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Research Article

Multiobjective Optimization Approach for Coordinating Different DG from Distribution Network Operator

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Integrating with analysis of uncertainties, this paper presented a multiobjective optimization approach for coordinating different DG from the perspective of Distribution Network Operator (DISOPER). Aiming to three uncertain factors including fuzzy variable, random variable, and interval variable, the information entropy and interval analysis methods are adopted to construct multistate models of multisource uncertainty. The information entropy method is to convert fuzzy variable into equivalent random variable. Interval analysis method is to transform random variables into interval variables by setting a confidence level. Then plenty of simulation analysis based on the small probability event and expectation are investigated to reduce the computational burden and eliminate invalid computation. Subsequently, multiobjective formulations based on multistate are built by analyzing systematical power loss, voltage quality, reliability, and environment change provide some reference for DISOPER in dealing with access of privately owned DG units. Furthermore, based on network topology analysis and modified nondominated sorting genetic algorithm (NSGA), a combinatorial optimization method is proposed to reduce search space and solve the constructed formulations efficiently. Simulations are carried out on IEEE 37-bus systems and results are presented and discussed.

1. Introduction

Environmental deterioration, energy shortages, and climatic anomaly compel many countries to take renewable energy as future alternatives [1]. Consequently, distributed generation (DG) such as wind turbines (WTs) and photovoltaic (PV) systems are considered the most promising technologies to meet electrical loads because of their outstanding advantages such as environmentally benign, clean, and inexhaustible [1, 2]. Constrained by traditional power grid, one main application of DG in China is DG access to distribution system for the purpose of giving full play to the function of interests' integration [3, 4]. However, different from conventional power sources, DG penetration has a significant influence on power system due to its stochastic nature [2, 3]. Previous research has shown that the effect of DG access is closely related to siting and size of DG [4]. Therefore, the appropriate planning of DG in distribution system plays a crucial role in fully exerting DG advantages as well as restraining its disadvantages [5–7].

Apparently, DG planning in distribution network is an extraordinarily complicated problem, which is attributed to not only the diversity and intermittent nature of DG but also the complex structure and abundant metadata information of distribution network. So far, loads of researches have been reported [7–23]. Earlier studies focused on certain situation because of restrictions imposed by the treatment of uncertainty. In Reference [8], Shuffled frog leaping algorithm is presented for the placement of DG in distribution systems to reduce the real power losses and cost of the DG. When constructing multiobjective formulas, influence of load models is considered in siting and sizing of DG [9]. In Reference [10], the authors optimized three objectives including maximum DG utilization, minimizing system loss, and minimum environmental pollution by improving Pareto evolutionary algorithm. From DG Owner's and Distribution Company's Viewpoints, multiobjective optimization is proposed from the operational aspects and economic analysis [11]. These models and calculation methods can be used for optimum design of controlled DG and good effect can be obtained.

However, due to the profound effect of uncertainty on optimization results, certain programming models and algorithms lack adaptability for dealing with planning problem with plenty of uncertainties, which is especially prominent in planning renewable energy like WTs and PV generation. Therefore, uncertainty modeling and optimization algorithm are focused on recently published documents [9–29]. In describing uncertainty, the probability density functions is usually employed to model load, wind power, PV power, electricity market price, and so on [12–22]. Also, few studies have explored fuzzy mathematics models to describe uncertainties like load [3, 20] and constraints for voltage profile, feeder current, and substation capacity [25]. Treatment techniques of uncertainty involved Monte Carlo simulation [22, 24], scenario analysis [19, 23, 25, 26], and multistate model constructed by applying probability density functions [17, 18, 22]. In objective formulations, most of them were analyzed from economic benefits [9, 27–30], environmental concerns [30, 31], and technical constraints [9, 27, 28]. In optimization solution, some intelligent algorithm [28] and uncertain programming theory [14] were introduced to adapt to planning problems with plenty of uncertainties. Based on chance-constrained programming, a planning model is presented integrated with random characteristic of load and renewable DG power [14]. In Reference [29], Monte Carlo simulation is employed to deal with uncertainties, and NSGA-II is applied to find Pareto optimal front of two minimum objectives including system total cost and technical risk. Considering technical constraint dissatisfaction, costs, and environmental emissions, stochastic dynamic multiobjective model is constructed in Reference [25], and it applied a binary particle swarm algorithm and a fuzzy satisfying method to obtain the optimal solution. A sample average approximation algorithm-based technique is proposed in Reference [32] to solve the optimal placement of DG units, which is formulated as a stochastic optimization problem.

All these researches offer valuable contributions, but they lack the following important features. For one thing, multisource uncertainty is rarely considered together in distribution network optimization studies. For another thing, access control mechanisms for privately owned DG units are overlooked in terms of DISOPER.

In fact, there has been all kind of available DG in the market. It will be an inevitable trend that multitype and multiresource DG access power grid simultaneously, which is dominated by different factors such as policy interventions, benefit actuation, and traditional resource restriction. The advent of more charging stations for electric cars, whose charging were noted for variation in time and space, gave rise to frequent load fluctuation [17, 19, 20]. The implications of DG and load change make it necessary for DISOPER to integrate considerations regarding multisource uncertainty into DG planning of the distribution network. For the treatment of uncertainty, Monte Carlo Simulation requires enormous computational burden and is unsatisfactory to deal with complex models [33]. When multistate models and scenario analysis techniques [17–19, 22, 23, 25, 26] are applied to cope with uncertainties, selection of state or scenario apparently influences on the accuracy of optimization results. In this paper, three uncertainties including fuzzy variable, random variable, and interval variable are analyzed by information entropy and interval analysis methods to construct multistate model of uncertainties. Simultaneously, small probability event and expectation for multistate models as well as proportion compensation method are investigated to obtain representative state which can reduce invalid computation, improve computational efficiency, and guarantee the accuracy of results.

