Ride-hailing Emissions Modeling and Reduction through Ride Demand Prediction

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Abstract: Transportation is the largest contributor of greenhouse gas emissions in the United States. As Transportation Network Companies (TNCs), such as Uber and Lyft, grow in prevalence, it is imperative to quantify their emissions impact. We studied the case of Austin, Texas through its primary ride-hailing service - RideAustin - that has released data on 1.4+ million individual rides over an 11-month period. We estimated a total of 6014.95 metric tonnes of CO_2 emissions from deadheading (when there are no passengers in freight) over the given time period. We clustered Austin into different zones and built an LSTM-based neural network for hourly ride demand forecasting on each zone through spatiotemporal features (weather, federal holidays, day of the week, and a look-back interval). Despite a large out-of-time validation window (7 months), our model outperforms the XGBoost-based baseline model by 34.86% and the next best comparable model in current literature by 15.3% in terms of MAE. In addition, we estimated a 10.624% reduction in total deadheading emissions for the same period given that the ride-hailing drivers on road are routed according to the proposed hourly ride demand forecasts.

1 INTRODUCTION

Transportation is the largest contributor of greenhouse gas (GHG) emissions in the United States, accounting for over a quarter of total US greenhouse gas emissions (Hockstad and Hanel, 2018). These GHG emissions are a primary cause of climate change. Over recent years, companies such as Uber and Lyft, henceforth referred to as Transportation Network Companies (TNCs), that provide on-demand ride-hailing services have grown in prominence. These companies leverage the convenience of mobile apps and provide shared mobility services, more specifically referred to as ride-hailing, ride-sourcing, or e-hail services. In Massachusetts, for example, TNCs had a ridership of over 91.1 million in 2019, 12% more than that in 2018 (DPU, 2019). In San Francisco, TNCs made up 15% of all intra-city trips in 2016 (Erhardt et al., 2019). Throughout the United States, TNCs transported a total of 2.61 billion passengers in 2017 - 37% more than the year before (Schaller, 2018).

With this increasing prevalence of TNCs in our lives, it is imperative to understand the environmental impact of these services. This need is only reinforced by the fact that in contrast to other public transit services and the traditional taxi industry, TNCs operate as private entities with minimal regulation - there is largely no minimum threshold for the emissions efficiency of operating vehicles and no limitations on the fleet size or on the hours of operation.

In recent years, much work has been done to analyze the effects of ride-sharing services (Wang and Yang, 2019). In particular, a recent study summarizes how the interplay of different factors - namely, ride pooling, fuel efficiency of ride-hailing fleets, car-shedding, deadheading[1], and modal shift[2] - results in a net environmental impact of a TNC on its service area (Wenzel et al., 2019). Specifically, while ride pooling, car-shedding, and the inclusion of electric vehicles in ride-hailing fleets may reduce Vehicle Miles Traveled (VMT)[3] and total emissions, induced rides due to the convenience of such services and deadheading may increase VMT and emissions.

One key focus of such analysis is the modal displacement of ride-hailing journeys - what forms of transit they replace, and to what extent ride-

[1] *Deadheading* is the distance traveled by a vehicle without passengers in freight (Henao and Marshall, 2019).

[2] *Modal shift* is the overarching trend of change in the mode of transportation.

[3] *Vehicle Miles Traveled (VMT)* is the total travel by all vehicles in a given geographic area for a given time period.

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hailing induces rides which otherwise would not have taken place. Intercept surveys of ridesourcing users (Clewlow and Mishra, 2017; Feigon and Murphy, 2016) have led to inconsistent results for the rate of induced rides and for specific mode replacement. More technical approaches attempt to predict dynamic mode substitution through spatiotemporal analysis, but the effectiveness of these techniques relies on the availability of specific behavioral data to build models. The first study of this sort identified some specific patterns in mode substitution among riders: in particular, substitution of more sustainable modes of transit was highest among passengers who did not own a car (Henao and Marshall, 2019). Nevertheless, the authors acknowledged a complex relationship between those patterns and real outcomes in the short and long term. The difficulty of this experimental design (in which a researcher personally drove for a ride-hailing service) and the challenges in generalizing local behaviors to other regions makes specific ride-level behavioral data broadly inaccessible, and limits more detailed analysis of this relationship.

