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RELIABILITY ASSESSMENT OF SPATIAL-TEMPORAL EV CHARGING PENETRATED DISTRIBUTION NETWORK

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ABSTRACT

Due to the introduced spatial-temporal uncertainty and flexibility of the increasing Electric vehicle (EV) charging load, distribution network operation will be greatly impacted by the large-scale EV charging power. This paper proposes a reliability assessment approach considering the stochastic EV charging and movement in an integrated power and traffic system. The improved sequential Monte Carlo method is applied to evaluate the reliability of distribution network. Based on a spatial-temporal charging load model, the influence of different factors on the reliability for distribution network is analyzed in a case, including permeability and the ratio of trip chain, which provides a theoretical basis for the formulation of orderly charging strategies and the planning of charging stations. Furthermore, the reliability analysis considering the future distributed generators (DGs) and EVs development mode is given.

Keywords: Electric vehicle (EV), charging load, reliability assessment, distribution network, improved Monte Carlo method

NONMENCLATURE

Abbreviations	
LOLP	Loss of load probability
SAIFI	system average interruption frequency index
SAIDI	system average interruption duration index
EENS	expected energy not supplied
Symbols	
i	Travel times
T_{ch}^{i}	Charging duration time in i-th trip
SOC_t	State of charge at time t
X_d	Travel distance
w	Power consumption per unit mileage
$P_{(.)}$	Charging power
C	Battery capacity
$R(s_n)$	A route set within s_n road
P_{EV}	Electric vehicle permeability
P_{DG}	Distributed generator permeability
N_2	Maximum number of MC simulations

1. INTRODUCTION

To reduce greenhouse gas emissions by replacing traditional combustion-engine driven vehicles, the increasing distributed generators (DGs) and moving electric vehicles (EVs) are introduced into distribution network [1]. Electric vehicles play the important role in the future energy system. EVs have the advantages of environmental and high energy conversion efficiency. Governments, auto companies and researchers have taken great efforts to promote the development of EVs. Electric vehicles may gradually replace traditional fuel vehicles. The increasing charging demand of moving EVs significantly accelerates the integration of transportation systems and power systems [2]. Moreover, EVs are low-carbon travel as well as consumption part of intermittent renewable energy.

Due to the introduced spatial-temporal uncertainty and flexibility of the increasing EV charging load, distribution network operation will be greatly impacted by the large-scale EV charging power [3]. The normal operation of the power system will be fundamentally affected by a new load peak, consisting of uncontrolled EV charging load and the original load peak. Especially, the reliability could be reduced [4]. Therefore, the research of reliability assessment for distribution network within EVs is necessary.

At present, the research on the impact of charging load on distribution network reliability mainly focuses on such factors including charging mode, permeability and plug-in location. And the charging load model used in this study is relatively simple [5-7]. In [5], the reliability influence of plug-in EV is analyzed from three aspects, including load control type, plug-in location and permeability. EV user behavior and power system dispatching rules are considered in [6], and the impact of plug-in EV grid-connected capacity on power supply reliability is assessment. In [7], according to Monte Carlo method, the sequential operation data of components is obtained, and the influence of PHEV on the reliability of distribution network is discussed. In [8], the information security risk of user side is taken into account, and analyses the reliability of distribution network according to different attack types. In fact, in addition to the above effects, the future impact of distributed generation (DG) in urban distribution network cannot be ignored [9].

The precise spatial-temporal distribution results of charging load can improve the accuracy of reliability assessment. Electric vehicle is closely related to the traffic system and distribution network. Therefore, the research on charging load modeling of EV needs to consider the coupling system [10]. The trip chain takes the randomness of spatial-temporal charging load into consideration and the date of national household travel survey can be utilized [11]. Therefore, on the basis of trip chain and traffic system model, this paper forecasts the spatial-temporal charging load. Based on the relatively accurate forecast results, the analyses the reliability considering the future DGs and EVs development mode.

The rest of this paper consists of four main sections. Section 2 introduces an EV charging load forecasting approach. In Section 3, the improved sequential Monte Carlo method is discussed to assess reliability. An integrated traffic system and distribution network in Section 4 to verify the availability of the proposed method. Section 5 is the conclusion of this paper.

