The Charging Characteristics of Large-Scale Electric Vehicle Group Considering Characteristics of Traffic Network

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ABSTRACT
Electric vehicles, as a new generation of road transport, are primarily used for transportation. For this reason, the topological characteristics of traffic network may make great influence on the macroscopic characteristics of electric vehicle group. However, little attention is drawn to the study in this field. Therefore, typical approach to studying the impact of traffic network topological characteristics on the charging characteristics of large-scale electric vehicle group is presented by adopting the charging power distribution as analysis indicator. In this paper, a model of complex adaptive system is constructed including the electric vehicle group, traffic network and charging stations, where the tempo-spatial distribution of charging power can be obtained via the simulation with the multi-agent technique. The charging power of regional electric vehicles is found obedient to logarithmic normal distribution after analysis, while the mathematical expectation of probability density shows obvious cyclicity. Finally, the traffic networks of various cities in comparison testify to that improving the connectivity of traffic network and increasing the average clustering coefficient can effectively reduce the effect on power system brought by the charging load of large-scale electric vehicle group.

INDEX TERMS
Average clustering coefficient, charging power probability distribution, electric vehicle, multi-agent, traffic topology.

I. INTRODUCTION
Travel revolutions such as electric vehicle (EV), shared mobility and automatic driving are increasingly affecting the energy demand of road traffic [1], playing an important role in modern transportation [2], [3]. In the future, the proportion of the total odometer traveled by shared mobility and automatic driving will be greatly increased, which is expected to reach nearly 20% by 2040 [4]. In the field of shared mobility, EVs have a competitive advantage due to their lower cost of driving one kilometer than traditional internal-combustion powered vehicles. According to BP Energy Outlook: 2019 edition, up to around 25% of passenger vehicle odometer will be powered by electricity in 2040 [5]. Along with a large number of EVs connected to power system in the future, the charging behavior considering the randomness of space and time will add great difficulty to the power grid operation and control [6], [7]. The primary purpose of EVs is to meet users’ travel requirements, and it is impractical to carry out study neglecting traffic characteristics [8]. Therefore, it is significant to research on the charging characteristics of EVs in traffic network.

Relevant study recently is mainly focused on the charging characteristics and charging load forecasting of small-scale EVs. Reference [9] studies the behavior pattern of one single EV in details and defines the single charging behavior of a certain EV, seeking for the solution to decision problem of the lowest charging electricity price and shortest charging route. But the behavior pattern of a single EV is complicated and special, which may make it hard to reflect the global characteristics. Thus [10]–[13] research on EV group and analyze how EV’s driving and charging behavior can affect the global load characteristics. Then the driving area is divided into residential, industrial and commercial areas in [14]–[15], analyzing the difference of EV charging load in different areas. With the modified shortest path algorithm, [16] conducts a study on the effect of EV’s driving and charging behavior under various driving conditions on power system. The traffic characteristics of EVs are taken into consideration based on the previous studies.
Noticing that the traffic constraints will influence the charging characteristics of EV, scholars set about adopting the actual traffic network data for study. In [17], [18], arterial roads of actual urban traffic network are opted as maps, digging into the optimization tactic of deploying public EV charging stations. Reference [19]–[22] forecast the spatial distribution of city EV charging load based on the actual traffic data. But so far, we still find no further research on the relation between the topological characteristics of traffic network and the macroscopic charging characteristics of EVs.

From the studies above, we conclude that a majority of previous study on EV charging characteristics is conducted based on virtual networks or over-simplified actual traffic networks, with defects of little reflection on the actual topological characteristics of traffic network. Furthermore, although many papers forecast the tempo-spatial distribution of EV charging load, it remains a problem to reflect the macroscopic characteristics of the charging behavior in large-scale EV group, since those studies are always with only a small quantity of vehicles and a small scale of map in modeling. Thus, it is worth going further into the influence of traffic topological characteristics on EV charging characteristics and scaling up the EV group for research.