Another key area of study is *deadheading* and the impact on VMT. The distances that drivers cover while cruising in search of a ride or driving between rides have been found to add up considerably. Such travel without passengers can account for 36-45% of all of the miles traveled by ride-hailing drivers (Cramer and Krueger, 2016; Komanduri et al., 2018), leading to significant increases in vehicular emissions. The researchers found that these miles traveled represent half or more of the additional energy use caused by ride-hailing vehicles (Wenzel et al., 2019). As an alternative to deadheading, drivers have the option to park their cars while waiting to be assigned a rider, but few choose to do so, largely to avoid parking costs. When drivers do choose to park, they may often receive a ride request during or immediately after parking, so doing so may be inconvenient and drivers may instead prefer to actively look for riders in popular areas based on their experience (Kontou et al., 2020).

It is possible to reduce such deadheading by forecasting ride demand and routing drivers to areas with an impending demand surge. However, much of the work in ride-hailing demand prediction focuses on reducing "waiting time and traffic congestion," in order to improve the passenger experience and enable dynamic scheduling and pricing adjustment (Jin et al., 2020a). It should be noted that optimizing for these outcomes does not necessarily produce a reduction in VMT or total emissions. In particular, Uber matches riders to vehicles with the objective of concurrently minimizing riders' waiting time in specific areas (Uber Marketplace, 2019). Research has shown that the energy impact of even traditional origin-destination routing can be improved by another 3-9% when routing models are optimized for emissions impact instead of time (Ahn and Rakha, 2013). When deadheading routes are optimized with the purpose of reducing VMT, methods and results vary widely. Some researchers have used LSTMs for ride demand forecasting (Hou et al., 2019), some have used Convolutional Neural Networks (Wang et al., 2019; Ke et al., 2018), and some researchers have used stacking ensemble learning approaches (Jin et al., 2020b) as well. However, these models have typically been tested on smaller test sets due to the limited availability of data and are often hard to compare due to different data granularity, regions, time periods, and services in focus.

Our research contributes to this field in three ways:

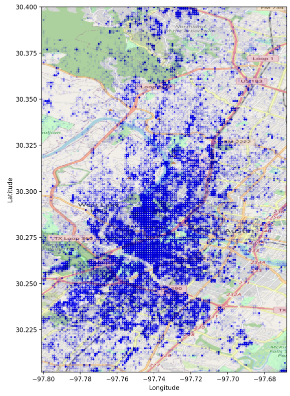
1. We model the emissions impact of ride-hailing services through directly measuring deadheading and total emissions per each unique driver and vehicle.
2. We develop a robust ride demand forecasting model using deep learning techniques that predicts hourly demands for different regions in a city, and outperforms existing models.
3. We estimate the reduction in deadheading emissions given that drivers are re-routed hourly based on the aforementioned forecasts.

The rest of this paper is organized as follows: Section 2 briefly describes the data and our methodology; Section 3 details the results from our models; Section 4 presents a discussion of the results and relevant limitations; Section 5 summarizes the study and suggests future work; and Section 6 acknowledges those who have supported us throughout the study.

