Optimal Power System Dispatch With Wind Power Integrated Using Nonlinear Interval Optimization and Evidential Reasoning Approach

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***Abstract*—This paper presents the nonlinear interval optimization (NIO) model to solve optimal power system dispatch (OPSD) with uncertain wind power integrated. In this model, not only the average of the dispatching objective, but its deviation are also taken into account. Therefore, the NIO model based on OPSD is formulated as a multi-objective optimization problem. An optimization algorithm, group search optimizer with multiple producers (GSOMP) is applied to obtain Pareto solutions, which show the tradeoff relationship between the average and deviation of the dispatching objective. Then, a decision-making method, the evidential reasoning (ER) approach, is applied to determine the final dispatch solution. Simulation results based on the modified IEEE 30-bus system prove the applicability and effectiveness of the NIO model to deal with the OPSD, considering the integration of the uncertain wind power.**

***Index Terms*—Evidential reasoning (ER), group search optimizer with multiple producers (GSOMP), multi-objective optimization, nonlinear interval optimization (NIO), wind power.**

I. Introduction

OPTIMAL power system dispatch (OPSD) is one of the most important issues of power system analysis and control, mainly including the optimal power flow (OPF) and the economic load dispatch (ELD) [1]. OPSD is targeted to obtain the optimal dispatch solution of a specific objective function, usually the total fuel cost of a power system. Essentially, it is a constrained optimization problem, which can be solved by conventional optimization techniques based on mathematical programming [2] and evolutionary algorithms [3], [4]. In recent decades, wind energy has been greatly pursued and utilized all over the world, and there is no doubt that this kind of energy is a good alternative to the traditional thermal power generation [5], [6]. However, the uncertainty of wind power leads to the huge difficulty of its prediction [7], [8]. Therefore, it is difficult to solve OPSD if the uncertain wind power is integrated into power systems [6], [9]–[11].

Two main methodologies have been used to deal with OPSD with wind power integrated, i.e., the fuzzy and the probabilistic methods. In the fuzzy method, the wind power is regarded as the fuzzy variable, and the fuzzy set theory is used to model the corresponding issue by using membership functions [12]–[15]. The advantage of this method is that its solution can well reflect dispatchers' attitude, but in some cases it may be subjected to strong subjectiveness, which cannot well adjust to the objective situation. Moreover, it is difficult to specify an appropriate membership function when the fuzzy method is used [12], [13].

For the probabilistic method, wind speed, wind power, and wind forecast error are regarded as random variables and their probabilistic distributions are assumed to be known. For instance, references [5], [6], and [16] assumed that the wind speed follows the Weibull distribution. However, OPSD is usually conducted in a short time, for example, OPF is usually conducted within 60 min. Consequently, the Weibull distribution is not suited to be used [7]. References [17] and [18] indicated that the wind speed forecast error follows the Gaussian distribution during a short time. Therefore, this distribution has been widely applied in OPSD with uncertain wind power integrated into a power system [7], [9], [10], [19].

The Monte Carlo (MC) method is often used to generate wind speed or power samples using their probabilistic information, then the stochastic optimization is conducted to obtain the optimal solution [10], [20], [21] in the probabilistic method. It is well known that the MC method applied for probabilistic assessments is accurate, and it has been widely used in the area of computational biology, computer graphics, finance, and business [22]. However, this method is a scenario-based approach for simulating uncertainties using probabilistic distributions, and a large number of scenarios should be generated to simulate the probabilistic characteristics of uncertain variables [10], [23]. Therefore, it is time-consuming to obtain the optimal dispatch solution when dealing with OPSD with wind power integrated, as massive scenarios should be sampled according to the probabilistic information of wind power or wind speed [10], [19]–[21], [24].

Recently, wind power can be forecasted by another method, i.e., the direct interval forecasting method, by which the actual wind power is within the upper and lower forecasting bounds [25]. It is well known that conducting OPSD needs the forecast

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information of load and wind power. Therefore, we attempt to solve the problem of OPSD assuming the forecasting information of wind power is obtained by the direct interval forecasting method. In this way, wind power can be represented as an interval variable for power system dispatching. Indeed, interval variables have been used to solve some power system problems with uncertainty [26]–[28]. However, to the best of the authors' knowledge, very few papers have introduced interval variables and the interval optimization approach [29], [30] to deal with uncertain optimization problems in power system operations. References [31] and [32] used the interval linear programming to deal with unit commitment, considering the prediction of the volatile ranges of wind and node loads. However, the work [31] and [32] only considered the expected fuel cost, which means the corresponding risk is not taken into account under the uncertain environment.

In this paper, we attempt to use the interval optimization approach to solve OPSD for the first time, to the best of our knowledge. As most OPSD problems are nonlinear, such as OPF, we call the approach proposed in this paper as nonlinear interval optimization (NIO) model. First, in this model, unlike [31], not only the expected value of dispatching objective is considered but its deviation (risk) is also taken into account. Second, unlike [30], we directly solve the NIO model using a multi-objective optimization approach, instead of converting it to a single-objective optimization problem. The reason is that it is difficult for dispatchers to determine the weighting factor between the average and deviation of the uncertain dispatching objective. Then, Group Search Optimizer with Multiple Producers (GSOMP) is used for obtaining Pareto solutions to reflect the tradeoff relationship between the average and deviation. In the end, power system dispatchers should determine the final dispatch solution (only one chosen from Pareto solutions), and this belongs to the multiple attribute decision analysis (MADA) [33]. To well consider the uncertain cognition of dispatchers, the evidential reasoning (ER) approach [34] is applied to conduct the decision making in this paper.

