Electric vehicles in smart grid: a survey on charging load modelling

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Abstract: Electric vehicles (EVs) have been rapidly developed during the last few years due to the low-carbon industry and smart grid initiatives. Meanwhile, the impact of large-scale EVs’ integration on the reliability and safety of power grids is becoming increasingly prominent. To address these problems, challenges on EV charging control have been presented. Besides, the EV charging load modelling with improved accuracy and rationality is required. To investigate the influencing factors of EV charging load, this survey summarises the existing EV charging load modelling methods. In addition, a new research framework for a scale EV evolution model of charging load is proposed, with an emphasis on reducing the deficiencies of the existing research in dealing with the EV scale development. Moreover, the future research prospect of EV charging load modelling on power system planning, operation, and market design has also been discussed.

1 Introduction

Nowadays, the world is facing problems of ecological deterioration and energy shortages. Meanwhile, conventional vehicles (CVs) consume a large amount of fossil fuels and cause environmental pollution due to carbon emissions. Currently, the electrification of CV has become one of the most promising measures to solve above problems [1]. Comparing with CV, electric vehicle (EV) has significant advantages in terms of energy conservation, emission reduction, and grid security, which leads to widespread attention by governments, automakers, and energy companies [2, 3]. Governments around the world have taken EV promotion as national strategic initiatives and have issued relevant policies to promote the development of the EV industry [4], such as the EV project in the United States [5], the ‘vehicle popularity for next generation’ in the ministry of environment and economy of Japan [6], and the ‘TenCities & Thousand Units’ in China [7]. Besides, Toyota, GM, Volkswagen, and other automakers also intend to actively join the EV industry. Research shows that with the expected development speed, by 2020, 2030, and 2050, the EV proportion in the United States will reach 35, 51 and 62%, respectively [8]. In 2020, 10–20% of the vehicle in China will be pure EVs, plug-in hybrid EVs and other new energy vehicles [9]. However, with the development of the EV charging load, the randomness and uncertainty in regional load and the total required load capacity has been increased. Without effective control, considerable impact on planning, operation and market mechanism of the power system would eventually turn up [10]. To address and solve such issues, the current research on the EV mainly focuses on load modelling-based impact analysis and control strategy. Thus, the accurate identification and scientific modelling of the EV charging load becomes the key aspects of EV development.

Indeed, the temporally and spatially stochastic features of EV users’ behaviour make EV charging load modelling distinct from the conventional modelling method. From a microscope perspective, it is necessary to consider the time series process and spatial location variation of individual EV. Moreover, the space-time distribution of scales EV charging load is essential to have impacts on the macroscopic such as power grid. Thus, numerous EV charging load modelling methods were involved in the existing study, including Monte–Carlo method, Markov chain theory, dynamic traffic flow model, parking generation rate model, trip chain theory etc., but few research studies systematically summarise the EV charging load modelling methods to evaluate their application and effectiveness. Besides, it needs to be noted that, this survey focuses on the physical modelling methods for natural EV charging loads in smart grid, but not discharging behaviours (i.e. vehicle-to-grid (V2G)). Since we believe that the V2G technology tends to focus on the control strategy aspects, which has gone beyond but can be complementary to the scope of this study.

In this survey, we analyse various influence factors that could impact the EV charging load. Based on this, we firstly review the existing EV charging load modelling methods and summarise into three main categories: temporal stochastic, spatial stochastic, and temporal–spatial stochastic. Then we point out the irrational simplification of EV scale problem in existing research and present the possible research framework. Finally, the future development path of EV charging load modelling is paved from the perspectives of power grid planning, operation, and power market mechanism.

The rest of the survey is organised as follows: Section 2 will analyse the main factors that affect the EV charging characteristics. Section 3 will summarise the EV charging load modelling methods in existing research. The novel EV scale evolution research framework will be presented in Section 4. Section 5 will outlook the future research and Section 6 will conclude the survey.

2 Factors affecting EV charging load

The EV charging behaviours are complex, which usually contains spatial and temporal randomness. The identification and analysis of different factors will make a great difference in the modelling of the charging load characteristics. Thus, to establish the accuracy of EV charging load models, many relevant factors are supposed to be taken into consideration. In this section, we summarise the influencing factors involved in the existing literature, and classify them into seven categories, as shown in Table 1.

