Dynamic Demand Prediction for Expanding Electric Vehicle Sharing Systems: A Graph Sequence Learning Approach

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ABSTRACT

Electric Vehicle (EV) sharing systems have recently experienced unprecedented growth across the globe. Many car sharing service providers as well as automobile manufacturers are entering this competition by expanding both their EV fleets and renting/returning station networks, aiming to seize a share of the market and bring car sharing to the zero emissions level. During their fast expansion, one fundamental determinant for success is the capability of dynamically predicting the demand of stations as the entire system is evolving continuously. There are several challenges in this dynamic demand prediction problem. Firstly, unlike most of the existing work which predicts demand only for static systems or at few stages of expansion, in the real world we often need to predict the demand as or even before stations are being deployed or closed, to provide information and support for decision making. Secondly, for the stations to be deployed, there is no historical record or additional mobility data available to help the prediction of their demand. Finally, the impact of deploying/closing stations to the remaining stations in the system can be very complex. To address these challenges, in this paper we propose a novel dynamic demand prediction approach based on graph sequence learning, which is able to model the dynamics during the system expansion and predict demand accordingly. We use a local temporal encoding process to handle the available historical data at individual stations, and a dynamic spatial encoding process to take correlations between stations into account with graph convolutional neural networks. The encoded features are fed to a multi-scale prediction network, which forecasts both the long-term expected demand of the stations into account with graph convolutional neural networks. We demonstrate that our approach significantly outperforms the state of the art, showing up to three-fold performance gain in predicting demand for the rapidly expanding EV sharing system.

KEYWORDS

Electric Vehicle Sharing; Dynamic Demand Prediction; Expansion

1 INTRODUCTION

Car sharing services have long been recognised as an environmentally friendly mobility option, reducing vehicles on the road while cutting out unnecessary CO₂ emissions. With the recent advances in battery technologies, a new generation of car sharing services is going one step further, by offering full electric vehicle (EV) fleets with fast expanding infrastructures in major cities, e.g. Bluecity ¹ in London, WeShare ² in Berlin, and BlueSG ³ in Singapore. Traditional car sharing providers have also started to populate their EV fleets, e.g., ZipCar seeks to provide over 9,000 full electric vehicles across London by 2025 ⁴. According to a recent study [14], the global market of EV sharing services is poised for much faster growth in the near future, due to the incentives and regulations put in place by governments across the world to encourage overall EV usages.

Despite their increased popularity, the practicality and utility of EV sharing systems still rely heavily on the infrastructure at renting/returning stations. In particular, for systems with the need to rapidly expand their station networks, it is paramount to be able to dynamically predict the accurate demand as or even before implementing any expansion strategy. This is not only the key for the stakeholders to make informed decisions as to where and when to deploy new stations or close the poorly performing ones, but also of great importance to the effective operation of currently used stations, since understanding the potential impact of proposed expansion to their demand can provide valuable insights on a number of vital tasks such as scheduling and rebalancing.

However, this dynamic demand prediction problem is not trivial, especially in the context of fast expanding EV sharing systems. Most of the existing work on demand prediction [3, 7, 10, 11, 13, 18] assumes the stations in the system are static, or only predicts demand after fixed expansion stages [12]. These assumptions often collapse in the real world. Fig. 1(a)-(c) visualise the expansion process of a major EV sharing platform in Shanghai during 2017. We see that in the beginning stations are scattered within limited areas, while at the end of 2017 the entire city has been densely covered. As shown in Fig. 1(d), within just 12 months the total number of stations
in operation has doubled, as each month there are continuously hundreds of stations being deployed. In this context, predicting demand at those newly deployed or to be deployed stations is very challenging, since there is no sufficient historical data available as prior knowledge.

