

Electric Vehicle Charging Simulation Framework Considering Traffic, User, and Power Grid

Weicheng Liu, Xujiang Shi, Jianfeng Zhao, Xiao-Ping Zhang, and Ying Xue

Abstract—The traffic and user have significant impacts on the electric vehicle (EV) charging load but are not considered in the existing research. We propose a novel integrated simulation framework considering the traffic, the user, and power grid as well as the EV traveling, parking and charging based on cellular automaton (CA). The traffic is modeled by the traffic module of the proposed framework based on CA, while the power grid and user are modeled in the EV charging module. The traffic flow, user's charging preference, user's charging satisfaction, and the total supply capability (TSC) in the surveyed region are considered in the proposed framework. Two cases are carried out to show the interactions between the user and power grid. It is shown that the proposed framework can accurately simulate the interactions among traffic situation, user's behavior and TSC, which are significantly lacking in the existing research. The proposed framework is scalable in considering additional interrelated elements.

Index Terms—Electric vehicle (EV), integrated simulation framework, cellular automaton, traffic, user, power grid.

I. INTRODUCTION

ELECTRIC vehicle (EV) is critical for alleviating energy dilemmas and the greenhouse effect [1]. The large-scale deployment of EV will bring a non-negligible impact on the planning and operation of the power grid [2], [3]. The charging demand for the district area is closely related to the user's behavior and traffic flow. Meanwhile, the total supply capability will affect the charging process and the user's charging experience. Total supply capability (TSC) of a distribution system is defined as the maximum load, which serves under the $N-1$ guideline, considering the capacities of substation transformers and feeder, network topology, and some operation constraints [4]. The importance of the interactions between the user and power grid has been highlighted in recent years [5], [6]. Therefore, a method considering

the traffic, user, and power grid should be adopted to analyze the interactions.

The research on the influence of EV charging process of the traffic flow and power grid has been carried out in [7], [8]. The restrictions of the traffic flow and power grid also have the impact on EV charging process. The distributed decision-making method [9] has been used to model the charging behavior under different transmission conditions. The user's satisfaction is considered in the charging sequence optimization [10] and a bi-level tariff scheme [11].

With the development of intelligent transportation and smart grid, researchers have further studied the relevance between the traffic flow and the EV charging load. The traffic flow data and power load profile are used to navigate EV users to best fit the charging station, where both the power grid and user can benefit based on the intelligent transportation system [12]. Using geographical traffic data to plan the charging station location and navigate the users is the application of transportation information. Besides the charging station planning, [13] utilizes the information of traffic flow and power grid to improve the EV charging navigation strategy by locational marginal price (LMP), which reduces the charging time and cost. The transportation information is also suitable to construct the integrated simulation framework. The multi-agent model has been applied to simulate the interaction between EV and charging infrastructure in [14]. Multi-agent transportation simulation model is proposed to assess the impact of EV traveling and charging process on the power grid with different electricity pricing strategies and different charging prioritizations. The multi-agent method is also used to obtain a large-scale tempo-spatial distribution of EV charging in [15], which proposes a simulation method of EV charging characteristics considering the traffic situation.

In addition to the multi-agent method, the cellular automaton (CA) method is able to simulate the bilateral effects between the traffic flow and EV charging load. Reference [16] proposes a traffic-power model to investigate the charging power in the charging station based on CA by modeling the charging station alongside the road in a CA system. Reference [17] combines the CA method with the agent method to describe the dynamic process of EV charging and analyzes the charging load in a 25-node traffic network. The charging tempo-spatial distribution is obtained through Monte Carlo method. However, the user's behavior is not considered in this method and the accuracy of Monte Carlo method is

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insufficient in the simulation of dynamic traffic process.

The traffic flow and the EV charging load are two principal elements in the EV charging process and are well studied by the research mentioned above, whereas the user's behavior is not sufficiently considered. Some researchers have taken the EV user into account, but do not consider the interaction with the traffic flow and power grid. The traffic-constrained multi-objective planning method combining geographic location information and vehicle battery information to optimize the location of the charging station is proposed in [18]. Traffic information is also used by considering the user's behavior and trip chain [19] to reflect the user's travel path and travel time in order to plan the location of the charging station [20], [21]. The trip chain method improves the efficiency of the charging station by modeling the vehicle travel path so as to optimize the planning of the charging station. Reference [22] considers the user's behavior to predict EV charging demand, but the user's behavior is simplified

as a function of travel distance that neglects the user's charging behavior. More importantly, none of the above models have considered the mutual interactions among the traffic, the user, and power grid at the same time. Therefore, it would be highly beneficial to develop an overall integrated simulation framework to explore the interactions in the coupled driving, parking, and charging system, which considers the traffic, user, and power grid as a whole. The traffic, user, and power grid all have a significant impact on each other, and the negligence of any one of them will result in a considerable error in the analysis.

The main contribution of this paper is the development of an integrated simulation framework considering the traffic, user, and power grid to analyze the interactions among them. To highlight the advantages of the proposed framework, Table I presents the comparison between the proposed framework and the existing methods.