In Table 1, policy factors do not have direct effects on the EV charging behaviour, instead, it guides EV users with subsidies, support stipulation etc. Environmental factors such as temperature and meteorological conditions (season, disasters etc.) will have an impact on the EV outdoor performance and users’ travel plan. Besides, the traffic conditions (including traffic network structure, road control, traffic jams etc.) can affect the EV users’ travelling route and journey time. The economic factors such as market and benefit will affect the individual EV user’s charging behaviour and

IET Smart Grid, 2019, Vol. 2 Iss. 1, pp. 25-33
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doi: 10.1049/iet-stg.2018.0053
Accepted on 12th October 2018
Revised 22nd September 2018
Received on 29th March 2018
IET Smart Grid
Review Article
The Institution of Engineering and Technology
Journals
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Table 1 Classification of charging load influence factors

| Type               | Factor                                                                 |
|--------------------|------------------------------------------------------------------------|
| indirect factors   | EV subsidies, support stipulation etc.                                 |
| policy [11]        | temperature, meteorological conditions, traffic conditions etc.         |
| environment [12, 13]| charging price, gasoline price, operation model etc.                    |
| market [14]        | emission reduction, charging facilities income etc.                      |
| benefit [15]       | the capacity of power supply, the radius of charging services, quantity, and distribution of charging equipment etc. |
| direct factors     | battery characteristics, power supply mode, charging/discharging control etc. |

In Fig. 1, the interactive relationship between multi-factors is implied by the arrows. The factors such as the scale of EVs, battery characteristic, traffic condition, operation pattern of EV charging, travel pattern, coupling with grid power supply etc., are directly related to charging demand. Other factors such as fuel and CV price will affect attractive factors, the policy factors will affect the developing and operation patterns of EVs, the environmental factors will affect EV travel pattern. Those factors will have further indirect impacts on charging demand.

In addition, there are also closed-loop feedbacks related to various factors, such as the impact of the EV scale on the evolution of road traffic, long-term cumulative effects of expansion planning, and further incentives for a new vehicle in urban areas. Therefore, multi-factors interact with each other and lead to the dynamic characteristics of charging demand modelling [20]. Comparing with conventional power load, EV charging load has distinct features in interaction with multi-factors. How to represent the explicit/recursive and direct/indirect relationship between these factors, develop effectively mathematical expressions of multi-factors, and explore the dynamic characteristics of charging requirements are the main challenges. The traditional methods have prominent limitations on modelling of charging requirements with dynamic features. Also, it is difficult to effectively characterise the inter-dependent characteristics of multi-factor interaction.

3 Modelling of the EV charging load

Considering the influence of individual or partial factors in section 2, various EV charging load modelling methods are proposed. In this survey, they are summarised as shown in Table 2, while the technical classification is concluded in Fig. 2.

3.1 Stochastic modelling of EV charging load in the temporal dimension

3.1.1 Monte–Carlo method: This type of method determines the charging duration and charging power of EV based on the probability distribution of CVs (or a small number of EVs), following the simulation of the driving process and the charging process of EVs. Commons, charging start time can be formulated as

\[
f_S(x) = \frac{1}{\sigma_\pi \sqrt{2\pi}} \exp\left(\frac{-(x - \mu_\pi)^2}{2\sigma_\pi^2}\right), \quad \mu_\pi - 12 < x \leq 24,
\]

(1)

Also, the probability distribution function of daily mileage is

\[
f_D(x) = \frac{1}{\sigma_D \sqrt{2\pi}} \exp\left(\frac{-(x - \mu_D)^2}{2\sigma_D^2}\right), \quad 0 < x \leq \mu_D - 12.
\]

(2)

where \(\sigma_S, \mu_S, \sigma_D, \mu_D\) are the corresponding shape parameter of the probability distribution.

The data sources of the user driving patterns mainly include: (i) assuming that the use of EVs does not change the user's driving patterns, the data of the user's driving patterns come from the national traffic department (mainly based on the National Household Travel Survey (NHTS) in the United States); (ii) actual driving patterns of users, which can be analysed from GPS database; (iii) actual operation monitoring data of charging stations (mainly bus charging stations).

