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M. Du, X. Wang

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A data-driven polynomial chaos expansion-based method for microgrid ramping support capability assessment and enhancement

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Abstract : Microgrids (MGs) are regarded as effective solutions to provide ramping support to the main grid during heavy-load periods. Nevertheless, the uncertain renewable energy sources (RES) and electric vehicles (EVs) integrated into an MG may affect the ramping support capability (RSC) of an MG. To address the challenge, this paper develops a data-driven sparse polynomial chaos expansion (DDSPCE)-based method to accurately and efficiently evaluate the hour-by-hour RSC of an MG. The DDSPCE model is further exploited to identify the most influential random inputs, based on which a scheduling method of BESS is developed to enhance the RSC of an MG. Simulation results in the modified IEEE 33-bus MG shows that the proposed method takes less than 3 minutes for evaluating and enhancing the hourly RSC.

Keywords : Data-driven sparse polynomial chaos expansion (DDSPCE), electric vehicle (EV), global sensitivity analysis, microgrid, ramping support capability, renewable energy sources (RES)

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1 Introduction

Integrating renewable energy sources (RES), such as photovoltaics (PVs) and wind turbines (WTs) to power systems is promising to decelerate global warming and achieve net-zero emission by 2050 [1]. However, the advantages of RES are accompanied by variability, which poses profound challenges to the operation of traditional vertically integrated power systems [2]. According to the report [3] by California Independent System Operator in 2013, the discrepancy between the RES's generation and customer's demand profiles will intensify the supply-load unbalance and result in a steep net-load ramp. The transmission system operators urgently require the service of fast-response power generation during heavy-load periods [1].

This service of fast-response power generation can be provided by microgrids (MGs), which are specific distribution grids integrated with dispatchable, e.g., diesel generators (DGs) and battery energy storage systems (BESS), and non-dispatchable, e.g., distributed generators powered by RES. Indeed, the MG is considered a viable and effective solution to provide ancillary services to main grids for improving stability, resiliency, and reliability [4]. Despite the categorization of ancillary services varies from country to country, essential ancillary services widely adopted by large power systems include voltage-VAr control, frequency-Watt control, load shedding, black start, and ramping support [1, 4].

Particularly, this paper considers the capability of MGs to provide ramping support during heavy-load periods. The ramping support capability (RSC) is defined as the available active power that the corresponding MG can transfer to the connected grid during a certain period [1, 2, 5, 6]. Nonetheless, the RSC of an MG may also be affected by the variability of RES and electric vehicles (EVs) inside an MG. In [7], the RSC is determined by a min-max problem, aiming to calculate a worst-case ramping power at every time interval during a day. Based on the calculated RSC, an optimization model was developed to coordinate the MG loads to settle the intense ramping issue. Similarly, various optimization models for energy scheduling and management were developed in [1, 4, 7], in which the time-varying property of RES and/or loads are described by pre-assumed profiles. The authors of [8, 9] employed probabilistic forecasting models to predict the profiles of RES and load and quantified the size of the spinning reserve from the predicted errors by assuming a certain risk level. The authors of [10] proposed an estimation model of spinning reserve in MGs, in which the uncertainty of WTs, PVs, and loads are aggregated to reduce the computational burden. However, the power flow constraints and other security constraints such as voltage and thermal limits were not considered in [8, 9, 10]. To incorporate the security constraints and quantify the impacts of uncertainties of RES, a sparse polynomial chaos expansion (SPCE)-based method was developed in [11] to estimate the available delivery capability of a distribution system accurately and efficiently. Nevertheless, the applied method requires accurate marginal distributions of random inputs that may not always be available in practice. Besides, control measures to increase the available delivery capability were not discussed.