2. EV CHARGING LOAD FORECASTING

2.1 The trip chain

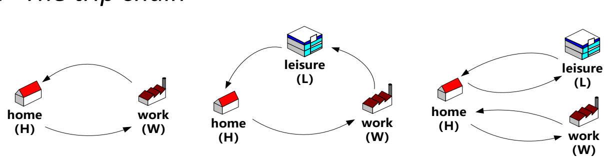


Fig 1 Diagram of the trip chain

The travel demand of EV in urban traffic network can be represented by the trip chain shown in Figure 1. The main destinations of EV are home(H), workplace(W), leisure-related location(L).

The established process of a simple or complex trip chain is as followed: i) According to the survey data, the travel location is classified, and the lognormal probability function is utilized to obtain the first time travel time and last time departure time. ii) The daily destinations with home as the starting point are generated by Monte Carlo sampling method.

2.2 Transportation system modeling

Graph theory [12] is used to establish traffic network model. According to the topology of traffic system, vertex sets ***V*** and road set ***E*** can be obtained by the intersection points of multiple road sections and the number of roads. The shortest path between the vertices is obtained by road weight matrix ***D*** and the shortest path algorithm.

In this paper, considering the traffic network constraints, trip chain and MC method is used to simulate the travel. Assuming that the driver does not detour the original path, he chooses the shortest path. The driving path can be obtained by the Dijkstra shortest path method.

2.3 Charging demand modeling

The charging duration time can be obtained by formula (1).It is took unnecessary time for charging in midway. Therefore, users will only choose midway charging under the condition of formula (2). The location and duration of charging in midway are determined by formula (3-5).

$$T_{ch}^{i} = (1 - SOC_{T_o}^{i} + \frac{w \cdot X_d^{i}}{C}) \cdot C / P_{(\bullet)} \tag{1}$$

$$X_d^{SOC_t} = SOC_{T_0}^{i} \cdot C / w, X_d^{SOC_t} < X_d^{i} \tag{2}$$

$$\sum^{n} d_h < X_d^{SOC_t} (n < g) \rightarrow n \in \{1, 2, ..., N\} \tag{3}$$

$$s_n = \max\{1, 2, ..., \mathrm{N}\},\ s = R^i(s_n) \tag{4}$$

$$T_{mid} = (1 - SOC_{T_0}^{i} + \frac{w \cdot \sum_{h=1}^{s_n} d_h}{C}) \tag{5}$$

where, T_{ch}^{i} is the charging duration time for destination of the i-th trip; w is the power consumption per unit mileage; C is the capacity; $X_d^{SOC_t}$ is the distance corresponding to the initial SOC; $\sum d_k$ is the distance of the N section in a trip; $\{1,2,\ldots,N\}$ is the set satisfying inequality (2); max represents get the maximum of the set; $R^i(s_n)$ represents the node number s_n of the route R in trip i ; $P_{(\bullet)}$ is the charging power, kw ; P_q is the fast charging power.

3. RELIABILITY ASSESSMENT

In composite reliability evaluation studies, repetitive solutions of an optimization problem with an objective function of minimum load curtailment are performed. The sequential Monte Carlo simulation method is used to sample the "operation-failure-operation" process of the system components according to the failure rate and repair rate of the components. Assuming that the duration of components in each state obeys an exponential distribution, the random state of the system is obtained by combining the operation states of components, and the system reliability index is calculated based on the optimal load curtailment model. In the simulation, 10 years is chosen as a Monte Carlo simulation period, and the system load curtailment is solved by the MATPOWER optimal power flow.

The relevant steps of the reliability assessment based on the sequential Monte Carlo are as follows:

1) Set up the initial state of the system and input the original data, including grid structure, conventional load, charging load, power generation, etc.

2) According to the failure rate and repair rate of components, the time series state of components is extracted and the component state matrix is generated.

3) Combined with the component state matrix, when the system is in fault state or satisfies formula (6), the optimal power flow is calculated and the load curtailment is obtained, i.e. EENS.

$$P_{SG}(t) + P_{DG}(t) < P_L(t) \tag{6}$$

Where, $P_{SG}(t)$ is the active power provided by the system generator supply at time t; $P_{DG}(t)$ is the power of DG at time t; $P_L(t)$ is the sum of load and loss at time t, and the loss can be set 5% of load.