For driving process parameters such as driving time and distance, it is usually assumed that the driver's start time, driving distance, and end time are independent of each other, and then the probability density function is obtained by fitting the traffic statistics data, where Monte-Carlo sampling is generated separately. By analysing the statistical data, it is found that there is a correlation between driving time and driving distance, by using two methods: (i) the conditional probability function to generate relevant driving data; (ii) copula function to construct a multidimensional joint probability distribution function of driving start time, end time, and driving mileage. Both methods generate a coupling characteristic random number sequence, which can accurately simulate the user's driving behaviour.

However, most of the studies perform appropriate simplification based on certain conditions in order to reduce the computational complexity. In [22], different types of EV charging methods with charging duration distribution were acquired, regardless of the
The study assumes that the initial state of charging and the charging duration are subject to a simple distribution, in which Monte–Carlo simulation sampling is used to obtain the charging load curve. By considering two types of electric energy supply modes of EVs: battery charging and battery swapping, the Monte–Carlo method was used to model and analyse the charging load of battery swapping in [25]. Besides, seasonal factors and holiday behaviours were introduced to achieve a probabilistic modelling of the demand volume and power capacity of an EV battery pack in [26].

At the current stage of EV development, the endurance capacity and high-manufacture cost of pure EV make hybrid EV dominate the share of the market. In the normal operation, the hybrid EV works in the hybrid mode, which coordinates the motor and the internal combustion engine working together to provide drive energy. Therefore, the hybrid EV was divided into two modes: power consumption and power conservation [3]. The vehicle first operates in the power consumption mode, and after the power is exhausted, it transfers to the power conservation mode. During driving in the power consumption mode, the driving energy part is provided by the battery. By considering various scenarios such as area (urban/rural), time (working day or weekend), and charging location (charging only at home or charging at supermarkets, workplaces etc.), and by using the NHTS data from the United States for electricity consumption behaviour in 2009, the random power consumption and fuel consumption of EVs are simulated and obtained based on the analysis of the central limit theorem and the large number theorem.

To analyse the change of charging load, the relationship between multiple influence factors is studied. By considering the battery type (lead battery and lithium ion), price structure (fixed electricity price, time-dependant electricity price, and real-time electricity price), purpose of using vehicle (domestic and business), EV penetration rate, charging location, control measures etc., the

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**Table 2** Modelling methods for EV charging load in existing research

| Dimension                  | Modelling method               | References | Policy | Environment | Market | Benefit | Infrastructure | User | Technology |
|---------------------------|--------------------------------|------------|--------|-------------|--------|---------|----------------|------|------------|
| temporal dimension        | Monte–Carlo method             | [21]       | √      | √           | √      | √       |                 |      |            |
|                           |                                | [22]       |        |              |        |         |                 |      |            |
|                           |                                | [23]       |        |              |        |         |                 |      |            |
|                           |                                | [24]       |        |              |        |         |                 |      |            |
|                           |                                | [25]       |        |              |        |         |                 |      |            |
|                           |                                | [26]       |        |              |        |         |                 |      |            |
|                           |                                | [27]       |        |              |        |         |                 |      |            |
|                           |                                | [28]       |        |              |        |         |                 |      |            |
|                           | Markov chain theory            | [29]       |        |              |        |         |                 |      |            |
|                           |                                | [30]       |        |              |        |         |                 |      |            |
|                           |                                | [31]       |        |              |        |         |                 |      |            |
|                           |                                | [32]       |        |              |        |         |                 |      |            |
|                           |                                | [33]       |        |              |        |         |                 |      |            |
|                           |                                | [34]       |        |              |        |         |                 |      |            |
|                           | fuzzy logic system             | [35]       |        |              |        |         |                 |      |            |
|                           |                                | [36]       |        |              |        |         |                 |      |            |
|                           |                                | [37]       |        |              |        |         |                 |      |            |
| spatial dimension         | dynamic traffic flow model     | [38]       |        |              |        |         |                 |      |            |
|                           |                                | [39]       |        |              |        |         |                 |      |            |
|                           |                                | [40]       |        |              |        |         |                 |      |            |
|                           |                                | [41]       |        |              |        |         |                 |      |            |
|                           |                                | [42]       |        |              |        |         |                 |      |            |
|                           |                                | [43]       |        |              |        |         |                 |      |            |
|                           |                                | [44]       |        |              |        |         |                 |      |            |
|                           | parking generation rate model  | [45]       |        |              |        |         |                 |      |            |
|                           | demographic model              | [46]       |        |              |        |         |                 |      |            |
|                           |                                | [47]       |        |              |        |         |                 |      |            |
|                           |                                | [48]       |        |              |        |         |                 |      |            |
|                           | traffic simulation software     | [49]       |        |              |        |         |                 |      |            |
| temporal-spatial dimension| trip chain theory              | [50]       |        |              |        |         |                 |      |            |
|                           |                                | [51]       |        |              |        |         |                 |      |            |
|                           |                                | [52]       |        |              |        |         |                 |      |            |
|                           |                                | [53]       |        |              |        |         |                 |      |            |
|                           |                                | [54]       |        |              |        |         |                 |      |            |
|                           |                                | [55]       |        |              |        |         |                 |      |            |
|                           |                                | [56]       |        |              |        |         |                 |      |            |

