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Reducing ridesourcing empty vehicle travel with future travel demand prediction

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ABSTRACT

Ridesourcing services provide alternative mobility options in several cities. Their market share has grown exponentially due to the convenience they provide. The use of such services may be associated with car-light or car-free lifestyles. However, there are growing concerns regarding their impact on urban transportation operations performance due to empty, unproductive miles driven without a passenger (commonly referred to as deadheading). This paper is motivated by the potential to reduce deadhead mileage of ridesourcing trips by providing drivers with information on future ridesourcing trip demand. Future demand information enables the driver to wait in place for the next rider's request without cruising around and contributing to congestion. A machine learning model is employed to predict hourly and 10-minute future interval travel demand for ridesourcing at a given location. Using future demand information, we propose algorithms to (i) assign drivers to act on received demand information by waiting in place for the next rider, and (ii) match these drivers with riders to minimize deadheading distance. Real-world data from ridesourcing providers in Austin, TX (RideAustin) and Chengdu, China (DiDi Chuxing) are leveraged. Results show that this process achieves 68%–82% and 53%–60% reduction of trip-level deadheading miles for the RideAustin and DiDi Chuxing sample operations respectively, under the assumption of unconstrained availability of short-term parking. Deadheading savings increase slightly as the maximum tolerable waiting time for the driver increases. Further, it is observed that significant deadhead savings per trip are possible, even when a small percent of the ridesourcing driver pool is provided with future ridesourcing demand information.

1. Introduction

Transportation network companies (TNCs) or ridesourcing providers are rapidly gaining market share and redefining the way people view urban travel. Major ridesourcing providers such as Uber, Lyft, DiDi Chuxing (DiDi), and other services including Via and RideAustin, rely on users' proclivity to ride in someone else's vehicle instead of one they own themselves. Ridesourcing use is not all that different from how people traditionally use taxis except, in this case, travelers are able to hail a ride using their smartphone instead of physically hailing a taxi from the curb (Shaheen et al., 2016). This tech-enabled hailing has encouraged the rise of TNCs which is evident in the volume of trips conducted by these companies (Dickey, 2017), even though TNC vehicles are still a small portion of daily modes used (Conway et al., 2018). The impact of ridesourcing will only increase with major investments by firms such as Google

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(Muoio, 2017) and Uber (Holley, 2017) in connected and automated vehicle technologies. While these companies intend to improve and enhance transportation service options (Tirachini, 2019), they also contribute to worsening urban traffic conditions (LeBlanc, 2017). Several research studies uncover congestion effects and quantify the negative impacts of increased travel and energy use from TNC operations (Erhardt et al., 2019; Wenzel et al., 2019).

Ridesourcing options are available in several cities in North America and worldwide (Iqbal, 2020; Uber, 2017) and are a prevalent mode alternative in large metropolitan areas such as New York City (NYC Department of Transportation, 2018). Increased demand for ridesourcing may affect transportation system operations by inducing vehicle miles traveled (VMT) on already congested roads (Erhardt et al., 2019), shifting ridership from other modes such as taxis and public transit (Hall et al., 2018), potentially changing vehicle ownership attitudes (Ward et al., 2019), and altering land use needs, such as curb space usage and parking (Jin et al., 2018; Rayle et al., 2016). Questions relevant to understanding the impacts of ridesourcing on the urban road network could be addressed through global positioning system or survey data analysis of TNC drivers' and riders' trips. Relevant literature in this domain has underlined one of the major concerns of ridesourcing use: estimating the mileage corresponding to "deadheading" trips, i.e., trips that are conducted without a passenger while a TNC driver is cruising and waiting to pick up their next rider (Henao and Marshall, 2018).

TNCs employ drivers who use their own vehicles or lease ones to transport riders from their origins to their destinations. Once a TNC driver receives a trip request, they initiate their travel from their current location to pick up the passenger. Once the passenger is on-board and dropped off at their destination, the TNC driver, assuming they are still in service, can perform one of the following four actions: (i) park in a close by location and wait for the next trip request; (ii) accept another request and travel to pick up the next passenger; (iii) travel to a known or suggested high-demand location such as an airport or the central business district while waiting to be assigned to a rider, or (iv) cruise around until they receive another request to serve. The TNC driver's vehicle would cover a share of unproductive or empty miles, without a rider, in all the above scenarios except when parked at the previous trip destination. The TNC driver's behavior could be influenced by anticipated riders' demand information, which they might receive from the ridesourcing company, as is the case for regular drivers with travel choices and information provision (Jha et al., 1998). While on a trip (or around the completion of a trip), TNC drivers usually receive an indication if another trip request is made. The decision regarding the assignment of trips to drivers is made by ridesourcing companies, via matching algorithms, which are then relayed through their web apps. However, drivers are not provided with information regarding future demand at their drop-off location. This is partly because TNCs aim to optimally match their current demand with their current vehicle supply and minimize waiting time for their passengers, sometimes even at the expense of their drivers' time use and often resulting in additional miles traveled.

This study is motivated by the hypothesis that providing TNC drivers with information regarding future trip demand at their last trip destination could reduce deadhead or empty mileage without necessarily impacting passenger wait times and TNC platform's performance. Theoretically, sufficient ridesourcing demand generated close to the driver's last destination will incentivize them to park and wait for their next trip request to arrive, and in the process save fuel and money. Similar information, such as eco-routing instructions (Ahn and Rakha, 2013), when provided to drivers, is found to result in fuel consumption savings and encourage eco-friendly behavioral shifts.

This paper aims to quantify ridesourcing empty mileage savings per trip achieved via providing future travel demand information to TNC drivers. Goals also include estimating cost and energy savings per trip to inform both ridesourcing providers and policymakers of the potential benefits of future travel demand prediction and provision. Ridesourcing origin–destination data from RideAustin, a TNC service offered in Austin, Texas (RideAustin, 2017), and DiDi, a major ridesourcing firm based in the People's Republic of China (DiDi Chuxing, 2018), are leveraged to evaluate the proposed framework. The computational framework involves three major processes: (i) a machine learning model, similar to that of Wang et al. (2020), to predict ridesourcing demand generated within the impending time interval in a given geospatial unit: (ii) an algorithm that determines which drivers are more likely to act upon given information on future ridesourcing demand at their current location: and (iii) an assignment process that allocates drivers to subsequent trip origins while minimizing their deadheading distance to pick up the next rider. The computational process is applied with sample data from the North American and Chinese ridesourcing markets to demonstrate its potential in achieving the objective of trip-level empty vehicle miles traveled minimization. The RideAustin data sample is representative of a week's worth of ridesourcing trips in a seven-zip code area in Austin, Texas, and the DiDi data sample is representative of a week's worth of ridesourcing travel in Chengdu, China.

