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Probabilistic Evaluation of Voltage Quality on Distribution System Containing Distributed Generation and Electric Vehicle Charging Load

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Abstract – Since there are multiple random variables in the probabilistic load flow (PLF) calculation of distribution system containing distributed generation (DG) and electric vehicle charging load (EVCL), a Monte Carlo method based on composite sampling method is put forward according to the existing simple random sampling Monte Carlo simulation method (SRS-MCSM) to perform probabilistic assessment analysis of voltage quality of distribution system containing DG and EVCL. This method considers not only the randomness of wind speed and light intensity as well as the uncertainty of basic load and EVCL, but also other stochastic disturbances, such as the failure rate of the transmission line. According to the different characteristics of random factors, different sampling methods are applied. Simulation results on IEEE9 bus system and IEEE34 bus system demonstrates the validity, accuracy, rapidity and practicability of the proposed method. In contrast to the SRS-MCSM, the proposed method is of higher computational efficiency and better simulation accuracy. The variation of nodal voltages for distribution system before and after connecting DG and EVCL is compared and analyzed, especially the voltage fluctuation of the grid-connected point of DG and EVCL.

Keywords: Composite sampling method, Distributed generator, Electric vehicle charging load, Probabilistic load flow, Voltage quality

1. Introduction

With the vigorous development of new energy generation technologies and smart grid technologies, the electric power distribution system plays an extremely active and significant role in power systems [1]. The stochastic nature of electric power distribution system be strengthened by integrating the large-scale DGs characterized by randomness, volatility, intermittence and uncontrollability in the form of cluster [2-4]. However, the integration of ever-increasing renewable energy resources and the emergence of more active and stochastic new loads such as electric vehicles have the incomparable advantages over conventional cars in alleviating energy crisis, energy conservation, emissions reduction [5], there are more and more uncertainties being introduced in the operation and control of electric power distribution systems [6, 7]. How to properly deal with the randomness and uncertainties has become a severe and practical challenge for the planning and operation of the electric power distribution system. The gradually increasing permeability of wind power generation, solar photovoltaic power generation and electric vehicles in the electric power distribution system is bound to bring impacts and challenges in aspects of voltage modulation, voltage stability as well as evaluation of voltage quality of the electric power distribution system [8-10]. Therefore, considering the output randomness of wind power generation and solar photovoltaic power generation as well as the uncertainty of electric vehicles carries out a probabilistic evaluation of voltage quality, which has great significance in aspects of the economy, security and stable operation in the system [11-15].

The PLF calculation has been put forward and taken for an effective, high-performance, practical research method [16-17], which can evaluate the performance of electric power distribution system considering the stochastic characteristic of DGs and load demand and calculate the output states of the stochastic variables with the numerical characteristic and probabilistic density functions (PDF) and cumulative density functions (CDF) [18]. The main approach of PLF is classified into two categories: the analytical method [19-20] and simulation method [21-22]. Analytical method can lead to great errors by the linearization of nonlinear AC power flow equations around the expected input value region. The representative method of simulation is Monte Carlo (MC) method, which can accurately obtain the probability description of the state variable. Although the MC method can acquire exceedingly precise numerical solutions for PLF, it always takes a large amount of time and suffers from exceedingly heavy computational burden because of the need of a huge number of samples and repeated calculations [23].

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Therefore, the MC method is often used as accuracy references and touchstones for most PLF applications.

Recently, the domestic and overseas scholars have done of numerous investigations in the field of PLF calculation. [24-25] has introduced the point estimate method to perform PLF analysis of the power system considering the stochastic characteristic of DGs and EVCL, which has comprehensively taken into account the EVCL. In [26], the PLF of the power system containing wind turbine and photovoltaic cell system has been calculated with the adoption of the Latin hypercube sampling (LHS) method and Nataf transformation, but the random state of the transmission line has not been considered. In [27], the related investigations have been carried out through the LHS method. Combining LHS method with the important sampling method, a new LHIS method has been put forward. In [28], LHIS method has been introduced to carry out the reliability evaluation of power systems. In contrast with SRS-MCSM, The LHIS method can observably reduce sampling variance and effectively improve sampling efficiency, convergence speed, computational precision, but it is only suitable for random sampling of continuous probability distribution. In [29], the Markov Chain Monte Carlo (MCMC) method is adopted to sample the random state of the transmission line based on discrete probability distribution, which has had the advantages of simple model, fast convergence and so on. The light intensity of photovoltaic cells based on Beta distribution can be sampled by Neyman method, which is simple in mathematics, flexible in calculation, easy in operation, and exact in approximation [30].

Based on the above analyses, a Monte Carlo method based on composite sampling method is put forward to perform probabilistic assessment analysis of voltage quality. According to different characteristics of random factors, different sampling methods are applied. Specifically, LHIS is adopted to sample wind speed, basic load, EVCL, which have continuous probability distribution. Neyman method is adopted to sample light intensity based on a continuous probability distribution, and MCMC method is adopted to sample the random state of the transmission line based on a discrete probability distribution. Simulation results on IEEE9 bus system and IEEE34 bus system demonstrates validity, accuracy, rapidity and practicability of the proposed method.

