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Assessing Impacts of EV Parking Lots on Distribution System Reliability with Consideration of User Behavioral Uncertainties

In recent years, the popularization of electric vehicles (EVs) brings about the spring-up of chargeable parking lots (PLs). In practice, since a PL system with hundreds of integrated EVs may act as either a controllable load during the charging period or an alternative distributed energy resource for the grid during the discharging period, it could provide various technical and economic benefits which can be exploited by the future energy systems. Under this background, this paper carries out a study to analyze the potential contribution of EV PLs for the reliability of future distribution grids. Reliability indices are calculated using a stochastic generation capacity model of a PL together with the load and the component outage data of the distribution feeder. A compound algorithm based on sequential Monte-Carlo simulations is employed to implement the entire evaluation. Numerical results show that the appropriate utilization of PL energy storage capability can largely improve the supply adequacy of distribution systems, which proves the effectiveness of the proposed method.

Keywords: Electric vehicle; Parking lots; Vehicle-to-Grid; Operating reserve; Behavior.

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1. Introduction

With the deterioration of fossil energy shortage and environmental crisis, improving the efficiency of energy usage has become an important trend throughout the globe. On the other hand, the development of smart-grid technology also enables more and more distributed energy resources, such as electric vehicles (EV) to be connected to the distribution network [1]. However, with the increasing penetration of distributed energy sources, the distribution network is confronted with significant challenges due to increasing energy demand arising from EV charging loads.

Among the numerous challenges as stated above, one of the most remarkable pertains to the reliability of supply. As is widely known, as a special type of electricity loads, the energy needs/charging behaviors of EVs is highly stochastic in nature [2]. When connecting to power grid with large quantities, they will increase the power supply pressure of the grid due to the uncoordinated charging [3]. Besides, simultaneous EV charging would also increase the energy loss of distribution network and exacerbate the voltage quality of electricity supply, thus bringing adverse impact to the reliability performance of distribution system. However, on the other hand, with the development of Vehicle-to-Grid (V2G) technology [4] in recent years, it makes EVs capable of providing power back to the power grid by using the energy stored in their own batteries. So the EVs integrated with V2G can be used in peak shaving/valley filling or participate in the economic operation of power systems. Moreover, they can be utilized as alternative supplies under dynamic pricing conditions, when feasible. At this point, the aggregated form of EV batteries via public charging infrastructures may

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behave a crucial role for restoration of critical loads during emergencies and thus make a positive contribution to the reliability performance of distribution systems.

Having realized the potential significant role that EVs may play in the future power grid and its double-planedness nature, a growing number of researches have been conducted that focus on the reliability analysis of distribution system with parking lots (PLs) recently. For example, a novel two-stage stochastic programming model that utilizes PLs to promote wind power usage is proposed in [5]. Also, in [6], the impact of controlled EV charging on the voltage profile of smart distribution system is investigated by conducting unbalanced three-phase load flow calculation. Reliability impacts of electric vehicles under battery exchange mode on distribution system reliability was demonstrated in [7]. Besides, some other researches mainly focus on the influence of EV load randomness on the performance of distribution network and its optimal solution strategy. Reference [8] proposed a comprehensive methodology to evaluate the improvement of the reliability of distribution systems in the presence of PLs. By using the sequential Monte Carlo simulation (SMCS) technique, Xu and Chung [9] assessed the potential improvement of supply adequacy by incorporating V2G via PLs, under different modes of system operation. Besides, in [10], a novel multi-objective EV charging station planning model with the consideration of distribution network reliability is proposed. By utilizing statistical modeling method, reference [11] put forward an EV charging and discharging model and applied it to the distribution system analysis with PLs. The impact of EV aggregation on the distribution system performance were also discussed in [12]. Similarly, a reliability evaluation algorithm for distribution network under V2G mode with consideration of equipment breaking probability and load transfer were developed in [13]. Finally, the authors of [14] also provided an evaluation framework for analyzing the reliability of distribution network which takes into account the interaction between EV users and the grid.

Through the above literature review, it can be seen that considerable works have been done about the distribution system reliability analysis including the effects of EVs. However, in these existing studies, it has always been assumed that the charging profiles of EV users could be fully determined in advance and the EV users would be fully willing to involve in the V2G program. However, in practice, since different individuals may have different attitudes towards V2G participation [15], the uncertainties involved may considerably impact the generation capability of PLs.