The remainder of the paper is organized as follows. The second section presents a brief literature review on ridesourcing trip prediction, matching, and assignment research. The third section provides descriptive statistics of the ridesourcing trip data samples used. The fourth section describes the computational process, followed by results that are presented in the fifth section. The final section summarizes the findings, discusses limitations, and proposes directions for future research.

2. Literature review

This section presents a brief overview of the literature in the domains of ridesourcing and taxi trip prediction, vehicle and rider matching, and planning for TNC operations.

Ridesourcing and travel demand prediction research advanced significantly in recent years with the application of time series and machine learning methods on large historical trip datasets. As an example, forecasting techniques such as time-varying Poisson and autoregressive integrated moving average models have been used to predict taxi travel demand in Porto, Portugal (Moreira-Matias et al., 2013). Behavioral choice models have been integrated into forecasting models to predict the adoption of ridesourcing services (Alemi et al., 2019; Dias et al., 2017; Lavieri et al., 2018; Shen et al., 2020). Deep learning approaches used for ridesourcing demand prediction also yield accurate prediction results (e.g., Liu et al., 2017). In Ke et al. (2017), a fusion convolutional Long-Short Term

Memory (LSTM) network is used to capture the spatio-temporal correlations of variables included in the prediction and provide accurate DiDi travel demand predictions for the city of Hangzhou, China, reducing the travel demand error to around 20% (compared to benchmark historical averages approaches). LSTM networks have been harnessed to effectively capture non-linear demand behaviors in space and time (Xu et al., 2017a; Yao et al., 2017) and are deemed appropriate for our analysis.

With the introduction of TNCs in the mobility space, research interest in simulating their operations has spiked. Efforts in maximizing the effectiveness of ridesourcing primarily focus on meeting riders' demand, e.g. Alonso-mora et al. (2018); He and Shen (2015). Other researchers mathematically formulate ridesourcing operations to minimize the TNCs fleet size to meet a given demand (Vazifeh et al., 2018) or aim at understanding drivers' strategies for finding passengers, e.g., Li et al. (2011). Modeling, simulations, and data analytics of ridesourcing services are used to assess deadheading, cost, energy, and environmental externalities of the mode (Bauer et al., 2018; Nair et al., 2020; Wenzel et al., 2019; Xue et al., 2018), analytically derive fair (He et al., 2018) and dynamic pricing (Lei et al., 2019) or predict surge pricing multipliers (Battifarano and Qian, 2019). Ridesourcing competition with the taxi industry is also modeled in the most recent literature (Contreras and Paz, 2018; Kim et al., 2018) and regulatory structures for their market coexistence are discussed by Nie (2017).

In this work, matching ridesourcing vehicles to riders is conducted via minimizing the vehicle's empty travel or deadheading distance. This objective is deliberate: a local transportation planning agency or a regulator is expected to nudge TNCs to minimize deadheading through policies, incentives, or penalties. At the moment, ridesourcing platforms like Uber conduct batched matching to meet rider demand with existing vehicle supply, setting the objective of concurrently minimizing riders waiting time in a specific area, as noted in Uber Marketplace (2019). The methodology we propose will be useful as cities and public agencies suggest interventions that can reduce the share of TNC unproductive miles per trip, while not jeopardizing the desirable level of service (i.e., riders waiting time). In fact, minimizing deadheading miles is expected to be of great importance when operating TNC vehicles in regions such as the state of California, which has enacted a Clean Miles Standard policy requiring TNCs to restrict greenhouse gas emissions (California Air Resources Board, 2020). Our method is applied with open-source origin–destination data provided by two TNCs in two different cities. To our knowledge, this is the first study to demonstrate the potential of future travel demand information prediction and diffusion in reducing deadheading mileage in both North American and Chinese regions by leveraging granular urban data and estimating travel, energy, and cost savings of such an initiative.

3. Data description

A non-profit ridesourcing company, RideAustin, operating in Austin, Texas, made data available from approximately 1.5 million trips that span a 10-month period during 2016–2017 (RideAustin, 2017), when no other major TNC, like Uber or Lyft, was operating in that region. A small sample of the RideAustin dataset that consists of trips from 01/16/2017 (Monday) to 01/22/2017 (Sunday) was extracted and utilized in this research effort. The sample consists of 28,586 ridesourcing trips conducted by 16,930 drivers. Their trip destinations fall within seven of the busiest zip codes in Austin. Information on the future trip demand is provided only to drivers that served trips staring in these seven zip codes (i.e., 78701, 78702, 78703, 78703, 78704, 78705, 78741, and 78719). Most trips within the timeframe of the analysis end in the downtown Austin region and at the airport, as shown in Fig. 1a.