In this paper, we will leverage the data-driven SPCE (DDSPCE) method proposed in [12] to accurately and efficiently estimate the RSC of an MG considering the uncertainties of RES and EVs as well as the security constraints of an MG. Particularly, the method requires no knowledge of marginal distributions of WTs, PVs, loads, etc. It should be noted that the DDSPCE was not exploited to design control measures in [12]. In contrast, in this paper, the established DDSPCE model will be further used to calculate the Sobol' indices that can identify the dominant random inputs, based on which control measures utilizing BESS are developed to increase the quality of the RSC of an MG. Simulation results in a modified IEEE 33-bus MG integrating PVs, WTs, and EVs show that the developed method can increase the quality of the RSC of the MG significantly.

The rest of the paper will be organized as follows. Section 2 introduces the concept and formulations of probabilistic RSC. Section 3 introduces the formulations of DDSPCE and DDSPCE-based Sobol' indices. Section 4 introduces the developed method to increase the RSC. Section 5 validates the effectiveness of the developed RSC-enhancement method in the test grid. Section 6 presents the conclusion.

2 Probabilistic RSC

In this paper, the continuous power flow for an N -bus power system is used to calculate the RSC of an MG

$$f(\boldsymbol{\varphi}, \lambda) = f(\boldsymbol{\varphi}) - \lambda \mathbf{b} = 0, \quad (1)$$

where $f(\boldsymbol{\varphi})$ is the solution to the power-flow equation $f(\boldsymbol{\varphi}) = 0$ [11], the state vector $\boldsymbol{\varphi} = [\boldsymbol{\theta}^\top, \mathbf{V}^\top]^\top$, $\boldsymbol{\theta} \in \mathbb{R}^N$ and $\mathbf{V} \in \mathbb{R}^N$ are voltage angle and magnitude vectors, respectively, and $\lambda \in \mathbb{R}$ refers to the RSC of an MG. The vector $\mathbf{b} = [\mathbf{b}_1^\top, \mathbf{b}_2^\top, \dots, \mathbf{b}_N^\top]^\top \in \mathbb{R}^{2N \times 1}$ describes the direction of power transfer variation:

$$\begin{aligned} \mathbf{b}_1 &= \begin{bmatrix} -\Delta P_{L,1} \\ -\Delta Q_{L,1} \end{bmatrix}, \\ \mathbf{b}_i &= \begin{bmatrix} \Delta P_{G,i} - \Delta P_{L,i} \\ -\Delta Q_{L,i} \end{bmatrix}, \quad i = 2, 3, \dots, N, \end{aligned} \quad (2)$$

where \mathbf{b}_1 is a unit vector, i.e., $\|\mathbf{b}_1\|_2 = 1$, bus 1 is the connected utility bus; $\Delta P_{G,i}$ is the assigned increase of active generation power from the MG; $\Delta P_{L,i}$, and $\Delta Q_{L,i}$ are the increase of active load, and reactive load inside the MG, respectively. Particularly, bus 1 is modeled as a PQ load bus such that the the real power of an MG will transfer power to the main grid.

Considering the uncertainties of RES and EVs in the MG, the continuous power flow equation (2) can be modified to the probabilistic continuous power flow equation [11], which reads

$$f(\boldsymbol{\varphi}, \lambda, \mathbf{x}) = f(\boldsymbol{\varphi}, \mathbf{x}) - \lambda \mathbf{b} = 0, \quad (3)$$

where the random vector \mathbf{x} describes the random inputs, i.e., solar radiation, wind speed, and the charging power of EVs, that affect the power generations and loads in the MG. The formulation of the probabilistic RSC reads:

