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A Novel Generation Rescheduling Algorithm to Improve Power System Reliability with High Renewable Energy Penetration

Miao Fan, *Senior Member*, *IEEE*, Kai Sun, *Senior Member*, *IEEE*, Derek Lane, *Member*, *IEEE*, Wei Gu, *Senior Member*, *IEEE*, Zhengshuo Li, *Member*, *IEEE*, Fang Zhang, *Member*, *IEEE*

***Abstract*—The uncertainties of renewable energy may bring impacts to power system reliability. This paper proposes a novel generation rescheduling algorithm which adjusts generation outputs to mitigate the variations of branch power flows and relieve the overload probability. This algorithm helps prevent power congestion and balance the aggregate renewable generations and loads in power systems. Besides, the paper also proposes a probabilistic method evaluating the system uncertainty issue in the power system considering generation rescheduling operation. The proposed generation rescheduling algorithm has been tested on the Arizona transmission system. The generation rescheduling method enhances power system reliability analysis with a high penetration of renewable energy resources.**

***Index Terms*--Generation rescheduling algorithm, renewable energy, uncertainty, variance, overload probability, power system reliability.**

I. Introduction

RENEWABLE generation resources, e.g., solar power and wind power, are beginning to be significant energy resources in power systems since they provide clean power and overcome the environmental and economic issues of conventional generations. Power system complexity is increasing progressively with the deepening penetration of renewable energy. Compared to the existing conventional generation, renewable energy is easily influenced by weather conditions, so it raises uncertainty issues in power system operation and may cause various power system reliability issues [1]-[7]. In the transmission system with high renewable energy penetration, operators need to pay more attention to whether the total generation power can match load demand and whether power congestion could happen due to renewable uncertainty [8]. Power system reliability has always been an important issue in transmission system operations and planning.

One of the most important requirements of a power system with renewable energy penetration is that the system timely and appropriately adjusts its total generation outputs according to the uncertain changes of renewable energy. Generation power rescheduling operation is taken as the means to balance such uncertainties with renewable energy and to also enhance power system reliability.

A significant number of researches have been conducted introducing different generation rescheduling approaches [9]-[19]. In [10], the sensitivities of reactive power generation with respect to demand were calculated to determine the generators to be rescheduled for the purpose of enhancing voltage stability. To minimize the control and operating costs, the corrective and preventive actions were determined in [11] using optimization. In [12], the direct equilibrium tracing approach was used to examine the voltage stability of the system. Generation rescheduling and load curtailment were used in [13] as preventive control against voltage instability. The amount of control actions was found by using optimization [14]–[18] with system operating constraints to determine the correct amount of rescheduling. References [19]-[21] indicated that the Participation Factor Control (PFC) algorithm is well-suited to perform generation rescheduling. The participation factor (PF) is an indicator of the importance of the generation's contribution to the system. The PFC method has already been applied in commercial power system simulation software (e.g., PowerWorld and PSS®E).

To validate the generation rescheduling strategy, the uncertainty issue of power systems with renewable energy resources needs to be evaluated. Characterization of uncertainty concerns the possible distribution of the expected variable based on its historical statistical data [22]. There are a number of studies which proposed various uncertainty evaluation methods for power system reliability analysis. Reference [22][23] formulated a stochastic power flow method, which calculated the expected value and variances of the result variables. Thus, the system variables can be characterized not by a single number but by a range of values. In [24]-[36], the probabilistic power flow method is applied to approximate the resultant cumulative distribution function (CDF) and probability density function (PDF) and avoids the convolution operation. This approach can reduce computational burden and is suitable for large power systems with a huge number of power injections.

This paper focuses on dealing with the influence of renewable energy on transmission system reliability. The traditional PFC algorithm does not consider the generators' locations. To enhance the power system reliability, a novel generation re-

Miao Fan (miao.fan@siemens.com) and Derek Lane (derek.w.lane@siemens.com) are with Siemens Industry, Inc., Schenectady, NY 12305, US.

Kai Sun (kaisun@utk.edu) is with the Department of Electrical Engineering & Computer Science, University of Tennessee, Knoxville, TN 37996, US.

Wei Gu (wgu@seu.edu.cn) is with the School of Electrical Engineering, Southeast University, Nanjing, Jiangsu 210096, China.

Zhengshuo Li (li.zhengshuo@sz.tsinghua.edu.cn) is with Tsinghua-Berkeley Shenzhen Institute, Tsinghua University, Shenzhen 518055, China.

Fang Zhang (thu.zhangfang@gmail.com) is with Department of Electrical Engineering, Tsinghua University, Beijing 100084, China.

scheduling algorithm for compensating the variation of renewable energy based on the system network model is proposed in this paper. Since renewable energy output usually has huge uncertainty, this paper describes the renewable energy production by using cumulative distribution function curve, instead of a single value. This algorithm is to find a generation rescheduling strategy for the conventional generator outputs to help restrict the overload violation problems caused by renewable energy and reduce the potential cost to deal with overload violation. The overload issue of transmission lines could cause power congestion in power systems and may increase locational margin price of real power market. The proposed generation rescheduling algorithm can be applied in short time power system operation, since the power production of renewable energy is usually changed frequently. The algorithm can also provide useful statistical parameters and indices to power system planning studies. To evaluate the uncertainty influence of renewable energy on a power system with generation rescheduling algorithm, a probabilistic method is proposed to assess the uncertainty indices (e.g., variance and over limit probability) of branch power flows. The correlation among renewable generators is considered in this algorithm, since the renewable energy resources at neighboring locations with similar environmental conditions are likely to be highly correlated.