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**Fig. 2** Technical classification of EV charging load modelling methods

influence of user behaviours. The study assumes that the initial state of charging and the charging duration are subject to a simple distribution, in which Monte–Carlo simulation sampling is used to obtain the charging load curve. By considering two types of electric energy supply modes of EVs: battery charging and battery swapping, the Monte–Carlo method was used to model and analyse the charging load of battery swapping in [25]. Besides, seasonal factors and holiday behaviours were introduced to achieve a probabilistic modelling of the demand volume and power capacity of an EV battery pack in [26].

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To analyse the change of charging load, the relationship between multiple influence factors is studied. By considering the battery type (lead battery and lithium ion), price structure (fixed electricity price, time-dependant electricity price, and real-time electricity price), purpose of using vehicle (domestic and business), EV penetration rate, charging location, control measures etc., the
3.1.2 Markov chain theory: The EV charging behaviour mainly depends on its mobility characteristics and available charging facilities. However, it is difficult to predict charging behaviour but can be assisted with some random methods, such as state, dwell time, and state transition probability to describe the expected behaviour. The Markov process can be used to describe the relationship between the starting point, the destination, and the residence time of each different EV as shown in Fig. 3 [29].

Unlike the discrete-time Markov process and the continuous-time Markov process, the residence time in the semi-Markov process can be modelled in the form of a non-exponential distribution, which is more suitable for modelling the EV charging behaviour. In addition, the state transition probability and residence time distribution involved in the EV charging behaviour have time dependence. For example, since the state transition probability of the user who starts working at 8 am will be different from the afternoon active user. The mobility characteristics and charging behaviours of EVs were described in [34] by using a nonhomogeneous semi-Markov process, which combined relevant factors that affect the charging load such as state transition probability, dwell time, driving distance, and the state of EV charging.

3.1.3 Fuzzy logic system: Under normal driving circumstances, the EV users cannot accurately assess the battery charging state, and estimate residence time and other parameters to make charging decision, but simply based on whether the status of charging as ‘low’, ‘medium’, ‘high’ with expected residence time ‘short’, ‘middle’, ‘long’. These are described as fuzzy criteria to establish rules for users to determine charging behaviour for their journey. For example, the fuzzy criteria of charging probability are shown in Fig. 4.

Therefore, the fuzzy logic inference system is also used to simulate the decision-making process of the user's charging behaviour. When the decision is made for charging, the user mainly considers two factors: state of charge and expected residence time. Other factors such as electricity price, distance from home, charging power, and personal income level may all be included in the model [57].

The process for users to make charging decision is similar: when the state of charge is ‘low’ and the expected stay time is ‘long’, the probability of charging at this time is ‘high’. These linguistic variables can be described by the corresponding construction membership functions. On this basis, the parameters such as battery capacity and charging power are combined to evaluate the EV charging load curve.

3.2 Stochastic modelling of EV charging load in the spatial dimension

3.2.1 Dynamic traffic flow model: In a power distribution network, the EV charging load will change according to vehicle's spatial variance. Due to the mobility characteristics of the EV, its large-scale access will be inevitably linked to the grid, transportation network and charging service network. To predict the charging load of a charging station in a transportation network, dynamic traffic flow models in the traffic field are also used to evaluate the EV arrival rate at charging stations. Then, charging load forecasting is performed in combination with queuing theory, Monte–Carlo simulation and other methods. The Floyd algorithm was used to calculate the shortest path from all the starting points to the ending point D in the traffic network [58], and to identify all the nodes through the EV travelling path. A similar approach is used to calculate the traffic flow on the corresponding path through the gravity space interaction model.