The remainder of this paper is organized as follows. Section II introduces the OPF problem, and the NIO model corresponding to OPF with uncertain wind power integrated. Section III presents the multi-objective optimization algorithm, i.e., GSOMP. Section IV adopts the decision making method, the ER approach based on MADA, to determine the final dispatch solution. Then, Section V carries out experiments and discusses simulation results. In the end, Section VI draws the conclusion.

II. NIO Model for OPF With Wind Power Integrated

A. OPF Problem Formulation

OPF is one of the most significant constrained optimization problems in terms of power system dispatch, which can be formulated as follows:

$$\begin{aligned} \min \quad & J(X,U) \\ \text{s.t.} \quad & g(X,U)=0 \\ & h(X,U)<0 \end{aligned} \tag{1}$$

where J is the objective function, X and U are the vectors of state variables and decision variables, respectively, and g and h represent the equality and inequality constrains of OPF, respectively.

The objective function of OPF is usually the total fuel cost F, and the thermal generators are modelled as a quadratic cost curve [1], [35], which can be represented as

$$J=F=\sum_{i=1}^{N_{\mathrm{G}}} c_i P_{\mathrm{G}_i}^2 + b_i P_{\mathrm{G}_i} + a_i \tag{2}$$

where a_i, b_i and c_i are fuel cost coefficients corresponding to the ith generator, respectively. P_{G_i} is the real power output generated by the ith generator, and N_{G} is the total number of generator units.

X is the vector of state variables, which can be presented as follows:

$$X^T=[P_{\mathrm{G}_1}, V_{L_1}, \ldots, V_{L_{\mathrm{N_D}}}, Q_{\mathrm{G}_1}, \ldots, Q_{\mathrm{G}_{\mathrm{N_G}}}, S_1, \ldots, S_{\mathrm{N_E}}] \tag{3}$$

where P_{G_1} and V_L are the slack bus active power and voltages of load buses, Q_{G} and S are generator reactive power outputs and apparent power flows in the power network, respectively, and N_{E} is the total number of power network branches.

U is the vector of decision variables, and it can be presented as follows:

$$\begin{aligned} & U^T \\ & =[P_{\mathrm{G}_2}\cdots P_{\mathrm{G}_{\mathrm{N_G}}}, V_{\mathrm{G}_1}\cdots V_{\mathrm{G}_{\mathrm{N_G}}}, T_1\cdots T_{\mathrm{N_T}}, Q_{\mathrm{C}_1}\cdots Q_{\mathrm{C}_{\mathrm{N_C}}}] \end{aligned} \tag{4}$$

where P_{G} and V_{G} are generator active outputs and voltages, respectively. T and Q_{C} represent transformer tap ratios and shunt device reactive power outputs, respectively. N_{T} and N_{C} are the total numbers of transformer branches and shunt compensators, respectively.

The equality constraints $g(x,u)$ represents the requirements of active and reactive power balance, and the inequality constraints $h(x,u)$ demonstrates physical limits of electrical power equipment, such as the working limits of generation units, power transformers and shunt compensator, and power system security constraints, such as the limits on bus voltages and branch apparent power flow. The formulations of $g(x,u)$ and $h(x,u)$ can be referred to [1], [35].

B. NIO Model for OPF With Wind Power Integrated

In contrast to the traditional thermal power generation, wind power is volatile in its nature, which leads to its variability and a high level of uncertainty for OPSD. It is evident that forecasting wind power generation is critical for OPSD, for instance, OPF. Recently, the direct interval forecasting method has been proposed [25], by which the wind power generation can be predicted within the upper and lower forecasting bounds, as shown in Fig. 1. Suppose when dispatchers determine the dispatch solution at time t, they should consider the forecasting information of the uncertain wind power during dispatching period T. If the direct interval forecasting method is used, the actual wind power

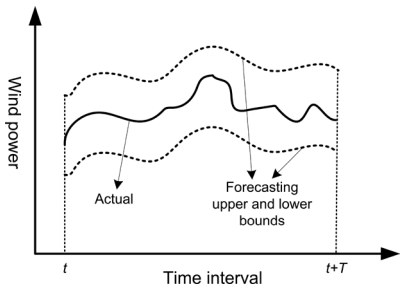

Fig. 1. Interval forecast of wind power.

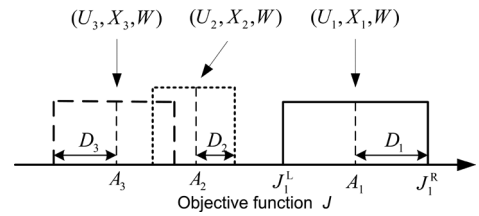

Fig. 2. Intervals of objective function J corresponding to different decision vectors.

