

A Review on Plug-in Electric Vehicles: Introduction, Current Status, and Load Modeling Techniques

Ali Ahmadian, Behnam Mohammadi-Ivatloo, and Ali Elkamel

Abstract—Plug-in electric vehicle (PEV) load modeling is very important in the operation and planning studies of modern power system nowadays. Several parameters and considerations should be taken into account in PEV load modeling, making it a complex problem that should be solved using appropriate techniques. Different techniques have been introduced for PEV load modeling and each of them has individual specifications and features. In this paper, the most popular techniques for PEV load modeling are reviewed and their capabilities are evaluated. Both deterministic and probabilistic methods are investigated and some practical and theoretical hints are presented. Moreover, the characteristics of all techniques are compared with each other and suitable methods for unique applications are proposed. Finally, some potential research areas are presented for future works.

Index Terms—Plug-in electric vehicles, load modeling, deterministic and probabilistic techniques, distribution networks.

I. INTRODUCTION

INDUSTRY, transportation, residence, and commerce are the four important sectors of energy consumption in the world. The amount of each sector for the United States (U. S.) in 2017, for example, is as follows: 32% industrial, 29% transportation, 20% residential, 18% commercial, and 1% others [1]. The concerns about fossil fuel depletion and its impact on greenhouse warming have motivated the governments to find the alternative resources. As the transportation sector has a considerable amount of energy consumption (about 30%), it has gained more attention to replace the gasoline vehicles with other types of vehicles such as electric,

hydrogen, etc. Currently, most of transportation vehicles consume fossil fuels. The transportation energy resources in the U. S. in 2017, for example, include 55% gasoline (petroleum), 22% distillate (petroleum), 12% jet fuel (petroleum), 5% biofuel, 3% natural gas, and 1% others [2]. It is obvious that about 90% of transportation energy is produced by petroleum. Therefore, the transportation electrification can significantly reduce the dependency of fossil fuels.

Currently, there are several types of electric vehicles (EVs) in the market. Hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), plug-in electric vehicles (PEVs), and battery electric vehicles (BEVs) are the main types of EVs.

In HEVs, the batteries cannot be charged by power grid. There are two energy resources for battery charging that include gasoline and regenerative braking. The energy of braking system is converted to heat in combustion engine vehicles to charge the battery of HEVs. Also, the gasoline can be converted directly to electric energy to charge the battery using an electricity generator. Under the light load and low-speed conditions, the electric motor is used to drive the wheels, while both electric and gasoline motors are used under the heavy load and high-speed conditions.

The PHEVs can be powered by both gasoline and electric energies. The battery of PHEVs can be charged by regenerative braking system, similar to HEVs, and the external power grid. The PHEVs can be plugged into the power grid and charged completely. The use of both energy resources extends the driving range of PHEVs.

The PEVs or BEVs are powered fully by the electricity. They can be plugged into an external power grid to charge the batteries. This type of EVs can drive about 200 km using one or more electric motors.

The financial perspective of EVs is important for people who are interested in purchasing an EV. A comprehensive study is carried out in [3], where the fuel and maintenance costs of electric and gas vehicles are compared. It is concluded in this paper that about 71% of fuel and maintenance costs of Canadian household will be saved by EV utilization. Therefore, the operation cost of EVs will be less than that of gas vehicles. However, the purchasing price of EVs is usually higher. The comparison of an EV and a gas vehicle with similar characteristics, for instance, Nissan Leaf as an EV and Honda Civic as a gas vehicle, shows that the price of

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EV (about \$29000) is much higher than that of the gas vehicle (about \$19000). Therefore, the governments should give interesting incentives to EV buyers if they want to increase the penetration of EVs in their countries. Many countries have designed several incentives and subsidies to encourage people to buy the EVs. In the U.S., for example, the federal government grants a tax credit up to \$7500 depending on EV battery capacity. Moreover, the citizens of the U.S. give another subsidy from their particular state as well [4]. The residents in Canada, for instance, in Ontario province, can receive up to C\$14000 to buy an EV based on vehicle type

and battery capacity [5]. Other countries such as France, UK, Sweden, Japan, etc., have also designed incentives to encourage their citizens. Due to the government incentives and technological improvement of EVs specially in batteries, it is forecasted that the penetration of EVs will increase in the future. Reference [6] has predicted considerable growth of the penetration of EVs in Canada in the future. There are many types of the EVs in the market and each of them has individual specifics. The main attributes of the most popular EVs in the market are presented in Table I [7]-[9].

TABLE I
MAIN ATTRIBUTES OF MOST POPULAR EVS IN MARKET

No.	Brand	Price (\$)	Travel range (mile)	Battery capacity (kWh)	Battery type	Efficiency (kWh/mile)
1	Nissan Leaf	30000	107	30.0	Lithium-ion	0.28
2	BMW i3	46500	114	33.0	Lithium-ion	0.27
3	Jaguar i-Pace	85900	234	90.0	Lithium-ion	0.36
4	Tesla Model S-75	75000	249	75.0	Lithium-ion	0.33
5	Renault Zoe	52000	250	41.0	Lithium-ion	0.26
6	Hyundai Ioniq Electric	32000	124	28.0	Lithium-polymer	0.23
7	Tesla Model X-75	77000	238	75.0	Lithium-ion	0.34
8	VW e-Golf	46000	120	35.0	Lithium-ion	0.26
9	Kia Soul EV	33700	111	30.5	Lithium-polymer	0.27
10	Smart Fortwo Electric Drive	25500	65	17.6	Lithium-ion	0.25

EVs are high-power consumers that should be supplied by power grid. The battery capacity of Nissan Leaf, for instance, is 30 kWh [7] that is equal to 3-5 times the daily electricity demand of a household. The power grid will be faced with challenges and stresses if the high penetration of EVs are plugged into the grid. Therefore, the load demand of EVs should be modeled in order to study their impact on power systems. Several techniques are introduced by researchers to model the load demand of EVs, and each of them has individual characteristics. In this paper, the most popular methods for EV load modeling are presented and their characteristics are reviewed. Some tips and hint are also proposed for the better simulation of techniques. Moreover, the charging strategies including non-smart and smart charging are investigated, and the advantages and disadvantages of each strategy are presented.

II. PEV CHARGING STRATEGIES

The overall classification of PEV charging strategies is shown in Fig. 1. Generally, PEVs can be charged using two

main charging strategies, e.g., non-smart and smart charging. For non-smart charging, which is also called uncoordinated charging, the PEVs start to charge right after the arrival home or at the charging station. The charging power rate is fixed in this strategy that can be one of the three standard charge levels. The standard charging levels based on SAE J1772 standard [10] are presented in Table II.

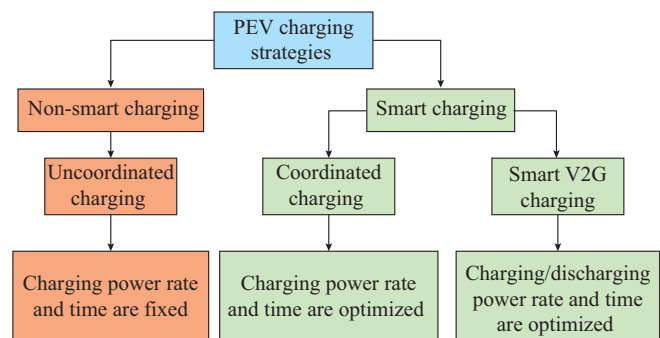


Fig. 1. PEV charging strategies.