According to distribution network planning studies, the objective functions involving active power losses, emission, and reliability have been presented in many researches. However, existing papers have the drawback of overlooking the private ownership feature of DG units. Under current rules, it does not state clearly that DISOPER can randomly reject privately owned DG units whose accesses have an adverse impact on distribution network operation. But as the operator of distribution network, DISOPER has the right to change connected location of privately owned DG units to assure safe operation of distribution network. In addition, DG access concerned to multifaceted problems such as technicality, economics, environment, and social characteristics, which potentially correlate to DISOPER's benefits. However, it is difficult for DISOPER to qualify some of them in monetary terms alone. Therefore, based on the proposed multistate model, this article developed multiobjective optimization formulations through analyzing power loss improvement, voltage quality, systematical reliability, and environment change so as to provide some reference for DISOPER in dealing with access of privately owned DG units.

Furthermore, it has been studied and concerned widely in solving multiobjective optimization problems of strong constrained condition in the fields of engineering. At present, nondominated sorting genetic algorithm (NSGA-II) has been recognized as one of the most promising algorithms, primarily because it has the feature of high convergence speed, low computational complexity and good global convergence property [34, 35]. Compared with contemporary constraint-handling strategy, application of NSGA-II is encouraged to solve more complex and real-world multiobjective optimization problems [34]. NSGA-II has also played an indispensable role in solving constrained multiobjective optimization of the electric industry [35–37]. Fast and elitist NSGA-II algorithm is employed to avoid artificially balanced solutions [35]. In Reference [36], NSGA-II is applied to deal with simultaneously determining optimal capacities of active and reactive power reserve. NSGA-II and fuzzy set theory is chosen to find the best compromise solution [37]. In Reference [38], the authors adopted a novel building energy/exergy simulation tool with multiobjective optimization capabilities based on NSGA-II for carrying out simultaneously analysis of building energy use and design's Net Present Value. NSGA-II algorithm is used to the design of a standalone HRES comprising WTs, PV panel and battery bank [39]. In this paper, we proposed a combinatorial algorithm integrating network topology analysis and modified NSGA in order to reduce search space and efficiently solve the constructed formulations. The purpose of network topology is to eliminate obvious impossible access location of DG and avoid entire network search. In NSGA-II, the modified contents refer to nondominated sorting operator, individual crowding distance operator, and genetic operators. The purpose is to obtain effective Pareto solutions, assure uniform distribution of solutions, accelerate convergence rate of algorithm, and avoid local optimal or missing Pareto optimal solutions.

The main contribution of this paper is as follows. Firstly, three uncertainties including fuzzy variable, random variable, and interval variable are analyzed by information entropy and interval analysis methods to construct multistate model. Simultaneously, small probability event and expectation for multistate models as well as proportion compensation method are investigated to obtain representative state. Subsequently, from the perspective of DISOPER of dealing with privately owned DG units, multiobjective formulations based on multistate are constructed by analyzing power loss improvement, voltage quality, systematical reliability, and environment change. Also a combinatorial algorithm integrating network topology analysis and modified nondominated sorting genetic algorithm (NSGA) is presented to reduce search space and efficiently solve the constructed formulations.

2. Descriptions and Treatment for Multisource Uncertainties

The involved uncertainties in DG planning are related to not only connotation (e.g., load variations and renewable DGs fluctuation) but also extension (e.g., electricity market change, policy and regulation adjustment, and availability of system facilities). For simplification and integrating with research contents, three uncertainties including random variable, fuzzy variable and interval variable, which are related to load variations and DG fluctuation, are portrayed and treated.

2.1. Descriptions for Load and DG Uncertainties. Uncertainties of load and DG have been widely studied. Here, frequently used load and electric vehicle charging stations [40] are considered, and RES-based DGs include wind turbines (WTs) and photovoltaic generators (PVs).

Integrating with existing researches, the frequently used load is modeled by using uniform distribution of interval and truncated Gaussian distribution [14–16], which is a normal distribution that restricts the range of variable value [41]. Simultaneously, taking into account the unavailability of historical data, here, electric vehicle charging stations are modeled in (1) according to quick charging mode [17, 19, 20]:

$$P = \frac{QV}{\eta}, \tag{1}$$

where η is the charging efficiency for charger, V is the Charging voltage for the electric vehicle, and Q is the current sum of all recharging battery. Here, assume that Q is a fuzzy variable with the triangular membership function.

Output power of WTs is directly related to wind speed, which is usually taken as Weibull distribution. Research for the intermittent and stochastic of WTs has been relatively mature [13, 22]. The expression of wind power can be found in Reference [22].

Similar to WTs, PVs is also related to natural factors, geographic envissronment, season variation, etc. Here, PVs output power is given according to the composition of Grid-connected PV generation system [3]:

$$P = \eta_{\text{mod}} A r_{\text{tilt}} \eta_{\text{wr}} \eta_{\text{pc}}, \tag{2}$$

where η_{mod} is the efficiency under the ambient temperature, A is the total area of illumination, r_{tilt} is solar radiation intensity of inclined plane, η_{wr} is the distribution efficiency, and η_{pc} is the efficiency of power regulating system, which has very strong diurnal patterns [3, 23, 42]. η_{mod} can be shown in the following equation:

$$\eta = \eta_0 \left[1 - \gamma_{\text{T}}\left(T_p - T_{\text{r}}\right)\right], \tag{3}$$

where T_{r} is reference temperature, whose value is 298 K. η_0 is the conversion efficiency of PVs at the reference temperature. γ_{T} is the temperature coefficient of solar cell, which generally is 0.005. T_p is the temperature at time p. From (2) and (3), uncertainty of PVs output power is concerned to solar radiation intensity and the temperature. It is well known that temperature is affected by sunlight and changed with different weather conditions. That is, the temperature changes quickly in sunny days while it changes slowly in cloudy or rainy weather [43]. Furthermore, real output of PVs is still relate to illumination inhomogeneity, dust, production deviance, installation error, etc. Apparently, it is not easy to express such change through random uncertainty model. For simplification and ensuring rationalization, here PVs output power is simplified into (4) according to (2):

$$P_{\text{PV}} = A r_{\text{tilt}} \eta_1, \tag{4}$$

where P_{PV} is real output and η_1 is the conversion efficiency related to weather conditions. Here, assume that η_1 is a fuzzy variable considering that there is an inevitable fuzziness in conversion efficiency of representing the weather conditions. And integrated with under sunny, cloudy, and rainy days given in [3], here η_1 is modeled as trapezoid membership function shown in the following equation:

$$\mu(\eta_1) = \begin{cases} \dfrac{10\eta_1}{3}, & 0 \le \eta_1 \le 0.3, \\ 1, & 0.3 \le \eta_1 \le 0.55, \\ \dfrac{14-20\eta_1}{3}, & 0.55 \le \eta_1 \le 0.7, \\ 0, & \text{others}. \end{cases} \tag{5}$$

