Accounting for driver-passenger matching decisions in a ridesharing simulation platform

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Abstract

This paper presents a new ridesharing simulation platform that accounts for dynamic driver supply and passenger demand, and complex interactions between drivers and passengers. The proposed simulation platform explicitly considers driver and passenger acceptance/rejection on the matching options, and cancellation before/after being matched. New simulation events, procedures and modules have been developed to handle these realistic interactions. The capabilities of the simulation platform are illustrated using numerical experiments. The experiments confirm the importance of considering supply and demand interactions and provide new insights to ridesharing operations. Results show that larger matching window could have negative impacts on overall ridesharing success rate. These results emphasize the importance of a careful planning of a ridesharing system.

Keywords: ridesharing; simulation; driver supply; passenger demand

1. Introduction

Innovative shared mobility, namely ride-sourcing services, have reshaped our urban transportation. Ride-sourcing companies, such as Uber, Lyft, and Didi, provide convenient mobility services with lower fares, by utilizing drivers' own vehicles instead of company fleets to provide services (Wang and Yang, 2019). One type of these services is ridesharing, in which peer drivers serve more than one passenger in each ride. Ridesharing services potentially can reduce vehicles kilometer traveled (VKT), compared to other service types. This is because peer drivers in ridesharing, who are assumed to perform activities other than only pick up and drop off passengers (as is the case of dedicated ride-hailing drivers), have their designated destinations and do not cruise in the network (Wang and Yang, 2019). Despite various policies implemented for encouraging ridesharing (e.g., HOV lanes), the market share of ridesharing is still relatively low (Hensley et al., 2017).

From a planning perspective, designing and evaluating the effectiveness (expected "real-world" performance) of ridesharing systems is challenging. Many studies addressed the operational decisions of service providers, specifically, dynamic ridesharing driver-passenger matching problems (e.g., Agatz et al., 2012; Alonso-Mora et al., 2017).

In a realistic ridesharing setting, peer drivers and passengers may also make various matching decisions that affect ridesharing operations. For example, as new passenger requests continue to emerge during ridesharing, existing schedules might be modified to serve these new passengers. Consequently, for passengers already waiting for pickups, they may cancel their trips due to delayed pick-up after being assigned a driver (He et al., 2018; Wang et al., 2020). Similarly, for drivers and on-board passengers, they may reject the assigned matchings due to extra detours (Chu et al., 2018; Rosenblat et al., 2017). Other decisions could be passengers cancelling their trips because of a long wait before being matched with a driver (Wei et al., 2020), and passenger reorder and rebooking after cancellation. In terms of evaluating a ridesharing system, if these possible driver and passenger actions were not considered in the ridesharing models, the system performance could not be properly estimated. We summary the existing ridesharing models in Table 1.

Table 1 A comparison between the proposed and existing ridesharing models.

Literature	**Dynamic supply demand**	**Multiple passengers**	**Cancellation before being matched**	**Matching option acceptance/rejection**	**Cancellation after being matched**
Network assignment models					
Xu et al. (2015)		√			
Di and Ban (2019)		√			
Ma el al. (2020)		√			
Li et al. (2020)				√	
Wei et al. (2020)	√		√		

Literature	Dynamic supply demand	Multiple passengers	Cancellation before being matched	Matching option acceptance/rejection	Cancellation after being matched
Market equilibrium models					
He et al. (2018)					√
Wang et al. (2020)					√
Ke et al. (2020)		√			
Simulation models					
Djavadian and Chow (2017a, b)	√	√			
Wang et al. (2017)	√	√	√		
Beojone and Geroliminis (2021)	√	√	√		
Shen et al. (2018)	√		√		
Nahmias-Biran et al. (2019)	√				
Thaithatkul et al. (2019)	√			√	
Linares et al. (2016)	√	√		√	
Nourinejad and Roorda (2016)	√	√		√	
This paper	**√**	**√**	**√**	**√**	**√**

As shown in the table, there are still gaps in the literature for developing a comprehensive ridesharing simulation platform, with explicit considerations of driver and passenger matching decisions. We propose to develop a novel simulation platform to capture these complex dynamic interactions, to provide new insights, and to handle more realistic scenarios.

2. Methodology

The proposed ridesharing simulation platform captures the complex dynamic interactions between passengers and drivers in a ridesharing system, and it is able to handle: a) Dynamic passenger demand and driver supply; b) Acceptance/rejection on matching options; c) Order cancellation and no-show. We outline the overall ridesharing simulation process in Figure 1.