TABLE II
PEV STANDARD CHARGING LEVELS BASED ON SAE J1772 STANDARD

Charging level	Voltage (V)	Current (A)	Power (kW)	Charging time (hour)
AC level I	120 (single phase)	12-16	1.44-1.92	7.0-17.0
AC level II	240 (single or three phase)	Up to 80	Up to 19.20	3.0-7.0
DC level III (fast charging)	200-450 (direct current)	Up to 80	Up to 36.00	0.5-1.5

The current rate of charging level III is very high (up to 80 A). Therefore, the domestic power grid cannot supply

this type of charging station. It might be used for public charging station. Charging levels I and II are suitable for do-

mestic charging stations. However, the power rate of charging level I is very low. Using this charge level, the PEVs batteries cannot be fully charged, especially if the battery is already fully discharged or the battery capacity is high. Moreover, in smart charging strategies where the battery charging throughput is high, this charging level will be less efficient. Therefore, the charging level II is suitable for both smart and non-smart charging strategies, which can be supplied by the electric grid.

The smart charging can be categorized into sub-strategies that are named coordinated charging and smart vehicle-to-grid (V2G) charging. In coordinated charging strategy, the time and power rate of PEV charging are determined optimally using an optimization algorithm. In this strategy, an objective function should be defined and the decision variables (time and power rate) should be determined subject to technical constraints. The technical constraints include both power grid and PEV battery constraints. The objective function can be the minimization of charging power cost, power loss, or voltage regulation enhancement, etc.

In the smart V2G charging, the time and power rate of charging and/or discharging of PEVs are determined optimally. In this strategy, not only the charging scheduling of PEVs are optimized, but also the PEVs can support the power grid by power injection into the grid.

Each of the mentioned charging strategies has individual advantages and disadvantages. Several aspects should be considered to select a proper charging strategy. Figure 2 shows the main aspects of each charging strategy. According to this figure, four main perspectives are important in PEV charging strategies. These perspectives have several technical and economic considerations. Therefore, a comprehensive cost-benefit analysis is needed to determine the best charging strategies for each case study.

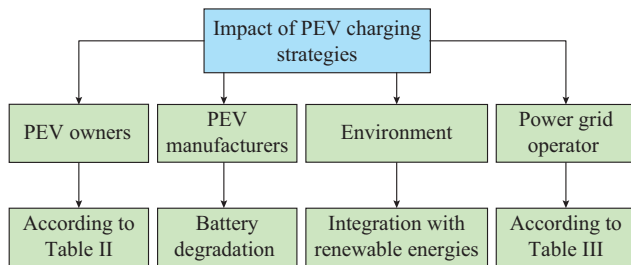


Fig. 2. Different perspectives of PEV charging strategies.

From the perspective of PEV owners, there are four considerations that should be taken into account as presented in Table III. The charging cost in uncoordinated charging is very high. The reason is that the PEV arrival time has a high correlation with peak load hours of power grid [11]. Therefore, the PEVs are charged with high electricity price that results in high charging cost. The charging cost may be the only disadvantages of uncoordinated charging from the perspectives of PEV owners. As the batteries are charged using the standard charging stations, their lifetime will be long. Moreover, the owners can use the warranty if the batteries are damaged in this charging station. In addition, the owners ensure that their vehicles will be fully charged until

the departure time. Their welfare will be good as well. Therefore, the overall preference of PEV owners is the uncoordinated charging strategy.

TABLE III
PERSPECTIVE OF PEV OWNERS IN CHARGING STRATEGIES

Perspective	Uncoordinated charging	Coordinated charging	Smart V2G charging
Charging cost	High	Low	Low
PEV lifetime	Long	Long	Short
Owner welfare	Good	Poor	Poor
Full charging insurance	Good	Medium	Poor

From the perspectives of PEV manufacturers, the main consideration is the battery degradation. The manufacturers guarantee the batteries for normal usage under the normal condition. The smart V2G charging of PEVs damages the batteries as the charge throughput and power rate of batteries are increased in this charging strategy [12], [13]. Reference [14] has claimed that in the coordinated charging, not only the PEV is undamaged, but also the lifetime of batteries is increased. The reason is that the impacts of standing time and state of charge (SOC) on battery degradation are decreased in coordinated charging. Therefore, the overall preference of PEV manufactures is the uncoordinated charging strategy.

From the environmental perspective, PEVs will be more beneficial if they are charged using renewable energies. The integration of PEVs with renewable energies is not very interesting in uncoordinated domestic charging. The reason is that the correlation of solar energy available time (between sunrise and sunset) and PEV available time (between arrival time and departure time) is very low. It can be modified if the PEVs are charged during daytime at the workspaces such as commercial or official regions, etc. In [15], PEVs are integrated with renewable energies in parking lots. However, as the space price is very high in these regions, the penetration of solar energy at these regions is low. The wind energy has also the same condition. If renewable energies are combined with stationary energy storage, their integration with PEVs would be interested, especially in the smart charging strategy. Several researches in the literature have investigated the integration of PEVs and renewable energies in both smart charging [16]-[18] and non-smart charging strategies [19]-[21]. Therefore, from the environmental perspective, the overall preference is the smart charging strategy.

The most important perspective in charging strategies is the power grid. Several considerations should be taken into account to evaluate this perspective. The most important considerations are presented in Table IV. PEVs are huge consumption components in power grid. Therefore, their load demand should be modelled using an appropriate methodology. The impact of uncoordinated charging strategy on several grid parameters is investigated in the literature such as load profile [22]-[24], charging cost [25], [26], power loss [27], [28], power grid component lifetime [29], voltage profile [30], grid component loading [31], etc.

TABLE IV
PERSPECTIVE OF ELECTRIC GRID OPERATOR IN CHARGING STRATEGIES

Perspective	Uncoordinated charging	Coordinated charging	Smart V2G charging
Peak load reduction	Poor	Good	Good
Power loss cost	High	Low	Low
Voltage regulation	Poor	Good	Good
Power grid reliability	Low	Medium	High
Component lifetime	Short	Long	Long
Component capacity	Low	High	High
Power grid operation cost	High	Low	Low
Infrastructure cost	Low	Medium	High

The uncoordinated charging strategy has negative impact on most of the mentioned factors. This charging strategy can increase the peak load and power loss considerably, violate the grid voltage and current constraints, and decrease the lifetime of electric grid components. However, the infrastructure cost of this charging strategy is low as the charge stations provide the fixed rate power without the control of time or power rate. Therefore, the smart charging strategies should be provided to overcome the mentioned challenges.