2. Probability Distribution Model for DG, EVCL, Random-state of Transmission Line

2.1 Probability distribution model of wind power generation

1) Probability distribution model of wind speed: since the randomness and uncertainty of wind power generation is directly related to the randomness of wind speed, it's exceedingly significant to select the appropriate model of wind speed, analysis of a large number of measured data shows that the wind speed in most areas obeys double parameter Weibull distribution [4], PDF of wind speed for wind farm is

$$f(v) = \frac{K}{C}\left(\frac{v}{C}\right)^{K-1}\exp\left[-\left(\frac{v}{C}\right)^{K}\right] \tag{1}$$

where K is the shape parameter, $K = (\sigma/\mu)^{-1.086}$. C is the scale parameter, $C = \mu/[\Gamma(1+1/K)]$, μ is the average wind speed, σ is the standard deviation. Γ is the Gamma function.

2) Power output model of wind turbine generator: the variable speed constant frequency wind power generator is adopted, and the relationship between the power output and wind speed meets the power characteristic curve of wind turbine [4].

$$P_{wind} = \begin{cases} 0, & v < v_{ci} \\ a + bv, & v_{ci} \le v \le v_r \\ p_{r,} & v_r \le v \le v_{co} \\ 0, & v > v_{co} \end{cases} \tag{2}$$

where v_{ci}, v_{co} and v_r are cut-in wind speed, cut-out wind speed and rated wind speed, respectively. P_r is the rated active power of wind turbine. P_{wind} is random output of wind turbine generator. $a = P_r v_{ci}/(v_{ci} - v_r)$, $b = P_r/(v_r - v_{ci})$.

Reactive power output of wind turbine generator is

$$Q_{wind} = \frac{\sqrt{1-\cos^2\varphi}}{\cos\varphi} P_{wind} \tag{3}$$

where $\cos\varphi$ is power factor.

2.2 Probability distribution model of solar power generation

1) Probability distribution model of light intensity: the light intensity of photovoltaic cells can be regarded as Beta distribution in a certain period of time [15]. Its PDF expression is

$$f(r) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\left(\frac{r}{r_{\max}}\right)^{\alpha-1}\left(1-\frac{r}{r_{\max}}\right)^{\beta-1} \tag{4}$$

where α and β are the Beta distribution parameter, respectively. $\alpha = \mu\left[\frac{\mu(1-\mu)}{\sigma^2} - 1\right]$, $\beta = (1-\mu)\left[\frac{\mu(1-\mu)}{\sigma^2} - 1\right]$, μ is the average light intensity, σ is the standard deviation. $r_{\max}$ is the maximum light intensity. Γ is the

Gamma function.

2) Power output model of solar photovoltaic power generation: solar power generation is known as intermittent, periodic and non-scheduling, the total power output of photovoltaic power generation is approximately [15]:

$$P_{PV} = rA\eta \tag{5}$$

where r is the light intensity, A is the total area of photovoltaic array, η is the overall conversion efficiency.

2.3 Probability distribution model of basic load

The probability distribution of active power and reactive power of the basic load in PLF calculation is normally distributed [15], whose PDF is

$$f(P) = \frac{1}{\sqrt{2\pi}\sigma_P}\exp[-\frac{(P-\mu_P)^2}{2\sigma_P^2}] \tag{6}$$

$$f(Q) = \frac{1}{\sqrt{2\pi}\sigma_Q}\exp[-\frac{(Q-\mu_Q)^2}{2\sigma_Q^2}] \tag{7}$$

where μ_P and μ_Q are the mean value of active and reactive power, respectively. σ_P^2 and σ_Q^2 are the variance of active and reactive power, respectively.

2.4 Probability distribution model of EVCL

EVCL characteristics are mainly affected by the charging rate, the charging start time and the charging duration [31]. The daily mileage of vehicle is lognormally distributed, whose PDF is

$$f(d) = \frac{1}{d\sigma_d\sqrt{2\pi}}\exp[-\frac{(\ln d-\mu_d)^2}{2\sigma_d^2}] \tag{8}$$

where d is daily mileage, $\mu_d = 3.2$, $\sigma_d = 0.88$.

E is defined as starting value of electric vehicle battery`s SOC, $E = (1-d/R)$, R is mileage range of electric vehicle after a full charge, the value of R is 100 km. Combining with formula (8), whose PDF is

$$f(E) = \frac{1}{R(1-E)\sigma_d\sqrt{2\pi}}\exp[-\frac{\{\ln[R(1-E)]-\mu_d\}^2}{2\sigma_d^2}] \tag{9}$$

Start charging time are normally distributed, its PDF is

$$f(t) = \begin{cases} \frac{1}{\sigma_t\sqrt{2\pi}}\exp[\frac{(t-\mu_t)^2}{2\sigma_t^2}], (\mu_t-12) < t \le 24 \\ \frac{1}{\sigma_t\sqrt{2\pi}}\exp[\frac{(t+24-\mu_t)^2}{2\sigma_t^2}], 0 < t \le (\mu_t-12) \end{cases} \tag{10}$$

where μ_t=17.6, σ_t =3.4.

