Clairvoyance: Intelligent Route Planning for Electric Buses Based on Urban Big Data

Xiangyong Lu, Kaoru Ota, Member, IEEE, Mianxiong Dong, Member, IEEE, Chen Yu, Member, IEEE, and Hai Jin, Fellow, IEEE

Abstract—Nowadays many cities around the world have introduced electric buses to optimize urban traffic and reduce the local carbon emissions. In order to cut the carbon emissions and maximize the utility of electric buses, it is important to choose suitable routes for them. Traditionally, route selection is on the basis of dedicated surveys, which are costly in time and labor. In this paper, we mainly focus attention on planning electric bus routes intelligently, depending on the unique needs of each region throughout the city. We propose Clairvoyance, a route planning system that leverages a deep neural network and a multilayer perceptron to predict the future people’s trips and the future transportation carbon emission in the whole city, respectively. Given the future information of people’s trips and transportation carbon emission, we utilize a greedy mechanism to recommend bus routes for electric buses that will depart in an ideal state. Furthermore, representative features of the two neural networks are extracted from the heterogeneous urban datasets. We evaluate our approach through extensive experiments on the real-world data sources in Zhuhai, China. The results show that our designed neural network-based algorithms are consistently superior to the typical baselines. Additionally, the recommended routes for electric buses are helpful in reducing the peak value of carbon emissions and making full use of electric buses in the city.

Index Terms—Intelligent route planning, electric bus, urban big data, multilayer perceptron, deep neural network.

I. INTRODUCTION

ELECTRIC buses are the significant contributors to reduce transportation carbon emission and energy consumption. Besides, the cost savings from fuel more than offset the cost of electric bus and infrastructure over the lifetime of a bus. In recent years, a growing number of cities have taken steps to introduce electric buses, in order to optimize urban transport structure and reduce carbon emissions and fuel consumption. However, the number of electric buses introduced in cities is constantly limited. Meanwhile, given the large-scale infrastructure investment necessary to support electric bus transportation, it is essential for policy makers to maximize the utility of electric buses. A key factor in making full use of electric buses is to choose the proper routes for them according to the local conditions.

Due to the unique geographical, environmental and cultural characteristics in each region of the city, transportation carbon emission and people’s trips vary drastically with place and time. When a limited number of electric buses are allocated the fixed routes, it is difficult to meet the dynamic demand of people’s trips and reducing carbon emissions. To meet the diverse demand of the city, routes should be assigned dynamically for electric buses. In this paper, we want to answer the practical question: When a limited amount of electric buses are introduced in a city, which route should be dynamically selected for each electric bus that will depart in an ideal state? We aim to predict the potential transportation carbon emission and the potential number of people’s bus trips throughout the city to guide the electric bus route selection. The task is extraordinary challenging due to the following three reasons:

First, transportation carbon emission is affected by multiple factors, such as human mobility, traffic flow, and meteorology. The factors differ in different regions and change over time. For example, traffic flows on the main roads are often larger than those of ordinary roads during peak commuting hours. The changes of these factors contribute to the difference in transportation carbon emission between all regions of the city. Consequently, we should identify the main factors that influence the transportation carbon emission and extract the efficient features from the heterogeneous data sources in each region.

Second, on each road in the city, the number of people’s bus trips significantly changes over location and time. As shown in Fig. 1(a), eight routes are randomly selected from all bus routes in Zhuhai. Each bus route locates in different areas of the city. Fig. 1(b) outlines the average numbers of people’s trips on the eight routes in one hour after 11 a.m. during the period from Sept. 1 to Sept. 15, 2015. Meanwhile, as described in Fig. 1(c) and 1(d) the number of people’s trips on the first five routes are diverse and vary with time tremendously. For example, there is a dramatically increase in the amount of trips during peak commuting hours, such as between 8 and 9 a.m. and between 6 and 7 p.m.. Accordingly, to obtain the future number of people’s trips on all bus routes, we should dig out the unique spatial-temporal characteristics of each route.

Third, traditionally policy makers obtain transportation carbon emission information, by calculating the combustion of fossil fuel in the whole transportation sector [1]. The information of people’s bus trips is collected by dedicated surveys. However, these two methods are almost impossible to obtain...
Based on these two prediction results, we devise a greedy mechanism to recommend suitable bus routes for each electric bus that will depart.

- We extract efficient representative features from the heterogeneous urban data sources for our learning methods. Moreover, our mining features not only contribute to our application, but also contribute to the general problems of sensing urban dynamics.

- We evaluate our approach utilizing the multiple datasets in Zhuhai, China, that is meteorological data, urban road data, points of interest data, bus IC card data, bus GPS trajectories generated by over 1,500 buses from July 1st to October 14th, 2015 and the taxi GPS trajectories generated by over 3,000 taxicabs from July 1st to October 14th, 2015. We justify the advantages of our designed neural network-based algorithms over several baselines.

The rest of this paper is organized as follows. In section II, we introduce the works related to our research. Preliminary definitions and the framework of our system are described in section III. Feature extraction are listed in section IV. Feature learning and inference are discussed in section V. Experimental evaluation is shown in section VI. Finally, we conclude our work in section VII.

II. RELATED WORK

A. Urban transit planning

In recent years, many cities have invested heavily in urban traffic construction and transit planning. Transit planning and optimization are mainly focused on two aspects, that is cost and service [2]. Through the effective transit planning, the urban transit systems will serve a greater number of people and obtain a high level of customer satisfaction. In recent decades, urban transit systems have benefited hugely from the increasing number of sensors deployed in roads, vehicles and buildings. Moreover, based on the innovative data processing [3] [4] and mining technologies [5] [6], a series of studies on urban transportation have appeared, such as traffic planning [7] [8], vehicle scheduling [9] [10], and traffic flow [11] [12].

