$$

$$P_{jk} \leq P_{ik} - m_{ij} + Q(1 - E_{ik}), \forall i \in N, \forall j \in N, i \neq j, \forall k \in M \tag{11}$$

$$E_{ik} \leq \sum_{j=1}^{N} X_{ijk}\,, \forall k \in M\,, \forall i \in N \tag{12}$$

$$E_{OK} = B, \forall k \in M \tag{13}$$

$$E = \left[\frac{rR^2}{K^2}(ma + f_a v^2 + f_{rl} mg + mgsin\theta)^2 + v(f_a v^2 + f_{rl} mg + mgsin\theta) + m\alpha v\right] \times t \tag{14}$$

$$X_{ijk}, E_{ik}, S_{ik} \in \{0,1\}, \forall k \in M, \forall i, j \in N \tag{15}$$

The objective function (1) denotes the minimisation of the cost of clearing the waste, including fixed cost, power change cost, driving cost, waiting cost, and environmental pollution cost of waste spillage; constraint (2) denotes the maximisation of the amount of waste cleared in the planning time T; constraint (3) denotes that each smart bin is visited at least more than once; constraint (4) denotes that the vehicle can only arrive at the next smart bin after clearing a one smart bin; constraint (5) denotes that the vehicle leaves from the waste collection centre and returns to the waste collection centre; constraint (6) denotes that the time for clearing the waste must not exceed the planning period; constraint (7) denotes that the time for clearing the waste from smart bin i should be less than or equal to the time that the vehicle k is in its place; constraint (8) denotes that the vehicle's travelling distance between two smart bins must not exceed the vehicle's longest travelling distance; constraint (9) indicates that the vehicle cannot drive with insufficient power; constraint (10) indicates that the amount of rubbish in each smart bin needs to be greater than a threshold value when it is being cleaned; constraint (11) indicates that the remaining power for the electric vehicle to drive to node j is equal to the amount of power that it has left the previous node i minus the amount of power consumed by the vehicle that is required to drive from the previous node i to node j, where: the electric vehicle drives from node i to node j to node j; constraint (12) indicates that if vehicle k performs a power change at smart bin i, it must have previously visited smart bin i; and constraint (13) indicates that the vehicle departs from the car park with a full charge. Constraint (14) represents the electric vehicle power consumption equation. where EV power consumption E = P × t, According to the basic theory of vehicle dynamics, the instantaneous power of an EV is affected by several factors, mainly including vehicle speed, acceleration, road gradient as well as air resistance and rolling resistance. Constraint (15) indicates the range of values of the decision variables.

2.2. Algorithm Design

Genetic algorithm is a search and optimisation algorithm that mimics the principles of natural selection and genetics, and it has been shown to be a universally applicable method for solving path planning problems, but traditional genetic algorithms still have shortcomings, such as taking longer to converge to an acceptable solution or falling into a local optimum, as well as not being as efficient as other, more specialised algorithms. For this reason, this paper combines the greedy algorithm with the genetic algorithm, so that the speed and efficiency of the greedy algorithm can be used to conduct a fast local search, and the global search ability of the genetic algorithm to jump out of the local optimal solution, so as to select the most suitable rubbish trucks to collect and transport intelligent bins reaching the threshold by integrating the factors such as the distance, the capacity, and the electric power, so as to form the optimal dynamic paths for the collection and transportation of rubbish. The specific steps are as follows:

Step 1: Population coding: Determine the location and number of rubbish collection centres, intelligent rubbish bins and electric vehicles, as well as the distance between each point. The existing chromosome is encoded to determine the initial population size of the optimisation problem, the parameters of the algorithm termination iteration problem. In this paper, we set the initial population size ps=400 and the maximum number of iterations iter=200.

Step2: Initial population generation: make the number of iterations iter=0, use the greedy algorithm to generate part of the initial population, so that the population has a better starting path for the algorithm loop.

Step3: Selection of fitness function: calculate individual fitness by selecting fitness function.

Step4: Roulette selection:A way of selecting genes to prepare for crossover and mutation.

Step5: Crossover:Use greedy strategy for guided selection of two paths for crossover to generate sub-paths. In this paper, crossover probability pc=0.7 is chosen.

Step6: Mutation: use greedy strategy to select a certain path and optimise or rearrange it to introduce mutation. In this paper, mutation probability pm=0.1 is used.