TABLE I
COMPARISON BETWEEN PROPOSED FRAMEWORK AND EXISTING METHODS

Method		Function list					
Type	Theory	Vehicle microcosmic behavior	Different charging mode	Impact of TSC	User's charging preference	User's charging experience	Scalability
EV charging load simulation	Monte Carlo [23]	×	√	×	×	×	×
Charging station planning	Trip chain [19]	×	√	×	√	×	×
Traffic-power comprehensive simulation	Multi-agent [14], [15]	×	√	√	√	×	√
	CA [16]	√	√	√	×	×	√
	Agent-cellular [17]	√	√	√	×	×	√
Proposed framework	CA	√	√	√	√	√	√

Note: √ means that the method has the function and × means that the method does not have the function.

The proposed framework has the advantage of microcosmic scale simulation, reflecting the behavior of each vehicle such as vehicle lane changing process, vehicle acceleration and deceleration processes and user's charging preference, which all contribute to a more detailed and accurate simulation results. In addition, the proposed framework utilizes the concept of agent, and superimposes the user's attributes as an agent upon the vehicle cell, which makes the proposed framework much more accurate in describing the user's behavior. The advantages of the proposed framework will be further explained and highlighted in case studies. The two objectives of this paper are as follows.

1) Development of the proposed framework: detailed modeling of the traffic is based on CA, the consideration of user's behavior as built-in attributes of each vehicle, and the interactions among the traffic, the user, and power grid during the charging process.

2) Case study based on the proposed framework: after constructing the proposed framework, two cases about the interactions are simulated and analyzed.

The rest of this paper is arranged as follows. Section II introduces the design of the proposed framework. Section III details the design and function of the modules which are

used in the proposed framework. Section IV shows the results of two cases based on the proposed simulation framework. Discussions on the results are presented. At last, Section V concludes the paper.

II. SIMULATION FRAMEWORK DESIGN

The proposed framework is based on a two-dimensional CA traffic model shown in Fig. 1, where the cross marks indicate the zone exits and others without cross marks indicate zone entrances. One two-lane road has been considered and simulated with focus on the interactions among the traffic, user, and power grid. Figure 2 shows the structure of the proposed framework, which includes two main modules: traffic module and vehicle parking module. The traffic modules are used to simulate the traffic. The vehicle parking modules are used to simulate vehicle parking and EV charging. The functions of these modules are shown in Table II and explained in Section III. These modules operate together based on the CA framework to form the proposed framework. In order to focus on the interactions among the traffic, user, and power grid, the buses of the power grid are simplified in the proposed framework [24], [25], where TSC and total charging power are used.

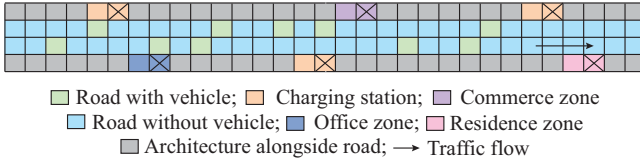


Fig. 1. Simulation based on CA framework.

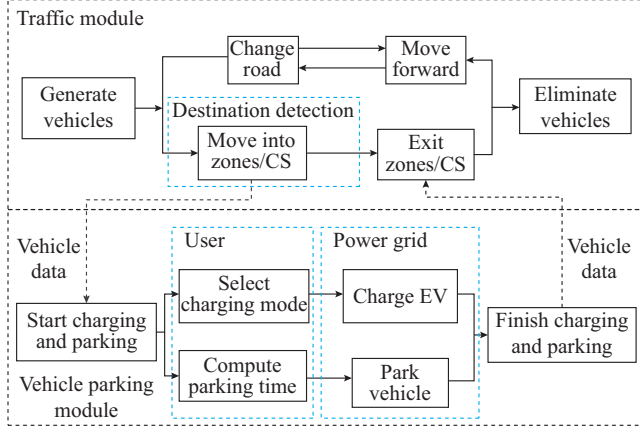


Fig. 2. Structure of proposed framework.

TABLE II
FUNCTIONS OF MODULES

Type	Objective	Module	Function
Traffic modules	Simulate the traffic flow precisely	Vehicle generation module	Generate new vehicles at the left boundary in Fig. 1
		Vehicle scan module	Scan the surroundings of vehicle in order to ensure safety
		Vehicle motion module	Achieve the lane changing and moving forward of the vehicle
		Vehicle elimination module	Eliminate the vehicles at the right boundary of the road
Vehicle parking modules	Simulate the user's charging behavior in zones or charging stations	Entrance and exit module	Deal with the exit and entry between road and zones/CS
		Parking time computation module	Compute the parking time of each vehicle
		Charging mode selection module	Choose charging mode according to user's preference
		Parking and charging process module	Accomplish parking and charging process

A. CA Framework

CA is a discrete system where space, time, and state are discrete [26]. The space dimensionality is D , and the vehicle cell exists in a set of infinite states S , where Z is a set of integers; n is the discrete step number; and Δt is the stepsize. Assuming $D=1$, S_z is the distribution of S with Z . The dynamic evolution process supervised with the rule of evolution F can be described as:

$$F: S_z^{n\Delta t} \rightarrow S_z^{(n+1)\Delta t} \quad (1)$$

The dynamic evolution is determined by the local evolu-

tion rule f of each cell. For one-dimensional CA, the local function of the cell and its neighbor S_{2r+1} is:

$$F(S_i^{(n+1)\Delta t}) = f(S_{i-r}^{n\Delta t}, \dots, S_i^{n\Delta t}, \dots, S_{i+r}^{n\Delta t}) \quad (2)$$

where $S_i^{n\Delta t}$ is the state of the cell at time $n\Delta t$; and i , $i-r$, and $i+r$ stand for neighbor cells.