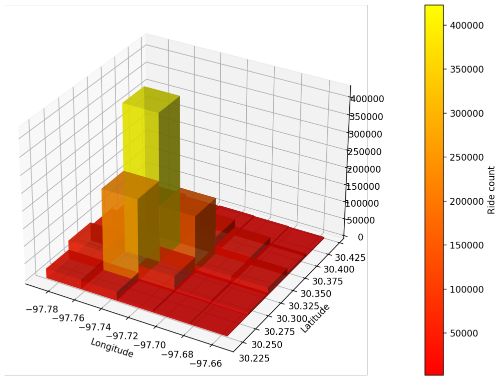
2 DATA AND METHODOLOGY

2.1 Data Description

We use three public datasets throughout the study: year-long origin-destination trips and drivers data from a ride-hailing service called RideAustin (RideAustin, 2017), vehicular energy efficiency data for different car models from The U.S Environmental Protection Agency (EPA) (EPA, 2017), and zip-code specific hourly weather data (humidity, precipitation, heat index) from World Weather Online (WorldWeatherOnline, 2020).



(a) RideAustin pick-up locations in Austin, TX.



(b) RideAustin ride demand distribution.

Figure 1: Pick-up locations and cumulative demand for RideAustin rides (2016-17).

RideAustin Data. RideAustin is a TNC operating in Austin, Texas, United States, that came into limelight after the departure of Uber and Lyft from Austin. RideAustin published data on over 1.4 million rides, conducted by over 5000 drivers, over a 11-month period (2016-17). Figure 1 describes the pickup locations and cumulative ride counts for all RideAustin rides for the given time period. This dataset is a origin-destination dataset, that has geo-coordinates of the requested location, start location, end location, along with corresponding times and distances. Since riders and drivers are identified by unique IDs, it is possible to aggregate by drivers and gain more insight into their behaviors as well. Figure 2 describes the daily count of rides and unique drivers. The figure indicates a consistent weekly oscillation of the counts, following a trend of much higher supply as well as demand on the weekends compared to weekdays. This suggests that most riders in Austin used RideAustin for entertainment and recreational purposes as opposed to daily commute to work or school. The significant peak near March of 2017 correlates with the major *South by Southwest* festival that took place in Austin. Overall, the number of rides seemed to increase at a greater pace in comparison to the number of rideshare drivers.

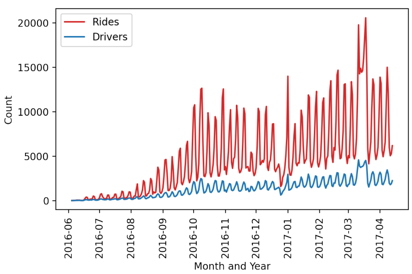


Figure 2: Daily count of rides and drivers through RideAustin.

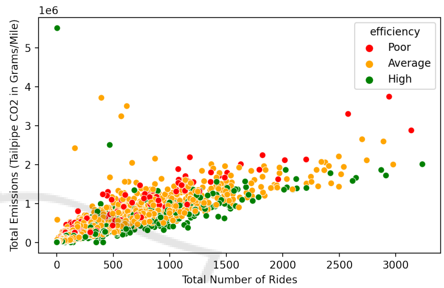
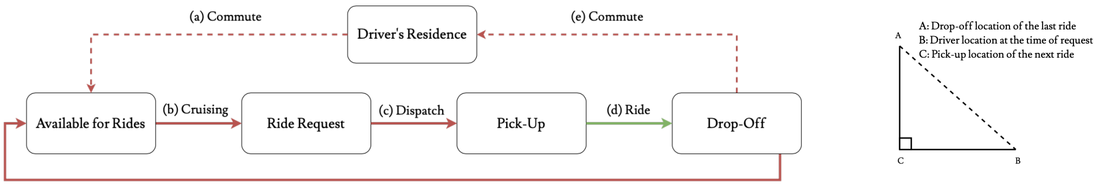


Figure 3: Total emissions by vehicle efficiency for fleet.