$$\begin{aligned} &\max \lambda \\ &\text{s.t.} \quad \mathbf{f}(\boldsymbol{\varphi}, \mathbf{x}) - \lambda \mathbf{b} = 0 \\ &\quad V_{\min} \leq V_i(\boldsymbol{\varphi}, \lambda, \mathbf{x}) \leq V_{\max} \\ &\quad I_{ij}(\boldsymbol{\varphi}, \lambda, \mathbf{x}) \leq I_{ij,\max} \\ &\quad P_{\min,i} \leq P_{Gi}(\boldsymbol{\varphi}, \lambda, \mathbf{x}) \leq P_{\max,i}, \\ &\quad Q_{\min,i} \leq Q_{Gi}(\boldsymbol{\varphi}, \lambda, \mathbf{x}) \leq Q_{\max,i}, \\ &\quad i, j \in \{1, 2, \dots, N\}, \end{aligned} \quad (4)$$

where V_{\max} and V_{\min} are upper and lower limits of bus voltages, respectively, $I_{ij,\max}$ is the thermal limit of line ij , $P_{\max,i}$ and $P_{\min,i}$ are the maximum and minimum output powers of the generator on bus i , respective, which applies to $Q_{\max,i}$ and $Q_{\min,i}$ similarly. The maximum λ without violating any constraint in (4) is the RSC of an MG.

It should be noted that λ is a random variable because of the random input \mathbf{x} in (4). Once the MG configuration and \mathbf{b} are determined, $\lambda(\mathbf{x})$ can be described as a function of \mathbf{x} according to (4). The traditional method to estimate the distribution of $\lambda(\mathbf{x})$ is to perform Monte Carlo simulations (MCS) on (4). However, whatever efficient sampling method, e.g., Latin hypercube [13] or importance sampling [14], is used, the MCS is inevitably computationally expensive [11]. To overcome the problem of time consumption, the DDSPE-based method [12] is developed.

3 DDSPE and DDSPE-Based Sobol' Indices

The DDSPE method aims to use a sparse finite degree model $\hat{\lambda} = g(\mathbf{x})$ to approximate a stochastic model, e.g., (4), with a target stochastic response $\lambda \in \mathbb{R}$ and a random input vector $\mathbf{x} = [x_1, x_2, \dots, x_D]^\top$ [12, 15, 16]. The DDSPE method can achieve both time efficiency and accuracy by building the stochastic model $\hat{\lambda} = g(\mathbf{x})$ using only a few sample pairs of (\mathbf{x}, λ) . Mathematically, the

DDSPCE model $\hat{\lambda} = g(\mathbf{x})$ can be described as:

$$\hat{\lambda} = g(\mathbf{x}) = \sum_{\alpha \in \mathcal{A}} c_{\alpha} \Psi_{\alpha}(\mathbf{x}), \quad (5)$$

where the 1-norm truncated set $\mathcal{A} = \{\alpha \in \mathbb{N}^D : \|\alpha\|_1 \leq q\}$, q is the degree of truncation, $\alpha \in \mathcal{A}$ is an N -dimensional index, and $c_{\alpha} \in \mathbb{R}$ and $\Psi_{\alpha}(\mathbf{x})$ are the coefficient and polynomial basis corresponding to α , respectively [16]. $\Psi_{\alpha}(\mathbf{x})$ is calculated as [12]:

$$\Psi_{\alpha}(x_1, \dots, x_D) = \prod_{i=1}^D \left(\sum_{k=0}^{\alpha_i} p_{\alpha_i, k} x_i^k \right). \quad (6)$$

The univariate polynomial basis $p_{\alpha_i, k}$ is the solution to

$$\begin{bmatrix} \mu_{0,i} & \mu_{1,i} & \cdots & \mu_{\alpha_i,i} \\ \mu_{1,i} & \mu_{2,i} & \cdots & \mu_{\alpha_i+1,i} \\ \vdots & \vdots & \ddots & \vdots \\ \mu_{\alpha_i-1,i} & \mu_{\alpha_i,i} & \cdots & \mu_{2\alpha_i-1,i} \\ 0 & 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} p_{\alpha_i,0} \\ p_{\alpha_i,1} \\ \vdots \\ p_{\alpha_i,\alpha_i-1} \\ p_{\alpha_i,\alpha_i} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}, \quad (7)$$

where $\mu_{k,i} = \int_{x_i \in \Omega_i} x_i^k d\Gamma(x_i)$ is the raw moment of x_i , and Ω_i is the space set of x_i . Particularly, $\mu_{k,i}$ can be obtained from historical/predicted data or probabilistic models of x_i .