Using CA as the connection is suitable to simulate the integrated system since the nature of CA is suitable for traffic simulation and the discrete characteristics of each cell are suitable for modelling the user's behavior. There is an advantage of using CA to simulate the integrated system, e.g., CA has a clear physical meaning which means that the framework based on CA has strong interpretability compared with other probabilistic-based methods, where the cells stand for a part of the road, and the states of the cells stand for the properties of the vehicle.

The critical step in developing the proposed framework is to convert the traffic rules to CA generation update rules. The proposed framework is constructed based on CA framework, as is shown in Fig. 1. The freeway traffic module is based on CA. Zones alongside each road are built, representing different types of function and charging stations. The vehicle can move into or exit the zone or charging station according to its destination and battery state. The charging process takes place in zones and charging stations. The update of the vehicle is supervised by basic traffic rules considering the real road condition and traffic safety.

B. Design of Proposed Framework

The structural of the proposed framework is shown in Fig. 2. Vehicle travel safety and battery state of charge (SOC) are considered in the traffic module. If the zone matches the destination of the vehicle, the vehicle will move into that zone. If the battery SOC is less than the requirement of the journey to the destination, the vehicle will move into the charging station to be charged. The vehicle parking module deals with the parking and charging processes of vehicles. When the parking time ends or the charging process finishes, the vehicle will get back to the road.

III. SIMULATION FRAMEWORK MODULE

A. Traffic Modules

1) Vehicle Generation Module

This module is used to generate the new vehicles at the left boundary in Fig. 1. If the entrance cell is empty and the vehicle generation condition is satisfied, the new vehicle is added to the first cell with its attributes. The vehicle generation quantity of hour h Qg_h is calculated by $Qg_h = Q_{\max} \eta_h$. $Q_{\max}$ is the maximum vehicle generation quantity of one hour in one day, which is an adjustable parameter. η_h is the proportion of Qg_h to $Q_{\max}$ of hour h , which is a default parameter to control the proportion of traffic flow. The vehicle generation quantity per simulation step is calculated by dividing the vehicle generation quantity of each hour and the total number of simulation steps in one hour. The vehicle generation module will generate a random number between 0 and 1 and compare it with the calculated vehicle generation

quantity per simulation step. If the random number is larger than the vehicle generation quantity per simulation step, the vehicle generation condition is satisfied, which means that the vehicle generation module will generate a new vehicle and vice versa. The vehicle attributes in traffic flow are listed in Table III.

TABLE III
VEHICLE ATTRIBUTES IN TRAFFIC FLOW

Vehicle attribute	Explanation
Vehicle type	Types of vehicle, e.g., fuel vehicle and EV
Total time	Time spent in the district
Section time	Time spent after the last zone/CS
Battery energy	EV battery energy
SOC	SOC of EV
Charging requirement	Vehicle has enough energy to the destination or not
Charging preference	User's charging preference
Charging cost	EV charging cost

The maximum speed of the vehicle starts from 0 to the maximum speed where the number is normalized, and 1 stands for 5 km/h. The vehicle type is determined by EV ratio (EVR). The destination of vehicles is generated randomly. The initial SOC is generated by a function relevant to the time. The charging requirement is calculated by considering the energy consumption from the present position to the destination. The charging preference is a part of the user's behavior and is formulated according to the generation of vehicles. In this module, the structure of traffic attributes is developed and the initial states of the vehicle are set.

2) Vehicle Scan Module

In this module, the surrounding conditions of vehicles are scanned. Five distances are measured for one vehicle, which are rear left distance, rear right distance, front left distance, front right distance and front distance. Left label and right label are used to show whether two-side road is occupied or not. The distance element is used to show the distances with other vehicles in the respective directions. The surrounding information is used in the vehicle motion process and vehicle exit zone/CS process to ensure the safety.

3) Vehicle Motion Module

The vehicle motion module includes two parts, which are vehicle lane changing module and vehicle moving forward module. This module is used to realize the vehicle motion function with traffic rules.

The vehicle lane changing module is used to investigate the lane changing of the vehicle. Lane changing is the fundamental behavior of vehicles in traffic flow. This module takes the data generated by the vehicle scan module in order to judge the safety of changing.

1) Condition of lane changing is presented as $d_k < \min(v_k + a_0 \Delta t, v_{\max}) \Delta t$; $d_{k,other} > d_k$; and $lane_k \neq lane_{k,dest}$ ($d_{k,dest} < 2d_{safe}$).