W is then formulated as an interval variable, within the upper and lower forecasting bounds, U^L and U^{R}, i.e., $W \in [U^L, U^{\mathrm{R}}]$.

In this way, when the wind power is integrated into a power system, it evidently affects the power flow distribution, and finally the objective function of OPF, which then becomes an interval function [29], [30], [36]. Therefore, how to conduct OPF, i.e., optimizing the fuel cost considering nonlinear constraints, refers to the NIO model essentially. This model can be formulated as follows:

$$\begin{aligned} \min \quad & J(X, U, W) \\ \text{s.t.} \quad & g(X, U, W) = 0 \\ & h(X, U, W) < 0 \\ & W \in \Gamma = [U^L, U^{\mathrm{R}}]. \end{aligned} \tag{5}$$

It can be easily seen that $J(X, U, W)$ is an interval number corresponding to a specific U. Therefore, how to compare interval numbers remains a problem. In [31], the averaged value of fuel cost is optimized only by considering the expected load, which means the averaged performance of a dispatch solution is taken into account merely. However, it neglects the risk brought by the solution under the uncertain environment, and risk analysis is quite significant in terms of uncertain optimization problems [37].

Consequently, reference [30] considers the minimization of the averaged value and deviation of the uncertain objective function, simultaneously. In this way, the risk of a solution under an uncertain environment can be taken into account as well. For instance, it can be seen from Fig. 2 that different decision vectors U_1, U_2 and U_3 correspond to different interval objective values. If U_1 is adopted, the value of J_1 is then bounded by J_1^L and J_1^{R}, and the average and deviation of J_1 are $(J_1^{\mathrm{R}} + J_1^L)/2$ and $(J_1^{\mathrm{R}} - J_1^L)/2$, respectively. Obviously, the solution which has both the smaller averaged value and deviation of the objective function has better performance. In Fig. 2, solutions U_2 and U_3 outperform solution U_1, because the average and deviation of J_1, A_1 and D_1 are more than those of U_2 and U_3. However, it is hard to tell whether U_2 outperforms U_3, as the average of J_2, A_2 is higher while its deviation D_2 is less than that of J_3.

A weighting factor was introduced [30] to convert the average and deviation into a single value for the convenience of comparison between different solutions. However, the exact weighting factor is difficult to be obtained, especially in terms of engineering problems, such as OPSD [38]. Consequently, in this paper, we directly formulate the NIO model into a multi-objective optimization problem to obtain Pareto solutions, considering both the average and deviation of the objective function without using a weighting factor. In this way, the comprehensive trade-off relationship between the average and deviation can be obtained while avoiding the problem of selecting the exact weighting factor. On the other hand, it is straightforward and convenient for dispatchers to compare these alternatives (Pareto solutions) for decision making. Therefore, the NIO model can be formulated as follows:

$$\begin{aligned} \min \quad & [A(J(X, U, W)) \quad D(X, U, W))] \\ \text{s.t.} \quad & A(J(X, U, W)) = \frac{1}{2}(J^L(U) + J^{\mathrm{R}}(U)) \\ & D(J(X, U, W)) = \frac{1}{2}(J^{\mathrm{R}}(U) - J^L(U)) \\ & J^L(U) = \min_{W \in \Gamma} J(X, U, W) \\ & J^{\mathrm{R}}(U) = \max_{W \in \Gamma} J(X, U, W) \\ & g(X, U, W) = 0 \\ & h(X, U, W) < 0 \\ & W \in \Gamma = [W^L, W^{\mathrm{R}}] \end{aligned} \tag{6}$$

where $A(J(X, U, W))$ and $D(J(X, U, W))$ are the average and deviation of the uncertain objective function $J(X, U, W)$. $J^L(U)$ and $J^{\mathrm{R}}(U)$ are the lower and upper bounds in terms of $J(X, U, W)$ when a dispatch solution is chosen as a specific U.

It is noted that the double-fed induction wind power generator with a constant power factor is studied in this paper. In this way, a wind farm integrated into a power system is deemed as a PQ bus [39].

III. Group Search Optimizers With Multiple Producers

The aim of formulations shown in (6) is to find the optimal dispatch solutions (Pareto solutions), which should be obtained by multi-objective optimization algorithms. Recently, a novel one has been proposed, i.e., GSOMP [40]. This algorithm is based on group search optimizer (GSO) [41], which is a novel optimization algorithm proposed on the basis of swarm intelligence. Moreover, GSOMP was proved to be better at searching for Pareto solutions than other algorithms, such as Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [40]. Therefore, we use GSOMP to solve the NIO model in our research, and details of GSOMP are introduced as follows.