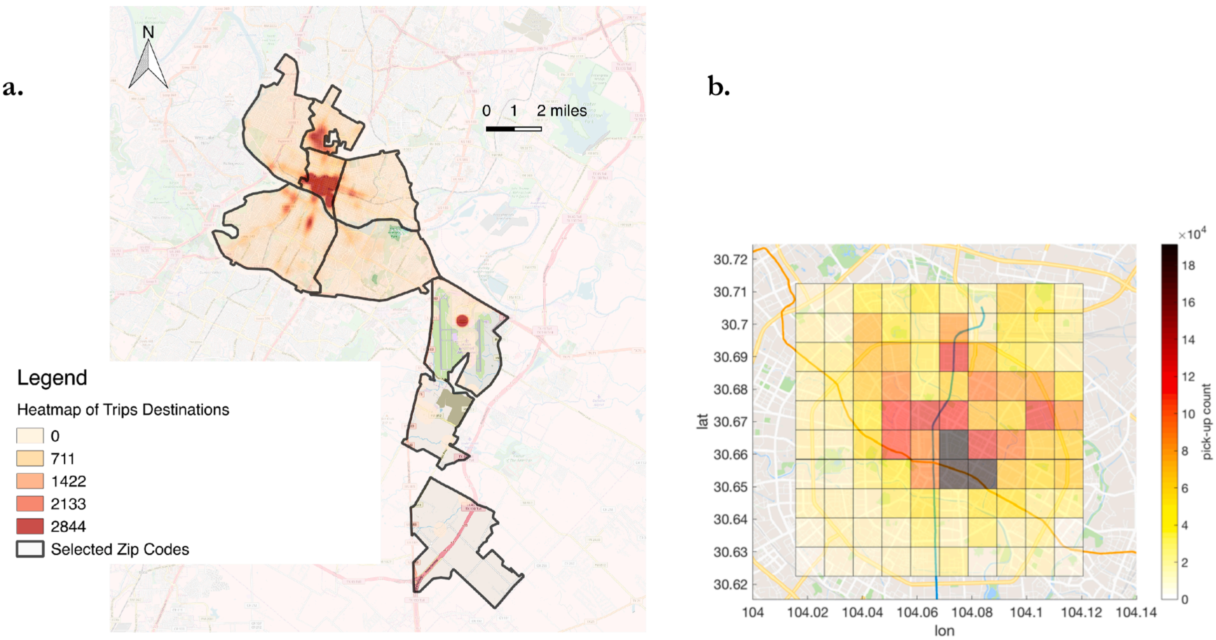

Fig. 1. Ridesourcing trip destinations and origins across (a) Austin zip codes and (b) the Chengdu grid, respectively.

DiDi is a leading ridesourcing provider based in China, receiving million trip requests per day. In 2017, DiDi established the GAIA Initiative and open-sourced a sample database of route traces and ride request data from the city of Chengdu, China, from 11/01/2016 to 11/30/2016 (DiDi Chuxing, 2018). The dataset contains 7 million ride request records, including origin–destination points and trip start and end times. The route dataset includes 1 billion data points of the trips' global positioning system trajectories with a sampling rate of 2–4 s. These dense records allow for more accurate local prediction of riders' trip demand generation. Fig. 1b shows the extent of coverage of the DiDi TNC trip dataset. The center of the Chengdu City area is partitioned into 100 square cells, each with a side length of 1 km (≅ 0.62 mi). A similar partition process has been followed by Kang et al. (2013), who explored taxicab movements from mobile phones in Singapore. The last week of November 2016 of the ride request dataset was selected for future demand prediction and information diffusion impact analysis in this study. It includes 1,048,575 trips conducted by 216,927 drivers.

Table 1 presents the RideAustin and DiDi data samples' descriptive statistics, and Fig. 1 portrays the spatial distribution of the trip destinations and origins selected for this analysis. Note that the databases we have access to do not provide the actual deadheading distance, since we are only aware of every trip's origin and destination coordinates or the GPS traces when a rider is on board. Therefore, we calculate the distance between each driver's previous trip destination and their next trip's origin using the haversine function (Robusto, 1957) and then convert the distance to a network one using a factor of 1.4 (Wenzel et al., 2019). Table 1 shows that the mean deadheading distance is 2.75 miles in Austin Texas, but the distribution is right-skewed with a median deadheading distance of 1.63 miles. For the DiDi sample data, the mean deadheading distance is 1.52 miles when the median mileage is only 0.84 miles. The shorter deadhead distances estimated leveraging the DiDi data could be attributed to higher density and mixed land use in the city of Chengdu compared to the city of Austin. Deadheading distances are shorter than the actual trip distances, which is consistent with expectations. The average time gap between trips is 31 min with a standard deviation of 29 min for the RideAustin sample and 32 min with a standard deviation of 22 min for the DiDi sample. Note that the average time between trips is calculated as the difference between the time the new trip started minus the time the previous trip was completed.

4. Methodology

The first step in the computational workflow (see Fig. 2) is the employment of a machine learning model that can accurately predict the number of trips at each trip destination's zip code for each time of day. While the algorithms modeling drivers' response to future demand information and deadheading minimization are applied to both datasets, each dataset has its own trained machine learning model for ridesourcing predicting future ridesourcing trip demand. Two variants of the LSTM (which has a special recurrent neural network architecture) predict ridesourcing trip demand in Austin, and Chengdu. Demand prediction results serve as inputs in an algorithm developed to simulate providing drivers with trip demand prediction information for the impending time interval at their current drop-off location. A random selection process was adopted to determine which drivers are most likely to wait in place based on future demand information diffusion. It is assumed that these drivers wait at the current trip destination's zip code or grid cell. A second algorithm is developed to assign TNC drivers to their next trip by minimizing deadheading distance while accounting for temporal and spatial constraints. This effort aims at showcasing the potential of future demand information diffusion to reduce deadheading and, subsequently, reduce fuel consumption, operational costs, and environmental externalities of ridesourcing.

4.1. *Machine learning models for ridesourcing demand prediction*

The proposed methodology commences with the deployment of TNC demand prediction models. The demand prediction models are documented in more detail in a series of recent publications, including Hou et al. (2019) and Wang et al. (2020). The prediction results that are outputs of the machine learning processes are utilized here to understand travel demand information diffusion's effectiveness on empty vehicle miles minimization. The next subsections present the ridesourcing demand prediction models developed using RideAustin and DiDi data samples. The last subsection goes through the algorithms developed to simulate the assignment process that minimizes the deadheading distance.

4.1.1. *RideAustin demand prediction*

The ridesourcing demand prediction model adopts the LSTM structure, which is a special case of recurrent neural network architecture designed to learn time series data with long time spans and high dimensions, introduced by Hochreiter and Schmidhuber (1997). In the context of trip demand prediction, input arrays and matrices of the LSTM architecture include historical ridesourcing demand for all zip codes in Austin at time t, and additional information impacting demand such as time of day, day of week,

Table 1
Descriptive Statistics of RideAustin and DiDi Data Samples.