On the other hand, dynamics introduced by the expansion process can have very complex impact on the entire system. For example, as shown in Fig. 2, deploying stations at various places may have completely different consequences. Obviously the new station in Fig. 2(a) ‘steals’ demand from one of its neighbours in the following months (station A, see the changes of their order numbers in Fig. 2(b)), because we found the new station was deployed at a shopping centre which may attract more users. In contrast, deploying the new station in Fig. 2(c) has increased orders of its neighbour stations collectively (see Fig. 2(d)). This is because the new station was deployed at the terminal on the east side of the airport, and many users rent vehicles for convenient short-range connections to/from stations E, F, and G which are on the west side. This makes accurate demand prediction for the remaining stations also very challenging in the presence of such dynamics, due to the non-trivial impact caused by the expansion.

To address these challenges, in this paper we propose a novel dynamic demand prediction approach, which models the expansion of EV sharing systems using graph-based sequence learning, and is able to predict the accurate demand of stations along with the expansion process. Specifically, for each station that comes in operation, we employ a local temporal encoding process to capture the correlations within the historical data. The extracted features from all stations are then compiled by a dynamic spatial encoding process, which considers the spatial dependencies between them as multiple time-varying graphs, and fuses the station-level features with Graph Convolutional Neural Networks (GCN). Based on the encoded information and future expansion plan (i.e. which stations to be deployed/closed), our prediction network predicts station demand at multiple scales, from the instant demand in the immediate near future, to the long term expected demand, for both stations to be deployed and the ones remaining. Hence, the technical contributions of this paper are as follows:

- To the best of our knowledge, this is the first work that identifies and formulates the dynamic demand prediction problem in expanding electric vehicle sharing systems.
- We propose a novel graph sequence learning approach, which employs temporal and spatial encoding in tandem to model the complex dynamics of the continuous system expansion.
- We design a new multi-scale prediction network, which is able to forecast not only the expected demand of stations in the long term, but also the instant future demand in subsequent timestamps.
- We evaluate the proposed approach on real-world data collected from a major EV sharing platform for one year. Extensive experiments have shown that our approach significantly outperforms the state of the art, offering up to three-fold improvement in prediction accuracy.

2 PROBLEM FORMULATION

In this section, we first introduce some key concepts used throughout the paper, then we formulate the problem of dynamic demand prediction and provide an overview of the proposed framework.
2.1 Preliminaries

**EV Stations:** Let \( s_i \) be a station in the Electric Vehicle (EV) sharing system. In this paper, we assume \( s_i \) can be represented as a tuple \((x_i, m_i)\), where \( x_i \) are the coordinates (e.g., latitude and longitude) of \( s_i \), and \( m_i \) is the number of charging docks within \( s_i \). We also assume that for a given \( s_i \), we can extract a number of geospatial features based on its location \( x_i \), such as nearby Points of Interest (POI) or the distribution of road networks within a certain radius.

**Instant Station Demand:** We define the instant demand of station \( s_i \) at timestamp \( t \) as the rent/return frequency of \( s_i \) when it is available, denoted as \( d_i(t) \). In this paper the granularity of timestamp \( t \) is days, i.e., we focus on daily station demand, but it is straightforward to adopt other time granularity levels in our framework.

**Expected Station Demand:** For a station \( s_i \), the expected demand \( \hat{d}_i \) over a period \([t_e, t_e] \) can be defined as the mean \( \hat{d}_i(t_e, t_e) = |t_e - t_i|^{-1} \sum_{t=t_i}^{t_e} d_i(t) \). In practice, we often consider the expected demand from current time \( t \) towards the future, and aggregate it according to some index, e.g., days of the week. Without loss of generality, in this paper, we denote the future expected demand of station \( s_i \) as \( \hat{d}_i = [\hat{d}_i^1, \hat{d}_i^2, \ldots, \hat{d}_i^K] \) for different days of the week.

**Station Network:** The stations of the EV sharing system can be modelled as a graph \( G = (S, A) \), where the nodes \( s_i \in S \) are stations as defined above. An edge \( a_{ij} \in A \) may encode a certain type of correlation between two stations \( s_i \) and \( s_j \), e.g., the spatial distance between them, or similarity between their POI/road network features. Sec. 3 will discuss how our approach constructs multiple graphs to capture such inter-station relationships in more details.

