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Research on genetic algorithm-based car-sharing scheduling scheme

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Abstract: *Car sharing has become a popular temporary travel option. In order to develop the most beneficial car-sharing dispatching scheme for the enterprise with the aim of minimizing the cost, this paper quantifies the dispatching demand for the partial order data of car-sharing in a day, establishes a multi-traveler integer programming model with time windows and solves it using a genetic algorithm with the objective function of minimizing the dispatching cost of empty vehicles and the dispatching cost of employees. The number of vehicles and employees, as well as the vehicle dispatching paths required to minimize the joint dispatching cost of the system, are obtained. The research in this paper can provide reference for enterprise business model innovation.*

Keywords: *genetic algorithm, car sharing, car scheduling*

1. Introduction

The car-sharing industry in China started late and emerged in 2011. With the implementation of China's "mass entrepreneurship and innovation" policy, car-sharing gradually became hot and entered a rapid development stage in 2015, with a large number of investors and social capital pouring in. The number of car-sharing enterprises in China has grown further and the scope of business coverage has been expanded accordingly, and the services of enterprises have been upgraded continuously [1][2]. Car sharing in China has now been registered in several first-tier cities and is developing to second- and third-tier cities, with users mainly focusing on young people, low- and middle-income families, and those who need a car temporarily. In the car-sharing industry, although China has now kept pace with the world, car-sharing has reached a certain bottleneck in its development due to the lack of new technological innovations and the inevitable service problems in the car-sharing rental process [3][4].

In the previous research on car-sharing scheduling, China's car-sharing mainly used the staff scheduling model in solving the unbalanced allocation of vehicles [5], and secondly, to achieve the goal of minimizing the supply-demand mismatch between each node on the path, a supernetwork model was used to solve the supply-demand imbalance between the origin and destination of the car-sharing [6]. Not only that, using a hybrid incentive mechanism to promote users' active participation in dispatching [7] and bring into play the self-efficacy of participating users [8] provides a new idea to solve the car-sharing dispatching problem. Finally, adaptive scheduling cost and dynamic pricing are introduced to achieve a balance between corporate profit and user satisfaction through genetic algorithm solution, which improves the revenue and vehicle utilization of the operating company, saves cost and increases user satisfaction [9].

As the industry enters the market start-up period, the market is further shuffled and the technology is further matured, companies need to continuously explore new business models to improve their competitiveness. To this end, this paper develops the most beneficial car-sharing scheduling scheme for enterprises from a cost perspective, with a view to minimizing costs and improving their profitability. This paper considers joint scheduling optimization of shared cars, including empty car scheduling and employee scheduling between two orders. Firstly, we quantify the scheduling demand for some orders data of shared cars in a day, and build a multi-traveler integer planning model with time windows by minimizing the empty car scheduling cost and employee scheduling cost as the objective function. Then, we use a multi-traveler-based genetic algorithm to create a complex variational operator tree and solve the optimization model to obtain the number of vehicles and employees as well as the vehicle dispatch paths required for the lowest joint dispatch cost of the system. Finally, we combine the current situation of the development of car sharing and shared service economy, and propose rationalization suggestions for enterprise business model innovation from the perspective of cost reduction and profitability

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enhancement.

2. Joint scheduling of shared cars based on genetic algorithm

At present, the models for shared vehicle scheduling optimization applications mainly include network simulation models, integer programming models, 0-1 integer nonlinear programming models and bi-objective planning models. The algorithms involved mainly include exact algorithms including column generation method and dynamic planning method and heuristic algorithms represented by genetic algorithm and particle swarm algorithm. In this paper, we consider the multi-site traveler problem with time windows from the joint scheduling of shared cars, and use genetic algorithm to solve the number of shared cars required, the number of dispatchers and the joint scheduling path under the near-optimal scheme with the goal of minimizing the joint scheduling cost.