For public transit frequency setting, Hadas [13] proposes a cost-based approach, which contains two main cost elements: empty-seat driven and overload and unserved demand. Through minimizing the total cost incurred in connection with either frequency or vehicle capacity, his method can dramatically improve the accuracy in the frequency setting. For traffic flow prediction, Lv [14] devises a stacked autoencoder model, utilizing the datasets collected from the Caltrans Performance Measurement System (PeMS) database. While Zheng [15] designs a deep and embedding learning approach to improve the prediction accuracy of traffic flow, through explicitly extracting fine-grained information from massive traffic data, route structure, and weather conditions. Moreover, in order to solve the load scheduling problem of plug-in hybrid electric vehicles, Kang [16] proposes a novel weight aggregation multi-objective particle swarm optimization (WA-MOPSO), which is based on the existing multi-objective evolutionary algorithms, such as non-dominated sorting genetic algorithm-II. Based on the real case of bus operation in Shenzhen, China,
B. Urban Computing

Urban computing is an interdisciplinary field, where computer sciences are used in urban areas, contributing to the improvement of urban environment, human life quality, and city operation systems [20]. In recent decades, the rapid progress of urbanization and industrialization has caused lots of urban issues, such as traffic jams, energy consumption, environmental pollution. In order to tackle these issues, nowadays numerous research institutions around the world begin to do in-depth research in the area of urban computing. Based on the air quality data, meteorological data and weather forecasts, Zheng [21] proposes a hybrid predictive model to forecasting fine-grained air quality. This model consists of four major components, that is a linear regression-based temporal predictor, a neural network-based spatial predictor, a dynamic aggregator, and an inflection predictor. To predict the air quality, he also employs a semi-supervised learning approach based on a co-training framework, which comprises two separated classifiers: an artificial neural network and a linear-chain conditional random field [22].

Moreover, Shang [23] proposes an unsupervised Bayesian Network model and a context-aware matrix factorization approach to infer separately the traffic volume and travel speed on each road segment. Given the resulting traffic volume and travel speed, he calculates the gas consumption and emissions. Chen [24] formulates the bike station placement and travel speed, he calculates the gas consumption and emissions. For the lower-level charging scheduling problem, he proposes a greedy search strategy to minimize the charging cost. Compared with the previous works, we devise a neural network-based system to infer suitable routes for electric buses that will depart, based on urban big data. Two main parts in our system are to predict the future number of bus trips on each route and transportation carbon emission in each region throughout the city.

A. Preliminary

**Definition 1: Bus Trip Demand.** It is the number of people’s bus trips in an area during a specified time period in the future. For a specified time period $T$, the bus trip demand $Q_r$ on the bus route $r$ is the sum of bus trips $q_i$ generated at the bus station $s_i$ on the $r$, as formulated in Equation 1.

$$Q_r = \sum_{i \in Z^+} q_{s_i}, \quad s_i \in S_r$$  

where $q_{s_i}$ is the bus trips generated at the the bus station $s_i$ with index $i$. $S_r$ represents the set of bus stations on the $r$.

**Definition 2: Transportation Carbon Emission.** It is a measure of the total amount of carbon dioxide emissions, which are directly or indirectly caused by the traffic.

**Definition 3: Top-Down Approach.** It is a calculation method of transportation carbon emission, which is given by the 2006 IPCC guidelines [1]. This approach is formulated as:

$$W = \sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{N}} K_{i,j} \cdot n_{i,j} \cdot l_{i,j} \cdot e_{i,j}$$  

where $W$ is the total amount of transportation carbon emission. $i$ is a kind of vehicle types. $j$ is a type of fossil fuel. $K_{i,j}$ is the carbon dioxide emission coefficient of $j$ type fossil fuel, which is consumed by the $i$ type vehicles. $n_{i,j}$ and $l_{i,j}$ represent the number and transport mileage of the $i$ type vehicles, which consume the $j$ type fossil fuel. $e_{i,j}$ is the carbon emission intensity per $j$ type fuel and for the $i$ type vehicles.

**Definition 4: Grid.** A grid is an area of the city (e.g., $5km \times 5km$) [23]. The location of each grid is the geographic center of the grid. In the experiments, we divide the Zhuhai city into disjoint and uniform grids, and each grid $g$ has the unique amount of transportation carbon emission $g.W$.

**Definition 5: Affecting Region.** An affecting region $\gamma$ is an area around the bus station. The location of each region $\gamma.loc$ is the geographic coordinate of corresponding bus station. In the experiments, each affecting region is a square area with side length $0.5km$ ($d = 0.5km$) centered on the bus station, as shown in Fig. 2. On each bus route, we randomly select fifteen affecting regions.

**Definition 6: Trajectory.** A spatial trajectory is a sequence of time-ordered spatial points, $\tau: p_1 \rightarrow p_2 \rightarrow ... \rightarrow p_n$. Each point $p_i$ consists of a geographic location $l$ and a timestamp $t$, $p_i = (l, t)$.

**Definition 7: Point of Interest (POI).** A POI is a specific point location on the earth, where people may find useful or interesting. Each POI contains the name, category, location and other attributes.
B. Framework

Our Clairvoyance system provides route recommendations by predicting the future transportation carbon emission and the future bus trip demand according to local conditions, respectively. As shown in Fig. 3, the framework of our system mainly consists of three kinds of data flows, that is preprocessing, learning and inference data flow.

**Preprocessing data flow:** In this data flow, we screen out six raw datasets in the city, that is taxi trajectories, bus trajectories, bus IC card data, urban road data, POIs data and meteorological data. Given the bus IC card data, we then estimate the number of bus trips on each bus route during a specified time period and use it to label each bus route. Moreover, based on the taxi trajectories falling in the disjoint grids of the city, we utilize the Top-Down approach to calculate the amount of transportation carbon emission in each grid and regard it as a label for each grid.

**Learning data flow:** In this data flow, we first identify effective features in each grid and each affecting region. The features related to transportation carbon emission are extracted from the taxi trajectories, urban road data, POIs data and meteorological data in each grid. Moreover, the features related to bus trip demand are extracted from the bus trajectories, taxi trajectories, POIs and meteorological dataset in each affecting region. Then the features of each bus route are generated by incorporating the extracted features in each affecting regions on the route. See section IV for details.

Furthermore, the feature datasets and the labels of each grid and bus route are fed into a Trip Demand Predictor and a Carbon Emission Predictor, respectively. The Trip Demand Predictor is a deep neural network to predict the future number of people’s bus trips on each bus route. The Carbon Emission Predictor is a three-layer perceptron neural network to forecast the future transportation carbon emission in each grid. Detailed in section V.

