Mean-tracking model based stochastic economic dispatch for power systems with high penetration of wind power

Lin, Zhenjia; Chen, Haoyong; Wu, Qiuwei; Li, Weiwei; Li, Mengshi; Ji, Tianyao

Published in:
Energy

Link to article, DOI:
[10.1016/j.energy.2019.116826](https://doi.org/10.1016/j.energy.2019.116826)

Publication date:
2020

Document Version
Early version, also known as pre-print

[Link back to DTU Orbit](#)

Citation (APA):
Lin, Z., Chen, H., Wu, Q., Li, W., Li, M., & Ji, T. (2020). Mean-tracking model based stochastic economic dispatch for power systems with high penetration of wind power. *Energy*, 193, [116826].
<https://doi.org/10.1016/j.energy.2019.116826>

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Mean-tracking model based stochastic economic dispatch for power systems with high penetration of wind power

Zhenjia Lin^a, Haoyong Chen^{a,*}, Qiuwei Wu^b, Weiwei Li^a, Mengshi Li^a, Tianyao Ji^a

^a*School of Electric Power Engineering, South China University of Technology, Guangzhou 510000, China*

^b*Center for Electric Power and Energy, Department of Electrical Engineering, Technical University of Denmark, Kgs. Lyngby DK 2800, Denmark*

Abstract

The random wind power that accounts for a growing proportion in power systems imposes higher challenge on the reliable operation of power system under uncertain circumstances. Since forecasted values of wind speed are accessible to system operators in advance, the corresponding calculated pre-schedule can be regarded as a reference for the stochastic economic dispatch (SED) problem. Existing methods seldom take the pre-schedule into account when determining an optimal dispatch solution, and the resulting dispatch solutions generally differ greatly from the pre-schedule. In this paper, aiming to readjust from the reference schedule as little as possible, the mean-tracking model is proposed for the first time to search for optimal dispatch solutions with the minimal expectation of generation cost and the minimal tracking errors, among which the tracking errors is implemented to each generator unit in terms of minimizing the deviation in generation cost between the trial solution and the pre-schedule. Moreover, the affine decision rule is applied in this paper to distribute the uncertain wind power proportionally to each generator unit. To guarantee the stable operation of power systems, the voltage operating limits are considered to ensure the voltage on each bus remains within the security margins of voltage. Numerical experiments are carried out on a modified IEEE-30 bus system, and simulation results demonstrate the effectiveness of the proposed mean-tracking model for the SED problem.

Keywords: Stochastic economic dispatch, uncertain wind power, mean-tracking model, generation cost, tracking errors.

1. Introduction

As one of the most easily transported, converted and used energy sources, electric power has become a widely used form of energy in modern society, and the efficient use of electric

*Corresponding author: Pro. Haoyong Chen. This work is financially supported by the National Key Research and Development Program of China (2016YFB0900100), the National Natural Science Foundation of China (51937005) and the Oversea Study Program of Guangzhou Elite Project (GEP).

Email address: eehychen@scut.edu.cn (Haoyong Chen)

energy plays an increasingly significant role in promoting social and economic development in countries all over the world [1, 2, 3]. Economic dispatch (ED) is an important optimization problem in the use of electric power, which is targeted to determine the most economical generation dispatch solution while satisfying various operational constraints. Generally, it can be achieved by reasonably allocating the power output among generators, adjusting the tap position of transformers and coordinating the terminal voltage of generators [4, 5]. However, as more and more renewable energy sources (RES) characterized by stochastic and intermittent power output are integrated into the power systems, it becomes more and more challenging to ensure the stable and economic operation of power systems [6, 7, 8].

Traditional deterministic dispatch that merely relies on the forecast values of renewable energy, rarely takes into account the uncertainty of RES, cannot ensure the power system with significant penetrations of RES to operate in an efficient manner [9, 10]. However, it may play a crucial part in determining an optimal intra-day dispatch solution, which will be mentioned in the following. Currently, there are three main methods for solving the economic dispatch problem with the integration of uncertain RES, i.e., robust optimization [11, 12, 13], interval optimization [14] and stochastic optimization [15, 16].

In the framework of robust optimization (RO), the uncertain power output of RES is expressed by a polyhedral uncertainty set. RO tends to be over-conservative since it has to hedge against the possible scenarios in uncertainty set, which is generally subjected to the vertexes of the polyhedral uncertainty set. However, the worst-case scenario actually happens at a very low probability. As indicated in paper [17], it has been theoretically derived that the fulfillment of constraints over the uncertainty set drives the random variable to reach at the boundary values, which will result in a low-efficiency economic dispatch solution. RO can only guarantee the applicability of the robust dispatch scheme, that is, to adapt to the uncertainty of wind power, but it greatly sacrifices the economy of the scheme. Especially when multi-objective is considered, it is difficult for RO to coordinate the multi-objective with a single min-max-min mathematical model. Interval optimization (IO) is based on the situation that uncertain information is not fully grasped and only the upper and lower boundaries of uncertainty are known. Owing to the limitation of information, the obtained scheme based on IO is often not the most efficient one. Under the condition of the high permeability of wind power, the random variables will fluctuate in a larger range, and the practicability of the scheme determined by the upper and lower boundaries is even worse. With the gradual implementation of the Internet of Things and the rapid development of sensing technology, more data related to renewable energy can be easily obtained, and based on data-driven analysis technology [18, 19], more accurate information about RES can be acquired. Therefore, IO gradually loses its competitiveness in uncertain optimization.

In contrast to RO and IO, the stochastic optimization has been another mainstream method to solve the uncertain wind power problem, among which the uncertainties are represented by a large number of scenarios generated based on the quasi-Monte Carlo (QMC) method [20, 21]. For the stochastic economic dispatch (SED) problem, authors in [22] found the optimal dispatch solution with the minimal expectation of generation under the uncertain wind power scenarios, however, the obtained solution may not well adapt to the uncertainty since the variance of generation cost regarding to different wind power scenarios is out of

consideration. Inspired by the mean-variance (MV) model for the portfolio optimization problem proposed by Markowitz [23, 24], Li *et al.* in [25] employed the MV model to search for optimal dispatch solutions with minimal generation cost and economic risk under the uncertainties of wind power, among which the risk is regarded as the variance of generation cost. Similarly, [26] uses the MV optimization to hedge the risk from the energy price uncertainties and choose an optimal energy storage scheduling. However, the variance in MV model makes no difference between the deficiency and abundance of the generation cost under different scenarios. Paper [27] proposes the downside risk to represent the lower semi-absolute deviation of generation cost, and paper [28] verifies that minimizing the lower semi-variance can avoid higher generation cost as much as possible which can help choose a more economic dispatch solution.

However, the aforementioned methods rarely consider the pre-schedule obtained from system operators who are aware of the forecasted values of wind power ahead of time, thus the resulting dispatch solutions generally differ greatly from the pre-schedule. In fact, the dispatch solution we desire is to be consistent with the pre-schedule solution as much as possible while accommodating the uncertain wind power, which means the less adjustments we need to make on the pre-dispatch when executing the dispatch solution. Roll in [29] proposed a tracking error model under the framework of the MV model, that is, the portfolio manager expects to give a benchmark portfolio and evaluates the investment performance by tracking the errors in the returns between the portfolio and the benchmark. Similarly, this tracking error model can also be applied for the SED problem.