	Descriptive Statistics	Trip Distance (mi)	Calculated Deadheading Distance (mi)	Time in Between Trips (min)
RideAustin Sample	Mean	4.27	3.91	31.24
	Median	2.81	2.31	20.17
	Standard Deviation	4.12	3.12	28.88
DiDi Sample	Mean	1.96	1.52	31.88
	Median	1.72	0.84	12.00
	Standard Deviation	1.29	1.66	22.34

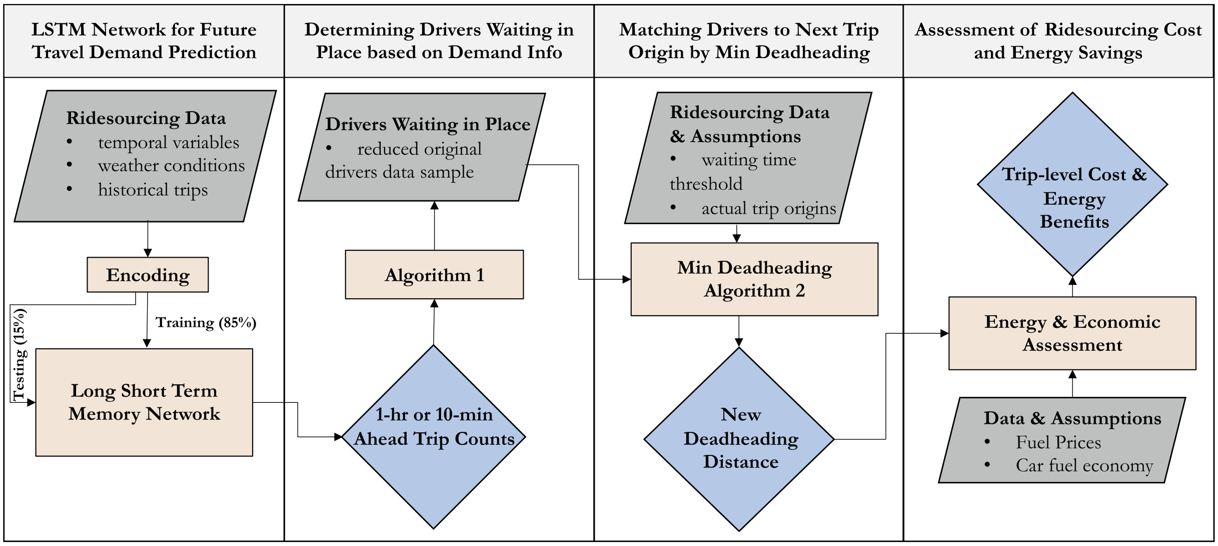

Fig. 2. Schematic representation of the proposed computational workflow.

precipitation information, and temperature in Fahrenheit degrees at time t. The final sigmoid layer provides output demand prediction at time $t+1$ (where 1 designates the 1-hour prediction interval). Details on the LSTM structure, training, and validation are available in Hou et al. (2019). The model was trained on 85% of six-month historical TNC trip data and tested on 15%.

Fig. 3 depicts the observed versus predicted ridesourcing trip demand for a downtown zip code in Austin, using the RideAustin trips dataset. It can be observed that the LSTM structure performs well in predicting ridesourcing trip demand. Results show that the model predicts TNC trip demand in all zones for the coming hour with high accuracy when compared to baseline models of historical average and instantaneous trip demand prediction. Specifically, the proposed LSTM model results in predicting trip demand with a mean absolute error of 7.2 trips per hour, reducing the error by approximately 37% and 24% compared to historical average and instantaneous trip demand methods respectively, as shown in Hou et al. (2019). When we examine the accuracy of the LSTM prediction in different zip codes for heterogeneous time intervals, it can be observed that the LSTM can effectively capture the variation in trip demand across peak and off-peak periods as well as weekdays and weekends.

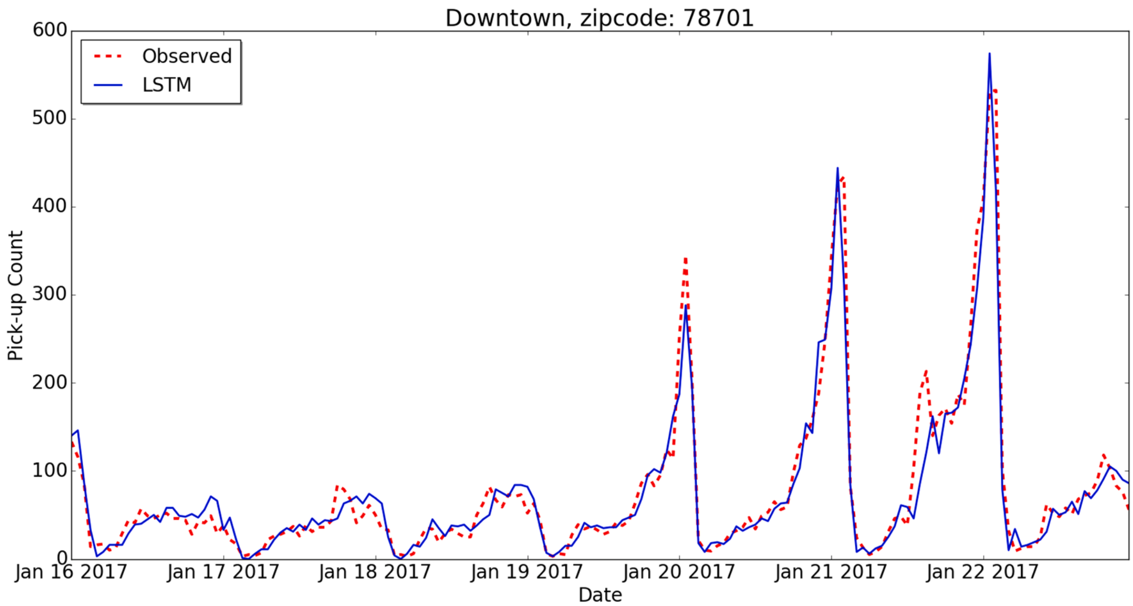

Fig. 3. Observed vs. predicted TNC trips, revised from Hou et al. (2019).

4.1.2. DiDi demand prediction

A trained LSTM network with a few adjustments is also used for demand prediction leveraging the DiDi ridesourcing dataset. The model input b_t consists of several parameters at time t, including temporal (such as month, day of week, time of day) and weather information (including humidity, temperature, and various other weather conditions and flags) denoted as an input array. The ridesourcing demand for grid cell zd at time t is denoted as a square 10×10 matrix C_t for all 100 grid cells of the city of Chengdu. This matrix is treated as an image frame of 10×10 pixels. Given input array parameters noted above, b_t and historic ridesourcing demand at a given location $[C_{t-m}, C_{t-m+1}, \cdots, C_{t-1}]$ for $m \geq 1$, the model output C_{t+k} is a matrix of predicted trip demand in all grid cells at time $t + \mathrm{k}$, where k denotes the time step of prediction. More details on the LSTM architecture, its activation function, convolutional layers, and iterative training process are presented in Wang et al. (2020). Application of this LSTM model with the DiDi data sample produces an accurate prediction of TNC trip demand with a weighted mean absolute percentage error reduction of 25% when compared to an instantaneous demand method. The performance of the predictive machine learning architectures applied using RideAustin and DiDi datasets is quite satisfactory when compared to benchmark trip demand prediction models such as historical averages based on our analysis. Our machine learning predictions outperform similar modeling outcomes in the existing literature, which have documented error reduction by around 20%. Hence, the proposed LSTM network models are deemed fit to provide input to the methodology's next step.