2.2. Treatment for Multisource Uncertainties. The purpose of treatment for multisource uncertainties is to convert various uncertainties into multistate variables to improve computational efficiency and reduce invalid computation. Based on the concept of possibility-probability consistency, information entropy is adopted to transform fuzzy number to stochastic variable. Interval analysis is applied to convert random variables into limited discrete intervals by setting a certain confidence level, and meanwhile, composite state is obtained by analyzing small probability event and expectation.

Entropy is the best measure to uncertainty. Fuzzy entropy G_x measures fuzziness of uncertainty, while probability entropy H_y measures randomness of uncertainty [44]. Here, set G_x is equal to H_y, then fuzzy variable is converted into an equivalent random variable in normal distribution with mean u_{eq} and variance σ_{eq} shown in the following equations:

$$\begin{aligned} \sigma_{\text{eq}} &= \frac{1}{\sqrt{2\pi}} e^{G_x - 0.5}, \\ \mu_{\text{eq}} &= \frac{\int_x x\mu(x)dx}{\int_x \mu(x)dx}, \end{aligned} \tag{6}$$

where $\mu(x)$ is the fuzzy membership function of fuzzy variable and σ_{eq} is variance. And mean u_{eq} is obtained when membership degree takes 1 [45, 46]. For improving calculating efficiency and ensuring data integrity, transformation of random variables to interval variable includes the following:

(i) Determination of the upper and lower limits. The method is to calculate cumulative probability of random variable. The value should be close to 1 and never lower than a specified confidence level, which is often more than 90%.

(ii) Division of interval variable. Setting interval number m, interval is divided by regularly or irregularly step-length on the basis of actual situation. Subsequently, a binary state sequence with state and its probability is obtained. The ith state probability in interval $[x_i, x_{i+1}]$ can be obtained by

$$P_i(\omega_i) = \int_{x_i}^{x_{i+1}} f(x)\,dx = F(x_{i+1}) - F(x_i). \tag{7}$$

Simultaneously, the normalization processing is carried out by the proportion compensation method to assure that the sum of state probability is 1 [47], whose principle is to assign loss probability based on the proportion of interval probability. The revised form of state probability is shown in the following equation:

$$P_i' = P_i + \frac{P_i\left(1 - \sum_{i=1}^{m} P_i\right)}{\sum_{i=1}^{m} P_i}. \tag{8}$$

The composite state for multisource uncertainty is analyzed under the independence assumption among random variables. Assuming that the kth composite state is composed of three binary sequence X: $\{\omega_{\text{F}i}^k, P'(\omega_{\text{F}i}^k)\}$, Y: $\{\omega_{\text{R}j}^k, P'(\omega_{\text{R}j}^k)\}$, and Z: $\{\omega_{\text{I}q}^k, P'(\omega_{\text{I}q}^k)\}$ from three uncertainties, the number of composite state and the kth joint probability are obtained by

$$N = \prod_{i=1}^{m_{\text{F}}} N_{\text{F}i} \prod_{j=1}^{m_{\text{R}}} N_{\text{R}j} \prod_{q=1}^{m_{\text{I}}} N_{\text{I}q}, \tag{9}$$

$$P_{X,Y,Z}(k) = P'\left(\omega_{\text{F}i}^k\right) P'\left(\omega_{\text{R}j}^k\right) P'\left(\omega_{\text{I}q}^k\right), \tag{10}$$

where m and N are the number of variables and interval, respectively. Subscript F, R, and I are orderly on behalf of fuzzy, random, and interval variables.

From (9), the number of composite state increases exponentially with increase of interval number. From (10), the consequence of interval division is noticeable. Too small interval will increase tendency to small probabilities, while too large range will reduce accuracy of solution. To avoid these, plenty of simulations based on the small probability event and expectation are carried out besides setting a confidence level. The simulations are to analyze the number of small probability events and guarantee reasonable expectation of the given formulation, while the application of confidence level is to reduce the number of composite state. Similarly, the normalization is also carried out by (8).

3. Multiobjective Formulations

DG penetration has significant impacts on systematical loss, voltage, reliability, etc. And compared with conventional power, DG cost is higher. However, DISOPER cannot randomly reject privately owned DG units although its accesses have an adverse impact on distribution network operation under the condition that the technical parameter is in conformity with access standard. Therefore, sometimes DISOPER has to change connected location of privately owned DG units or sacrifice personal economic interests to assure safe operation of distribution network. From the viewpoint of economics and technology, here, four maximum objectives are constructed by analyzing reduction of power loss, enhancement of voltage quality, improvement of reliability, and change of environment to optimize the location and capacity of DG, thereby providing reference for DISOPER in coordinating access of privately owned DG units.

3.1. The Reduction of Power Loss. The power loss rate in (11), which is defined as the ratio of power loss reduction with DG and power loss without DG, is proposed to reflect impact of DG on power loss:

$$\mathrm{IP}_{\mathrm{loss}} = \frac{\sum_{s=1}^{N_1} P(s) P_{\mathrm{loss}}^{s} - \sum_{q=1}^{N_2} P(q) P_{\mathrm{loss}}^{q}}{\sum_{s=1}^{N_1} P(s) P_{\mathrm{loss}}^{s}}, \quad (11)$$

where N_1 and N_2 denote the number of composite state without DG and with DG, respectively. $P(q)$ and $P(s)$ are state probability at the qth and sth composite state. P_{loss}^{s} and P_{loss}^{q} are power loss at the qth and sth composite state.

