Spatial-temporal Distribution Prediction of Charging Load for Electric Vehicle based on Dynamic Traffic Flow

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Abstract. On the basis of velocity-flow-density relationship and traffic-energy consumption relationship, this paper proposes a prediction method of the spatial and temporal characteristic of electric vehicle charging load using the traffic data. By analyzing the residential travel data, a probability model was built to generate trip chains of a day, which contain destination and start time. Then vehicle transfer model was used to simulate driving vehicles on the roads and SOC could be calculated by the road condition and temperature. Drivers would charge vehicles when SOC is below the charging threshold. Finally, by using the Monte Carlo method, charging load of a real traffic model was calculated according to charging demand from all electric vehicles at different time and location during the area.

1. Introduction
Recently, global warming and air pollution have become increasingly prominent, and motor vehicle exhaust pollution is one of the main sources of atmospheric pollution. Many countries and regions have set timetables for banning sales of oil-fueled vehicles. The scale and charging demand of EV will surely embrace a new round of growth. Large-scale charging load access will have a greater impact on the safe and stable operation of the power grid [1] and [2]. Therefore, studying the spatial-temporal distribution characteristics of charging load of EV is of great significance for analyzing its impact.

In recent years, effective analyses on the spatial-temporal distribution characteristics of the charging load were carried out by researchers through introducing the trip chain theory, OD (Origin-Destination) analysis and other theories. The authors in [3] proposed a spatial-temporal prediction method of the charging load of EV that takes driving and parking characteristics into consideration on the basis of predicting parking demands. The authors in [4] established a probability model of the duration of EV parking in different regions and analyzed the charging demands of EV in different regions by the Monte Carlo method. The authors in [5] adopted the Markov decision theory to simulate travel routes and calculated the real-time energy consumption through traffic and temperature energy consumption models. However, there were still shortcomings of the above research methods: ① Traffic conditions only affected the vehicle spatial-temporal transfer model. The interaction between the traffic network model and the vehicle spatial-temporal transfer model should be bidirectional and real-time. ② The coupling between travel destinations and departure time was insufficient. Existing travel models considered the independent modeling of departure time and travel destinations respectively and set the trip chain length to 2 and 3. However, the actual EV
Based on above analysis, this paper proposed a spatial-temporal distribution probability modeling method of charging load for EV based on dynamic vehicle flow. Through the relationship of velocity-flow-density and the relationship of traffic-energy consumption, the bidirectional real-time information interactions between the traffic road network model and the spatial-temporal transfer model of EV were realized. Based on the NHTS2017 data\(^6\), a joint probability distribution model of different types of travel destinations and departure time was established. The current position and time are taken to get the destination and departure time of the next trip, and there is no need to preset the trip chain type and length.

2. The traffic road network model

2.1. Road network topology

The traffic network consists of roads of different lengths and intersections at different locations, which can be abstracted into a network composed of a set of branches and nodes. We use \( bi(i=1,2,\ldots,n, n \) is the number of nodes) as nodes, and the branch from node \( i \) to node \( j \) is represented by \( < b_i, b_j > \). Then \( B \) is represented the assembly of all the nodes, while \( L \) is represented the assembly of all the branches, thus \( G(B,L) \) is represented the network.

![Figure 1. Road network model.](image)

In the equation, \( l_{ij} \) is the length between node \( i \) and node \( j \), inf means infinity. Based on the functions of the area in urban planning, urban area are divided into residential area, work area, and commercial area, and the driving routes, and distribution of charging demands of EV are affected by the structure of road network.