The paper is organized as follows. In section II, the uncertainty model of branch power flows in power systems considering generation rescheduling operation is established. Section III presents the proposed generation rescheduling model, which indicates how a potential branch power variance is calculated. The weighting factors of branch flows are also included in the rescheduling strategy. Section IV gives the outline of the uncertainty evaluation method, which applies moments and Gram-Charlier Type A expansion to approximate the variances and overload probabilities of branch power flows. In section V, a case study on the Arizona transmission system is presented, and the simulation results of the proposed rescheduling algorithm are discussed. The case study is based on the system with solar energy, but the proposed method can also be used to deal with load uncertainties or wind power uncertainties. Conclusions are included in section VI.

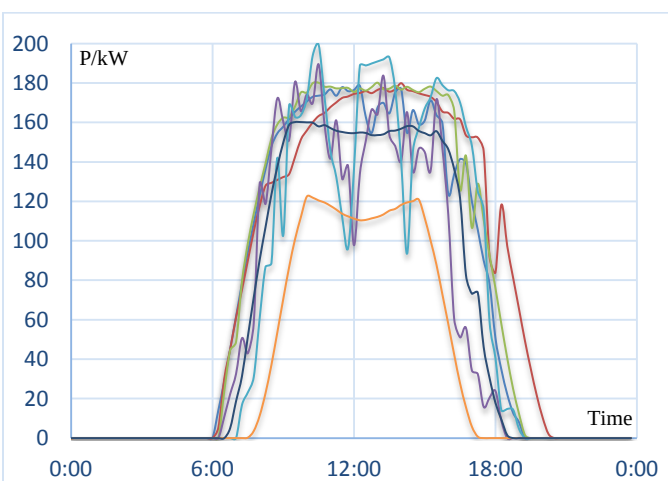

Fig. 1. Daily output curves of solar energy.

II. Uncertainty Model of Power System with Renewable Energy

Due to the stochastic characteristic of renewable energy, the renewable energy uncertainty might exert detrimental impacts on the power balance in power systems. These impacts will become significant as renewable energy capacity increases. Fig. 1 shows the daily curves of a solar energy resource.

This paper proposes the generation rescheduling algorithm to schedule the conventional generator outputs in response to the increased penetration of renewable energy and restrain the power uncertainty impact. The advantage of this method is that it considers the generation locations and can help relieve the system uncertainty and overload violation.

A. Linearized model of branch power flows with generation rescheduling operation

Considering generation rescheduling operation, the generator outputs are dispatched for balancing the uncertainty of renewable generation production. The linear model of generation rescheduling operation is given by,

$$\Delta P_{gen} + T\Delta P_r = 0 \tag{1}$$

where ΔP_{gen} and ΔP_r are the uncertainty vectors of conventional generators and renewable energy generators. T is the sensitivity matrix of conventional generators, and it represents the generation rescheduling algorithm. The uncertainty of renewable generator j is compensated by a number of conventional generators,

$$\Delta P_{r,j} = T_{1,j}\Delta P_{gen,1} + T_{2,j}\Delta P_{gen,2} + \ldots + T_{Ngen,j}\Delta P_{gen,Ngen} \tag{2}$$

The sum of $T_{1,j}$, $T_{2,j}$, …, $T_{Ngen,j}$ should be 1.

$$T_{1,j} + T_{2,j} + \ldots + T_{Ngen,j} = 1 \tag{3}$$

The bus voltage and branch flow equations are shown as follows.

$$\begin{cases} P_i = V_i \sum_{k=1}^{n} V_k (G_{ik}\cos\theta_{ik} + B_{ik}\sin\theta_{ik}) \\ Q_i = V_i \sum_{k=1}^{n} V_k (G_{ik}\sin\theta_{ik} - B_{ik}\cos\theta_{ik}) \end{cases} \tag{4}$$

$$\begin{cases} P_{ik} = -t_{ik}G_{ik}V_i^2 + V_iV_k(G_{ik}\cos\theta_{ik} + B_{ik}\sin\theta_{ik}) \\ Q_{ik} = t_{ik}B_{ik}V_i^2 - \frac{B_{ik}}{2}V_i^2 + V_iV_k(G_{ik}\sin\theta_{ik} - B_{ik}\cos\theta_{ik}) \end{cases} \tag{5}$$

where P_i and Q_i are injected powers at bus i. P_{ik} and Q_{ik} are the active and reactive branch flow in branch ik. θ_{ik} is the difference in voltage angles between bus i and k. $G_{ik} + jB_{ik}$ are the admittance of branch ik. t_{ik} is the transformer off nominal turn ratio of branch ik.

The power flow equations (4) and (5) can be expressed as,

$$\begin{aligned} y &= g(x) \\ z &= h(x) \end{aligned} \tag{6}$$

where y is the vector of power injections, x is the vector of bus voltages, z is the vector of branch power flows. Then, the linear model of the power system is used to represent the power system uncertainty.

$$\Delta x = S\Delta y$$
$$\Delta z = G\Delta x = GS\Delta y = K\Delta y \tag{7}$$

where Δx, Δy and Δz are the uncertainty vectors of x, y and z; S is the sensitivity matrix of bus voltages; G can be expressed as $G=\partial h(x)/\partial x$ at the operating point; K is the sensitivity matrix of branch power flows.

Considering the uncertainty of renewable energy output, the linear model of branch power flow uncertainty is,

$$\Delta P_{branch} = \left(K_{P_r}, K_{P_{gen}}\right)\begin{pmatrix}\Delta P_r \\ \Delta P_{gen}\end{pmatrix} \tag{8}$$

Substituting (1) in (8),

$$\Delta P_{branch} = \underbrace{\left(K_{P_r} - K_{P_{gen}} T\right)}_{L}\Delta P_r \tag{9}$$

where L is the adjusted sensitivity matrix of branch power flows to renewable energy uncertainties. The uncertainty influence of renewable energy on branch flow is represented by (9).