The existing literature has shown the number of EVs arriving at a charging station meets the Poisson distribution considering the uncertainties from the traffic and operation condition, etc. Thus, the queuing theory could be utilized to simulate the charging process. In [59], regarding charging in public charging stations, the behaviour could be regarded as the M/M/c queuing system. In terms of charging in residential area the behaviour could be described as an M/M/c/k/Nmax queuing system. A probabilistic model for the single plug-in hybrid electric vehicle was established in [43]. Firstly, the queuing theory was used to model a large number of EVs in charging stations and residential areas. Based on the queuing theory, it was assumed that the arrival time meets the two-stage Poisson distribution with parameter \((\lambda_1, T_1, \lambda_2, T_2)\) and the state of charge (SOC) of the EV cell meet the normal distribution with parameter \((\mu, \sigma)\) [44]. By using a genetic algorithm to identify the random parameter, and based on the initial SOC of the EV cell and the random distribution of EVs’ arrival time, the load accumulation characteristics of the residential area were obtained according to the charging curve of the battery cell.
3.2.2 Parking generation rate model: By dividing the EV charging area into different regions, and considering the usage of different types of land in each region with parking characteristics, the spatial distribution of forecasted parking demand within the area was obtained in [46]. The parking demand of each region is calculated through the improved parking generation rate model, which is shown as

\[ P_i(t) = \sum_{j=1}^{n} f_{ij} \times P_i^* L_{ij}, \]

where \( P_i(t) \) is the parking demand for region \( i \) at time \( t \), \( R_j \) is the \( j \)th type of parking demand generation rate of region \( i \), \( L_{ij} \) is the usage (building square) of the \( j \)th kind land of region \( i \), \( P_i^* \) is the per-unit curve of parking demand of region \( i \) at time \( t \), \( f_{ij} \) is the correction factor of the parking generation rate in different regions which covers location, economy, and population density.

Then, based on the EV driving characteristic, the charging demand model is established. The Monte–Carlo method is adopted to simulate the driving, parking, and EV charging behaviour in each region. Thus, the distribution of the EV charging load in each region could be obtained.

3.2.3 Demographic model: The main purpose of EVs is for users to commute in different places. The number of vehicles in an area depends mainly on the number of users in the area and the type of area. Furthermore, the number of vehicles that stay in the area will also change over time. For residential areas, due to the limited number of workplaces, only a small number of vehicles stay in the area during the day, but at night when the people arrive home from work, the area will be used as the peak for parking. For the industrial and commercial areas, it has the opposite phenomenon. Therefore, a demographic model is necessary to be used for modelling the EV charging load.

Generally, demographic modelling studies are mainly divided into two implementation steps: first, demographic data (e.g. the number of households, workplaces, the density of residents and employees etc. in a certain area) can be used to evaluate the number of EVs at different time and location. Thereby, the possible EV charging location can be obtained. Then, the user's habit can be obtained from the national traffic survey data, for assessing the expected EV charging time and duration. Finally, by combining with the charging management strategy, we can calculate the charging load curve in different regions. In particular, the specific impacts of EV inbound flow, charging duration, and capacity of the station on the charging load were discussed in [48]. Then, a simplified formula, which is suitable for rapid calculation of charging load at different charging stations, was proposed. The case study was carried out on the Beijing Olympic electric bus charging station and compared with the measured data. The concept of the EV full charge margin was presented in [49], which establishes a mathematical model based on certain assumptions for the vehicle owner's habit and charging management strategy. Demand replacement is also analysed corresponding to the number of reserve batteries during different time periods.

3.2.4 Traffic simulation software: Real-time traffic conditions can be obtained by the behaviour simulation of the individual vehicle. Each vehicle can be simulated as an intelligent agent with their own daily plan and decision making based on the utility function (such as route selection, fuel supplementary location etc.).