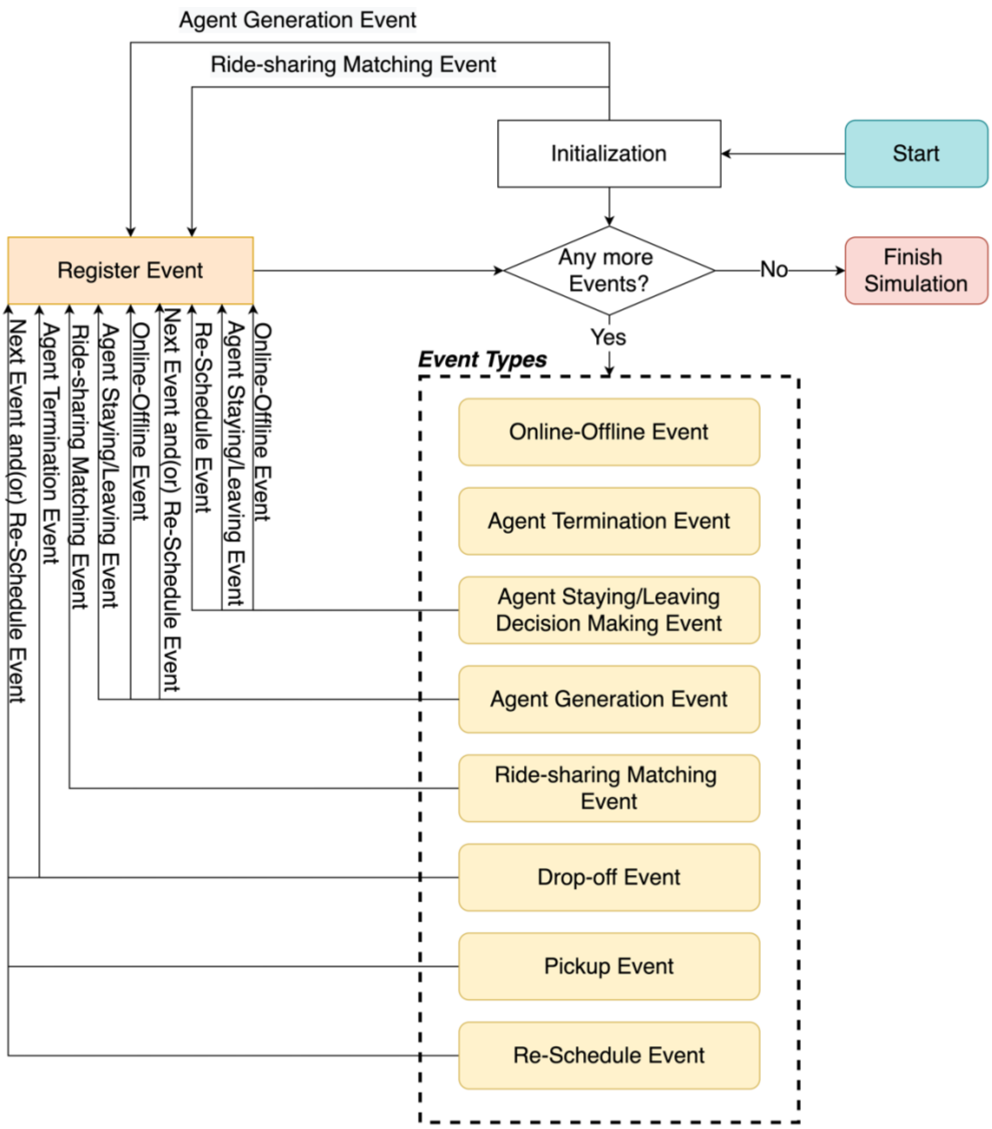

Figure 1 Flowchart for ridesharing simulation process

Our ridesharing simulation platform primarily incorporates the driver-passenger matching decisions in the ***Ridesharing Matching Event*** and the ***Agent Staying/Leaving Decision Making Event.*** In the following subsections, these two simulation events, and the corresponding modules will be explained in detail.