Once $p_{\alpha_i, k}$ is solved, the multivariate polynomial basis $\Psi_{\alpha}(\mathbf{x})$ can be built from (6), the remaining task is to calculate the coefficients c_{α} , which can be obtained by some advanced regression methods, e.g., the ordinary least-square method [12]:

$$\mathbf{C} = (\Psi(\mathbf{X})^{\top} \Psi(\mathbf{X}))^{-1} \Psi(\mathbf{X})^{\top} \boldsymbol{\lambda}, \quad (8)$$

where $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N]^{\top} \in \mathbb{R}^N \times \mathbb{R}^D$ and $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \dots, \lambda_N]^{\top} \in \mathbb{R}^N$ are random inputs and stochastic responses used for the regression, $\mathbf{C} = [\dots, c_{\alpha}, \dots]^{\top} \in \mathbb{R}^{N_{\alpha}}$ and $\Psi(\mathbf{X}) = [\dots, \Psi_{\alpha}(\mathbf{X}), \dots] \in \mathbb{R}^N \times \mathbb{R}^{N_{\alpha}}$ are matrices of c_{α} and $\Psi_{\alpha}(\mathbf{X})$, respectively, $\Psi_{\alpha}(\mathbf{X}) = [\Psi_{\alpha}(\mathbf{x}_1), \Psi_{\alpha}(\mathbf{x}_2), \dots, \Psi_{\alpha}(\mathbf{x}_N)]^{\top} \in \mathbb{R}^N$, and N_{α} is the number of elements in \mathcal{A} .

After the calculation of c_{α} , the DDSPCE model (5) is built. Next, the Sobol' index of each random variable can be calculated. The Sobol' index S_i quantifies the effect of x_i on the variance of $\hat{\lambda}$ [17]. A larger S_i indicates that x_i plays a more important role in affecting $\text{Var}[\hat{\lambda}]$. For this reason, Sobol' indices can be used to identify the dominant influencers among all uncertainty sources. The Sobol' decomposition is defined as [17]

$$\hat{\lambda} = g(\mathbf{x}) = g_0 + \sum_{\substack{\mathbf{u} \subseteq \{1,2,\dots,D\} \\ \mathbf{u} \neq \emptyset}} g_{\mathbf{u}}(\mathbf{x}_{\mathbf{u}}), \quad (9)$$

where for any non-empty set $\mathbf{u} \subseteq \{1, 2, \dots, D\}$, $\mathbf{x}_{\mathbf{u}} = \{x_i \in \mathbf{x} | i \in \mathbf{u}\}$ and $g_{\mathbf{u}}(\mathbf{x}_{\mathbf{u}})$ is a function of $\mathbf{x}_{\mathbf{u}}$.

We can easily perform Sobol' decomposition on (5) by defining [17]

$$g_{\mathbf{u}}(\mathbf{x}_{\mathbf{u}}) = \sum_{\alpha \in \mathcal{A}_{\mathbf{u}}} c_{\alpha} \Psi_{\alpha}(\mathbf{x}), \quad (10a)$$

$$\mathcal{A}_{\mathbf{u}} = \{\alpha \in \mathcal{A} | \alpha_{\mathbf{u}} \neq 0 \Leftrightarrow \mathbf{u} \in \mathbf{u}, \mathbf{u} = 1, 2, \dots, D\}. \quad (10b)$$

Equation (10a) holds because the basis $\Psi_{\alpha}(\mathbf{x})$ is irrelevant to random variables $x_i \in \{x_i \in \mathbf{x} | \alpha_i = 0\}$. According to (10), (5) can be re-expressed as

$$\hat{\lambda} = g(\mathbf{x}) = c_0 + \sum_{\substack{\mathbf{u} \subseteq \{1,2,\dots,D\} \\ \mathbf{u} \neq \emptyset}} \sum_{\alpha \in \mathcal{A}_{\mathbf{u}}} c_{\alpha} \Psi_{\alpha}(\mathbf{x}), \quad (11)$$

where c_0 is the expectation of $\hat{\lambda}$.