2.1 Car-sharing joint scheduling analysis

Joint scheduling of car sharing includes vehicle scheduling and staff scheduling. If the number of vehicles at a site is saturated, the number of orders at that departure station is satisfied; if there exists a site where the number of vehicles does not meet the demanded orders, additional employees need to be considered for dispatching. If you want to determine the optimal solution for the number of vehicles parked at stations in each region and the number of dispatching employees to be deployed, you need to consider joint dispatching. Although joint dispatching increases the staff cost, it also makes it possible to reduce the number and cost of vehicle dispatching for the same number of orders, thus achieving a balanced state with the lowest cost level and higher resource utilization.

Tang Jie and Cao Jinxin [10] assume four orders a,b,c,d when defining personnel scheduling and vehicle scheduling, and the orders are independent of each other. The destination and departure stations between orders a, b, c, and d are not connected, and an employee driving a vehicle from the destination station of order a to the departure station of order b means completing a vehicle dispatch. The employee does not use a shared vehicle, and the process of using a folding bicycle or public transportation to get from the starting station of order b to the destination station of order c is personnel dispatching.

2.2 Integer planning models for multiple travelers

The joint car-sharing scheduling model developed in this paper can be transformed into an integer planning model for the multi-traveler problem. Where K is the set of all orders, Q denotes the set of empty vehicle dispatching tasks, and U is the combination of all parking stations. (a,b) denotes the personnel dispatching vehicles from the destination station of order a to the departure station of order b. The decision variables of this planning model are.

$$x_{ab} = \begin{cases} 1, & Personnel\ scheduling\ exists\ between\ order\ b\ and\ order\ c \\ 0, & There\ is\ no\ empty\ vehicle\ scheduling\ between\ order\ a\ and\ order\ b \end{cases} (1)$$

If the dispatcher is required to continue the task of dispatching between orders c and d after completing the dispatch of empty cars between a and b. The process requires the employee to travel from the starting station of order b to the destination station of order c so that $y_{ab,cd} = 1$. The process requires the employee to travel from the order b origin station to the order c destination station such that $y_{ab,cd} = 1$. So another decision variable is defined.

$$y_{ab,cd} = \begin{cases} 1, & Empty\ vehicle\ scheduling\ exists\ between\ order\ a\ and\ order\ b \\ 0, & There\ is\ no\ personnel\ scheduling\ between\ order\ b\ and\ order\ c \end{cases} (2)$$

The objective function of the integer programming model in this paper is to minimize the total system cost, i.e., to minimize the sum of vehicle dispatch cost and employee dispatch cost.

$$minZ = V + S (3)$$

$$V = n_v * C_v + \sum_{(a,b)\in Q}[x_{ab} * T(D_a, O_b)] * P_v (4)$$

$$S = n_p * C_p + \sum_{(a,b)\in Q}\left[y_{ab,cd} * T(D_a, O_b)\right] * P_p (5)$$

Constraints are divided into two perspectives: vehicle scheduling and personnel scheduling.

(1) Vehicle scheduling

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Ensure that all orders are accepted and that the service.

$$\sum_{a\in K} x_{ab} = 1, b \in K(6)$$

To keep the vehicle dispatch flow constant.

$$\sum_{a\in K} x_{ab} = \sum_{a\in K} x_{ba}, b \in K(7)$$

To meet the time constraint so that the difference in time within two orders is greater than the dispatch time of the vehicle.

$$x_{ab} * [(G_a - A_a) - T(D_a, O_b)] \geq 0, a, b \in K(8)$$

The total number of vehicles is equal to the number of vehicles that completed all orders.

$$\sum_{a\in K} \sum_{r=1}^{n_v} x_{m_r,j} = n_v, b \in K(9)$$

where, O_a,D_a denote the departure site and destination site of order a, respectively.m_r denotes the departure site of the rth vehicle. G_a,A_a denote the departure time and arrival time of order a, respectively. C_v,C_p denote the daily fixed cost of each shared vehicle and the daily fixed wage of each employee, respectively. P_v denotes the unit cost of empty vehicle dispatch. $t(\alpha,\beta)$ denotes the travel time of the vehicle from $T(\alpha,\beta)$ denotes the travel time required for a vehicle to travel from site α to site β. $t(\alpha,\beta)$ denotes the time required for an employee to travel from site to site α β. n_v,n_p denote the number of vehicles and personnel required to complete all ordered tasks, respectively.