B. Variance of branch power flow

Let X_1, X_2, $\cdots$, X_n be n random variables with known expected value μ_{X_i} and variance $\sigma^2_{X_i}$, and Z has a linear relationship with the n variables $Z= a_1X_1+ a_2X_2+\cdots+a_nX_n$, a_1, a_2, $\cdots$, a_n are coefficients for Z. The expected value μ_Z and variance σ^2_Z of Z are calculated as,

$$\begin{aligned}\mu_Z &= E\left(\sum_{i=1}^{n} a_i X_i\right) = \sum_{i=1}^{n} a_i \mu_{X_i} \\ \sigma_Z^2 &= E\left[\left(\sum_{i=1}^{n} a_i X_i\right)^2\right] - \left[E\left(\sum_{i=1}^{n} a_i X_i\right)\right]^2 \\ &= \sum_{i=1}^{n} a_i^2 \sigma_{X_i}^2 + 2\sum_{i=1, i<j}^{n} a_i a_j \rho_{X_i, X_j} \sigma_{X_i} \sigma_{X_j}\end{aligned} \tag{10}$$

where ρ_{X_i,X_j} is the correlation coefficient between X_i and X_j, and its definition is as follows.

$$\rho_{X_i, X_j} = \frac{E[(X_i - \mu_{X_i})(X_j - \mu_{X_j})]}{\sigma_{X_i}\sigma_{X_j}} \tag{11}$$

If X_1, X_2, $\cdots$, X_n are totally independent, $\rho_{X_i,X_j}=0$. The variance of Z is as,

$$\sigma_Z^2 = \sum_{i=1}^{n} a_i^2 \sigma_{X_i}^2 \tag{12}$$

The variance of branch power flow indicates the uncertainty issue of branch flow and can be calculated by using the variance of renewable energy output.

$$\sigma_{branch_i}^2 = \sum_{i=1}^{N_r} L_i^2 \sigma_{\Delta P_{r,i}}^2 + 2\sum_{i=1, i<j}^{N_r} L_i L_j \rho_{ij} \sigma_{\Delta P_{r,i}} \sigma_{\Delta P_{r,j}} \tag{13}$$

where ρ is the correlation coefficient between renewable energy productions. Especially, if the renewable energy outputs are totally independent, correlation coefficient ρ is 0.

$$\sigma_{branch_i}^2 = \sum_{i=1}^{N_r} L_i^2 \sigma_{\Delta P_{r,i}}^2 \tag{14}$$

III. Generation Rescheduling Algorithm

In actual situation, the renewable energy production would cause serious uncertainty problems. In statistical analysis, the variance or standard deviation is used as a descriptor of the result uncertainty, and it describes how far the values lie from the mean value. For example, Fig. 2 shows a cumulative distribution function curve of a bus voltage. When the standard deviation value doubles, the CDF curve becomes much broader and the uncertainty of the voltage becomes larger.

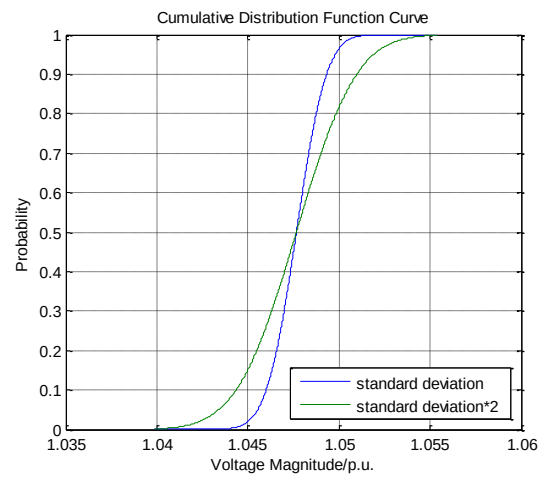

Fig. 2. CDF curve with different standard deviations.

Based on the above analysis, the variance of branch power flow is an indication of power system uncertainty issue. Therefore, the proposed rescheduling algorithm aims to find an optimal solution by minimizing the variances of branch power flows caused by the uncertainties of renewable energy resources and loads. However, in actual systems, the power flows near the thermal limits could cause power congestions in power system operation and are supposed to be paid more attention. Therefore, weighting factors are included in the rescheduling model.

A. Generation rescheduling model

To minimize the weighted sum of branch power flow variances, the model of generation rescheduling is established as follows.

$$\begin{aligned}\min \quad J &= \sum_{i}^{N_{branch}} w_i \sigma_{branch_i}^2 \\ &= \sum_{i}^{N_{branch}} w_i \left(\sum_{i=1}^{N_r} L_i^2 \sigma_{\Delta P_{r,i}}^2 + 2\sum_{i=1, i<j}^{N_r} L_i L_j \rho_{ij} \sigma_{\Delta P_{r,i}} \sigma_{\Delta P_{r,j}}\right)\end{aligned} \tag{15}$$

$$s.\ t.$$
$$L = K_{P_r} - K_{P_{gen}} T$$
$$\sum_{i=1}^{Ngen} T_{i,j} = 1$$
$$0 \le T_{ij} \le 1$$

where w_i is weighting factor of branch i. Based on the proposed optimal model in (15), this is a quadratic optimization programming.

The weighting factor w_i is used to designate the importance of branch flow in the optimization model. The weighting factors can be set to any values by users. In this paper, the branch power flows near their thermal limits are assigned larger weighting factors. The flow chart of the generation rescheduling algorithm is summarized in Fig. 3.