**Station Network Dynamics:** Unlike existing work, in this paper we assume the station network is continuously evolving over time. More specifically, let \( G_{t-1} = (S_{t-1}, A_{t-1}) \) represents the station network at time \( t-1 \). We assume at time \( t-1 \), there is an expansion plan to be deployed before time \( t \), which shall expand the current station network from \( G_{t-1} \) to the planned network \( G^P_{t-1} \). Let’s assume during this a set of new stations \( S^* \) will be deployed, while existing stations \( S^- \) will be removed. If the expansion plan goes through, then at time \( t \) the station network \( G_t \) becomes \( G^P_{t-1} \), where \( G_t = (S_t, A_t) \), \( S_t = (S_{t-1} \cup S^*) \) and \( A_t = (A_{t-1} \setminus \{a_{ij} | s_i \in S^- \text{ or } s_j \in S^- \}) \cup \{a_{ij} | s_i \in S^+ \text{ or } s_j \in S^+ \} \).

2.2 Dynamic Demand Prediction Problem

Suppose that at time \( t \), we have the previous topology \( G_1, \ldots G_t \) and demand \( D_1, \ldots, D_t \) of the station network, where \( D_t = \{d_i(t)|s_i \in G_t\} \). Let \( G^P_t \) be the planned station network. The dynamic demand prediction problem tackled in this paper is that given the historical demand \( d_i(t) \) and the current station network from \( t \) to \( t+\delta_t \), we aim to estimate both its expected future demand \( \hat{d}_i \) and the subsequent \( k \) instant demand \([\hat{d}_i(t + 1), \ldots, \hat{d}_i(t + k)]\), which minimise the mean square errors with respect to the ground truth \( d_i \) and \( \hat{d}_i \):

\[
\delta_i = |\hat{d}_i|^{-1} ||\hat{d}_i - d_i||^2, \quad \text{and} \quad \delta_{\hat{d}_i} = k^{-1} \sum_{t=t+1}^{t+k} ||\hat{d}_i(t) - d_i(t)||^2 \tag{1}
\]

In practice, the expected demand \( \hat{d}_i \) can be viewed as a metric for the long-term performance of stations \( s_i \), e.g., if \( s_i \) is a station to be deployed, \( \hat{d}_i \) quantifies the average level of demand it may be able to attract. On the other hand, the sequence of instant demand \([\hat{d}_i(t + 1), \hat{d}_i(t + 2), \ldots, \hat{d}_i(t + k)]\) describes the immediate trend of station demand under the impact of the expansion plan, which can help to optimise key future operation strategies such as marketing and resource allocation.

2.3 Framework Overview

Fig. 3 shows the overview of the proposed framework for dynamic demand prediction, which consists of three major components:

**Local Temporal Encoding:** During the life cycle of a station \( s_i \) (from being deployed to shut down), its demand can be viewed as a time series, where the current demand \( d_i(t) \) should correlate with the local historical demand \( d_i(t-1), \ldots, d_i(1) \). In addition, there may exist other temporal factors that can influence the demand of individual stations, such as weather conditions, air pollution levels, days of the week and public holidays etc. To model such temporal dependencies, we assign a Long Short-Term Memory (LSTM) network at each individual station when being deployed, and use them to encode local temporal information at station level.

**Dynamic Spatial Encoding:** Intuitively, the demand of a station \( s_i \) should also be affected by the others in the station network. To capture the spatial correlations, at each time \( t \) we construct multiple graphs to encode different spatial relationships between the stations, e.g., inter-station distances, POI similarity, and road network distributions. Then we use graph convolutional neural networks (GCN) to fuse those graphs and encode the previously computed local features of individual stations. In particular, as the station network is evolving over time, we consider a dynamic version of GCN which is able to process such time-varying graphs.

**Multi-scale Demand Prediction:** Based on the results of the above temporal and spatial encoding, we aim to predict both the expected demand and subsequent instant demand of stations after the planned expansion. To achieve that, we design a multi-scale prediction network, which firstly compiles the previously learned features into a context vector. For expected demand, it uses a fully connected branch to perform the prediction, while on the other hand, it considers a decoder LSTM network with attention mechanism to forecast instant demand at multiple future timestamps.