Environmental Protection Agency (EPA) Data. The U.S. Environmental Protection Agency (EPA) published a dataset regarding the energy efficiencies of different cars by their model and make. Specifically, the dataset provides a reliable and standardized method of comparing vehicles and their fuel economies. The dataset included various vehicles' make and model as well as the associated fuel economy indicators such as transmission and miles per gallon (MPG) estimated for "city", "highway", and "combined" conditions. We use this along with the RideAustin dataset to calculate the emissions produced by each ride, and consequently for performing deadheading calculations. We categorize vehicle efficiencies into three categories based on the EPA emissions standards and the underlying data distribution. The projected EPA CO_2 emissions standard was 225 g/mi (Agency, 2012), and the calculated 25th empirical quartile of the EPA dataset is 403.95 g/mi. Therefore, we take a very conservative approach and categorize vehicles with less than 330 g/mi CO_2 emissions per mile under high efficiency, greater than 330 g/mi and less than 404 g/mi under average efficiency, and over 404 g/mi under poor efficiency. Figure 3 shows how vehicles under the RideAustin fleet with poor efficiency create higher emissions.



(a) Driving segments in a standard ride-hailing ride.

(b) Inter-ride deadheading.

Figure 4: Calculation of deadheading for a ride-hailing rides.

2.2 Methodology

2.2.1 Overall Deadheading Miles and Emissions

As detailed in Figure 4a, a standard ride-hailing driver's mileage and emissions can be divided into five segments: (a) commute from a driver's residence to the area of service, (b) cruising in search for a ride, (c) drive to the passenger location on request, (d) ride from the passenger pick-up location to the passenger drop-off location, and (e) commute from the last ride to the driver's residence. Segments (b) - (d) recur for as long as the driver decides to be in service for the day, all segments but (d) contribute to overall deadheading emissions, and segments (b), (c), and (e) contribute to ride deadheading emissions.

To calculate (a) and (e), i.e. deadheading miles and emissions due to the driver's daily commute, we first calculate an approximate residential location for each driver by computing the geometric mean of the first daily coordinates of that driver's aggregated trips (Wenzel et al., 2019). We then calculate the haversine distance[4] between the approximated residential location and location of the first ride starting point, and between the last ride's ending point and the approximated residential location. To account for the distance over the road network, the origin-destination straight-line distances for these commutes are multiplied by a scaling factor of 1.4, as derived in Wenzel et al. (2019) from ride-level data, which is annotated with a GPS-measured distance in addition to origin and destination coordinates.

To calculate (b), i.e. inter-ride stalling or cruising, we estimate segment AB in Figure 4b. The dataset does provide the number of miles driven to get to a user's ride request location from the driver's current location (BC). However, corrupted dispatch location data from the dataset resulted in an inability to directly compute AB. Therefore, we assume a 90°angle between segment AC and segment BC. This value was obtained as a representative of the median between the angle that would produce the largest amount (180°) and the angle that would produce the lowest amount (0°) of deadheading. By aggregating drivers by day, we compute the haversine distance between the ending location of the previous trip and the starting location of the following trip to calculate AC. We then simply compute the Pythagorean distance and get an estimate for deadheading due to cruising (AB).

The (c) segment, i.e. the dispatch distance, is already given in the dataset as the *driving_distance_to_rider* parameter.

Finally, we sum (a), (b), (c), and (e) to get the deadheading miles for each driver for a given day. This value is multiplied by the emissions efficiency of each driver's vehicle model and make to estimate the total deadheading emissions for that driver for that day. While we identify it necessary to interpolate these values due to the lack of availability of other information, we acknowledge that these values may not be wholly accurate and anticipate that more research into driver patterns may be beneficial in development of a more accurate model. Furthermore, we only calculate CO_2 emissions for simplicity of comparison, but recognize that other pollutants such as PM, NOx, NMOG, CO, Formaldehyde, etc. could also serve as important metrics.