In this paper, the mean-tracking model is first proposed to take the wind power volatility into consideration, with the objective of providing a robust dispatch solution for system operators that minimizes the generation cost as well as the tracking errors in the cost between the trial solution and the pre-schedule. Different from the mean-variance model, here the tracking errors is implemented to each generator unit. This improved model takes into account the reference schedule, which will lead to a more practical dispatch that can accommodate the uncertain wind power while readjusting from the pre-schedule as little as possible. Therefore, under the framework of mean-tracking model, the SED problem is formulated as a multi-objective optimization problem and can be solved through the group search optimizer with multiple producer (GSOMP) [30, 31].

There are three major improvements in this paper, which includes:

- The tracking errors is implemented to each generator unit in terms of the minimization of deviation in generation cost between the trial dispatch solution and the pre-schedule. In this respect, we can find an optimal dispatch solution with the minimal tracking errors, which means much fewer adjustments are needed to make on the power outputs of generator units in the pre-schedule when executing the dispatch solution.
- The correlations of wind power among different wind farms are taken into consideration based on the copula theory, and five wind farms are integrated at buses 7, 10, 16, 24, 30 of the IEEE 30-bus system. The generated wind speed samples of five wind farms are closely related to each other, which are more suitable to actual situations and can be utilized in the subsequent economic dispatch model to help generate a more practical dispatch solution.
- The affine decision rule is applied in this paper to distribute the uncertain wind power

proportionally to the generator units, avoiding the abnormal fluctuations in generation cost under various wind power scenarios caused by the large fluctuation of power output of generators at the slack bus. Moreover, the voltage operating limits of the grid are included to guarantee the reliability of the derived dispatch solution based on the proposed mean-tracking model, in which the violation is implemented by means of the penalty function. With the introduction of voltage violation constraint, the voltage magnitude of bus fluctuates within the reasonable range.

The rest of the paper is organized as follows: Section 2 introduces the presentation of uncertain wind power considering the correlation among multiple wind farms and formulates the mathematical model for the SED problem. Section 3 illustrates the superiority of the mean-tracking model and incorporates it into the SED problem for more practical dispatch solutions. Numerical simulations are carried out in Section 4 to verify the effectiveness of the proposed mean-tracking model, and the conclusion is finally drawn in Section 5.

2. The formulation of stochastic economic dispatch problem

2.1. Presentation of uncertain wind power

With the increasing proportion of renewable energy resources (RES) in the power systems, the intermittent characteristic of RES poses a great challenge to the stable operation of system. To solve the stochastic economic dispatch problem, we have to first tackle the uncertain power output of RES, here in this paper the uncertainties we study mainly focus on the wind power.

2.1.1. Quasi-Monte Carlo simulation

Monte Carlo simulation (MCS) is widely used in stochastic problem analysis for its great applicability [32]. To represent the uncertainties of wind power, the MCS method is first used to generate the random numbers, which are then inverted to the actual wind speed domain according to the probabilistic distribution functions (PDFs), and the resulting wind power scenarios can be applied to evaluate the impact of uncertainties. However, there is always a probabilistic bias between the pseudo random number and real sequence. To get more satisfactory results, it is necessary to generate a large number of random samples, which leads to the low computational efficiency. To reduce the computation burden of MCS, Niederreiter in [20] proposed the quasi-Monte Carlo (QMC) method that greatly improves the quality of the uniformly distributed random numbers by implementing the Sobol sequence technology. The generation process of Sobol sequence is elaborated as [33]:

- 1). For any decimal number n , it can be expressed in a form of van der sequence associated with base 2:

$$n = \sum_{i=0}^M a_i 2^i \quad (1)$$

where M is the lowest integer not less than $\log_2(n)$, and a_i is a binary variable that equals either 0 or 1.

Figure 1: Random numbers generated by the Sobol sequence and pseudo random number technique

2). Define a primitive polynomial of degree d as:

$$P = x^d + h_1x^{d-1} + h_2x^{d-2} + \cdots + h_{d-1}x + 1 \quad (2)$$

where h_j ($j = 1, 2, \dots, d-1$) is either 0 or 1, and the number of d can be determined through $\phi(2^d - 1)/d$, where ϕ is the Euler function. Thereafter, a sequence of positive integer m_i ($i = 1, 2, \dots, M, M > d$) are defined by the recurrent relation:

$$m_i = 2h_1m_{i-1} \oplus 2^2h_2m_{i-2} \oplus \cdots \oplus 2^dm_{i-d} \oplus m_{i-d} \quad (3)$$

where $\oplus$ denotes a bit-by-bit exclusive-or operation, and the value of $m_1, m_2, \dots, m_d$ can be chosen freely provided that m_i is odd and $m_i < 2^i$ ($1 \leq i \leq d$). The subsequent $m_{d+1}, m_{d+2}, \dots$ are then determined by the recurrence, which is easily programmed using integer arithmetic.

3). Finally, the n^{th} point in a Sobol sequence is calculated as:

$$\Theta(n) = a_1(n)v_1 \oplus a_2(n)v_2 \oplus \cdots \oplus a_i(n)v_i \quad (4)$$

where v_i ($i = 1, 2, \dots, M$) is the direction number that equals to $m_i/2^i$.

As a result, we can generate a sequence of value $x^1, x^2, \dots, 0 < x^i < 1$, with low discrepancy over the unit cube, and the discrepancy D_N^* has declined to $o((\log N)^s N^{-1})$. Here x^i ($i = 1, 2, \dots, N$) are the N independent and identically distributed random numbers that extracted from the s -dimensional problem. Moreover, the convergence rate of QMC becomes much faster than MCS, especially in low dimensional problems. Fig. 1 shows the

2-dimensional uniform random sequences generated by pseudo random number and Sobol sequence technique, with the numbers of samples as 30, 300 and 3000, respectively. It can be easily observed that the 2-dimensional random numbers generated by the Sobol sequence technique (QMC) are more uniform than the random numbers obtained from the pseudo random number technique (MCS). In this regard, a small number of low-discrepancy sequences from QMC can entirely represent a large number of samples from MCS.

Therefore, by performing the QMC in which the Sobol sequence technique is implemented, we can represent the uncertainty with considerable number of wind power scenarios, thus getting rid of the computational burden caused by large number of samples generated by MCS.

2.1.2. Dependent permutation

Although the low-discrepancy sequence generated by QMC can well describe the uncertainty of wind power, it is difficult to directly characterize the correlations among multiple wind farms by using these random numbers. In fact, wind farms are usually concentrated in areas with abundant wind resources. The power outputs of wind farms in adjacent areas are highly correlated, that is, when the power output of one wind farm increases or decreases, the output of other wind farms will also increase or decrease with a high probability. In Fig. 2 we list the actual wind speeds data of northwest China from August 2012 to July 2014, with a resolution of one hour. Obviously, we can find that the particles are scattered around the main diagonals, which indicates that the five wind farms are closely related to each other. In this regard, the formulation of wind power output considering correlations among multiple wind farms can help to produce more accurate wind power scenarios.

