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Network performance under different levels of ride-sharing: A simulation study

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1 Introduction

In recent years, intelligent transportation systems made it possible for operators to adapt in real-time the transportation supply to travel demand via new mobility services. Among these services, ride-sharing is becoming popular. Ride-sharing is a transportation mode in which passengers can share a car and travel costs. Dynamic ride-sharing refers to a system which supports an automatic ride-matching process between participants on very short notice or even en-route [1]. The dynamic ride-sharing problem involves two subproblems: 1) How to serve the upcoming trips (optimal fleet management) - 2) How to accurately predict the travel times to determine vehicles availability and pick up/drop off times.

The first subproblem is complex and has attracted a great number of research proposals ([2, 3, 4]). Following this track of research, we express the optimal fleet management problem as a constrained multi objective integer linear programming.

The second subproblem is less studied in the literature but is very important for real field operations. Network congestion can have significant impacts on the ride-sharing service. The optimization system of the ride-sharing service uses estimates for the predicted travel time coming from a "prediction model". When the rides are realized, a gap can exist between the estimation and the real traffic condition, that is represented by the "plant model". This gap may require dynamic adjustment of the initial assignment to fit with the observed conditions. When simulating a dynamic ride-sharing service, it is important to properly distinguish the prediction and the plant

model to propose a realistic solver.

In most of the researches, the plant model and the prediction model are the same [4, 5]. However, there are some researches that consider dynamic traffic conditions on ride-sharing. Goel et al. [4] consider an overhead randomly chosen of 10-20 percent to reflect different traffic conditions when computing the end time for a driver in their proposed approach. Nevertheless, They just use the prediction model and assume that the travel times used in the assignment process stay the same during the execution of the vehicle schedules. In some researches, only the plant model is considered. They use a simulator to assess the dynamic ride-sharing but it is not the optimal matching [5, 6, 7]. Other works use only static travel times in the optimization process [8].

In this paper, we define the plant model besides the prediction model to assess the impact of traffic conditions on the dynamic ride-sharing system performance for large-scale problems. The considered prediction model is based on the last observed travel times, while the considered plant model is a trip-based Macroscopic Fundamental Diagram (MFD) model which is able to reproduce the time evolution of mean traffic conditions for a full road network using the MFD as a global behavioral curve [9, 10]. In this paper, for a given urban network, we are going to compare the reference situation where all trips are done with personal cars with a situation where a fraction of the trips (market-share: 20%,60% and 100%) are served by a fleet of vehicles with different levels of maximum sharing (1,2,3) for all passengers.

2 Methodology

Our system has two main parts. The fleet management part works to assign the optimized match of riders to the vehicles. Then the simulation part executes the optimal car schedule while considering the complete dynamic traffic conditions.

We have defined an algorithm to find the optimized schedule for the shared cars. The algorithm solves a constrained optimization problem to minimize the total travel time and distance for vehicles and the total travel time and waiting time for passengers. The constraint functions in the problem are on capacity, time window, number of sharing (a number defined by the passengers to show their willingness to share their ride) and the quality of service. Let us to recall here that the optimization problem is solved with predicted travel time but then the simulation of the vehicle operation is matched with another model with a more refined description of the system dynamics.

To solve the optimization problem efficiently, we could refer to heuristic methods but we notice that a proper exploitation of the constraints can help to narrow the search of feasible solutions even if the size of the space is very large. This is why we design our own solution method based on the classical branch and bound algorithm but with specific properties to fit with fleet management problem.

A simulation platform is used as the plant model to simulate the function of both shared and personal cars. This simulator should be able to simulate the time evolution of traffic flows on the road network. In this research, we use the trip-based MFD to accommodate individual trips while keeping a very simple description of traffic dynamics. The general principle of this approach is to derive the inflow and outflow curves noting that the travel distance L by a driver entering at time $t - T(t)$ when $n(t)$ is the number of en-route vehicles at time t and the mean speed of travelers is $V(n(t))$ at every time t , should satisfy the following equation:

$$L = \int_{t-T(t)}^t V(n(s))ds \quad (1)$$

At each time step, the simulator computes the current speed of the cars considering the current traffic situation (the number of en-route vehicles). Then the vehicle can cover a distance based on the current speed, every time step (10 seconds). So the state of en-route cars is updated every 10 seconds in our simulation. To make travel time prediction for the optimization part, In our prediction model, we predict the traffic situation for the next assignment time horizon (every 10 minutes) and we assign the passengers to the cars based on this prediction.