2.2.2 Clustering on Geographical Proximity

The density of ride origins and destinations in Austin varies greatly with region. For instance, the density of ride demand around the Airport is much higher than in any other area (Figure 1b). Therefore, we conduct silhouette analysis to determine the optimal k for k-Means clustering and segment the ride data into k clusters based on geographical proximity. Silhouette analysis is a popular graphical technique that allows for analysis of cluster cohesion and separation, and is reliable in determining the appropriate number of clusters for unsupervised learning techniques such as k-Means (Rousseeuw, 1987).

[4]The *haversine formula* determines the great-circle distance between two points on a sphere given their longitudes and latitudes.

2.2.3 Ride Demand Forecasting

We adopt a deep learning approach to forecast hourly ride demand through spatiotemporal features for each cluster (or *zone*). The feature set for each model includes weather data (humidity, precipitation, heat index), day of the week, and if that day is a federal holiday. We use a Long Short Term Memory (LSTM) network to predict the ride demand for the following hour for each zone. The efficacy of the model is evaluated by comparing it against an Extreme Gradient Boosting (XGBoost) model, which we consider as the baseline. Each model is described in detail below.

Since our goal is to estimate the reduction in deadheading emissions through the construction of this ride demand forecasting model and gauge how it would generalize in the real world, we choose against training on several months of data only to evaluate our results on less than a quarter of the data (as is prevalent in current literature). Instead, we adopt a rolling out-of-time evaluation approach to maximize data coverage and test how our model generalizes throughout a larger time period. We do this through running seven sequential iterations of our overarching model on progressively increasing time windows. These seven iterations, listed in Table 1, allow for out-of-time validated ride demand forecasts for a seven-month period for a given zone.

Table 1: Rolling out-of-time evaluation iterations.

Train	Test
Jun ‘16	Jul ‘16
Jun ‘16 - Jul ‘16	Aug ‘16
Jun ‘16 - Aug ‘16	Sep ‘16
Jun ‘16 - Sep ‘16	Oct ‘16
Jun ‘16 - Oct ‘16	Nov ‘16
Jun ‘16 - Nov ‘16	Dec ‘16
Jun ‘16 - Dec ‘16	Aug ‘16

Extreme Gradient Boosting. Gradient boosting is an algorithm that combines weak base learning models into a strong learner in an iterative fashion. Extreme gradient boosting (XGBoost) an improvement on standard gradient boosting, that most notably uses (i) second-order Taylor expansion, as opposed to the first-order, of the loss function of the base model; and (ii) L1 and L2 regularization to improve generalization (Chen and Guestrin, 2016).

Our model is comprised of 1000 sequential decision trees and a threshold of 50 for early stopping to prevent overfitting. This simple model is considered as our baseline model for ride demand forecasting.

Long Short-Term Memory. A Long Short-Term Memory (LSTM) network is a special case of Recurrent Neural Networks (RNNs) that is capable of learning long-term dependencies well enough for practical purposes. RNNs have a short-term memory - they can carry information from only the time steps immediately before. As the time steps increase, the information from the earlier time steps is diminished, which makes RNNs unsuitable for forecasting in cases of longer time-series sequences.

In contrast, a typical LSTM network constitutes four layers: a cell state, and three gates - input gate, forget gate, and output gate - that control the cell state (Hochreiter and Schmidhuber, 1997). These four layers iteract and comprise a working model through the following steps:

1. The **forget gate** (f_t) decides what information is to be discarded from the previous cell state, based on the output of the previous step h_{t-1} and current input X_t. The decision is made through a *sigmoid* activation function (σ) and the range is (0, 1), where 0 indicates ‘forget all’, and 1 indicates ‘keep all’. Here, W_f represents weights of the respective neurons and b_f represents bias.
$$f_t = \sigma(W_f[h_{t-1}, X_t] + b_f) \tag{1}$$
2. In order to decide what new information gets stored in the cell state, there are two steps that are later combined. First, the **input gate** (i_t) - a sigmoid (σ) layer - decides what information is to be updated. Second, a *tanh* layer creates C_t - a vector with new candidate values.
$$i_t = \sigma(W_i[h_{t-1}, X_t] + b_i) \tag{2}$$
$$C_t = tanh(W_c[h_{t-1}, X_t] + b_c) \tag{3}$$
$$tanh = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{4}$$
3. The output is also decided by the **output gate** (o_t) through a two-step process. First, a sigmoid (σ) layer is run. Second, the cell state (C_t) is passed through *tanh* and multiplied by the output of the previous sigmoid layer.
$$o_t = \sigma(W_o[h_{t-1}, X_t] + b_o) \tag{5}$$
$$h_t = o_t * tanh(C_t) \tag{6}$$