Considering the orthonormality of polynomial chaos bases [16], the variance of the DDS-PCE model reads:

$$\begin{aligned}\text{Var}[\hat{\lambda}] &= \sum_{\substack{\alpha \in \mathcal{A} \\ \alpha \neq 0}} \hat{c}_\alpha^2, \\ \text{Var}[g_{\mathbf{u}}(x_{\mathbf{u}})] &= \sum_{\substack{\alpha \in \mathcal{A}_{\mathbf{u}} \\ \alpha \neq 0}} \hat{c}_\alpha^2.\end{aligned}\tag{12}$$

The Sobol' index of $x_{\mathbf{u}}$ is expressed as

$$S_{\mathbf{u}} = \frac{\sum_{\substack{\alpha \in \mathcal{A}_{\mathbf{u}} \\ \alpha \neq 0}} \hat{c}_\alpha^2}{\sum_{\substack{\alpha \in \mathcal{A} \\ \alpha \neq 0}} \hat{c}_\alpha^2}.\tag{13}$$

4 The DDS-PCE-based Algorithm for RSC Assessment and Enhancement

Due to the uncertainty of random inputs, the RSC of an MG may have a large variance which indicates a worse quality. This section utilizes the DDS-PCE-based Sobol' indices to identify the influential random inputs and smooth out their outputs with BESS. Once the outputs of the most influential random inputs are smoothed, the variance of the RSC is reduced, and the RSC quality is increased. The detailed steps of the proposed RSC-enhancement algorithm are provided below.

Step 1: Acquire N_0 samples of D random inputs \mathbf{x} (e.g., wind speed, solar radiation, and EV power) from historical/predicted data or probabilistic models. The samples are denoted as a $N_0 \times D$ matrix $\mathbf{X}_0 = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_{N_0}]^\top$, where each row and column correspond to a sample and random variable, respectively.

Step 2: Calculate the corresponding RSC $\boldsymbol{\lambda}_0 = [\lambda_1, \lambda_2, \dots, \lambda_{N_0}]^\top$ by solving (4), where each λ_i corresponds to the input \mathbf{x}_i .

Step 3: Build the DDS-PCE model $\hat{\lambda} = g(\mathbf{x})$ based on the sample pairs $(\mathbf{X}_0, \boldsymbol{\lambda}_0)$ according to (5)-(8).

Step 4: Substitute $N_s \gg N_0$, a large number of samples of \mathbf{x} , i.e., \mathbf{X}_s , to the established DDS-PCE model to calculate the corresponding $\hat{\boldsymbol{\lambda}}_s$, i.e., $\hat{\boldsymbol{\lambda}}_s = g(\mathbf{X}_s)$. From the probability distribution function (PDF) of $\hat{\boldsymbol{\lambda}}_s$ and a given a confidence level $\gamma\%$ (e.g., 95%), the RSC of an MG with a confidence level $\gamma\%$ can be estimated by $P(RSC > \hat{\lambda}) = \gamma\%$.

Step 5: Calculate the Sobol' index S_i of each random variable x_i by (13) and identify the top N_b random variables such that $\sum_{i=1}^{N_b} S_i \geq 80\%$.