3.2. Enhancement of Voltage Quality. Currently, besides the consumers' higher requirements for power supply because of the rapid development of modern power electronic devices, electric market reform has brought fierce competition among enterprises. To improve vitality and competitiveness, DISOPER has to reinforce system to better control over voltage variations [48, 49], which is closed linked to technical and potential economic interest. Therefore, the quantification of DG impact on voltage quality is very necessary. Here, the improvement of systematical voltage offset, which is defined as the ratio of nodal voltage offset before and after DG installation, is given in (12) to quantify DG enhance on voltage quality:

$$\mathrm{IV}_{\mathrm{enha}} = \frac{\sum_{s=1}^{N_1} P(s) \sum_{i\in\phi} \left(V_{\mathrm{wo}i}^{s} - V_{i}^{\mathrm{rated}}\right)^2}{\sum_{q=1}^{N_2} P(q) \sum_{i\in\phi} \left(V_{\mathrm{w}i}^{q} - V_{i}^{\mathrm{rated}}\right)^2}, \quad (12)$$

where subscripts wo and w are without and with DG, respectively; φ is the load node set; V_i and V_i^{rated} are the real voltage magnitude and the nominal voltage at the ith load node.

3.3. Improvement of Reliability. DG access can improve reliability of load in island if DG island operation is feasible after system fault. Here Ratio of Expected Energy Not Supplied Reduction shown in (13) is employed to measure DG impact on systematical reliability:

$$\mathrm{IR}_{\mathrm{imp}} = 1 - \frac{\sum_{q=1}^{N_2} P(q) \mathrm{EENS}_{\mathrm{w}}^{q}}{\sum_{s=1}^{N_1} P(s) \mathrm{EENS}_{\mathrm{wo}}^{s}}, \quad (13)$$

$$\mathrm{EENS} = \sum_{i\in\phi} \beta_i T_i L_i, \quad (14)$$

where EENS is expected energy not supplied; β_i is the ith load fault rate (number of faults per year); and T_i is the average durations of fault (hour per time). The equations for β_i and T_i are proposed in [48–50].

3.4. Improvement of Environment. Without a doubt, electricity industry is playing an inescapable role for environmental pollution. DG is also propelled to meet requirements of low carbon emissions. Here, only carbon emission is taken into account because the others are looked as being proportion to it. The environmental improvement is investigated by the rate of carbon emission reduction in the following equation:

$$\mathrm{IE}_{\mathrm{imp}} = 1 - \frac{\sum_{q=1}^{N_2} P(q) \left(E_{\mathrm{main}}^{q} C_{\mathrm{con}} + \sum_{i=1}^{N_{\mathrm{DG}}} E_{\mathrm{DG}i}^{q} C_{\mathrm{DG}i}\right)}{\sum_{s=1}^{N_1} P(s) E_{\mathrm{wo}}^{s} C_{\mathrm{con}}}, \quad (15)$$

where E_{wo} is the electricity from main grid without DG (kWh); E_{main} is the electricity from main grid with DG (kWh); E_{DG} is the electricity from DG; and C is the amount of carbon emission per unit electricity (kg/kWh). Subscript con is the conventional energy.

3.5. The Constraints. For safe and stable operation, the optimization problem is subject to power flow equations constraint and some inequation limits like node voltage, branch capacity, etc. These constraints are shown in the following equations:

$$\begin{cases} P_{\mathrm{main}}^{q} + \sum_{i=1}^{N_{\mathrm{DG}}} P_{\mathrm{DG}i}^{q} = \sum_{i\in\phi} P_{\mathrm{L}i}^{q} + P_{\mathrm{loss}}^{q}, & \\ \Pr\left\{V_i^{\min} \le V_i^{q} \le V_i^{\max} \mid i \in \phi\right\} \ge 1 - \varepsilon_V, & \\ \Pr\left\{S_{ij}^{q} \le S_{ij}^{\max} \mid i, j \in \phi\right\} \ge 1 - \varepsilon_S, & q = 1, 2, \ldots, N, \\ N_{\mathrm{DG}} \le N_{\mathrm{DG}}^{\max}, & \\ \sum_{i=1}^{N_{\mathrm{DG}}} P_{\mathrm{DG}i} \le k\% * \sum_{i\in\phi} P_{\mathrm{L}i}, & \end{cases} \quad (16)$$

where P_{main} is the power from the main grid; P_{DG} is DG power; P_{loss} is systematical losses; N are the number of operating state; $\Pr\{\cdot\}$ represents the probability of an event; $V_i^{\max}$ and $V_i^{\min}$ are the ith nodal upper and lower of voltage; S_{ij}^{q} and $S_{ij}^{\max}$ are real line capacity at the qth state and permitted maximum line capacity; N_{DG} and $N_{\mathrm{DG}}^{\max}$ are the real number and the allowable ceiling of DG location; ε_V and ε_S are confidence level of bus voltage and line capacity; $P_{\mathrm{L}i}$ and $P_{\mathrm{DG}i}$ are base load and DG power at node i; and $k\%$ is the penetration rate of DG.

4. Optimization Method Based on Network Topological Analysis and Modified NSGA-II

Besides the inherent complexities of power flow calculation in DG planning, the previously constructed multiobjective optimization formulations are obviously constrained, nonlinear, with mixed integer variables. Consequently, optimization computation is a tremendously complex task. In order to improve the computational efficiency without influencing the accuracy of solutions, the topological analysis and modified NSGA are adopted to carry on combinatorial optimization. The purpose of topological analysis is to reduce search space by determining DG candidate locations in accordance with the actual situation, while that of modified NSGA is to improve convergence speed as well as avoid falling into local best during optimizing the constructed formulations.