For the problem discussed above, we will extract the actual traffic network data of Guangzhou and several other cities in China, combine the future driving pattern of shared mobility and automatic driving, and study the charging characteristics of large-scale EV group by simulation. Firstly, the behavior of EV will be analyzed, appointing the distribution of charging power as an analysis indicator. And then we build an agent model based on agents of the map, time, charging station and EV introducing the multi-agent technique, and simulate 100,000 EVs to get the data of EV charging power. The next step is data analysis so that one can find out the characteristics of EV charging power probability distribution. Last but not least, a comparison between traffic networks of various cities is made to draw a conclusion on the impact of traffic topological characteristics on charging power distribution characteristics.

II. PROBLEM DESCRIPTION

In recent years, success has been witnessed after the theory of complex adaptive system (CAS) has extensive application in many fields. CAS, whose components are called adaptive agents, is formed of the interaction between plentiful micro units [23]–[24]. With their own targets, adaptive agents can continuously learn and adjust their patterns of behavior under environmental constraints and thus adapting the environment better. As a large scale of EVs are coming out in the future, lots of EVs spontaneously interact with each other and exchange with both traffic network and power system, hence causing variations of regional traffic flow and changing power distribution. The combination of EV group, traffic network and power system can be regarded as a CAS.

As an initiative and active agent, EV has a clear target and possesses the ability to make adjustments on its driving strategy according to the road conditions, traffic rules, the placement of charging infrastructure and other environmental constraints. Meanwhile regional charging stations serve as the bond between EVs and power system, and the distribution of their charging power consequently reflect the driving trend and charging behavior of the EV group, indicating the traffic and charging characteristics of EV. One can get hold of the entire charging behavior of EV group by analyzing the distribution characteristics of charging power. On the other hand, the distribution of charging power shows apparent traffic characteristics, which has close relationship with the traffic network structures where the charging station locates. As a result, it is of great essence to study on the rule between traffic topological characteristics and charging power distribution characteristics.

However, for such a complex system, it is usually difficult to figure out the charging power directly by means of conventional linear approach. Then the multi-agent technique seems to be effective in study on complex systems [25]. By setting up several agents with independent calculating ability can the multi-agent technique simulate the interactions of each adaptive agent in the real system, solving the problem with the help of simulation. Resulting from this, one can apply multi-agent technique to acquiring power data and go into the charging characteristics of large-scale EV group based on the analysis indicator of charging power distribution and the influence factor of traffic topological characteristics. The research framework of this paper is shown in Figure 1.

III. MULTI-AGENT SIMULATION OF LARGE-SCALE ELECTRIC VEHICLE GROUP

A. BASIC HYPOTHESES OF THE MODEL

Reference [26] points out that individual characteristics have a much less effect on the entirety than interactions do when there are a great number of individuals. Therefore, though one EV possesses different attributes and complex behavior patterns, we can simplify the EV individual behavior when the scale of EVs is large enough. In this paper, we adopt the future travel mode of shared mobility and automatic driving mentioned in BP Energy Outlook: 2019 edition for simulation. Normally speaking, EVs come in four states, namely, static state, running state, charging state and vehicle-to-grid (V2G) state, among which static EVs can hardly affect the power grid or the traffic network. We can find that the utilization of EVs is significantly improved in shared mobility mode,
while the amount of idle EVs will therefore be obviously decreased. Furthermore, EVs in V2G state will, as a result, take up a relatively little part. To simplify the model and solve the major problem in this study, we will design our model taking no account of EVs in static or V2G state. Followings are hypotheses of our model:

1) Our simulating maps are expressed as topological graphs with graph theory concepts. The elements of actual traffic network can be simplified into two kinds of objects in topological graphs, namely edges and nodes, where edges denote roads and nodes denote junctions and roadheads in traffic network. The degree of node implies the amount of edges which are attached to this node, in other words, the branches of this junction.

2) Only 2 states of an EV are considered, that is, driving state and charging state. The driving state means decreasing the state of charge (SOC) of the EV, increasing the distance and moving in position. On the other hand, the charging state indicates constant distance, invariant position and increasing the SOC.