In this paper, we introduce the desired correlations between dependent variables into the generated Sobol sequences from QMC, which is named as the dependent permutation here. As illustrated in our previous research [16], the copula function is applied to capture the correlations of wind speeds among multiple wind farms. The detailed sampling procedure of wind power scenarios can be referred the Appendix A. Based on the formulated copula function, we can generate the random numbers in which the correlations have been taken into account. In this paper, the matrix storing the correlation information of different wind farms is expressed as $\mathbf{D}_{N \times M}$, $\mathbf{D}_{N \times M} = [\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_M]$. In essence, the correlation information is maintained in the order of each column in $\mathbf{d}_j$ ($j = 1, 2, \dots, M$), here N and M represent the number of random samples and wind farms, respectively. However, the random numbers of $\mathbf{D}_{N \times M}$ might have low quality and require a large number of samples, i.e. a much larger N , to obtain the desired precision, which will undoubtedly lead to the inefficient computation. In order to take advantage of the high quality low-discrepancy sequence as well as the correlation of multiple wind farms, some improvements should be made to the Sobol sequence.

Supposed that the generated random numbers based on the Sobol sequence are denoted as $\mathbf{S}_{N \times M} = [\mathbf{s}_1, \mathbf{s}_2, \dots, \mathbf{s}_M]$. By performing the dependent permutation, we merge the correlation information of $\mathbf{D}_{N \times M}$ into $\mathbf{S}_{N \times M}$, and the procedure of dependent permutation is expressed as follow:

- For each column $\mathbf{d}_j$ ($j = 1, 2, \dots, M$), we arrange the elements of $\mathbf{d}_j$ in ascending order

Figure 2: The correlations of wind speeds among five wind farms

and denote the rank index of element d_{kj} as $R(d_{kj})$, $k = 1, 2, \dots, N$, which means d_{kj} is in the $R(d_{kj})^{\text{th}}$ position in the sorted output.

- Accordingly, column $\mathbf{s}_j$ ($j = 1, 2, \dots, M$) is sorted in ascending order with the rank index $R(s_{ij})$.
- For each element s_{ij} in $\mathbf{s}_j$, find $R(s_{ij}) = R(d_{kj})$, $i = 1, 2, \dots, N$, then rearrange the position of s_{ij} from i to k .

In this way, we can get the Sobol sequences with the expected dependence among multiple wind farms in order to acquire better wind speeds samples.

2.1.3. Mathematical model for wind power

The power output of wind turbine is affected by its rated capacity and the design parameters that mainly embodied in cut-in, cut-out and rated wind speeds. Here, the mathematical model for wind power indicating the relationship among these parameters is given as [34]:

$$P_{\text{wg}} = \begin{cases} 0 & 0 \leq v < v_{\text{ci}} \\ \frac{v_{\text{ci}}^3 + v^3}{v_{\text{r}}^3 - v_{\text{ci}}^3} P_{\text{wg}}^{\text{ra}} & v_{\text{ci}} \leq v < v_{\text{ra}} \\ P_{\text{wg}}^{\text{ra}} & v_{\text{ra}} \leq v < v_{\text{co}} \\ 0 & v \geq v_{\text{co}} \end{cases} \quad (5)$$

where $P_{\text{wg}}^{\text{ra}}$ is the rated power generated by the wind turbine and set as 2 MW in this paper, v_{ci} , v_{co} and v_{ra} representing the cut-in, cut-out, and rated wind speeds are set to be 4 m/s, 18 m/s and 12.5 m/s, respectively.

2.2. Mathematical formulation of SED problem

For the stochastic economic dispatch problem, we aim to find a dispatch solution with the minimal generation cost under different scenarios while well accommodating the uncertain wind power, and the mathematical model is described in the following subsections.

2.2.1. The generation cost function

When the stream inlet valve of thermal power units is opened, the generation cost will rise sharply in a short time due to the wire drawing effect [35]. Here the active power generated by the i^{th} thermal power unit is denoted as P_{Gi} . To describe the power generation cost more accurately, this paper takes the valve point effect into account in the generator cost, which is precisely formulated as follows:

$$f(P_{\text{G}}) = \sum_{i=1}^{N_{\text{G}}} (a_i P_{\text{Gi}}^2 + b_i P_{\text{Gi}} + c_i) + |d_i \sin(e_i (P_{\text{Gi}}^{\text{min}} - P_{\text{Gi}}))| \quad (6)$$

where N_{G} denotes the number of generators, a_i , b_i , c_i are coefficients of the quadratic cost function, coefficients d_i and e_i in the sinusoidal function represent the impact of the valve point effect on the generation cost.

2.2.2. Decision variables

The decision variables of SED are classified as control variables (expressed as u , including the real power generation of generator buses, voltage magnitude of the generator buses, ratios of the transformers and the output of the shunt capacitors) and state variables (expressed as x , including the real power generation of the slack bus, voltage magnitude of the load buses, reactive power of the generator buses and the apparent power flow of network branches), which are given as:

$$u = [P_{\text{G}2} \cdots P_{\text{G}_{N_{\text{G}}}} \ V_{\text{G}1} \cdots V_{\text{G}_{N_{\text{G}}}} \ T_1 \cdots T_{N_{\text{T}}} \ Q_{\text{C}1} \cdots Q_{\text{C}_{N_{\text{C}}}}] \quad (7)$$

$$x = [P_{\text{G}1} \ V_{\text{L}1} \cdots V_{\text{L}_{N_{\text{D}}}} \ Q_{\text{G}1} \cdots Q_{\text{G}_{N_{\text{G}}}} \ S_1 \cdots S_{N_{\text{E}}}] \quad (8)$$

2.2.3. Constraint for power flow

Suppose that the wind turbines are the doubly-fed induction wind turbines that operate at a constant power factor, the active and reactive power output of the i^{th} wind farm is formulated as:

$$P_{\text{W}i} = N_{\text{wi}} P_{\text{wg}i} \quad (9)$$

$$Q_{\text{W}i} = \frac{P_{\text{W}i}}{\cos \varphi_i} \sqrt{1 - \cos^2 \varphi_i} \quad (10)$$

where N_{w_i} denotes the number of wind turbines in the i^{th} wind farm, φ_i is the power factor angle in the i^{th} wind farm. It should be noted that the power output of wind farms, P_{W_i} and Q_{W_i} are treated as negative load on the corresponding node.

Thereafter, in the power system considering the integration of wind power, since the derivation of Kirchhoff's law [36] is applicable to the balance of active and reactive power of each node, the sum of all active and reactive power in and out of each node equals zero, that is:

$$P_{G_i} - P_{D_i} + P_{W_i} - V_i \sum_{j \in N_i} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0, \quad i = 1, \dots, N_0 \quad (11)$$

$$Q_{G_i} - Q_{D_i} + Q_{W_i} - V_i \sum_{j \in N_i} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0, \quad i = 1, \dots, N_0 \quad (12)$$

where P_{G_i} and Q_{G_i} are the active and reactive power generation of generator at node i , respectively. Similarly, P_{D_i} and Q_{D_i} represent active and reactive load demand at node i , respectively.