There are N electric vehicles in the system, the daily mileage of vehicle d and the charging start time t are mutually independent, at the $t(t \ge T)$ moment [32], the expected value of active demand for electric vehicle is

$$P(t,T) = N\int_0^1 f(E)p(t)dE \tag{11}$$

The expected values of active demand for N electric vehicles are obtained at t moment from the formula (11). Combining with central limit theorem, EVCL approximately obeys the normal distribution at t time [33]. On the basis of the known mean value μ_{EV} and standard deviation σ_{EV}, thus EVCL`s PDF is

$$f(P_{EV}) = \frac{1}{\sqrt{2\pi}\sigma_{EV}}\exp[-\frac{(P_{EV}-\mu_{EV})^2}{2\sigma_{EV}^2}] \tag{12}$$

2.5 Probability distribution model of random state for transmission line

The network topology is affected by the probability distribution of random state for transmission line, which adopts two states model, namely, normal state and fault state. The random state of transmission line is expressed by the random variable $X_k = [X_{k1}, X_{k2}, \cdots X_{ki}, \cdots X_{km}]^T$.

$$X_{ki} = \begin{cases} 1 & \textit{the}\ \text{Kth sampling, the line i is normal} \\ 0 & \textit{the}\ \text{Kth sampling, the line i is fault} \end{cases} \tag{13}$$

where $i = 1, 2, \cdots, m$, m is the number of lines, k is the sample size. X_{ki} is the random state of line i on the basis of the $k\ th$ sampling.

3. Composite Sampling Modeling for DG, EVCL, Random-state of Transmission Line

3.1 LHS modeling of probability distribution for wind speed, basic load, EVCL

LHS is able to perform a stratified and random sampling technique that can efficiently cover a much larger sampling space and entire distribution interval of random variables with the same sample size and provide an efficient approach to sample input random variables from CDF [27]. Comparing with SRS-MCSM, LHS is able to carry out a more precise and stable estimation and avoid repeated sampling and improve the computational efficiency [27].

The main idea of the LHS method is based on the inverse function method. The sample size N of a random variable is supposed; $X_1, X_2, \cdots, X_m$ are m input random variables; X_i is any random variable. With each variable mutually independent, the CDF of variable $X_i (1 \le i \le m)$ is $Y_i = F_i(X_i)$; the value range [0,1] of this distribution function is divided into evenly spaced and non-overlapping and N intervals, as $[0,1/N]$, $[1/N,2/N]$, $\cdots$, $[N-1/N,1]$. The one sample in the middle of each interval is adopted as sample value Y_i, and the k th sample value for X_i can be obtained by calculating the inverse function $F_i^{-1}(Y_i)$ of F_i. Then the sampling matrix of LHS is $m \times N$ size, which is obtained with each row consisting of the samples of each random variable.

In order to take into account the tail characteristics of the probability distribution, combining Latin hypercube sampling method with the important sampling method, LHIS method is put forward. The principle of this method is that at first the probability distribution of the sample space of the original system is changed by the important sampling, and the approximate optimal distribution is structured [28]. In addition, LHS method is adopted to carry out the sampling of approximate optimal distribution, thus the purpose of reducing variance and improving sampling efficiency is achieved. Based on the above analyses, the sampling point of LHIS method is

$$x_{ki} = \begin{cases} F_i^{-1}(k/N) & k/N \le 0.5 \\ F_i^{-1}((k-1)/N) & k/N > 0.5 \end{cases} \tag{14}$$

where $i = 1,2,\cdots,m$, $k = 1,2,\cdots,N$.

The power output of the wind farm is determined by the wind speed and power output of each wind turbine generator. The CDF of wind speed is

$$F(v) = 1 - \exp[-(\frac{v}{c})^K] \tag{15}$$

According to LHIS method, the k th sample value v_{ki} of random variable V_i for i th wind speed is obtained through formula (14) and (15). From the sampling value of m wind speeds, finally, a sampling matrix $m \times N$ is formed. According to the sampling value of wind speed, the power output of wind turbine generator is calculated by formula (2), and then the power output of entire wind farm is obtained.

In addition, according to formula (6), (7), and (8), the uncertainty of basic load and EVCL is simulated by random numbers of normal distribution. The sampling values of basic load and EVCL are obtained by LHS method.

$$x_{ki} = Nor^{-1}(\frac{k-0.5}{N}) \tag{16}$$

where x_{ki} is the k th sample value of i th load; $Nor^{-1}()$ is the inverse transform operation of the normal distribution.