4.1. Determination of DG Candidate Locations Based on Network Topology Analysis. Previous researches showed that DG impacts on distribution network are related to the connected bus as well as all others buses, but the bigger influence occurs on the bus near DG [51]. And DG layouts should try to keep decentralized to limit potential of interfering with each other in undesired ways. In addition, DG location is restricted by geographical position and local natural resources. Therefore, here DG candidate locations area is proposed to determine one DG location when carrying out multiobjective optimization. The number of DG candidate locations areas is corresponding to the maximum number of DG installation locations. Each area, which determines DG candidate locations set, is obtained through the limited depth-breadth priority algorithm. A DG candidate locations set is obtained according to nodal electric distances, nodal load moment, and reliability requirement. The detailed process is described as following:

Step 1. Obtain the DG candidate location area. Based on the maximum number of DG installation location h, the distribution network is divided into k area. Partitioning method is to add the base load starting from the end of line according to the limited depth-breadth priority algorithm. The sum of all base loads in one area is approximately equal to the value of the total base load divided by h.

Step 2. Select DG candidate locations based on the principle of reducing the power loss. Generally, the bus far from substations produced more power line losses. Therefore, here the nodal electric distance d is applied to determine the DG candidate locations. The selected node i is obtained by

$$d_i \geq \frac{\max\{d(j) \mid j \in \phi\}}{3}, \tag{17}$$

where d is electric distance and j is the alternative bus.

Step 3. Select DG candidate locations based on the principle of improving the nodal voltage. It has been proved that the constant PQ DG can definitely boost up the nodal voltage, while PV DG also can achieve the same effect under the condition that the connected nodal voltage is lower than the voltage of PV DG [51]. Furthermore, the voltage loss is in correspondence with the nodal load moment. Therefore, through the descending order of the nodal load moment, the first half is selected as DG candidate location.

Step 4. Select DG candidate locations based on the reliability requirements. As mentioned previously, DG access can improve the reliability in island load. Thus, buses having high reliability requirements are chosen as candidate location.

Step 5. Form DG candidate locations sets by combining and abandoning candidate locations in view of the partitioning area. One candidate location set is corresponding to one area. The principle of abandon and combination includes the following: (a) to reserve all candidate locations based on reliability, (b) to abandon the candidate locations without locating in installation locations area, (c) to abandon inaccessible geographical location, and (d) to keep candidate locations coming from both step 2 and step 3.

4.2. DG Island Separation Based on Network Topology Analysis. As mentioned in [48], DG impact on reliability is mainly concerned to the island's load. Then improvement of reliability is closely associated with the formation of the island. Consequently, DG island separation has a significant influence on reliability. Starting from DG connected bus, this paper goes into distribution network's structure using breadth search, giving the island scope by the following equation:

$$P_{\mathrm{DG}i}^{s} - \sum_{j=1}^{N_{\mathrm{il}}} P_j^s \leq \gamma, \tag{18}$$

where N_{il} is the number of load points in island; P_j^s are the load value at the sth state; $P_{\mathrm{DG}i}^{s}$ is power output at the ith DG; and γ is the threshold.

The formation of the island is described as following:

(i) Select the connected bus of DG as the reference node of determining electrical distance, and then obtain the electrical distance of all loads.

(ii) Give a lateral stratification of loads in accordance with electrical distance. Loads on the same layer are ranked in order of importance, which is represented in weighted coefficients of load.

(iii) Perform breadth search starting from the innermost layer. When the total load in the island is closed to threshold, the loads on the outermost layer are chosen according to the weighted coefficients of load.

To understand it more clearly, take Figure 1 as an example. Assume that threshold γ is constant, and bus 4 is selected as DG location. By carrying on the width search, the next-linked buses 3, 5, 7, 8 are selected. If the sum of these load value is not satisfied with (18), buses 2, 9, 6 are considered. If they are all chosen, the sum will gone beyond the threshold γ. Therefore, according to weighted coefficients of loads at buses 2, 9, 6, bus 9 with larger weighty is chosen. Then the buses in island include 3, 5, 7, 8, 9.

4.3. Multiobjective Optimization Based on NSGA. NSGA-II is currently one of the most popular multiobjective evolutionary algorithms because of its rapidly converging rate. However, considering that NSGA is inclined to result in prematurely converging to local Pareto optimal front, here the proposed modified NSGA-II can not only manage a variety of decision variables such as DG type, DG capacity, and DG location, but also deal with the complicated constraints expediently. The modified content mainly refers to genetic algorithm (GA) implementation to improve the GA's local searching capacity, accelerate the convergence rate, and effectively prevent the premature convergence. About population code, decimal encoding scheme based on

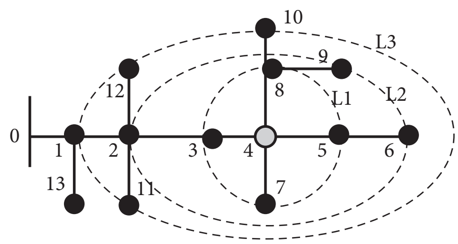

FIGURE 1: Schematic of island division.

segmented chromosome management is applied to adapt to characteristic of DG planning involving DG type, DG capacity, and DG location. That is, each solution is coded by using three segments, which orderly represent DG type, DG location, and DG size. Each segment is a vector, whose size is equal to maximum number of installation DG units [49]. In genetic manipulation, the selection, crossover, and mutation operator are properly collected besides the segmented point cross and mutation proposed in [49]. Figure 2 describes a coding example and the implementation details of the segmented point cross and mutation.

Selection operator is improved by using elitist preservation strategy and dual tournament selection to enhance the global convergence performance of algorithms and enlarge search space. Elitism preservation strategy is to copy a small proportion of the fittest candidates into the next generation to improve convergence and avoid loss of optimal solution. Dual tournament selection is to randomly pick up individuals from the population.

Crossover is preceded by correlation between two individuals to maintain population diversity and improve global search ability. The correlation is shown in the following equation [52]:

$$r(x_1, x_2) = \sum_{i=1}^{N_{\mathrm{ch}}} x_1^i \cap x_2^i, \tag{19}$$

where $r(x_1, x_2)$ is the correlation between individuals x_1 and x_2; N_{ch} is the segment number of population; superscript i is the ith component of individuals x_1 or x_2; and $\cap$ is a binary operator, which is satisfied with the following equation:

$$x_1^i \cap x_2^i = \begin{cases} 0, & x_1^i = x_2^i, \\ 1, & x_1^i \neq x_2^i. \end{cases} \tag{20}$$

Obviously, the bigger the r is, the smaller the correlation is. Therefore, two individuals with bigger r are matched for crossover.