2.2.4. Operational constraints

The operational constraints limit the upper and lower bounds for the control variables and state variables, which are expressed as:

$$P_{G_i}^{\min} \leq P_{G_i} \leq P_{G_i}^{\max}, \quad i = 1, \dots, N_G \quad (13)$$

$$Q_{G_i}^{\min} \leq Q_{G_i} \leq Q_{G_i}^{\max}, \quad i = 1, \dots, N_G \quad (14)$$

$$Q_{C_i}^{\min} \leq Q_{C_i} \leq Q_{C_i}^{\max}, \quad i = 1, \dots, N_C \quad (15)$$

$$V_i^{\min} \leq V_i \leq V_i^{\max}, \quad i = 1, \dots, N_B \quad (16)$$

$$T_i^{\min} \leq T_i \leq T_i^{\max}, \quad i = 1, \dots, N_T \quad (17)$$

$$|S_k| \leq S_k^{\max}, \quad k = 1, \dots, N_E \quad (18)$$

where N_B , N_G , N_C , N_T and N_E represent the total number of total buses, generator buses, reactive power compensators, transformer branches and network branches, respectively.

3. The mean-tracking model for stochastic economic dispatch problem

3.1. The classical mean-variance model

In recent years, wind energy has been increasingly utilized and integrated into power grids. However, due to its inherent nature of uncertainty, wind power increases the difficulty in determining the optimal dispatch solution. Inspired by the mean-variance (MV) model for the portfolio optimization problem proposed by Markowitz, Li in [25] employed the MV model to search optimal dispatch solutions with minimal generation cost and economic risk under the uncertainties of wind power, among which the risk is regarded as the variance of generation cost. As shown in Fig.3, the optimal dispatch solutions we desire are those have

Figure 3: Generation cost under different wind power scenarios

the minimal expectation and variance of generation cost under the numerous wind power scenarios which are generated based on the QMC method as mentioned in Section 2.1.

Therefore, the mean-variance model for the SED problem can be described as a multi-objective optimization problem, which is formulated as:

$$\min [G(\mathbf{u})^{\text{exp}} V(\mathbf{u})] \quad (19)$$

$$\text{s.t. } g(\mathbf{x}, \mathbf{u}, P_W) = 0 \quad (20)$$

$$h(\mathbf{x}, \mathbf{u}, P_W) < 0. \quad (21)$$

where g and h are the equality and inequality constraints for optimal power flow, as the equations (9) - (18) shown above, P_W denotes the uncertain wind power outputs integrated into the power systems, and the expectation of generation cost function under various scenarios, $G(\mathbf{u})^{\text{exp}}$ is expressed as follows:

$$G(\mathbf{u})^{\text{exp}} = \left\{ \frac{1}{N_S} \sum_{k=1}^{N_S} f_k(P_G) \Big|_{P_{wk,1}, P_{wk,2}, \dots, P_{wk,n}} \right\} \quad (22)$$

where N_S is the number of scenarios generated based on quasi-Monte Carlo simulation (QMC), $f_k(P_G)$ is a quadratic function representing the generation cost of power system when the k^{th} wind power scenario is integrated, $P_{wk,1}, P_{wk,2}, \dots, P_{wk,n}$, $k = 1, 2, \dots, N_S$, indicate the power outputs of n wind farms in the k^{th} wind power scenario.

Meanwhile, considering the economic risk, $V(\mathbf{u})$ is designed to minimize the variance of the total generation cost, which is given as:

$$V(\mathbf{u}) = \left\{ \frac{1}{N_S} \sum_{k=1}^{N_S} \left(f_k(P_G) \Big|_{P_{wk,1}, P_{wk,2}, \dots, P_{wk,n}} - G(\mathbf{u})^{\text{exp}} \right)^2 \right\} \quad (23)$$

where $G(\mathbf{u})^{\text{exp}}$ is the expectation of generation cost under various wind power scenarios, and the economic risk is figured out in terms of the uncertain wind power outputs.

However, the MV model in existing researches rarely takes the pre-schedule into account, so the obtained dispatch solution may differ greatly from the pre-schedule and major adjustments are required on the pre-schedule, which is impractical in the actual operation of power systems.

3.2. The proposed mean-tracking model

3.2.1. Mathematical formulation for mean-tracking model

In actual scheduling of power systems, a pre-schedule is derived in advance based on the forecasted values of wind power. This deterministic dispatch scheme is not well adapted to the uncertain wind power with stochastic fluctuations, which may lead to power imbalance or the unnecessary load shedding and wind curtailment in practice. However, the pre-schedule plays a crucial role in finding an optimal intra-day dispatch solution. It provides a reference for system operators to make appropriate preparation measures and execute the scheduling plan. It also guides the decision making of electricity markets, which helps to reduce the cost of power generation.

Roll in [29] proposed a tracking error model under the framework of the MV model, that is, the portfolio manager expects to give a benchmark portfolio and evaluates the investment performance by tracking the errors in the returns between the portfolio and the benchmark. Similarly, this tracking error model can also be applied for the pre-schedule based on the forecasted wind power.

In this paper, aiming to choose an optimal dispatch by means of readjusting from the base pre-schedule as little as possible while accommodating the uncertain wind power, the mean-tracking model is firstly proposed for the SED problem, which is also described as a multi-objective optimization problem:

$$\min [G(\mathbf{u})^{\text{exp}} E(\mathbf{u})] \quad (24)$$

$$\text{s.t. } g(\mathbf{x}, \mathbf{u}, P_W) = 0 \quad (25)$$

$$h(\mathbf{x}, \mathbf{u}, P_W) < 0. \quad (26)$$

where $G(\mathbf{u})^{\text{exp}}$ is defined as the expectation of generation cost under various wind power scenarios, which is identical to equation (22) in the MV model.

Compared with the minimization of economic risk as equation (23) shown in the MV model, the most distinguishing feature in the mean-tracking model is to find a schedule with minimum tracking errors relative to the base pre-schedule, which is more valuable in practice. In this paper, the tracking errors is implemented to each generator unit in terms of minimizing the deviation in generation cost between the trial solution and the pre-schedule, which is formulated as follow:

$$E(\mathbf{u}) = \left\{ \frac{1}{N_S} \sum_{k=1}^{N_S} \left(\sum_{i=1}^{N_G} [f_k(P_{G_i}) - f(P_{G_i}^0)]^2 \right) \right\} \quad (27)$$

where N_G is the number of generators and P_{G_i} denotes the active power generated by the i^{th} generator, $f(P_{G_i}^0)$ represents the generation cost of i^{th} generator in the base pre-schedule which is predetermined in the hours-ahead scheduling. In this respect, we can find an optimal dispatch solution with the minimal tracking errors, which means much less adjustments are needed to make on the power outputs of generator units in the pre-schedule when executing the dispatch solution.