3) After an EV obtains its random departure point and driving destination, the shortest path of this trip can be figured out according to Dijkstra algorithm [27]. On condition that the EV’s SOC is lower than a certain level during the trip, it is the EV’s first choice to reach the nearest charging station and get charged for the unaccomplished trip.

4) Selection of the charging stations. In complex network theory, nodes with a higher degree are connected to more edges, leading to greater significance in probability [28]. In traffic network, these nodes usually serve as transportation hubs, hence with heavier traffic. Meanwhile the simulation results of the [17] proves the strong consistency between the placement of EV charging stations and traffic flow. In this paper, we select the top 1% of nodes with a highest degree as charging nodes equipped with charging stations.

B. FRAMEWORK OF THE SIMULATION MODEL

Our model is built up on the platform of Java agent development framework (JADE), a mainstream multi-agent development framework based on Java [29], aiming at serving various agents as a communication platform. To achieve the goal of simulating the driving and charging behavior of EV group in the actual complex system, we totally set up four types of agents, namely the map agent, the time agent, the charging station agent and the EV agent. The information communication between each type of agent is shown as Fig. 2.

The map agent provides traffic navigation for EVs, exchanging information with the EV agent and thus offering the EV agent service of position initialization, destination selection, shortest route planning and route planning for charging.

We turn to OpenStreetMap for map data of traffic network to carry out simulation. OpenStreetMap, which is open source, is a collaborative project to create an online data set of vector maps. In this data set, point, line, plane and other geographic geometric elements are expressed as Node, Way, Relation and other elements of XML [30]–[32]. Traffic networks of multiple cities in China are selected as our study objects and among them the traffic network of Guangzhou city is displayed in Fig. 3.
As our main study object, the EV agent has parameters such as power, speed, power consumption, charging power, battery capacity, odometer, driving route and so on. On account of the large-scale EV group charging characteristics we study in this paper, there requires a great quantity of EV agents. Therefore, we will program on the platform of JADE so that the EV parent agent can generate child agents automatically.

As soon as generated, each EV agent will ask the map agent for initializing its start location, driving destination and power as well as sending its own name to the time agent. After the time agent has received the required amount of EV agents, it will start timing and all EV agents will turn to the driving state. When charging is needed for a certain EV agent during the simulation, it will require for the location of the nearest charging station from the map agent and head for the charging node after feedback received. When arriving at the charging node, the EV will ask the charging station agent for charging and turn to the charging state. After reaching its target node, the EV will request the map agent for the next driving destination and a new driving trip starts. When simulation time ends, the EV agent will stop its current activity immediately after getting the halt signal from the time agent and delete the EV agent itself. Fig. 4 below shows the algorithm flow of the EV agent.

Algorithm 1 provides the relevant pseudocode for the flow chart.

Path planning takes up the majority of the algorithm, essentially corresponding to the vehicle navigation algorithm. As for the rest of the algorithm such as the initialization of EVs’ properties and battery measurement, they are much less complex than path planning. Therefore with the algorithm of EV agent, which is less complex, and that of common vehicle navigation sharing similar complexity, the algorithm can definitely work on mobile EVs in real-time in real scenarios. The design of the simulation is reasonable.

C. PARAMETER SETTING OF SIMULATION

The relative parameter setting of our simulation model is listed in Table. 1. The map we choose for the first simulation is the city traffic network of Guangzhou, China. Besides, since BYD is one of the most well-known EV manufacturing
TABLE 1. The basic parameter setting of simulation.

| Agent          | Parameter settings                                                                 |
|----------------|-------------------------------------------------------------------------------------|
| Map            | Using the city traffic network of Guangzhou as the simulation map, with 4677 nodes and 5752 roads. |
| Time           | Starting from 0, ending in 86400s, with a time step size of 60s.                     |
| Charging station | Totally 46 charging stations, with the charging power of 90kW per EV.                |
| EV             | Totally 100,000 EVs, with an average speed of 40kms/h, battery capacity of 50kWh and the average power consumption of 0.3kWh/km. |

company in China, the parameters of the EV agent are set referred to BYD electric vehicles with an amount of 100,000.