2.3 Genetic Algorithm Design

Genetic algorithm (GA) is a computational model based on natural selection and genetically motivated biological evolutionary process simulating Darwinian biological evolution, and is a method to search for optimal solutions by simulating the process of natural evolution. The genetic algorithm introduces the principle of "survival of the fittest" into the coding string population formed by the parameters to be optimized, and selects the individuals according to a certain fitness function and a series of genetic operations, so as to retain the individuals with higher fitness values and form a new population. The new population contains a large amount of information from the previous generation and introduces new individuals due to the previous generation. This cycle repeats itself, and the fitness of individuals in the population increases until certain conditions are met. The individual with the highest fitness value in the population is the optimal solution of the Dai Youhua parameter. The problem is a multi-traveler problem, and in solving it, the genetic algorithm is chosen to solve for the optimal number of vehicles and personnel needed to complete the order task in order to minimize the cost because of its high robustness and global search capability. The specific process is shown in Figure 1.

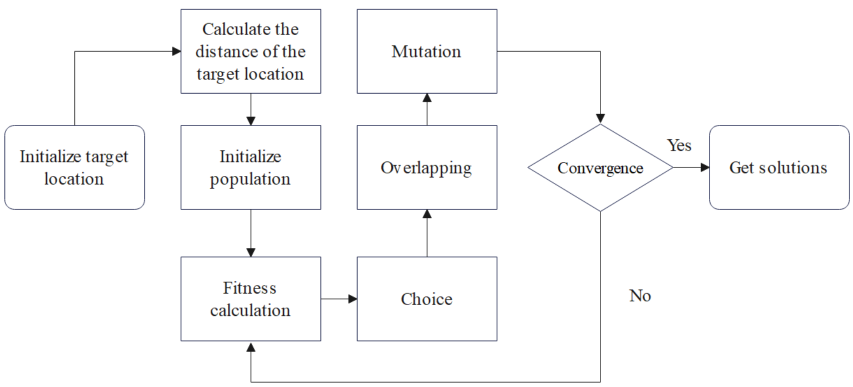

Figure 1: Genetic algorithm flow chart

(1) Coding

When using genetic algorithms to solve any kind of problem, the first step to be accomplished is the correct encoding of the chromosomes. In the case of the traveler problem, the path representation uses an arrangement of n cities, so the traditional crossover and variation operators in binary encoding in genetic algorithms cannot be applied to the traveler problem. For the order and car scheduling trajectories, a new path representation is chosen in this paper to encode multiple chromosomes. No duplicate genes can appear in the chromatic encoding of any path, i.e., each parking site is visited once.

(2) Adaptation function

The traditional traveler problem mostly uses the total time on travel or do distance as the fitness function. In this paper, we choose the cost as the adaptability function, the problem adaptability function for the total cost of the system, as the sum of the total cost of personnel and the total cost of vehicles.

The fitness function is expressed as follows:

$$f = S + V(10)$$

(3) Genetic operator

The genetic operator is an important factor affecting the search performance of genetic algorithm, which contains selection, crossover and mutation operators. In this paper, based on the actual problem analysis and related literature survey, the following four mutation operators are used to divide the mutation operator tree.

a) Path variation operator: This mutation operator is generated in one chromosome, i.e., any two gene fragments within a single chromosome are exchanged with each other without any effect on its chromosome.

b) Exchange variation operator: this mutation operator involves multiple chromosomes. Now two chromosomes within the population are arbitrarily selected, and then the sequences of randomly selected gene fragments are exchanged, i.e., the gene fragments between two chromosomes are exchanged.

c) Sliding mutation operator: transferring the last gene of a chromosome to the beginning of another chromosome.

d) Breakpoint mutation operator: the number of travelers is changed by increasing or decreasing the number of insertion breakpoints, thus changing the number of chromosome entries.

