How Scheduling Advances Affect Critical Mass and Fleeting in Smartphone-Based Vanpooling

Donghui Li
Department of Industrial Engineering
Tsinghua University

Constantinos Antoniou
Department of Civil, Geo and Environmental Engineering
Technical University of Munich

Hai Jiang
Department of Industrial Engineering
Tsinghua University
Email: haijiang@tsinghua.edu.cu

Wei Shen
Asia Pacific Research
Ford Motor Company

Liang Zhang
Asia Pacific Research
Ford Motor Company

Weijian Han
Research and Advanced Engineering
Ford Motor Company

1 Introduction

Smartphone-based vanpool services have become an emerging trend, which has attracted much attention in the research field [1, 2]. In smartphone-based vanpool services, passengers request vans from their smartphones for point-to-point pickups and deliveries, and vans are dynamically routed to passengers with committed pickup and delivery times. However, sharing vans and the dynamic nature of this service mode increases the difficulty of deploying and operating vanpool services. There are many interesting research topics related to vanpool services, some researchers focus on the daily planning for vanpool services, such as designed efficient scheduling algorithm, and some researchers focus on long term planning for dynamic vanpool services, such as how to decide the optimal fleet size for a service area, the minimum density of demand to support a vanpool services (i.e., the critical mass). This research focuses on the long term planning.

We found that most studies related to long term planning of dynamic vanpool services only consider simple scheduling methods. The existing studies can be summarized into two categories. The first category use simulation based method to model the operation of transportation system [3, 4, 5, 6]. In these research, the historical distribution of requests are usually used as the input. However, these studies use simple heuristics for scheduling. They do not use future information and do not consider the capacity of vans. The second category use approximate mathematical method[7, 8], since we usually do not have detailed information [8]. These studies usually assume the requests is from a simple distribution, such as uniform distribution. Similarly, only simple heuristics are considered in these studies.

From the existing studies related to daily planning of dynamic vanpool services [9, 10, 11, 12], there are some scheduling algorithms with advanced features which can improve scheduling performance. In recent studies [13, 14, 15], there are advanced scheduling algorithms which considers future information and prepositioning and it is found that these advanced features can improve the scheduling performance. These scheduling advances create complexity in deployment and have their associated requirements on input data. It is therefore of interest to quantify the impact of these scheduling advances in long term planning.

In this research, we test scheduling algorithms with advanced features under different settings. We compare the LOS metrics with or without looking-ahead and prepositioning to measure the impact of scheduling advances. We also test the LOS metrics under different fleeting settings to get the response surfaces of LOS metrics (rejection, waiting time, excess time) vs fleet size (number and capacity of vans). We then try to fit the surface and get an approximate function to represent the relationship between LOS metrics and fleet size. With this function, we can build a generalized profit function to balance the operating profit and the user experience. To test whether our proposed method can be used for different service area, we run a series of sensitivity tests by mutating the demand data and road network. From these tests, we found that the proposed method can be used for requests with different patterns. The test results also indicate some noteworthy characteristics of our real-world request datasets.

We summarize the contributions of this research as follows:

- Different algorithm features and fleet size are tested to measure the impact of scheduling advances, we also use functions to fit the relationship between LOS metrics and fleet size;

- According to the relationship between LOS metrics and fleet size, we build a model to predict the critical mass of given area and a fleet planning model considering both operating profit and user experience; and

- By mutating the characteristics of request data, we find that the dataset have specific spatial pattern, and the proposed method can be applied to new areas with different demand patterns.

2 Research framework

In smartphone-based vanpool services, the service providers use several vans to provide transportation services for passengers within a service area. They have a smartphone app for passengers to send requests. Each request usually has a pickup location, a delivery location, and expected pickup time. They also have a smartphone app for drivers to receive scheduled routes and locations of requests.

There are several key factors in vanpool services. In this research, we focus on the interaction among the demand pattern, fleet size, and level of service (LOS) metrics when using scheduling algorithms with advanced features. The demand pattern represents the characteristics of request data, such as, the spatial and temporal distribution of requests, and the density of requests. The demand density is the major factors which influence the load of services. And for a specific density, if the spatial and temporal distribution of requests change, the service performance may also change. The fleet size means the number and capacity of vans. Existing studies usually consider the number of vans but ignore the capacity of vans. However, both of them can influence the scheduling performance and the fleet cost. The level of service includes three aspects. The rejection ratio which is the fraction of rejected requests in all received requests. The waiting time measures how long each passenger waits before being picked. The excess ride time ratio which is the fraction of excess ride time in direct ride time by taxi or private car.

The goal of this research focus on the long term planning of vanpool services. When we plan to enter a new market, we may get the request data of the new area. We need to determine whether the market can support a vanpool service and how to determine the best fleet size for this market. We would like to know how the advanced features of the scheduling algorithm can save cost or improve user experience. We also want to know whether the proposed method can be used on different areas with different characteristics, since we use simulation based method on historical data to build and test the proposed model.

The core idea of this research is response surface method from simulation based optimization. When using advanced scheduling methods, it is difficult to get a closed form relationship between scheduling performance with fleet size. To build a fleet size model, we can run simulation tests on different fleet size, which includes the number of vans m and the capacity of each van Q. From the simulation result, we can get the response surface of LOS metrics against the fleet size. We can fit the response surface and get the average rejection rate $AR(Q, m)$, the average waiting time $AW(Q, m)$, and the average excess ride time ratio $AE(Q, m)$.

