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Vehicle Relocation Scheduling Method for Car Sharing Service System based on Markov Chain and Genetic Algorithm

Tingying Song, Tomohiro Murata

***Abstract*—As the aggravation of environment pollution, increase of the number of private cars and the development of shared economic, one-way car sharing system is a substitute for traditional two-way car system. And free-floating car sharing system is most dynamic, in which users can rent and return vehicles in different stations just by smart phone. Therefore, no reservation information and imbalance between available cars and user demand of each station is a serious problem that lead to low user satisfaction and car working rate. In this paper, we produce a scheduling method generates short-term forecasting and relocation. In forecasting, we use Markov chain model （MCM） to forecast the number of available cars in future three time-period to catch the gap between it and demand. Then make relocate scheduling based on Genetic algorithm(GA) to minimize the gap. We apply this method to the data generated by simulator, randomly generating running condition, and we can find improvement in user satisfaction rate and car working rate.**

***Index Terms*—vehicle relocation, Markov chain model, genetic algorithm, dynamic, user satisfaction**

I. Introduction

THE free-floating car sharing service system(FFCSS), most dynamic and convenient, in which users can rent vehicles in one station after search on mobile application and ensure there are available car. Arriving destination, user can return and park in the nearest station. Compare with traditional car sharing system, there are no perfect reservation information and no destination and exact arrival time. Since the lack of these user information, it is more difficult for car organization to do efficiently relocation operation.

In previews research, many authors considered this imbalance problem in minimizing cost of relocating vehicles and staff, like Mehdi Nourinejad[1](2015) proposed using two integer multi-traveling salesman formulation to do relocation. Some authors considered user satisfaction, like Maurizio[2](2014) used simulator to link the user request and car working one by one to determine the unbalance between demand and inventory, and remove cars. Some authors considered the time window between the reservation and car supply, like Alvina G. H. Kek[3](2009) proposed decision support system to reduce the number of relocation and ensure the shorter zero car time in station. However, all above researches, the solving method are all based on the same prerequisite that users' reservation has been known, and car organization have enough time to make a long-term relocation scheduling to minimize the cost or improve user satisfaction. It is the disadvantage of FFCSS, which prefer to provide more quick，convenient, and in time user experience, it receives user information some minutes early. It is difficult for organization to relocate vehicles in such short time gap to meet user demand.

In this paper, we propose a scheduling method generating forecasting and relocation, which can solve the problem of relocating cars not timely caused by incomplete information. In forecasting part, we use Markov chain model(MCM) to predict the number of available cars A_i of each station in future time period, and estimate user demand D_i of each station in each time period as the average of historical data. Minimizing the gap between the number of available cars and user demand is the object of our next relocation part. In relocation, we encode gene in FFCSS, and use Genetic algorithm(GA) to do relocation scheduling. We use a heuristic algorithm for genetic algorithms. Restriction crossover patterns to achieve more rapid convergence. Finally, we compare the result of relocation scheduling with integer programming(IP). The GA method will cost less time with the increasing of station amounts, compared with IP.

II. Methodology

A. Markov chain model(MCM)

A Markov chain is a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event.

$$P(X_{n+1}=x|X_1=x_1,X_2=x_2,\ldots,X_n=x_n)= P(X_{n+1}=x_{n+1}|X_n=x_n)$$

In this car sharing system, car driven from on station to another station and it just depends on the last station, and it can be considered as a Markov process. In this model, each car station represents the state in MCM, and the transition probability is the proportion of vehicle driving out from this station to the total number of vehicles of this station in a certain time period. When the car system be in a stable condition, each state has station distribution of while system, which only associate with the transition probability matrix P. A stationary distribution π is a vector, whose entries are non-negative and sum to 1, is unchanged by the operation of

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transition matrix P on it and so is defined by $\pi P=\pi$.

We use the Markov chain model to forecast the running state (amount of vehicle usage) of each station in FFCSS. Compare with other method of time series forecasting, Markov chain do not need a large data support, and fast. The model can both reflect the growth trend and random properties of fluctuations in the time series.

B. Genetic algorithm(GA)

Genetic algorithm(GA) is a search-based optimization technique based on the principles of genetics and natural selection. It is frequently used to find optimal or near-optimal solutions to difficult problem which will take long time to solve. In our problem, we define each chromosome on behalf of a staff. And a DNA is defined as relocation scheduling, composed by multiple staff scheduling sheet. The gene includes three staff information, time period, the way to the next station and station number. Car sharing system runs from 8 am. to 8 pm. one day, twelve times periods, from T1 to T12. The traffic way to the next station is divided into three kinds, a1 is that staff rides bicycle or public transport to remove themselves; a2 is that staff drives a vehicle to relocate it; and a3 is that the staff is in the middle of the moving or stay at station without task.