We are now in a position to elaborate the proposed dynamic demand prediction approach in more detail.
3 METHODOLOGY

3.1 Local Temporal Encoding

Like in many other shared mobility systems, we observe that the demand of stations in the EV sharing platform exhibits strong temporal correlations, as shown later in Fig. 6(b). For instance, although it fluctuates largely over time, the demand at a station approximates certain periodical patterns at different days across the week. In that sense, exploiting such knowledge can help significantly in estimating the accurate future demand of current stations, which will have a positive knock-on effect when predicting demand for new stations during expansion. However, those demand patterns are typically influenced by multiple complex factors such as weather, air quality and events, and individual stations may react to those factors very differently. Therefore, it is often not optimal to only incorporate the temporal information globally for the station network, but instead in this paper we model such microdynamics at station level.

Concretely, when a station $s_i$ is deployed, we instantiate a local LSTM network which keeps processing its demand records and the additional temporal information available, e.g., weather, days of the week and public holiday/events. In our implementation, we train the LSTMs with shared weights across stations. Then at a later time $t$, the LSTM encodes the station’s historical demand $d_i(t), d_i(t-1), ...$ of $s_i$ as well as the auxiliary information into a temporal feature vector $\mathbf{f}_i(t)$. Moreover, in this paper we also condition $\mathbf{f}_i(t)$ with a static station feature $\mathbf{c}_i$, which describes key attributes of $s_i$ such as its number of available charging docks $m_i$, nearby POIs and environmental characteristics etc. Therefore, $\mathbf{f}_i(t)$ and $\mathbf{c}_i$ carry important local information about individual stations since they started operating, which are then passed on as the input for spatial encoding. Fig. 4 shows the workflow of the proposed approach, where we see that at each timestamp we maintain a collection of local LSTMs to encode information of individual stations.

3.2 Dynamic Spatial Encoding

3.2.1 Constructing Multiple Graphs. As discussed in Sec. 2.1, at a given time $t$ we represent the station network as a graph $G_t = (S_t, A_t)$, where $S_t$ are the set of current stations and $A_t$ is the adjacent matrix describing the pairwise correlations between them. In practice there are often more than one types of correlations, which can’t be effectively captured by a single graph. Therefore in this paper we construct multiple graphs to encode the complex inter-station relationships, particularly the distance graph, the functional similarity graph, and the road accessibility graph (see Fig. 4).

Distance: In most cases, we observe that the demand of stations close to each other are highly correlated, e.g. they may be deployed around the same shopping centre, and thus tend to be used interchangeably. We capture such correlations with a distance graph $A^D$, whose elements are the reciprocal of station distance:

$$a_{ij}^D = \frac{1}{\|x_i - x_j\|_2^2}$$

where $x_i, x_j$ are the station coordinates, and $\| \cdot \|_2$ is the Euclidean distance. We also set $\text{diag}(A^D)$ to 1 to include self loops.

Functional Similarity: Intuitively, stations deployed in areas with similar functionalities should share comparable demand patterns. For instance, stations close to university campuses typically have significantly higher demand during weekends. We characterise the functionalities of stations by considering the distributions of their surrounding POIs. Suppose we have $P$ different categories of POIs in total, and let $p_i$ be the distribution of the $P$ types of POIs within a certain radius of station $s_i$. The functional similarity graph $A^F$ is then defined as:

$$a_{ij}^F = \text{sim}(p_i, p_j)$$

where $\text{sim}() \in [0, 1]$ is a similarity measure which quantifies the distance between feature vectors. In our experiments, we use the soft cosine function.