**Inference data flow:** In this data flow, we respectively extract features from each grid and affecting region. Subsequently, for each bus route, we feed the corresponding features into the trained Trip Demand Predictor to forecast the future number of bus trips. For each grid, we feed the extracted features into the trained Carbon Emission Predictor to predict the future amount of transportation carbon emission. Based on the two predicted scores, we utilize a greedy mechanism to recommend suitable bus routes for each electric bus that will leave. Detailed in section V.

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**Problem Formulation**

Given a collection of bus routes $R = \{r_1, r_2, ..., r_n\}$, where each bus route $r$ crosses a collection of grids $G = \{g_1, g_2, ..., g_m\}$, a bus trajectory dataset $T_b$ and a taxi trajectory dataset $T_t$ passing $R$ and $G$, the POIs located in $G$, and a meteorological dataset, we intend to recommend the suitable bus route $r$ for each electric bus that will depart, based on the inference of $r.BTD$ and $g.W$. The $r.BTD$ is the future number of bus trips on the bus route $r$ and $g.W$ is the future amount of transportation carbon emission in the grid $g$.

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**IV. Feature Extraction**

In this section, we define and discuss the features that are mined from the heterogeneous data sources in the city. The features related to bus trip demand are classified into three broad categories: *mobility features* which extract information about vehicle movements on road, *geographic features* which integrate information about the POI categories and spatial interaction between people and places, and *meteorological features* which exploit knowledge about the weather. Moreover, we identify five kinds of feature sets for the Carbon Emission Predictor [28].

A. Mobility Features: $F_{vm}$

The daily trip demand of people drives the movement of vehicles on the road. The movement information of vehicles contributes to the analysis of trip demand significantly. However, the running state of vehicles on each road varies dramatically during the same time period. Even on the same road, the vehicle movement state is extremely diverse in different sections of the road. Accordingly, we divide the road into many small affecting regions and extract the unique movement information in each region. For each affecting region, we identify three types of features: traffic volume, average passing speed and standard deviation of speed. Then
we generate the mobility features of the road by aggregating all
the identified features in each affecting region on the road. In
the experiments, these features are calculated from the spatial
trajectories of taxicabs in Zhuhai.

**Traffic volume:** $N(\gamma,T)$. The $N(\gamma,T)$ is the number of
vehicles passing through the affecting region $\gamma$ during a
specified period of time $T$. Given all the spatial trajectories
$\tau_{all}$ generated by vehicles during the period of time $T$, we
retrieve all the spatial points on each trajectory $\tau$. If the spatial
point $p$ of one trajectory $\tau$ are observed in the affecting region
$(p,l \in \gamma, p.t \in T)$, we believe that there is one vehicle
passing through the affecting region $\gamma$. Even if the same
vehicle may pass through the affecting region $\gamma$ many times
during the period of time $T$, we only record once. $N(\gamma,T)$
can be formulated as:

$$N(\gamma,T) = \{|\tau \in \tau_{all} : p \in \tau, p.l \in \gamma, p.t \in T\}$$

(3)

where $p.l$ and $p.t$ represents the geographic location and the
timestamp of $p$ respectively.

**Average passing speed:** $E(\gamma,T)$. The $E(\gamma,T)$ is the average
speed of vehicles passing through the affecting region $\gamma$
during the period of time $T$. From all vehicle trajectories $\tau_{all}$
generated over the period of time $T$, we extract the sequences
of points that fall in the affecting region $\gamma$. In the Equation
$[4]$, $S_{\eta}$ is the length of one sequence $\eta$, $\eta \in \tau_{all}$. Accordingly,
$E(\gamma,T)$ can be obtained by the Equation $[5]$

$$S_{\eta} = \sum_{p \in \eta} dist(p_i,p_{i+1}), \quad p.t \in T$$

(4)

$$E(\gamma,T) = \frac{\sum_{\eta \in \tau_{all}} S_{\eta}}{\sum_{p.l \in \gamma, p.t \in T}}$$

(5)

where the $dist(p_i,p_{i+1})$ is the traveling distance between any
two adjacent points on each spatial trajectory $\tau$.

**Standard deviation of speed:** $D(\gamma,T)$. The $D(\gamma,T)$ denotes
the discrete degree of the passing speed in the affecting region
$\gamma$ during the specified period of time $T$.

$$D(\gamma,T) = \sqrt{\frac{\sum_{i \in Z^+} [E(\gamma,T) - p.v]^2 \cdot |p_{i+1}.t - p_i.t|}{\sum_{i \in Z^+} |p_{i+1}.t - p_i.t|}}$$

(6)

where $p$ is the point on the trajectories that falls in the affecting
region $\gamma$ during the period of time $T$. $p.v$ denotes the speed of
vehicle at the location $p.l$.

**B. Geographic Features: $F_g$**

The geographic features describe the geographical distribu-
tions of $POIs$ and the spatial interactions between people and
places. $POI$ distributions in a region indicate the regional
economic and physical attributes, which have high correlation
to vehicle trips in the region. Moreover, the spatial interaction
states the movement of people between the places. For instance,
the high trip needs are more often associated with the residential
and industrial areas. Consequently, we identify several corre-
lated features for each affecting region, that is entering flow, leaving
flow and $POI$ feature.

**Entering flow:** $f_{in}(\gamma,T)$. The $f_{in}(\gamma,T)$ is a feature to mea-
sure the flow of people into the affecting region $\gamma$ during
the period of time $T$. Formally, we utilize a tuple $(O,D)$ to
represent the starting point and the end point of a trip. $I$
indicates the total set of the tuple $(O,D)$ of all trips, that
are generated in the specific time $T$.

$$f_{in}(\gamma,T) = |\{(O,D) \in I : O.l \notin \gamma \land D.l \in \gamma \land O.t,D.t \in T\}|$$

(7)

where $O.l$ and $D.l$ represent their geographic locations. $O.t$
and $D.t$ denote their timestamps.