Nonuniform mutation operator is employed to improve local searching ability of GA and maintain diversity. Nonuniform mutation operator in Reference [39] can adaptively adjust the searching step size in genetic evolution.

In addition, application of segmented point cross and mutation maybe result in occurrence of individual beyond threshold due to diversity of heredity encoding. Therefore, according to [53], treatment of DG capacity border in (21) is used to maintain the crossed or mutated individual within normal range:

$$x_1^C = \begin{cases} k\% * \sum_{i\in\phi} P_{\mathrm{L}i} - \sum_{i=1}^{N_{\mathrm{DG}}-1} P_{\mathrm{DG}i}, & \rho = 0, \\ 0, & \rho = 1, \end{cases} \tag{21}$$

where ρ is random variable of the Bernoulli distribution.

4.4. The Framework for Multiobjective Optimization. The proposed optimization method includes determination of DG candidate location sets and multiobjective optimization based on modified NSGA-II. Flowchart for multiobjective optimization is shown in Figure 3.

5. Numerical Example

5.1. Example for Multistate Model of Multisource Uncertainty. As stated in Section 2, fuzzy variables are transferred into random variables with normal distribution. Therefore, based on research contents, the discretization of the variable with standardized normal distribution is presented in details. Subsequently, multistate models for output power of PV power and output power of wind power. The composite state for PV power and a load are given.

Here, multistate models of a standardized normal random variable are investigated, and then others can be extended to the demanded range. For a standardized normal random variable, the probability in interval [−3, 3] is over 9.7%. So, the upper and lower bounds are specified as 3 and −3. When interval number is equal to 10, the schematic diagram is shown in Figure 4, which is obtained in accordance with the relationship between standardized normal distribution and general normal distribution. The multistate models corresponding to general normal distribution are obtained. Setting random variable $L_1 \sim N_{l1}$ (0.5, 2), the state value and its probability is shown in Table 1.

Multistate models of wind power, whether its wind speed is taken as Weibull distribution or interval variable, are similar with that of load because they are all treated as stochastic variable here. In addition, WTGs has a requirement of cut-in wind speed, rated wind speed, and cut-out wind speed, so the lower and upper of wind discretization is confirmed in cut-in wind speed and cut-out wind speed. Supposing that $V_i = 4$ (m/s), $V_{\mathrm{r}} = 14$ (m/s), and $V_{\mathrm{o}} = 25$ (m/s), the shape parameter and the scale parameter of wind are 2 and 8 m/s, interval number is 10, the rated power P_{r} is 45 kW, and then the binary state of wind power are {{0, 0.2213}, {4.725, 0.2197}, {12.175, 0.2094}, {23.625, 0.1591}, {33.075, 0.1001}, {42.525, 0.0531}, {45, 0.0374}}.

Different from wind power, output of PVs is concerned to fuzzy variable η_1. The parameter of fuzzy variable η_1 refers to Equation (5). Integrated with previously proposed method, the mean and variance of the equivalent normal distribution transformed from fuzzy variable are 0.4537 and 0.104. Binary sequences of fuzzy variable η_1 are {{0.1729, 0.0069}, {0.2353, 0.0278}, {0.2977, 0.0794}, {0.3601, 0.1596}, {0.4225, 0.2264}, {0.4849, 0.2264}, {0.5473, 0.1596}, {0.6097, 0.0794}, {0.6721, 0.0278}, {0.7345, 0.0069}}.

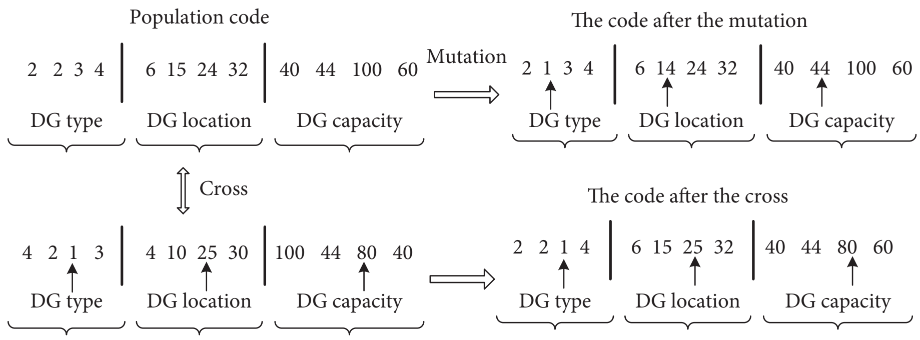

Figure 2: The segmented point cross and mutation.