4.2. Information diffusion, and trip assignment

Two algorithms are proposed for completing this step. The first algorithm addresses the selection of drivers who receive information regarding impeding ridesourcing demand (projected trips for the next 10 min or one hour) at the current trip's destination zip code. The second algorithm matches a driver to the next trip origin's location by minimizing the deadheading distance. Fig. 4 presents the pseudo-code for both algorithms.

The first algorithm determines which drivers would wait in place (to pick up another passenger) after completing their previous trip i. The probability that a driver waits for a trip origin j to be generated while serving a trip in the zip code (or grid cell) zd_i of their last trip destination i is binomially distributed with maximum probability of success equal to a threshold a (in the baseline numerical experiment scenario we assume that a is equal to 0.5). The maximum probability a is multiplied by the ratio of the predicted trips $PT_{zd_i t}$ in the vicinity of the driver (i.e., the outcome of the machine learning model), to the maximum number of predicted trips (anywhere in

Algorithm 1 Determining drivers waiting in place after receiving future ride-sourcing demand information

Initialize: Import trip destinations $i \in I$, zd_i the zip codes of trip destinations, $PT_{zd_i t}$ the trips predicted at destination i during hour, day, and month t. Assume threshold a and $r_{it} \in [0, 1]$ are uniformly distributed.
for $t \in T$ **do**
  for $i \in I$ **do**
    $X_{it} = a\frac{PT_{zd_i t}}{\max PT_t}$
    if $X_{it} > r_{it}$ **then**
      $W_{it} = 1$
    else
      $W_{it} = 0$
    end if
  end for
end for

Algorithm 2 Matching ride-sourcing vehicle to next pick-up by minimizing deadheading

Initialize: Import trip destinations i, trip origins j, zd_i and zs_j as zip codes of trip destinations and trip origins, and td_i, ts_j as the time of reaching destination i and the time of pick up at origin j respectively.
$C \leftarrow \{j \text{ where } W_j = 1\}$
for $i \in C$ **do**
  $minD_i = 100000, minA_i = -1$
  for $j \in J$ **do**
    dh_{ij}=haversine(i,j)
    if $ts_j > td_i + \frac{dh_{ij}}{s}$ *and* $szd_i = zs_j$ *and* $ts_j - (td_i + \frac{dh_{ij}}{s}) \leq \beta$ **then**
      $j \in O$
    else
      $j \notin O$
    end if
    for $j \in O$ **do**
      if $temp < dh_{ij}$ **then**
        $minD_i = temp$
        $minA_i = j$
      end if
    end for
  end for
end for

Fig. 4. Heuristic algorithms for (1) determining drivers waiting in place after receiving future travel demand information and (2) next trip assignment.

the study area) in the following hour t, $\max PT_t$. Random numbers (r_{it}) within the interval [0,1] are generated to determine which drivers would wait in place based on the information regarding future trip demand. The driver of a trip where $X_{it} > r_{it}$ (with $X_{it} = a \cdot \frac{P_{zd_i t}}{\max PT_t}$) waits in place for the next rider pickup, setting $W_{it} = 1$. If $X_{it} \le r_{it}$, then the driver does not wait and sets $W_{it} = 0$, deeming trip i ineligible for the following trip matching process.

In this analysis, we assume that the drivers choose whether to stay put or move to a different location based on the future ride-sourcing demand information provided to them. This assumption suggests that the higher the predicted demand at their current destination's zip code or grid cell, the higher the ratio $\frac{P_{zd_i t}}{\max PT_t}$. Li et al. (2011) confirm our hypothesis, showing that waiting and searching are two passenger-finding strategies mainly adopted by taxi drivers based on a large sample of real-world taxi trips. Zhang et al. (2015) demonstrate that the decisions to wait or to hunt for passengers are primarily driven by the time of day and location, which are good indicators of travel demand in a region.

Note that the threshold parameter a plays an important role in estimating X_{it} since it captures drivers' attitudes by serving as an indicator of the proclivity to consume information regarding future travel demand. It is worth noting that in addition to information on future ridesourcing demand, a driver's decision to wait in place (or not) may also be influenced by the availability of short-term parking. Owing to the unavailability of comprehensive spatio-temporal parking occupancy data in both cities (Austin and Chengdu), issues related to passenger loading, unloading, and short-term parking could not be captured in this analysis. We posit that parking availability (or the lack thereof) could be incorporated into the threshold parameter a in future research efforts in a straightforward manner. For example, the magnitude of the threshold parameter could vary spatially and be reduced in locations with low parking availability or time periods of high parking occupancy.

The second algorithm determines candidate trip origins, j, to which drivers who decided to wait at destination i (for which $W_i = 1$) could be matched. The drivers adhere to time and space constraints, as indicated by the RideAustin and DiDi datasets. For example, the starting time of the next trip ts_j should be greater than the arrival time td_i at the current destination plus the time it takes to cover the distance between the origin and destination, denoted by dh_{ij}, at an average speed s $\left(ts_j > td_i + \frac{dh_{ij}}{s}\right)$. Also, the candidate origin of the next trip should be within the same zip code or grid cell as the previous trip's destination ($zd_i = zs_j$). Lastly, the driver's wait time is

