Real-time ride-sharing systems performance considering network congestion

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Extended abstract submitted for presentation at the hEART 2019 7th Symposium
Sept. 4–6, 2019, Budapest, Hungary

Word count:
2383 words (excluding the references)
February 27, 2019

Extended abstract

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 (Agatz *et al.*, 2012). The dynamic ride-sharing problem involves two sub-problems: 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 sub-problem is complex and has attracted a great number of research proposals (Ota *et al.*, 2017, Qian *et al.*, 2017, Goel *et al.*, 2017). Following this track of research, we express the optimal fleet management problem as a constrained multi objective integer linear programming.

Many of the researches try to find the near-optimal solution to the matching problem in ride-sharing systems considering some specific constraints like the vehicles capacity or the time window, to minimize the total additional distance (Ota *et al.*, 2017, Qian *et al.*, 2017, d'Orey & Ferreira, 2014) or to maximize the matching between vehicles and passengers (Stiglic *et al.*, 2016, Ma *et al.*, 2013, Goel *et al.*, 2017). They usually rank the possible feasible matches for closed passengers and cars based on the objective function and then choose the best match for the requests. Hyland & Mahmassani (2018) assign the passenger to the vehicle only if the vehicle is 20% closer than any idle shared vehicle to the passenger. The assignment problem is solved with different heuristic methods in the literature. Herbawi & Weber (2012b) use a genetic algorithm to find a sub-optimal solution for the ride-matching problem and then an insertion heuristic answers the newly received offer or request by modifying the solution of genetic algorithm when possible. In our research, our aim is to find the global optimal solution for the ride-sharing problem without uncertainty in demand to have a vision of these services performance in optimal situation. Then we can compare the results and experiments with the exact optimal condition. We have designed an algorithm to find the exact solution for matching problem based on the branch and bound algorithm.

The second sub-problem 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 (Goel *et al.*, 2017, Ma *et al.*, 2015). However, there are some researches that consider dynamic traffic conditions on ride-sharing. Goel *et al.* (2017) 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 (Linares *et al.*, 2016, Ma *et al.*, 2015, Jia *et al.*, 2017). Other works use only static travel times in the optimization process (Herbawi & Weber, 2012a).

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 (Lamotte & Geroliminis, 2016, Mariotte *et al.*, 2017). 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.

Optimization problem design for dynamic ride-sharing

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. The main components of the system are shown in figure 1.

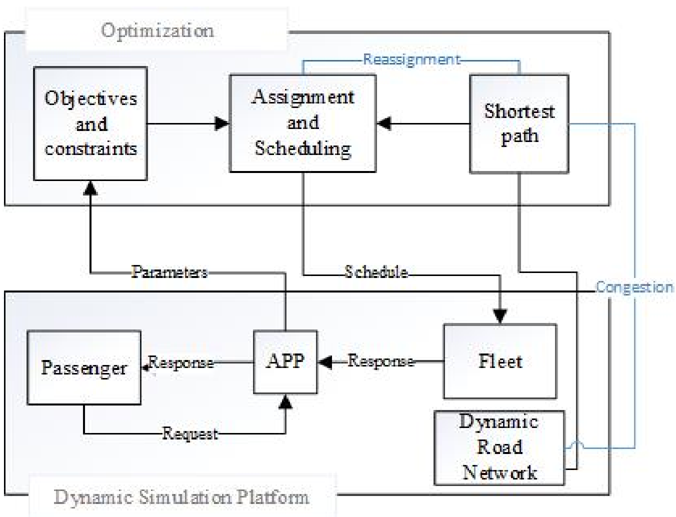

FIG. 1 – *System components*

In our problem, a system of cars works to serve the passengers that desire to share their trip with other passengers. We have defined an algorithm to find the optimal 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. The optimized solution for the model will be sent as the schedule to the fleet. Then the assigned cars leave their location or take a detour to serve the new demands.

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. First, we solve the matching problem with the first part of our algorithm which is described in the next paragraph, with all the demand. Then we can have the optimal situation for ride-sharing system performance. Then to assess the system in real-time we optimize the matching in rolling horizon.