**Leaving flow:** $f_{out}(\gamma,T)$. The $f_{out}(\gamma,T)$ is a feature to
calculate the flow of people out of the affecting region $\gamma$ in
the specified time $T$. Similar to Equation $[7]$, the leaving flow
$f_{out}(\gamma,T)$ out of area $\gamma$ is formulated with Equation $[8]$

$$f_{out}(\gamma,T) = |\{(O,D) \in I : O.l \in \gamma \land D.l \notin \gamma \land O.t,D.t \in T\}|$$

(8)

![Fig. 4. POI categories relevant to vehicle trip demand with the Pearson Correlation Coefficient (PCC).](#)

**POI feature:** $P(C,\gamma)$. The $POI$ feature $P(C,\gamma)$ is a set of
$\theta(C_i,\gamma)$. Each $\theta(C_i,\gamma)$ denotes the number of $POIs$
with category $C_i$ in the region $\gamma$. $P(C,\gamma)$ and $\theta(C_i,\gamma)$ are
defined as:

$$P(C,\gamma) = \{\theta(C_i,\gamma) : C_i \in C\}$$

(9)

$$\theta(C_i,\gamma) = |\{\varepsilon \in P_i : \varepsilon.l \in \gamma\}|$$

(10)

where $P_i$ denotes the set of $POIs$ with category $C_i$. $\varepsilon.l$ is
the location of the $POI$ $\varepsilon$. The set $C$ consists of all the
$POI$ categories, which are the most relevant to vehicle trip
demand. For each category, we use the Pearson Correlation
Coefficient (PCC) to calculate its correlation with the vehicle
trip demand, as displays in Fig.4. For category $C_i$, its $PCC$
value is calculated as:

$$\rho(\theta(C_i,\gamma),\nu) = \frac{\text{cov}(\theta(C_i,\gamma),\nu)}{\sigma_{\theta(C_i,\gamma)} \sigma_{\nu}}$$

(11)

where $\nu$ is the vehicle trip demand generated in the re-
region $\gamma$ during a specified period of time. $\text{cov}$ is the vari-
ance of $\theta(C_i,\gamma)$ and $\nu$. $\sigma_{\theta(C_i,\gamma)}$ is the standard devia-
tion of $\theta(C_i,\gamma)$. $\sigma_{\nu}$ is the standard deviation of $\nu$. In
the experiments, we select the top-8 $POI$ categories that are
most relevant to the vehicle trip demand in Zhuhai, $C = \{C_7,C_4,C_2,C_3,C_{12},C_{10},C_5,C_1\}$. 
TABLE I

| Weather condition categories | |
|-----------------------------|-----------------------------|
| 1 : Sunny                   | 11 : Light rain to moderate rain |
| 2 : Cloudy                  | 12 : Moderate rain to heavy rain |
| 3 : Shower                  | 13 : Heavy rain to torrential rain |
| 4 : Thunder shower          | 14 : Hot                     |
| 5 : Light rain              | 15 : Rain to sunny            |
| 6 : Moderate rain           | 16 : Rain to sunny            |
| 7 : Heavy rain              | 17 : Sunny to rain            |
| 8 : Torrential rain         | 18 : Cloudy to sunny          |
| 9 : Foggy                   | 19 : Sunny to cloudy          |
| 10 : Haze                   | 20 : Rain to cloudy           |

C. Meteorological Features: \( F_m \)

Changes in meteorological conditions could have several potential consequences for people’s travel demand on a global and regional scale. Especially the weather changes have a significant impact on the traffic pattern, the purpose of the trip and the travel time [29]. For instance, the increased frequency of extreme precipitation events may substantially reduce the number of trips, particularly those for leisure purpose. Accordingly, we give special attention to the impact of weather on people’s trip in our study. We identify three features, that is highest temperature, lowest temperature, and weather condition. More specifically, the \( F_m \) of each bus route can be formulated as follows [12]

\[
F_m(r) = \{(f_h, f_o, f_w) : f_w \in M\}
\]

where \( F_m(r) \) represents the meteorological feature set of the bus route \( r \). \( M \) is the set of weather condition categories. The weather conditions are classified into 20 categories, as displayed in the table [1]. \( f_h \) is the highest temperature. \( f_o \) is the lowest temperature. \( f_w \) is the weather condition.

Fig. 5 displays the correlation matrix between the meteorological features and bus trip demand. As an illustration, the value 0.95 in the plot on the second row and the first column indicates the Pearson Correlation Coefficient between the \( f_h \) and \( f_o \).

V. LEARNING AND INFERENCE

Based on the features extracted from urban big data in the previous part, our Clairvoyance system is trained to predict the number of people’s bus trips on each bus route and forecast the transportation carbon emission in each grid during a future period of time. Given the predicted information, we propose a greedy strategy to recommend suitable bus routes for electric buses that will depart.

A. Two-task Forecasting

Two main parts of our Clairvoyance system are Trip Demand Predictor and Carbon Emission Predictor. As presented in Algorithm 1, the Trip Demand Predictor forecasts the future number of people’s buses trips (BTD) on each bus route, utilizing a deep neural network pre-trained by stacking four layers of denoising autoencoders (SDAE-4). The Carbon Emission Predictor predicts the future transportation carbon emission (TCE) in each grid, using a three-layer perceptron neural network (PNN-3). Moreover, we train them based on the datasets of \((F(r), \mu_r)\) and \((F(g), \nu_g)\), respectively. \( F(r) \) is a feature set of \( F_{wm}, F_g, \) and \( F_m \) on the bus route \( r \), and \( \mu_r \) is the corresponding BTD value. \( F(g) \) and \( \nu_g \) are another feature set and the corresponding TCE value, which are described in detail in [28]. Subsequently, given the two trained predictors, we forecast separately the BTD values on each bus route and the TCE values in each grid throughout the city within a future period of time.
Algorithm 1 Two-task Forecasting

Input: A training dataset \( D_{SDAE} \) of \( (F(r), \mu_r) \), where \( F(r) \) is a feature set of \( F_{vm}, F_g \), and \( \mu_r \) is the BTD value on the route \( r \); A training dataset \( D_{PNN} \) of \((F(g), \nu_g)\), where the feature set \( F(g) \) and the TCE value \( \nu_g \) are extracted in the grid \( g \); A specified period of time interval \( T \).

Output: The set \( \nu_G \) of BTD values on all bus routes; the set \( \nu_G \) of TCE values in all grids.