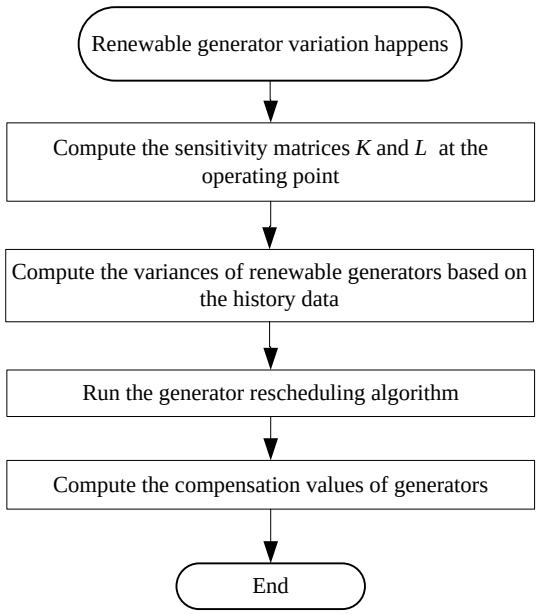

Fig. 3. Flow chart of the generation rescheduling algorithm

B. Weighting Factors of branch power flow

As shown in (15), the objective of the proposed rescheduling strategy is to minimize the uncertainty of branch power flow caused by renewable energy. In actual conditions, power system operators should pay more attention to the branch flows which nearly reach their thermal limits. Therefore, this proposed strategy applies weighting factors on branch flows. In this paper, the weighting factor of branch i is defined as follows.

$$w_i = \left(\frac{\mu_{branch_i}}{Limit_i} \right)^2 \tag{16}$$

where μ_{branch_i} is the expected power flow value of branch i; $Limit_i$ is the thermal limit of branch i.

The proposed algorithm in (15) is influenced by the weighting factors such that a branch flow near thermal limit should be set a larger weight in the objective function to prevent overload during generation rescheduling. In actual applications, the weighting factors can be set to zero if the branch flows are far away from their thermal limits.

IV. Probabilistic Algorithm for Uncertainty Evaluation

A probabilistic method is proposed to evaluate the uncertainty issue and test the advantage of the proposed generation rescheduling performance in power systems. It can provide a full reflection of the power system influenced by the power uncertainty injections and generation rescheduling operation. This method permits the power input variables to vary probabilistically and provides results in terms of probabilistic values. It calculates the variance of a branch power flow and its probability being greater than its thermal rating. These are extremely useful parameters in power system reliability studies.

A. Moments

The probabilistic method based on moments is applied to evaluate the uncertainty influence on power systems. First, the moments of input variable X is defined as,

$$\alpha_v = \int_{-\infty}^{+\infty} X^v f(X) dX \tag{17}$$

where v is the order of the moments, and $f(X)$ is the PDF of the variables.

If X is a sample discrete variable written as $x_1, x_2, \ldots, x_m$, the moments of X is,

$$\alpha_v = E(X^v) = \frac{1}{m} \sum_{i=1}^{m} x_i^v \tag{18}$$

The expected value μ_X and the variance σ_X^2 are as,

$$\begin{aligned} \mu_X &= \alpha_1 \\ \sigma_X^2 &= \alpha_2 - \alpha_1^2 \end{aligned} \tag{19}$$

Considering the correlations among the input variables, the joint moments of the n input variables $X_1, X_2, \ldots, X_n$ are calculated as [30],

$$\begin{aligned} \alpha_{v1,v2,\cdots,vn} &= E(X_1^{v1} X_2^{v2} \cdots X_n^{vn}) \\ &= \underbrace{\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \cdots \int_{-\infty}^{+\infty}}_{n} X_1^{v1} X_2^{v2} \cdots X_n^{vn} f(X_1, X_2, \ldots, X_n) dX_1 dX_2 \ldots dX_n \end{aligned} \tag{20}$$

The joint moments indicates the correlation among the variables. Especially, the neighboring renewable generators are easily influenced by similar weather condition, so the correlation cannot be ignored.

If $Z = a_1X_1 + a_2X_2 + \cdots + a_nX_n$, the vth order moments of Z are given by,

$$\alpha_{Z,v} = \sum_{\{v1,v2,\cdots vn\}} \frac{v!}{v1!v2!\cdots vn!} a_1^{v1} a_2^{v2} \cdots a_n^{vn} \alpha_{v1,v2,\cdots,vn} \tag{21}$$

where $\{v1, v2, \cdots, vn\}$ consists of all non-negative integer solutions of the equation $v1 + v2 + \cdots + vn = v$. The first three orders of moments are as,

$$\begin{aligned} \alpha_{Z,1} &= \mu_Z = \sum_{i=1}^{n} a_i \alpha_{X_i,1} = \sum_{i=1}^{n} a_i \mu_{X_i} \\ \alpha_{Z,2} &= \sum_{i=1}^{n} a_i^2 \alpha_{X_i,2} + 2 \sum_{i=1,i<j}^{n} a_i a_j \alpha_{X_i,X_j} \\ \alpha_{Z,3} &= \sum_{i=1}^{n} a_i^3 \alpha_{X_i,3} + 3 \sum_{i=1,i\neq j}^{n} a_i^2 a_j \alpha_{X_i^2,X_j} + 6 \sum_{i=1,i<j<k}^{n} a_i a_j a_k \alpha_{X_i,X_j,X_k} \\ &\ldots \end{aligned} \tag{22}$$

B. Approximation Expansions

When the moments of the result variables are calculated, the CDFs and PDFs can be approximated by using Gram-Charlier

Type A expansion, which is defined as follows [32].