The coordinated charging strategy is utilized to prepare several services such as power loss reduction [32]-[34], peak load reduction [35]-[39], frequency regulation [40]-[42], voltage regulation [43]-[45], charging cost reduction [46]-[49], component loading improvement [50], renewable energy integration [51], [52], etc.

Similarly, the smart V2G charging strategy is utilized to prepare several services such as charging cost reduction [53]-[55], voltage regulation [56]-[58], frequency regulation [59]-[61], peak load reduction [62]-[64], reliability enhancement [65], renewable energy dispatching [66]-[68], maximization

of PEVs number in charging station [69], [70], participation in demand response program [71], grid balancing [72], participation in ancillary service market [73], reactive power compensation [74]-[76], etc.

The comparison of the provided services shows that the smart V2G charging strategy is more beneficial than the coordinated charging strategy. The reason is that in smart V2G charging, the PEV load demand is more flexible and the PEVs can be charged/discharged optimally. The charging infrastructure cost in smart charging strategies is more than that in uncoordinated charging, as the charging time and power rate should be controlled in this strategy.

Due to the fact that the distribution network has a limited capacity, only a few PEVs can be charged simultaneously. On the other hand, according to the PEV dataset analysis, most PEVs arrive home in the evening together. Furthermore, if the PEVs are charged by the non-smart charging strategy, the electric grid constraints will be violated, and the grid cannot charge all of them together. However, in smart charging strategy (in both coordinated charging and V2G), the PEV charging rate and time are optimized so that all PEVs will be charged until their departure time. Therefore, the main preference of electric grid operator is the smart charging strategies. Of course, the smart V2G needs more advanced infrastructure and consequently more time to be practical. However, the coordinated charging is currently practical and may be the best strategy from all aspects.

III. CENTRALIZED AND DECENTRALIZED CHARGING CONTROL METHODS

The PEV charging management is categorized into two groups namely centralized and decentralized charging control. The advantages and disadvantages of the centralized and decentralized charging control are presented in Table V.

TABLE V
COMPARISON OF CENTRALIZED AND DECENTRALIZED CHARGING CONTROL

Control mode	Advantage	Disadvantage
Centralized charging control	<ul style="list-style-type: none"> - Provision of considerable capacity in comparison with grid capacity - Including demand response programs using direct load control - Provision of better ancillary services - Compatible communication protocols - Better security on smart metering infrastructures 	<ul style="list-style-type: none"> - Need of a large communication bandwidth - Need of a high-tech control center - Need of high-speed computation machines - Complex management of large numbers of PEVs
Decentralized charging control	<ul style="list-style-type: none"> - Need of small communication bandwidth - Low infrastructure cost - Simpler implementation - Provision of several charging options for the user - Higher user welfare 	<ul style="list-style-type: none"> - Limited control of power network - Availability and utilization of several communication protocols - Provision of less capacity in comparison with grid capacity - Limited ancillary services provision - Less cyber security and low capability against attacks - Availability and utilization of various metering infrastructures - High uncertainty of charging behaviors of users

In the centralized charging control, the power grid operator manages the PEV charging demand considering the electric grid conditions and parameters such as power loss, voltage and current constraints. In some cases, a third part, namely aggregator, needs to coordinate the charge demand between the grid operator and vehicle owners. Based on the

objective functions, the aggregators manage the PEV demand considering both the constraints of grid operator and vehicle owners. In addition to charging control, the aggregators can also participate in electricity markets such as day-ahead energy market and ancillary service market. The minimization of total charging cost [77], [78], minimization of

grid power loss [79], [80], enhancement of grid reliability [81], [82], frequency regulation [83], [84], voltage regulation [85], [86], and maximization of the aggregator benefits [87], [88], can be considered as the objective functions in the centralized charging control. Overall, in the centralized methods, the grid operator or PEV aggregator manages the charging demand directly so that the PEV load demands are considerable in comparison with power. In the decentralized methods, the PEV charging demands are managed by the PEV owners individually. In other words, the PEV charging is controlled locally. In this method, each PEV owner autonomously optimizes the charging demand considering the preferences of the PEV driver. As the capacity of one vehicle is much less than the whole grid capacity, the participation of PEVs in electricity market such as ancillary services is a challenge in the decentralized method. The objective function of decentralized charging control is the minimization of charging cost in most works [89]-[92]. However, other objectives have also been investigated in literature such as frequency regulation [93], valley filling [94], voltage regulation [95], and renewable energy integration [96].

IV. PEV DATASETS

In order to model the PEV load demand, the data of vehicles should be collected. The data should include home arrival/departure time, daily travelling distance, vehicle types, and battery capacity. The study will be more accurate if the EV data of studied region is available. However, if the data are not available, it is possible to use a typical dataset. An example dataset is presented in the supporting materials of

this paper. This dataset contains the parameters of 500 EVs. The battery capacity of all EVs is 20 kWh and it consumes 0.25 kWh electric energy per kilometer. Another dataset contains the data of National Household Travel Survey (NHTS) that can be found in [97]. This dataset contains the data of 1 million vehicles including their home arrival/departure times, daily travelling distance, and percentage of each type of vehicles. Tables VI, VII and Figs. 3-5 show the related datasets. The nominal mileages of PEV30, PEV40, and PEV60 are 30, 40, and 60 miles, respectively.

TABLE VI
BATTERY CAPACITY FOR DIFFERENT VEHICLES IN NHTS 2009

Type	Vehicle	Battery capacity (kWh)		
		PEV30	PEV40	PEV60
1	Compact Sedan	7.8	10.4	15.6
2	Medium-size Sedan	9.0	12.0	18.0
3	Medium-size SUV	11.4	15.2	22.8
4	Full-size SUV	13.8	18.4	27.6

TABLE VII
PERCENTAGE OF VARIOUS VEHICLES IN NHTS 2009 AND THEIR ENERGY CONSUMPTION PER MILE (ECPM)

Type	Vehicle	Percentage (%)	ECPM (kWh/mile)
1	Compact Sedan	50	0.26
2	Medium-size Sedan	5	0.30
3	Medium-size SUV	25	0.38
4	Full-size SUV	20	0.46