2.1. Ridesharing Matching Event.

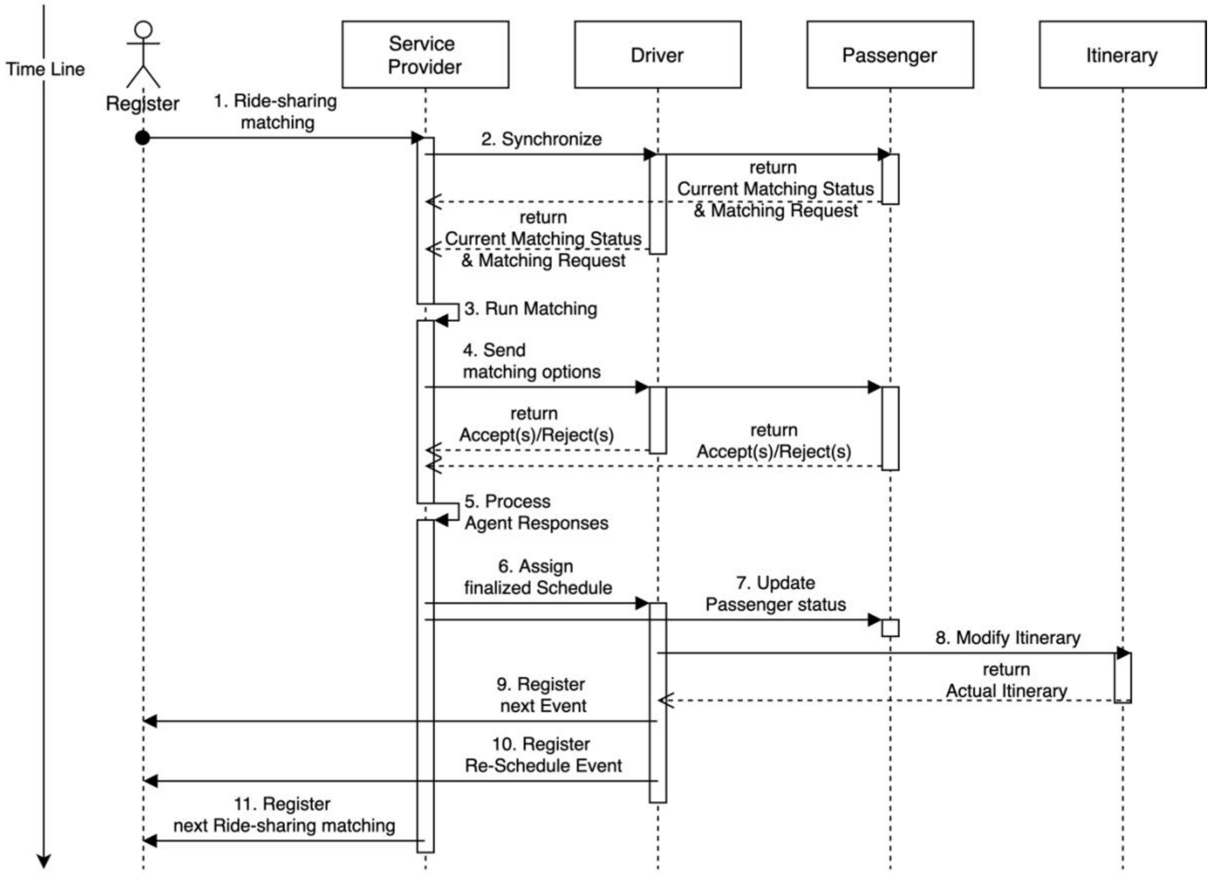

Figure 2 Sequence diagram for *Ridesharing Matching Event* routine

During *Ridesharing Matching Event* execution, the Passenger and Driver agents first synchronize their matching status with the Service Providers. Then, the Service Providers perform ridesharing matching between these Drivers and Passengers, and provide information on the matching options.

Upon receiving these matching options, Driver and Passenger agents compare the utilities among various options, and choose to accept/reject the provided options. Later, after Service Provider receiving these responses, and performing necessary modifications on the matching schedules, these finalized matchings are sent to the Drivers and Passengers.

The Driver is set to perform the finalized matching, by register one of the possible following events: *Pickup Event*, *Drop-Off Event*, *Agent Termination Events*, or *Re-schedule Event*. Finally, if there is any remaining event in the event queue, another *Ridesharing Matching Event* will be scheduled at next matching window.

In the following paragraphs, we illustrate examples of ***Agent Matching Response Module*** and ***Matching Option Responses Handling Module***.