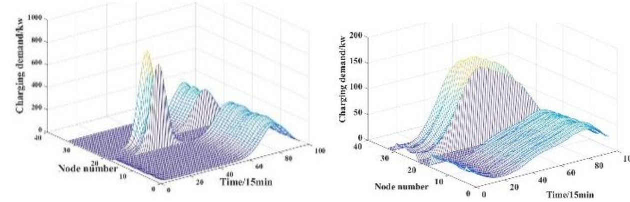
4) The simulation terminates when the maximum number of simulations is N_2 or the convergence condition of equation (7) is satisfied.

$$\beta = \frac{\sqrt{\mathrm{Var}(\rho n)}}{E[\rho n]} \le \varepsilon \tag{7}$$

In the formula, β is the coefficient of variance, $\mathrm{Var}(\rho n)$ is the function of variance, ρn is the estimated value of reliability index (e.g. EENS) after n-th simulation, and ε is the convergence accuracy.

4. CASE STUDY

The 33-bus distribution network [1] is used for case study. The charging behavior can be simulated on the transportation network based on models in Section 2. Then the charging demand of each node in the regional distribution network on typical working days and rest days could be given and shown in Fig 2.



(a)workday (b) holiday

Fig 2 Spatial-temporal distribution of daily charging load

The ratio of peak charging load to peak basic load is taken as the EV penetration P_{EV}. When the generation is enough, the system reliability evaluation results are shown in Table Ⅰ. From the table, it can be seen that large-scale EV connected to distribution network for disorderly charging reduces the reliability, and the higher the P_{EV}, the greater the impact on the reliability of distribution network. Table Ⅱ gives the results of node load loss under different P_{EV}. The results show that bus 7, 8, 9, 18, 26 and 27 have higher loss, which is determined by the distribution network topology. Adding standby power supply near these buses can improve node reliability, which provides data basis for distribution network planning.

Tab. Ⅰ Reliability assessment results

P_{EV}	Reliability results			
	LOLP	SAIFI	SAIDI	EENS
0	0.00141153	11.4986	4.5103	44.5302
20%	0.00141201	11.6148	4.5532	48.3733
38%	0.00140354	11.7960	4.6057	52.1021
50%	0.00145738	11.8218	4.7376	58.4960

Tab. Ⅱ Comparison of node energy not supplied results

bus	P_{EV}		bus	P_{EV}		bus	P_{EV}	
	20%	38%		20%	38%		20%	38%
1	0	0	12	1.948	2.490	23	0.464	0.576
2	0.514	0.597	13	1.728	2.315	24	1.217	1.223
3	0.455	0.497	14	1.356	2.062	25	1.190	1.267
4	0.955	1.167	15	1.082	1.790	26	3.583	3.945
5	1.828	2.003	16	0.822	1.283	27	3.622	4.046
6	2.476	2.619	17	2.059	3.081	28	1.271	1.546
7	4.189	4.624	18	3.215	3.897	29	1.216	1.413
8	4.126	4.528	19	0.513	0.598	30	1.667	2.072
9	4.138	4.560	20	1.458	1.603	31	1.631	1.825
10	2.798	3.369	21	1.157	1.350	32	1.633	1.821
11	2.078	2.661	22	0.791	0.876	33	1.620	1.819

The relationship between different travel chain combinations and reliability indicators is shown in Fig 3. RC is the ratio of simple chain to complex chain. From the graph, EENS increases with the increase of the ratio of complex chain. Based on the development of DG, the influence of charging load on distribution network is analyzed, which may lead to system load loss due to insufficient DG output. Fig 4 shows EENS in two DG scenarios with EV integration.

Scenario 1: Generation limitation is 23 MW, DG installed capacity changed from 2 MW to 10 MW, and P_{DG} gradually increased.

Scenario 2: The total capacity is maintained at 23MW. DG gradually replaces the superior power supply. The installed capacity of DG gradually increases from 2MW to 10MW.