In order to provide a more effective analysis on the capacity benefits of PL, this study use real data from a PL project and a real distribution feeder test case to establish a distribution reliability evaluation model. Moreover, a new compound model for PL characterization which takes into account the effects of both technical and human factors is also developed. The proposed reliability model of PL is applied into the reliability evaluation procedures of distribution system, wherein SMCS is utilized to realize the estimation of PL benefits.

The rest of this paper is organized as follows: Section 2 presents the reliability model of distribution system components including transformer, feeders and load demand. Section 3 elaborates on the reliability modelling of EV PL. On the above basis, in Section 4, the evaluation algorithm used for performing system reliability analysis with PLs is described. The numerical studies and the relevant result analysis are provided in Section 5. Finally, Section 6 presents the conclusion of this work.

2. Reliability modeling of system components

In this paper, we consider a general distribution system comprising substations, load users, and EV PLs, etc., which operates under the centralized control scheme. An overview of a typical distribution system with EV PLs is illustrated in Fig.1. In this section, the reliability representation for different system components are described.

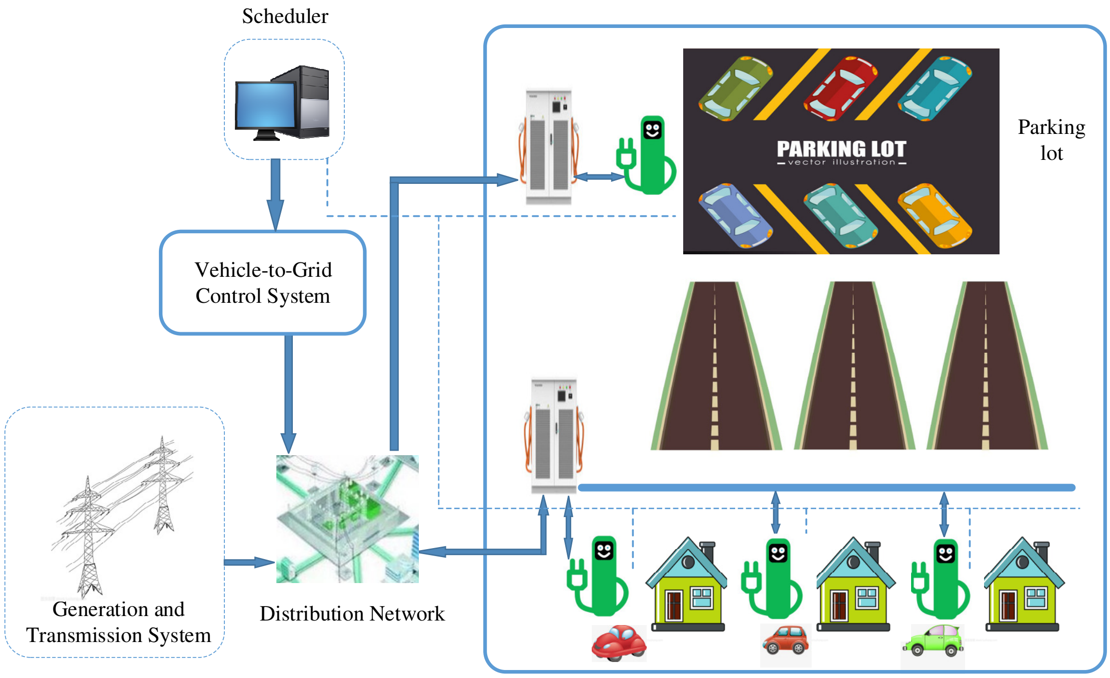

Figure 1: Configuration of a distribution system with EV PL

2.1. Distribution transformers

As the main power source for distribution grids, transformers are controllable stationary devices. In practice, since the possible contingencies in the external grid may cause uncertainties for the operation of distribution transformers, to account for this effect, it is assumed that the available power from the external grid follows a uniform distribution relative to the capacity of the substation [0.8, 1], as suggested in [16].

2.2. Feeders

The system under study is a practical urban distribution grid, which comprises six feeders and corresponds to a standard voltage level of 10kV. The structure of the network is shown in Fig. 2. The concerned distribution system is connected to the transmission network via a main substation at bus 0. The substation has been installed with four identical transformers and each has nominal capacity of 6 (MW). The failure rate, and repair time of different components in the system (e.g., cables, busbars, breakers, etc.) are determined based on the real survey data in Beijing, and are summarized in Table 1.