Regarding the mobility characteristics of the EV, traffic simulation software has also been used to study the EV charging load. By using MATSim, the EV energy consumption model was simulated as the agent decision utility function, which considered the electricity cost consumption in [50]. The geographical location, charging duration, and energy demand of all EVs can be obtained through simulation to obtain EV charging load curve.

3.3 Stochastic modelling of EV charging load in the temporal–spatial dimension

Trip chain theory: The trip chain theory describes the whole process of a destination-based individual travel from the starting point to the termination point through several transit places in a certain time order. The method based on the travel chain theory synthesises the temporal and spatial dimension as a combination of the above two methods. The temporal–spatial models of travel behaviour are constructed from the development of interactive trajectory of the EV, such as Monte–Carlo sampling [54], vehicle classification [55], Markov process [60], associated modelling of characteristic variables etc. These models are used to quantify the correlation between the characteristic variables of the EV trip chain. Multi-factor coordinated development, multi-agent modelling [61], system dynamics [62] and other methods are used to analyse the charging demand of EVs. A charging load prediction method, based on the trip chain, was proposed in [55]. This method mainly considers the EV charging frequency. The purpose usage of the domestic EV was classified into five categories, by using the three-parameter Weibull function and lognormal probability distribution function to fit the end time and travel distance of each trip, the simple and complex trip chain was constructed, thus to build the temporal–spatial distribution model of the EV. Besides, other methods like cellular automaton can also be utilized to model the temporal–spatial characteristics of EV charging load.

4 Research framework on EV charging load modelling

In the existing literature, there are mainly three methods for determining the EV scale:

- Assuming it as a known quantity.
- Using predicted data from related organisation or institution.
- Setting different EV penetration scenarios, a certain ratio in load demand at each bus.

The majority of modelling analysis for EV charging load characteristics is based on a certain scale. However, the scale and distribution of the EV is an important parameter for EV charging load forecasting, which can be further used to guide charging service network construction for distribution network planning. Furthermore, it is found that the process of EV market diffusion is spatial imbalance and showing clustering [63], due to the social economic factor. Even if the overall EV penetration rate appears to be low, it may still result in an overload on regional power components. In the long run, the EV scale evolution could drive the dynamic development of charging demand and in turn determine the requirements of charging. Therefore, the temporal–spatial forecasting model for the EV scale is required to be built, with the possible prediction of the cross-time scale of charging load, combining with driving laws, charging characteristics, charging duration and other factors.

A framework for charging load evolution on temporal and spatial dimension is proposed. It integrates the time-space evolution model of plug-in electric vehicles (PEVs) on a long-term scale, and the PEVs charge operation model on a short-term scale. The specific research framework is given in Fig. 5.

In this research framework, the long-term market evolution model is proposed to generate the user attributes that are related to vehicle purchase behaviour based on social demographic data. The input includes residential population spatial density, income distribution, annual travel distance, current vehicle status (number of vehicles, purchase price, and technical parameters), social network, user types (e.g. innovators, early adopters, early majority, late majority, and laggards), environmental attitudes, market price etc. Secondly, a comprehensive PEVs market evolution model is established that comprehensively considers the economy, technology, social influence, and environmental benefits. Then, the PEV scale evolution simulation system is developed. In addition, different development scenarios are constructed which include different oil prices, technical levels, vehicle price development etc.
Generally refer to the traffic statistics (e.g. the time of departure, charging management strategy, a charging behaviour model is combined to obtain the charging demand. Then, based on the optimisation (PSO) algorithm and weighted Voronoi diagrams are established, which is added to the behaviour library. Finally, PEV charging behaviour is simulated on the selected operating day, and the temporal-spatial characteristics of the PEV charging demand profiles are produced as output.

5 EV charging load in power system

With the increase of EV ownership, large-scale EV charging load would bring great challenges to power system planning, operation, and electricity market. Due to the non-equilibrium spatial distribution of EVs, even under the low EV ownership level, problems would still exist in the local power grid. The natural (uncontrollable) EV charging load will cause problems such as overload of equipment, power loss, voltage drops, component life reduction, and power supply unreliability [64]. Therefore, existing and future research is required to mitigate the above issues.