2.2. Velocity-flow-density relationship

Velocity, flow and density are three basic indicators for measuring traffic flow characteristics, and their changing laws can reflect the basic properties of traffic flow. If there are \( N_{ij}^t \) vehicles running on the road \( < b_i, b_j > \) at time \( t \), the traffic density \( K_{ij}^t \) can be expressed by equation (2):

\[
K_{ij}^t = \frac{N_{ij}^t}{l_{ij}}
\]

The authors in [8] draws a velocity-density relationship scatter plot based on the measured data of urban traffic flow in Beijing, and fits it with a mathematical model which can be expressed by equation (3):

\[
V_{ij}^t = \frac{V_0 e^{-K_{ij}^t/227}}{227}
\]
Where $V_{ij}^t$ is the average velocity of the road, $V_0$ is the initial velocity of the road with no vehicles, 80 km/h for the expressway, and 60 km/h for the main road. The traffic flow is vehicles passing through a section on the road per unit time, which can be obtained by multiplying the density and velocity.

3. The spatial-temporal transfer model of EV based on dynamic traffic flow

3.1. Modeling idea

Based on urban functional area division and travel chain theory, the authors in [5] and [9] established travel simulation model of EV. The model can be represented by the travel chain and road chain in Figure 2. For a certain road, vehicles may enter or leave at any time, and the density of traffic flow and the driving state of vehicles interact with each other in real time and change dynamically. The existing model cannot reflect the real-time interaction between traffic condition and vehicle driving condition. Therefore, this paper further decomposes the road chain according to the simulation step time chain, and establishes a vehicle spatial-temporal transfer model based on dynamic traffic flow.

![Figure 2. Travel chain - road chain - simulation step time chain.](image)

3.2. The spatial-temporal transfer model for EV

The driving condition of EV from $t_1$ to $t_2$ can be calculated by equation (4) and (5):

$$D^3 = D^0 + \int_{t_1}^{t_2} V_{ij}^t(K_{ij}^t)dt$$  (4)

$$E^3 = E^0 - \int_{t_1}^{t_2} \omega_{ij}(V_{ij}^t)W_{ij}^t(K_{ij}^t)dt$$  (5)

Where $D^0$, $D^3$, $E^0$, $E^3$ represent the position and the remaining battery power of EV at $t_1$ and $t_2$, respectively, $\omega_{ij}$ represents the energy consumption per kilometer. Since the driving velocity $V_{ij}^t$ and the traffic flow density $K_{ij}^t$ influence each other in real time and change dynamically, the traffic flow density $K_{ij}^t$ is obtained by the monitoring of road flow, and it cannot be expressed as an explicit mathematical formula, so that $D^0$ and $E^3$ cannot be directly solved.

In order to solve the integral in equation (4) and (5), the idea of Riemann Integral is used to divide the time quantum from $t_1$ to $t_2$ into $n$ segments, with each duration of $\Delta t$. Assuming that the traffic density and running velocity of each section during $\Delta t$ remain unchanged, the integral calculation is converted to the calculation of the area of $n$ bars with the same width of $\Delta t$. When the number of segments $n$ is large enough, this approximate calculation is reasonable.
The EV doesn’t always run on one road during the simulation step time $\Delta t$ when driving actually. Starting, ending a travel or changing to another road may appear during $\Delta t$. As shown in figure 3(a), the vehicle is running on road $<b_i, b_j>$, during $\Delta t$, and the displacement $\Delta D^t$ and energy consumption $\Delta E^t$ can be calculated as equation (6) and (7):

$$\Delta D^t = V'_t \Delta t$$ (6)

$$\Delta E^t = -\omega'_t \Delta D^t$$ (7)

Figure 3(b)(c) show the situations of starting, stopping and road changing during $\Delta t$, and the displacement and energy consumption calculation are similar to equation (6) and (7). In the simulation, attention should be paid to update the traffic density, driving velocity and energy consumption when vehicles enter or leave a certain road.

### 3.3. Energy consumption

The energy consumption model is built mainly around traffic condition and environmental temperature. The authors in [10] and [11] analyzed the actual data and established traffic-energy model and temperature-energy model. The comprehensive energy consumption model can be demonstrated as equation (12):

$$\omega = k \cdot \omega_l$$ (8)

Where $k_l$ is temperature energy consumption ratio, $\omega$ and $\omega_l$ represent the energy consumption per kilometer when temperature is considered and not considered respectively.