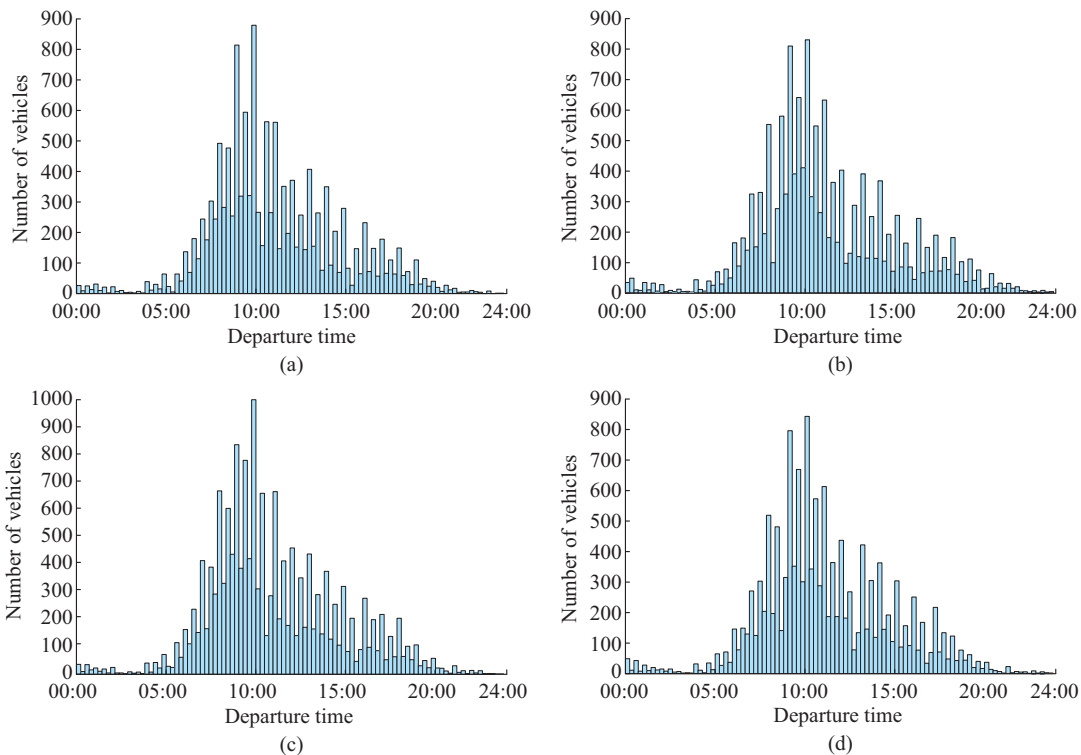


Fig. 3. Patterns of home departure time. (a) Spring. (b) Summer. (c) Fall. (d) Winter.

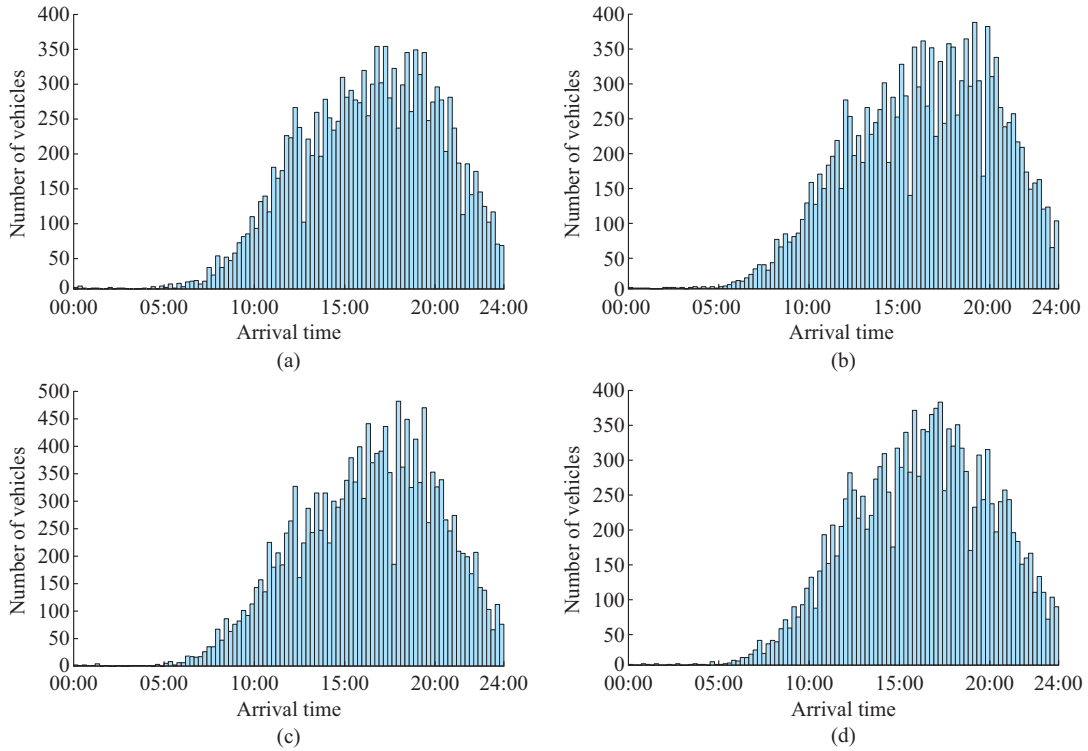


Fig. 4. Patterns of home arrival time. (a) Spring. (b) Summer. (c) Fall. (d) Winter.

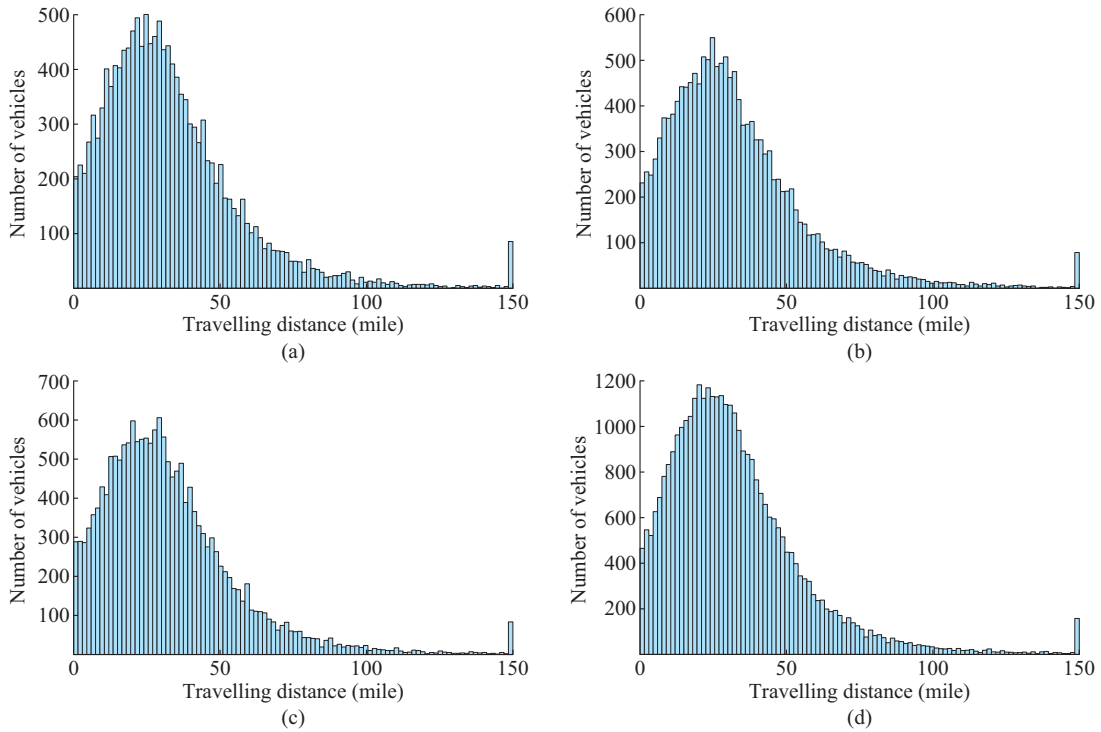


Fig. 5. Patterns of travelling distance. (a) Spring. (b) Summer. (c) Fall. (d) Winter.