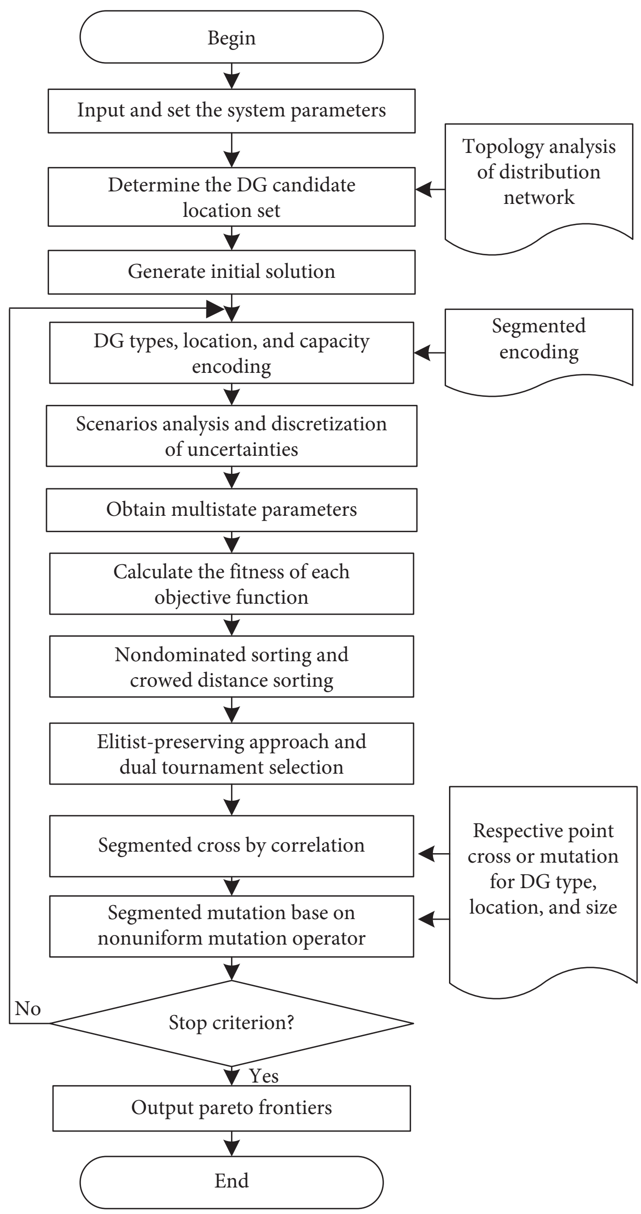

Figure 3: Flowchart for multiobjective optimization.

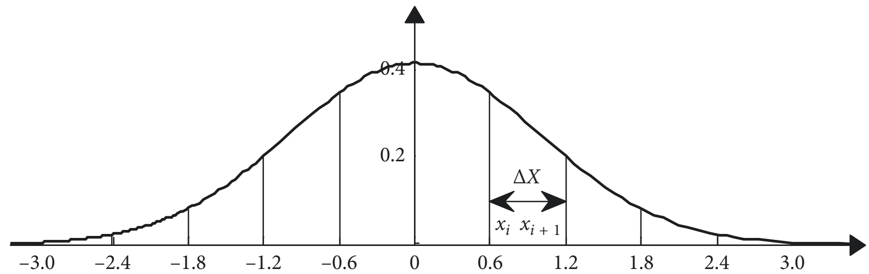

Figure 4: Schematic diagram for discretization of standardized normal distribution.

Table 1: State variables and probability of $N(0,1)$ and $N_{I1}(0.5,2)$.

State for $N(0,1)$	State for $N_{I1}(0.5,2)$	Probability	Corrected probability
−2.7	−4.9	0.0068	0.0068
−2.1	−3.7	0.0277	0.0278
−1.5	−2.5	0.0791	0.0794
−0.9	−1.3	0.1592	0.1596
−0.3	−0.1	0.2257	0.2264
0.3	1.1	0.2257	0.2264
0.9	2.3	0.1592	0.1596
1.5	3.5	0.0791	0.0794
2.1	4.7	0.0277	0.0278
2.7	5.9	0.0068	0.0068

In order to obtain proper composite state for PV power and wind power, plenty of simulation has been carried out provided that small probability event refers to less than 0.001 and confidence level is no less than 95%. The peak power $P_{\max}$ of PV is 44 kW. The load obeys a truncated Gaussian distribution, of which, lower and upper bounds are 28 kW and 35 kW and the mean and variance are 30 and 2. The parameters for wind are as above. The simulation results under different interval number are listed in Table 2.

Plenty of simulation shows a fact that the expected value for output power of PV, wind, and the load are affected by interval number. With the increase of interval number, the expected value gradually turns to be stable. However, another fact that should not be overlooked is that small probability events will go up sharply as interval number increases, e.g., in Table 2, there is 24 small probability events in interval number (5, 5, 5), while there exist 668 small probability events in (10, 10, 10) and even it amounts to 42561 in (35, 35, 35) which is far beyond effective joint-state 314. Too much small probability not only complicates calculation but also results in mass of invalid computation, which greatly decreases computational efficiency. Therefore, the moderate selection of interval number is very important. In this example, the interval number (5, 5, 5), (5, 5, 10), and (5, 5, 15) are recommended values because their small probability events are small and the expected value for PV, wind, and the load are at an acceptable level.

Table 2: The simulation results of different interval number.

Interval number of load, PV, wind	Effective joint-state number	Small probability events	Expected value of P_{load}, P_{PV}, P_{wind} (kW)
(5, 5, 5)	101	24	30.56, 19.96, 47.99
(10, 10, 10)	332	668	30.54, 19.96, 47.85
(15, 15, 15)	237	3138	30.54, 19.96, 47.83
(20, 20, 20)	198	7802	30.54, 19.96, 47.82
(25, 25, 25)	254	15371	30.54, 19.96, 47.82
(30, 30, 30)	296	26704	30.54, 19.96, 47.82
(35, 35, 35)	314	42561	30.54, 19.96, 47.81
(5, 5, 10)	167	83	30.56, 19.96, 47.85
(5, 5, 15)	217	158	30.56, 19.96, 47.83
(5, 5, 20)	264	236	30.56, 19.96, 47.82
(5, 5, 30)	343	407	30.56, 19.96, 47.82
(10, 20, 30)	170	5830	30.54, 19.96, 47.82

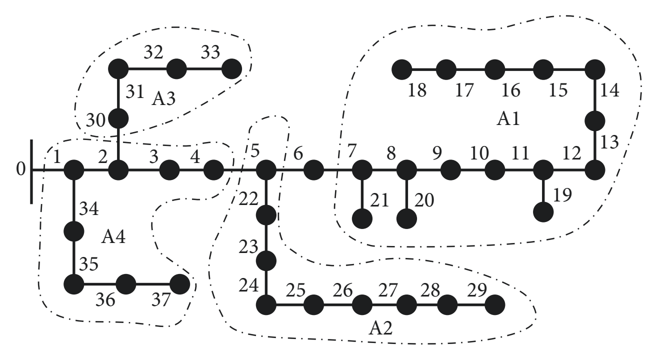

Figure 5: IEEE 37-bus system.

5.2. Simulation Parameters for Multiobjective Optimization Based on NSGA. To demonstrate the performance of the proposed optimization method, simulation is carried out on IEEE 37-bus system, whose topological structure is shown in Figure 5.