1: \( SDAE-4 \leftarrow \) build a 4-hidden-layer neural network pre-trained by stacking denoising autoencoders.
2: \( PNN-3 \leftarrow \) design a 3 layer perceptron
3: \textbf{for} small batch in \( D_{SDAE} \) \textbf{do}
4: \( \text{MiB}_{SDAE} \leftarrow \) the small batch in \( D_{SDAE} \)
5: \( SDAE-4 \leftarrow \) SDAE-4.Learning(\( \text{MiB}_{SDAE} \))
6: \textbf{end for}
7: \textbf{for} small batch in \( D_{PNN} \) \textbf{do}
8: \( \text{MiB}_{PNN} \leftarrow \) the small batch in \( D_{PNN} \)
9: \( PNN-3 \leftarrow \) PNN-3.Learning(\( \text{MiB}_{PNN} \))
10: \textbf{end for}

11: \( \mu_{LR} \leftarrow \) using the trained SDAE-4 to predict BTD values \( \{\mu_1, \mu_2, \ldots, \mu_n\} \) on all bus routes \( R \) in the future period of time \( T \), \( R = \{r_1, r_2, \ldots, r_n\} \).
12: \( \nu_G \leftarrow \) using the trained PNN-3 to predict TCE values \( \{\nu_{g1}, \nu_{g2}, \ldots, \nu_{gn}\} \) in all grids \( G \) in the future period of time \( T \), \( G = \{g1, g2, \ldots, gn\} \).

return \( \mu_{LR} \) and \( \nu_G \)

B. Trip Demand Predictor

As depicted in Fig. 6, the Trip Demand Predictor is composed of four main parts: input, four layers of denoising autoencoders (SDAE), logistic regression (LR) layer, and output. The initial input vector \( x \) consists of \( F_{vm}, F_g, F_m \) and the corresponding BTD label. The four layers of SDAE build a deep neural network architecture by feeding the latent representation found on the layer below as input to the current layer. In each layer of SDAE, the black solid and broken arrows represent the learning process, and the blue broken arrows represent the inference process. In the LR layer, a multi-class logistic regression method is used to generate the predicted BTD values. The input of LR layer is the output of the last level SDAE.

The training of our deep neural network SDAE-4 includes two stages, that is unsupervised pre-training and supervised fine-tuning. The unsupervised pre-training of the deep network is done by the four layers of SDAE. Each autoencoder is trained to minimize the input reconstruction error. As shown in Fig. 6, the first level SDAE takes an input vector \( x \). Subsequently, the initial input \( x \) is partially destroyed to get a corrupted input \( \tilde{x} \), using the means of a stochastic mapping \( \tilde{x} \sim q_D(\tilde{x}|x) \). In the experiments, in order to obtain the corrupted input, we randomly assign a fixed number of elements in each input vector to zero. Then, the corrupted input \( \tilde{x} \) is mapped to a hidden representation \( x_f \), using the sigmoid non-linearity:

\[
x_f = f_{\alpha}(\tilde{x}) = s(W\tilde{x} + b), \tag{13}
\]

where \( \alpha \) denotes the parameter set of \( f_{\alpha} \), \( \alpha = \{W, b\} \). \( W \) is a \( d' \times d \) weight matrix. \( b \) is an offset vector of dimensionality \( d' \). \( s \) is the sigmoid function, which can be formulated as follows:

\[
s(x) = \frac{1}{1 + e^{-x}} \tag{14}
\]

where \( s(x) \) is the sigmoid function, which can be formulated as follows:

\[
s(x) = (s(x_1), s(x_2), \ldots, s(x_d))^T.
\]

Meanwhile, in order to minimize the average reconstruction error, the parameters of denoising autoencoder are optimized by the following Equation [16] to generate produce reconstruction \( x' \):

\[
x' = g_{\alpha'}(x_f) = s(W'x_f + b'), \tag{15}
\]

where \( \alpha' \) denotes the parameter set of \( g_{\alpha'} \), \( \alpha' = \{W', b'\} \). The weight matrix \( W' \) is the transpose of the matrix \( W \). Accordingly, for each training \( x^{(i)} \), we can get the corresponding \( x^{(i)}(i) \) and reconstruction \( x^{(i)}(r) \). Meanwhile, in order to minimize the average reconstruction error, the parameters of denoising autoencoder are optimized by the following Equation [16]:

\[
\alpha^*, \alpha'^* = \arg \min_{\alpha, \alpha'} \frac{1}{n} \sum_{i=1}^{n} (x^{(i)} - x^{(i)}(r))^2 = \arg \min_{\alpha, \alpha'} \frac{1}{n} \sum_{i=1}^{n} (x^{(i)} - g_{\alpha'}(f_{\alpha}(\tilde{x}^{(i)})))^2,
\]

where \( n \) is the number of input samples. In the experiments, we measure the reconstruction errors by mean squared error. The mean squared error can be formulated as follows:

\[
L(x, x') = \frac{1}{n} \sum_{i=1}^{n} (x^{(i)} - x^{(i)}(r))^2. \tag{17}
\]

After the first-level SDAE is trained, its mapping function \( f_{\alpha} \) will be used on clean inputs, as represented by broken blue arrows. Utilizing the learnt function \( f_{\alpha} \), we map the uncorrupted input \( x \) to produce the hidden representation \( y \), which will serve as clean input to the second-level SDAE.
Subsequently, the remaining layers of SDAE are trained, similar to the process in the first-level SDAE.

The supervised fine-tuning of SDAE-4 will be done, after the four layers of SDAE are trained. In the LR layer, we generate the probability that the predicted Y is class \( c_i \), by the formula:

\[
P(Y = c_i | x, W_L, b_L) = \frac{e^{W_L^{(c_i)} x + b^{(c_i)}}}{\sum_{j=1}^{k} e^{W_L^{(c_j)} x + b^{(c_j)}}},
\]

where \( k \) denotes the number of categories, \( x_L, W_L, \) and \( b_L \) are separately the input, weight matrix, and bias vector of the multi-class logistic regression method in the LR layer, given the input \( x \) of SDAE-4. Subsequently, the output \( y^{pred} \) of the LR layer is the class whose probability is maximal, specifically:

\[
y^{pred} = \arg \max_i P(Y = c_i | x_L, W_L, b_L).
\]

Moreover, the loss function of our SDAE-4 is the negative log-likelihood (NLL), which is formulated as:

\[
NLL(\beta, D^{(x)}) = - \sum_{i=1}^{|D^{(x)}|} \log(P(Y = y^{(i)} | x^{(i)}, \beta)),
\]

where \( \beta \) is the set of all parameters in the SDAE-4. \( D^{(x)} \) denotes the input dataset. \( y^{(i)} \) indicates the corresponding BTD label. To optimize our SDAE-4, stochastic gradient descent is applied to minimize NLL.