Based on the reliability data as given in Table 1, the mechanical model of each system component can be then created. In reliability studies, the up and down states of the network components would be normally represented using a two-state Markov model [17]. If a component is in the down state, it means that this unit would be out of service and is unable to transmit power from the power sources (i.e., substation) to loads; otherwise, it implies that the component is in service and is operating in a healthy state.

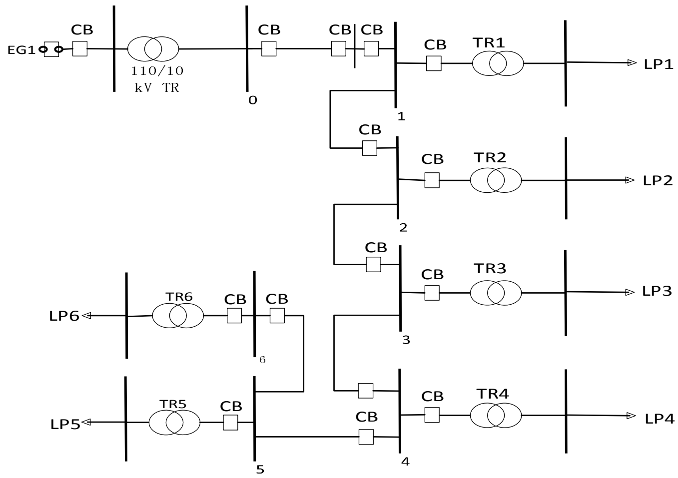

Figure 2: Distribution network

Table 1: Reliability data of studied system

Index	Transmission grid	110 /10kV transformers	Busbar
Failure rate (time/year)	0.1	0.6	0.22
Average repair time (hour)	7.5	3	5

2.3. Loads

The distribution network concerned in our study generally comprises six load points, which has an annual peak load of 18.73 (MW). Total 1281 households are connected and get power supply from this system. These customers can be roughly divided into four categories (namely residential, commercial, office, small industrial), according to their load profile for a typical day as in Fig.3. The composition of system users for each load feeder is shown in Table 2. With these information, the chronological demand pattern of the system can be determined, which will be used as input parameters for the reliability analysis in this study.

Table 2: Load data

Bus	Load (MW)	Percentage of system load (%)
1	2.30	12.28
2	4.72	25.20
3	2.19	11.69
4	3.78	20.18
5	1.58	8.44
6	4.16	22.21
Total	18.73	100.00

