A SHORT-TERM CHARGING WAIT TIME ESTIMATION APPROACH USING RECURRENT MIXTURE DENSITY NETWORKS AND QUEUING MODEL

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ABSTRACT

With the rapid development of sustainability in urban mobility, electric vehicles (EVs) have become a pivotal role in Mobility-on-Demand (MoD) systems. However, compared to conventional gasoline vehicles, EVs have to spend plenty of time on battery charging. Due to the limited charging facility, a long wait time brings challenges on the supply side from the perspective of the urban mobility market. To guide the EVs to the appropriate charging station (CS) with a short charging wait time, we propose a novel short-term charging wait time estimation approach that integrates an M/M/c/c queuing model and a charging demand forecasting model based on recurrent mixture density networks named XRMDN. To validate the performance, we conducted a case study based on real data sets in New York. The comparative results demonstrate that our XRMDN-augmented queuing model outperforms the ARIMA-integrated queuing model in terms of charging wait times forecasting.

Keywords: electric vehicle, charging wait time, queuing theory, time series forecasting

1 INTRODUCTION

Electric vehicles (EVs) are rapidly emerging as a cornerstone of shared mobility and sustainable transportation, marking a significant stride towards environmental conservation and energy efficiency [1]. In urban settings, where pollution and greenhouse gas emissions are major concerns, EVs offer a cleaner alternative to traditional internal combustion engine vehicles. By running on electricity, they emit no tailpipe pollutants, significantly reducing urban air pollution and contributing to cleaner, healthier city environments [2]. This shift is crucial in the face of global climate change challenges. Additionally, EVs tend to have lower operating costs, thanks to the high efficiency of electric motors and the decreasing cost of batteries, making them economically attractive in the long term. Their integration into smart grids and potential in energy storage solutions also positions EVs as dynamic players in future urban energy systems.

The widespread adoption of EVs has brought to light a significant challenge in urban mobility: the wait time associated with charging EVs. Unlike the relatively quick process of refueling a gasoline-powered vehicle, charging an electric car can take anywhere from 30 minutes to several hours, depending on the type of charger and the vehicle's battery capacity [3]. This disparity creates logistical issues, particularly in densely populated areas where the charging demand in charging stations (CS) often exceeds supply, leading to long queues and charging wait times. Most of the existing studies focus on either the variants of the charging wait time minimization problem [4, 5, 6, 7] or the charging demand prediction issue [8, 9, 10, 11], while the prediction of charging wait time at CS is neglected. Recently, a few works [12] have begun to

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investigate the charging wait time estimation issue via the queuing theory [13] modeling technique. Despite the effectiveness of queuing theory in charging wait time modeling, the stochastic process (especially the Poisson process in most of the literature) is assumed to be stationary. The number of charging requests evolves over time, which renders high *volatility* in the practical scenario. Hence, the EV arrival rate follows a *non-stationary* pattern, which is ignored by most of the works.

In this study, we propose a novel short-term charging wait time estimation approach that integrates a queuing model and a time series probabilistic forecasting deep learning model called XRMDN [14]. XRMDN leverages the time series of historical charging request data to forecast the distribution of charging demand for the next time interval. Taking the forecasting results as the input, the queuing model can estimate the charging wait time under the non-stationary stochastic process. The rest of this article is organized as follows: the problem statement and the proposed approach, which is discussed in Section 2. A case study based on New York trip records and CS data sets is conducted to validate our approach in Section 3. Finally, the contribution is summarized, and future research directions are discussed in Section 4.

2 THE APPROACH ON SHORT-TERM CHARGING WAIT TIME ESTIMATION

In this section, we briefly describe the problem first, followed by the proposed charging wait time estimation approach, which integrates a deep learning-based model and a queuing model as the end-to-end solution.

2.1 Problem Statement

We consider a general charging wait time estimation problem, given a fleet of EVs that travel around a region waiting for charging. Meanwhile, a group of CSs with different numbers of chargers are scattered in the specific region. Further, it is assumed that the historical charging demand information at each time interval is available. Finally, the objective is to estimate the expected changing wait time in the region at the given time interval.

2.2 The Modeling Approach

We adopt an $M_1/M_2/c_1/c_2$ queuing model in this study, where M_1 denotes the arrival rate in a given time interval (e.g., varies from several minutes to hours), which is modeled as a non-stationary Poisson process, M_2 denotes the charging time (i.e., the service time from the perspective of queuing theory), which is assumed to follow negative exponential distribution in this work, c_1 and c_2 denote the number of CS and the average number of chargers, respectively.