A. Producers

In GSOMP, N producers are determined from a searching group at the kth iteration with the best fitness value $f_p(\mathbf{X}_p^k)(p =$

$1, \ldots, N)$ for the pth objective function. The pth producer in the searching group owns the best fitness values as for the pth objective function of a multi-objective optimization problem, located in the best position $\mathbf{X}_p^k$ at the kth iteration. Then it uses a scanning mechanism to randomly sample three positions. One point ($\mathbf{X}_z^k$) is at the zero degree, the other two points ($\mathbf{X}_l^k$ and $\mathbf{X}_r^k$) are on the right and left in the searching area, respectively. It is shown as

$$\begin{aligned}\mathbf{X}_z^k &= \mathbf{X}_p^k + \mathrm{circshift}(r_1 l_{\max} \mathbf{D}_p^k(\boldsymbol{\varphi}_p^k), k)\\ \mathbf{X}_l^k &= \mathbf{X}_p^k + \mathrm{circshift}\left(r_1 l_{\max} \mathbf{D}_p^k\left(\boldsymbol{\varphi}_p^k - \frac{\mathbf{r}_2 \theta_{\max}}{2}\right), k\right)\\ \mathbf{X}_r^k &= \mathbf{X}_p^k + \mathrm{circshift}\left(r_1 l_{\max} \mathbf{D}_p^k\left(\boldsymbol{\varphi}_p^k + \frac{\mathbf{r}_2 \theta_{\max}}{2}\right), k\right) \quad (7)\end{aligned}$$

where $\mathrm{circshift}(\cdot)$ is a circular shifting operator used in [40], $r_1 \in \mathbb{R}^1$ is a standard normally distributed random number and $l_{\max} \in \mathbb{R}^1$ is maximum pursuit distance. $\boldsymbol{\varphi}_p^k$ is the producer's scanning angle, and $\mathbf{D}_p^k(\boldsymbol{\varphi}_p^k)$ is its corresponding unit vector, which can be obtained from the method proposed in [40] for simple computation. $\mathbf{r}_2 \in \mathbb{R}^{n-1}$ is a uniformly distributed random sequence in the range of $(0, 1)$ and $\theta_{\max} \in \mathbb{R}^1$ and are the maximum pursuit angle.

B. Scroungers and Rangers

In GSOMP, scroungers in the searching group always follow a random producer based on the producer-scrounger model. What is more, to maintain the diversity of Pareto solutions, they are also attracted by a solution randomly selected from the Pareto set, $\chi = \{\chi_1, \chi_2, \ldots, \chi_s\}$[40]. Then, the behavior of the ith scrounger at the kth iteration can be formulated as follows:

$$\mathbf{X}_i^{k+1} = \mathbf{X}_i^k + \mathbf{r}_3(\mathbf{X}_p^k - \mathbf{X}_i^k) + \mathbf{r}_4(\chi_q - \mathbf{X}_i^k) \quad (8)$$

where $\mathbf{X}_i^{k+1}$ and $\mathbf{X}_i^k$ are the positions of the ith scrounger at the $(k+1)$th and kth iteration, respectively. p is a positive integer randomly selected from $\{1, 2, \ldots, N\}$ and $q \in \{1, 2, \ldots, s\}$. $\mathbf{r}_3 \in \mathbb{R}^{n-1}$ and $\mathbf{r}_4 \in \mathbb{R}^{n-1}$ are normally distributed random numbers with mean 0 and standard deviation 1, respectively.

In addition to the producer and scroungers, other members are rangers in the searching group, which adopt random walk to resort to other resources, helping GSO escape local optima. Therefore, the behavior of the ith ranger at the kth iteration can be shown in the following equation:

$$\mathbf{X}_{p,i}^{k+1} = \mathbf{X}_{p,i}^k + \mathrm{circshift}(a \cdot r l_{\max} \mathbf{D}_{p,i}^k(\boldsymbol{\varphi}_{p,i}^k), k) \quad (9)$$

where $a \in \mathbb{R}^1$ is a constant and r is a uniformly random number in the range of $(0, 1)$[40].

C. GSOMP Archive Update

To update the external archive of GSOMP, the fast nondominated sorting approach [42] is used. Initially, the archive is set to be empty, and the producers are added to it. Then at the end of each iteration, the newly generated solutions by GSO are sent to the archive, and the fast non-dominated sorting approach is applied to select the new Pareto solutions. It is noted that the number of elements in the repository is set to be a constant number in this paper, using the crowding distance method to save and discard some solutions [42]. Afterwards, the final solutions saved in this repository are processed by a kind of decision making methods.

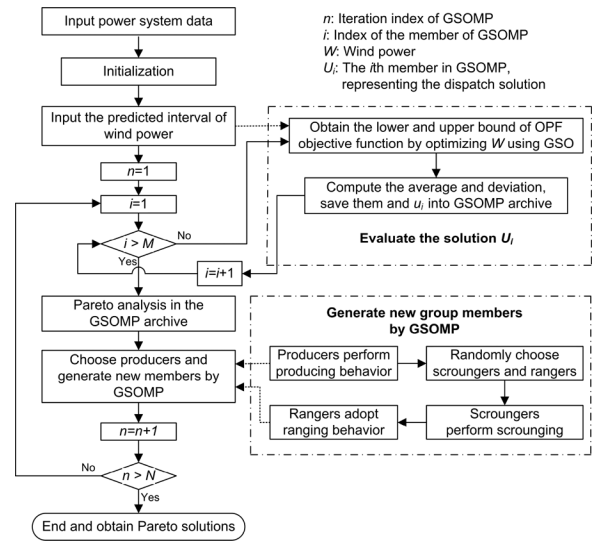

Fig. 3. Computing procedure of NIO model using GSOMP.