3.2.2. The perfection of mean-tracking model

It is worth noting that in the mean-variance model applied in [15, 25, 27], the uncertain wind fluctuation in various wind power scenarios are offset by the generator units at the slack bus. In this regard, the fluctuation of the total generation cost under different scenarios is actually equivalent to the fluctuation of generation cost of units at slack bus caused by the accommodation of uncertain wind power. Any uncertain injection of wind power will cause the fluctuation of generation cost in the balanced units, and the variance of generation cost under numerous scenarios is more subjected to the uncertainties of wind power than the obtained optimal dispatch solution. With the wind power fluctuations increase, the variance of generation cost becomes larger regardless of the obtained dispatch solution.

To tackle this issue, the affine decision rule [37, 38] is applied to each generator unit to make the uncertainties of wind power uniformly distributed in the grid. In this way, we can accommodate the uncertain wind power in a more effective manner, and the power output of each generator unit is expressed as:

$$P_{G_i} = P_{G_i}^0 + \xi_i \sum_{j=1}^{N_W} P_{W_j} \quad (28)$$

$$\xi_i = \frac{P_{G_i}^{ra} - P_{G_i}^0}{\sum_{i=1}^{N_G} (P_{G_i}^{ra} - P_{G_i}^0)} \quad (29)$$

where $P_{G_i}^{ra}$ is the rated capacity of the i^{th} generator unit and ξ_i represents the ratio of available capacity of each generator unit. Therefore, by applying the affine decision rule, we can obtain the global optimal approximate solution at a faster speed, and the fluctuating wind power output can be distributed proportionally among generator units, avoiding the abnormal fluctuations in generation cost under various wind power scenarios caused by the large fluctuation of power output of generators at the slack bus.

Moreover, to guarantee the stable operation of power systems, the voltage operating limits of grid is considered in this paper, which is added to the objective function of generation cost by means of the penalty function as:

$$G(\mathbf{u}) = G(\mathbf{u})^{\text{exp}} + \lambda_V \sum_{k=1}^{N_S} \sum_{i=1}^{N_B} V_{ki}^{\text{lim}} \quad (30)$$

where the penalty factor λ_V is set sufficiently large to ensure the voltage on each bus remains within the security margins of voltage for all acquired dispatch solutions, and V_{ki}^{lim} is defined

Figure 4: The flowchart of GSOMP for solving the mean-tracking model

as:

$$V_{ki}^{\text{lim}} = \begin{cases} V_{ki} - V_{ki}^{\text{max}}, & V_{ki} > V_{ki}^{\text{max}} \\ V_{ki}^{\text{min}} - V_{ki}, & V_{ki} < V_{ki}^{\text{min}} \\ 0, & V_{ki}^{\text{min}} < V_{ki} < V_{ki}^{\text{max}} \end{cases} \quad (31)$$

where V_{ki} represents the voltage of the i^{th} bus in the k^{th} wind power scenario, and V_{ki}^{max} and V_{ki}^{min} represent the upper and lower margins of the voltage operating limits, respectively.

In this paper, the group search optimizer with multiple producers (GSOMP) is introduced to solve the stochastic economic dispatch problem [31]. Fig. 4 displays the flowchart of GSOMP for the mean-tracking model, among which the dotted box indicates the procedure for the generation of wind power scenarios.

4. Numerical simulations

Simulation studies are carried out on a modified IEEE 30-bus system to demonstrate the effectiveness of the proposed mean-tracking model for the stochastic economic dispatch problem, with the installed capacity of wind power being set as 100 MW and 200 MW, respectively. Suppose that the wind turbines are double-fed induction wind generation with the constant power factor of 0.95 and the rated power of 2 MW, and 5 wind farms are connected at buses 7, 10, 16, 24, 30. It should be noted that the installed capacity of wind power of 100 MW and 200 MW approximately correspond to the penetration of wind power

as 12 % and 24 %, respectively. In this paper, the correlations of wind power of different farms are considered to model more accurate output of wind power based on copula theory [16], and the quasi-Monte Carlo simulation technique is applied to generate the wind power scenarios considering the correlations among multiple wind farms. All case studies in this paper are programmed in MATLAB and conducted on a PC with Intel(R) Core(TM) 3.40 GHz CPU and 16 GB memory.

4.1. The validity of the affine decision rule

Two experimental simulations based on the mean-variance model are conducted on a modified IEEE 30-bus system, among which the uncertainties of wind power in one simulation are accommodated by the generator units at the slack bus while the uncertainties of the other are offset based on the affine decision rule. The GSOMP is introduced to solve the multi-objective SED problem, and the Pareto fronts which illustrates the trade-off relationship between the economic cost and economic risk are showed in Fig. 5. It can be easily found that the Pareto fronts obtained by the slack bus model have a higher generation cost as well as the economic risk, comparing with the Pareto fronts obtained by the affine decision rule, regardless of the penetration of uncertain wind power. Thus the affine decision rule has a more reliable performance when accommodating the uncertain wind power.

Figure 5: The Pareto fronts under different mechanism based on the mean-variance model

Moreover, we make a comparison between the affine decision rule based method and the global optimization, and the simulation is conducted on a IEEE-30 bus system with 100 MW installed wind power capacity. For each wind power scenarios, it can be recognized as a deterministic dispatch model, thus the globally optimal dispatch solution based on the global optimization can be easily figured out. As a contrast, the affine decision rule is applied to solve the economic dispatch problem under various wind power scenarios. As can be seen from Fig. 6, the affine decision rule based method has a higher generation cost under the 200 wind power scenarios. However, compared with the drastic fluctuation of generation cost under different wind power scenarios, there is a slight difference in the generation cost between the affine decision rule based method and the global optimization. In other words, the unnecessary line power loss caused by the affine decision rule is quite small, which can be

Figure 6: The comparison of generation cost under 200 wind power scenarios

neglected compared with other factors such as the wind power fluctuations. In this paper, we pursue the computational efficiency and engineering practical value at the expense of certain precision, and the affine decision rule is directly applied in the mean-tracking model in the following part.

4.2. The validity of the mean-tracking model

4.2.1. The selection of pre-schedule

As the basis of the mean-tracking model, the pre-schedule will affect the quality of the optimization results. Here, the pre-schedule schemes are determined based on the long-term (day-ahead) and the short-term (hours-ahead) forecast value of wind power, respectively, which are then set as a reference and incorporated into the mean-tracking model. Simulation studies are conducted on a modified IEEE 30-bus system with the integration of 100 WM installed wind power, and the uncertainty of wind power is represented by the 300 wind power scenarios that generated based on the QMC method. As a comparison, the mean-variance model is applied to optimize the dispatch solution under the same condition.