Agent Matching Response Module. We assume that Driver or Passenger will choose one of the matching options, including the existing matching option (if matched) or staying alone option (if not matched yet). The utility of the matching option m for Driver agent v_i is specified as equation (1):

$$U_{v_i,m} = \beta_{time,v_i} \cdot tt(m) + \beta_{cost,v_i}[cost(m) - earning(m)] \tag{1}$$

Where, β_{time,v_i} is the coefficient for travel time and β_{cost,v_i} is coefficient for costs. $tt(m)$ is the driver's total travel time. $cost(m)$ is the operational cost, and $earning(m)$ is the total payout received from the Passengers. If Driver v_i is currently not matched with any Passenger, then $earning(m) = 0$ in equation (1), and tt and $cost$ correspond to Driver's shortest path. Similarly, the utility of the matching option m for Passenger agent p_j is specified as equation (2):

$$U_{p_j,m} = \beta_{time,p_j} \cdot tt(m) + \beta_{cost,p_j} \cdot payment(m) \tag{2}$$

where, the payment of matching option m, $payment(m)$, based on the pricing scheme. If Passenger p_j is currently not matched, then tt and $payment$ correspond to Passenger's shortest path as if traveling alone by car.

For demonstration purposes, we assume a simple MNL model to capture the Driver/Passenger's choice behavior. The probability of choosing matching option m is calculated for Driver v_i and Passenger p_j respectively using equation (3):

$$P_{v_i/p_j}(m) = \frac{e^{U_{v_i/p_j,m}}}{\sum_n e^{U_{v_i/p_j,n}}} \tag{3}$$

Then, the Driver and Passenger's decision can be assumed to be the matching option with highest probability, or optionally be simulated. Note that, previous studies considered only 1 alternative (the assigned matching). Therefore, the probability of accepting the assigned matching was explicitly assumed to be 100%.

Matching Option Responses Handling Module.

In a multi-passenger ride-sharing setting, driver and the corresponding passengers can decide on a given matching option, in which they might (not) agree with each other. We employ a majority-voting scheme for finalizing the matching options as shown in Figure 3. The matching options, that include new Passengers, are first sent to the Driver and all previously matched Passengers. If the majority agrees to accept the new matching option with the new Passengers, these new Passengers can then decide whether to accept the matching option. If the new Passengers agree, then the new matching option is finalized. Otherwise, the Driver and all previously matched Passengers' matching options will not be changed. In case there are even votes, the Driver has the final decision.

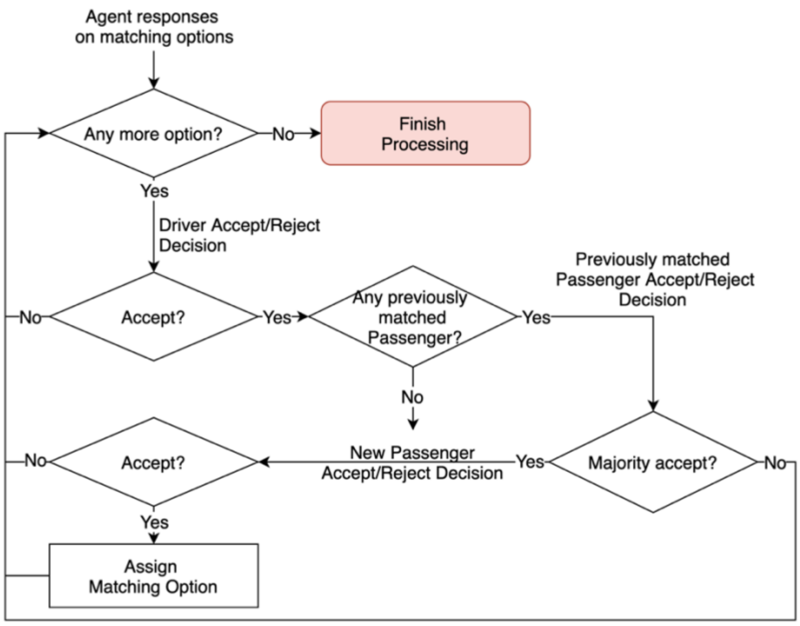

Figure 3 Service Provider processing agent accept/reject responses

2.2. Agent Staying/Leaving Decision Making Event.

There are three possible outcomes associated with *Agent Staying/Leaving Decision Making Event:* a) stay with current matching, b) leave current matching but still use the ridesharing service, or c) leave the ridesharing service. If a Driver or Passenger chooses to leave the current matching (outcome b) or even leave the ridesharing service (outcome c), there will be some complex interactions between the agents. We illustrate these interactions in Figure 4.