Step7: Local search and update the population: apply the greedy algorithm to locally optimise some or all of the paths in each generation of the population, and select the next generation of the population based on the fitness of the newly generated offspring and the current population. Care is taken to maintain the diversity of the population to ensure that it does not fall into a local optimum prematurely.

Step8: Termination condition checking: check whether the preset maximum number of iterations is reached, if it is reached then output the path with the best fitness and consider fine-tuning the algorithm parameters or strategies to further optimise the solution; if not, make iter = iter+1 to go to Step3.

3. Results and Discussion

Table 2. parameterisation

Parameters	Numerical Value
vehicle capacity	$30m^3$
Trash can capacity	$5m^3$
average vehicle speed	80km/h
Vehicle battery replacement cost once	￥250
battery maximum capacity	500 kWh
fixed costs	￥1200
rolling resistance coefficient f_{rl}	0.006
air resistance coefficient f_a	1.3
Product of armature constant and magnetic flux	10.08
Motor resistancer	0.11
tire radius R	0.5
initial population size ps	400
crossover probability pc	0.7
mutation probability pm	0.1
Maximum number of iterations of genetic algorithm	200
Garbage generation speed	0.03t/s
vehicle capacity	$30m^3$
Trash can capacity	$5m^3$
average vehicle speed	80km/h
Vehicle battery replacement cost once	￥250
battery maximum capacity	500 kWh
fixed costs	￥1200
rolling resistance coefficient f_{rl}	0.006
air resistance coefficient f_a	1.3
Product of armature constant and magnetic flux	10.08
Motor resistancer	0.11

In order to verify the feasibility of the algorithm, based on the benchmark arithmetic example of the vehicle path optimisation problem constructed by Solomon, this chapter is appropriately adapted for the smart bin problem by compiling compliant small-scale and large-scale arithmetic examples, with the objective of minimising the cost of removing rubbish within the planning time T, and solving the results using an improved genetic algorithm. The basic parameters of the model and algorithm are set as shown in Table 2.

As can be seen from Table 3,for the example of this paper, the values of total cost and waste collection volume show a concave-convex trend as the waste collection threshold increases from 0.5 to 0.9. When = 0.7, the total cost and volume of rubbish collection are better. Therefore, this paper sets the rubbish collection threshold as = 0.7.

Table 3. Optimisation of threshold comparisons

ω	total costs	Quantity of rubbish collected and transported /m^3
0.5	6034.1	80.1
0.6	5967.3	93.1
0.7	5917.5	96.5
0.8	6067.5	79.1
0.9	6123.3	60.3

In the small-scale example, this paper is based on Solomon example C101 randomly selected 30 nodes, the introduction of intelligent bins in the rubbish generation rate and other dynamic information, according to the improved large-scale neighbourhood search - genetic algorithm solution results, the minimum cost of its 100 iterations of the trend of change in the various generations as shown in Figure. 1, it can be seen that the 75th iteration, a feasible solution, and its vehicle collection and transportation path as shown in Figure. 2.The required vehicles are 4.