V. PEV LOAD MODELING TECHNIQUES

A. Deterministic Load Modeling of PEVs

In the deterministic PEV load modeling, it is assumed that the parameters of PEVs are already known. In other words, the PEVs are scheduled as the stationary energy storages

that their available period is predetermined. For example, the arrival and departure times of vehicles are already known by the power grid operator. Therefore, the operator can schedule the PEVs similar to energy storage system. The daily travelling distance is the other simplification parameter so that it is assumed that the travelling distance of PEVs is

fixed. Therefore, the required energy for PEV charging can be calculated easily. Other simplification assumptions include starting charging at fixed time, fixed energy required for all PEVs, known departure time, and the same battery capacity for all vehicles. In some cases such as in [98], the stored PEV driving database is utilized for load demand extraction directly.

B. Scenario Reduction Method

In this method, some predefined scenarios are used for PEV load modeling in which the impact of each scenario is considered in the objective function. In [99], for example, the NHTS data are concentrated in some scenarios that represent PEV behaviors. In the discrete probabilistic scenarios method, some scenarios of PEV load demand are considered where each has individual probability or weight. The values of probabilities or weights can be found based on the historical data or the experience of the researcher. In this method, the objective function for each scenario is calculated individually and the final objective function can be represented as:

$$\min OF = \sum_{i=1}^n p_i F_i \quad (1)$$

where OF , p_i , F_i , and n are the objective function, the probability of the i^{th} scenario, objective function value of the i^{th} scenario, and number of all scenarios, respectively. In (1), the summation of probabilities of all scenarios should be equal to 1, which can be written as below.

$$\sum_{i=1}^n p_i = 1 \quad (2)$$

Figure 6 shows the mean of PEV load demand for 6 scenarios. In this figure, 6 different scenarios are considered where the PEVs can be operated in both grid-to-vehicle (G2V) and V2G modes. The negative values represent the V2G power demand, while the positive values are the G2V power demand. The numerical values of these scenarios are presented in the supporting materials of this paper [100].

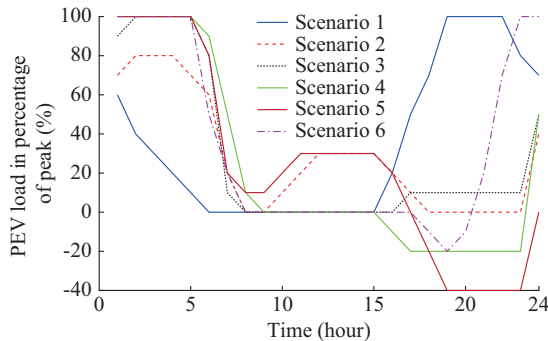


Fig. 6. Mean of PEV load demand for 6 different scenarios.

C. Monte Carlo Simulation (MCS)

In the MCS method, the PEV load estimation procedure is conducted for a large number of samples generated using the probability density functions (PDFs) of the input data. To this end, various PEV parameters including home arrival/departure time, daily travelling distance, PEV type, PEV battery capacity, etc., are considered as the input data of MCS.

Since these input data are inherently uncertain, they exhibit stochastic behaviors. Therefore, it is possible to use samples of these input data to perform the MCS method. Figure 7 shows the flowchart of MCS for PEV load extraction.

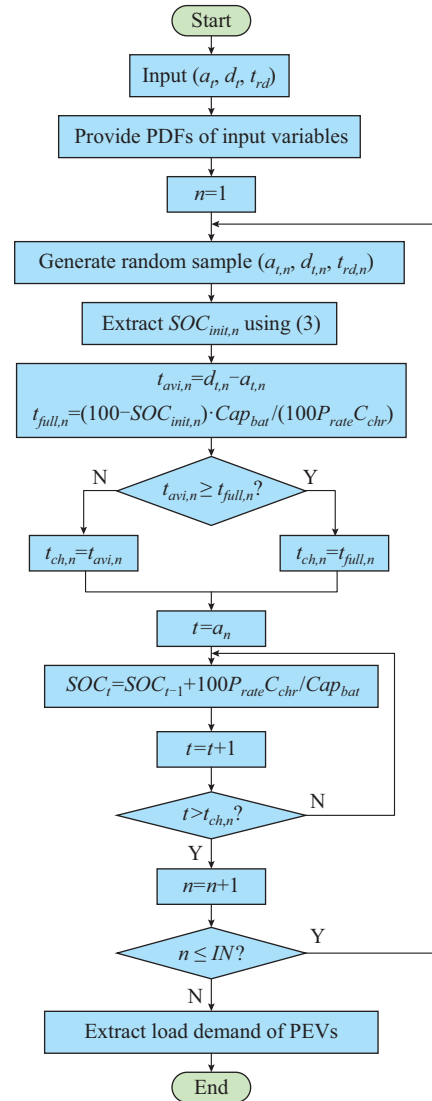


Fig. 7. Flowchart of MCS for PEV load demand extraction.

The MCS method needs a large number of input samples. Therefore, if the number of the input data is not large enough, a PDF can be fitted on the collected data so that a desired number of samples could be generated from the fitted PDFs. The correlations between the PEV data are not considered in the MCS method. Therefore, if the samples from each dataset (home arrival and departure time and travelling distance) are selected consequently, the selected data from three datasets may not be rational. For example, consider that the selected samples in MCS for home arrival time, departure time, and travelling distance are equal to 09:00 a. m., 10:00 a. m., and 60 miles, respectively, which are not rational and realistic. Although the probability of these samples is low, it may occur in MCS procedures. To avoid this problem, it is suggested to generate a sample from only one dataset (e.g. home arrival time), and the corresponding data

are selected with the generated samples from other datasets (departure time and travelling distance). For this purpose, the original sorting of the datasets should be kept during the simulation.

Figure 7 illustrates the overall flowchart of the employed MCS method. In this figure, a_r , d_r , and t_{rd} are the home arrival time, home departure time and travelling distance of the PEVs, respectively; $a_{t,n}$, $d_{t,n}$, and $t_{rd,n}$ are the n^{th} samples of MCS for home arrival time, home departure time, and travelling distance of PEVs, respectively; $t_{avi,n}$, $t_{full,n}$, and $t_{ch,n}$ are the available time, the required time for full charging, and charging time of the n^{th} PEV, respectively; and IN is the maximum sample number of MCS. More details about this method can be found in [11].

The initial SOC of PEV batteries should be calculated in this method. Equation (3) can be used for initial SOC calculation.

$$SOC_{init,n} = 100 - \frac{t_{rd,n}}{C_{eff} \cdot Cap_{bat}} \times 100 \quad (3)$$

where $SOC_{init,n}$ is the initial SOC of the n^{th} PEV; $t_{rd,n}$ is the daily travelling distance of the n^{th} PEV; C_{eff} is the efficiency coefficient of PEVs during driving; and Cap_{bat} is the battery capacity.