3.2 Neyman method modeling of probability distribution for light intensity

In general, the variation of light intensity ξ is in a definite interval (a,b), whose PDF is $y = f(r)$. With

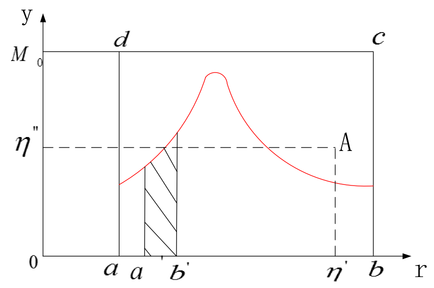


Fig. 1. Probability distribution of light intensity

reference to Fig. 1, the value of PDF $f(r)$ should not be more than M_0. Uniformly distributed random numbers γ' and γ'' are chosen. The coordinate of random point A is

$$\eta' = a + \gamma'(b-a) \tag{17}$$

$$\eta'' = \gamma'' M_0 \tag{18}$$

The random point A is below $y = f(r)$, and ξ is equal to η'. Conversely, the random point A is above $y = f(r)$, and then random number γ' and γ'' are chosen again [30].

The power output of solar power generation is determined by light intensity and power output of each photovoltaic cell. According to Neyman method, the k th sample value v_{ki} of random variable R_i for i th light intensity is obtained. According to the sampling value of light intensity, the power output of photovoltaic cell is calculated by formula (5), and then the power output of entire photovoltaic power station is obtained.

3.3 MCMC method modeling of random state for transmission line

MCMC method is able to establish a Markov chain based on a stationary distribution with the same probability distribution by repeated sampling, and obtain the state sample of the system. In contrast to SRS-MCSM, MCMC method can take into account the interaction between the various states of the system comprehensively and systematically. In addition, MCMC can obtain the independent sample sequence and accurately simulate the actual operation of the power system and improve the calculation accuracy and convergence speed.

The random state of the transmission line is sampled by MCMC method. Assuming that the initial state of all lines is in normal operation, the initial value of the probability related to the probabilistic distribution of system is P_{past}, there are steps to obtain the $k+1$ th sampling state X_{k+1} of fault line [29]:

(1) According to the state (0 or 1) of the line at this time, the probabilistic correlation value P_{future} of this line state changed at the next time is obtained by the transfer of nuclear $P\{X_{k+1,i} \mid X_{k/i}\}$ for conditional probability distribution under the current condition. In the transfer of nuclear,

$X_{k/i} = \{X_{k+1,1}, X_{k+1,2}, \cdots, X_{k+1,i-1}, X_{k,i+1}, ..., X_{k,m}\}$, the previous $i-1$ elements are the sampling point of line on the basis of the $k+1\,th$ sampling, P_{future} value after the logarithm, whose value is between 0 and 1.

$$P_{future} = \ln[\prod_{j=1}^{i-1} P_j^{1-X_{k+1,j}} (1-P_j)^{X_{k+1,j}} \prod_{l=i+1}^{m} P_l^{1-X_{k,l}} (1-P_l)^{X_{k,l}}] \tag{19}$$

(2) The probability that the value of next state for this line is equal to 1 can be calculated.

$$\lambda = 1/[\exp(P_{future} - P_{past}) + 1] \tag{20}$$

(3) Computer is adopted to generate a random number u that can be regarded as uniform distribution, and then the $k+1\,th$ sampling state is

$$X_{k+1,i} = \begin{cases} 0 & u < \lambda \quad \textit{the}\ \mathrm{K+1\ th\ sampling, the\ line\ i\ is\ fault} \\ 1 & \mathrm{u} \geq \lambda \quad \textit{the}\ \mathrm{K+1\ th\ sampling, the\ line\ i\ is\ normal} \end{cases} \tag{21}$$

(4) If the state of this line has changed, thus P_{future} obtained in the conditional probability distribution should be taken as the correlation probability of faulty line.

According to the cyclic sampling of preceding steps, a Markov chain based on a stationary distribution with the same probability distribution by repeated sampling is established, which should be considered as the state sample of fault line to perform random sampling.

4. Non-parametric Kernel Density Estimation

Nonparametric kernel density estimation (NKDE) is a commonly and widely applicable non-parametric way of evaluating the PDF of a random variable [34]. The general formulation is

$$\hat{f}_h(y) = \frac{1}{Nh} \sum_{i=1}^{N} K(\frac{y - y_i}{h}) \tag{22}$$

where h is the bandwidth, K is the kernel function, N is the sample size, y_i is the sample value of node voltage. $\hat{f}_h(y)$ is the estimated density function. Gaussian function is chosen as the kernel and the optimized bandwidth for Gaussian distribution is used. The assumption for using NKDE is that the resulting density function is smooth enough.

5. Probabilistic Assessment of Voltage Quality Based on Composite Sampling Method

The general process of Monte Carlo method based on composite sampling method is depicted as follow:

(1) Input basic data, including the data for power flow calculation of power system, distribution of the nodal injection power, the parameters of wind farm and photovoltaic power station, the parameters of basic load and EVCL, sample size, the parameters and failure rate of lines.