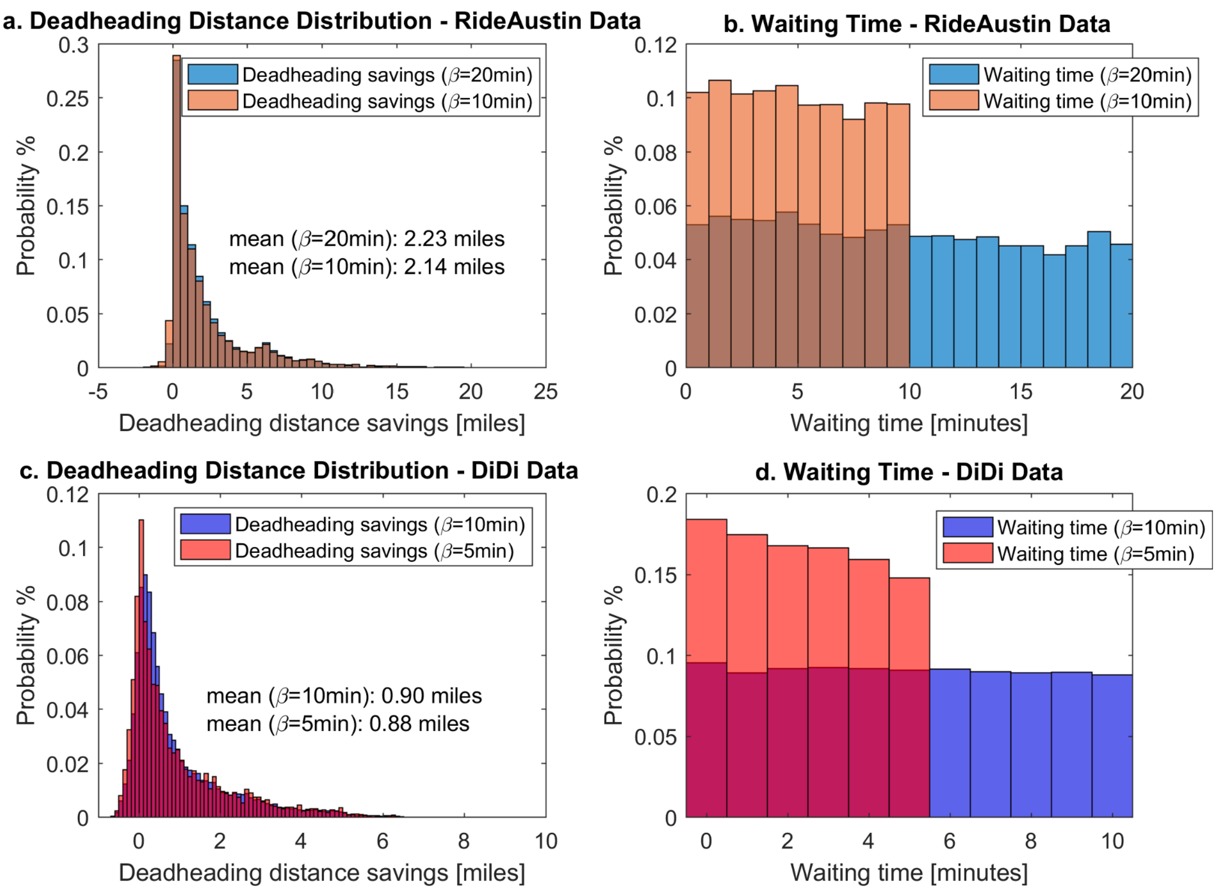

Fig. 5. Ridesourcing trip-level deadheading distance savings and drivers' waiting time distributions (applying the algorithms with RideAustin and DiDi data when $a = 0.5$).

capped at the threshold β, denoted by the constraint $ts_j - \left(td_i + \frac{dh_{ij}}{s}\right) \le \beta$. Trip origin j belongs to the set O when it adheres to all of these constrains. Note that dh_{ij} corresponds to the deadheading distance between the current trip's destination i, and next trip's origin j, calculated using the haversine formula and multiplied by a factor greater than 1 to capture network distance (1.4 here). If a trip's origin k meets all these constraints, and dh_{ik} is the minimum from all the candidates $j \in O$ with deadheading distances dh_{ij}, then k is matched to i. The constraints assume that drop-off, and pick-up times are not flexible and that the ridesourcing service driver's objective is to minimize deadheading operational distance based on the information they receive regarding future trip demand.

5. Results

The algorithms presented above are applied to both the RideAustin and DiDi sample datasets. We ran 100 different scenarios where random values r_{it} are generated and the W_{it} variable is appropriately assigned to each trip. The distribution of the trip-level deadheading savings achieved with future demand information provision to TNC drivers and the drivers' waiting times based on one scenario results are shown in Fig. 5. Fig. 6 shows the distributions of the mean, median, and standard deviation of deadheading savings achieved due to information diffusion, averaged across all the 100 scenario runs for different driver waiting time thresholds β.

Results presented in Figs. 5 and 6 show that information diffusion regarding future trip demand can in fact result in considerable trip-level deadheading distance reductions. It should be noted that the scenario results are compared with the observed empty vehicle/deadheading miles from each of the datasets. For the RideAustin data, trip-level savings vary from −2 miles (as distance gains are also possible with information provision) to 22 miles. Note that these numbers are not significantly impacted by the maximum waiting time threshold (β) assumption. For the DiDi data application, savings per trip vary from −0.5 miles to 9.5 miles. Under each β assumption, drivers' waiting times are uniformly distributed from 0 min to the maximum minute interval allowed, as shown in Fig. 5b and 5d. Percentiles of these distributions are presented in Fig. 6 for the deadheading distance savings and the waiting times' distribution. Based on the results, we conclude that the maximum waiting time threshold β has a limited impact on the distribution of trip-level deadheading savings, primarily because a driver's next trip within the allowable waiting interval is selected by the criterion of minimum deadheading distance. The mean waiting time increases as the allowable drivers' waiting time interval increases, consistent with expectations.

On average, a trip-level deadheading mileage reduction (average based on 100 scenarios runs) of 67.7% was observed in the