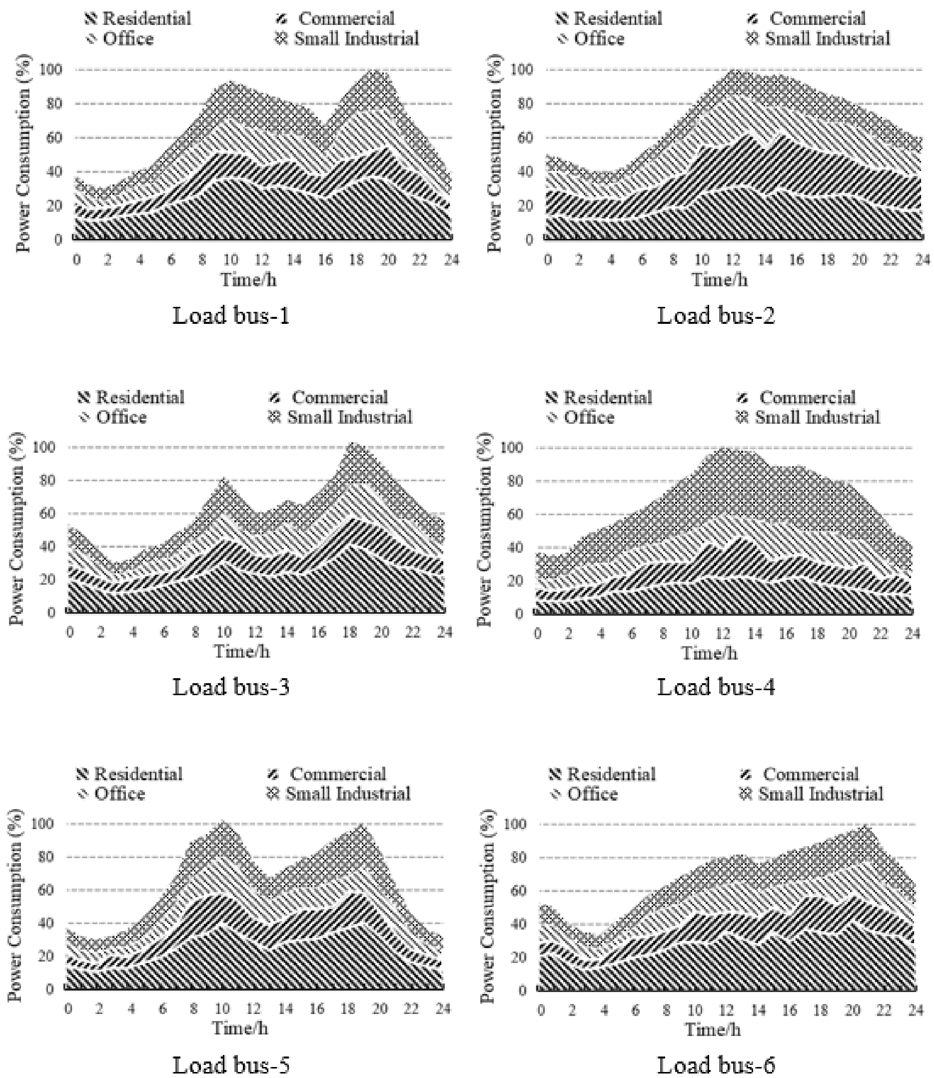

Figure 3: Daily load curve for different system buses

3. Reliability modelling of EV PLs

Precise modelling of EV PL operation characteristics is the first step for distribution system reliability assessment. In practice, the available power output of EV PLs, depends on many factors, such as arrival/departure pattern of EVs, battery capacity of EVs, and operation constraints of charging/discharging facilities. In this study, we propose a compound modelling framework to represent the benefits of PL for the reliability of distribution system. In this section, a series of mathematical models are developed to describe the effects of each component.

In practice, the energy storage capability of PLs is stemmed from the presence of EV batteries, which is essentially dictated by the charging behaviors of EV users. Driving pattern and parking time depends on the driver behavior. To consider this, this study is based on the real data of a representative PL located in the downtown of Beijing. The capacity of the PL is 300 cars with an average 520 arriving/departing cars in a weekday. In this work, the traffic flow of EVs are modelled by probability density functions (PDF). For not losing generality, it is assumed that the arrival times follow the Normal distribution as expressed in (1):

$$f(t_{arr}) = \frac{1}{\sqrt{2\pi}\sigma^l} \exp[-\frac{(t_{arr} - \mu^l)^2}{2(\sigma^l)^2}] \tag{1}$$

where μ^l and σ^l are the mean value and standard deviation of the load demand.

Unlike arriving times pattern, departing times are more dispersed along the day. They depend on the users' intentions and have close correlation with the arrival times. For example, the cars arriving in the morning hours generally stay all the day, whereas, cars arriving after 9:00 a.m. stay relatively shorter in the PL. Therefore, we preferred using parking duration instead of departure time as a function of arrival time [8]. To achieve this, kernel smoothing function [18] is used for better fitting. Through the best-of-fit analysis, the Weibull distribution is identified to be the optimal form of PDF for representing the parking duration of EVs, and its mathematical expression is presented in (2).

$$f(t_{duri}) = \frac{k}{c}(\frac{t_{duri}}{c})^{k-1} \exp[-(\frac{t_{duri}}{c})^k] \tag{2}$$

where k and c are the shape parameter and the scale parameter, respectively.

Then, the expected departing time of an EV from the PL can be derived as:

$$t_{dep} = t_{arr} + t_{duri} \tag{3}$$

Besides the abovementioned EV driving patterns, in reality, not all EVs passing by the PL will enter the PL to get charged. In general, whether will they choose to charge in the PL is determined by the battery state and the charging price provided by the PL operator. If the state-of-charge (SOC) of EV battery is enough to drive towards home, then the user can choose to charge at home, otherwise, he will charge in the station. Besides, even if the state of battery is sufficient, the owners will be likely to charge in the station when the retail price to customers is low. The willingness of EV users reflects the occupancy rate of charging piles in the PL. We statistically analyze relevant historical data from the PL in Beijing. The cross-correlation among these data is presented in Fig. 4.