After fit the response surface, we can build a generalized profit function. This function includes both operation profit and user experience. Assume the average number of daily requests is p, the average revenue per request is r, the value of waiting time per minute is v, the excess ride time ratio penalty is e, and the daily cost of fleet is $C(Q, m)$. We have the generalized daily profit as

$$f(Q, m) = p[1 - AR(Q, m)][r - vAW(Q, m) - eAE(Q, m)] - C(Q, m),$$

where $p[1 - AR(Q, m)]$ is the number of passengers served and $[r - vAW(Q, m) - eAE(Q, m)]$ is the revenue per request minus the value of waiting time per request and the penalty of excess ride time. Then we can use this function to find the optimal fleet size which can optimize the generalized profit.

To find the critical mass, we need to include the demand density in our function. Since we only have a dataset with a specific demand density. We use a simple method to create data with different density. We combine the requests from k consecutive days and treat them as requests in one day. With this method, we can get datasets with k times density as the original dataset. Similarly, we run simulation under these settings to get the level of service metrics and get the average rejection rate $AR(Q, m, k)$, the average waiting time $AW(Q, m, k)$, and the average excess ride time ratio $AE(Q, m, k)$. Then generalized profit function can be modified to

$$f(Q, m, k) = kp[1 - AR(Q, m, k)][r - vAW(Q, m, k) - eAE(Q, m, k)] - C(Q, m),$$

where $kp[1 - AR(Q, m, k)]$ is the number of passengers served and $[r - vAW(Q, m, k) - eAE(Q, m, k)]$ is the revenue per request considering the user experience.

In existing studies about scheduling algorithms, it is found that the advanced features of scheduling algorithm, such as looking-ahead and prepositioning, can improve the scheduling performance a lot. In this research, we would like to measure the impact of these advanced features under different settings. Thus for the simulation tests, we set up three groups to inspect the benefit of these advanced features: Group 1, deterministic, we set the horizon of scenarios to zero, which means we do not consider future requests; Group 2, stochastic, we use normal horizon of scenarios and only consider dispatching vans to received requests; and Group 3, prepositioning, we use normal horizon of scenarios and consider sending the vans to locations with potential requests.

3 Conclusions

In this research, we test the impacts of advanced features in dynamic vanpool service scheduling algorithms. We find that the tested advanced features, such as looking-ahead and prepositioning, can improve level of service metrics. We propose a methods to derive the optimal fleet size and critical mass of given service areas by fitting the response surfaces and building a generalized profit function. We use operation settings to validate the proposed model and find that the advanced features can help to improve the generalized profit. It may be not profitable to run a dynamic vanpool service without these advanced features. Sensitivity tests are also performed to test whether proposed methods can be used in service areas with different demand patters and road networks.

References

[1] M Grazia Speranza. Trends in transportation and logistics. *European Journal of Operational Research*, 264(3):830–836, 2018.

[2] Sin C Ho, WY Szeto, Yong-Hong Kuo, Janny MY Leung, Matthew Petering, and Terence WH Tou. A survey of dial-a-ride problems: Literature review and recent developments. *Transportation Research Part B: Methodological*, 2018.

[3] Luca Quadrifoglio, Maged M. Dessouky, and Fernando Ordez. A simulation study of demand responsive transit system design. *Transportation Research Part A: Policy and Practice*, 42(4):718–737, May 2008.

[4] An Neven, Kris Braekers, Katrien Declercq, Geert Wets, Davy Janssens, and Tom Bellemans. Assessing the impact of different policy decisions on the resource requirements of a Demand Responsive Transport system for persons with disabilities. *Transport Policy*, 44:48–57, November 2015.

[5] Daniel J. Fagnant and Kara M. Kockelman. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. *Transportation*, 45(1):143–158, August 2016.

[6] Nikola Marković, Myungseob Edward Kim, and Paul Schonfeld. Statistical and machine learning approach for planning dial-a-ride systems. *Transportation Research Part A: Policy and Practice*, 89:41–55, 2016.

[7] Marco Diana, Maged M. Dessouky, and Nan Xia. A model for the fleet sizing of demand responsive transportation services with time windows. *Transportation Research Part B: Methodological*, 40(8):651–666, September 2006.

[8] Mahyar Amirgholy and Eric J. Gonzales. Demand responsive transit systems with time-dependent demand: User equilibrium, system optimum, and management strategy. *Transportation Research Part B: Methodological*, 92:234–252, October 2016.

[9] Jean-François Cordeau and Gilbert Laporte. A tabu search heuristic for the static multi-vehicle dial-a-ride problem. *Transportation Research Part B: Methodological*, 37(6):579–594, 2003.

[10] Sophie N Parragh and Verena Schmid. Hybrid column generation and large neighborhood search for the dial-a-ride problem. *Computers & Operations Research*, 40(1):490–497, 2013.

[11] Ulrike Ritzinger, Jakob Puchinger, and Richard F Hartl. Dynamic programming based metaheuristics for the dial-a-ride problem. *Annals of Operations Research*, 236(2):341–358, 2016.

[12] Gerardo Berbeglia, Jean-François Cordeau, and Gilbert Laporte. A hybrid tabu search and constraint programming algorithm for the dynamic dial-a-ride problem. *INFORMS Journal on Computing*, 24(3):343–355, 2012.

[13] Michael Schilde, Karl F Doerner, and Richard F Hartl. Metaheuristics for the dynamic stochastic dial-a-ride problem with expected return transports. *Computers & Operations Research*, 38(12):1719–1730, 2011.

[14] Michael Schilde, Karl F Doerner, and Richard F Hartl. Integrating stochastic time-dependent travel speed in solution methods for the dynamic dial-a-ride problem. *European Journal of Operational Research*, 238(1):18–30, 2014.

[15] Li Donghui, Antoniou Constantinos, Jiang Hai, Xie Qianyan, Shen Wei, and Han Weijian. The value of prepositioning in smartphone-based vanpool services under stochastic requests and time-dependent travel times. *Transportation Research Record*, 2019.