The algorithm performs in two parts. In the beginning, when there is no en-route vehicle, the first part of the algorithm builds a tree of routes and tries to add feasible points to the best branch of the tree at each step. The feasibility of points is checked with respect to the model constraints. A destination point can be added if and only if its origin has been added to the route before. When the algorithm finds a feasible point for a route, it makes a new route by adding this feasible point and put it in the previous routes set. In the following, the branches that cannot satisfy any of the model constraints will be removed from the tree. In the end, the best route is the route that has a minimum objective function. Then, if there are en-route cars in the system, when receiving new demands, the second part of the algorithm starts to work. It checks the vehicles schedules remaining points to find the routes that can still be feasible after adding a new demand to them. If the algorithm finds any feasible route, then it adds the new demand to the route and if there are more than one feasible route, it adds the demand to the route that leads to the minimum increase of the objective function. But if it can not find such a feasible route, in the first part of the algorithm it assigns the optimal branch (as explained before) to an empty car which is waiting in the nearest depot.

Figure 2 shows a small example of the algorithm functioning. At a specific time, the algorithm receives 5 requests. Requests 2 and 5 can be added to the en-route vehicles in the first part of the algorithm. But there are no feasible solutions for requests 1,3 and 4. So the second part of the algorithm works to find the optimal route to serve these three requests. All these requests can be served by just one vehicle. The car should pick up passenger 3 and then 4. After dropping off the passenger 3, the car goes to the passengers 4 origins and then it drops off passenger 1 and finally passenger 4.

Simulation models

A simulation platform is used as the plant model to simulate the function of the dynamic ride-sharing service cars and personal cars that are in the network at the same time. 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:

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

In our research, the state of all the vehicles is clear for the system at every time t. The cars can have two situations. They are waiting in depots for new passengers or they are servicing the assigned passengers. In addition to the shared cars that are circulating to serve the passengers, there are other cars that are serving the rides that are not shared in the network. So the accumulation at each time

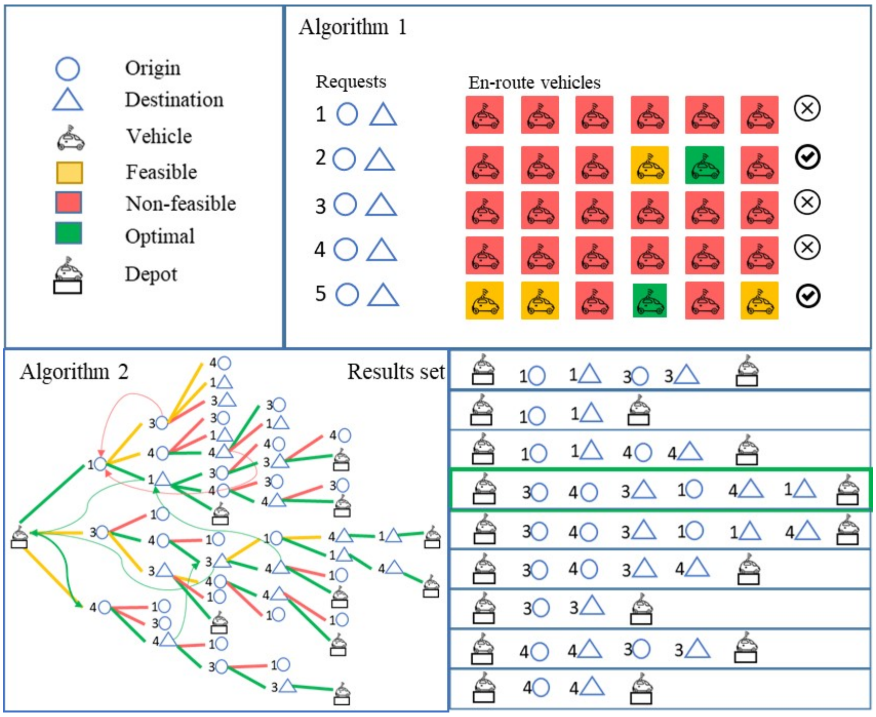

FIG. 2 – *Optimization algorithm*

t is the summation of the number of shared cars and number of what we call personal cars in the system. Therefore, at each time t the mean speed of travelers can be computed. Both shared trips and non-shared or personal trips can pass the length in a time period, based on the current mean speed at that time. We use this principle in our plant model which is described in the next section.