2) Condition of safety is presented as $d_{k,back} > d_{safe}$.

With a unit of power grid as shown in Fig. 1, d_k is the distance between the k^{th} vehicle and the first vehicle ahead of it; v_k is the velocity of the k^{th} vehicle with a unit of power grid per time step; $v_{\max}$ is the maximum vehicle velocity

which is a fixed value for all vehicles; a_0 is the acceleration coefficient for the vehicles; $d_{k,other}$ is the distance in the forward direction, i.e., the direction of lane, between the k^{th} vehicle and the first vehicle ahead of it in other lanes; $lane_k$ is the present lane of the k^{th} vehicle; $lane_{k,dest}$ is the destination lane of the k^{th} vehicle; $d_{k,dest}$ is the distance in the forward direction between the k^{th} vehicle to its destination; d_{safe} is the safety distance behind the vehicle which is a fixed value of all vehicles; and $d_{k,back}$ is the minimum distance between the k^{th} vehicle and first vehicle backward in $lane_k$ and the neighbor lanes.

The vehicle motion module is used to control the velocity and movement of vehicles according to the velocity-dependent-randomization (VDR) model. Considering the practical driving principle, the vehicle accelerates or decelerates on the premise of driving safety. x_k is the vehicle position of the k^{th} vehicle.

Step 1: detect random decelerate probability.

Step 2: accelerate $v_k \rightarrow \min(v_k + a_0 \Delta t, v_{\max})$.

Step 3: decelerate $v_k \rightarrow \min(v_k, d_k / \Delta t)$.

Step 4: randomly decelerate $v_k \rightarrow \max(v_k - a_0 \Delta t, 0)$.

Step 5: move forward $x_k \rightarrow x_k + v_k (\Delta t)$.

Meanwhile, the battery SOC is updated in this module according to the speed-time sequence of EV running status. The vehicle running equation [27] is:

$$F(n\Delta t) = mgf + mgi + \delta m \frac{dv(n\Delta t)}{dt} + \frac{\rho C_D A}{2} v^2(n\Delta t) \quad (3)$$

where $F(n\Delta t)$ is the vehicle tractive force, which is a function of $n\Delta t$; $v(n\Delta t)$ is the velocity of the vehicle, which is a function of $n\Delta t$; m is the vehicle kerb weight; f and g are the rolling resistance coefficients; i is the road incline; δ is the correction coefficient of rotating mass; $\rho = 1.2258 \text{ kg/m}^3$ is the air density; C_D is the coefficient of air resistance; A is the coefficient of the wind; and v is the velocity of the vehicle. Based on (3), the energy consumption formula for vehicle running is derived as (4).

$$E_c = \frac{\sum_{n=n_s}^{n_e} \frac{F(n\Delta t)v(n\Delta t)}{1000} \Delta t}{3600} \quad (4)$$

Assume the additional consumption is (5).

$$E_a = \frac{P_a (n_e - n_s) \Delta t}{3600} \quad (5)$$

The total energy consumption can be derived as (6).

$$E = \frac{E_c}{\eta} + E_a \quad (6)$$

where E_c is the energy consumption of vehicle running; n_s is the beginning discrete simulation time step of vehicle motion, valued as the simulation time step when the vehicle is generated; n_e is the latest simulation time step; P_a is the additional power which is a constant value; and η is the transmission efficiency. Based on (6), the SOC of EV is updated.

4) Vehicle Elimination Module

When the vehicle travels out of the simulated district, the vehicle is eliminated from the simulation system. The elimination process takes place at the right boundary of the road

where all vehicle attributes are eliminated, and vital data are stored for analysis. The data gathered from this module will be used to analyze the congestion and the user's average parking duration.

B. Vehicle Parking Modules

Vehicle parking modules are designed to simulate the user's charging behavior in zones or charging stations, which is not included in previous research. The events that happen in zones are modeled as two processes which are vehicle charging process and vehicle parking process. The SOC of EV measures the vehicle charging process, and the parking duration measures the vehicle parking process.

1) Entrance and Exit Module

In this module, the vehicle enters into the vehicle parking module from the traffic module as shown in Fig. 2. The data of vehicles are transformed into the vehicle parking module. There are two exit conditions: the first is the ending of parking and the second is the completion of the charging process. The exit condition for the charging station is that the charging process of EV is finished. If these exit conditions are satisfied, the vehicle will be put into the waiting list and ready to move out.

2) Parking Time Computation Module

In this module, the parking duration is generated according to the normal distribution in (7), where the probability density function is shown in (8):

$$T \sim N(amt, \sigma^2) \quad (7)$$

$$f(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(n\Delta t - amt)^2}{2\sigma^2}} \quad (8)$$

where T is the time; σ is the standard deviation; and amt is the average parking time. The type of zone determines the average parking time. Typically, the residence zone has the longest amt , while the office zone has a shorter amt , and the commerce zone has the shortest amt . σ of commerce zone is the largest, and σ in the office zone is the smallest.