The branch, base load parameters can be found in [4, 9]. Meanwhile, assuming that load on bus 16 is uncertain variable which obeys normal distribution with mean $U_{16} = 0.06$ (p.u.) and standard deviation $\sigma = 0.01$. Buses 32 and 28 are taken as interval variables, whose values are orderly [0.4, 0.425], [0.205, 0.220], and others are taken as constant power load. The parameters for uncertain loads and information for single DG unit are listed in Tables 3 and 4. The parameters and probability distribution for uncertain loads are listed in Table 3. For DGs, detailed information is listed in Table 4. The power

Table 3: The parameters and probability distribution for uncertain loads.

Bus	State/interval (p.u.)	Probability distribution
16	0.036	0.0347
	0.048	0.2390
	0.06	0.4527
	0.072	0.2390
	0.084	0.0347
32	[0.400, 0.410]	0.1
	[0.410, 0.420]	0.5
	[0.420, 0.425]	0.4
28	[0.205, 0.210]	0.3
	[0.210, 0.215]	0.4
	[0.215, 0.220]	0.3

Table 4: Informations for different DG units.

DG	Bus type/base capacity	Failure rate (time/year)	Average interruption duration (hour/time)	Binary state {power, probability}
T1	PQ/100	5	50	{0, 0.2213}
				{15, 0.3138}
				{45, 0.2554}
				{75, 0.1383}
				{100, 0.0713}
T2	PQ/200	1	10	{180, 0.4}
				{190, 0.4}
				{200, 0.2}
T3	PV/44	2	25	{0.0818, 0.7359}
				{0.9086, 0.1432}
				{1.3844, 0.0659}
				{2.3743, 0.0347}
				{3.6179, 0.0202}
T4	PV/60	1	10	60

Note. Power factor of PQ DG is 0.8 and voltage magnitude of PV DG is 1.0.

Table 5: The objective function values for some Pareto front solutions.

No.	DG type	DG location	DG size	IP_{loss}	IV_{enha}	IR_{imp}	IE_{imp}
1	T2, T2, T1	14, 27, 37	200, 200, 100	0.0878	0.0009	0.9979	0.0523
2	T2, T3, T3, T2	13, 26, 31, 35	200, 44, 44, 200	0.3188	0.0011	0.9546	0.0721
3	T4, T3, T4, T1	9, 27, 35	360, 44, 100	0.3700	0.0007	0.9648	0.0742
4	T4	37	480	0.1579	0.0013	0.9450	0.0201
5	T1, T4	17, 24	400, 120	0.2546	0.0013	0.9345	0.0220
6	T2, T2, T4	13, 24, 32	200, 60, 180	0.2596	0.0012	0.9566	0.0238
7	T3, T4, T1, T3	14, 27, 32, 36	44, 300, 100, 44	0.3275	0.0006	0.9660	0.0732
8	T4, T3, T3	11, 28, 32	300, 176, 44	0.3606	0.0007	0.9458	0.0721

base is 10 MVA and convergence accuracy is 10^{-4}. Maximum and minimum limits of the nodal voltage are positive and negative 7% of the nominal voltage. The maximum penetration of DG is 10% of total base load, while the maximum number of DG installation N_{DG}^{max} is four. The fault rate on distribution feeder is 0.05 time per year, and average interruption duration each time is 5 hours. The parameters of NSGA are orderly 0.9 for select rate, 0.9 for crossover rate, 0.05 for mutation rate, 50 for chromosome numbers, and 30 for maximum iterations.

5.3. Simulation Results for Multiobjective Optimization Based on NSGA. The simulation is carried on Matlab 2008 rb. Based on the topological structure and the maximum N_{DG}^{max}, four areas are shown in Figure 4. DG candidate locations based on nodal electric distances are {18 16 17 19 15 14 20 12 13 21 29 27 28 9 11 10 26 25 8 24 37 33 32 7}. DG candidate locations based on the nodal load moment are {32 28 31 26 17 27 13 7 16 25 15 14 12 6 29 9 11 37}. Assuming that load bus of high-reliability requirements are {36 35 28 16}. Therefore, four candidate location sets are {16 17 15 14 13 12 11 9}, {28 27 25 26 24}, {33 32 31}, and {37 36 35}. Table 5 lists some Pareto front solutions at the 30th iterations. By analyzing simulations results, some conclusions are listed as following:

(i) The proposed multistate model and application of confidence level not only ensure the accuracy of results, but also reduces search space notably on the premise that the result is hardly affected.

(ii) If anyone of DG type, location, and size changes, four objective function values will all change. It is extremely difficult that four objective function values simultaneously arrive at the optimal at one solution. Therefore, when installing DG, policy-makers has to combine the main object of individual decision to choose appropriates solution from the Pareto front solutions.

(iii) The application of DG candidate location set and genetic operators can reduce greatly search space of GA and improve computational efficiency of algorithm.

The proposed modified NSGA can solve efficiently constrained, nonlinear multiobjective optimization problem with multisource uncertainty. And the solution approach presented here is simple, reliable, and efficient.

6. Conclusion

From the view of DISOPER, this study presented a multi-objective optimization for DG planning considering with multisource uncertainty. The employment of information entropy and interval analysis can resolve the multisource uncertainty problems effectively. The constructed multi-objective formulations can not only reflect DG different influences on distributed network but also take care of the multisource uncertainty. Applications of small probability event and confidence level decreased greatly search space without affecting the accuracy of results. In optimizing processes, the developed DG candidate location set and genetic operators avoided redundant calculation to improve the efficiency. Furthermore, introduction of multiobjective optimization based on modified NSGA can get a comparative satisfying result as well as coordinate the conflict between various objects. Plenty of simulations also showed the proposed methodology is simple and reliable. And it is suitable for allocation of multisources and multitype DG in a given distribution networks under multisource uncertainty.

Data Availability

Datasets, which are used to support the findings of this study, can be found as Supplementary Materials.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Supplementary Materials

Datasets, which are used to support the findings of this study, are submitted by a Data Availability Statement File. It includes parameters for IEEE 37-bus system and some descriptions for wind speed and photovoltaic generation. (*Supplementary Materials*)

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