For an arbitrary distribution X with a mean value μ and a standard deviation σ, the CDF and PDF of X can be represented as a series of normal distribution and its derivative functions:

$$F(x)=\sum_{i=0}^{\infty}\frac{c_i}{i!}\phi^{(i)}(\frac{x-\mu}{\sigma})$$
$$f(x)=\sum_{i=0}^{n}\frac{c_i}{i!}\varphi^{(i)}(\frac{x-\mu}{\sigma}) \tag{23}$$

where $\phi(x)$ and $\varphi(x)$ represent the CDF and PDF of the normal distribution.

The coefficient c_i in the Gram-Charlier Type A expansion can be calculated as:

$$c_i=(-1)^i\int_{-\infty}^{\infty}f(x)H_i(x)dx \tag{24}$$

where $H_i(x)$ is the Hermite polynomial, and is defined as,

$$H_i(x)=(-1)^i e^{x^2/2}\frac{d^n}{dx^n}e^{-x^2/2} \tag{25}$$

This, the Hermite polynomial is calculable as,

$$H_n(x)=n!\sum_{k=0}^{[n/2]}\frac{(-1)^k x^{n-2k}}{k!(n-2k)!2^k} \tag{26}$$

Therefore, the coefficient c_i and moments have the following relations:

$$\begin{aligned}
&c_0=1\\
&c_1=c_2=0\\
&c_3=-\frac{\alpha_3-3\alpha_1\alpha_2+2\alpha_1^3}{\sigma^3}\\
&c_4=\frac{\alpha_4-3\alpha_2^2-4\alpha_1\alpha_3+12\alpha_1^2\alpha_2-6\alpha_1^4}{\sigma^4}\\
&c_5=-\frac{\alpha_5-5\alpha_1\alpha_4-20\alpha_2\alpha_3+30\alpha_1^2\alpha_3+60\alpha_1\alpha_2^2\text{-}50\alpha_1^3\alpha_2+44\alpha_1^5}{\sigma^5}\\
&\cdots
\end{aligned} \tag{27}$$

When the moments of the results variables are calculated, the CDFs and PDFs can be approximated by using the moments and Gram-Charlier Type A expansion in (23), and the over limit probability of the result variable can be obtained from the CDF directly.

$$P(x>\text{limit})=1-F(\text{limit}) \tag{28}$$

Since the uncertainty model of branch power flows shown in (9) is established by using the proposed algorithm in (15), the uncertainty of branch power flows can be evaluated. The computation procedure is summarized in Table I.

V. Case Study

This paper uses the Arizona transmission system with solar energy as the test system. The proposed generation rescheduling algorithm can also be used for other types of renewable resources such as wind generation. The transmission system consists of 2497 buses and 2971 lines. The system also has 1070 loads, 174 conventional generators and 179 solar energy resources. The renewable energy penetration is performed at 20% of the load. The proposed generation rescheduling control (GRC) algorithm has been implemented using MATLAB. To examine the proposed GRC algorithm advantage, a participation factor control (PFC) algorithm is applied. The network diagram of the test system is shown in Fig. 4.

TABLE I. Uncertainty Evaluation Procedure

Input: History data of renewable energy outputs and loads.
Output: CDF, PDF and over limit probability of the result variables.
Procedure:
1. Obtain the history data and calculate the moments of input variables by using (17);
2. Compute the joint moments among the input variables by using (20);
3. Compute the sensitivity matrix L in (15) from the proposed generation rescheduling algorithm;
4. Compute the moments of result variables by using (21);
6. Compute the coefficient c_i by using (27);
7. Approximate the CDF and PDF of the result variables by using (23);
8. Obtain over limit probability of result variables from the CDF curves.

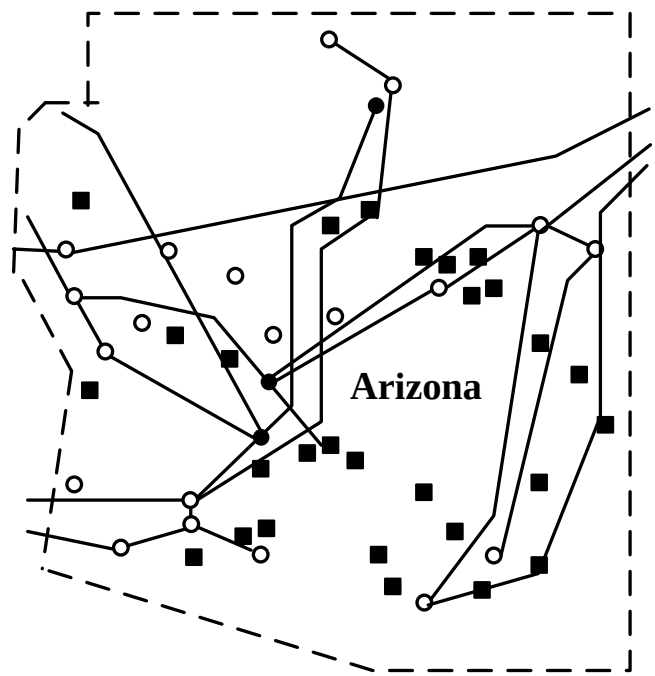

Fig. 4. Simplified diagram of the Arizona transmission system.