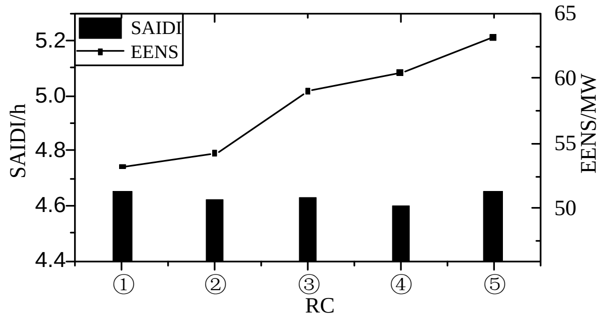


Fig 3 Reliability index of different trip chain ratio

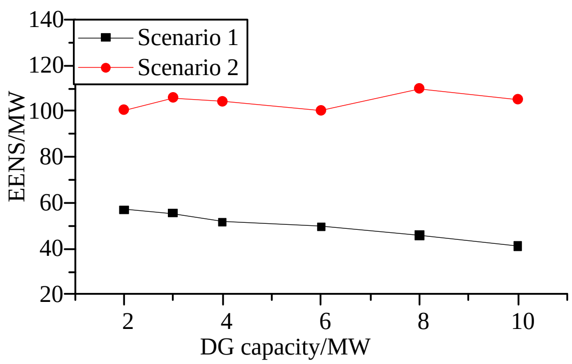


Fig 4 EENS results with different DG capacity settings

The system loss of scenario 2 is significantly higher than scenario 1, and system reliability decreases. This is due to the intermittent output of DG, which cannot meet the new load peak formed after EV access, resulting in system load loss.

5. CONCLUSION

This paper proposed a reliability assessment method considering the stochastic EV charging load. The validity of the method is verified by an example of a coupled traffic network and a distribution network. The results show that electric vehicle penetration, trip chain ratio and different DG scenarios have significant impact on distribution network reliability. In the follow-up study, the relationship between parameters and reliability can be further explored.

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REFERENCE

[1]Xiang Y, Liu J, Li R, et al. Economic planning of electric vehicle charging stations considering traffic constraints and load profile templates. Applied Energy, 2016; 178:647-659.

[2]Cheng X, Hu X, Yang L, et al. Electrified vehicles and the smart grid: The ITS Perspective. IEEE Transactions on Intelligent Traffic Systems 2014; 15(4):1388-1404.

[3]Zhang H, Hu Z, Xu Z, et al. An integrated planning framework for different types of PEV charging facilities in urban area. IEEE Transactions on Smart Grid 2017; 7(5):2273-2284.

[4]Shafiee S, Fotuhi-Firuzabad M, Rastegar M. Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems. IEEE Transactions on Smart Grid, 2013; 4(3): 1351-1360.

[5]Falahati B, Fu Y, Darabi Z, et al. Reliability assessment of power systems considering the large-scale PHEV integration[C]//Vehicle Power and Propulsion Conference (VPPC), IEEE, Chicago,2011: 1-6.

[6]Wu C X, Chung C Y, Wen F S, et al. Reliability cost evaluation with PEV and wind generation system.IEEE Transactions on Sustainable Energy, 2014; 5(1): 273-281.

[7] Wang Z, Yang R, Wang L, et al. Reliability assessment of integrated residential distribution and PHEV systems using Monte Carlo simulation// Power and Energy Society General Meeting (PES), IEEE, 2013: 1-5

[8] Wu Y, Li J, Chen X, et al. Risk analysis of distribution network with large-scale controllable loads being attacked .Automation of Electric Power System， 2018;42(8)： 1-8.

[9]Ge S, Wang H. Reliability evaluation of distribution networks including distributed generation based on system state transition sampling.Automation of Electric Power Systems, 2013; 37(2):28-35.

[10] Mu Y, Wu J, Jenkins N, et al. A spatial-temporal model for grid impact analysis of plug-in electric vehicles. Applied Energy 2012; 94:395-405.

[11]Tao S, Liao K, Xiao X, et al. Charging demand for electric vehicle based on stochastic analysis of trip chain. IET Generation Transmission & Distribution 2016; 10(11):2689-2698.

[12] Tang D, Wang P. Probabilistic modeling of nodal charging demand based on spatial-temporal dynamics of moving electric vehicles. IEEE Transactions on Smart Grid 2016; 7(2):627-636.