Step 6: Implement N_b BESS at the buses where the dominant random variables locate to smooth out the output powers, i.e., reduce the variances of dominant random variables' output powers to zero. Specifically, for each BESS $i, i = 1, \dots, N_b$ at bus b_i , the output power $P_{B,i}$ of BESS i is determined by

$$\begin{aligned}\min_{P_{B,i}} & |P_{B,i} - (\mathbb{E}[P_{G,b_i}] - P_{G,b_i} - \mathbb{E}[P_{L,b_i}] + P_{L,b_i})|, \\ \text{s.t.} & P_{\min,B,i} \leq P_{B,i} \leq P_{\max,B,i}, \\ & 0 \leq SOC_{B,i} \leq SOC_{\max,B,i}, \\ & i = 1, 2, \dots, N_b\end{aligned}\tag{14}$$

where $P_{\min,B,i}$ and $P_{\max,B,i}$ are the minimum and maximum output power of BESS i , $SOC_{B,i}$ is the state of charge of BESS i , and $SOC_{\max,B,i}$ is the capacity of BESS i .

Note that once the DDS-PCE model is built, the evaluation of $\hat{\boldsymbol{\lambda}}_s$ in **Step 4** takes negligible time as the DDS-PCE model is a simple algebraic model that is very fast to evaluate compared to the original model (4). That is how the DDS-PCE-based algorithm can expedite the evaluation of the RSC of an

MG. The computational effort will be further discussed in the next section. Besides, the implementation of BESS in **Step 6** can be modified if the identified dominant random variables are located on the same branch of an MG. In such a case, the BESS located on the branch can be implemented to smooth out multiple random variables on the same branch. Also, it relaxes the assumption of having one BESS installed for each uncertainty source. Please see the results in the next section for details.

5 Simulation results

We applied the DDSPE-based algorithm to assess and enhance the RSC of a modified IEEE 33-bus MG [18] presented in Fig. 1. The MG has four 2-MW PVs with a unit power factor, four 2.25-MW WTs with a power factor of 0.85, and four 2-MW EV charging stations with a unit power factor, i.e., 12 independent random inputs in total. Besides, four 6-MW DGs with a uniform power factor of 0.93 and four 6-MW BESS with a uniform capacity of 12 MWh and unit power factor are installed in the MG. The data on solar radiation and wind speed is acquired from [19], and the EV charging data is from [20]. For each PV farm, the radiation set-point is 150 W/m^2 , and the standard radiation is 2000 W/m^2 . For each WT, the rated wind speed is 25 m/s , the cut-in speed is 4 m/s , and the cut-off speed is 40 m/s .

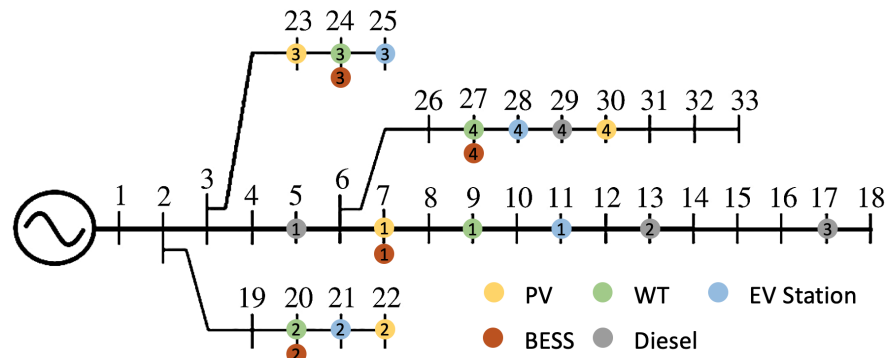


Figure 1: Diagram of the test MG.