C. Recommending Bus Route

Our aim is to recommend \( k \) routes, so that the transport of electric buses on these routes will meet people’s trips needs and cut transportation carbon emission to the maximum extent. Given the pre-trained SDAE-4, we obtain a set of the BTD values \( \mu_R \) on all bus routes \( R \) and a set of the TCE values \( \nu_G \) in all grids \( G \) during a period of time \( T \) in the future. Meanwhile, we calculate the TCE value \( \vartheta_r \) of the bus route \( r \), by adding the TCE values in all the grids on the route \( r \). Subsequently, we normalize the \( \mu_R \) and \( \vartheta_R \), as the following:

\[
\mu_R = \{ \mu_{r_1}, \mu_{r_2}, ..., \mu_{r_n} \}, \quad \mu_{r_i} = \frac{\mu_{r_i} - \mu_{min}}{\mu_{max} - \mu_{min}}, \quad r_i \in R,
\]

\[
\vartheta_R = \{ \vartheta_{r_1}, \vartheta_{r_2}, ..., \vartheta_{r_n} \}, \quad \vartheta_{r_i} = \frac{\vartheta_{r_i} - \vartheta_{min}}{\vartheta_{max} - \vartheta_{min}}, \quad r_i \in R,
\]

where \( \mu_{max} \) and \( \mu_{min} \) are the maximum and minimum values in \( \mu_R \), \( \mu_{r_i} \). \( \vartheta_{max} \) and \( \vartheta_{min} \) are the maximum and minimum values in \( \vartheta_R \), \( \vartheta_{r_i} \). \( \mu_{r_i} \) is the BTD value on the bus route \( r_i \) in a future period of time \( T \). \( \vartheta_{r_i} \) is the future total TCE value of the grids that the bus route \( r_i \) crosses. Accordingly, when the value of \( \mu_{r_i}^{top} \) plus \( \vartheta_{r_i} \) is larger enough, people’s bus trips and transportation carbon emissions will peak in the area that the bus route \( r \) crosses.

Based on the future peak information, we recommend \( k \) bus routes for each electric bus that will depart, specifically:

\[
O_r = \{ r_i : Max_{top_k} (\mu_{r_i}^{top} + \vartheta_{r_i}) \}, \quad \mu_{r_i}^{top}, \vartheta_{r_i}^{top} \in \mu_R, \vartheta_R.
\]

VI. EXPERIMENTS

In this section, we will introduce the source datasets used in the experiments. Several advanced and baseline methods are selected to compare with our proposed methods. Subsequently, we present experimental results showing the performance of our proposed methods and baseline methods.

A. Datasets

In the experiments, we use five real world datasets collected in Zhuhai, China. The statistics of datasets are displayed in Table I.

1) Taxi trajectories: The dataset was generated by over 3,000 taxicabs in Zhuhai from July 1st to October 14th, 2015. Specifically, each GPS record in the taxi trajectory dataset is produced every 10 seconds and consists of seven parts, that is taxicab ID, record time, latitude, longitude, speed, direction and passenger status. Furthermore, in one day all the taxicabs can drive a mileage of about 0.116 million kilometers and generate over 38 million records. More than 4.5 million vehicle trips will occur one day, and the trips of taxicabs and small passenger cars account for about 31.8%, in accordance with the annual report of the 2014 traffic development in Zhuhai. Accordingly, this source dataset is large enough to reflect local traffic patterns there (22).

2) Bus trajectories: The dataset was produced by about 1,540 buses in Zhuhai from July 1st to October 14th, 2015. More specifically, each record in the bus trajectory dataset is composed of eight main components, that is bus ID, record time, latitude, longitude, speed, last position, current bus stop, and route name. When each bus passes any bus stop on the routes, two records will be generated. Moreover, there are about 168 bus routes in Zhuhai.

3) IC card data: The dataset was produced by IC cardholders on all buses in Zhuhai from January 1st to October 31st, 2015. Each record in the IC card dataset consists of four main parts, that is bus route ID, bus ID, consumption date, and card ID. Moreover, there are more than 600 thousand user consumption records generated in one day in Zhuhai.

4) POIs: The dataset was extracted from the Auto Navi MAP in Zhuhai. Specifically, each record in the POI dataset mainly contains five parts, that is POI ID, name, type, latitude, and longitude. In addition, according to the type of each POI, the whole POIs can be divided into twelve categories, and each
category contains different number of records, as displayed in Fig. 7.

5) Meteorological data: The dataset was collected from National Meteorological Center of China Meteorological Administration \([31]\) in Zhuhai from January 1st to October 31st, 2015. Each record in this dataset is composed of three main messages, that is highest temperature, lowest temperature, and weather condition.

| Data sources          | Zhuhai          |
|-----------------------|-----------------|
| Taxi Trajectories     | GPS Trajectories|
| Bus Trajectories      | GPS Trajectories|
| IC Card Data          | IC Card Records  |
| POIs                  | 2015            |
| Meteorology           | Hours           |
|                       | 8760            |
| Gird Sizes            | 5 × 5 km        |
| Affecting Region Sizes| 0.5 × 0.5 km    |

### Table II

Statistics of the source datasets in Zhuhai, China.

B. Comparison Methods

We compare our SDAE-4 with five baselines, that is logistic regression, support vector machine, restricted Boltzmann machine, deep belief networks, artificial neural network. Meanwhile, we compare our 3-layer perceptron neural network with five other baselines \([28]\).

1) Logistic Regression: \(LR\) is a linear classifier. Moreover, \(LR\) is often employed in an regression analysis to describe the relationship between the categorical response variable and one or more explanatory variables \([32]\) \([33]\). Mathematically, the \(LR\) model can be formulated by the Equation \([18]\) and \([19]\) which are parametrized by a initial weight matrix and a bias vector.

2) Support Vector Machine: \(SVM\) \([34]\) is a supervised learning model. In this baseline, we apply an SVM with RBF kernel \((SVM_{RBF})\) for classification and regression analysis. Furthermore, the radial basis function \(RBF\) kernel on two sample vectors \(x^{(r)}\) and \(x'^{(r)}\) can be formulated as:

\[
K(x^{(r)}, x'^{(r)}) = \exp(-\frac{\| x^{(r)} - x'^{(r)} \|^2}{2\sigma^2}),
\]

where \(\| x^{(r)} - x'^{(r)} \|^2\) denotes the the squared Euclidean distance between \(x^{(r)}\) and \(x'^{(r)}\), \(\sigma\) is a free parameter.