Our model is comprised of one LSTM layer with 128 hidden neurons and a corresponding dropout layer (p = 0.2; where p is the probability of a neuron being excluded from the network) for regularization. The model has a look-back interval of 6 time-steps (i.e. 6 hours), 45 epochs, a batch size of 32, and 10% of the training data reserved for validation in each epoch. The chosen loss function is Mean Squared

Error (MSE) but Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are also considered important indicators of model performance. These are represented below, where n is the number of observations, Y_i is the actual ride demand, and $\hat{Y}_i$ is the predicted ride demand.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{7}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \mid Y_i - \hat{Y}_i \mid \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{9}$$

2.2.4 Evaluating Reduction in Deadheading Emissions

By predicting the location of the next ride, given an hour-day time bucket, we aim to reduce overall inter-ride deadheading. We first aggregate our set of rides into buckets for each driver and date. Then, for each ride and zone, we compute a weighted average of the distance between the centroid of that zone (obtained from the earlier k-means clustering) and the current location of the driver, and the predicted ride demand for the given hour at that centroid. Through an iterative approach, we found a nearly optimal weighting of roughly 60% attributed to distance to the centroid of the driver and 40% to ride demand at that zone.

Given this weighted average, we calculate the optimal centroid for each zone as longitude-latitude coordinates. We then calculate the haversine distance between the location of the last drop-off point and the centroid (Segment AB, Figure 4b) and the haversine distance between the location of the centroid and the next pick-up point (Segment BC, Figure 4b). As earlier mentioned, this value is computed under the assumption that individual drivers are being sent to a zonal centroid. In other words, after assigning each driver-ride endpoint to one of 10 zones - computed by k-means clustering and ride demand forecasting - we re-route the driver to the centroid of that zone and stall at that location in preparation for a subsequent ride. We then aggregate the harversine values to compute an overall prediction for deadheading mileage.

Finally, in a similar manner as in Section 2.2.1, we utilize the EPA data on vehicular emissions efficiency to compute a value for overall emissions for each trip by multiplying the calculated deadheading mileage and the emissions efficiency for the vehicle used for the trip.

3 RESULTS

In this section, we present the results of the aforementioned components of this paper: estimated overall deadheading miles and emissions, clusters based on geographical proximity, efficacy of ride demand forecasts, and the estimated reduction in deadheading emissions given our ride demand forecasting model.

3.1 Estimated Deadheading Miles and Emissions

We estimated that a total of 17,920,612.565 deadheading miles and 6014.952 metric tonnes of deadheading emissions were produced by the RideAustin fleet in Austin, Texas from June 2016 - July 2017 (Table 2). These constitute approximately 59% of all vehicle miles traveled and emissions by the fleet. Therefore, more empty CO_2 emissions were produced than emissions during actual rides. The share of ride deadheading miles and emissions, which excludes the deadheading during a driver's assumed commute to and back from the service area (as described in 2.2.1), is slightly lower at 44.4%.

Table 2: Total and deadheading miles and emissions for the RideAustin fleet (June '16 - April '17).