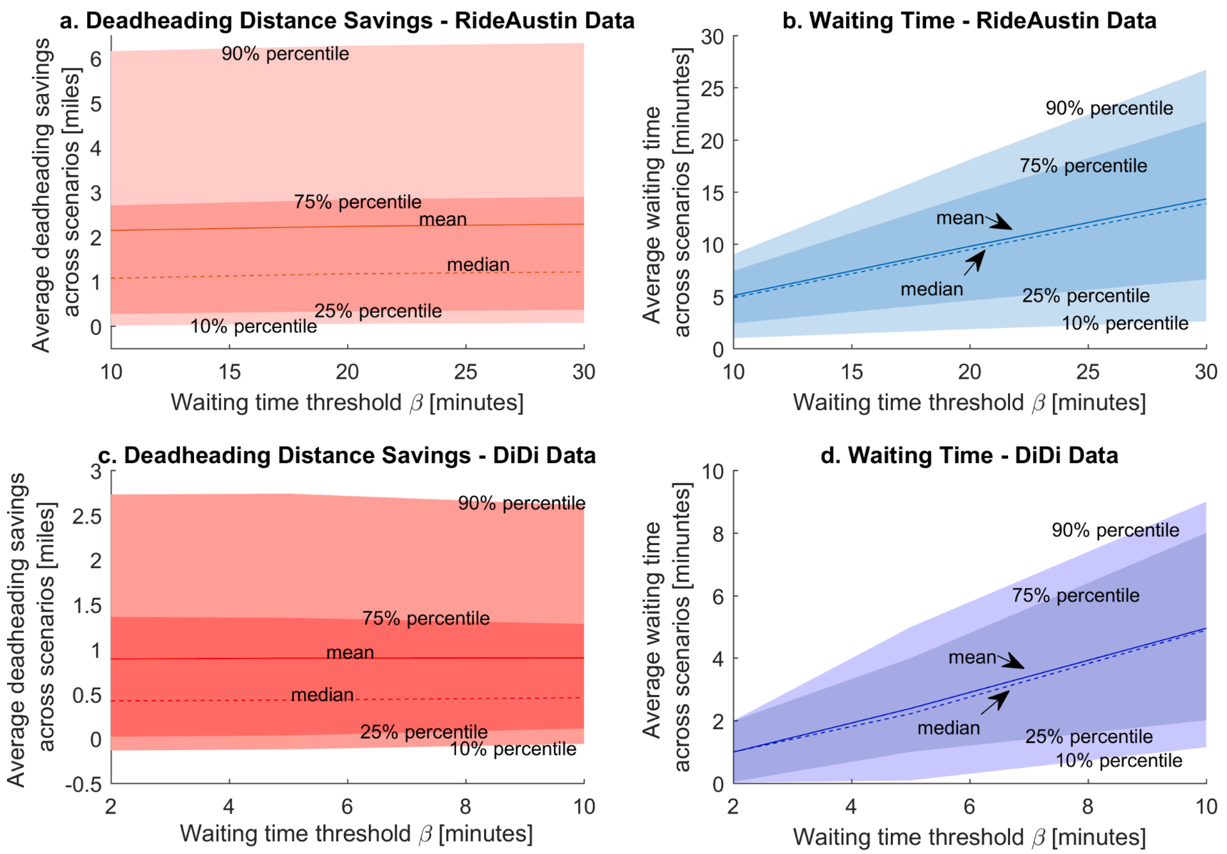

Fig. 6. Percentiles of ridesourcing deadheading distance savings per passenger trip and driver's waiting time.

RideAustin dataset when the maximum waiting time threshold β is set to 10 min. These savings further increased to 78.4% when $\beta = 20$ min and 82.5% when $\beta = 30$ min. Assuming that the average fuel economy of the RideAustin vehicle fleet is close to the most common vehicle in the RideAustin dataset, a 2015 Toyota Camry with a city fuel economy of 25 miles per gallon (U.S. Department of Energy DOE, 2018), the fuel consumption savings due to future demand information diffusion vary from 0.08 to 0.10 gallon per trip. Along similar lines, assuming gasoline retail prices of $ 2.78 per gallon in the Austin region using fuel cost data reflecting prices of January 2017 (U.S. Energy Information Administration, 2018), operational cost savings range from 23 to 26 cents per trip.

Similarly, for the DiDi data application, an average of 59.2% reduction in deadheading miles per trip was observed, when the maximum waiting time threshold β is set to 10 min. These savings decreased, as expected, to 56% when β is set to 5 min. If similar values of the aforementioned average vehicle fuel economy and gasoline price were to be applied to the DiDi operational outputs (as information on vehicle fleet was not available in the DiDi dataset), the range of fuel consumption savings and gasoline cost reductions would vary between 0.035 and 0.05 gallon per trip and 11 to 13 cents per trip, respectively.

Further analysis is carried out to explore the impacts of variation in future trip demand information consumption by varying the maximum percent of drivers who acted on the hour-ahead and 10-minute ahead trip demand predictions. This analysis reflects realistic cases where even if all the drivers in a TNC fleet are provided with demand prediction information, only a proportion of them will choose to act on that information. A similar analogy has been explored in existing transportation literature in the route choice context (Xiong et al., 2016). A specific scenario is considered where the driver is willing to wait up to a threshold of β equal to 10 and 20 min for the DiDi and the RideAustin data, respectively. Then, the first algorithm detailed above is applied repeatedly by varying threshold a, where a denotes the maximum percent of drivers that will be waiting based on the information received. The results of this exercise are shown in Fig. 7. In the RideAustin application, the results indicate that the maximum savings for β equal to 20 min (averaged across 100 runs with different random parameters r_{it}) are achieved when a maximum of 20% of the drivers wait at the location of the current trip's destination. It should be acknowledged here that this result is heavily dependent on the data. However, as shown in Fig. 7, the range of average trip-level deadheading savings when a varies is small. Hence, different threshold (a) values would still result in significant savings per trip for the proportion of the drivers that decide to wait at the drop off location of the current trip.

6. Discussion

Ridesourcing providers such as Uber, Lyft, and DiDi rapidly penetrated the urban transportation market space in the past few years. Most of the companies providing ridesourcing and pooling alternatives could induce behavioral shifts toward car-light or car-free lifestyles (Hall et al., 2018; Ward et al., 2019). On the other hand, there has also been criticism that these companies make congestion worse in cities they operate in (e.g., Erhardt et al., 2019). Much debate has ensued on the amount of travel TNC drivers undertake without a passenger in the car (deadheading), and existing studies have quantified the amount of empty vehicle miles as anywhere ranging between 36% and 45% of the daily travel (Cramer and Krueger, 2016; Komanduri et al., 2018). Understandably, reducing deadheading might not be the top priority of ridesourcing companies whose business model hinges on providing their riders with the least amount of waiting times even at the expense of increasing total VMT in the system. In the research arena, strategies to minimize or reduce deadheading have not been explored much, owing largely to the unavailability of real-world TNC operations data. To address this gap in research, this paper proposes algorithms that use information diffusion as a tool to reduce trip-level TNC empty mileage.