IV. THE CHARGING POWER DISTRIBUTION CHARACTERISTICS OF ELECTRIC VEHICLE GROUP

We process the data of each station’s charging time and charging power collected by the charging station agent after simulation, dividing the total charging time into 24 3600-second periods. It should be highlighted that the time we mention here is the reference time of our simulation, rather than the actual time. Then we work out the average charging power of all charging stations in each period, shown in Fig. 5.

![FIGURE 5. The average charging power of each period.](image)

Fig. 5 exhibits the obvious average charging power variation. Next, we fit each charging node’s charging power distribution of each period by Minitab, a data analysis tool, and recognize that at 95% confidence interval, charging nodes’ power distribution can be well fitted using logarithmic normal distribution. Because of the space limitations, only data of the first period is taken as an example. Fig.6 below is the charging power probability distribution chart of the first period, with the charging power as the abscissa and the percentage of charging nodes, whose charging power is below the abscissa, as the ordinate. In the legend, the position stands for the position variable, that is mean value. It reflects how even is the time distribution of EV charging power, namely how concentratedly distributed is the time for EV charging. A larger position variable of a period means a larger quantity of EVs in charging mode than other periods and a heavier charging load; The scale stands for the scale variable, that is standard deviation reflecting how even is the space distribution of EV charging power. A larger scale variable usually implies a trend that EVs are more likely to get charged concentratedly at several charging stations, leading to less balanced power distribution. The opposite situation then conversely indicates that EVs are more likely to disperse to different charging stations with a relatively balanced power distribution; N stands for the number of samples, that is the number of charging nodes; P stands for hypothesis testing, where a general value of over 0.05 deems the data obedient to logarithmic normal distribution.

![FIGURE 6. The charging power probability distribution chart of the first period.](image)

From Fig. 6 we can see that, speaking of the charging power distributions characteristics of the EV group, although there exist a few charging nodes whose charging power shows uncertainty, regular rules can be observed clearly in the macroscopic characteristics of global charging power distribution exhibits. Meanwhile when P, the fitting probability distribution of each period, is over 0.05, it is reasonable to believe that logarithmic normal distribution fits the charging power distribution well under circumstance of 95% confidence interval, and its probability density can be expressed as (1), in which \(x\) represents the average charging power of each charging station during a particular period, with the position variable \(\mu\) and scale variable \(\sigma\) representing the mean value and standard deviation of \(\ln x\) respectively.

\[
p(x) = \frac{1}{x\sigma \sqrt{2\pi}} e^{-\frac{\ln(x-\mu)^2}{2\sigma^2}}
\]

(1)

Taking the first period as an example, we can put related data into (1) to get the average charging power probability distribution function of each charging node during this period as (2).

\[
p(x) = \frac{1}{2.342x} e^{-\frac{\ln(x-7.613)^2}{1.746}}
\]

(2)

Similarly, the charging power distribution of other periods follows the same form, hence the comparison of \(\mu\) as well as \(\sigma\) of each period as Table. 2.
TABLE 2. Comparison of $\mu$ as well as $\sigma$ of each period.

| Period | $\mu$   | $\sigma$ | Period | $\mu$   | $\sigma$ |
|--------|---------|----------|--------|---------|----------|
| 1      | 7.61    | 0.93     | 13     | 9.59    | 0.93     |
| 2      | 8.75    | 0.93     | 14     | 8.88    | 0.92     |
| 3      | 9.49    | 0.95     | 15     | 7.73    | 0.96     |
| 4      | 9.85    | 0.94     | 16     | 7.62    | 0.99     |
| 5      | 9.78    | 0.91     | 17     | 8.62    | 0.97     |
| 6      | 9.24    | 0.91     | 18     | 9.4     | 0.93     |
| 7      | 8.25    | 0.88     | 19     | 9.79    | 0.95     |
| 8      | 7.15    | 0.96     | 20     | 9.78    | 0.95     |
| 9      | 8.2     | 0.98     | 21     | 9.34    | 0.94     |
| 10     | 9.09    | 0.99     | 22     | 8.47    | 0.95     |
| 11     | 9.68    | 0.95     | 23     | 7.46    | 0.96     |
| 12     | 9.87    | 0.9      | 24     | 8.16    | 0.92     |

Fig. 7 shows the curve of $\mu$ versus time, from which we can find the cyclical variation rule of $\mu$ apparently with the variation cycle of 8 periods and greater average charging power in periods of a higher $\mu$.