As the generation cost shown in Fig. 7, it can be easily found that the blue line fluctuates violently from 623.1 (\$/h) to 867.8 (\$/h) under the various wind power scenarios, while the red line stabilizes from 687.3 (\$/h) to 816.2 (\$/h). Since the day-ahead pre-schedule is determined based on the long-term forecast value of wind power, the fairly high forecast errors makes the mean-tracking model to be inferior and cannot adapt to hours-ahead scheduling. On the contrary, the mean-variance model is not affected by the pre-schedule, so it can acquire better results in the hours-ahead scheduling, which has a smaller mean and variance of generation cost under 300 wind power scenarios. However, when the time scale declines to the hours-ahead prediction (the forecast error is as little as 10%), as the results displayed in Fig. 8, the generation cost under 300 wind power scenarios of two models have roughly the same fluctuation trend, with the expected generation cost as much as 760

Figure 7: The generation cost under 300 wind power samples based on the day-ahead pre-schedule

(\$/h). It is found that the blue line fluctuates slightly more sharply than the red line. That is because the variance of generation cost is taken into consideration in the mean-variance model. However, it neglects the value of the pre-schedule, so the final obtained dispatch may be impractical in practical operation. As a contrast, the pre-schedule has been considered in the mean-tracking model, thus the obtained optimal dispatch solution has a minimal tracking errors and less adjustments are required on the pre-schedule.

Therefore, the pre-schedule is obtained based on the hours-ahead scheduling in this paper, with the forecast error of wind power being as little as 10% [39], which is within an acceptable range. Thus, the resulting pre-schedule is of certain value and some improvements are needed to accommodate the random wind power. On the contrary, when the pre-schedule is derived based on the forecasted wind power of long-term prediction, the pre-schedule will become ineffective due to the forecast errors of up to 50%, and the final gained dispatch solution will be conservative for the system.

4.2.2. The integration of 100 MW installed wind power capacity

Here, we first figure out the base pre-schedule based on the hours-ahead forecasted value of wind power output, which are accessible to the system operators in advance. The deterministic dispatch model can be referred to the Appendix B. Thereafter, with the integration of 100 MW installed wind power capacity, the mean-tracking model is applied to search for an optimal dispatch solution with the minimal expectation of generation cost as well as the minimal tracking errors in the cost between the trial solution and the pre-schedule.

The Pareto front solved by GSOMP shows the trade-off relationship between the expectation of generation cost and tracking errors, as showed on the left side of Fig. 9. It can be found that there always is a conflict between the tracking errors and the generation cost.

Figure 8: The generation cost under 300 wind power samples based on the hours-ahead pre-schedule

For instance, solution a_1 achieves the minimal generation cost as 736.3 \$/h, however, it may not be an optimal solution with its tracking errors as high as 7.686×10^4 \$/h, which means that the dispatch solution cannot well adjust the uncertain wind power. On the other hand, although the tracking errors of solution a_4 declines to 1.219×10^4 \$/h, it is dominated since the generation cost is highest as 781.4 \$/h. Totally, the smaller tracking errors indicates the less readjustments are made on the base pre-schedule, and the technique for order preference similar to an ideal solution (TOPSIS) [31] is used here to choose the optimal solution as a_3 .

To verify the effectiveness of the proposed method, 300 wind power samples generated based on QMC are used to evaluate the performance of the selected optimal solution a_3 and the base pre-schedule in terms of the generation cost. As showed in Fig. 10, the pre-schedule fluctuates dramatically while solution a_3 can well adapt to the uncertain wind power, with the generation cost fluctuates slightly around 760 \$/h.

To further validate the superiority of the mean-tracking model, the optimal solution b is obtained from the mean-variance model [25] with the mean and variance of generation cost being 760.1 \$/h and 2511.5 \$/h, respectively, and comparisons between solution a_3 and solution b are carried out on the modified IEEE 30-bus system. It should be noted that solution a_3 and solution b have the same expected generation cost as 760.1 \$/h. In Fig. 11, it can be observed that solution b has a much larger tracking errors comparing to solution a_3 under the uncertain wind power scenarios, which means that solution b differs more greatly from the pre-schedule and major adjustments are needed to make on the base pre-schedule if it is executed.

More specifically, the average value of tracking errors of the generators in the modified IEEE 30-bus system under solution a_3 and solution b are illustrated in Fig. 12. It should be noted that the #1 generator unit has a higher rated capacity, so it has to take more responsibility in adapting to the uncertain wind power, which explains why the tracking

Figure 9: The Pareto solutions obtained by GSOMP

errors of the first generator is much larger than that of other generators. It can be easily found that solution a_3 has a relatively smaller tracking errors in the six generators since the tracking errors is implemented to each generator unit in the mean-tracking model. Solution a_3 can well accommodate the uncertain wind power while readjusting from the pre-schedule as little as possible, thus making it more practical in actual operation of power systems.

4.2.3. The integration of 200 MW installed wind power capacity

To make the proposed mean-tracking model more convincing, experimental simulations are conducted on a modified IEEE-30 bus system with the installed wind power capacity of 200 MW. As mentioned above, wind power with an installed capacity of 200 MW will eventually lead to the wind power penetration of power systems at a level of about 25%, which coincides with the current background of large-scale renewable energy integrating into the power systems. Based on the hours-ahead forecasted wind power output, the base pre-schedule can be obtained from the deterministic dispatch model, then GSOMP is utilized to search for the optimal Pareto front of the mean-tracking model. As displayed on the right side of Fig. 9, with the increasing penetration of wind power, the power output of generator units decreases, so does the expected generation cost. At the same time, the tracking errors increases greatly due to the increase of uncertain wind power, ranging from 3.984×10^4 \$/h to 8.756×10^4 \$/h. Here, by performing the TOPSIS technology, we can select the optimal dispatch solution c_3 with the expected generation cost and tracking errors being 712.55 \$/h and 4.464×10^4 \$/h, respectively. Similarly, we choose the optimal dispatch solution d in the mean-variance model with the same generation cost as c_3 as 712.55 \$/h.

To verify the superiority of the mean-tracking model, 300 uncertain wind power scenarios are generated based on QMC to evaluate the performance of solutions c_3 and d . Fig. 13 displays the comparison of tracking errors of two models under 300 wind power scenarios, from which we can observe that the tracking errors of c_3 fluctuates around 0.512×10^5 \$/h while the tracking errors of d reaches as much as 2.353×10^5 \$/h. Since the mean-variance model only takes the uncertain wind power into consideration and overlooks the practical value of the base pre-schedule, the resulting optimal dispatch solution has a much larger

Figure 10: The performance of generation cost under 300 wind power samples

tracking errors, which means major adjustments are required on the base pre-schedule when executing solution d .

Moreover, when comparing the tracking errors of the two cases under 100 MW and 200 MW installed wind power capacity, as illustrated in Fig. 11 and Fig. 13, we can find that the proposed mean-tracking model is more adaptive to the uncertain wind power with the moderate fluctuation tracking errors between the dispatch solution and the base pre-schedule. However, for the mean-variance model, the tracking errors under different wind power scenarios fluctuate much more dramatically as the penetration of wind power increases. Similar conclusion can also be drawn from Fig. 14, which illustrates the average tracking errors of each generation under 300 wind power scenarios. When the installed capacity of wind power increases as 200 MW, the average value of tracking errors of the #1 generator unit reaches as 3.772×10^4 \$/h, which is more than three times as those with the installed capacity of 100 MW. On the contrary, the mean-tracking model has a stable performance when exposing to higher penetration of uncertain wind power, with a total tracking errors being around 3×10^4 \$/h, which indicates that not much adjustments are needed. Therefore, by fully exploiting the value of the base pre-schedule, the dispatch solution under the mean-tracking model becomes more practical in uncertain environment.