Measure	VMT (x 10^7 mi)	CO_2 (tonnes)
Ride DH	1.34 (44%)	4,527.26 (44%)
Overall DH	1.79 (59%)	6,014.95 (59%)
Total	3.03	10,194,499.33

3.2 Geographical Clusters

Through silhouette analysis, we obtained an optimal value of k = 10 for k-means clustering. As a result of this clustering, the region covered by the RideAustin fleet was divided into 10 zones, as depicted in Figure 5. The clusters have different densities - for example, the Downtown Austin area (represented by Zone 2) has a much higher density than Zone 5.

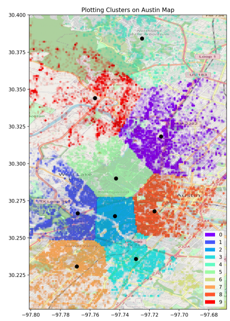


Figure 5: Ride demand clusters in Austin, TX.

3.3 Ride Demand Forecasts

Table 3: Model performance (July '16 - Jan '17).

Model	MAE	RMSE
XGBoost (Baseline)	9.36	26.392
LSTM	6.098	18.421

The proposed models were run on the given time intervals and the predictions for the seven-month period for each zone were combined for each model. The LSTM-based neural network, which uses spatial features in addition to the 6-hour look-back period, far outperforms the XGBoost model, which we considered the baseline model for our study (Table 3).

Figure 6 represents the comparison of ride demand forecasts from both models with the actual ride demand for a randomly selected 3-week time period (Nov 4, 2016 - Nov 25, 2016). The LSTM model is able to forecast well even on unnatural peaks during weekends. Figure 7 specifically emphasizes the superior performance of the LSTM model over the baseline model.

3.4 Estimated Reduction in Deadheading

If drivers are rerouted based on the hourly ride forecasts as estimated by our LSTM model, we estimated there to be a cumulative 10.624% decrease in total deadheading miles and emissions in the Austin region. Figure 8 highlights this difference between the observed emissions and the revised emissions.

4 DISCUSSION

Our LSTM model outperforms the baseline model by 34.86% and 30.20% in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) respectively. The model also outperforms a comparable hourly ride demand forecasting model on the same dataset (Hou et al., 2019) by 15.3% despite a more robust testing procedure comprised by a much larger out-of-time validation window. The cumulative MAE for our model is 6.09 (considering all 10 zones); this indicates that for any given hour, the model would predict with an error of around 6 rides on average.

We also estimated the total deadheading emissions for the recorded period to be 6,014,952 kg CO_2. Using our LSTM model, we estimated there to be a 10.624% reduction in these deadheading emissions. To give perspective to this number, the amount of emissions reduced by our proposed model is equivalent to over 661,110 pounds of coal burned, 1,380 barrels of oil consumed, carbon sequestered by 780 acres of US forests in one year, or 130 passenger vehicles driven for one year (EPA, 2020).

We acknowledge that the models and methods used by us have limitations. Most importantly, while our estimate of 44.4% ride deadheading is well within the range of estimates by other researchers (Wenzel et al., 2019; Cramer and Krueger, 2016; Komanduri et al., 2018), we do not have a reliable way to validate our calculations for deadheading miles and emissions. Specifically, deadheading commute calculations, i.e. (a) and (e) in Figure 4a, are based on assumptions and existing literature, and may differ with each driver's specific behavioral patterns. In addition, the number of rides through RideAustin progressively increase over time (Figure 2), especially after August, which may have affected the forecasting accuracy for earlier months. Lastly, computational power limitations rendered us unable to optimize the weighted average in Section 2.2.4 further, but we acknowledge the necessity for improving this ratio.

5 CONCLUSION

In this study, we leveraged data from a ride-hailing service RideAustin, with over 1.4 million rides and more than 5000 drivers over an 11-month period, to perform three tasks: estimate the total deadheading emissions impact of the RideAustin fleet, build a neural network to forecast hourly ride demand in it's service area, and estimate the reduction in deadheading emissions given the aforementioned forecasting model.