Consequently, the NIO model of OPF considering the integration of wind power can be solved by GSOMP as the following steps, and the detailed computing procedure is shown in Fig. 3.

1) Step 1: Initialization: Input the power system data, such as parameters of generators, power grid, and electricity load. Then, initialize all of the M group members U_i $(i = 1, 2, \ldots, M)$ and the total number of iterations N of GSOMP. Input the predicted wind power W (interval numbers).

2) Step 2: Pareto Solutions Update: At each iteration, the group member U_i (solution) is evaluated by (6). Afterwards, all members are analyzed by the nondominated sorting to select Pareto solutions, which are then saved into the GSOMP archive. Moreover, GSOMP generates new members.

3) Step 3: Stopping Criterion: The procedure stops if the iteration index of GSOMP reaches N. Otherwise, it continues from *Step 2*.

Furthermore, computation efforts required for solving this optimization problem is discussed as follows. Firstly, it can be seen from (6) that it is critical to calculate the upper and lower bounds of the dispatching objective function, i.e., $J^L(U)$ and $J^{\mathrm{R}}(U)$, using the interval forecast information W. If W is in a large range, the values of $J^L(U)$ and $J^{\mathrm{R}}(U)$ will be obtained by greater computation efforts. Secondly, it is obvious that some parameters of GSOMP directly affect the computation. For instance, the number of group members can help find better Pareto solutions, but increase computation efforts.

IV. Evidential Reasoning Approach

Dispatchers should determine a final dispatch solution by selecting only one from the obtained Pareto solutions. It is regarding to the MADA [34], and an "attribute" is equivalent to an "objective" or a "criterion". However, such a MADA problem of selecting a final dispatch solution is not yet well solved. Most papers uses the Fuzzy Decision Making (FDM) method

[43]–[46], which does not consider dispatchers' preferences towards objectives and their uncertain cognition. Although Order Preference Similar to an Ideal Solution (TOPSIS) adopts relative weights, assigned to multiple objectives, this technique also ignores dispatchers' uncertain cognition [34], [40]. It is noted that this kind of uncertainty plays an important role in the process of decision making, which should not be neglected [34]. For instance, in assessment of a dispatch solution, the dispatcher is 20% sure that the fuel cost is at the "average" level, and 70% sure that it is at the "good" level. It is noted that in this case the above assessment is incomplete, as the total possibility of assessment is $20\% + 70\% = 90\% < 100\%$ (the missing 10% represents a degree of dispatchers' uncertain cognition [34]).

The ER approach can be used to process the decision makers' uncertain cognition to support MADA. The kernel of this approach is the ER algorithm developed on the basis of an evaluation framework and the evidential combination rule of the Dempster-Shafer (D-S) theory [47]. The ER approach has also been successfully used for the condition assessment of power transformers [48], environmental impact evaluation [49], engineering design [50], etc. Therefore, in this paper, we use this approach to select a final dispatch solution, considering the uncertainty of dispatchers' cognition.

A. Evidential Reasoning Algorithm

To outline the ER algorithm, consider a three-level hierarchy of attributes, with the overall evaluation at the top level and a set of basic attributes at the bottom level, as shown in Fig. 4. The set of basic attributes is presented as follows:

$$\boldsymbol{E} = \{e_1, e_2, \ldots, e_i, \ldots, e_L\}. \tag{10}$$

Each attribute e_i is assigned with a corresponding weight ω_i ($0 \le \omega_i \le 1$). The weights of L attributes represent their relative importance during an evaluation process and L is the total number of attributes. A set of weights is defined as follows:

$$\begin{aligned} &\boldsymbol{\omega} = \{\omega_1, \omega_2, \ldots, \omega_i, \ldots, \omega_L\} \\ &\text{s.t.} \ \sum_{i=1}^{L} \omega_i = 1. \end{aligned} \tag{11}$$

A set of predefined evaluation grades, shown in the middle layer of Fig. 4, is used to assess the state of an attribute.

$$\boldsymbol{H} = \{H_1, H_2, \ldots, H_n, \ldots, H_{\mathrm{N}}\} \tag{12}$$

where N is the total number of evaluation grades.

The generated assessment $\boldsymbol{S}(e_i)$ evaluated by the decision maker for attribute e_i is expressed as the following distribution of degree of beliefs over different evaluation grades:

$$\boldsymbol{S}(e_i) = \{(H_n, \beta_{n,i}), \quad n = 1, 2, \ldots, N\} \tag{13}$$

which means that attribute e_i is assessed to grade H_n with a degree of belief of $\beta_{n,i}$ ($\beta_{n,i} \ge 0$ and $\sum_{n=1}^{N} \beta_{n,i} \le 1$). The assessment $\boldsymbol{S}(e_i)$ is complete if $\sum_{n=1}^{N} \beta_{n,i} = 1$ and incomplete if $\sum_{n=1}^{N} \beta_{n,i} < 1$.