3) Restricted Boltzmann Machine: \(RBM\) is a variant of Boltzmann machines \([35]\) \([36]\). In this baseline, we make use of \(RBM\) to learn a probability distribution \(P\), based on our training dataset, specifically:

\[
E(v, h) = -a^T v - b^T h - v^T W^{(m)} h,
\]

\[
P(v, h) = \frac{e^{-E(v, h)}}{\sum e^{-E(v, h)}},
\]

where \(v\) and \(h\) denote the visible vector and hidden vector, respectively. \(a\) and \(b\) separately represent the offset vectors of the visible and hidden layers. \(a^T\) and \(b^T\) indicate the transpose of \(a\) and \(b\). \(W^{(m)}\) is a matrix of weights connecting hidden and visible units in layer \(m\).

4) Artificial Neural Network: ANN \([37]\) is designed as a one-hidden-layer Multi-Layer Perceptron (MLP) in the experiment. Mathematically, the single-hidden-layer MLP is formulated as:

\[
f(x) = \text{softmax}(W^{(2)}(a^{(2)} + b^{(2)}))
\]

\[
= \text{softmax}(W^{(2)}(s(W^{(1)}x + b^{(1)}) + b^{(2)})),
\]

where \(a^{(2)}\) denotes the output vector of the hidden layer. \(W^{(1)}\) and \(W^{(2)}\) are separately matrices of weights connecting input and hidden units, and connecting hidden and output units. \(b^{(1)}\) and \(b^{(2)}\) respectively represent the bias vectors for hidden and output units. \(s\) represents the logistic sigmoid function.

5) Deep Belief Networks: \(DBN\) is a deep network model pre-trained by stacking RBMs \([38]\) \([39]\). Furthermore, \(DBN\) tries to learn the joint probability distribution between the \(\ell\) hidden vector \(h^k\) and observed vector \(x\), specifically:

\[
P(x, h^1, \cdots, h^\ell) = \prod_{k=0}^{\ell-2} P(h^{k+1} \mid h^k)P(h^{\ell-1}, h^\ell),
\]

where \(P(h^k \mid h^{k+1})\) denotes a conditional distribution for the visible units given the hidden units of the RBM at level \(k + 1\). \(P(h^{\ell-1}, h^\ell)\) represents the visible-hidden joint distribution in the top-level \(RBM\).

C. Results

1) Evaluating with the fusion of different features:

In the experiments, we first justify the effectiveness of the extracted features for the Trip Demand Predictor. Specifically, through the combination of \(F_{vm}\), \(F_g\), and \(F_m\) in different ways, we obtain seven kinds of feature sets, that is \(F_{vm}\), \(F_g\), \(F_m\), \(F_{vm}+g\), \(F_m+vm\), \(F_{g+vm}\), and \(F_{all}\). \(F_{vm}, F_{g}, F_{m}, F_{vm}+g, F_m+vm, F_{g+vm}\), and \(F_{all}\) respectively are the fusions of \(F_m\) and \(F_g\). \(F_{vm}, F_g\) and \(F_{vm}+g\), \(F_m\) and \(F_{vm}\), and \(F_{g+vm}\), and all the feature sets. Furthermore, utilizing the proposed SDAE-4 algorithm and other baseline methods, we experiment with the seven feature sets to predict the number of people’s bus trips (\(BTD\)) at different periods in the future. The prediction accuracy of these methods is displayed in the Fig. 8.

In this figure, the first six sub-figures describe the prediction accuracy of people’s trips on the bus routes in the next one to six hours. In the first six sub-figures, the x-axis represents the seven feature sets. The y-axis indicates the prediction accuracy of \(BTD\) in the future period of time \(T\). As shown in the sub-figure \(S(g)\) each prediction method is represented by the unique line and color. The \(DBN\) is a two-hidden-layer \(DBN\). Given the results of different methods, the prediction accuracy of people’s bus trips varies dramatically with the change of feature sets. By fusing all the \(F_m\), \(F_g\), and \(F_{vm}\), we can always achieve a dramatically improvement on the accuracy of the SDAE-4 and other baselines at the different time intervals \(T\). Moreover, whether based on individual feature set or their combinations, our proposed SDAE-4 outperforms other baselines at each future time interval in most instances. Consequently, these studies further demonstrate that the feature sets we extracted are considerably useful for predicting \(BTD\) and are noticeably effective for improving the prediction accuracy.
2) Evaluating with different number of layers and different number of hidden units per layer:

In this section, we mainly study the influence of the number of layers and the number of hidden units per layer on the prediction accuracy. More specifically, we aim to examine the behaviors of the SDAE and the baseline DBN on all the feature sets, as modifying the number of hidden layers and the number of neurons per layer. Fig. 9 displays the variation in the prediction accuracy of SDAE and DBN, as we increase the number of hidden layers from 1 to 5 and the number of hidden units per layer from 50 to 200. With the change of conditions, the prediction accuracy of the DBN varies extremely, while the prediction accuracy of the SDAE is relatively stable. Furthermore, compared with DBN, the advantages of SDAE become even more obvious with the increase of number of layers and number of hidden units. Additionally, for all the feature sets, the SDAE with 4 hidden layers and 100 neurons per layer appears to perform better than other SDAE variants and all DBN variants.

3) Evaluating with different time spans:

In previous experiments, the feature sets related to people’s bus trips are extracted during a specified period of time. Here we evaluate how the length of time span affects the prediction performance of the proposed SDAE-4 and other baselines. In the experiments, based on all the corresponding feature sets, we change the time span from 1 to 12 hours and measure the prediction precision of the proposed SDAE-4 and other baselines for each time span, as displayed in Fig. 10. The results indicate that the SDAE-4, DBN-2, RBM, SVM rbf, and LR all can obtain better prediction accuracy of people’s bus trips for the next one hour. In addition, for all the methods except ANN, in general their prediction accuracy will becomes worse with the increase of time span. Moreover, in most cases, our proposed SDAE-4 is always superior to other baselines for all the time spans from 1 to 12 hours and has a stronger robustness to predict people’s bus trips in the future.
In this paper, we devise a Clairvoyance system to solve a route planning problem for electric buses that will depart in an ideal state, based on the extracted spatial-temporal and semantic features about vehicle movement, human mobility, geographic location, and weather. Specifically, the proposed Clairvoyance leverages the SDAE-4 network to predict the future number of people’s bus trips on each bus route and utilizes our three-layer perceptron network [28] to forecast the future transportation carbon emission in each region throughout the city.