We segmented RideAustin's service area in Austin, Texas into 10 zones through a popular unsupervised learning technique - k-means clustering. We then built an LSTM-based neural network using spatiotemporal features to forecast hourly ride demand for each zone. As a result, we gathered out-of-time ride demand forecasts for a 7-month period for all zones, which allowed us to develop a model for rerouting drivers based on ride demand. Finally, we estimated the total reduction in deadheading emissions given such re-routing. Our LSTM-based ride demand forecasting model outperforms the XGBoost-based baseline model by 34.86%, and another state-of-the-art model on the same dataset by 15.3% in terms of Mean Absolute Error (MAE). Furthermore, we estimate a 10.624% reduction in deadheading emissions over the 7-month period that the model was tested on.

We conclude that ride demand forecasting and the

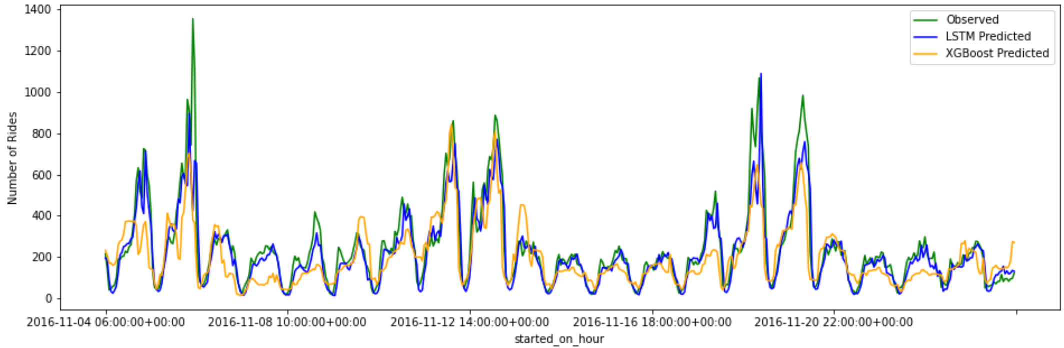


Figure 6: Comparison of ride demand forecasts (Nov ‘2016).

(a) XGBoost

(b) LSTM

Figure 7: Observed vs Predicted ride demand for the following hour.

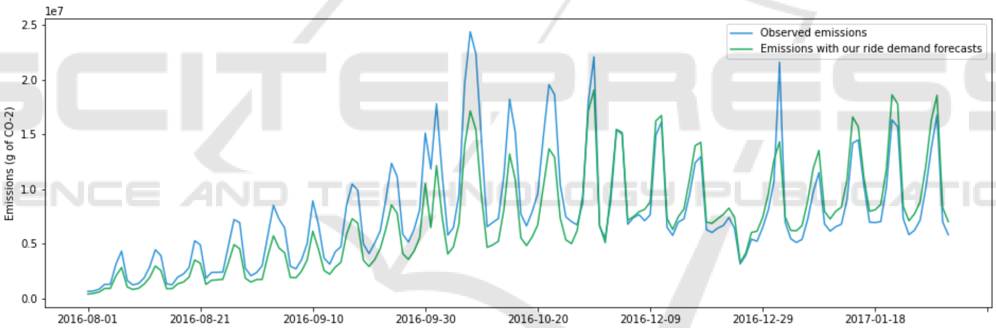


Figure 8: Emissions reduction through our hourly ride demand forecast.

consequent rerouting of drivers to different geographical zones in a region has the ability to concretely reduce deadheading emissions. We strongly believe that such models could help TNCs reduce their carbon footprint in an inexpensive way. In addition to extending our work through more robust data, potential future research efforts in this field include recording driver activity in inter-ride periods to better estimate deadheading and analyzing the impact of facilitating dedicated parking spaces for ride-hailing drivers on deadheading emissions. Furthermore, ride-level data like that collected by Henao et al. (2019) can be generalized to interpolate mode substitutions for unlabeled ride data and thus concretely describe patterns in ridership impacts.

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