3) Charging Mode Selection Module

In this module, the charging mode M for EV is determined using the user's decision objective function considering the user's preference $c_{user, prefer}$, energy price $c_{energy, price}$, the urgency of charging time $c_{urgency}$ and the charging location $c_{location}$.

$$M(c_{user, prefer}, c_{energy, price}, c_{urgency}, c_{location}) \quad (9)$$

Three types of user's preferences are modelled, which are speed-sensitive x_{speed} , price-sensitive x_{price} and time-sensitive x_{time} charging preferences.

$$x_{speed} = \min\{g_1, g_2, \dots, g_k\} \quad (10)$$

$$x_{price} = \begin{cases} \min\{c_1, c_2, \dots, c_k\} & t_k \in t_{peak} \\ \min\{g_1, g_2, \dots, g_k\} & t_k \in t_{valley} \end{cases} \quad (11)$$

$$x_{time} = \begin{cases} \min\{c_1, c_2, \dots, c_k\} & g_{p,k} \geq g_{slow,k} \\ \min\{g_1, g_2, \dots, g_k\} & g_{slow,k} > g_{p,k} \end{cases} \quad (12)$$

where g_k is the charging duration of the k^{th} EV; c_k is the charging cost of the k^{th} EV; t_k is the charging start time of the k^{th} EV; t_{peak} and t_{valley} are the peak and valley time for

electricity price, respectively; $g_{p,k}$ is the parking duration of the k^{th} EV; and $g_{slow,k}$ is the charging duration when the k^{th} EV selects slow charging. The charging cost stands for the cost when the EV selects slow charging mode and the minimum charging duration refers to the fast charging mode.

The speed-sensitive preference minimizes the charging time regardless of other elements. The time-sensitive preference selects the charging mode based on the time schedule. The price-sensitive preference selects the charging mode based on the charging price.

4) Parking and Charging Process Module

In this module, EVs are charged according to their charging mode. TSC limits the charging power of EV, affecting the charging process, the traffic flow, the user's charging preferences and charging satisfactions. The parking time is calculated at the same time. The attributes of both vehicle and EV are updated.

C. Scalability of Proposed Framework

Based on the simulation system, case studies can be carried out to analyze the interactions among the traffic, user, and power grid. The proposed framework can be easily expanded to investigate other elements due to the nature of the module design. For example, investigating the influence of EV charging load caused by severe weather can be realized by amending the modules and users in the proposed framework. For more specific user's behavior, it can be modelled by altering the driving rules in traffic module and the rules in the vehicle parking module. The scalability cannot be easily achieved by other methods.

IV. CASE STUDY

A. System Initialization

The simulation time duration is 86400 s (one day), and the simulation time step is set to be 6 s. EVs account for 50% of all vehicles. In this paper, the default maximum Q_{max} is set to be 200. The normalized vehicle number is the proportion of vehicle generation quantity of each hour to Q_{max} , which is shown in Fig. 3 and calculated using the data from [28]. One road length stands for 5 m in reality, which is similar to the length of a vehicle.

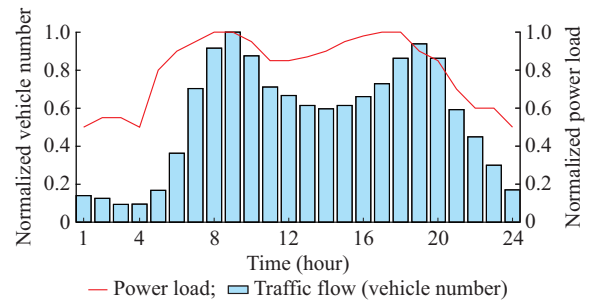


Fig. 3. Daily traffic flow and power load profile.

The position of the office zone is at the right side of the second lane, and the entrance and exit of the office zone are at 480 road lengths and 481 road lengths. The position of

the residence zone is at the same side of the office zone, and the entrance and exit are at 720 road lengths and 721 road lengths, respectively. The position of the commerce zone is at the left side of the first lane, and the entrance and exit are at 600 and 601 road lengths, respectively. Three charging stations locate at 20%, 30%, 70% of the road lengths, the first and third stations locate in the first lane, and the second station locates in the second lane. The per-hour traffic flow profile is based on the data from [28]. The typical daily traffic flow and power load profile are shown in Fig. 3.

The initial SOC for EV are set to be:

$$SOC_{int} = \begin{cases} N(0.25, 0.04) & t \in (00:00, 08:00] \\ N(0.95, 0.05) & t \in (08:00, 10:00] \\ N(0.65, 0.15) & t \in (10:00, 15:00] \\ N(0.40, 0.10) & t \in (15:00, 20:00] \\ N(0.30, 0.15) & t \in (20:00, 24:00] \end{cases} \quad (13)$$

where $N(\cdot)$ is the normal distribution.

Assume the rational drivers with the time-sensitive charging preference are the majority. The typical ratio of three user's preferences is 15% of speed-sensitive charging preference, 70% of time-sensitive charging preference and 15% of price-sensitive charging preference. The peak electricity demand happens during 07:00-19:00 according to the power load profile shown in Fig. 3. The office zone, commerce zone and residence zone are the destinations of vehicles. The probability of each destination is 1/3. The parking duration of these zones are $N(4, 1.0)$ for office zone, $N(2, 0.3)$ for commerce zone, and $N(10, 3.0)$ for residence zone.