5. Conclusion

In this paper, we propose the mean-tracking model for the first time to deal with stochastic economic dispatch with uncertain wind power integrated. Deterministic dispatch merely relies on the wind power forecast values, rarely takes into account the uncertainty of wind power. The stochastic scheduling based on the mean-variance model considers the uncertainty, however, it ignores the importance of the pre-scheme based on predictive val-

Figure 11: Comparison of tracking errors under 100 MW installed wind power capacity

Figure 12: The average tracking errors of generators under different solutions

ue. In this paper, the mean-tracking model is applied for the stochastic economic dispatch (SED) problem for the first time to search for optimal dispatch solutions with the minimal expectation of generation cost and the minimal tracking errors, aiming to readjust from the base pre-schedule as little as possible. The SED problem is formulated as a multi-objective problem and solved through GSOMP, simulation results verify that the proposed method fully explores the value of the base pre-schedule and the obtained dispatch solution becomes more practical in the actual operation of power systems.

Appendix A. The sampling procedure of wind power scenarios

In this paper, we estimate the correlation matrix of the multivariate Gaussian distribution to fit the distribution of historical wind power errors and adopt an inverse transform

Figure 13: Comparison of tracking errors under 200 MW installed wind power capacity

Figure 14: The average tracking errors of generators under different solutions

sampling from a multivariate Gaussian distribution to generate scenarios. The joint cumulative distribution function (CDF) is given as:

$$C(d_1, d_2, \dots, d_M; \rho) = \Phi_\rho(\Phi^{-1}(d_1), \Phi^{-1}(d_2), \dots, \Phi^{-1}(d_M)) \quad (\text{A.1})$$

where $\Phi_\rho(\cdot, \cdot, \dots, \cdot)$ is the CDF of multivariate Gaussian distribution with the correlation matrix ρ , $\Phi^{-1}(\cdot)$ are inverse CDF of the standard Gaussian distribution. Intuitively, the parameters ρ can be easily figured out from the historical data, i.e. from $z_1, z_2, \dots, z_M$, where $z_i = \Phi^{-1}(d_i)$.

For the Gaussian copula function, the multi-dimensional sampling can be realized when sampling from $\Phi_\rho(\cdot, \cdot, \dots, \cdot)$, which has elaborately illustrated in the Gibbs sampling. Here we denote $z_{ij} = \Phi^{-1}(d_{ij})$ for Gaussian copula and $d_{ij} = F_j(x_{ij})$, where $F_j(\cdot)$ is the marginal

distribution function of the j th dimension, and the sampling procedure of wind power scenarios is elaborated as:

- Generate random vectors $\mathbf{Z}_{N \times M} = [\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_M]$ that obey the multivariate Gaussian.
- Obtain the copula samples $\mathbf{D}_{N \times M} = [\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_M]$ by $\mathbf{d}_j = \Phi(\mathbf{z}_j), i = 1, 2, \dots, M$
- Obtain the wind speed forecast error samples $\mathbf{X}_{N \times M} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_M]$ by $\mathbf{x}_j = F_j^{-1}(\mathbf{d}_j), i = 1, 2, \dots, M$

Appendix B. The deterministic dispatch model

Since the forecasting information of wind power are accessible to system operators beforehand, the corresponding pre-schedule can be set as a reference for the intra-day scheduling. Thus, the deterministic dispatch model is formulated as follows:

$$\left\{ \begin{array}{l} \min F = \sum_{i=1}^{N_G} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i) \\ \text{s.t.} \\ P_{Gi} - P_{Di} + P_{Wi}^{pre} - V_i \sum_{j \in N_i} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0, \quad i = 1, \dots, N_0 \\ Q_{Gi} - Q_{Di} + Q_{Wi}^{pre} - V_i \sum_{j \in N_i} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0, \quad i = 1, \dots, N_0 \\ -F_l^{\max} \leq \sum_{i=1}^{N_G} \pi_{l,i} P_{Gi} + \sum_{m=1}^{N_W} \pi_{l,m} P_{wm}^{pre} - \sum_{q=1}^{N_D} \pi_{l,q} P_{Dq} \leq F_l^{\max} \\ P_{Gi}^{\min} + r_{Gi} \leq P_{Gi} \leq P_{Gi}^{\max} - r_{Gi}, \quad i = 1, \dots, N_G \\ Q_{Gi}^{\min} \leq Q_{Gi} \leq Q_{Gi}^{\max}, \quad i = 1, \dots, N_G \\ Q_{Ci}^{\min} \leq Q_{Ci} \leq Q_{Ci}^{\max}, \quad i = 1, \dots, N_C \\ V_i^{\min} \leq V_i \leq V_i^{\max}, \quad i = 1, \dots, N_B \\ T_i^{\min} \leq T_i \leq T_i^{\max}, \quad i = 1, \dots, N_T \\ |S_k| \leq S_k^{\max}, \quad k = 1, \dots, N_E \end{array} \right. \quad (\text{B.1})$$

where r_{Gi} is the spinning reserve capacity offered by generator unit i , P_{wm}^{pre} is the forecasted power output from wind farm m , π_l is the power transfer distribution factor and $F_l^{\max}$ represents the maximum transmission capacity of line l . Here the upper and lower limits of power output of generators units, the balance conditions of power flow and DC power flow of each transmission line are taken into account for the determination of the pre-schedule.

- [1] Q. H. Wu, W. J. Tang, S. He, Y. J. Cao, Dispatching, Wiley Encyclopedia of Electrical and Electronics Engineering.
- [2] H. Chen, H. Ngan, Power System Optimization: Large-scale Complex Systems Approaches, John Wiley & Sons, 2016.
- [3] H. Narimani, S.-E. Razavi, A. Azizivahed, E. Naderi, M. Fathi, M. H. Ataei, M. R. Narimani, A multi-objective framework for multi-area economic emission dispatch, Energy 154 (2018) 126–142.
- [4] Z. Li, W. Wu, B. Zhang, B. Wang, Adjustable robust real-time power dispatch with large-scale wind power integration, IEEE Transactions on Sustainable Energy 6 (2) (2015) 357–368.

