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# Distribution Network Reconfiguration with Multi-Objective Optimization of Distributed Generation based on Chance Constrained Programming

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## Abstract

**For distribution network with distributed generation, reducing the network loss has always been the focus of research. With increasing proportion of distributed generation in the distribution network, how to improve the power consumption capacity of the distribution network which consider the randomness of distributed generation is increasingly concerned. Firstly, A multi-objective optimization model for distribution network reconfiguration based on maximum consumption of distributed generation and minimum network loss is established in this paper, then, uncertainty of photovoltaic and wind power output are handled by chance-constrained programming model. Subsequently, an improved NSGA-II algorithm is proposed to solve the model which combined with a global Pareto set maintainance strategy. Finally, Taking IEEE 33-node system as an example to compare and analyze multi-objective and multi-scenario optimization. The results show that the model built in this paper can effectively improve the ability of consumption of distributed generation while reducing network losses.**

## Keywords

**Distribution Network Reconfiguration; Distributed Generation; Chance-Constrained Programming; NSGA-II.**

## 1. Introduction

Against the backdrop of increasingly tight global primary energy supplies and the growing urgency of energy conservation and emissions reduction, distributed power generation-as an alternative to traditional fossil fuels-has been vigorously promoted due to its advantages, such as the ability to generate and consume electricity on-site and avoid power losses caused by long-distance transmission. However, with the rapid development of distributed generation, some demonstration distribution grids with high densities and high penetration rates of distributed generation have already encountered issues with insufficient integration capacity. These issues manifest as local voltage exceeding limits due to reverse power flow from distributed generation and excessive active power losses caused by excessive branch currents. This paper proposes restructuring the distribution grid to maximize the integration of distributed generation while taking network losses into account.

Distribution network restructuring refers to the process of altering the structure of a distribution network by changing the states of interconnection switches and sectionalizing switches within the network, with the aim of reducing power losses, balancing loads, improving node voltage quality, and enhancing system safety and reliability [1–3]. The integration of distributed generation sources into the distribution network directly affects power flow distribution and has a significant impact on distribution network reconfiguration. To address this issue, Reference [4] considers the impact of distributed generation sources on distribution network reconfiguration and establishes a multi-objective optimization model with network losses and the load balancing rate as objective functions,

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using switch states and distributed generation output as optimization variables. To fully utilize distributed generation, Reference [5] proposed a distribution network reconfiguration method aimed at maximizing the integration of distributed generation; however, it did not account for network losses.

As more and more distributed generation sources are connected to distribution grids, the randomness of their output has introduced new challenges for distribution grid restructuring. These challenges primarily include how to establish a distribution grid restructuring model that accounts for the randomness of distributed generation output, and how to solve the distribution grid restructuring problem involving distributed generation sources. Reference [6] proposes a multi-objective dynamic stochastic fuzzy optimal power flow method for power systems incorporating wind farms that accounts for transmission-distribution interaction. Addressing the issue that the scenario analysis method cannot adequately simulate the randomness of wind power output, Reference [7] applies multi-state system theory to describe the random output characteristics of uncontrollable distributed generation sources. To comprehensively account for the stochastic nature of distributed generation, Reference [8] proposed a quantitative optimization method for wind-solar hybrid power supply systems based on a probabilistic model, and established a multi-objective stochastic optimization model for power plant configuration with objective functions aimed at minimizing the combined costs of thermal power plant operation and start-up/shutdown, as well as minimizing pollutant emissions.

Currently, distribution network restructuring that accounts for the randomness of distributed generation output is primarily used to improve power quality and reduce network losses; however, further research is warranted into using such restructuring to increase the penetration rate of distributed generation. This paper considers the stochastic nature of wind and solar power generation and establishes an optimization model for distribution network restructuring aimed at maximizing the integration of distributed generation and minimizing system line losses. By employing opportunity constrained programming, the uncertainty problem is transformed into a deterministic problem, and the NSGA-II algorithm is improved to solve the model. Finally, a case study using the IEEE 33-node system is conducted to validate the effectiveness of the proposed model.