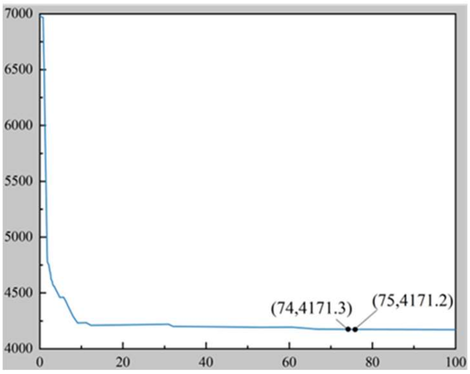

Figure 1. Minimum cost iteration trend graph for small-scale arithmetic cases

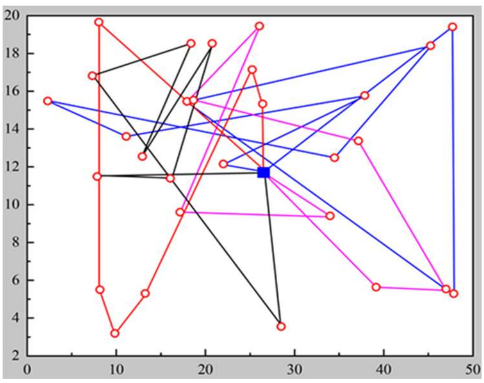

Figure 2. Small-scale example of waste collection and transport routes

The specific collection and transport routes are shown in Table 4, showing vehicle 1 [0, 4, 2, 25, 23, 26, 27, 0], vehicle 2 [0, 10, 9, 8, 28, 6, 3, 11, 22, 0], vehicle 3 [0, 20, 13, 19, 1, 21, 17, 16, 0], and vehicle 4 [0, 12, 24, 18, 15, 5, 14, 7, 0]. For vehicle operational utilisation, the lowest power consumption rate was 74.06 per cent and the highest 87.39 per cent, while capacity utilisation reached 100 per cent for one vehicle and 64.43 per cent for the lowest.

Table 4. Small-scale example of waste collection routes

Vehicle serial number	Collection and transport routes	costs	Rubbish removal /m^3	Power consumption rate %
1	0-4-2-25-23-26-27-1-0	1468.145	19.33	74.06
2	0-10-9-8-28-6-3-11-22-1-0	1500	30	82.80
3	0-20-13-19-21-17-16-1-0	1470.23	22.82	75.23
4	0-12-24-18-15-5-14-7-1-0	1479.375	24.12	87.39

In addition, in order to verify the effectiveness of the dynamic waste collection system, this paper also uses the same algorithm to solve the static collection scheme under the same conditions, i.e., without considering the smart bin collection threshold, the algorithm is run for 30 times, and finally the best result is selected, and the dynamic collection scheme of the smart waste collection system proposed in this paper improves the amount of rubbish collected by 9.3% and the total cost improves by 1.7%, as compared with the traditional static collection scheme. The total cost is improved by 1.7%. Therefore, the dynamic collection scheme designed in this paper can not only reduce the total cost of the vehicle to reduce the waste of resources and achieve low-carbon transport, but also improve the waste collection capacity and effectively reduce the harm of secondary environmental pollution due to untimely removal.

In the large-scale algorithm, this paper randomly selects 100 nodes based on Solomon's algorithm C101, assuming that the maximum capacity of the vehicle is 60m^3and the maximum capacity of the battery is 500 kWh, and other things remain unchanged. According to the improved genetic algorithm and traditional genetic algorithm solution results, its 100 iterations of the minimum cost of each generation trend comparison graph is shown in Figure 3, it can be seen that the improved algorithm converges faster relative to the traditional genetic algorithm, and the solution is better, indicating that the improved greedy-genetic algorithm works well. Its vehicle collection and transport path is shown in Figure 4, and the required vehicles are 10.

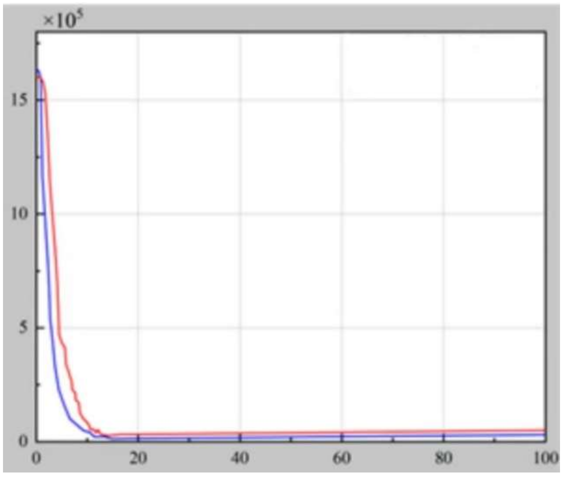

Figure 3. Comparison of algorithmic iterations for large-scale arithmetic examples