3 Numerical experiments

In the proposed research, we use a realistic O-D trip matrix for the city of Lyon in France. The network is loaded with travelers of all ODs with given departure time in order to represent 4 hours of the network with more than 62000 requests based on the study of [11]. 23 different scenarios are defined with number of sharing 0,1,2 and 3 (Number of sharing 0 means that the car serves just one passenger without sharing like traditional taxi services, number of sharing 1 means that it is possible to share the passengers trip with 1 other passenger and so on), market shares 20%,60% and 100% (Only the trips that are fully inside the studied area are considered as candidates for the service. So the market share of 100% corresponds to 22% of all trips), two intervals for pick up and drop off time window (5 minutes and 10 minutes). Here, we put a part of results to show the system performance. Figure 2 shows the accumulation of cars in the network for different market shares when there is no sharing (like traditional taxi services). As the market share increases, the travel distance increases so the accumulation of cars moving in the system increases. In other words, the traffic conditions are deteriorated if we replace all the internal personal trips with service trips because idle vehicles are adding extra travel distances between two trips to be served.

Table 1 shows the cars travel time and number of cars for different numbers of sharing when the market share is 20 percent comparing with the case that all the trips are done with personal cars. Results show that with sharing, the number of cars and total travel time is less than the case without sharing or even the case with zero market rate.

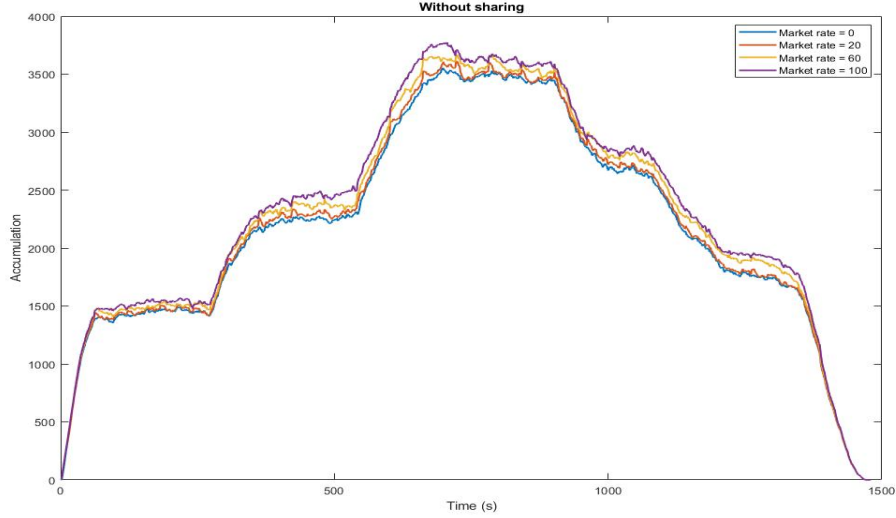


Figure 1: Cars accumulation for different market shares

Table 1: Simulations results for market-share = 20%

Sharing properties		Simulation results					
Market rate	Number of sharing	Total travel time for shared cars (s)	Total travel time for personal cars (s)	Total travel time for all cars	Number of shared cars	Number of personal cars	Total number of cars
0	0	0	38723249	38723249	0	62450	62450
20	0	1092250	37827210	38919460	2113	60214	62327
	1	993790	37749480	38743270	1184	60214	61398
	2	975050	37744950	38720000	992	60214	61206
	3	962170	37721130	38683300	929	60214	61143

When 20 percent of internal trips are served with service cars without any sharing, the number of needed service cars is 2113 and the total travel time for shared trips is 1092250 seconds. But then with sharing the ride between just two travelers, the number of needed cars decreases to 1184 and the total travel time is 993790. It means that with almost half number of cars, the travel time is 98460 seconds less than before. With applying more sharing, the number of needed cars and the total travel time decrease then for number of sharing 2 and 3, our proposed ride-sharing system works even better than the situation that all the trips are done with personal cars. It should be mentioned that the increase in passengers travel time and waiting time is negligible compared to the service improvements in our results.

In future researches, we will implement our system on larger networks with more number of trips. We will improve the optimization algorithm introducing spatial clustering on the network. Also we try to switch the plant model to a more refined one. Sensitivity analysis can be done on the system setting characteristics to select proper values based on the network and demand size.

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