Road Accessibility: Another important factor that affects station demand is the accessibility to road networks. Intuitively, stations close to major ring roads, or within areas that have densely connected streets would have higher demand. To model this, we consider the drivable streets in the vicinity of a station $s_i$ as a local road network, containing different types of road segments and their junctions. We extract a feature vector $r_i$ from the local road network, which encodes information such as the road segments density, average junction degree and mean centrality etc. Given those features, the road accessibility graph can be defined with certain similarity function $\text{sim}()$:

$$a_{ij}^R = \text{sim}(r_i, r_j)$$

3.2.2 Dynamic Multi-graph Convolution. At time $t-1$, given the constructed graphs $A_{t-1} = (A_{t-1}^D, A_{t-1}^F, A_{t-1}^R)$ which describe the inter-station relationships, we propose a dynamic multi-graph GCN...
to fuse such spatial knowledge with local features $f(t-1)$ and $c_t$ computed by the station-level temporal encoding. We perform multi-graph convolution as follows:

$$H_{t-1}^{(l)} = \sigma \left( \sum_{A_{t-1} \in \mathcal{P}_{t-1}} f(A_{t-1}) H_{t-1}^{(l-1)} W_{t-1}^{(l-1)} \right)$$  \hspace{1cm} (5)$$

where $H_{t-1}^{(l-1)}$ and $H_{t-1}^{(l)}$ are the hidden features in layers $l-1$ and $l$ respectively, and $W_{t-1}^{(l-1)}$ is the feature transformation matrix learned through end-to-end training. In particular, the input $H_{t-1}^{(0)}$ is the collection of local features computed at individual stations. $f(A_{t-1})$ is a function on graphs $A_{t-1}$, e.g. the symmetric normalized Laplacian [8] or $k$-order polynomial function of Laplacian [6], and $\sigma$ is a non-linear activation function such as ReLU.

As discussed before, in our case the station network evolves over time, i.e. new/existing stations can be opened/closed at any time. For simplicity, suppose at $t$ there is only one new station $s^+$ has been deployed. To capture that, we recalculate the inter-station graphs $A_{t-1}$ by appending new rows and columns to them, where the new graphs $A_t$ contain pairwise correlations between the new $s^+$ and each existing stations. Note that the GCN input also changes, i.e. now $H_t^{(0)}$ has an extra feature for this newly deployed station, computed by the local encoding process.

On the other hand, let $s_j$ be the station closed at time $t$. In our implementation, instead of removing elements from the graphs, we simply apply a mask of zeros to the corresponding rows and columns of $A_t$, and set the $j$-th row of the input $H_t^{(l)}$ to zeros since there won’t be local features generated from $s_j$ anymore. The intuition is that in our graph representation, $a_{ij} = 0$ means station $s_j$ has no correlation with any other station at all, and thus won’t propagate information in the graph convolution. In addition, note that although $f(A_t)$ produces filters with the same size of the feature $H_t^{(l)}$ at each layer $l$, Eq. (5) can still be viewed as a local convolution given the graphs $A_t$. The reason is that by definition many elements in $A_t$ are near zero (e.g. in the distance graph $A^0_t$), i.e. for a given station, it will be only affected by features of stations with sufficiently high correlations (large non-zero elements in $A_t$) with it. Conceptually, the dynamic GCN operates on snapshots of the inter-station graphs which are constructed on-the-fly, and fuses the local temporal features at individual stations with the spatial dependencies encoded in those graphs.

3.3 Multi-scale Demand Prediction

As discussed in Sec. 2.2, the dynamic prediction problem addressed in this paper is to forecast the future demand of arbitrary EV sharing stations under the planned expansion, given the historical data and previous dynamics of the station network. We have shown in the previous sections how we use local LSTM and GCN to encode the spatial-temporal dynamics of the system, and in this section we explain how to make predictions at multiple scales based on the knowledge extracted from the models. Fig. 5 shows the architecture of the proposed multi-scale demand prediction network.