The available charging time $t_{avi,n}$ for the n^{th} PEV can be defined as the time span between the home arrival time a_i and the departure time the next day d_p , as expressed below:

$$t_{avi,n} = d_{t,n} - a_{t,n} \quad (4)$$

The charging time is determined based on $t_{avi,n}$. Moreover, the hourly drawn power and SOC of PEVs are calculated taking into account the PEV battery power rating, PEV battery capacity, and the efficiency of chargers.

The hourly PEV demand calculation procedure is performed many times to simulate the PEV charging demand within the distribution network. The estimation of the aggregated power demand of PEVs is completed when MCS is converged to a stochastic demand profile with hourly PDFs.

Figure 8 shows an example of extracted PEV load, where the load demand of each hour is presented in boxplot form.

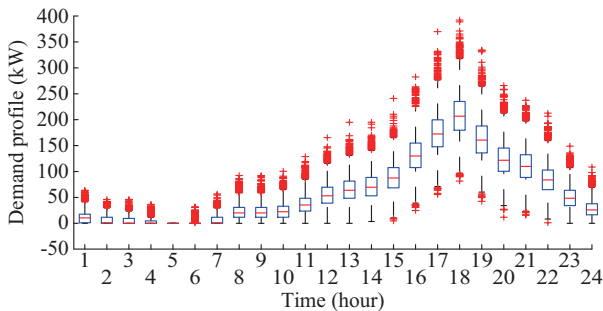


Fig. 8. Extracted probabilistic load demand of PEVs for 24 hours using MCS method.

D. Fuzzy Method

In this method, triangular fuzzy numbers are used to model the uncertainty of PEVs. This model does not require precise information regarding the power profile of the fleet over a long time interval, which makes it suitable for optimal

planning of distribution network components. Therefore, a series of approximately estimated scenarios can be used to dedicate fuzzy numbers to PEV power profiles in 24-hour time period.

Let a_{i1} , a_{i2} and a_{i3} denote the minimum, average and maximum values of the estimated scenarios for the PEV power at i^{th} hour, respectively. Then, the PEV power can be represented by a fuzzy number illustrated in Fig. 9. In this figure, the negative number denoted by a_{i1} represents V2G operation model of PEVs. A triangular fuzzy number can be expressed by $\tilde{a}_i = (a_{i1}, a_{i2}, a_{i3})$. The membership function in fuzzy sets represents the degree of reality. It has been used to generalize the indicator function in classic sets. More details can be found in [73]. The largest membership value is assigned to a_{i2} (i.e. average power) because it is the most possible state. In the same vein, the values a_{i1} and a_{i3} denote the possible power interval. Also, the mean value can be obtained by considering all the scenarios.

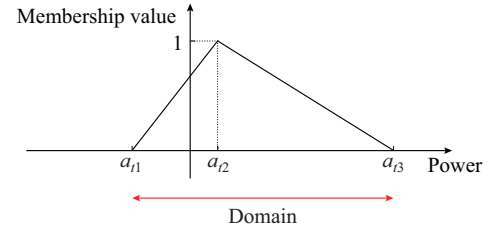


Fig. 9. PEV load demand as a fuzzy number.

After load modeling by fuzzy method, the fuzzy numbers can be used in load flow analysis with fuzzy equations and operators. More details of this method can be found in [100].

Moreover, as mentioned in [101], using the fuzzy technique, the important factors in PEV load modeling can be classified into some groups. For examples, the SOC of PEVs can be clustered to three classes (low, medium, and high) and the PEV parking duration can be clustered to three classes (short, average, and long). Therefore, the PEV load demand and charging time can be calculated using fuzzy logic. In addition, the charging probability can be modeled as a possibilistic problem by categorizing it into some classes such as very low, low, medium, high, and very high.

E. Hybrid Fuzzy-MCS Method

In this hybrid method, as other probabilistic methods, PDFs or datasets of PEV input parameters are required for load extraction. As explained earlier, most of these datasets are uncertain by nature, thus, they should be handled by proper methods. In the hybrid fuzzy-MCS method, the parameters are modelled in either probabilistic or possibilistic forms, based on their nature. This method can be implemented for both smart and non-smart charging strategies.

The hybrid fuzzy-MCS method makes an opportunity to model both spatial and temporal uncertainties of PEVs. In the most of the methods, only temporal uncertainty of PEVs can be modeled and the PEV charging locations are assumed to be the same. In other words, the PEV loads are assumed to be similar across the distribution network. This assumption results in inaccurate decisions for distribution network

studies mainly in component planning.

To model the spatial uncertainty of PEV load, the studied case can be clustered into some groups. In this method, the travelling distance is modeled using fuzzy triangular, while the arrival and departure times are modeled using MCS. Observing both spatial and temporal characteristics of the PEV loads leads to unique load profiles for every region of the distribution network, and results in more accurate PEV load extraction. By using this method, the domestic loads in the distribution network can be estimated for every region. This spatial classification of load profiles is of greater importance in component planning than in operation applications.

Traditionally, the uncertain characteristics of the PEV fleet such as home arrival time, daily travelling distance, and home departure time are modelled using their PDFs fitted to standard distributions, e.g., normal, Weibull and generalized expected value (GEV). Typically, in most distribution networks, the medium voltage feeders are passed through different regions with specific types of consumers (e.g., residential, commercial, fleet). In residential areas, PEVs are mainly used for commute to work on weekdays. However, it is not valid for all PEVs.

The travelling distance across the studied distribution network can be clustered in three or five classes as shown in Figs. 10 and 11, respectively. The three classes are N (near), M (medium), and F (far), and the five classes are VF (very far), F (far), M (medium), N (near), and VN (very near).

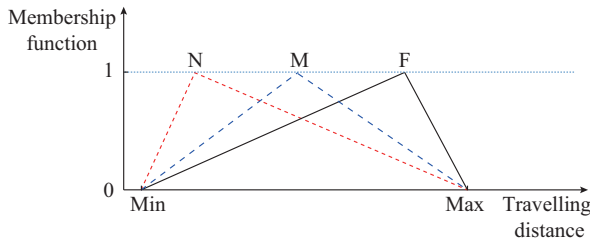


Fig. 10. Fuzzy model of three clusters of travelling distance considering location of parking lots.

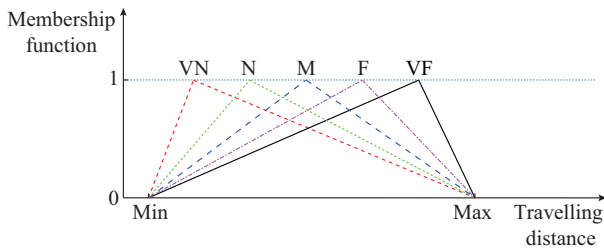


Fig. 11. Fuzzy model of five clusters of travelling distance considering location of parking lots.