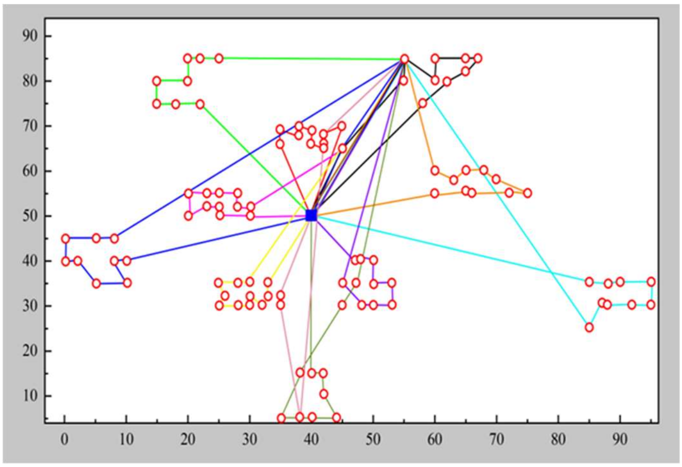

Figure 4. Large-scale example of waste collection and transport routes

Specific collection routes are shown in table 5, and for vehicle operational utilization, the electricity consumption rate was 47.12 per cent at the lowest and 74.56 per cent at the highest, and the capacity utilization rate reached 100 per cent for five vehicles at the lowest and 54.45 per cent at the lowest. Comparison of the large- and small-scale examples shows that the number of vehicles is 2.5 times that of the small-scale, the total cost is 6.3 times that of the small-scale, and the volume of rubbish removal is 5.6 times that of the small-scale, and that the indicators increased slightly after the scale was expanded, but the results of the large-scale solution led to a decrease of the average rate of electricity consumption of the vehicles by 17.5 per cent, which indicates that the effectiveness of each vehicle was highly utilized.

Table 5. Large-scale example of waste collection paths

Vehicle serial number	Collection and transport routes	costs	Rubbish removal /m^3	Power consumption rate %
1	0-67-63-62-74-65-72-61-69-64-8-1-0	3545.89	57.74	65.78
2	0-33-32-31-35-37-39-38-36-34-10-1-0	4123.86	45.71	65.56
3	0-42-44-46-45-43-48-51-50-52-3-49-47-1-0	3781.45	60	66.28
4	0-24-20-25-27-29-30-22-26-23-28-21-75-9-1-0	4012.78	60	70.56
5	0-95-96-98-94-92-97-93-6-1-0	3021.58	53.12	56.97
6	0-81-5-78-100-76-71-70-73-77-79-80-1-0	4481.53	60	63.65
7	0-57-54-7-53-56-60-59-55-68-66-1-0	4367.12	60	64.28
8	0-13-19-18-17-15-16-14-12-11-1-0	3264.82	46.27	57.84
9	0-89-87-86-83-82-84-85-88-90-91-99-1-0	4115.71	60	65.23
10	00-40-41-58-4-2-100-1-0	2834.67	32.67	47.12

4. Conclusion

With the acceleration of urbanisation, the rapid growth of urban household waste has led to a series of problems, and how waste is collected and transported has also become an important

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part of urban sanitation and environmental protection, double carbon field of concern, and its traditional mixed collection and transportation has been difficult to meet the existing problem of waste classification and collection. In this paper, a dynamic vehicle path optimisation model for smart waste collection system is investigated based on smart bins using purely electric collection vehicles with the objective of minimising the total cost. In the algorithm, a combination of greedy algorithm and genetic algorithm is proposed. The greedy algorithm selects some relatively excellent individuals as the initial population of the genetic algorithm, and guides the evolutionary genetic algorithm to conduct local search for individuals in each generation, which helps to maintain the diversity of the population and converge to the optimal solution more quickly.

Through the large and small scale solution cases and their analysis, the advantages of using smart bins and the decision-making necessity of reasonably scheduling the nearby electric vehicles with capacity, power, and proximity to collect and transport in time are verified, which not only reduces the cost of rubbish cleaning by sanitation agencies, but also improves the amount of rubbish collected and transported, and reduces the carbon emission. In addition, this paper confirms the effectiveness and efficiency of the improved algorithm, which provides a good algorithmic basis for solving the problem of waste classification and collection. Therefore, it is suggested that when local sanitation departments carry out waste classification and transportation, on the one hand, they can purchase intelligent bins and electric collection vehicles to participate in waste classification and transportation, so as to reduce carbon emissions; on the other hand, they should take the characteristics of waste collection and transportation timeliness into account, and reasonably deploy vehicles to plan routes, so as to reduce the secondary pollution caused by waste overflow. In future research, multi-vehicle collection and transportation can be considered to improve efficiency, and machine learning, reinforcement learning, etc. can be combined with the algorithm to further improve the performance of large-scale algorithm solving.

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