While data from real-world TNC operations have been scarce for the past few years, availability is gradually changing with small sets of TNC data being open-sourced by companies such as DiDi (DiDi Chuxing, 2018) and RideAustin (RideAustin, 2017). This study uses data made available by RideAustin based in Austin, Texas, and DiDi from its operations in Chengdu, China (ChinaDaily, 2018). For

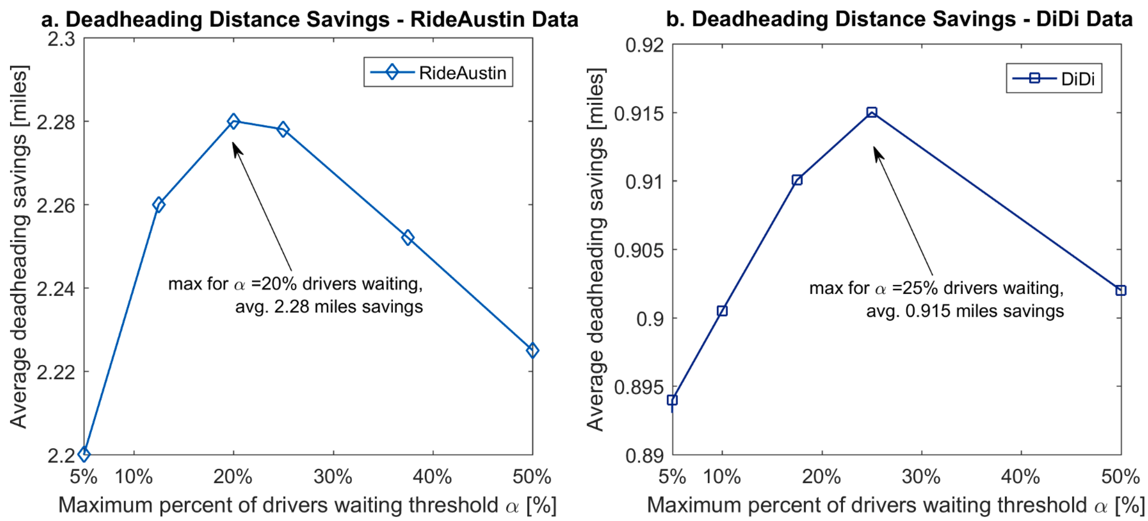

Fig. 7. Impact of the maximum number of drivers waiting (threshold a) on deadheading distance savings achieved.

the purposes of the analysis carried out in this paper, a weeks' worth of origin–destination data was extracted from each of the datasets. The RideAustin dataset includes about ~ 29,000 trips made by 17,000 drivers, while the DiDi dataset includes approximately 1 million trips made by more than 200,000 drivers. From the data exploration exercise, we find that the average deadhead distance (percent of travel made by a driver without a passenger) is close to the average trip distance (percent of travel made by a driver with a passenger), underscoring the importance of identifying ways to reduce deadhead TNC travel. This finding is consistent with existing literature estimates, showing that deadheading comprises up to 45% of total TNC travel. The methodology proposed in this paper builds upon LSTM models predicting TNC trip demand at any given location in a city using machine learning models (e.g., Hou et al., 2019; Wang et al., 2020). Separate machine learning models were estimated and validated for predicting trip demand using temporal resolutions of an hour for seven zip codes in Austin, Texas, and a 10-minute prediction interval in 100 sq.km. grid cells in Chengdu, China. We integrate this travel demand prediction and diffusion process with two algorithms to simulate its effectiveness in nudging drivers to reduce deadheading. Conceptually, the algorithmic process provides trip demand information to a driver at their current drop-off location. The idea behind this information prediction and diffusion strategy is that there is room for changing TNC driver deadheading behavior by providing information to them regarding future trip demand at their current location.

Results from the application of the computational framework show promise for trip-level deadheading reduction by providing information to drivers. Potential deadhead mileage reductions range from 68% to 82% for RideAustin sample and 53% to 60% for DiDi operations per trip. It was also observed that the maximum savings occur when 20%–25% of the TNC drivers act on the information provided to them, with a caveat that the proportion of drivers responding to information has a relatively minor effect on trip-level deadhead mileage savings. This shows that TNCs could implement strategies such as the one suggested in this paper to provide their passengers with a good level of service while also reducing trip-level deadheading. Our paper's strategy, enabling drivers to receive information on future ridesourcing demand, could be leveraged to meet goals of public agencies that aim at controlling vehicle greenhouse gas emissions and adhere to standards such as the Clean Mile Standard of the California Air Resource Board (California Air Resources Board, 2020). Other strategies, such as targeting drivers who drive more deadhead miles or providing trip demand information to drivers during daily peaks could be tested. Other ways that such deadhead mileage savings can be achieved are by regulating TNCs by setting thresholds on the total amount of deadhead travel that each company (through all of its vehicles) can undertake in a day or collecting mileage-based fees for their operation on the transportation network.

While this paper presents one of the first attempts, to our knowledge, to simulate and uncover the effects of reducing ridesourcing empty vehicle miles by providing future information to TNC drivers, the study has a few limitations. Firstly, this study's demand prediction horizon is set at one hour for the RideAustin implementation, which is quite large, given the average time between stops is about 30 min. For the DiDi operations sample dataset, smaller intervals of 10-minute predictions are explored. Future studies should enhance the proposed machine learning models to predict demand information at even finer temporal resolutions. Second, the algorithm developed does not optimize trip-to-vehicle assignments over the day. The proposed algorithm is heuristic and matches each trip destination with an origin, creating pairs that minimize deadheading. Therefore, this assignment showcases savings that could be achieved at the trip level. The assignment does not address total daily system savings since each trip-matching process is independent of the rest in the dataset. Finally, it is recognized that distributing information to ridesourcing drivers and enabling them to wait for their next trip in place (to reduce their operational and fuel costs) would require parking availability or dedicated space to be allocated specifically for this use. The results of this analysis should not be interpreted as encouragement for designing and offering more on– and off-street parking spots for ridesourcing use. Instead, our findings highlight the need for more efficient parking management, per minute pricing, or other policies presented in Butrina et al. (2020). Xu et al. (2017b) present interesting insights on ridesourcing parking demand and parking supply. It could be construed that free parking is not always a given, and at times, drivers who choose to wait in place would be charged for occupying an on-street parking space. The decision drivers will have to make is whether it is worthwhile to pay for parking by the minute or incur fuel costs from cruising. Future efforts could extend the framework presented in this paper to incorporate parking as an additional factor that influences a driver's decision to wait or cruise.

CRediT authorship contribution statement

Eleftheria Kontou: Conceptualization, Methodology, Software, Data curation, Visualization, Writing - original draft, Writing - review & editing. **Venu Garikapati:** Conceptualization, Methodology, Writing - review & editing. **Yi Hou:** Data curation, Visualization.

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