The actual historical data of solar power production obtained from [37] is used for the case study. A typical daily curve of solar generator with a confidence interval is shown in Fig. 5. The PDF curve of a solar generation production is shown in Fig. 6. Based on the historical data of solar generators, the coefficient of variation (CV) of solar generation production is 25%. That is a large power uncertainty and may cause power fluctuation issues in power systems. CV is defined as the ratio of standard deviation to expected value.

$$CV=\frac{\sigma}{\mu} \tag{29}$$

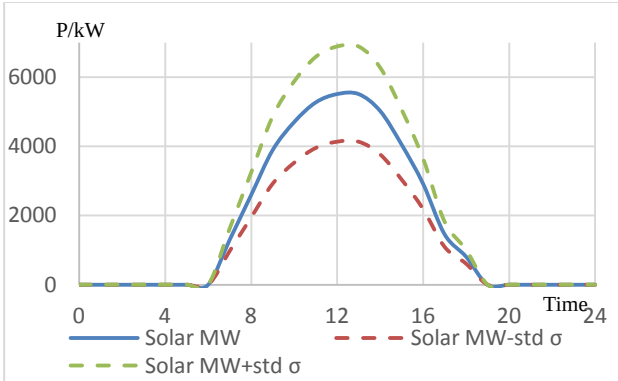

Fig. 5. Daily curve of PV generator with a confidence interval.

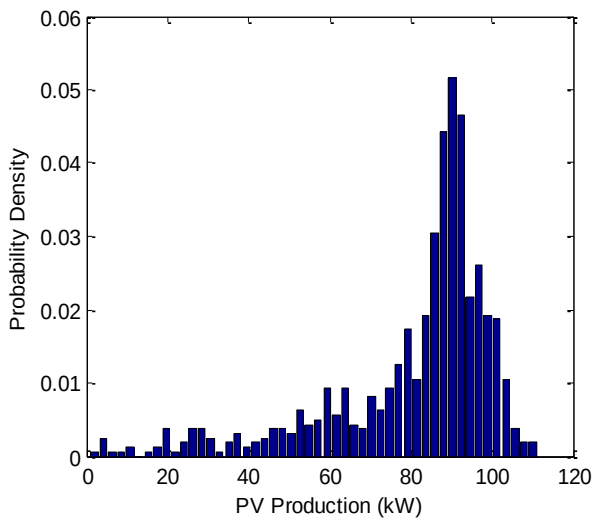

Fig. 6. PDF curve of a PV generation production.

The load actual data are from the Electric Reliability Council of Texas (ERCOT) [38], and the PDF curve is shown in Fig. 7. The matrix T is calculated by solving the quadratic optimization in (15). In this case study, the weighting factors of branch power flows are set by using (16), and the branch thermal limits are applied for calculating the weighting factors.

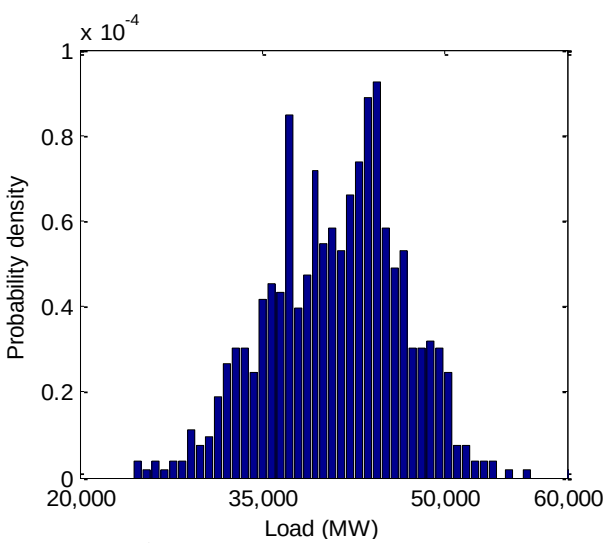

Fig. 7. PDF curve of a load demand.

A. *Uncertainty results for generation rescheduling algorithm*

To test the proposed GRC algorithm's advantage, the results with no generation rescheduling and the PFC method are also calculated for comparisons with the results of proposed generation rescheduling algorithm.

In PFC algorithm, the participation factors of each generator are constant and indicate the importance of the generation contribution to the system [21]. The change of each conventional generator output is adjusted in proportion to that generator's participation factor divided by the total of the participation factors for all the generators in the system to balance the variances of system's renewable energy. The generator that has the largest PF contributes the most, and the generator that has the smallest PF contributes the least. The PFC algorithm does not consider the generators' locations.

The objective function values J of different generation rescheduling algorithms are shown in Table II.

TABLE II. OBJECTIVE FUNCTION VALUE OF DIFFERENT GENERATION RESCHEDULING ALGORITHM

Algorithm	Objective function J
No rescheduling	39.28
PFC	17.99
GRC[a]	4.15

a. GRC – generation rescheduling control.

The uncertainty results (expected values and variances) of branch power flows for different rescheduling algorithms are shown in Table III.

TABLE III. UNCERTAINTY RESULTS OF DIFFERENT GENERATION RESCHEDULING ALGORITHMS

Branch	Expected value (pu)	No rescheduling	PFC	GRC
		std[b] (pu)	std (pu)	std (pu)
86291-14006	3.334	2.2069	0.1351	0.0554
86337-86338	3.159	2.0216	0.0696	0.0490
14003-86337	3.159	2.0215	0.0696	0.0490
86338-14018	3.136	1.9669	0.0677	0.0477
14011-14005	1.970	0.9878	0.0415	0.0393
15033-15034	4.129	0.6022	0.0224	0.0163
15034-86326	4.121	0.5992	0.0223	0.0163
19038-86325	0.5795	0.0216	0.0157	0.0146
14020-14259	5.083	0.3809	0.1144	0.0218
15021-15061	12.635	0.3403	0.0753	0.0151
14001-86290	6.311	0.3177	0.0943	0.0197
15090-15089	1.672	0.2441	0.1209	0.0545
15089-15011	14.972	0.1936	0.1574	0.0177
14259-14207	4.089	0.1837	0.0166	0.0123

b. std – standard deviation.