Further, let λ_t, μ_t denote the mean charging request rate at time t, and the mean charging time at time t, respectively. The service rate ρ_t at time t, and the occupation rate of CS ρ_t' at time t can be denoted as follows:

$$\rho_t = \frac{\lambda_t}{\mu_t}; \tag{1}$$

$$\rho_t' = \frac{\lambda_t}{c\mu_t}, \tag{2}$$

where $c = c_1 c_2$, and the idle rate of all the CSs at time t can be calculated as follows:

$$p_t = \left[\sum_{m=0}^{c-1} \frac{\rho_t^m}{m!} + \frac{\rho_t^c}{c!(1-\rho_t')} \right]^{-1}. \tag{3}$$

Further, the average queue length waiting at CS at time t can be computed as follows:

$$L_t = \frac{p_t \rho_t^c \rho_t'}{c!(1-\rho_t')^2}. \tag{4}$$

Eventually, the average charging wait time at time t (WT_t) is given by:

$$WT_t = \frac{L_t}{\lambda_t}. \tag{5}$$

Notice that the most critical parameter in the queuing model above is the arrival rate λ_t (i.e., the forecasting charging request in this study). Since the charging request follows a time series pattern [15], and the demand fluctuates over time, which renders high volatility. In this work, we adopt a deep learning time series forecasting model XRMDN [14], which is based on recurrent mixture density networks, to predict the rate of EV charging requests by leveraging time series historical data.

The XRMDN extends the Recurrent Mixture Density Networks (RMDN) model [16] by adding three correlated recurrent neural networks, which are combined via the demand residual to capture the trends and dependencies of charging demand. The recurrent neural network in XRMDN can capture the high volatility in the charging demand, which can redefine the charging demand probabilistic forecasting by approximating a Gaussian mixture model whose parameters are obtained from three correlated recurrent neural networks.

3 CASE STUDY

In this section, the experimental environment and data process are introduced. Subsequently, the comparative results are discussed. The experiment is implemented using Python 3.11 and runs on a PC with an Intel Core i7, 32 GB RAM, and Windows 11.

3.1 Data Process and Visualization

Two real data sets - New York green taxi trip records [17] and CSs in New York [18] are leveraged for the experiment validation. We filtered a subset of attributes, including rider drop-off datetime, drop-off latitude, and longitude, which are applied in the following experiment. Meanwhile, we randomly draw 5,000 samples of rider drop-off coordinates from the trip records and plot the heatmap in Fig. 1. In addition, there are 3,652 CSs in the raw data set, and we select 388 CSs in the selected area, as shown in Fig. 2. Based on the visualization results, we select two regions as marked in the rectangles. One contains a large number of CSs, which is located in Mid-Manhattan, and the other one contains a small number of CSs, which is located in Brooklyn.

Since we consider a short-term charging wait time forecasting issue, we discretize one day into 144 time slots. Therefore, the length of each time slot is 10 minutes. We assume that during each time slot, one-third of EVs are required to be recharged after the riders are dropped off. Therefore, we aggregate one-third of trip records whose drop-off times range every 10 minutes as the charging requests historical data. Consequently, the historical charging demand data can be leveraged to forecast the arrival rate, which is the input parameter of the M/M/c/c queuing model.

3.2 Results and Discussion

We adopt the queuing model that uses the true demand as the benchmark model labeled as True. In addition, we introduce another queuing model, where the charging request is predicted by ARIMA [19] for

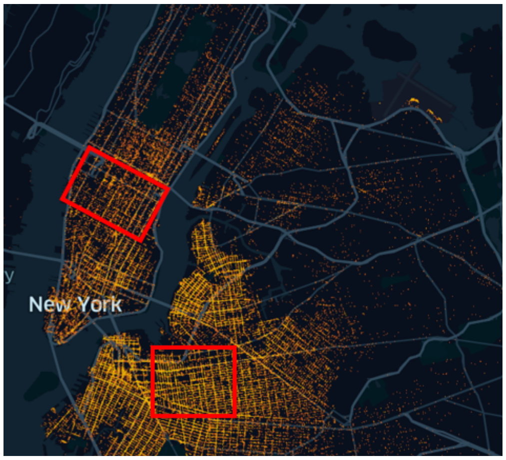

Figure 1: Heatmap of Drop-Off Density.

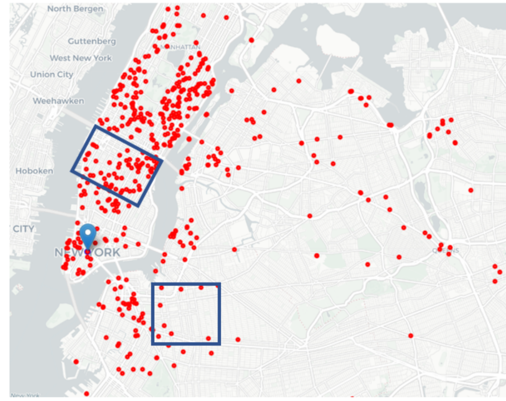

Figure 2: Charging Station Distribution.

the comparison, which is labeled as ARIMA. The proposed approach that integrates the queuing model and XRMDN is labeled as XRMDN. The comparative results are divided into two regions (Mid-Manhattan and Brooklyn) and two scenarios (weekdays and weekends); therefore, there are four scenarios for the validation comparison. Further, to reduce the deviation, the validation results were averaged over four weekdays and four weekends in January 2016.