The main challenge of this method is the integration of fuzzy values in the MCS algorithm. In this method, the initial SOC for the n^{th} PEV can be calculated using (5).

$$\widetilde{SOC}_{ini,n} = 100 - \frac{\tilde{t}_d}{C_{eff} \cdot Cap_{bat}} \times 100 \quad (5)$$

where \tilde{t}_d is a fuzzy value of PEV travelling distance. Consequently, the linked parameters such as $\widetilde{SOC}_{ini,n}$ are fuzzy values as well. Therefore, the fuzzy operators are required to

derive the output profile.

Since d_t and a_t are stochastic variables with known PDFs, while \widetilde{SOC}_i is a fuzzy value, the final estimated 24-hour profiles will be in possibilistic-probabilistic form. In essence, the load profile of PEVs in each hour is a triangular fuzzy value whose characteristics are stochastic variables. The possibilistic-probabilistic load demand model is shown in Fig. 12, where l_{i1} , l_{i2} and l_{i3} are the stochastic variables with known PDFs. The overall flowchart of the proposed hybrid fuzzy-MCS method is shown in Fig. 13, where f_{d_t} and f_{a_t} are PDFs of PEV home departure and arrival times, respectively. More details about this method can be found in [102].

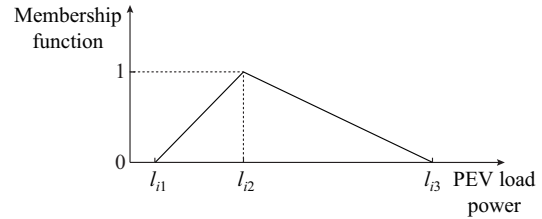


Fig. 12. Typical possibilistic-probabilistic load demand model of PEVs extracted by MCS.

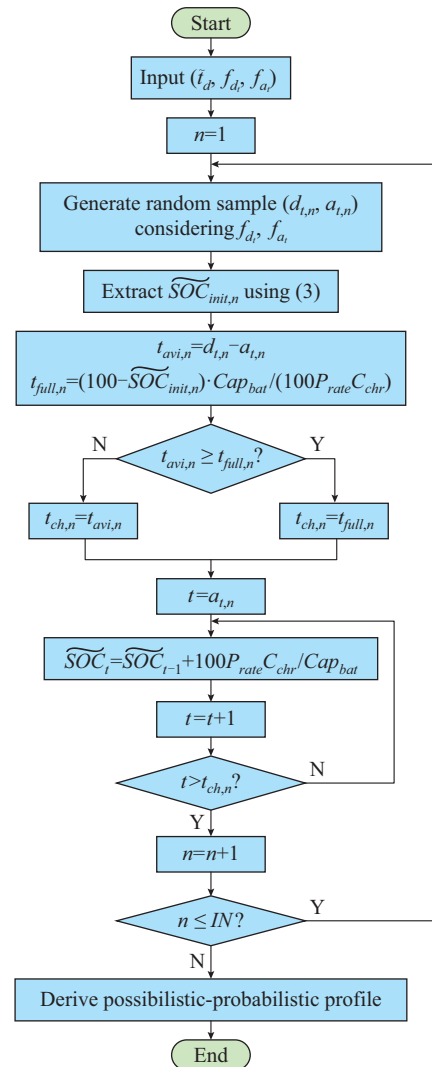


Fig. 13. Overall flowchart of hybrid fuzzy-MCS method.

Using this technique, not only the temporal uncertainty is modeled, but also the spatial uncertainty is taken into account. The temporal-spatial uncertainty modeling of PEVs is investigated in some literatures such as [103]. As presented in [103], a hybrid MCS and Markov chain technique is utilized for spatial-temporal uncertainty modeling of PEVs. More details about Markov chain is presented in Section V-G.

F. Artificial Neural Network (ANN) Method

A large number of data should be handled in PEV load modeling. Therefore, the ANN and machine learning methods will be useful for PEV load modeling. In modeling by ANNs, firstly, the parameters that influence the target should be identified. These parameters are given as inputs to the ANNs and the network predicts the target using them. The accuracy of this method can be verified after the training stage.

The structure of ANN is designed according to the complexity of behavior of the studied phenomena. Many parameters such as arrival time, departure time, and average speed are effective on the travelling distance. The behavior of the drivers are also very different, and the forecasting problem is highly complex. Deep ANNs should be used to model the behavior of PEV. The ANN acts like a black box. Once the network is fully trained and tested, it receives input data in the new situation and predicts the value of the target variable. To train the ANN, the back-propagation method based on gradient descent strategy can be applied. The main goal in training ANNs is to minimize the loss function. The overall structure of ANNs for PEV modeling is shown in Fig. 14.

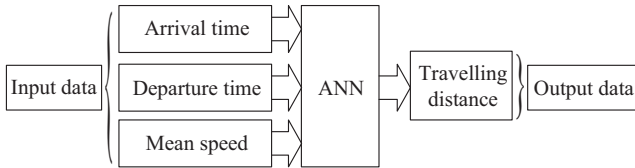


Fig. 14. Overall structure of ANNs for PEV modeling.

The significant feature of this method is that it can coordinate the travelling distance with the arrival time and departure time of the PEVs that can increase the accuracy of the results.

It should be noted that the ANNs in this section are deep ANNs and the conventional networks do not have the ability to model PEV. Furthermore, special methods such as restricted Boltzmann machines and metaheuristic algorithms are needed for network pre-training.

G. Markov Chain Theory

In the Markov method, with the historical data, the future state of the system is investigated. Markov chain has many applications in anticipating different phenomena. The main feature of the Markov chain method is its efficiency in both statistical and temporal appearances of the datasets. The procedure for PEV modeling using the Markov chain method is comparatively clear. Primarily, all the values of the studied phenomena are dispersed into several states. Next, consider-

ing that the series of states are lined by a homogeneous Markov chain, a transition probability matrix of these states is determined. Then, this matrix is applied to create a new chain of states. Finally, each state in this new chain is transformed into a PEV parameter value with a firm random generator. In fact, in the Markov method, the predicted values are based on the probabilities obtained from the historical data of the PEVs. In this method, the parameters such as arrival time, departure time and travelling distance are predicted independently by specific Markov chain models. The states categorization for each variable is unique and these states are determined with regard to the training data set.

It is important to note that the optimal selection of state interval has a significant impact on the computation time and the accuracy of the results. Since the Markov chain method has a strong memory and examines the problem space carefully, it is an appropriate method for modeling the behavior of PEV.

H. Stochastic Modeling Using PDFs

Due to the fact that all PEVs do not start to charge simultaneously, the charging starting time for the PEVs can be modelled using a PDF that can be determined by several factors such as electricity tariff and PEV driving patterns [104]. In this method, the PDFs can be applied on several parameters of PEVs such as initial SOC, travelling distance, starting time of charging, etc. The main issue that should be considered in this method is the selection of the proper PDFs. Unsuitable PDFs result in unreliable output. In addition, the correlation between the PEV data is not considered in this method, which is its main drawback.

I. Copula Method

In this technique, the correlations between the PEV parameters are firstly modeled using Student's copula distribution. Then, the MCS is utilized to extract the PEV load demand. The copula utilization before MCS makes the extracted load more reliable and more accurate. Some researches are carried out to model the PEV load demand [105]-[107].