The results indicate that the proposed generation rescheduling algorithm performs much better than PFC algorithm to reduce the variances of branch power flows. The proposed algorithm can help the power system restrain uncertainty influence of renewable energy power injections.

The CDF curves and uncertainty results of the branch flow through branch 86291-14006 are shown in Fig. 8 and Table IV. The thermal limit of the branch power flow 86291-14006 is 3.50 pu.

TABLE IV. OVERLOAD PROBABILITY OF POWER FLOW THROUGH BRANCH 86291-14006 WITH DIFFERENT RESCHEDULING ALGORITHMS

Algorithm	Standard deviation (pu)	Overload probability
No rescheduling	2.2069	0. 4700
PFC	0.1351	0.1095
GRC	0.0554	0.00137

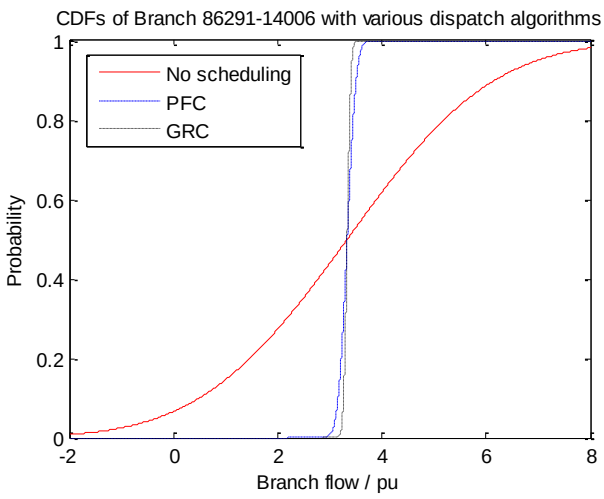

Fig. 8. CDF curves of power flow through branch 86291-14006 with different rescheduling algorithms.

Comparing the results, both algorithms can balance the uncertainties of renewable energy productions, and the proposed algorithm brings a clear improvement to help relieve the overload problem in the power system, especially for the branch flow close to its thermal limit. The results demonstrate the advantage of the proposed method.

B. *Comparison of different weighting factors*

In the proposed rescheduling algorithm, the variances of branch power flows use weighting factors which indicate if the branch flows are easily over limit and should be paid more attention in system operation. This case study also compares the uncertainty results considering weighting factors with the results which do not consider weighting factors in the objective function of the generation rescheduling model.

Table V and Table VI shows the uncertainty results of branch flows near and far away from their thermal limits, respectively.

TABLE V. UNCERTAINTY RESULTS OF BRANCH FLOWS NEAR THERMAL LIMIT

Branch	Expected value (pu)	Thermal limit (pu)	std (pu) without WF[c]	std (pu) with WF
86291-14006	3.334	3.500	0.0760	0.0554
84285-84119	1.172	1.076	0.0027	0.0013
84215-84199	2.112	2.390	0.2693	0.2415
14003-15981	7.100	9.240	0.6801	0.6793
84049-84001	0.936	1.076	0.0102	0.0048
84261-84136	1.649	2.390	0.0328	0.2628

c. WF – weighting factor.

TABLE VI. UNCERTAINTY RESULTS OF BRANCH FLOWS FAR FROM THERMAL LIMIT

Branch	Expected value (pu)	Thermal limit (pu)	std (pu) without WF	std (pu) with WF
14231-19062	3.100	7.130	0.0090	0.0094
19115-14259	0.670	3.740	0.0224	0.5567
14204-14215	0.377	2.809	0.0236	0.1002
15213-15205	1.062	6.374	0.0122	0.0242
86310-86311	12.290	19.053	0.0052	0.0232
15207-15205	4.430	7.967	0.0233	0.0388

Based on the results in Table V and Table VI, the branch power flows close to the thermal limits considering the weighting factors get smaller variances than the branch results without weighting factors. If the branch flows are far away from their limits, the variances considering weighting factors could be larger.

Fig. 9 and Table VII show the CDF curves and overload probability results of the branch flow through branch 86291-14006 with different weighting factors. The expected value of the branch is close to the thermal limit 3.50 pu. Therefore, the overload probability gets more relieved with the rescheduling algorithm considering weighting factors.

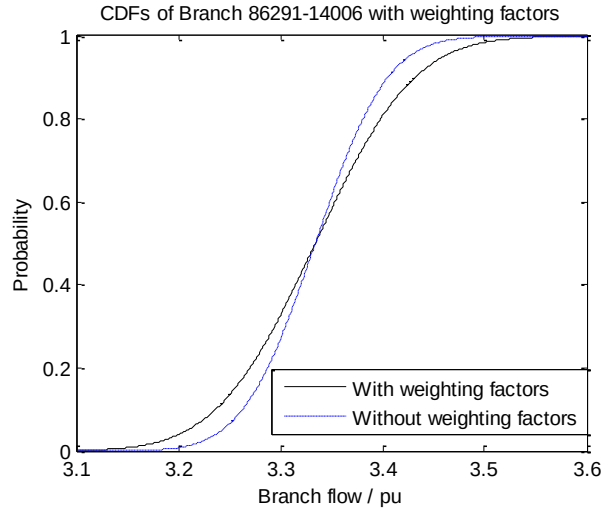

Fig. 9. CDF curves of power flow through branch 86291-14006 with different weighting factors.