5.1 Power system planning with EV charging load

The planning of power grids with charging facilities is closely related to the EV development. The uncertainty of EV charging load has made the planning of power grids more complicated. Poor planning would not only bring great inconvenience for EV users but also increase the risk possibilities of power loss and voltage drop, which would impact the reliability of power supply. Therefore, relevant factors should be properly considered at the planning stage, such as traffic condition, charging demand, user experience, and the economy of power grid development.

Comprehensive studies have shown that the optimal planning of charging facilities would improve the EV utilisation efficiency and the reliability of power supply [65, 66]. By considering the EV distribution, the power grid structure, and the transportation network, a maximum revenue model for the annual operation of charging stations was built in [67]. Then, the particle swarm optimisation (PSO) algorithm and weighted Voronoi diagrams are used for the charging station planning in terms of site selection, size evaluation and the optimal division of service areas. Following the concept of operating mode of ‘concentrated charging and unified delivery’ by considering both power and transportation networks, a siting and sizing model for a centralised charging station was established [68].

A comprehensive objective function was presented in [9] to address the problems of locating and sizing of EV charging stations. The objective function includes initial construction costs, equipment costs and running costs covering the risk of power loss, staff salaries etc. A quantum PSO algorithm was proposed to solve this problem. Firstly, the factors of environment and service radius were considered in [9], and a two-step screening method is used to determine the siting of charging station. Then, a mathematical model for the optimal sizing of EV charging stations is developed with the minimum total cost associated with EV charging stations to be planned as the objective function, which was solved by a modified primal-dual interior point algorithm. The simulation results show that this method is able to obtain a reasonable planning scheme, reduce network loss and improve the voltage quality. A comprehensive evaluation method was proposed in [69] to assess the impact of charging load on the power supply security. Research claims that in the smart charging scenario, high-penetration of EVs would not significantly affect the reliability of power supply. Furthermore, it is shown that large-scale EV had little impact on the source-side of the U.S. grid when orderly charging was adopted [70]. The battery swapping station (BSS) is regarded as a basic unit commitment in [71], thus a new unit commitment model considering BSS with charging/discharging was proposed. Variance optimisation is used to improve the adjustment of unit output efficiently. In addition, the adjustment frequency of the unit output was reduced, and the safe and economic operation of the power grid is improved. It was pointed out that in the evening scenarios, EV charging would result in the large growth of peak load [72]. Also, in 2030, 10 out of 30 U.S. power supply areas are anticipated to require additional generating capacity to meet the demand of EVs. Since the new installed power capacity is directly related to the charging mode of EVs, the new installed capacity would be minimised when considering V2G [73]. Even if the EV penetration rate is just 10%, it may lead to the overloading of the distribution power transformers [74]. The impact of charging load on distribution network investment and energy consumption at different penetration rates was quantified in...
5.2 Power system operation with EV charging load

Massive access of EV charging load may distort the traditional electricity load and bring challenges in daily power system operation. So, it is necessary to investigate the proper charging control strategy and load distribution method to smooth the charging load profile, improve the load factor of the power grid, reduce network losses, and ensure the safe and economic operation of the power grid. The existing research work shows that the charging strategy to reduce the simultaneous charging rate during the peak load period would defer the additional 60–70% of network investment [8]. By shifting partial peak load to a low point, 5–35% of the extra network investment would be saved. Hence, a smart charging method was proposed in [76] to minimise the sum of total loss and voltage excursion in the multi-period of the power grid. The method includes the constraints of loading rate, load demand, and basic power flow equations. In fact, the power generation capacity is largely unused during off-peak hours, with the low utilisation rate is considered as a waste of investment. As the charging period of EVs is controllable, an optimisation charging method was proposed in [28], which optimises the charging starting time, making the power system load curve smooth, and improving the equipment utilisation rate. A two-stage optimisation charge-discharge method was proposed in [78], which aims to minimise the fluctuation of the peak load curve, with additional benefits on the saving of generation capacity.