The fast charging power and the slow charging power are set to be 60 kW and 3.3 kW, respectively. There is no limitation on the number of charging devices, but the charging power in a zone or charging station is limited due to the power load profile shown in Fig. 3. Based on these initial settings, daily EV charging loads of different zones are shown in Fig. 4.

The peak charging loads are around 19:00 p.m., which is also the peak time of traffic flow. Since the parking duration of residence zone is much longer than other two zones, the parking in residence zone is inclined to use slow charging based on the charging preference, where the commerce zone has the maximum load fluctuation. After the initialization, the interactions among the traffic, user, and power grid can be investigated in the following section. The computing time for running the simulation is 226 s.

B. Case 1: Impact on Power Grid Caused by User and Traffic

Case 1 aims to investigate the impact on the power grid caused by the user's charging preferences and traffic flows.

1) Different User's Charging Preferences

The user's charging preference has apparent impacts on EV charging load, while the existing method cannot simulate the change of user's charging preference. The different setting scenario stands for the situation for different users and charging situations. The speed-sensitive preference mainly happens in the business department or office.

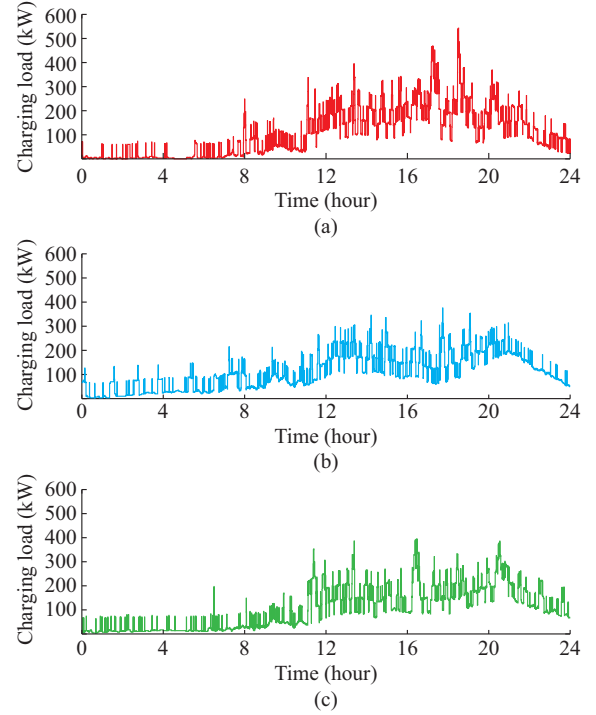


Fig. 4. Daily EV charging load of different zones. (a) Commerce zone. (b) Office zone. (c) Residence zone.

The daily charging load in the commerce zone is considered as an example. Three different ratios of the user's charging preferences, i.e., price-sensitive, time-sensitive and speed-sensitive, are simulated to investigate the impact on the charging load of the power grid, as shown in Fig. 5.

As shown in Fig. 5(d), the Monte Carlo method cannot deal with different user's charging preferences. 70% users are speed-sensitive, which result in the highest charging load fluctuation as shown in Fig. 5(a). The price-sensitive charging preference leads to the most considerable charging load fluctuation due to the change of electricity price at peak and valley time. The time-sensitive charging preference is the most friendly to the power grid as shown in Fig. 5(b), which has the smallest charging load fluctuations. The maximum charging load considering speed-sensitive users is 15% higher than that of time-sensitive users. It can be seen from the above results that the user's charging preferences have a significant impact on the charging load.

2) Different Traffic Flows

Two different traffic flow scenarios are simulated in the proposed framework and compared with the traditional Monte Carlo method. In scenario 1, Q_{max} is set to be 250, and in scenario 2, it is set to be 150. Other framework parameters are based on the initialization in Section III. The daily charging load at the office zone is chosen to analyze the impact on the charging load of the power grid caused by different traffic flows, which is simulated and shown in Figs. 6 and 7. It can be seen from Figs. 6 and 7 that the charging load in the commerce zone of these two scenarios shares the same trend, which is generally proportional to the traffic flow profile in Fig. 3.