TABLE VII. OVERLOAD PROBABILITY OF POWER FLOW THROUGH BRANCH 86291-14006 WITH DIFFERENT WEIGHTING FACTORS

Algorithm	Standard deviation (pu)	Overload probability
Rescheduling with weighting factors	0.0554	0.0014
Rescheduling without weighting factors	0.0760	0.0145

C. Comparison of different solar energy penetrations

The proposed generation rescheduling algorithm is tested on the transmission systems with different solar penetration conditions of 10%, 20% and 40% of total load. The CDF curves and simulation results of the branch power flow through branch 86291-14006 for different solar energy penetrations are shown in Fig. 10 and Table VIII, respectively.

According to the simulation results, the proposed generation rescheduling algorithm can limit the variance and overload probability of branch power flows in different solar penetrations. The results confirm the validity of the proposed algorithm.

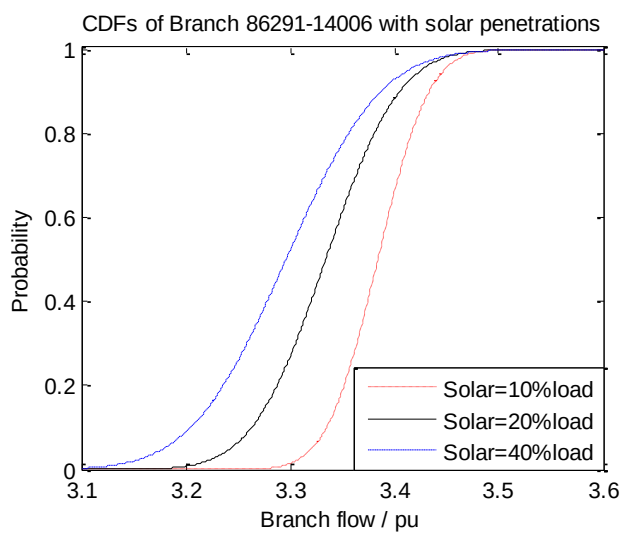

Fig. 10. CDF curves of power flow through branch 86291-14006 with different solar energy penetration.

TABLE VIII. OVERLOAD PROBABILITY OF POWER FLOW THROUGH BRANCH 86291-14006 WITH DIFFERENT WEIGHTING FACTORS

Solar penetration	Expected value (pu)	Standard deviation (pu)	Overload probability
10%	3.384	0.0384	0. 0013
20%	3.334	0.0554	0.0014
40%	3.296	0.0712	0.0021

VI. CONCLUSIONS

The uncertainties and intermittency of renewable energy resources may cause many problems to influence power systems. The generation rescheduling algorithm presented in this paper provides a novel method to adjust the conventional generation output according to the uncertainty of renewable production to restrain the uncertainty influence on power systems. The proposed generation rescheduling algorithm is to find an optimal generator scheduling solution to minimize the weighted sum of branch power flow variances and restrict overload issue. It helps prevent power congestion in power systems. Weighting factors are applied in the rescheduling model to indicate the importance of branches. The probabilistic method is applied to evaluate the probabilistic characteristics of a power system. The simulation results show that the proposed method can help relieve the system branch flow violation and the overload probability of the system. The negative impact of renewable energy is thus limited by using this approach. The case study is highlighted with solar power, and the proposed method can be also applied to the system with other types of renewable energy. If the system has a very high penetration of renewable energy, the renewable generators can also participate in the rescheduling to mitigate the influence from their uncertainties.

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VIII. Biographies

Miao Fan (St'11-M'15-S'17) received the Ph. D. degree in the electrical engineering from Arizona State University, Tempe, in 2012, and the B. S. and M. S. degree in electrical engineering from Tsinghua University, Beijing, China, in 2007 and 2009, respectively. He was a postdoctoral research associate at the Department of EECS, University of Tennessee in Knoxville. Currently, he is a senior software engineer at Siemens Industry Inc., Schenectady, NY. His research interest area is in power system reliability analysis, power flow calculation and renewable energy.

Kai Sun (M'06-S'13) received the B.S. degree in automation in 1999 and the Ph.D. degree in control science and engineering in 2004 both from Tsinghua University, Beijing, China. He was a postdoctoral research associate at Arizona State University, Tempe, from 2005 to 2007, and was a project manager in grid operations and planning areas at EPRI, Palo Alto, CA from 2007 to 2012. He is currently an assistant professor at the Department of EECS, University of Tennessee in Knoxville.

Derek Lane (M'01) received a B.S. degree in engineering physics in 1990 from Abilene Christian University, a Ph.D. degree in experimental high energy physics in 1999 and a M.E. in systems engineering in 2002 from Iowa State University. He has worked as a consultant focused on electric power system market and was a lead developer for an LMP market simulator. He has worked in the software engineering group at Siemens as a manager of quality assurance and, currently, of the power engineering team at Siemens PTI, Schenectady, NY.

Wei Gu (M'06-S'16) received his B.Eng degree and Ph.D. degree in Electrical Engineering from Southeast University, China, in 2001 and 2006, respectively. From 2009 to 2010. He is now a professor in the School of Electrical Engineering, Southeast University. His research interests include distributed generations and microgrids, active distribution networks.

Zhengshuo Li (St'12-M'16) received his Bachelor and PhD degrees from the Department of Electrical Engineering, Tsinghua University, Beijing, China, in 2011 and 2016. Currently, he is working as a postdoctoral fellow at Tsinghua-Berkeley Shenzhen Institute (TBSI). His research interests include economic dispatch and security analysis of smart transmission and distribution grids, distributed storage utilization and demand response in smart grids.

Fang Zhang (St'13–M'15) received the B.S. and Ph.D. degrees from Tsinghua University, Beijing, China, in 2010 and 2015, respectively. Currently, he is a post doctor with the Department of Electrical Engineering at Tsinghua University. His research interests are in the areas of power system measurement and control.