The above four simple variation operators are combined to create a variation operator tree. In this paper, we use "path variation", "exchange variation", "sliding variation", "breakpoint variation", and "path variation + breakpoint variation". "path variation + breakpoint variation", "exchange variation + breakpoint variation", "sliding variation + breakpoint variation", "path variation + exchange variation + sliding variation + breakpoint variation", and "path variation + exchange variation + sliding variation + breakpoint variation". +The structure of "sliding variation + breakpoint variation" is used to create variation trees to improve the accuracy of genetic algorithm solutions.

2.4 Path simulation

According to the public data of third- and fourth-tier cities in China as the basis for integer planning, with reference to the daily rental prices of shared cars related to platforms such as Gofun, EVCARD, and Movan Travel, most of them are in the range of 100-200 RMB/day depending on the model, so the fixed cost of shared cars is defined as 150 RMB/day in this paper. The unit cost of empty car dispatch is RMB 0.5/minute, and the unit cost of employee dispatch is RMB 0.1/minute. From national public statistics, the average monthly salary of employees in third- and fourth-tier cities in China was about 5,200 yuan in 2018, and thus the average salary of dispatchers is defined as 140 yuan/day in this paper. The details are shown in Table. 1.

Table 1: Table of Staff and Vehicle Dispatching Costs

Project	C_v	C_p	P_v	P_p
Numerical value	150RMB/day	140RMB/day	0.5RMB/min	0.1RMB/min

To further demonstrate the solution process and simulation details of the multi-traveler simulation model with time windows, this paper conducts a statistical analysis of the data within 24 h on December 30, 2018 based on the public data of the selected cities, and filters out 12 representative order messages. The station information and time information involved in the car-sharing orders are shown in Table.2.

From Table. 2, it can be seen that there are continuous car-using tasks and non-continuous car-using tasks in different order demands, and empty car movement and personnel movement only occur between non-continuous order tasks, not between continuous order tasks. At the same time, we can see that continuous order tasks are mostly continuous for two orders, and less often continuous for multiple tasks, from which we can also see that empty vehicle dispatching and personnel dispatching demands are more

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frequent, thus making it necessary to simulate their paths and optimally solve for travelers.

Table 2: Sharing automobile user demand information

Order number	Departure Place	Destination	Departure time	Arrival time	Vehicle use duration/min
1	14	13	6:57	7:26	29
2	4	1	9:10	10:02	52
3	22	4	9:58	10:52	54
4	16	15	15:25	15:59	33
5	15	21	15:59	16:30	31
6	12	10	19:27	20:01	33
7	6	9	18:25	18:50	54
8	2	11	15:13	16:07	54
9	3	7	21:53	22:20	27
10	5	7	6:38	7:47	68
11	17	18	12:01	12:39	37
12	18	20	16:57	17:24	27

2.5 Simulation model solving

The genetic algorithm for multi-traveler was solved using Python software to simulate the shared car order path through continuous iterations to derive the optimal path solution and the number of vehicles required to complete the order. In writing the algorithm program using Python, the population size was set to 50 and the number of iterations was 3000. The geographical coordinates of the stations were determined using latitude and longitude based on the data set provided nearby. In order to make the vehicle path contain all the order demand paths, all the order stations are replaced in the program with the midpoint positions of 12 order start coordinates and end coordinates. After model solving, the simulation results of the vehicle dispatch path are shown in Figure 2. According to the latitude and longitude locations of each network in Table. 2, we determine its two-dimensional coordinates, and each point on this coordinate system corresponds to the vehicle's origin and destination respectively, and the connecting line between each point represents the dispatching path of vehicles between different locations, and different colors correspond to different vehicles in Figure 2.