(2) Calculate Weibull distribution parameters K, C and Beta distribution parameters α, β.

(3) According to formula (6), (7), (12), (14)-(16), LHS is adopted to sample wind speed, basic load and EVCL based on continuous probability distribution. According to formula (4), (17), (18), Neyman method is adopted to sample light intensity based on continuous probability distribution. In addition, according to formula (13), (19), (20), (21), MCMC method is adopted to sample the random state of the lines based on discrete probability distribution. And then the sampling values of wind speed, light intensity, basic load and EVCL are obtained.

(4) Combining with formula (2), (3), (5), the power output of wind turbine generator and photovoltaic power generation are obtained by the sampling values of wind speed and light intensity.

According to the sampling matrix of the random variables, combining with the random state of the lines, the power flow of the system is solved by Newton-Raphson method. Judge whether to satisfy the sample size. If not, then return to step 3, and then the numerical characteristic and PDF curve of node voltage are obtained by probability statistical method and NKDE.

6. Case Study

6.1 Verification of algorithm validity

In order to verify the validity of the Monte Carlo method based on composite sampling method, the result obtained by SRS-MCSM with the sample size of 20000 is set as a reference. The relative error indices obtained by the Monte Carlo method based on composite sampling method are compared with those obtained by SRS-MCSM. The expectation and standard deviation error of output variables are taken as indices of algorithmic performance, as defined in formula (23)

$$\varepsilon_s^{\gamma} = |\frac{X_{acc}^{\gamma} - X_{sim}^{\gamma}}{X_{acc}^{\gamma}}| \times 100\% \tag{23}$$

where ε_s^{γ} is the relative error index of output variables. γ is voltage magnitude V. s is the numerical characteristic, including expectation μ and standard deviation σ. X_{sim}^{γ} is the result obtained by SRS-MCSM or composite sampling method with a certain sample size, and X_{acc}^{γ} is

Table 1. Results of PLF calculation

Node	SRS-MCSM		composite sampling		error of expectation (%)
	expectation	standard deviation	expectation	standard deviation	
1	1.030275	0.001489	1.030062	0.001470	0.0206
2	1.015429	0.001585	1.015197	0.001531	0.0228
3	0.996316	0.001568	0.996115	0.001389	0.0202
5	0.988367	0.001427	0.988043	0.001450	0.0327
7	0.987692	0.001513	0.987399	0.001432	0.0297
9	1.002603	0.001436	1.002417	0.001311	0.0186

Table 2. Convergence speed of the proposed method

Sample size	expectation	standard deviation
1000	0.988043	0.001450
3000	0.988219	0.001333
5000	0.988506	0.001170
7000	0.989275	0.001223
9000	0.991526	0.001165

the reference. The convergence processes of the Monte Carlo method based on composite sampling method and SRS-MCSM are stochastic. In order to estimate the convergence of the two methods accurately, the procedure for each method runs 100 times with a certain sample size. The average value $\bar{\varepsilon}^{\gamma}_{smean}$ of the 100 calculation results $\bar{\varepsilon}^{\gamma}_{s}$ is employed as the final error of the output variables. The standard deviation $\bar{\varepsilon}^{\gamma}_{s100}$ and average maximum $\bar{\varepsilon}^{\gamma}_{s\max}$ of the 100 calculation results $\bar{\varepsilon}^{\gamma}_{s}$ are employed as the basis for evaluating the algorithmic performance.

IEEE9 bus system [35] includes 6 lines, 9 bus bars, 3 generators, which is employed as the test case. The analysis is carried out from two aspects without taking into account any random factor: 1) Performing PLF calculation by the proposed method and SRS-MCSM, respectively. From Table 1, the expectation error of node voltage with the sample size of 1000 is within an acceptable order of magnitude, which has verified the validity of the proposed method. 2) The expectation and standard deviation of the voltage amplitude for the node 5 obtained under different sampling times are compared by the proposed method. From Table 2, the standard deviation of the voltage amplitude decreases with the increase of the sampling times, which indicates that the calculation procedure of the proposed method is convergent.

6.2 PLF based on composite sampling method

IEEE34 bus system [36] is adopted to perform the case study, and the wind turbine generator, photovoltaic cell array, EVCL are installed on the basis of this system. The reference voltage

V_B of the system is 24.9kV, reference capacity is 1MVA, reference voltage of root node 1 is 1.03 p.u.. The expectation of the loads equals to their initial value, and the standard deviation equals to 10% of their expectation. The branch parameters, nodal datum and generator datum of the system refer to literature [36] and [37]. The parameters of