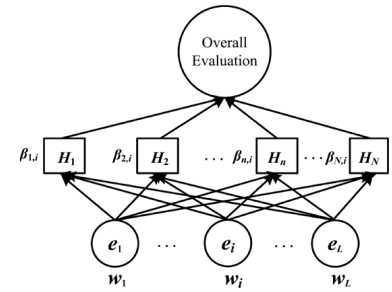

Fig. 4. Overall evaluation using the ER approach.

Then an overall assessment for the general attribute y can be represented by the following distribution of degree of beliefs:

$$\begin{aligned} \boldsymbol{S}(y) &= \boldsymbol{S}(e_1 \oplus e_2 \cdots \oplus e_i \oplus \cdots \oplus e_L) \\ &= \{(H_n, \beta_n), (H, \beta_H), \qquad n = 1, 2, \ldots, N\} \end{aligned} \tag{14}$$

where $\oplus$ denotes the aggregation of two attributes. β_n is the aggregated degrees of belief, which shows the decision maker has the β_n possibility to believe that the evaluated alternative solution belongs to the grade H_n. β_H is the unassigned degree of belief, which represents the decision maker's uncertain cognition. Due to the limited space of this paper, we omit the detailed ER algorithm here, which can be referred to [34].

B. Utility for Ranking

It can be seen that distributed descriptions shown in (14) are not straight forward to show the difference between two alternatives. To facilitate the direct comparison and rank alternatives, the concept of utility was proposed in the ER approach [34]. Suppose $u(H_n)$ is the utility of grade H_n, and if H_{n+1} is preferred to H_n, then $u(H_{n+1}) > u(H_n)$. $u(H_n)$ can be estimated using the probability assignment method [34]. β_H shown in (14) will be 0 if all assessments are complete and precise. In this case, the utility of attribute y can be used to rank alternatives, which can be calculated in the following equation:

$$u(y) = \sum_{n=1}^{N} \beta_n u(H_n). \tag{15}$$

However, in most cases, assessments for a basic attribute are incomplete, i.e., $\beta_H > 0$. Within the ER algorithm, β_n represents the belief measure in the D-S theory and thus provides the lower bound of the likelihood to which y is assessed to H_n, and the upper bound of the likelihood is given by $(\beta_n + \beta_H)$. Therefore, the likelihood to which y is assessed to H_n can be represented by the belief interval $[\beta_n, (\beta_n + \beta_H)]$. The ranking between two alternatives a_l and a_k is based on their averaged utilities, i.e., the alternative having the more averaged utility is then selected as the better one. It is easy to obtain the minimum and maximum utilities, formulated as follows [34]:

$$\begin{aligned} u_{\max}(y) &= \sum_{n=1}^{N-1} \beta_n u(H_n) + (\beta_{\mathrm{N}} + \beta_H) u(H_{\mathrm{N}}) \\ u_{\min}(y) &= (\beta_1 + \beta_H) u(H_1) + \sum_{n=2}^{N} \beta_n u(H_n) \end{aligned} \tag{16}$$

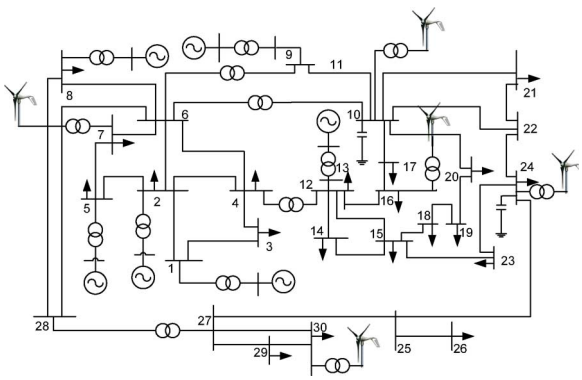

Fig. 5. Modified IEEE 30-bus test system.

TABLE I
INTERVAL FORECASTING OF WIND POWER

Bus	7	10	17	24	30
Wind Power (MW)	[12 20]	[2 6]	[5 8]	[0 6]	[2 12]

suppose H_1 is the least preferred grade having the lowest utility and H_{N} is the most preferred grade having the highest utility, i.e., $H_1 \prec H_2 \prec \cdots \prec H_{\mathrm{N}}$.

Then, the average of utility is the expectation of the minimum and maximum utilities, shown in the following equation:

$$u_{\mathrm{avg}}(y) = \frac{u_{\max}(y) + u_{\min}(y)}{2} \tag{17}$$

if $u_{\mathrm{avg}}(y(a_l)) > u_{\mathrm{avg}}(y(a_k))$, then a_l is preferred to a_k. Otherwise, a_k is better than a_l.

V. SIMULATION STUDIES

A. Simulation Settings

The NIO model of OPF is tested on the modified IEEE 30-bus power system with wind power integrated, which is shown in Fig. 5. The locations of wind farms are set to be on buses 7, 10, 16, 24, and 30, and it is assumed that the predicted wind power is obtained by the direct interval forecasting method, given in Table I.