As can be seen, the correlation between the EV owners' choices and their battery state is significant; besides, we also observe a meaningful correlation between owners' choices and the retail prices. In order to capture the cross-correlation among the EV owners' choices, SOC and the retail price, we define that the probability of EV owners selecting to charge via the PL as the synthesized results of EV's initial SOC and the price offer of PL operator. Using the classic weighted summation method, it can be represented as follows:

$$\gamma_t = \frac{A}{w \times SOC_t + (1-w) \times \left[\pi_t / \max_{\tau \in 1:t-1}(\pi_\tau) \right]} \tag{4}$$

where w is a parameter used to quantify the relevant weight of battery state and retail price; A denotes a parameter that needs to be derived through the data sample points.

As observed, the values of the retail price is normalized with respect to the corresponding maximum prices over time ($\tau \in 1 : t-1$). Given the time period t, we can collect different EV users' willingness, then the occupancy rate at this time could be derived by averaging these rates, as follows:

$$\bar{\gamma}_t = \frac{\gamma_{1,t} + \gamma_{2,t} + \ldots + \gamma_{K,t}}{K} \tag{5}$$

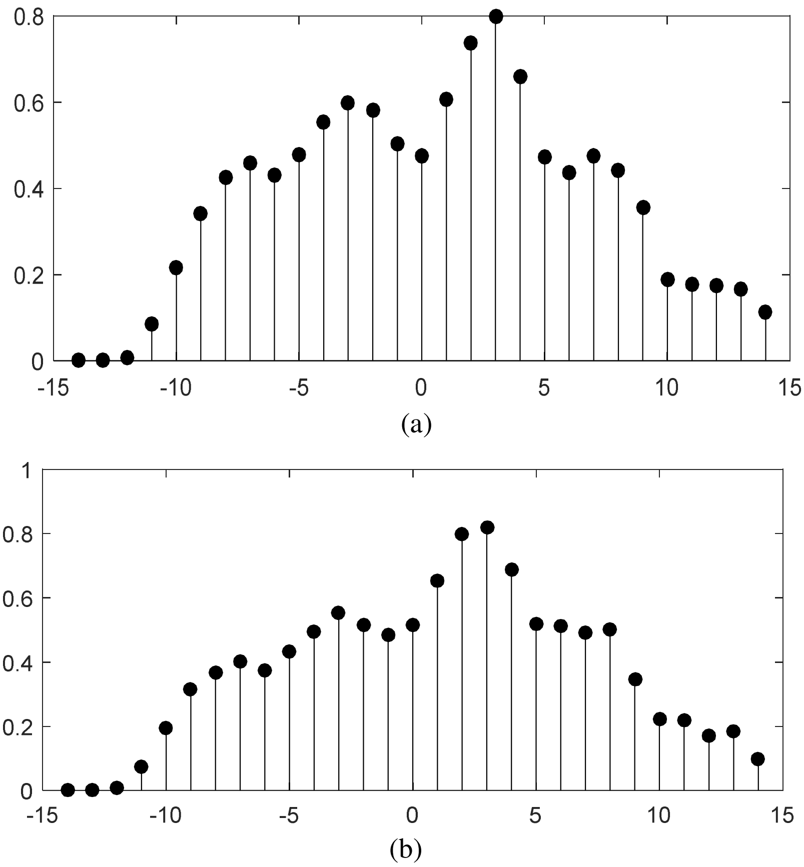

Figure 4: Cross-correlation between (a) probability of entering the PL and battery SOC, (b) probability of entering the PL and charging prices

Based on the above formulations, the available power output of PLs for each time-period can be computed. To do this, we consider that the maximum charger power is 12.5 kW; also, to ensure an EV can have an acceptable charge level to support its subsequent trip upon departure of the PL, it is also assumed that the SOC of EV in the PL should not be less than 30% of their rated value. On this basis, the SMCS is used to perform this computation. Following 1000 runs of the algorithm, the expected power output of the representative PL is calculated for each hour of a day and the results are depicted in Fig.5. The results show that available power output of EV PLs have a considerable storage capacity during midday hours whereas a lower value in the morning and evening. This means that the PL may have different contributions to the system supply capacity for different time of a day in the real-life application.