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. So we update the situation of cars every time step, with computing the speed on time. The time step that we use in our plant model is 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. So at each time step, the direct travel time from each point i to j is computed based on the current mean speed and the shortest path between two points, for the next 10 minutes. Then the optimization algorithm assigns all the requests for the next 10 minutes to the en-route cars or empty waiting cars.

Numerical experiments and conclusion

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 Krug *et al.* (2017). 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. Table 1 shows the cars travel time and number of cars for different numbers of sharing when the market share is 100 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.

When all the internal trips are served with service cars without any sharing, the number of needed service cars is 10138 and the total travel time for shared trips is 1557 hours. But then with sharing the ride between just two travelers, the number of needed cars decreases to 5433 and the total travel time is 1331 hours. It means that with almost half number of cars, the travel time is 226 hours 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.

Figure 3 shows the accumulation of cars in the network for different number of sharing compared with the case that all the trips are done with private cars. When a fraction of trips are served with service cars, the distance increases (because the car should also pass the distance between the waiting point and the origin and also the distance between the destination to the next waiting point) so the accumulation of cars moving in the system increases. But when we share the trips and increase the number of sharing, the accumulation of cars decreases and we have better traffic condition and less cars moving in the network. The results also show that for medium-scale network, the sharing cannot improve the congestion comparing with the case that we have just private cars in the network.

TAB. 1 – *Simulations results for market-share = 100%*

Sharing properties		Simulation results					
Market rate	Number of sharing	Total travel time for shared cars (h)	Total travel time for personal cars (h)	Total travel time for all cars (h)	Number of shared cars	Number of personal cars	Total number of cars
0	0	0	10756	10756	0	62450	62450
	0	1557	9480	11037	10138	51215	61353
100	1	1331	9386	10717	5433	51215	56648
	2	1291	9356	10647	4327	51215	55542
	3	1274	9345	10619	3833	51215	55048

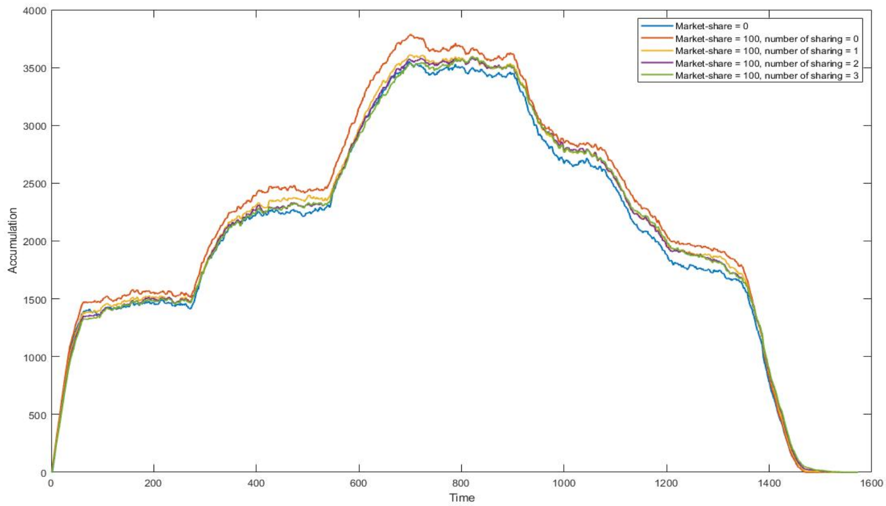

FIG. 3 – *Cars accumulation for different market shares*

In future researches, we will implement our system on larger networks with more number of trips to assess the effect of sharing on congestion in large-scale networks. We will improve the optimization algorithm introducing spatial clustering on the network. Also we will try to switch the plant model to a more refined one.

Acknowledgement

This work is supported by the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program. (Grant agreement No 646592 – MAGnUM project)

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