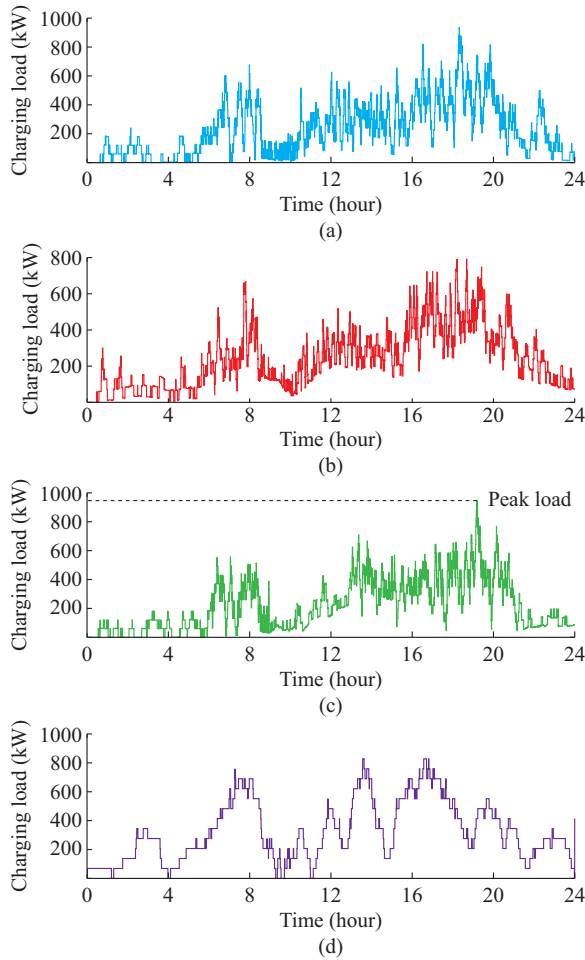


Fig. 5. Daily EV charging load of different user's charging preferences. (a) The highest charging load fluctuation. (b) The smallest charging load fluctuation. (c) The highest charging load. (d) Monte Carlo method.

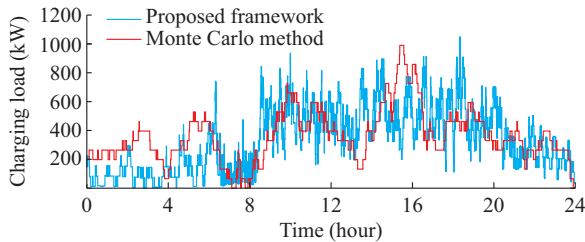


Fig. 6. Charging load of commerce zone by two simulation methods ($Q_{\max} = 250$).

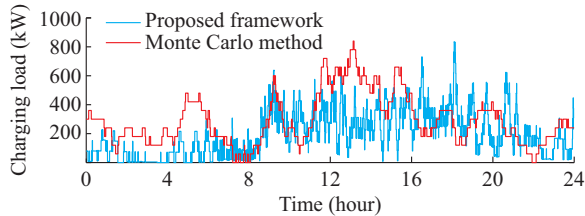


Fig. 7. Charging load of commerce zone by two simulation methods ($Q_{\max} = 150$).

However, the proposed framework has a better dynamic performance, especially when the traffic flow increases up to the maximum flow of the road, since the proposed frame-

work can simulate traffic jam condition as shown in Fig. 8. When an accident happens at 16:00 p.m., the charging load of the commerce zone gradually decreases to 0, which cannot be reflected in the Monte Carlo method. Monte Carlo method describes the traffic situation as a probabilistic function, so that it cannot deal with the chain reaction caused by a single vehicle.

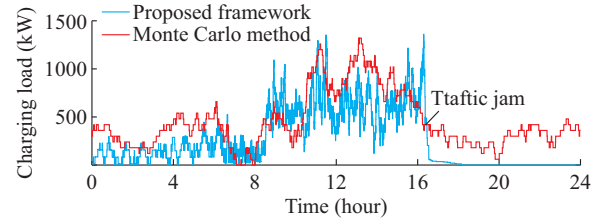


Fig. 8. Charging load of commerce zone by two simulation methods when traffic jam happens around 16:00 p.m..

To analyze the relationship between traffic flow and charging load, additional cases with different traffic flows are simulated to obtain the relationship between traffic flow and charging load.

Using the linear function to fit these two curves, the fitting polynomial equations are obtained as:

$$\begin{cases} A_{cl} = 1.0503Q_{\max} + 81.1771 \\ P_{cl} = 2.9091Q_{\max} + 419.6814 \end{cases} \quad (15)$$

where A_{cl} is the average charging load; and P_{cl} is the peak charging load. The curve fitting results are shown in Table IV, which indicates that the fitting results have a high confidence degree. The relationships among peak charging load, average charging load, and traffic flow are approximately proportional.

TABLE IV
CURVE FITTING RESULTS FOR (15)

Variable	SSE	R-square	Adjusted R-square	RMSE
A_{cl}	3391	0.9528	0.9511	10.81
P_{cl}	32070	0.9424	0.9404	33.26

Note: SSE stands for the sum of squares for error and RMSE stands for root mean squared error.

To sum up, if the traffic flow in a specific district increases, the electricity demand grows simultaneously. In this paper, the impact on the power grid, especially on the peak charging load caused by the traffic and user, is investigated using the proposed framework, which modularizes the behaviors of the traffic, user, and power grid and can simulate the coupling of the system precisely. Besides, the proposed framework is beneficial for transportation planning and demand forecasting.

C. Case 2: Impact on User Caused by Power Grid and Traffic

Case 2 investigates the impact on the user's satisfaction with the charging process caused by different TSCs and traffic flows. According to the previous research, user's satisfac-

tion is related to the waiting time [29], [30]. The measurable indicator can be set as the charging overtime when the charging duration exceeds the parking duration. Users are identified as satisfied if the charging overtime is less than 3 min.