In the base case, we dispatched the four DGs simultaneously to calculate the RSC λ of the MG. $N_0 = 250$ sample pairs were used to build the DDSPE model. Then $N_s = 10,000$ samples of \mathbf{x} were substituted to the established DDSPE model to estimate the PDF of the RSC λ in each time slot. Particularly, for each time slot, it takes 153 seconds on average to perform $N_0 = 250$ sample evaluations in **Step 2** and 0.178 seconds on average to obtain $N_s = 10,000$ estimations of λ in **Step 4** with Intel Core i7-8700 (3.20 GHz), 16 GB RAM. In other words, the average time to assess RSC for one time slot by the proposed DDSPE is about 153 seconds. The fast speed of the proposed method demonstrates its feasibility in online hour-by-hour RCS estimation. In contrast, 10,000 MCS take approximately 1.7 hours.

First, to illustrate the accuracy of the proposed DDSPE-based method in estimating the statistic properties of RSC, we compare the cumulative distribution functions (CDFs) of RSC obtained from MCS and those from the DDSPE in four scenarios—midnight (1:00) and noon (13:00) during pre- and post-smoothing scenarios. Fig. 2 shows that the estimated CDFs from the DDSPE are always overlapping with those from the benchmark MCS, demonstrating the accuracy of the proposed DDSPE-based method. Next, we present the estimated PDFs of the RSC bi-hourly by the proposed DDSPE in Fig. 3. The RSC with a 95% confidence level $\text{RSC}_{95\%}$ in each time slot is also given in Table 1. Due to the uncertainty brought by PVs in the daytime, the variance of RSC is larger than that in the night, which results in a smaller $\text{RSC}_{95\%}$ in the daytime as can be seen from Fig. 3 and Table 1. Furthermore, the Sobol' indices and dominant influencers in each time slot are presented in Fig. 4. The sum of Sobol' indices of dominant influencers is on the head of each subplot.

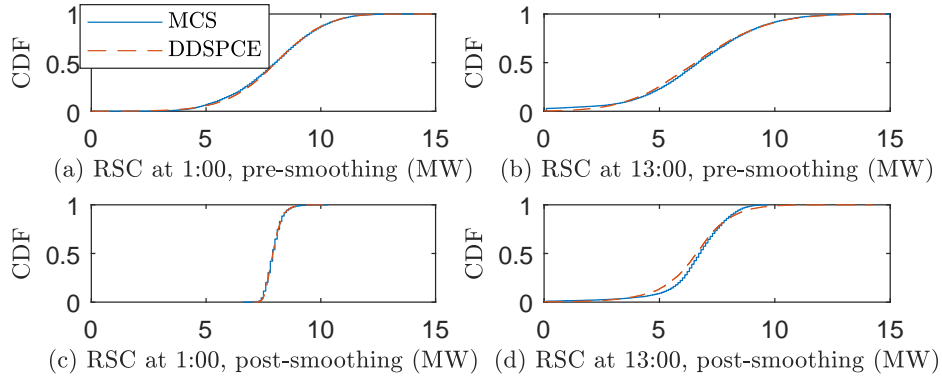


Figure 2: Comparison between the CDF of RSC obtained from MCS and DDSPCE in scenarios (a) 1:00 pre-smoothing and (b) 13:00 pre-smoothing and (c) 1:00 post-smoothing and (d) 13:00 post-smoothing.

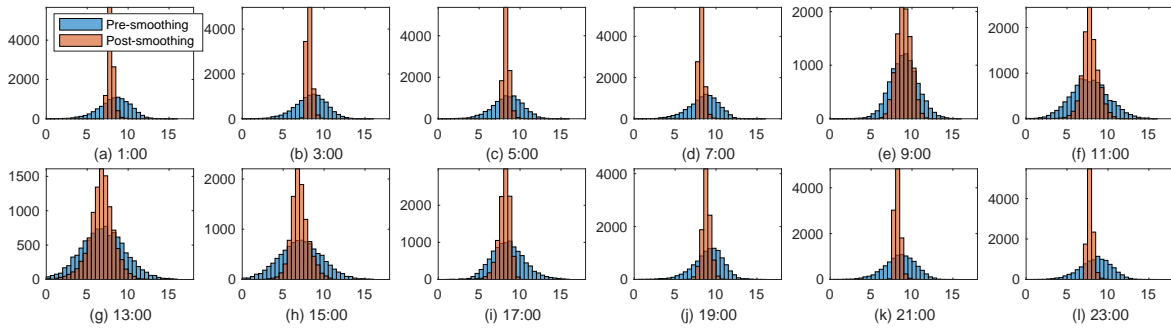


Figure 3: Distributions of pre-/post-smoothing RSC in selected time slots.