In some cases without enough available data, a distribution function is applied on the data. Generally, a normal distribution function is fitted to the data, while it may not present the PEV behavior properly. Therefore, a multi-variate stochastic model should be applied on the available data so that the correlations between the data are taken into account. For this purpose, the copula function can be used that characterizes the dependencies between the variables and creates the unique distribution for correlated multi-variate data modeling. More details about copula method can be found in [108].

J. Comparison of Methods

Each of the investigated methods have unique specifications that make them sufficient for individual applications. Table VIII represents the advantages and disadvantages of each method. The modeling complexity, output accuracy, time computation cost, uncertainty modeling of PEV data and their correlations are the main features that are investigated in this section.

TABLE VIII
LIST OF ADVANTAGES AND DISADVANTAGES OF ALL METHODS

Method	Advantage	Disadvantage	Specification and application
Deterministic method	<ul style="list-style-type: none"> - It is very simple - The historical data are not needed - The computation cost is very low 	<ul style="list-style-type: none"> - The output is not accurate - The PEV data uncertainty is not considered 	<ul style="list-style-type: none"> - It is suitable for the studies that intend to investigate the PEV impact approximately
Scenario reduction method	<ul style="list-style-type: none"> - It is simple - It can be modeled without historical data - The computation cost is low 	<ul style="list-style-type: none"> - The output is not accurate - The data uncertainty is modeled approximately 	<ul style="list-style-type: none"> - If the historical data are available the results will be more accurate
MCS	<ul style="list-style-type: none"> - The accuracy of the output is high - The data uncertainty is modeled properly 	<ul style="list-style-type: none"> - The correlation between the data is not considered - Its accuracy depends on the historical data accuracy and sample number 	<ul style="list-style-type: none"> - For any applications that the MCS should be carried out many times (e.g., metaheuristic based optimization), the computation cost will be very high
Fuzzy method	<ul style="list-style-type: none"> - It can be modeled without historical data - The load uncertainty is modeled - It can be combined with other methods (e.g., MCS) to reach more accurate results 	<ul style="list-style-type: none"> - The accuracy of the results depends on fuzzy logic setting that is based on the researcher experience 	<ul style="list-style-type: none"> - For any studies that the historical data are not available, this method is very sufficient
Hybrid fuzzy-MCS method	<ul style="list-style-type: none"> - In addition of temporal, the spatial uncertainty can be modeled - The accuracy of the output is excellent 	<ul style="list-style-type: none"> - The combined possibilistic and probabilistic modeling make it more complex - The computation cost is high 	<ul style="list-style-type: none"> - Both spatial and temporal uncertainties can be modeled
ANN method	<ul style="list-style-type: none"> - The uncertainty of input data with rough structure neurons can be handled - The behavior of under-study phenomenon is learned with high accuracy - The correlation of forecasted data with observed data is considered 	<ul style="list-style-type: none"> - It highly depends on the input data fluctuations - It has weak performance for the phenomenon with low dimension of previous data - In deep learning mode, it will be faced with convergence challenges 	<ul style="list-style-type: none"> - This method acts like a black box and forecasts the phenomenon just with previous data and without any background knowledge - The main features of input data in deep learning mode can be extracted
Markov chain method	<ul style="list-style-type: none"> - All of the events in the transition matrix with high precision memory are considered - The accuracy of the output is very high - For any case with high denoising data, it has good performance 	<ul style="list-style-type: none"> - It highly depends on the number of states and states interval - It highly depends on initial state - It has high computation cost for a case with a large number of states in the transition matrix - It has low performance in a case with low input data dimension 	<ul style="list-style-type: none"> - In any case that needs the PEV model as time series, it will have a good performance - The sequence of the events in PEV forecasting procedure can be modeled in this method
PDF fitting method	<ul style="list-style-type: none"> - It is simple - The load uncertainty is modeled approximately 	<ul style="list-style-type: none"> - The output is not accurate 	<ul style="list-style-type: none"> - It is suitable for any case that requires modeling of load uncertainty with least complexity
Copula method	<ul style="list-style-type: none"> - The output results are very accurate - The correlation between data can be modelled accurately 	<ul style="list-style-type: none"> - The complexity of the method is very high - The computation cost of the procedure is high 	<ul style="list-style-type: none"> - It is suitable for any study where the accuracy of output is very essential and the computation cost and complexity of the problem are not important

VI. POTENTIAL RESEARCH AREAS

In this section, some interesting and important research areas, that can be considered in the future works, are listed as follows.

1) Modeling a linear equation for PEV battery degradation

As mentioned in Section II, the battery degradation cost should be included in the objective function of smart charging. However, most of the proposed models for battery degradation are nonlinear or empirical-based. These models result in nonlinearity of optimal charging methods, which makes the optimization a sophisticated problem. The linear model for battery degradation causes the optimal charging of PEVs to be simpler and more accurate. Moreover, the battery type of several vehicles is different and has its own individual characteristics. Extracting a linear model that can be

applied to all battery types will be very helpful.

2) Assessing PEV charging impact on power quality

The PEV charging may has the potential impact on total harmonic distortion (THD) within the power grid. It is necessary to evaluate the impact of all charging levels, especially charging level III, on the power quality indexes such as voltage sag and swell, unbalancing and THD. The power quality index may be a constraint for penetration limitation of PEVs in the power grid.

3) Modeling temporal and spatial uncertainties

Although the temporal and spatial uncertainties are modeled in some works such as [102], [103], a developed probabilistic method is necessary to model both of these uncertainties properly.

4) Investigating social benefits of smart charging

As indicated in Section II, the smart charging of PEVs

has several benefits from different points of view. However, the social benefits of smart charging such as environmental profits need to be further investigated.

5) Considering unbalanced load flow

Even though the distribution networks are inherently unbalanced, they are often considered as the balance in power systems in the literature. The PEV load demand, especially in high penetration, increases the unbalance of power grid. The consideration of this unbalance will increase the accuracy of load flow analysis.

6) Forecasting PEV load

In most works, it is assumed that the penetration of PEVs increases with a fixed rate every year. If the PEV load demand is forecasted for the coming years, similar to conventional load, it will be very useful especially for component planning studies.

7) Evaluating DC fast charging in distribution networks techno-economically

The charging period of PEV is one of the main challenges for PEV owners. The DC fast charging can decrease the charging period properly. However, this charging method should be further evaluated from both technical and economic points of view.

VII. CONCLUSION

In this paper, firstly, the introduction of EVs and their challenges in nowadays power and energy systems are presented. Then, all EV charging strategies are classified and their characteristics are presented. It is shown that the preference of PEV owners and PEV manufacturers is the uncoordinated charging strategy, while the preference of power grid operator and environment is the smart charging strategies. The perspectives of EV owners, power grid operator, EV manufacturers, and environment are evaluated. Moreover, the most popular methodologies are investigated for EV load modeling, including deterministic method, scenario reduction method, MCS, fuzzy method, fuzzy-MCS method, ANN, Markov chain method, and copula method. The advantages and disadvantages of each method and some hints and tips for better simulation are presented. Finally, some potential research areas are presented for the future works.

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