The curve of $\sigma$ is plotted in Fig. 8, from which we can find $\sigma$ relatively stable with a value fluctuated between 0.88 and 0.99.

The charging behavior characteristics of EV group are discussed and it can be concluded from the above figures and tables that the charging power of each period obeys logarithmic normal distribution and the $\mu$ of probability distribution function varies cyclically while the $\sigma$ stays relatively stable.

Explanation of these characteristic is followed. For the position variable $\sigma$ shows how even is the space distribution of EV charging power, it is mainly influenced by the topological characteristics of the traffic network and other spatial factor. There is little relationship between the scale variable and time, and that is the reason why the scale variable appears relatively stable at different periods.

On the contrary, the position variable $\mu$ is affected markedly by temporal factors. We simulate on the actual EV travels in the mode of shared mobility and automatic driving. This new driving mode cannot make a difference in people’s travel time, but travel mode. In real scenarios, due to the similarity of people’s rest, life and work time, people tend to travel at concentrated time, resulting in travel peak hours like morning peak and evening peak. And the rush hours for EVs to get charged are following the travel peak, with the charging load and the position variable reaching their peaks. The distinction from traditional travel mode is that EVs in shared mobility and automatic driving mode will not stop at its destination but start a new trip right away as far as the battery allows. Once the battery is low, next rush time for charging comes. That is the cause for the continuity of EV driving and charging mode, hence cyclicity.

V. THE IMPACT OF TRAFFIC TOPOLOGICAL CHARACTERISTICS ON CHARGING POWER DISTRIBUTION

As a crucial constraint, the topological characteristics of traffic network essentially influence the behavior of EV group. This section provides analysis on how different traffic topological characteristics make changes in the charging power distribution characteristics of EVs.

A. COMPARISONS BETWEEN DIFFERENT TRAFFIC TOPOLOGICAL CHARACTERISTICS

The sections above have carried out simulation on traffic network of Guangzhou urban area. In this section, we will build multi-agent models for simulation based on traffic networks of Lhasa, Changchun and Beijing for the reason of collecting data of charging power. To begin with, we make a comparison among traffic data of these four cities. The first step is selecting a region with the same area size in each city and exporting the map data to Gephi, a software package specialized in network analysis. Then we can analyze the traffic networks of these four cities, concluding that the distribution characteristics of EV group’s charging power are closely related to the average clustering coefficient, an important traffic network topological characteristic.

According to graph theory, clustering coefficient is a coefficient describing how clustered a node is in the network. The clustering coefficient $C_i$ of node $i$ with a degree of $k_i$ is defined as:

$$C_i = \frac{2E_i}{k_i(k_i-1)} \quad (3)$$
In Equation (3), \( E \) embodies the actual edges connecting node \( i \) and its \( k \) neighbors. Likewise, the definition of the average clustering coefficient \( C \) of a network is the mean value of \( N \) nodes’ clustering coefficients in this network, that is:

\[
C = \frac{1}{N} \sum_{i=1}^{N} C_i
\] (4)

Table 3 lists the average clustering coefficients of the four cities.

From Table 3 we can find the traffic network in Beijing has the largest average clustering coefficient, followed by Guangzhou and Changchun, Lhasa ranking the last. So that Beijing traffic network is to the highest extent clustered, with a close link and strong connectivity, while the most sparsely connected traffic network lies in Lhasa with the lowest cluster degree.