3.3.1 Predicting Expected Demand. Let $G_t^F$ be the planned station network at time $t$. Without loss of generality, we assume that comparing to the current network $G_t$ we will deploy a candidate new station $s^N$, while we close an existing one $s_j$. The goal is to predict the future demand of stations in $G_t^F$. We process this planned network $G_t^F$ with the same approach as discussed in previous sections. Note that there is no historical data for station $s^N$ since it is not deployed yet, and therefore in local encoding we only construct its static features $c_{s^N}$, while keeping $c_{s_j}$ as zeros. Then we apply the same update to the inter-station graphs as discussed in Sec. 3.2.2 (adding and masking the corresponding rows/columns), and pass the new input $H_t^{(0)}$ (containing features of $s^N$) through the multi-graph GCN, producing an output $H'_t$. We consider this $H'_t$ as the context for prediction, since it encodes both historical data of existing stations and information on the new candidate station $s^N$, together with their spatial correlations.

In this paper, we consider the expected demand of station $s_i$ over different days of the week, i.e. $d_i = [d_i^{Mo}, d_i^{Tu}, ..., d_i^{Sa}]$. To predict $d_i$, we plug in a fully connected network to the context vector $H'_t$, which is trained to output the future expected demand for each station in the network $G_t^F$. For the station $s^N$, the predicted expected demand of itself and nearby stations indicate the potential benefits of deploying $s^N$ to the current station network. In Sec. 4.3 we will show that in real-world experiments our approach significantly outperforms the existing techniques in prediction accuracy.

3.3.2 Predicting Instant Demand. We also predict the future instant demand of stations in $G_t^F$ over a certain time window $[t+1, ..., t+k]$. This is also of great importance in practice, especially for the station $s^N$, since it forecasts the immediate impact and future trends of the station network once $s^N$ is in operation. However it is more challenging than predicting the expected demand, because essentially for each station we need to predict a sequence of $k$ concrete demand instead of the aggregated values.

To address that, we design a decoder LSTM network with attention architecture, which takes the sequence of features computed by the dynamic multi-graph GCN as input, and estimates the future $k$ instant demand. In this case, conceptually the prediction framework becomes an encoder-decoder architecture, where the processes of local temporal encoding and dynamic spatial encoding serve together as the encoder. Let $\{H_{t-n}, ..., H_{t-1}, H'_t\}$ be the sequence of features generated by our GCN. Unlike in the previous case where we only consider the last output feature $H'_t$ as the context for prediction, here for each timestamp $u$ in the prediction

Figure 5: The proposed multi-scale demand prediction network. Left: Decoder LSTM with attention mechanism for instant demand prediction. Right: Fully connected network for expected demand prediction.
window \([t + 1, ..., t + k]\), we construct the context by fusing the feature sequence with attention mechanism:

\[
C_u = \sum_{v=t-n}^{t} a_{uv} H_v
\]

where \(a_{uv}\) are the attention weights determining the contribution of a feature \(H_v\) \((v \in [t-n, t])\) in predicting the demand at time \(t+u\).

Those weights \(a_{uv}\) are trained through back propagation in the end-to-end optimisation. Then the decoder LSTM consumes the context vectors and predicts the \(k\) subsequent future demand. We found in our experiments that the attention mechanism is very helpful, since the station demand patterns tend to have strong periodic components, e.g., demand on this Monday is highly correlated with previous Mondays, and a single context vector is too compressed to encode such correlation.

4 EVALUATION

In this section, we evaluate the performance of the proposed dynamic demand prediction approach on a real electric vehicle sharing platform in Shanghai, China. We describe the datasets and baseline approaches considered in our experiments (Sec. 4.1 and 4.2), and then discuss the experimental results in Sec. 4.3.

4.1 Datasets

Electrical Vehicle (EV) Sharing Data: Our EV data is collected from real-world operational records of an EV sharing platform for one year (Jan. to Dec. 2017), containing information on its renting/returning orders, and the detailed expansion of the station network. In particular, there were 1705 stations and 4725 electric vehicles at the beginning of 2017, while as of Dec 2017 it had 3127 stations with a fleet of 16148 vehicles in operation. In total, the raw data contains 6,843,737 records, which were generated by approximately 0.36 million users. Fig. 6(a) visualises the spatial distribution of the orders (represented as lines between pick up and return stations) in a month. Fig. 6(b) shows the number of orders in different days over a month, which exhibits clear periodic patterns with peaks in weekends.