## 2. Uncertainty Models for Distributed Generation Sources

The distributed power sources studied in this paper primarily include wind power and solar power.

### 2.1 Wind Power Output Model

In traditional wind turbine modeling, average power output varies significantly due to the randomness and uncertainty of wind speed. In this paper, wind speed is treated as a function following a Weibull distribution, whose probability density function is

$$f(v) = \frac{k}{c}(\frac{v}{c})^{k-1}\exp[\left(-\frac{v}{c}\right)^{k}] \tag{1}$$

Here, v represents wind speed; c and k are scale and shape parameters, respectively.

At the same time, wind speed continuously affects the wind turbine's output power. Unlike most studies, which model wind power output as a smooth piecewise function, this paper employs a physical model of the wind turbine that accounts for parameters such as air density at the blades and blade dimensions. The relationship between the wind turbine's output power and wind speed is as follows [9]:

$$P_{WP}^{max} = \begin{cases} 0 & v < v_{ci} \; or \; v > v_{co} \\ \frac{P_r}{v_r^3 - v_{ci}^3} v^3 - \frac{v_{ci}^3}{v_r^3 - v_{ci}^3} P_r & v_{ci} \le v \le v_r \\ P_r & v_r < v \le v_{co} \end{cases} \tag{2}$$

ISSN: 2414-1895 DOI: 10.6919/ICJE.202607_12(7).0006

$$P_{WP}^{max} = P_r = 0.5\rho C_p \pi R^2 v_r^3 \tag{3}$$

In this context, $P_{WP}^{max}$ represents the maximum active power output of the wind turbine during that time period, which is determined by the wind speed v. vci is the cut-in wind speed (3.5 m/s); $v_{co}$ is the cut-out wind speed (25 m/s); vr is the rated wind speed (12 m/s); ρ is the air density; $C_p$ is the energy conversion efficiency; R is the radius of the wind turbine blade; and $P_r$ is the rated power of the wind turbine.

### 2.2 Photovoltaic Power Output Model

PV output can be regarded as a random variable, and a normal distribution can be used to reflect the uncertainty in PV output. This has been verified through long-term practical experience, and the probability density function for PV output is given by [10]:

$$f(P) = \frac{1}{\sqrt{2\pi}\sigma} e^{[-\frac{(P-\mu)^2}{2\sigma^2}]} \tag{4}$$

Here,

$$P_{PV} = \begin{cases} P_{PV,max}\frac{\gamma}{\gamma_\alpha} & \gamma \le \gamma_\alpha \\ P_{PV,max} & \gamma > \gamma_\alpha \end{cases} \tag{5}$$

In the equation: μ is the mathematical expectation; $\sigma^2$ is the variance; $P_{PV}$ is the photovoltaic output power; $P_{PV}^{max}$ is the maximum photovoltaic power; γ is the irradiance; $\gamma_\alpha$ is the rated irradiance.

## 3. A Multi-Objective Reconfiguration Optimization Model for Distribution Networks with Distributed Generation Based on Chance-Constrained Programming Model

Active distribution network restructuring is an effective method for addressing issues such as uneven power flow distribution and voltage deviations caused by the integration of large-scale distributed generation sources into distribution networks. Network restructuring allows for a more flexible and free distribution of power flows, enabling distribution networks to adopt more diverse operating modes and improving the operational status of the power grid. This study investigates the use of network restructuring to enhance the system's integration capacity, establishing a restructuring model aimed at maximizing the system's integration of distributed generation power while minimizing network losses.