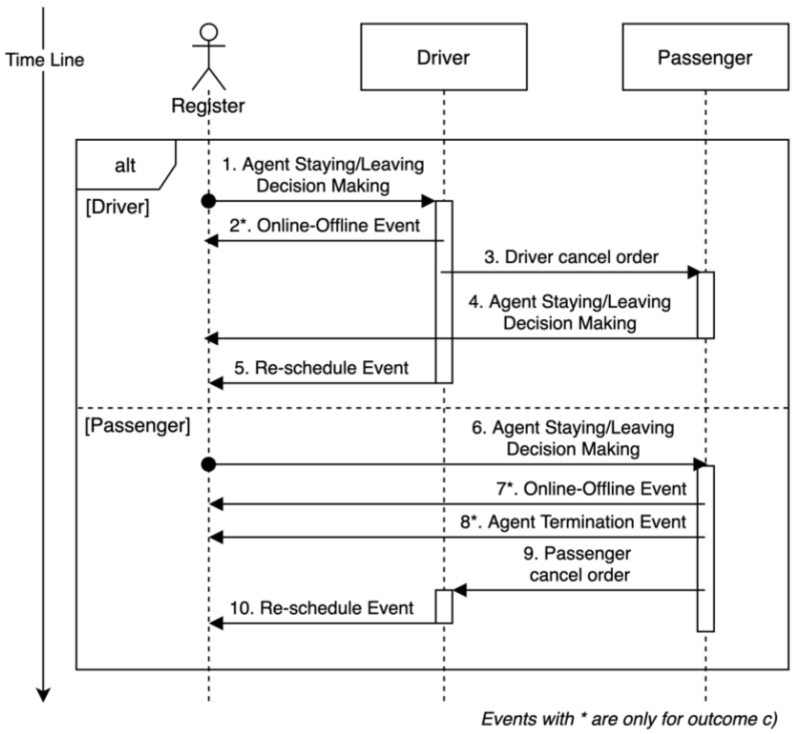

Figure 4 Sequence diagram for *Agent Staying/Leaving Decision Making Event* routine of decision outcome b) and c)

As shown in Figure 4, in case Driver agents decide to cancel existing orders, their canceled Passenger agents will be notified. For these canceled Passenger, they need to decide if staying in ridesharing service or not. If the Driver agents decide to leave the ridesharing service (outcome c), this Driver should be *Offline* from matching pool. Lastly, a *Re-schedule Event* is registered for updating the Schedule.

In case Passenger canceling the confirmed orders, the corresponding matched Driver will be notified and trigger *Re-schedule Events* for updating the Schedule. In case the Passenger quitting ridesharing, this Passenger will be removed matching pool (*Offline*), and terminated from simulation.

Agent Decision Making Module. Driver and Passenger agents' decisions are simulated on: a) whether keep using ridesharing service, and b) whether stay with current matching. If a Passenger agent is picked up, he/she is assumed to stay with current matching. Moreover, if a Passenger choose to stay with current matching, he/she cannot quit ridesharing service. For illustration purposes, a binary logit model that simulates the decisions is assumed. The utility of the staying with current matching option m for Driver agent v_i is specified as equation (1), and the utility of canceling/quitting the existing matching option m is defined by equation (4):

$$U_{v_i,m^-} = \beta_{time,v_i} \cdot tt(m^-) + \beta_{cost,v_i}[cost(m^-) + CancellationFee - earning(m^-)] \quad (4)$$

Where, m^- indicates removing Passengers not yet picked up. Accordingly, the travel time, operational cost, and earnings (and cancellation fees, Passenger payments) should be updated. We also assume that, if a Driver agent chooses to cancel Passenger orders, he/she quits the ridesharing service.

For Passenger p_j, the utility of canceling/quitting ridesharing service is the same as traveling alone (equation 2) if he/she is not matched. If matched, a cancellation fee is added:

$$U_{p_j,0} = \beta_{time,p_j} \cdot tt(p_j) + \beta_{cost,p_j} \cdot [payment(p_j) + CancellationFee] \quad (5)$$

If a Passenger is not matched (N), the utility of staying in ridesharing system is specified by equation (6):

$$U_{p_j,N} = \beta_{time,p_j} \cdot [tt(p_j) + wt(p_j)] + \beta_{cost,p_j} \cdot [\beta_{\exp\ pay,p_j} \cdot payment(p_j) - coupon] \quad (6)$$

Where, $wt(p_j)$ is the waiting since the Passenger sends his/her first ridesharing requests, and $\beta_{\exp\ pay,p_j}$ represents Passenger agent's expectation on the trip cost. The first part of the utility corresponds to the total travel time for a direct ride. The second part indicates the agent's experiences on the payment and captures their perceptions on the payments. For passengers waiting for a scheduled pickup (Y), the utility of staying in ridesharing system is specified using equation (6), with $\beta_{\exp\ pay,p_j} = 1$ indicating a determined trip cost. And the $wt(p_j)$ term captures the behavior of order cancellation, due to long pickup waiting times.