We defined the adaptive function as the demand accuracy

$$f(x) = \frac{1}{\sum_i(\frac{|D_i - A_i|}{D_i})}$$

There are three genetic operations. First, elitist selection, in which a certain percentage of highly fit parent gene individuals into next genetic operation. Second, heuristic crossover, in which we crossover a while chromosome randomly, means change a staff relocation scheduling. We set the probability of crossover is Pc. Finally, mutation, in which we mutate a single chromosome fragment, and the probability is Pm. And ensure the quantity of new population is same to old population.

III. Proposed Method

In this paper, we proposed a structure to forecast vehicles usage and to relocate vehicles in FFCSS, in Fig 1. This system contains two parts, forecasting parts and relocation scheduling parts.

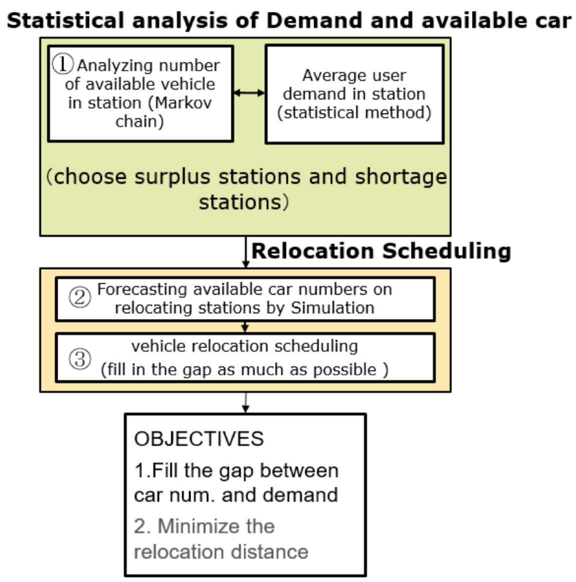

Fig 1. The structure of forecasting and relocation scheduling system.

In the first step, we analyze the number of available vehicle in station using Markov chain method. And estimate the average user demand of each station using past running record. We can evaluate the gap between two parts of data. It also means we evaluate the lack between supply and demand in FFCSS. At the end of this step, we will choose surplus stations and shortage stations. The surplus stations will supply the vehicle, and shortage stations will get the vehicle in relocation part.

The second step is forecasting available car number on relocating station by simulation. In this part, we will do prediction for each 3 hours. We think the short window time series forecasting will have a high accuracy. There are two reasons that we choose 3 hours to our forecasting window. It means we run the FFCSS 12 hours a day, we will finish 10 times forecasting. The first is if the forecasting window is too small, the car relocation will become hard (consider the running time error, the vehicle relocation might be unsuccessful). Another reason is long time forecasting window also means long distance relocation. It will due to waste during relocation, and increase the cost of FFCSS. In our system, we specify that only shortage station will be relocated by surplus station during the relocation scheduling.

The third step of our car relocation system is vehicle relocation scheduling. We aim to find a relocation schedule to meet the user demand as much as possible. Consider the time cost of IP, we determine using GA to do relocation schedule.

A. Forecasting available vehicle in station

At the first, we define $P_{a_{ij}}$ (probability of car driving from station i to station j in time period t).

$$P_{a_{ij}} = \begin{bmatrix} p_{11} & \cdots & p_{i1} \\ \vdots & \cdots & \vdots \\ p_{1j} & \cdots & p_{ij} \end{bmatrix}$$

According the $P_{a_{ij}}$, we equilibrium distribution of each station.

$$\pi = \pi * P, (\Sigma\pi_i = 1)$$

π is the stationary distribution of a Markov chain, it means π is the predicted vehicle number of each station.

We choose using the historical movement data to calculate the $P_{a_{ij}}$ of our forecasting system. As we have a historical movement data T in past several days, The $P_{a_{ij}}$ will be calculate as follow,

$$p_{ij-t} = \frac{\sum_{day1}^{daym} N_{ij-t}}{\sum_{day1}^{daym} \sum_{j\in s} N_{ij-t}}$$

B. Choose the surplus station and shortage stations

To reduce the computational complexity, we will do 3 times long term forecast (compared with 3-hours forecast) in one day. We will select the surplus stations and shortage stations, according three times forecasting. The surplus stations mean the station which demand is large then the predicted. The shortage stations mean the station which demand is short then the predicted.