### 3.4. The shortest travel time route planning

Dijkstra algorithm is often used to solve the route planning problem of the network graph model. When $L_h$ is used to represent the total length of route $h$, the goal of Dijkstra algorithm is to find out the path that minimizes the $L_h$ in all possible $h$. While, drivers are more likely to choose route that are not jammed. If the minimum value of $T_h$ is used as the goal of Dijkstra algorithm, where $T_h$ is used to represent the total time of route $h$, the dynamic shortest travel time route planning can be realized. The driver re-plans the shortest travel time route based on the current traffic condition when arriving at a intersection.

### 4. Probability model of resident travel

#### 4.1. The NHTS2017 data

The National household Travel Survey (NHTS)[6] data is often used in fields such as traffic safety, energy consumption, and mobile sharing economy. The resident travel probability model is established based on the NHTS2017 data. The variables $A$ and $B$ respectively represent the current position and travel destination, and the variables $C$ and $D$ respectively represent the current time and departure time.
4.2. The probability distribution of travel destination

According to the NHTS User Guide, travel purposes can be divided into five categories: Home (H), Work (W), Shopping/Eating (SE), Social/Recreation (SR), and others (O), where H and W correspond to residential area and work area, respectively, SE and SR correspond to commercial area, and O can correspond to three types of functional area. When the vehicle starts a travel at \( a \), the probability of departing to the destination \( b \) can be described by equation (13):

\[
P(b|a, c) = \frac{M(A = a, B = b, C \geq c)}{M(A = a, C \geq c)}
\] (9)

Where \( a, b \in \{H, W, SR, SE, O\}, c \in [0, 1440) \), \( P(b|a, c) \) indicates the probability of departing to the destination \( b \) when the starting node is \( a \), the current time is \( c \). \( M \) represents the number of corresponding trips. The starting node is set to H in this model. Whenever a trip ends, the next destination is extracted from Table 1 according to the current node type, and the vehicle returns home until the destination is H.

| Position | H  | W  | SE | SR  | O  |
|----------|----|----|----|-----|----|
| H        | 3.70% | 30.39% | 23.80% | 14.65% | 27.45% |
| W        | 58.97% | 13.51% | 16.04% | 3.88% | 7.60% |
| SE       | 50.57% | 9.05% | 26.18% | 6.00% | 8.18% |
| SR       | 63.08% | 3.77% | 16.82% | 9.04% | 7.29% |
| O        | 50.14% | 6.90% | 19.88% | 5.69% | 17.38% |

4.3. The probability distribution of departure time

4.3.1. The mixed normal distribution. Based on the classification statistics of trips, it could be found that one or more travel peaks existed in the departure time through drawing frequency histograms. The departure time of \( n \) peaks could be fitted by \( n \) normal distributions mixed by ratio. When it was known that the trip was from node \( a \) to node \( b \) and the current time was set to 0, the departure time could be fitted by a mixed normal distribution. The probability density function can be represented as equation (14):

\[
f_{mix}(d|a,b,0) = \sum_{i=1}^{\infty} p_i \cdot \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(\frac{-(d-\mu_i)^2}{2\sigma_i^2}\right)
\] (10)

Where \( d \in [0, 1440) \), \( \mu_i \) and \( \sigma_i \) were the mean and variance of the \( i \)th normal distribution, \( p_i \) was the corresponding mixture ratio and satisfied \( \sum p_i = 1 \). This paper used the double mixed or triple mixed model to fit the probability of departure time of all 25 types of trips.