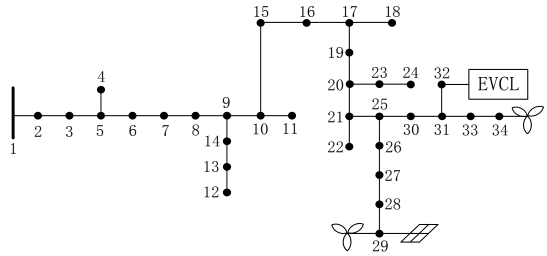


Fig. 2. IEEE34 bus system

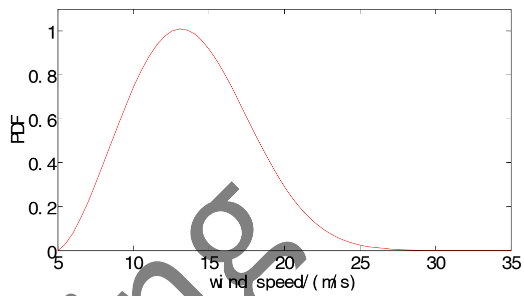


Fig. 3. PDF curve of wind speed

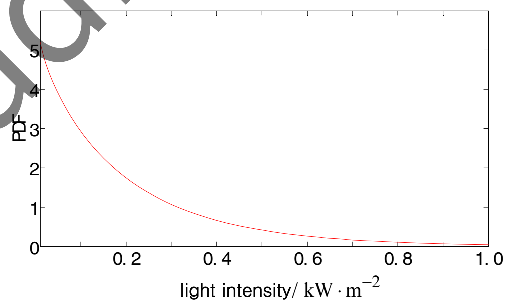


Fig. 4. PDF curve of light intensity

DG and EVCL are: K =2.80, C =5.14, v_{ci} =5m/s, v_r = 14m/s, v_{co} =25m/s, P_r =0.2MW, α =0.45, β =9.18, $r_{\max}$ = 1000 W/m^2, A =2000 m^2, η =13.44%. P_r of the single set of solar cell is 0.1MW. The electric vehicle battery has a capacity of 18kW·h, and the charging power of the single electric vehicle is 3.6kW. When the battery charges, conversion efficiency is 0.75. In addition, the charging power factor is 0.99. The wiring diagram of IEEE34 bus system is shown in Fig. 2.

The wind speed curve and light intensity curve are shown in Fig. 3 and Fig. 4.

The wind turbine generator and solar power generation system should be approximately taken as PQ node, and root node 1 is considered as $V\theta$ node. Analyzing the following 2 cases in this section:

Case1, considering the fluctuation of basic load without taking into account any random factor.

Case2, a set of photovoltaic cell array and a wind turbine generator are installed at node 29, 50 EVCLs at node 32, and a wind turbine generator at node 34. In addition, the random state of the line is taken into account.

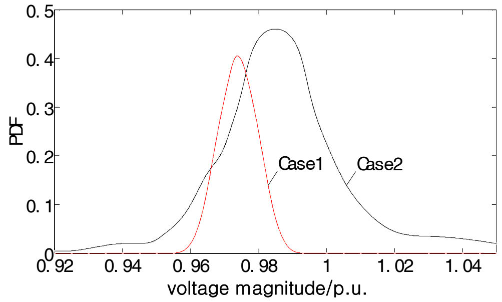


Fig. 5. PDF curve of voltage magnitude for Bus 29

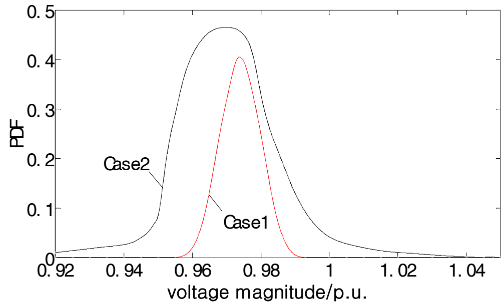


Fig. 6. PDF curve of voltage magnitude for Bus 32

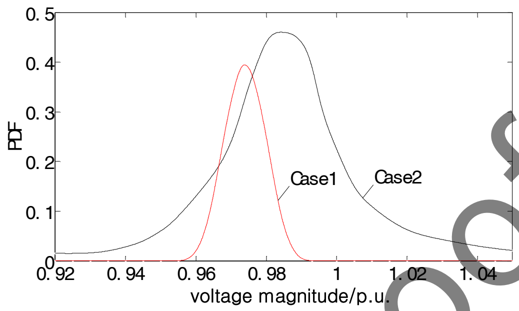


Fig. 7. PDF curve of voltage magnitude for Bus 34

The analysis of the probabilistic characteristics of IEEE34 bus system is based on the proposed method with the sample size of 1000 under different cases by method of probability and statistics and NKDE. The expectation, standard deviation and out-of-limit rate of voltage for voltage magnitude are shown in Table 3 and Table 4.

The PDF curves of node 19, 32 and 34 under the 2 cases are shown in Fig. 5, 6 and 7.