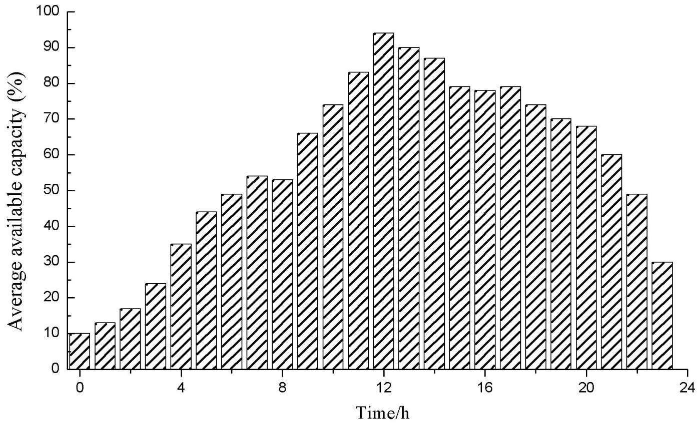

Figure 5: Average available power output from PL

4. Evaluation algorithm

In this study, to determine the PL contribution to the supply reliability of distribution system, a comprehensive evaluation algorithm based on the SMCS method is employed. Compared with other reliability analysis methods, the main advantages of SMCS lie in that it can accurately evaluate frequency and duration indicators and simulate any forms of distributions about the state duration. Moreover, SMCS gives expected value estimates of reliability indicators and provides samples of time-related reliability indicators, which is particularly suitable for power system reliability evaluation with inter-temporal constraints [19].

In this paper, the proposed PL model as described in Section 3 is used to evaluate the reliability of distribution system together with load and component data in Section 3. Three classical indices, namely the System Average Interruption Duration Index (SAIDI), the System Average Interruption Frequency Index (SAIFI) and the Expected Energy Not Supplied (EENS) are selected as the indicators for quantifying the reliability of supply from the perspective of electric power utilities; while interruption frequency (IF), interruption duration (ID) and energy not supplied (ENS) are used for reliability index of load point [20]. This study focused on the backup support from the PL when there is a deficit of generation supply due to system component outages. In practice, since PLs should act as a system load during the charging phase, we combine PL load curve with the load curve of the system to form the final load data used for the reliability calculations.

The entire simulation is programmed in the Matlab environment and executed in a PC. The relevant calculation results can be used to determine the impact of EV PLs on distribution system reliability indices. The flowchart of the reliability evaluation procedures with PLs is illustrated in Fig.6, and a brief description about the algorithm is provided below.

As can be seen, our proposed evaluation algorithm starts with the random generation of the state-duration time series for the system components (including transformers, feeders, and transmission grid) according to their reliability parameters (i.e. failure/repair rates) using the inverse transform method [21]. Based on these data, the available generation capacity in the system can be determined. On the other hand, according to the predefined operation policy of PL, the charging/discharging power the associated with the PL can be computed (in this study, we utilize the derived outcome in Fig.5 as the input data of the evaluation). Based on the charge/discharge schedule of PL, the final load curve (time-series) of the distribution grid will be determined, by synthesizing the regular load demand of customers. Then, a comparison will be made for the total available generation capacity with the system load demand for each time period to determine whether a loss of load situation occurs. If so, we will update the results of reliability indicators and record the data. Otherwise, the simulation will continue. The above procedures will be repeated until the convergence criteria of SMCS could be satisfied. Then, the values of reliability indices that obtained hitherto would be exported as the final evaluation results.