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C. Forecasting relocated car number

In this step, we will use Markov chain to forecast vehicle number in each station in every hour. Each forecast will contain 3 hours' data. For example, the first forecasting will forecast 2,3,4 hour vehicle number.

we can forecast the necessary relocated vehicle number in each station.

$$N_{RelocatedCar} = N_{demand} - N_{predicted}$$

$N_{RelocatedCar}$ is the necessary relocated vehicle number in each station. N_{demand} is the vehicle demand number in each station. $N_{predicted}$ is the predicted vehicle number by Markov chain of each station.

D. Vehicle relocation scheduling using GA

In our system, we proposed using genetic algorithms to make the relocation schedule after getting necessary relocated car number. We encode the relocation schedule to the chromosomal by heuristic, as in Fig 2.

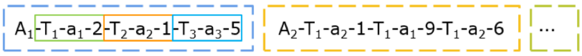

Fig 2. The structure of chromosomal in genetic algorithm.

Following, we define parameters in the structure. A_k : staff numbering, the head information of gene fragment. a_i is the way to the next station. a_1, bicycle or public transport to remove themselves; a_2, driving a vehicle to relocate it; a_3, in the middle of the moving or stay at station without task. j : the number of next arriving station. T_n : time series, relocation vehicle scheduling in one day has ? time periods.

We use the fitness to measure for discriminating good solutions from bad ones has been chosen. Use the adaptive function to evaluate the fitness of individual in the population.

$$f(x) = \frac{1}{\sum_i(\frac{|D_i - A_i|}{D_i})}$$

We can start to evolve solutions to the search problem using the following steps:

Selection: For each loop of genetic algorithms, the best 20% of individual will be selected in next generation.

Crossover: heuristic genetic crossover and the probability of crossover is P_c. The crossover way shows in Fig 3.

Mutation: single gene fragment mutation, and the probability is P_m. The mutation method shows in Fig 4.

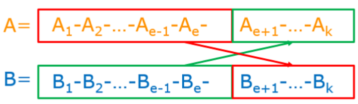

Fig 3. The crossover operation in chromosomal in genetic algorithm.

Elimination: For each loop of genetic algorithms, we will eliminate the worst 20% of individual in population.

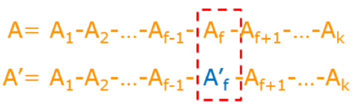

Fig 4. The mutation operation in chromosomal in genetic algorithm.

After the several steps operation, to maintain biological diversity, we will random add 20% randomly generated new individuals. To maintain the size of the population, we will control the size of the population, to keep the time cost of genetic algorithms.

In the genetic algorithm we will use random probability of crossover and mutation. In the begin of generation process, the probability will be random change in a small range. And the change probability will be large. In the end of generation process, the probability change probability will become small. On the other word, at the beginning of genetic algorithms, the change of crossover and mutation frequent. This operation will avoid our method falling into local optimality as much as possible.

IV. EXPERIMENT

To evaluate the effectiveness of system, our experiment will use hypothesis data generated by a data simulator, which simulate the system performance. The generate rule is showed in following.

The rule of simulator

I. Generate the number of station N.
II. Define the distance between each station as d_n .
III. Generate the vehicle number at each station qn, 0 ≤qn ≤ capacity.
IV. Generate the probability of running between each station.
V. Generate the running time factor between each station as k, depending on weather, traffic condition and other influence factors. Running time = dn/(k*speed).
VI. Generate the set of users as U.
VII. Generate system data in a whole day.

In our experiment, we generation 100 days of historical data:

a. Historical data: 100 days of operation data.
b. Map: 7200m *7200m.
c. The number of stations: 30.
d. Detection time point: 12, T0 ~T11, each time lag is 1h.
e. Total number of car: 100.
f. Station level: level-1, stations with small passenger flow on the edge of city; level-2, stations with medium passenger flow; level-3, stations with large passenger flow.

We to compare with other method on time series forecasting, we choice the compare with recurrent neural networks. Compare with the recurrent neural networks, the interpretability of Markov chain is better than the RNN. And the predictive stability of the Markov chain is also better, show in Fig 5 and Fig 6.

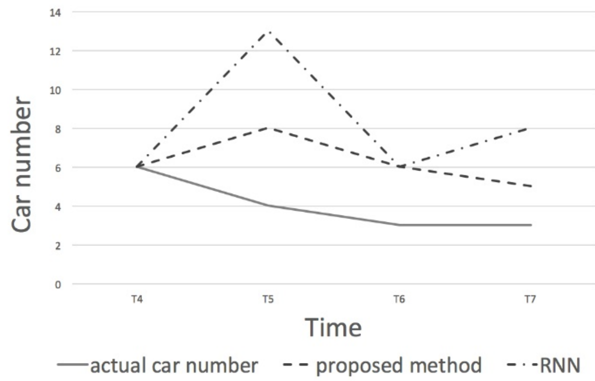

Fig 5. Compare the number of available car of real condition, forecasting by MCM and by RNN from T5 to T7.