As is shown in Table 3, 4 and Fig. 5-7, in Case1, the stochastic volatility of node voltage and normal distribution of load keep pace with an acceptable range owing to the probability distribution of basic load that is normally taken into account. In Case2, the EVCLs are installed at node 32, which are superimposed on the basic load of node. With the nodal load power demand enhanced and the branch active power transportation increased, the mean voltage at node 32 is reduced. And yet, the wind turbine generator installed at node 34, reduces the equivalent load demand of the node, thus reducing active power transportation of the branch, so that the mean value and standard deviation of

Table 3. Results of voltage magnitude for part of buses in the case 1

Node	expectation	standard deviation	over-limit rate of voltage
4	1.018120	0.000557	0.000000
11	0.993574	0.001823	0.000000
12	0.995539	0.001679	0.000000
18	0.987627	0.002157	0.000000
22	0.976272	0.002836	0.000000
24	0.976890	0.002792	0.000000
29	0.974932	0.002980	0.000000
32	0.974736	0.002963	0.000000
34	0.974716	0.002943	0.000000

Table 4. Results of voltage magnitude for part of buses in the case 2

Node	expectation	standard deviation	over-limit rate of voltage
4	1.020195	0.002563	0.000102
11	0.999825	0.006843	0.001187
12	1.001368	0.006689	0.001355
18	0.993745	0.008195	0.002346
22	0.986596	0.011837	0.006762
24	0.986725	0.011850	0.007051
29	0.984953	0.011976	0.008578
32	0.984714	0.011991	0.009568
34	0.984650	0.011982	0.009687

voltage for node 34 have increased. With the random fluctuation of wind turbine generator, the severe distortion of PDF curve for node voltage is shown in Fig. 7, so that the out-of-limit rate of voltage has significantly increased. From Table 4, the out-of-limit rate of voltage for node 29, 34 is 0.008578 and 0.009687, respectively. It is seen that the impact of wind-solar complementary generation mode on the voltage quality is smaller than the individual wind turbine generator, and the out-of-limit rate of voltage is correspondingly reduced, to a certain extent, which has made up for the instability of the power supply for the individual wind turbine generator.

6.3 Composite sampling method based performance evaluation

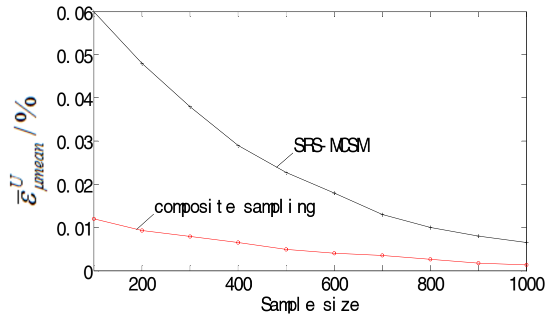
IEEE 34 bus system is adopted to evaluate the performance of the proposed method, and the results obtained by SRS-MCSM with the sample size of 20000 are set as the reference. The average value $\bar{\varepsilon}^{\gamma}_{smean}$ and the standard deviation $\bar{\varepsilon}^{\gamma}_{s100}$ and average maximum $\bar{\varepsilon}^{\gamma}_{s\max}$ of node voltage are employed as the indices of algorithmic performance. The error-changing tendency of node voltage is shown as curves in Fig. 8, 9.

The PDF curves of the voltage magnitude of node 34 in IEEE 34 bus system are shown in Fig.10, and the relative error indices of node voltage obtained by SRS-MCSM and composite sampling method with the sample size of 1000 are shown in Table 5.

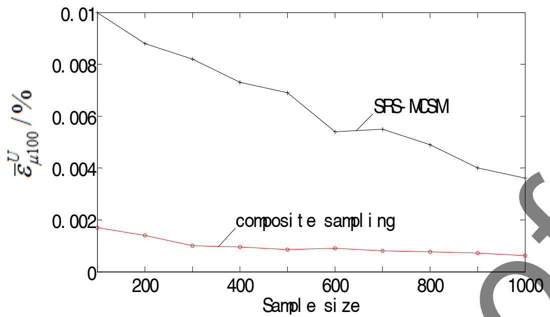
As is shown in Fig. 8, 9 and Table 5, with the increase of

Table 5. Error comparisons of two methods for IEEE34 bus system

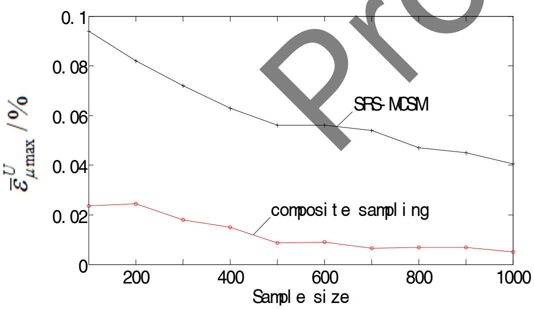
Error		SRS-MCSM	composite sampling
$\bar{\varepsilon}_{\mu}^{U}$	expectation	0.0232	0.0037
	standard deviation	0.0057	0.0008
	maximum value	0.0570	0.0076
$\bar{\varepsilon}_{\sigma}^{U}$	expectation	2.2822	0.7785
	standard deviation	1.3273	0.4559
	maximum value	5.3756	2.6334