- [5] A. T. Eseye, D. Zheng, J. Zhang, D. Wei, Optimal energy management strategy for an isolated industrial microgrid using a modified particle swarm optimization, in: 2016 IEEE International Conference on Power and Renewable Energy (ICPRE), IEEE, 2016, pp. 494–498.
- [6] S. S. Reddy, P. Bijwe, Real time economic dispatch considering renewable energy resources, *Renewable energy* 83 (2015) 1215–1226.
- [7] A. T. Eseye, D. Zheng, H. Li, J. Zhang, Grid-price dependent optimal energy storage management strategy for grid-connected industrial microgrids, in: 2017 Ninth Annual IEEE Green Technologies Conference (GreenTech), IEEE, 2017, pp. 124–131.
- [8] J. J. Chen, Y. L. Zhao, K. Peng, P. Z. Wu, Optimal trade-off planning for wind-solar power day-ahead scheduling under uncertainties, *Energy* 141 (2017) 1969–1981.
- [9] M. S. Li, Q. H. Wu, T. Y. Ji, RAO, Stochastic multi-objective optimization for economic-emission dispatch with uncertain wind power and distributed loads, *Electric Power Systems Research* 116 (11) (2014) 367–373.
- [10] L. Wang, L. Zhang, C. Xu, A. T. Eseye, J. Zhang, D. Zheng, Dynamic economic scheduling strategy for a stand-alone microgrid system containing wind, pv solar, diesel generator, fuel cell and energy storage:-a case study, in: IOP Conference Series: Earth and Environmental Science, Vol. 168, IOP Publishing, 2018, p. 012006.
- [11] Z. Liang, H. Chen, X. Wang, S. Chen, C. Zhang, A risk-based uncertainty set optimization method for the energy management of hybrid ac/dc microgrids with uncertain renewable generation, *IEEE Transactions on Smart Grid*.
- [12] L. Wang, Q. Li, R. Ding, M. Sun, G. Wang, Integrated scheduling of energy supply and demand in microgrids under uncertainty: A robust multi-objective optimization approach, *Energy* 130 (2017) 1–14.
- [13] S.-E. Razavi, A. E. Nezhad, H. Mavalizadeh, F. Raeisi, A. Ahmadi, Robust hydrothermal unit commitment: A mixed-integer linear framework, *Energy* 165 (2018) 593–602.
- [14] J. J. Chen, Y. B. Zhuang, Y. Z. Li, P. Wang, Y. L. Zhao, C. S. Zhang, Risk-aware short term hydro-wind-thermal scheduling using a probability interval optimization model, *Applied Energy* 189 (2017) 534–554.
- [15] Y. Z. Li, K. C. Li, P. Wang, Y. Liu, X. N. Lin, H. Gooi, G. F. Li, D. L. Cai, Y. Luo, Risk constrained economic dispatch with integration of wind power by multi-objective optimization approach, *Energy* 126 (2017) 810–820.
- [16] M. S. Li, Z. J. Lin, T. Y. Ji, Q. H. Wu, Risk constrained stochastic economic dispatch considering dependence of multiple wind farms using pair-copula, *Applied Energy* 226 (2018) 967–978.
- [17] H. Chen, P. Xuan, Y. Wang, T. Ke, X. Jin, Key technologies for integration of multitype renewable energy sources-research on multi-timeframe robust scheduling/dispatch, *IEEE Transactions on Smart Grid* 7 (1) (2015) 1–1.
- [18] K. Zhou, C. Fu, S. Yang, Big data driven smart energy management: From big data to big insights, *Renewable and Sustainable Energy Reviews* 56 (2016) 215–225.
- [19] V. C. Gungor, D. Sahin, T. Kocak, S. Ergut, C. Buccella, C. Cecati, G. P. Hancke, Smart grid technologies: Communication technologies and standards, *IEEE transactions on Industrial informatics* 7 (4) (2011) 529–539.
- [20] H. Niederreiter, Quasi-monte carlo methods and pseudo-random numbers, *Bulletin of the American Mathematical Society* 84 (1978) (1978) 957–1041.
- [21] G. Takhtamyshev, B. Vandewoestyne, R. Cools, Quasi-random integration in high dimensions, *Mathematics & Computers in Simulation* 73 (5) (2007) 309–319.
- [22] L. Ji, G.-H. Huang, L.-C. Huang, Y.-L. Xie, D.-X. Niu, Inexact stochastic risk-aversion optimal day-ahead dispatch model for electricity system management with wind power under uncertainty, *Energy* 109 (2016) 920–932.
- [23] H. Markowitz, Portfolio selection, *Journal of Finance* 7 (1) (2012) 77–91.
- [24] W. F. Sharpe, H. M. Markowitz, Mean-variance analysis in portfolio choice and capital markets, *Journal of Finance* 44 (2) (1987) 531.
- [25] Y. Z. Li, Q. H. Wu, M. S. Li, J. P. Zhan, Mean-variance model for power system economic dispatch

- with wind power integrated, *Energy* 72 (7) (2014) 510–520.
- [26] X. Fang, B.-M. S. Hodge, L. Bai, H. Cui, F. F. Li, Mean-variance optimization-based energy storage scheduling considering day-ahead and real-time lmp uncertainties, *IEEE Transactions on Power Systems*.
 - [27] Y. Z. Li, Q. H. Wu, Downside risk constrained probabilistic optimal power flow with wind power integrated, *IEEE Transactions on Power Systems* 31 (2) (2016) 1649–1650.
 - [28] Z. Q. Xie, T. Y. Ji, M. S. Li, Q. H. Wu, Quasi-monte carlo based probabilistic optimal power flow considering the correlation of wind speeds using copula function, *IEEE Transactions on Power Systems* 33 (2) (2018) 2239–2247.
 - [29] R. Roll, A mean/variance analysis of tracking error.
 - [30] S. He, Q. H. Wu, J. R. Saunders, Group search optimizer: An optimization algorithm inspired by animal searching behavior, *IEEE Transactions on Evolutionary Computation* 13 (5) (2009) 973 – 990.
 - [31] C. X. Guo, J. P. Zhan, Q. H. Wu, Dynamic economic emission dispatch based on group search optimizer with multiple producers, *Electric Power Systems Research* 86 (4) (2012) 8–16.
 - [32] R. Billinton, P. Wang, Teaching distribution system reliability evaluation using monte carlo simulation, *IEEE Transactions on Power Systems* 14 (2) (1999) 397–403.
 - [33] I. M. Sobol', On the distribution of points in a cube and the approximate evaluation of integrals, *Zhurnal Vychislitel'noi Matematiki i Matematicheskoi Fiziki* 7 (4) (1967) 784–802.
 - [34] V. Thapar, G. Agnihotri, V. K. Sethi, Critical analysis of methods for mathematical modelling of wind turbines, *Renewable Energy* 36 (11) (2011) 3166–3177.
 - [35] P. K. Roy, Teaching learning based optimization for short-term hydrothermal scheduling problem considering valve point effect and prohibited discharge constraint, *International Journal of Electrical Power & Energy Systems* 53 (2013) 10–19.
 - [36] G. Chang, S. Chu, H. Wang, An improved backward/forward sweep load flow algorithm for radial distribution systems, *IEEE Transactions on power systems* 22 (2) (2007) 882–884.
 - [37] S. J. Garstka, R. J.-B. Wets, On decision rules in stochastic programming, *Mathematical Programming* 7 (1) (1974) 117–143.
 - [38] F. Babonneau, J. P. Vial, O. Klopfenstein, A. Ouorou, Robust capacity assignment solutions for telecommunications networks with uncertain demands, *Networks* 62 (4) (2013) 255–272.
 - [39] X. Yuan, C. Chen, Y. Yuan, Y. Huang, Q. Tan, Short-term wind power prediction based on lssvm-gsa model, *Energy Conversion and Management* 101 (2015) 393–401.