The probability of staying or leaving is computed using equation (3), while the decision is simulated with these probabilities. Note again, to the best of our knowledge, most existing studies explicitly assumed the probability of cancelling/leaving ridesharing to be 0%.

3. Numerical Experiments

The experiments are conducted using the well-known Winnipeg network, which consists of 154 zones, 1067 nodes, 2535 links, and 4345 origin-destination (OD) pairs. The total hourly demand of the Winnipeg matrix is 54,459 trips (Bekhor et al. 2008), the OD spatial distribution and trip distance distribution are shown in Figure 5, representative of an AM peak period. To account for dynamics, we distribute the hourly demand into four 15-minute periods, with each period accounts for 10%, 40%, 40% and 10%, respectively. We also assume the hourly demand starts from 8:00 and time-dependent travel times associated with this demand pattern are also imported to the simulation.

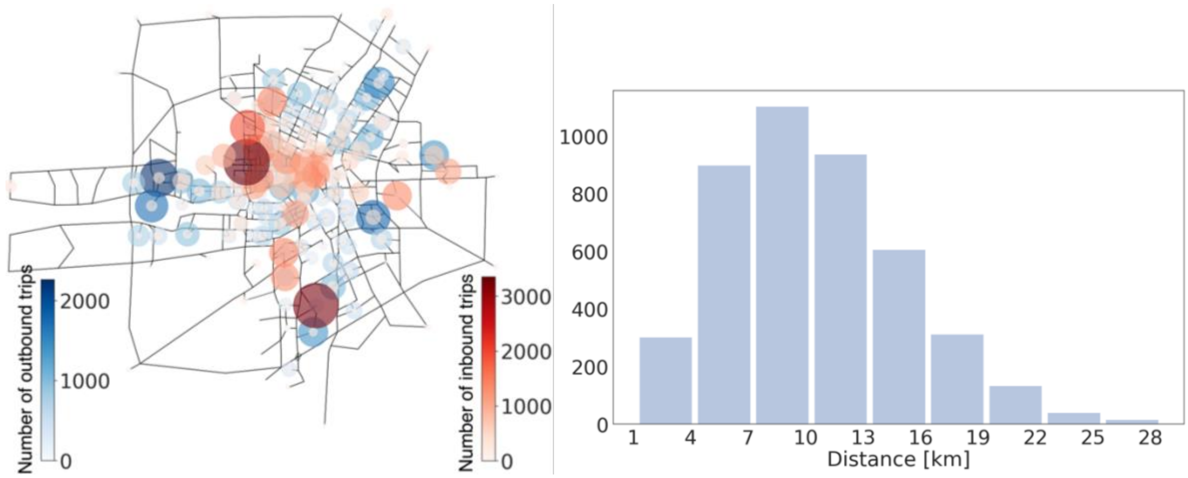

Figure 5 Distribution of OD matrix trips and distances

To obtain insights of the simulation process, we assume a default setting with 2,000 ridesharing Passenger trips and 1,600 ridesharing Driver trips. These trips are randomly sampled from the 54,459 trips without replacement, and distributed into four time periods, accordingly.

3.1. Impact of matching window

The proposed simulation platform could provide additional insights for ridesharing service planning. We illustrate evaluating the impact of different matching window, the time between two consecutive matchings (Table 2). To account for the impact of OD distribution, 10 replications are conducted for all the tests. Each point in the following figures (Figure 6) represents the average value of 10 replications and the shades indicate standard deviations.