(a) $\bar{\varepsilon}_{\mu mean}^{U}$ error curves comparison

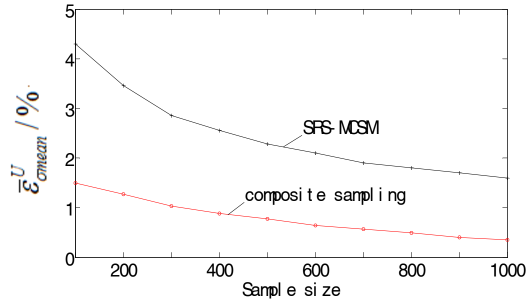


(b) $\bar{\varepsilon}_{\mu 100}^{U}$ error curves comparison

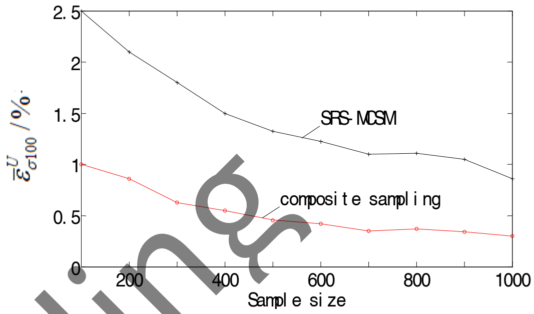


(c) $\bar{\varepsilon}_{\mu \max}^{U}$ error curves comparison

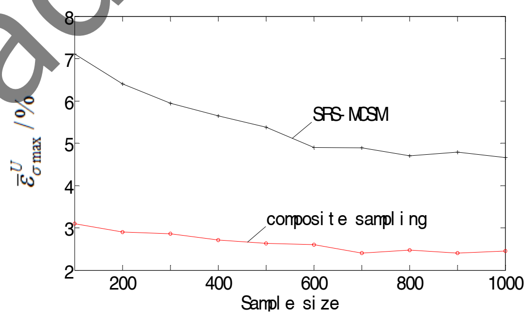
Fig. 8. $\bar{\varepsilon}_{\mu}^{U}$ error curves comparison of two methods



(a) $\bar{\varepsilon}_{\sigma mean}^{U}$ error curves comparison



(b) $\bar{\varepsilon}_{\sigma 100}^{U}$ error curves comparison



(c) $\bar{\varepsilon}_{\sigma \max}^{U}$ error curves comparison

Fig. 9. $\bar{\varepsilon}_{\sigma}^{U}$ error curves comparison of two methods

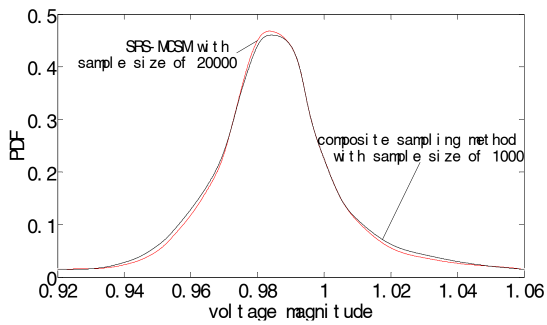


Fig. 10. PDF curve of voltage magnitude for Bus 34

sample size, the convergence speed of composite sampling method is faster than SRS-MCSM, and the higher accuracy in relatively short time is obtained by composite sampling method. Hence composite sampling method can improve the global convergence of PLF, and then obtain the probability distribution of output variables quickly and accurately. Under the background of the same sample size, the calculation accuracy and error convergence stability of composite sampling method are better than SRS-MCSM.

As is shown in Fig. 10, although the probability distribution of node voltage is significantly affected by uncertainty, the composite sampling method with the sample size of 1000 can obtain an excellent fitting effect, so the results obtained by composite sampling method with the sample size of 1000 are close to that of SRS-MCSM with the sample size of 20000. With the same calculation accuracy, the consuming time of composite sampling method is far less than that of SRS-MCSM, and the validity and accuracy of the proposed method are verified.

7. Conclusion

(1) Because the expectation error of node voltage with the sample size of 1000 is within an acceptable order of magnitude, the validity of composite sampling method is verified in the case study of IEEE 9 bus system.
(2) The voltage quality of distribution system is affected by the output randomness of DG and the uncertainty of basic load and EVCL significantly. Therefore, these random factors should be considered in practical application.
(3) In contrast with the individual wind turbine generator, it is seen that the wind-solar complementary generation mode can provide better voltage quality, to a certain extent, which has made up for the instability of the power supply for the individual wind turbine generator.
(4) With the same sample size, the calculation accuracy and error convergence stability of composite sampling method are better than SRS-MCSM. In addition, with the same calculation accuracy, the time consumed by the composite sampling method is far less than that of SRS-MCSM. Therefore, the convergence speed, accuracy, efficiency of composite sampling method are better than those of SRS-MCSM, which is able to accurately evaluate the voltage quality containing DG and electric vehicle and is therefore of promising prospect in engineering application.

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