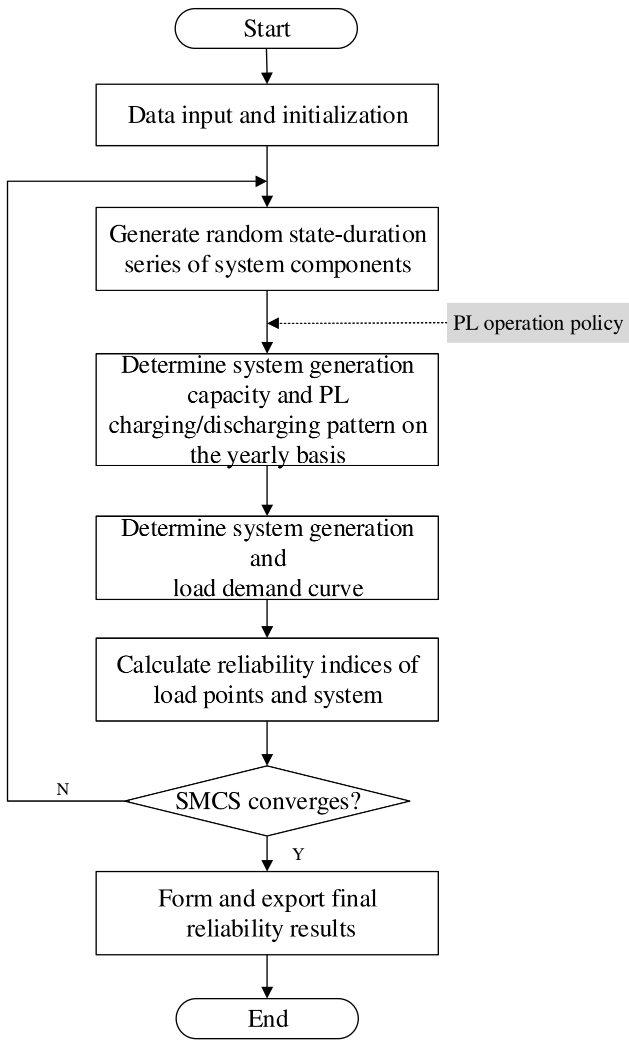

Figure 6: Flowchart of evaluation algorithm

5. Case study

In order to demonstrate the effectiveness of the proposed evaluation method, a series of numerical studies are conducted in this section.

To achieve this, it is arbitrarily assumed that the PL under discussion is connected to the concerned distribution network (Fig.2) through a distribution transformer at bus 6. The bidirectional charger (BC) deployed in the PL has a rated charging and discharging capacity of 12.5 (kW). Besides, for simplicity, we use the BAIC-EC200 [22] to represent the whole

EV population for the PL in this study. Five different scenarios as shown in Table 3 are defined and considered in our analysis since they represent the most common operation modes of PLs under the current market settings.

Table 3: Scenario settings

Case	Description
I	PL is consistently operating at the Grid-to-Vehicle (G2V) mode only.
II	1. PL may work at V2G mode from 7:00 to 12:00 in case of system contingencies, which is characterized by its available generation capacity in Fig. 5 and G2V mode in other time periods.
III	PL may work at V2G mode from 13:00 to 20:00 in case of system contingencies, which is characterized by its available generation capacity in Fig. 5 and G2V mode in other time periods.
IV	PL may work at V2G mode from 13:00 to 20:00 in case of system contingencies, which is characterized by its available generation capacity in Fig. 5 and G2V mode in other time periods. But the discharging rate of BCs is set to 70% of its rated value.
V	PL may work at V2G mode from 13:00 to 20:00 in case of system contingencies, which is characterized by its available generation capacity in Fig.5 and G2V mode in other time periods. But the discharging rate of BCs is set to 120% of its rated value.

Based on the above explanations, the calculation results of system and customer reliability indices under different cases are reported in Table 4.

Table 4: Calculation of reliability indices

Case	System		Customer	Load point					
				LP1	LP2	LP3	LP4	LP5	LP6
I	SAIFI (time/c-y)	6.19	LPIF (time/y)	7.91	10.53	5.11	6.72	3.98	7.91
	SAIDI (h/c-y)	23.15	LPID (h/y)	26.04	30.59	18.56	22.81	10.17	26.04
	EENS (kWh/y)	737.35	LPENS (kWh/y)	58.96	261.87	64.78	74.61	47.50	187.83
II	SAIFI (time/c-y)	5.82	LPIF (time/y)	6.63	7.12	4.80	6.07	2.56	6.63
	SAIDI (h/c-y)	22.23	LPID (h/y)	24.87	27.14	18.37	22.02	10.15	24.87
	EENS (kWh/y)	693.84	LPENS (kWh/y)	58.96	261.07	61.58	72.21	41.62	158.77
III	SAIFI (time/c-y)	5.87	LPIF (time/y)	6.75	7.25	4.91	6.12	2.78	6.75
	SAIDI (h/c-y)	23.02	LPID (h/y)	24.92	28.61	18.15	22.59	10.04	24.92
	EENS (kWh/y)	702.76	LPENS (kWh/y)	58.59	261.87	63.70	72.60	42.95	161.63