POI Data: We also collect the Point Of Interest (POI) data from an online map service provider in China. In total we have extracted 4,126,844 POI entries in Shanghai, each of which consists of a GPS coordinate and a category label. In our experiments, for each station we consider the POIs within 1km radius. Table 1 shows the statistics of some POI categories.

Road Network Data: We extract road network data in Shanghai using OSMnx [1] from OpenStreetMap, which is formatted as a graph (visualised in Fig. 6(c)). Similar with the POIs, we consider the subgraphs within 1km radius of the stations. In our data, on average a subgraph contains road segments of length 13.85km and approximately 39 junctions, with a mean degree of 4.28.

Meteorology Data: Finally, we collect the daily weather data in Shanghai for 2017 from the publicly available sources. Each record describes weather conditions of the day, which falls into four different categories: sunny, overcast/foggy, drizzling/light snow and heavy rain/snow. Fig. 6(d) shows the distribution of weather conditions in Shanghai over the 12 months.

4.2 Baselines and Metric

We evaluate two variants of the proposed dynamic demand prediction approach respectively: 1) DDP-Exp, which predicts the future expected demand of stations; and 2) DDP-Seq, which forecasts the instant demand of stations in a subsequent time window. Both of the two variants share the same local temporal and dynamic spatial encoding processes, but they implement the two different branches in demand prediction (as discussed in Sec. 3.3).

In particular, we compare our DDP-Exp with the following baselines:

- **KNN**, which uses a linear regressor to predict the expected demand of existing stations. For the planned stations, it estimates their demand with standard KNN, based on the similarity of features (e.g. POIs) between them and the existing stations.
- **Random Forest (RF)**, which shares the similar idea as KNN, but trains a random forest as the predictor.
- **Functional Zone (FZ)**, which implements the state of the art demand prediction approach for system expansion in [12]. Note that we don’t have taxi records in our data, but instead we directly feed the ground truth check-in/out to favour this approach.

For DDP-Seq which computes the instant demand, we consider three competing algorithms:

- **ARIMA + KNN**, which uses Auto-Regressive Integrated Moving Average (ARIMA) [16] to forecast multi-step demand at existing stations, and then uses KNN to estimate demand at new station based on station features such as POIs.
- **LSTM + KNN**, which is similar with A-KNN, but trains LSTM networks for temporal modelling.
- **Multi-graph GCN (MGCN)**, which implements a similar framework as the state of the art in [3]. To perform fair comparison, here we use our dynamic multi-graph GCN implementations that can handle new/closed stations, and consider the same data sources as in our approach.

For all approaches, we adopt the Root Mean Squared Error (RMSE) and the Error Rate (ER) as the performance metric:

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{z}_i - z_i)^2}, \quad \text{and} \quad \text{ER} = \frac{\sum_{i=1}^{N} |\hat{z}_i - z_i|}{\sum_{i=1}^{N} z_i}
\]

where \(\hat{z}_i\) and \(z_i\) are predicted and ground truth values respectively.

We implement the deep neural networks in the proposed approach with TensorFlow 1.10.0, and use the Adam optimiser with learning rate of 0.001. The networks are trained on a single Titan X GPU from scratch. For all approaches, we randomly select two months of data for training while the subsequent month for testing, and report the average performance.

| POI Type          | Number | POI Type          | Number |
|-------------------|--------|-------------------|--------|
| Hospitals         | 4745   | Banks             | 2988   |
| Tourist attractions | 2696   | Companies         | 89,747 |
| Gov. organizations | 16,425 | Higher education  | 6922   |
| Airport services  | 126    | Residences        | 51,089 |
| Subway stations   | 1,729  | Hotels            | 18,234 |
| Bus stations      | 41,475 | ...               | ...    |