Moreover, given the future information of people’s bus trips and carbon emissions, a greedy strategy is introduced to recommend top-k bus routes for each electric bus that will depart. Our experiments are carried out on the real-world urban big data in Zuhai, China. The results indicate that the extracted features are considerably effective for improving the performance of the proposed two networks. Depending on these features, our networks both outperform the other well-known baselines, such as SVM, RBN, ANN and DBN. Moreover, we also quantitatively evaluate the efficiency of route planning in terms of reducing carbon emissions.

Clairvoyance provides a novel deep learning-based strategy to assign suitable routes for electric buses, based on the heterogeneous urban big data. The available urban datasets play a crucial role in our system. Accordingly, the limitation of Clairvoyance is that 1) the extracted features are from limited available urban datasets; 2) the Clairvoyance does not consider the charging problem of electric buses. It is mainly based on a prior hypothesis that each electric bus that will depart is in an ideal battery state. In the future, we will first test the robustness of our system on diverse datasets extracted from different cities and study which datasets determine our system’s performance.
Second, this paper does not consider the impact of the electric bus charging problem, which needs further study. Third, we will explore the impact of urban emergency events on electric bus dispatching, in order to provide the necessary emergency strategy to our system.

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Xiangyong Lu is currently pursuing the Ph.D. degree in the Graduate School of Information Sciences at Tohoku University, Japan, under the guidance of Prof. Takayuki Okatani. He received the B.S. degree in computer science from Henan University, Kaifeng, China, in 2015. He received the M.S. degree in the Services Computing Technology and System Lab, Big Data Technology and System Lab, Cluster and Grid Computing Lab, School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan, 430074, China, under the guidance of Prof. Chen Yu. From April 2016 to March 2017, he was a visiting scholar in the Emerging Networks and Systems Lab and Wireless Networks Lab, the Department of Information and Electronic Engineering, Muroran Institute of Technology, Muroran, Hokkaido, Japan, under the guidance of Prof. Kaoru Ota. His research interests include computer vision, deep learning, ubiquitous computing and data mining.

Kaoru Ota was born in Aizu-Wakamatsu, Japan. She received M.S. degree in Computer Science from Oklahoma State University, the USA in 2008, B.S. and Ph.D. degrees in Computer Science and Engineering from The University of Aizu, Japan in 2006, 2012, respectively. Kaoru is currently an Associate Professor and Ministry of Education, Culture, Sports, Science and Technology (MEXT) Excellent Young Researcher with the Department of Sciences and Informatics, Muroran Institute of Technology, Japan. From March 2010 to March 2011, she was a visiting scholar at the University of Waterloo, Canada. Also, she was a Japan Society of the Promotion of Science (JSPS) research fellow at Tohoku University, Japan from April 2012 to April 2013. Kaoru is the recipient of IEEE TCSC Early Career Award 2017, and The 13th IEEE ComSoc Asia-Pacific Young Researcher Award 2018. She is Clarivate Analytics 2019 Highly Cited Researcher (Web of Science).

Mianxiong Dong received B.S., M.S. and Ph.D. in Computer Science and Engineering from The University of Aizu, Japan. He is the Vice President and youngest ever Professor of Muroran Institute of Technology, Japan. He was a JSPS Research Fellow with School of Computer Science and Engineering, The University of Aizu, Japan and was a visiting scholar with BBCR group at the University of Waterloo, Canada supported by JSPS Excellent Young Researcher Overseas Visit Program from April 2010 to August 2011. Dr. Dong was selected as a Foreigner Research Fellow (a total of 3 recipients all over Japan) by NEC C&C Foundation in 2011. He is the recipient of IEEE TCSC Early Career Award 2016, IEEE SCSTC Outstanding Young Researcher Award 2017, The 12th IEEE ComSoc Asia-Pacific Young Researcher Award 2017, Funai Research Award 2018 and NISTEP Researcher 2018 (one of only 11 people in Japan) in recognition of significant contributions in science and technology. He is Clarivate Analytics 2019 Highly Cited Researcher (Web of Science).

Chen Yu received the B.S. degree in mathematics and the M.S. degree in computer science from Wuhan University, Wuhan, China, in 1998 and 2002, respectively, and the Ph.D. degree in information science from Tohoku University, Sendai, Japan, in 2005. From 2005 to 2006, he was a Japan Science and Technology Agency Postdoctoral Researcher with the Japan Advanced Institute of Science and Technology. In 2006, he was a Japan Society for the Promotion of Science Postdoctoral Fellow with the Japan Advanced Institute of Science and Technology. Since 2008, he has been with the School of Computer Science and Technology, Huazhong University of Science and Technology, Wuhan, where he is currently a full Professor and a Special Research Fellow, working in the areas of wireless sensor networks, ubiquitous computing, and green communications. Dr. Yu was a recipient of the Best Paper Award in the 2005 IEEE International Conference on Communication and the nominated Best Paper Award in the Proceedings of the 11th IEEE International Symposium on Distributed Simulation and Real-Time Application in 2007.

Hai Jin is a Cheung Kung Scholars Chair Professor of computer science and engineering at Huazhong University of Science and Technology (HUST) in China. Jin received his PhD in computer engineering from HUST in 1994. In 1996, he was awarded a German Academic Exchange Service fellowship to visit the Technical University of Chemnitz in Germany. Jin worked at The University of Hong Kong between 1998 and 2000, and as a visiting scholar at the University of Southern California between 1999 and 2000. He was awarded Excellent Youth Award from the National Science Foundation of China in 2001. Jin is the chief scientist of ChinaGrid, the largest grid computing project in China, and the chief scientists of National 973 Basic Research Program Project of Virtualization Technology of Computing System, and Cloud Security. Jin is an IEEE Fellow and a member of the ACM. He has co-authored 22 books and published over 700 research papers. His research interests include computer architecture, virtualization technology, cluster computing and cloud computing, peer-to-peer computing, network storage, and network security.