### B. THE IMPACT OF TRAFFIC TOPOLOGICAL CHARACTERISTICS

In this part, Minitab will be utilized to process and analyze the charging power data after simulation and then we can plot the curve of \( \mu \) and \( \sigma \) in four cities as shown in Fig. 9 and Fig. 10.

As we can find out from Fig. 9 and Fig. 10, the charging power probability distribution of each period in Beijing, Changchun and Lhasa appears similar to that in Guangzhou, all of them are logarithmic normal distributions with a stable value of \( \sigma \) and a cyclic \( \mu \). Despite the effect of traffic networks topological characteristics in different cities on \( \mu \), it is the mean value of \( \mu \) instead of the changing law itself, namely its cyclicity, that is mainly affected. The cyclicity of \( \mu \) is determined by both travel time and travel mode, with little to do with the traffic network, which accounts for the cyclical change of the position variables in four referred cities.

However, Lhasa has the largest \( \sigma \), which results in the most uneven power distribution among the four cities. Besides, the highest peak of \( \mu \) also happens in Lhasa, hence the rush time for charging with Changchun following. Due to the smaller clustering coefficient, sparsely structured network, low cluster degree of nodes and weak connectivity among roads in Lhasa and Changchun, there may be difficulties for EV to reach the charging station right away when it needs to be charged, leading to the rush time for charging and heterogeneous power distribution.

Conversely owing to the largest clustering coefficient as well as closely interlinked and strongly connected roads in Beijing and Guangzhou, it is convenient for EVs at any position to arrive at nearby charging stations to get charged. In this way, EVs are more likely to disperse to different charging stations, resulting for the homogeneous power distribution of each charging node and hence related with a small \( \sigma \). Simultaneously because EVs can reach the charging stations quickly, the charging time will be separated with a relative low peak of \( \mu \).

The comparison between simulation of the four cities above illustrate that traffic topological characteristics will make effect on the charging power distribution of charging stations, in main aspect of the logarithmic mean value \( \mu \) and logarithmic standard deviation \( \sigma \) of charging power. A large average clustering coefficient of city traffic network usually reflects strong connectivity of network and dispersed charging power of EVs. On the contrary, a small average clustering coefficient of traffic network normally signifies poor network connectivity, unbalanced charging power distribution and rush time for charging, which may easily cause sharp increase of regional load and detrimental influence on power system.

In conclusion, improving the connectivity of traffic network and increasing the average clustering coefficient can effectively help to mitigate impact of large-scale EV charging load on power system.

### VI. CONCLUSION

In this paper, multi-agent technique is introduced to study on the charging characteristics of large-scale EV group. We first carry out multi-agent simulation based on the platform of JADE/Multi-Agent. According to the simulation data analyzed by Minitab, it can be clearly seen that charging power probability distribution of regional EV group obeys
logarithmic normal distribution with a cyclical variation. Finally, we compare traffic network data of different cities to figure out how traffic topological characteristics impact the charging characteristics of EV group. Our study can do benefit to practical applications, which is mainly divided into three parts.

1. In load forecasting, it is conducive to learn the charging laws of large-scale EV group’s charging load, forecast the rush time for charging and consequently plan the generation dispatch schedule ahead of time with the help of the tempo-spatial distribution characteristics of EV charging power found in this paper.

2. In the construction of urban traffic networks, improving the connectivity of traffic network and increasing the average clustering coefficient can reduce the effect on power system brought by the charging load of large-scale EV group.

3. In the future travel mode of shared mobility and automatic driving, EV users can obtain the real-time information of surrounding roads and charging stations to optimize their driving and charging strategy through the model and algorithm designed in this paper.

To put it in a nutshell, our study, as a basic work, can assist to comprehensively grasp the macroscopic characteristics of the system after large-scale EV group is accessed in the future, giving suggestion on the construction of traffic network and power system from the perspective of EVs.

In future study, we will quantitatively analyze the charging characteristics of EVs through theoretical derivation, research on the deeper mechanism of the interaction between the power system and traffic network. Additionally, we will try hard to apply our results to further research, such as load forecasting, optimization of EV charging strategy and charging station planning, which is conducive to practical applications.

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