Table 2 Selected factors and their levels for the sensitivity analysis

Factor	Default Level	Analysis Levels
Ridesharing matching window	2 minutes	0.1, 0.5, 1, 2, 3, 4, 5, 6, 7, 8 minutes

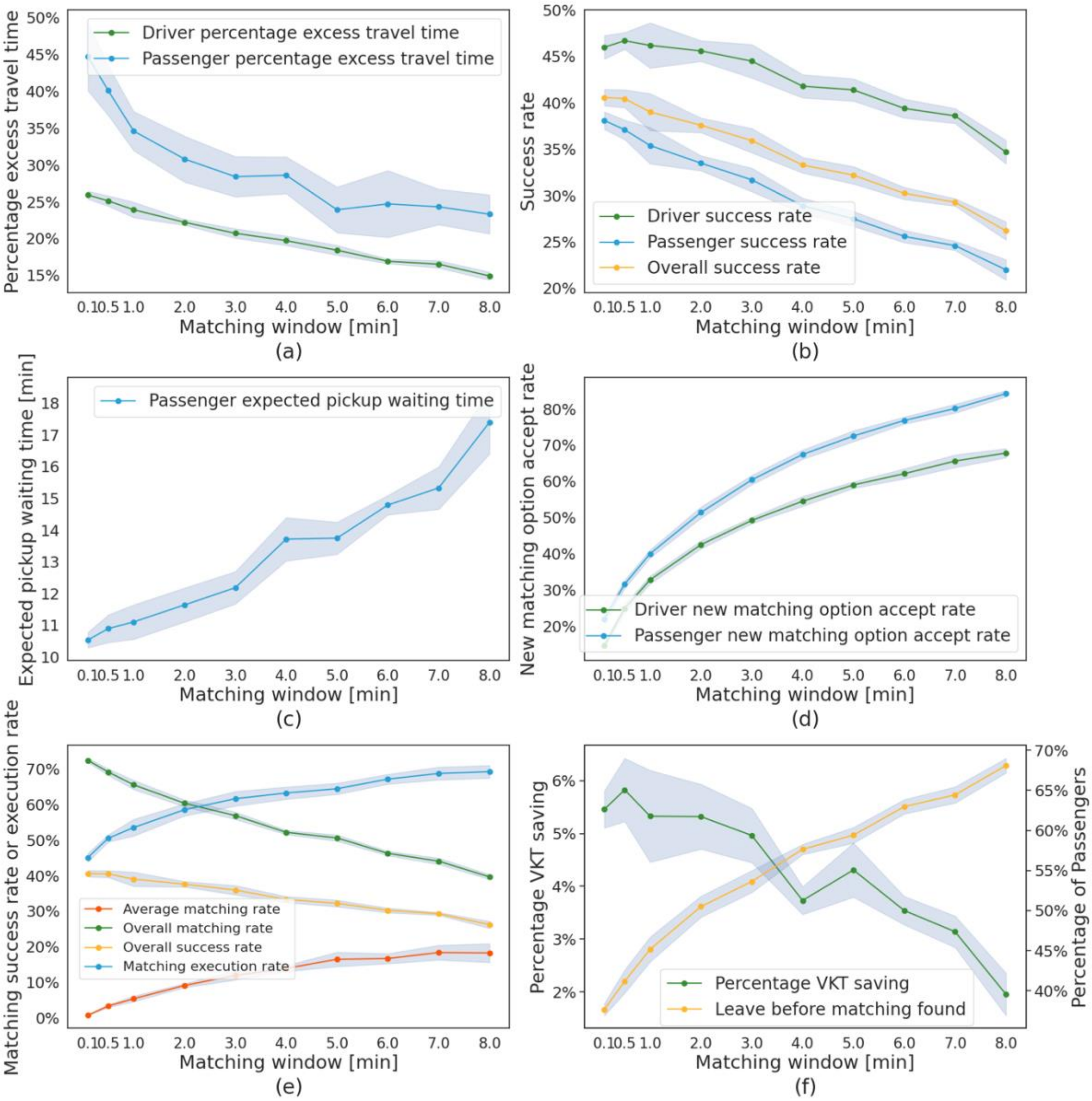

Figure 6 Performance metrics for ridesharing matching window sensitivity analysis

Figure 6(a, d, e) show the positive effects on increasing matching time window. With increases in time window, we are expecting to have higher quality matchings (i.e. shorter detours for the matched drivers and passengers, as in Figure 6(a)), therefore have higher Matching option accept rates (Figure 6(d)), and higher Matching execution rates (Figure 6(e)). The higher Matching execution rates also indicate smaller gaps between the Overall matching rate and Overall success rate (Figure 6(e)), suggesting less overestimates in system performances.

The Average matching success rate also gradually increases with larger matching windows (Figure 6 (e)). This result is consistent with the empirical matching probability in the literature, in which, the matching probability of ridesharing is modeled as $p(q_r, \phi) = 1 - \exp\,(-\gamma q_r \phi)$, with γ as the scale parameter, q_r as ridesharing demand rate, and ϕ as the matching window (Yan et al., 2020; Ke et al., 2021).