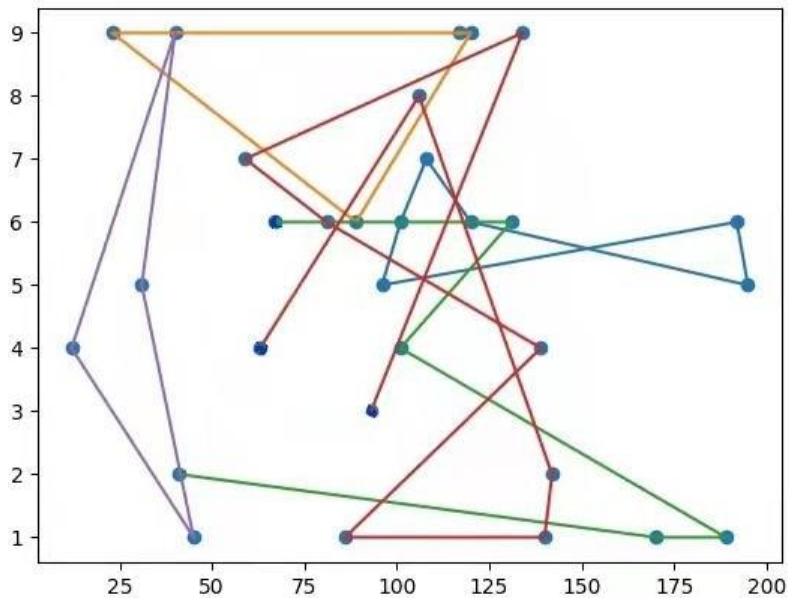

Figure 2: Empty train dispatching path

After 400 iterations, we obtained the optimal or near-optimal solution - the number of vehicles should be 5, and the corresponding total vehicle cost is $794.

And in order to make the results more considerable and representative, we selected the dispatch paths (red and green) of the two vehicles with relatively wide coverage in Figure 2 for further analysis, as shown in Figure 3, where we refer to the vehicle belonging to the red line as Vehicle 1 and the vehicle

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belonging to the green line as Vehicle 2. The solid line represents its car demand, while the dotted line represents its occurrence of vehicle dispatch.

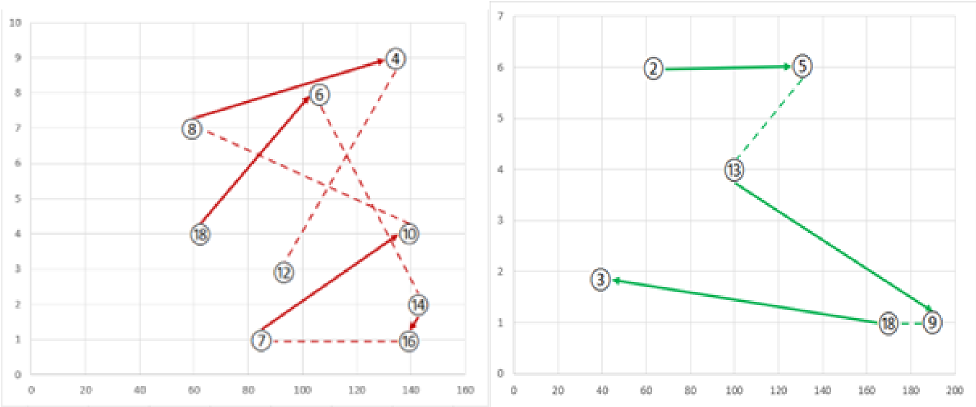

Figure 3: Sample vehicle scheduling path

From the final obtained vehicle optimization results, it can be seen that the current dispatching path of these two vehicles is the lowest cost optimization method among all their possible dispatching paths. The sequence of these two vehicles passing through different locations with the resulting information on the number of vehicle dispatches and time is shown in Table. 3, where the unit of empty vehicle dispatching time is minutes.

Table 3: Vehicle dispatching optimization data

Vehicle	Route	Number of empty train dispatching	Empty train dispatching time
Car 1	18→6→14→16→7→10→8→4→12	4	58
Car 2	2→5→13→9→18→3	2	30

3. Conclusions

In order to develop the most favorable car-sharing dispatching plan for the enterprise, with a view to minimizing the cost and improving the profitability of the enterprise, we select the car-sharing order situation in one day, take the lowest total system cost as the objective function, build a 0-1 integer programming model for the multi-traveler problem, use a multi-chromosome genetic algorithm, solve the model as well as simulate the joint dispatching path for cars and personnel, and find the number of vehicles required to satisfy the constraints for the lowest dispatching cost on the day is 5, and the lowest joint dispatching cost is $794.

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