4.3.2. The truncated mixed normal distribution. The departure time of the next trip could be extracted by the conditional probability model based on the current time. Assuming that the EV arrived at the destination at time \( c \) and finished the current trip, the next destination \( b \) was extracted based on the current destination \( a \), that means, the next trip type was determined. Then the next trip departure time \( d \) would obey the truncated probability distribution of equation (14). The probability density function and cumulative distribution function can be represented by equation (15) and (16):

\[
f_{tr,mix}(d|a,b,c) = \frac{H(c)f_{mix}(d|a,b,0)}{1 - F_{mix}(d|a,b,0)}
\] (11)

\[
F_{tr,mix}(d|a,b,c) = \frac{F_{mix}(d|a,b,0) - F_{mix}(c|a,b,0)}{1 - F_{mix}(d|a,b,0)}
\] (12)

Where \( c \in [0, 1440) \), \( d \in [c, 1440) \), \( H(c) \) was a step function, \( f_{mix}(d|a,b,0) \) and \( F_{mix}(d|a,b,0) \) were the corresponding truncated mixed normal distribution probability density function and its cumulative probability distribution function of the departure time of the next trip.
4.4. The joint probability distribution

The joint probability distribution can be obtained from the travel destination and travel time probability distribution. The cumulative probability distribution function can be calculated by equation (17):

$$F(b,d|a,c) = P(b|a,c)F_{t_i,n}(d|a,b,c)$$

(13)

When the current node $a$ and the current time $c$ are known, the next trip destination $b$ and the departure time $d$ can be extracted.

5. Case study

5.1. Parameter setting

Take the urban road network in the figure 4 as an example, there are 50 road nodes and 84 roads included in the main road network of this area. The total number of vehicles is set as 200,000. Take the Nissan Leaf 2018 electric car as an example for simulation, with 40 kWh battery capacity. Set the initial SOC to obey the normal distribution $N(0.6, 0.2^2)$, there is sufficient time for slow charging in the residential area with 7kW charging power, while in other area the charging power for fast charging is 50 kW.

5.2. The spatial-temporal distribution of charging load

Figure 5-7 shows the spatial-temporal distribution of charging load for EV in each functional area when penetration is 90%. It can be seen from the figure that the charging load curves of the same type of area has similar shape. The charging load in the work area has the morning peak period (8:00-11:00), while the charging load in the commercial area has the evening peak period (17:00-20:00). The charging load in residential area is mainly concentrated the period after returning home at night (18:00-24:00), which is significantly higher than that in the work area and commercial area. This is because all the vehicles commuting in the work area and commercial area during the daytime would return to the residential area.

Figure 4. Road network model of a city.  
Figure 5. Charging load in commercial area.
Figure 6. Charging load in work area. Figure 7. Charging load in residential area.

Figure 8 shows the comparison of the total charging load in various functional area. It can be seen that the charging load is significantly correlated with the travel purpose and time. The morning home-to-work rush hour is followed by the charging load peak in the work area, while the evening home-return rush hour is followed by the charging load peak in the residential area. The charging load peak in the commercial area is concentrated during the lunch and dinner periods.

Figure 9. Different methods predict regional total charging load (penetration is 90%).

5.3. Comparison with other methods
The total charging load of EV in this region was predicted with the method in reference [9] and [12]. As shown in figure 9, the charging loads obtained all peaked at 18:00-20:00 in the evening. The prediction charging peak of method in [9] was 2 hours earlier than the method in this paper, as [9] set the length of the trip chain to 2 or 3, which led to the early home return time. However, in this paper, the next trip was extracted based on the current time and place, which reflected the randomness of the travel behavior. There were two obvious peaks in the prediction results of paper [12], The peak was similar to the results of this paper. And there was a significant valley at noon, which did not exist in the results of this paper. This was because the method in [12] sets the charging period and the charging probability in advance, which resulted in fewer vehicles charging at noon, while this paper combined the traffic network and probabilities of travel, EV charging load was indirectly affected by traffic condition and trip chains.

6. Conclusion
1) The spatial-temporal transfer model of EV based on dynamic traffic flow could reflect the influence of traffic condition on vehicle velocity and energy consumption. The shortest travel time
route planning was realized based on dynamic traffic flow and the Dijkstra algorithm, which effectively avoided routes that were shortest but jammed and shortcomings of the shortest travel distance route planning.

2) The model of resident travel probabilities extracted the departure time and destination of the next trip based on the current time and location. It realized random simulations of trip chains of residents without setting the type and length of the trip chain in advance.

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