In order to verify the effectiveness of the NIO model, it is compared with the traditional interval optimization method [29], which only optimizes the average of fuel cost. It is evident that the optimization of the fuel cost's averaged value is a single-optimization problem, which can be solved by the single-optimization algorithm, for instance, GSO.

Also, the performance of GSOMP is tested in comparison with NSGA-II, which is one of the most widely used multi-objective algorithms for power system optimization. These two algorithms are evaluated in 30 independent runs, and the number of function evaluations are set to be the same, i.e., 15 000, in each run. The sizes of external repositories for GSOMP and NSGA-II are both set to be 8.

Regarding the ER approach, the basic attributes are the average and the deviation of fuel cost in this paper. The relative weights of these two attributes are set to be the same, i.e., 0.5. Moreover, the evaluation grades consist of five categories, i.e., poor (P), indifferent (I), average (A), good (G), and excellent (E).

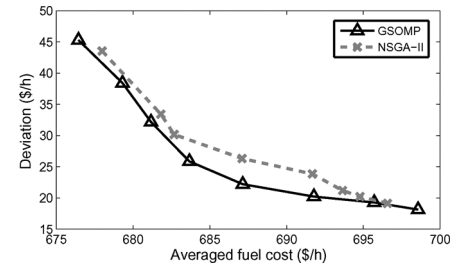

Fig. 6. Pareto solutions obtained by GSOMP and NSGA-II.

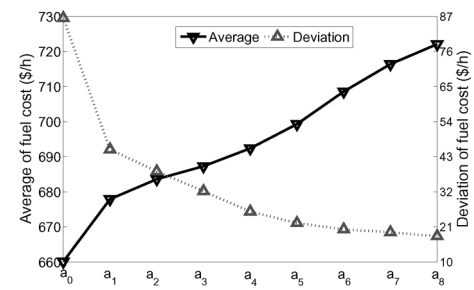

Fig. 7. Average and deviation of fuel cost as for $a_0, a_1, \ldots, a_8$.

B. Simulation Results

Fig. 6 shows the two best Pareto fronts obtained by GSOMP and NSGA-II in the 30 independent runs, which proves that GSOMP obtains better converged and more evenly distributed Pareto solutions. Moreover, the solutions found by GSOMP spread over the range of [677.9, 722.1] $\times$ [18.1, 45.3], which is wider than that of NSGA-II, [680.9,718.1] $\times$ [19.1,43.5].

The eight dispatch solutions obtained by GSOMP are donated as $a_1, a_2, \ldots, a_8$, and the solution which only optimizes the averaged fuel cost is donated as a_0. Their corresponding average and deviation of fuel cost are presented in Table II and Fig. 7. It is obvious that the two objectives of the NIO model conflict with each other, i.e., the higher average of fuel cost, the larger deviation. This means that a solution that obtains the minimization of the averaged value and deviation of fuel cost simultaneously does not exist.

It is noted in Table II that GSO is used to obtain the optimal dispatch solution a_0 by optimizing the averaged fuel cost, which is 660.1 \$/h. This value is much less than that of $a_1, a_2, \ldots, a_8$. However, the corresponding deviation of fuel cost is as high as 86.5 \$/h, calculated by (6), if a_0 is adopted by dispatchers. Therefore, a_0 can be viewed as an "aggressive" dispatch solution because it pursues just the least fuel cost without attempting to reduce the dispatching risk (manifested by the deviation) under the uncertain wind power environment. On the contrary, a_8 can be deemed as a "conservative" dispatch solution, as it can obtain the smallest deviation of fuel cost, compared with other solutions. This means that a_8 is the least sensitive to the uncertain wind power environment, and the corresponding average of fuel cost is around 722.1 \$/h. It can be more obviously seen from Fig. 8 that different dispatch solutions imply different levels of deviation (risk), and ultimately different fuel cost under

TABLE II
AVERAGE AND DEVIATION VALUES AS FOR $a_0, a_1, \ldots, a_8$

	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
Average (\$/h)	660.1	677.9	683.6	687.3	692.4	699.3	708.6	716.4	722.1
Deviation (\$/h)	86.5	45.3	38.4	32.2	25.8	22.2	20.2	19.3	18.1

TABLE III
DISTRIBUTION ASSESSMENT MATRIX FOR THE NINE DISPATCH SOLUTIONS

Attributes	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
Average	(E, 0.8) (G, 0.1)	(E, 0.3) (G, 0.4) (A, 0.2)	(E, 0.2) (G, 0.3) (A, 0.4)	(E, 0.1) (G, 0.2) (A, 0.6)	(G, 0.1) (A, 0.8)	(A, 0.6) (I, 0.3)	(A, 0.4) (I, 0.4) (P, 0.1)	(A, 0.2) (I, 0.5) (P, 0.2)	(I, 0.6) (P, 0.3)
Deviation	(P, 0.8) (I, 0.1)	(P, 0.2) (I, 0.4) (A, 0.3)	(I, 0.4) (A, 0.5)	(I, 0.1) (A, 0.6) (G, 0.2)	(A, 0.5) (G, 0.4)	(A, 0.4) (G, 0.5)	(A, 0.3) (G, 0.6)	(A, 0.2) (G, 0.5) (E, 0.2)	(A, 0.1) (G, 0.6) (E, 0.25)
AU	0.5100	0.5771	0.5916	0.6122	**0.6133**	0.5640	0.5669	0.5601	0.5569
Rank	9	4	3	2	**1**	6	5	7	8