However, these positive effects come at the expense of longer matching option waiting times (i.e., the Drivers and Passengers sent their ridesharing requests and were told to wait for matching). The longer waiting times may result Drivers and Passengers leave the ridesharing system before the Service Provider performing matching (Figure 6(f)), and decreases the Driver, Passenger, and overall success rate (Figure 6(b)), which in turn causes the average expected waiting time to be longer (Figure 6(c)).

The negative effect of longer matching window on percentage VKT savings (Figure 6(f)) could be counterintuitive at first glance. One may expect that, with longer matching time, more Drivers and Passengers could be considered in the matching, and result higher quality matchings, i.e., shorter detours and increase of VKT savings (the matching objective function). However, this is only correct if the Passengers are willing to wait for a relatively long time before he/she receives a matching option, i.e., Passenger order cancellation is not considered. As opposed to Yan et al., 2020 and Ke et al., 2021, our model endogenously captures ridesharing demand as a function of matching window $q_r(\phi)$ as well. When the matching window increases, the Average matching rate increases for the Drivers and Passengers remaining in the matching pool. However, in this case, more Drivers and Passengers left the system before matching, which results in less potential shared trips, and consequently lower Overall success rate and Percentage VKT savings.

These results emphasize that unrealistic assumptions related to Driver and Passenger behavior could lead to misleading conclusions, in particular, overestimating the performance of a ridesharing system. For example, if ignoring cancellations, one would choose a larger matching window based on metrics, for example, like the Average matching rate. However, larger matching window could cause Drivers and Passengers leaving services even before matching, and result in poor “real-world” performance (e.g., lower Overall success rate). Our simulation platform provides a realistic and comprehensive testbed for ridesharing service developments.

4. Comparison with previous approaches

In this subsection, we explicitly compare the performance metrics with three models: 1) static model (as in Yao and Bekhor, 2021); 2) dynamic model without interactions (e.g., Alonso-Mora et al., 2017); 3) dynamic model with interactions (this paper).

For this experiment, same sets of driver and passenger agents are used for the 3 models. Moreover, we assume that, in “reality”, drivers and passengers have only 60% chance to accept the matching. This results in a predefined “true” success rate of 58% ($= 60\% \times$ matching rate of the static model, 96.67%, which is the maximum matching rate considering the spatiotemporal constraints, as in Yao and Bekhor, 2021). Note that, if all 2,000 ridesharing passengers, and all 1,600 drivers can be matched, the “true” success rate will be 100%.

We perform 10 runs for each model and, the average and standard deviations of matching rate and simulated rates are shown in Table 3.

Table 3 Comparison of model simulated success rates and predefined "true" success rate

Metrics	Static		Dynamic without interaction		Dynamic with interaction	
	Mean	Stdev	Mean	Stdev	Mean	Stdev
Overall matching rate	96.67%	0.64%	90.11%	1.98%	86.72%	2.70%
Simulated success rate	-	-	90.11%	1.98%	60.39%	5.21%
t-test(58%) *predefined “true” success rate* $58\% = 60\% \times 96.67\%$	60.42		16.22		0.46	

The dynamic models provide lower overall matching rate due to the dynamic nature of the demand, in which future demands are not known in advance. With driver and passenger matching decisions, they might cancel/leave ridesharing, which further decrease the overall matching rate.

The results further show that, the proposed dynamic model with interaction, could replicate the predefined “true” success rate (i.e., the simulated success rate is not statistically significantly different from 58% with critical value of 1.96), while other models overestimate the ridesharing system performance.

5. Summary

This paper presents a new ridesharing simulation platform that accounts for dynamic driver supply and passenger demand, and complex interactions between drivers and passengers. Specifically, this paper is one of first models that explicitly considers driver and passenger acceptance/rejection on the matching options, and cancellation before/after being matched. New simulation events, procedures and modules have been developed to handle these realistic interactions in this paper.

The capabilities of the proposed ridesharing simulation platform are illustrated using numerical experiments in the well-known Winnipeg network. The proposed model produces logical results with respect to matching window. For example, larger matching window will cause drivers and passengers leaving ridesharing even before the matching occurred, and consequently result in lower overall success rate and lower VKT savings; but could improve matching rate and execution rate. Moreover, comparative experiments show that, only the proposed model can replicate the predefined “true” success rate.

Our numerical experiments are conducted using parameters (e.g., the driver and passenger VOTs) from the literature, there is a need to calibrate them in future research.

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