In general, the average charging wait time in Brooklyn is much higher than the one in Manhattan. This is because the CS density in Manhattan is higher than the one in Brooklyn, which shortens the queue length at CS. Therefore, the charging wait time is significantly reduced. In addition, it can be observed that the queuing model with XRMDN outperforms the queuing model with ARIMA in terms of the charging wait time. The results are consistent across the four comparative results. In particular, it is shown that the queuing model with XRMDN can better capture the charging time volatility compared to the queuing model with ARIMA. For example, 9 am and 11 am in Fig. 3, 5 am in Fig. 4, 1 pm and 3 pm in Fig. 5, and 4 am in Fig. 6. The reason is that XRMDN can capture the high volatility in forecasting charging request, which greatly impacts the charging wait time volatility.

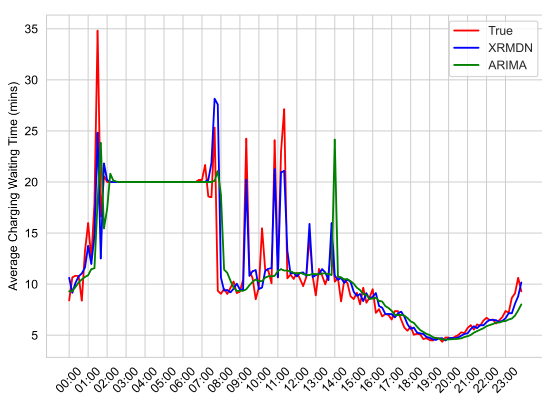

Figure 3: Comparative Results in Mid-Manhattan on the weekdays.

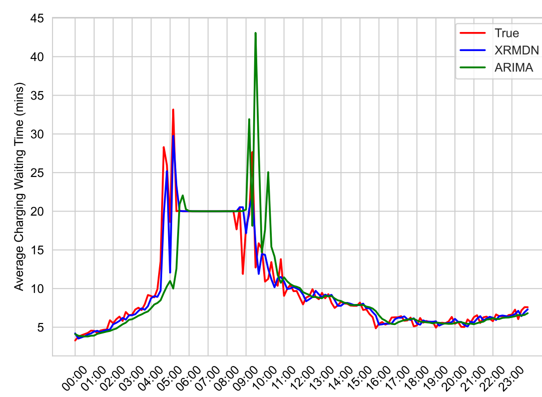

Figure 4: Comparative Results in Mid-Manhattan on the weekends.

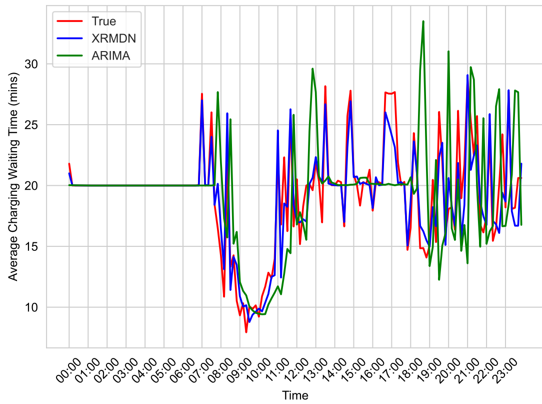

Figure 5: Comparative Results in Brooklyn on the weekdays.

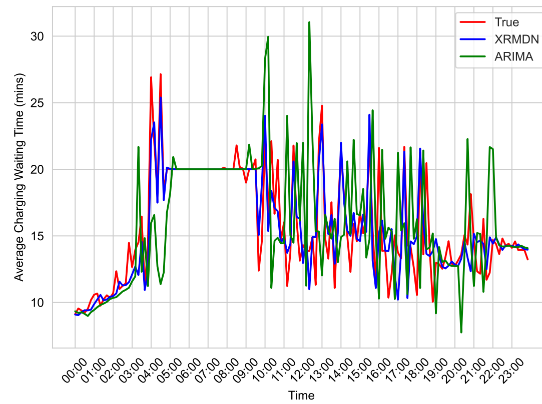

Figure 6: Comparative Results in Brooklyn on the weekends.

4 CONCLUSIONS AND FUTURE WORK

In this study, we introduce an innovative methodology for the estimation of short-term charging wait times, which amalgamates a queuing model with a recurrent mixture density network model. Utilizing historical time series data on charging demand, this novel approach demonstrates superior efficacy in predicting charging wait times when compared to established benchmark methodologies. Furthermore, this proposed model holds potential for integration within EV MoD services, facilitating enhancements in the joint optimization of electric vehicle rebalancing, matching, and charging schedule allocations. This area of application is considered a prospective direction for future research endeavors.

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