IV	SAIFI (time/c-y)	6.01	LPIF (time/y)	7.19	8.06	5.08	6.25	3.25	7.19
	SAIDI (h/c-y)	23.08	LPID (h/y)	25.03	28.65	18.43	22.45	10.11	25.03
	EENS (kWh/y)	723.50	LPENS (kWh/y)	58.59	261.87	64.78	73.24	43.73	170.58
V	SAIFI (time/c-y)	5.45	LPIF (time/y)	6.03	6.51	4.52	5.78	2.27	6.03
	SAIDI (h/c-y)	20.67	LPID (h/y)	22.13	23.95	18.01	21.47	10.02	22.13
	EENS (kWh/y)	653.63	LPENS (kWh/y)	58.60	260.32	60.87	69.55	38.61	149.88

As can be seen, in #1, since the PL does not provide capacity support to the grid during emergencies, the reliability performance of the distribution system is the most unfavorable among all the scenarios. Moreover, as the recharging needs of EVs increased the load demand of the entire system, the adequacy of supply in this case should be even lower than that without the installation of PL. In this sense, the presence of PL could degrade the reliability of distribution grid, without the involvement of V2G operations.

In Case II, we assumed that the PL could operate at the V2G mode in the morning session and provide the required capacity support to the grid if there is deficit of power due to source or component outages. The maximum discharge power of the BC is considered the same to its nominal value. According to the results in Table 4, it can be seen that the incorporation of V2G makes the system had a remarkable improvement in their reliability. Compared with #1, the indices of SAIFI, SAIDI, and EENS got a reduction by 5.8, 4.0, and 5.9 %, respectively. Besides, there is also obvious improvement in the supply adequacy at the demand side. The most significant change occurs at bus 6, since its location is the closest to the location of PL, thus its supply could be influenced by the V2G power to a larger extent.

In Case III, the operation scheme is the same as Case II, but the V2G implementation takes place in the afternoon session every day. As can be seen from Table 4, the improvements of system reliability indices due to PL installation are almost the same as in Case II; whereas customer reliability indices' improvements become more significant than Case II. Such contrast implies that the capability of PL for capacity support is not sensitive to the time moments of the day, but it could impose a considerable impact on the quality of power supply for customers.

In Case IV, the same PL operation policy is considered but we assume that the BC has a decreased discharging rate of 8.75 (kW). This scenario is designed mainly used for illustrating how the PL's reliability benefits would be changed if different type of BCs were considered. The calculation results in Table 4 show that, the reliability indices of the distribution system, as well as those with respect to the demand side all deteriorate as compared with Case III. This suggests that the capability of PLs to provide reliability benefits is strongly correlated to the technical specifications of its components. Since BCs with a smaller discharging rate could provide less capacity support during contingencies, therefore, it contributions to the system reliability would be less significant than that for Case III.

Finally, in Case V, we focus on the similar setting as to Case III and IV, but the V2G capability of BCs is assumed to be grown up to 15 (kW) in order to cover more severe generation deficiencies of the system. The obtained calculations in Table 4 show that the reliability indices of the system are improved to a large extent. Meanwhile, the reliability indices of load points are also significantly improved, where the most significant improvements take place at load bus 5 and 6. This implies that the presence PLs may bring about different benefits to the customers, which mainly depends on the location of the load points and on the power consumption patterns of the demand-side.

6. Conclusion

This work carries out a study for investigating the effects of EV PL on the reliability of distribution systems. To achieve this end, first, a new PL model was established which describes the available power output to the grid, based on the actual statistic traffic data in Beijing. On this basis, according to the outage data of a local distribution network, the reliability model for distribution system components is derived. By combining the formulation of PL and distribution grid, we develop a new evaluation framework for the reliability of smart distribution system with inclusion of PLs. Differing from existing studies, the impacts of both technical and human factors on the PL performance are all considered in our assessment. To prove the effectiveness of the proposed framework, a series of numerical analysis is conducted based on a real-world test case. The simulation results show that PLs could make significant contribution to the reliability of supply in the future smart distribution system, after considering PL as backup generation units during emergencies. However, to what extent the PL could make to system adequacy is affected by various issues, which primarily include the duration of V2G availability, the discharging capacity limit of BCs, and load distribution in the system, etc.. In practice, this implies that PLs may be not always capable of providing the required reserve service to the grid with an acceptable financial cost as conventional back-up resources. However, if the operation based on the power market is also taken into account, the economic benefits generated by the storage capacity of PLs may become more competitive in the future.

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