Table 1: Pre-/Post-smoothing RSC of the test MC in selected time slots.

Hour	1:00	3:00	5:00	7:00	9:00	11:00	13:00	15:00	17:00	19:00	21:00	23:00
RSC in the base case (MW)	4.96	5.05	5.27	5.13	6.32	4.02	2.47	2.85	5.38	5.71	5.25	5.14
RSC after implementing BESS (MW)	7.41	7.69	7.83	7.76	7.52	6.27	4.06	5.45	6.73	7.93	7.72	7.33
RSC increment (MW)	2.45	2.64	2.56	2.63	1.2	2.25	1.59	2.6	1.35	2.22	2.47	2.19

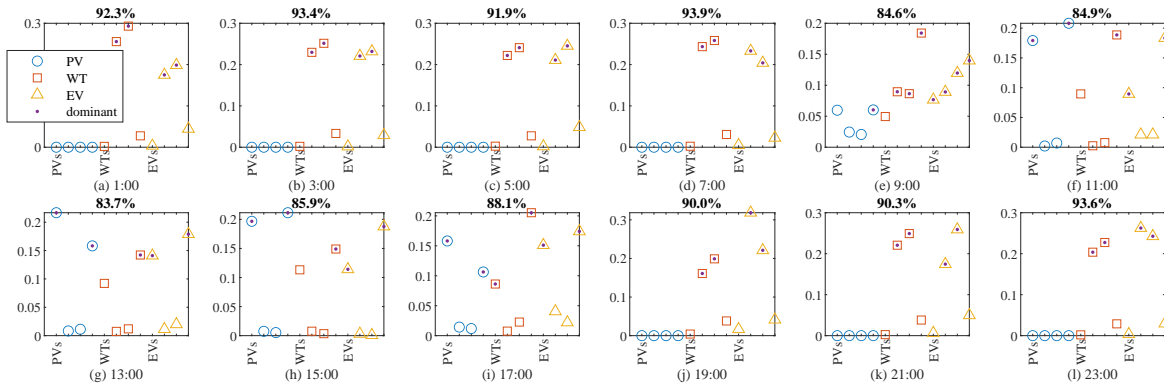


Figure 4: Sobol' index for each random input and the dominant random variables in selected time slots.

Since some dominant influencers are adjacent on the same branch, e.g., WT 2 and EV 2 on buses 20 and 21, respectively, one BESS adjacent to them is enough to smooth them out, i.e., reduce the variance of the power output from the dominant random variables on the same branch. The PDFs of RSC after implementing the BESS are presented in Fig. 3. Compared to the PDFs of RSC in the

base case, the post-smoothing ones are significantly narrower with smaller variances. As a result, the $RSC_{95\%}$ in each time slot is increased significantly, as shown in Table 1.

6 Conclusion

This paper proposes a DDSPE-based method to accurately and efficiently evaluate the RSC of an MG integrating volatile RES and EVs. Moreover, the developed DDSPE model is exploited to pinpoint dominant uncertainty sources, based on which a scheduling method of BESS is developed to enhance the RSC of an MG. The proposed DDSPE-based method, requiring no pre-assumed distributions of uncertain sources can use historical/predicted data to build the DDSPE model efficiently online for evaluating and enhancing the hour-by-hour RSC of an MG. Simulation results in the modified IEEE 33-bus MG showed that the proposed method takes less than 3 minutes to evaluate and enhance the hourly RSC.

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