1) Different TSCs

By setting different TSCs of the proposed framework, the average value and median value of charging overtime can be obtained in Table V. $Q_{\max}$ is set to be 200. The EV charging capability is determined by TSC of the power grid and the load except EV charging, which is shown in Fig. 3.

TABLE V
USER'S CHARGING OVERTIME IN DIFFERENT TSCs WITH 200
VEHICLES PER HOUR

TSC (kW)	Average overtime (s)	Maximum overtime (s)	Median overtime (s)	Charging satisfaction rate (%)
1700	185	9985	3.29	96.1
1600	191	9873	3.34	94.7
1500	195	9896	3.38	93.7
1400	208	10015	3.38	93.1
1300	223	11268	3.41	93.0
1200	264	11853	3.42	91.2
1100	311	10391	3.46	88.9
1000	998	38448	3.80	81.9

The average overtime increases remarkably when TSC decreases. However, the maximum overtime has no significant change unless TSC is too small to satisfy the demand in Table V. The number of dissatisfied users gradually increases, which results in a decrease in charging satisfaction rate. The change of dissatisfied user between 1100 kW TSC and 1000 kW TSC since 1100 kW TSC can barely meet the demand, but 1000 kW TSC cannot meet the demand at all. Constructing the TSC at the level of 1200 kW rather than at the level of 1700 kW could save more than 40% investment. However, the user's charging satisfaction rate decreases only by 5% and still at an acceptable high rate as shown in Table V. The charging load profile of different TSCs in commerce zone is shown in Fig. 9.

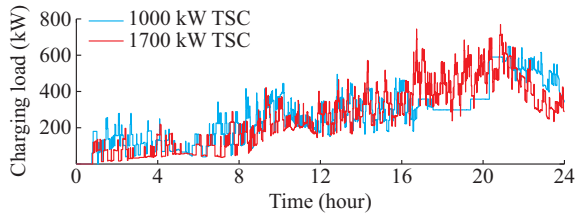


Fig. 9. Charging load profile of different TSCs in commerce zone.

2) Different Traffic Flows

By setting different traffic flows of the proposed framework, the average, median, and maximum values of charging overtime can be obtained as shown in Table VI, where TSC is set to be 1200 kW. Besides, the user's charging satisfaction rate increases gradually with the decline of traffic flow. However, the charging satisfaction rate stops to elevate at around 95.7% although the traffic flow still declines. It

means that the impact on the charging satisfaction rate caused by traffic flow is saturated when the traffic flow is too small to use all charging capacity. The charging load profile of different traffic flows with 1000 kW TSC in commerce zone is shown in Fig. 10. When $Q_{\max}$ drops to 50, TSC cannot restrict the charging load, i.e., TSC does not affect the user's charging satisfaction rate.

TABLE VI
USER'S CHARGING OVERTIME IN DIFFERENT TRAFFIC FLOW
WITH 1200 kW TSC

Traffic flow	Average overtime (s)	Maximum overtime (s)	Median overtime (s)	Charging satisfaction rate (%)
200	264	11853	3.41	91.2
170	249	10026	3.37	92.5
140	234	10299	3.36	92.8
110	188	10081	3.24	94.7
80	185	10266	3.19	95.7
50	170	10127	3.14	95.7

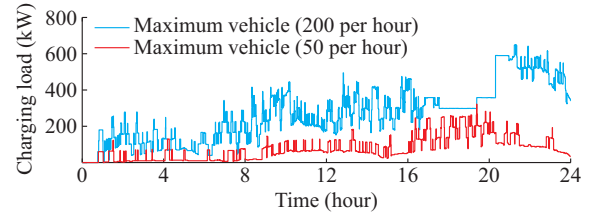


Fig. 10. Charging load profile of different traffic flows with 1000 kW TSC in commerce zone.

In general, increasing TSC or reducing the traffic flow can boost the user's charging satisfaction rate. More than 40% designed TSC can be saved by using the proposed framework to simulate the user's satisfaction rate as well as the investment.

V. CONCLUSION

We propose a framework for EV based on CA to investigate the interactions among the traffic, user, and power grid. The proposed framework lays the theoretical and modelling foundation for analyzing the complex interactions among the three elements. Based on the developed framework, the results from two case studies have been presented, which show that the user's charging preferences have significant impact on the charging load, e.g., more than 15% of the charging load fluctuations. Meanwhile, the traffic flow has a nearly proportional relationship with the average and peak values of the charging load. Case 2 shows that increasing TSC or reducing the traffic flow has the promotion effect on the user's charging satisfaction. However, the relationship between the user's charging satisfaction and traffic flow or TSC is nonlinear, which is similar to a hyperbolic function. By using the proposed framework, the user's satisfaction with different traffic flows under different power grid conditions can be investigated.

One of the future research directions is to consider the de-

tailed topology of traffic and power grid. The traffic module can be further extended by combining with the geographic information system to simulate a more diversified traffic situation.

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