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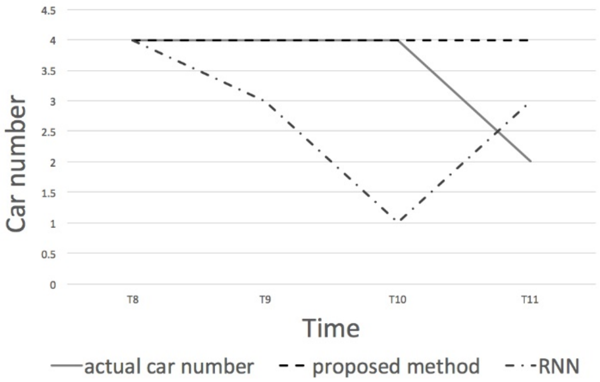

Fig 6. Compare the number of available car of real condition, forecasting by MCM and by RNN from T9 to T11.

And according the Fig.4 and Fig.5. The line of forecasting car number using Markov chain is much closer to the real number of cars in all time points. The mean square error(MSE) of MCM is 7, and MSE of RNN is 7.962. Forecasting by Markov chain can correctly predict the trend of quantity, and RNN will provide some value with high deviation.

To evaluate effectiveness of proposed GA optimizer for car relocation. The Table I show the accuracy before relocating and after relocating. The third point of time satisfaction has been fully improved cause of the scheduling. We do IP solver in same cases and find the average of fulfillment ratio is 94.73%, and our proposed method performs 99.07% optimality than IP global optimistic.

Table I. Fulfill ratio of station before relocation and after relocation

	Case 1		Case 2	
	No relocate	Relocate	No relocate	Relocate
Time1	93.70%	93.70%	95.13%	95.13%
Time2	94.69%	97.35%	90.12%	97.94%
Time3	93,83%	98.35	81.86%	88.61%
	Case 3		Case 4	
	No relocate	Relocate	No relocate	Relocate
Time 1	90.71%	90.71%	89.30%	89.30%
Time 2	89.71%	96.71%	85.23%	90.72%
Time 3	91.98%	98.73%	80.97%	88.94%

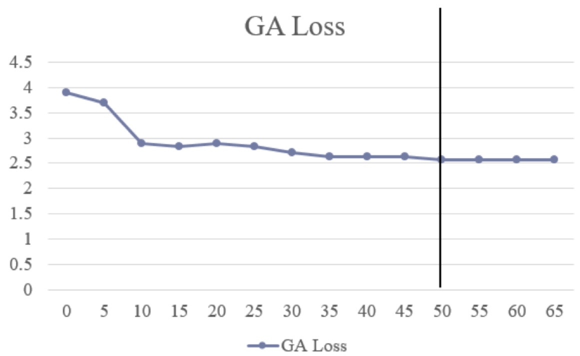

Fig 7. GA loss reduction. X-axis means the loop of GA. Y-axis means the value of loss.

Fig 7 shows the loss of each 5 loop in GA, the model converge is near loss-2.5. For each loop, it will cost 0.005s for 30 stations. And it will cost 0.025 for 300 stations situation. The time cost of the algorithm is reasonable. After the relocate, we can see the loss is not close to zero. The gap between available car and demand is not made up. In our model, the number of car is not meet the user demand, maybe we should input more cars.

V. Conclusion

Our research aims to find a good method to improve the utilization of vehicles in FFCSS. The high utilization of vehicles means low average cost and increase the user satisfaction. The system will useful to the FFCSS company. According the experiment, the relocation schedule using genetic algorithm could fully improve satisfaction of users. In most part of case, the improvement will increase more than 5% satisfaction. The time cost of 300 stations relocation is less than 1 minute. The method could successful use in a common computer.

For future work, for large data and much information get from the running data. The generalization performance of Markov chain is not good enough. HMM, RNN, LSTM-RNN could be try in the case of more real data. For car relocation, how to find a great balance point between cost and satisfaction is still a break point in the related field.

Acknowledgment

Tingying Song proposed the structure of our relocating scheduling method and implemented it, and conducted experiments to evaluate its effectiveness and optimality. Tomohiro Murata revised the paper, and gave many advices and guidance on this research process.

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