Moreover, based on the Nash deterministic equivalence principle, which considers the influence of the network, a distributed multi-agent charging control method was proposed in [79]. This model overcomes the disadvantages of centralised regulation that needs to process a large number of vehicles and network information. This method not only meets the requirements of large-scale EVs but also ensures the operating efficiency of the network could be achieved. The linear programming method was adopted to optimise the EV charging power and maximise the utilisation rate of power transmission capacity, which still satisfies the network constraints [80]. The response of the real-time electricity price to allocate preference for charging time of the EV user is also important for system operation, thus a real-time load management strategy was designed in [81], which coordinates the EV charging load to minimise generation cost and energy loss. The maximum sensitivity analysis was applied to meet the real-time performance as well. In addition, the relationship between the power loss, loading rate, and the load fluctuation were studied. Three optimal charging algorithms were proposed to reduce the impacts of EV charging load on the distribution network [82]. Simulation concluded that the three optimal performances of algorithms were similar, but the algorithms with the load factor and the load fluctuation as the objective function have a faster calculation performance, which provides system operation with a new method for real-time scheduling. The EV mathematical model by considering the economic benefits of spinning reserve and frequency control was presented in [83]. This model aims to maximise the total revenue based on the control strategy of EV charging through the EV agents. The simulation shows that it is economically feasible for the EV to provide auxiliary frequency control and spinning reserve services in the power market. Single index or multiple performance indexes of the power grid or EV users are used as an objective function, to optimise the EV charging control strategy. Such methods are based on the expected performance of given indexes to explore the corresponding strategic outcome. This method has achieved good control outcome in theoretical research. However, in the real-time analysis, it may not be able to meet the calculation efficiency following the dynamic changes in the system state. Therefore, based on the task of analysing the EV charging load characteristics, the typical EV charging load curves under different measures will be clustered, which will improve the calculation performance in real-time operation.

5.3 Electricity market development with EV charging load

The massive penetration of EVs could lead to the change of the market structure, and the aggregation of the EV charging load will add new consumers to the electricity market. This offers an opportunity for EV market participants to profit from the price difference between the purchase and sale of electricity. To reduce the risk of electricity fluctuation, contracts from long-term bilateral market and day ahead market are in place to meet real-time charging load, interactive with the real-time market. With the
evolution of energy storage technology, EVs could be used as ‘virtual power plants’ to participate in the active power market, auxiliary service market etc.

Thus, an operating framework for EV aggregators was proposed with a profit maximisation algorithm for planning and scheduling of EV aggregators in [84]. By considering the predicted electricity price and charging load of the EV, the minimum load planning cost algorithm is used to determine the electricity purchase volume in the day-ahead market. To facilitate participating in bilateral contract negotiations, the dynamic dispatch algorithm is developed to allocate the charging load in real time. Furthermore, the current electricity market mechanism needs further improvement to offer incentives for EV aggregators to help mitigate technical risks on the power system. The revenue of V2G to provide frequency regulation services in the German and Swedish power markets were calculated in [85], with a situation analysis to be conducted on service participation in the market competition. From the distribution companies’ point of view, the benefits of V2G were discussed [86] with a long-term business model to be defined [87], which includes the charging control strategy of the G2V, the secondary life utilisation of the V2G and lithium battery.

The EV commercial operation could ensure the sustainable development and maximise the benefits of the whole industry chain. How to determine the EV charging load characteristics in different business operation modes remain to be studied.

6 Conclusion

The integration of large scale EVs to power system has become an inevitable trend, which will have a significant impact on the safe, stable, economic operation of the power grid. Both opportunities and challenges are presented to deal with EV charging as a flexible resource in an optimal way. Therefore, the accurate and efficient modelling of the EV charging load has become a key requirement for the future development of EV charging facility and eventually the power grid.

This survey comprehensively reviews the modelling methods of EV charging load. The review could be summarised into three parts: modelling methods based on temporal uncertainty, spatial uncertainty, and temporal–spatial uncertainty. We found that the existing research work on dealing with large-scale EV charging load is less rigorous. The EV scale plays an important role in the load characteristic modelling. Inaccurate quantification of the scale and evolution characteristics of EVs will lead to the challenges in planning and operation of future power systems. Therefore, a new time-scale model framework for the EV charging load is proposed. The proposed framework is composed of a long time-scale market evolution model and a short time-scale charging operation model, which are able to accurately determine the EV scale development.

Furthermore, this survey points out the limitations of existing research on the EV charging load modelling for power system planning, operation, and market design purpose, with further research direction being discussed. This survey could contribute to the EVs’ development as well as the construction of smart grids.

7 Acknowledgments

This work was supported by the National Natural Science Foundation of China (51807127).

8 References

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