Table 1: Statistics of some POI categories in our data.
4.3 Evaluation Results

Accuracy of Predicting Expected Demand: The first set of experiments evaluate the overall accuracy when predicting the expected demand of stations. Fig. 7(a) and (b) show the RMSE and ER of the competing approaches (ARIMA, LSTM, and MGCN) and competing algorithms (KNN, RF, and FZ) over different days of the week. We see that comparing to naive KNN, the random forest based approach (RF) can reduce the RMSE by about 30% while ER by 20%. However, our approach (DDP-Exp) performs significantly better, and can achieve up to three times improvement in both RMSE and ER. In particular, on average the RMSE of DDP-Exp is approximately 1.961, which means when predicting the station’s expected demand, the value estimated by our approach is only about ±2 with respect to the ground truth. This confirms that the proposed approach can effectively model the complex temporal and spatial dependencies within the evolving station network, and exploits that to make more accurate predictions. In addition, we observe that the RMSE tends to increase on weekends compared to weekdays for all algorithms. This is because in practice the absolute demand on weekends is larger, which often leads to bigger RMSE. Note that the ER remains relatively consistent across different days.

Planned vs. Existing Stations: This experiment investigates the prediction performance of different approaches on the planned stations which haven’t been deployed yet, and existing stations which have already been in operation. Fig. 7(c) and (d) show the average RMSE and ER of the proposed approach (DDP-Exp) and...
We vary the length of the prediction time window from 1 to 7, i.e. observe that in general, the RMSE increases as the length of the time window grows, especially for our approach (DDP-Seq) and the state of the art MGCN. This makes sense because clearly predicting demand over a longer time window is more difficult. On the other hand, we see that the ER of baselines are higher for short window lengths comparing to the MGCN or our approach. We find that this is because the baselines tend to report random estimations on the future demand, where for shorter windows this can lead to larger ER, but will be averaged out for longer time windows as the ground truth demand grows in later days. Finally, we see that MGCN can offer comparable performance with our approach (DDP-Seq) when predicting for the immediate next timestamp. However as the prediction length increases, our approach consistently outperforms MGCN, with a performance gap of up to 26%.

**Augmentation of Station Network Dynamics:** The last set of experiments investigates the impact of augmenting station network dynamics during training. As discussed in previous sections, one of the key challenges addressed in this paper is to forecast the demand of planned stations which haven’t been deployed, in the presence of a continuously evolving station network. This means that we have to explicitly learn the particular dynamics caused by deploying new stations in order to make accuracy predictions. To account for that, in addition to the actual dynamics within the data, during training we artificially inject different levels of augmented dynamics to the station network, by simulating the process of deploying new stations. More concretely, at each timestamp we randomly pick a subset of existing stations according to a probability \( p \), and ignore their previous demand records, i.e. we assume that those stations have just been deployed. We vary \( p \) from 0 to 1, indicating the least (no) augmentation to the most. As shown in Fig. 10, we see that as \( p \) increases from zero, our approach tends to make more accurate predictions for both expected and instant demand. This confirms that by injecting the augmented dynamics, we essentially force the GCN to learn how to better react to the deployment of new stations. We also observed that for larger \( p \) values, the errors (both RMSE and ER) increase for both types of demand. This is also expected because in those cases the excessive injected dynamics would mute the useful information coming from local LSTMs at individual stations and confuse the GCN, leading to deterioration of performance. Therefore empirically we set \( p \) to values around 0.4~0.6 to achieve the desired balance.

### 5 RELATED WORK

**Demand Prediction for Shared Mobility:** Predicting user demand in shared mobility services (e.g. taxi and bike- or vehicle-sharing systems) has received considerable interest in various research communities. Most of the existing work takes the historical usage (e.g. picking-up and returning records), geospatial data such as POIs, and other auxiliary information (e.g. weather) into account, and builds prediction models that can forecast demand over certain periods or aggregated time slots. They also predict the demand at different spatial granularity, e.g. over the entire systems [15, 20], grids/regions [6], station clusters [5, 10, 13], or individual stations [3, 7, 11, 18, 21]. This paper falls into the last category since we aim to predict station-level demand of EV sharing platforms. However, our work is fundamentally different in that we assume the station network is not static, but dynamically evolving,
of the art in predicting both long-term expected and immediate future demand of the fast expanding system.

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