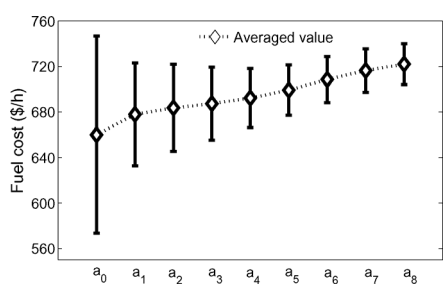

Fig. 8. Interval fuel costs as for $a_0, a_1, \ldots, a_8$.

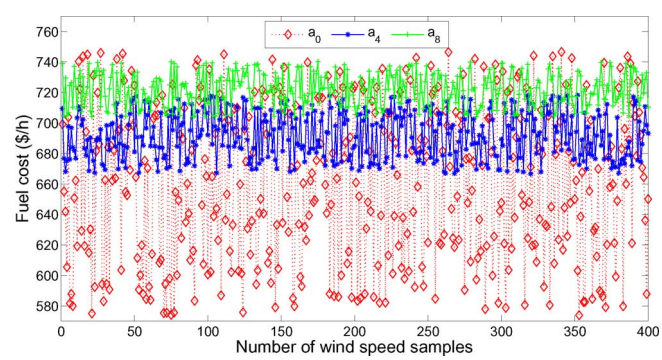

Fig. 9. Fuel cost corresponding to wind power samples of $a_0, a_1, \ldots, a_8$.

the uncertain wind power environment (i.e., the averaged values plus/minus the corresponding deviations).

Therefore, we should take the average and deviation of fuel cost into consideration simultaneously to obtain the most preferred dispatch solution. The ER approach is applied for this purpose, and the subjective judgements for evaluation of these 9 dispatch solutions are presented in Table III, together with their averaged utilities (AUs) and ranking. It can be seen that a_4 gains the most AU, and it is therefore selected as the final dispatch solution.

In order to further demonstrate the necessity of comprehensive consideration of both the average and deviation of the dispatching objective, Fig. 9 shows the samples of fuel cost in terms of the "aggressive" solution a_0, the selected solution by the ER approach a_4, and the "conservative" solution a_8 corresponding to 400 different wind power samples randomly obtained by the sampling method of Latin hypercube sampling with Cholesky decomposition [38], using the interval data shown in Table I. It is clear that, if solution a_0 is adopted by the power system dispatcher, the expected fuel cost among the 400 wind samples is 660.1 \$/h, better than those of a_4 and a_8. However, the deviation regarding solution a_0 is much higher, which demonstrates that this solution does not adjust the wind samples well. For instance, the fuel cost regarding many wind samples are higher than those of solution a_4, and even more than those of the "conservative" solution a_8. In this way, in the perspective of operational risk, it is not reasonable to choose solution a_0.

On the other hand, the deviation of fuel cost as for solution a_8 is much smaller, which proves it can adjust all the uncertain wind power samples well, but the averaged value of fuel cost is as high as 722.1 \$/h. Therefore, it is not advisable for power system dispatchers to choose this solution for the economic reason. In this way, solution a_4 is selected as the final dispatch solution by considering both the average and deviation of fuel cost based on the NIO model.

Furthermore, two factors should be considered if the highly accurate solution of a large-scale power system is expected to be obtained. First, it is necessary to obtain the accurate interval forecasting information of the large-scale power system. Because the solutions of the NIO model are obtained by transforming the problem into two subproblems corresponding to the upper and lower bounds of the dispatching objective function. It can be seen from (6) that the two bounds are directly related to the interval forecasting information. On the other hand, as the OPF model is used in our paper, an accurate method used for calculating the power flow of a large-scale power system is needed.

VI. CONCLUSION

In this paper, the NIO model has been used to solve OPSD with wind power integrated for the first time. The "profit" and "risk" of dispatch solutions are manifested by the average and deviation of the dispatching objective, respectively, under the environment of uncertain wind power. As the profit and risk are often in conflict with each other, we used the multi-objective optimization approach to deal with the two criteria. Moreover, a multi-objective optimization algorithm, GSOMP, was applied to solve the NIO model. In this way, Pareto solutions can be obtained by minimizing the average and deviation of fuel cost.

Then, the ER approach was used to process the dispatcher's preferences and uncertain cognition toward the profit and risk. Simulation results based on the modified IEEE 30-bus system have indicated the applicability and effectiveness of the NIO model, by comparing the dispatching effects of the "aggressive" and "conservative" solutions. In conclusion, both the profit and risk of dispatch solutions should be taken into account when solving OPSD with wind power integrated.

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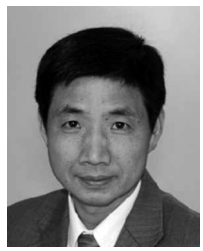

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