### 3.1 Object Function

This section proposes a distribution network restructuring model aimed at improving the system's ability to accommodate active power output from wind turbines and photovoltaic (PV) systems while reducing network losses. Based on forecasts of wind turbine and PV output at a specific future time, the model optimizes the network structure at that time to maximize active power output from wind turbines and PV systems and minimize network losses. In the model presented in this paper, the decision variables include network structure variables (i.e., the states of sectioning switches and interconnection switches) and the active power output of wind turbines and PV systems.

### 3.2 Wind and Solar Power Generate the Most Electricity

$$f_1 = \max\left(\sum_{i\in\Omega_{WP}} P_{i,WP} + \sum_{i\in\Omega_{PV}} P_{i,PV}\right) \tag{6}$$

ISSN: 2414-1895 DOI: 10.6919/ICJE.202607_12(7).0006

Here, $f_1$ represents the total active power output from wind and solar that the distribution network can accommodate at that moment, while $\Omega_{wp}$ and $\Omega_{pv}$ are the sets of nodes where wind power (WP) and photovoltaic (PV) power are connected, respectively.

### 3.3 Minimum Active Power Loss

$$f_2 = \min(\sum_{i=1}^{n} k_i R_i \frac{(P_i^2+Q_i^2)}{|V_i|^2}) \tag{7}$$

In this context, $P_i$ is the active power flowing out of the node, $Q_i$ is the reactive power flowing out of the node, $V_i$ is the voltage at the node, $R_i$ is the resistance of the branch between the node and , and $k_i$ represents the switching state of the branch between the node i and i+1 ; 0 indicates the switch is open, and 1 indicates the switch is closed.

### 3.4 Constraints

(1) Power Flow Constraints

$$\begin{cases} P_{i,WP} + P_{i,PV} - P_{i,\mathrm{L}} = V_i \sum_{\mathrm{j}\in\Omega_i} V_j (G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij}) \\ Q_{i,WP} + Q_{i,PV} - Q_{i,\mathrm{L}} = V_i \sum_{\mathrm{j}\in\Omega_i} V_j (G_{ij} sin\theta_{ij} - B_{ij} cos\theta_{ij}) \end{cases} \tag{8}$$

In this context, $P_{i,L}$ and $Q_{i,L}$ represent the active and reactive loads at node i, respectively; $V_i$ and $V_j$ represent the voltages at nodes i and j, respectively; $\Omega_i$ denotes the set of other nodes connected to node i; $G_{ij}$ and $B_{ij}$ represent the conductance and admittance of branch ij, respectively; and $\theta_{ij}$ represents the phase angle difference between nodes i and j.

(2) Voltage Constraints

$$V_i^{min} \le |V_i| \le V_i^{max} \tag{9}$$

Here, $V_i$ is the voltage at node i; $V_{\min i}$ and $V_i^{max}$ are the lower and upper limits of the voltage at node i, respectively, and the upper limit is set to 105% of the rated voltage.

(3) Current Constraints

$$I_i \le I_i^{max} \tag{10}$$

Here, Ii is the current flowing through the branch, and $I_i^{max}$ is the maximum current allowed to flow through branch i.

(4) Distributed Generation Output Constraints

$$P_{Gi}^{min} \le |P_{Gi}| \le P_{Gi}^{max} \tag{11}$$

Here, $P_{Gi}$ represents the output of the i-th distributed power source, and $P_{Gi}^{min}$ and $P_{Gi}^{max}$ represent the lower and upper limits of the output of the i-th distributed power source, respectively.

(5) Radial Grid Constraints

$$\mathrm{g_n} \in \mathrm{G_N} \tag{12}$$

ISSN: 2414-1895 DOI: 10.6919/ICJE.202607_12(7).0006

Here, $g_n$ refers to the current network structure, and $G_N$ refers to all permitted radial network structures-that is, networks that are radial in nature, with no loops or isolated nodes.

### 3.5 Chance-Constrained Programming Model

Chance-constrained programming is a programming method designed for optimization problems where the constraints contain random variables, and the probability that the random constraints hold is at least as high as the confidence level specified by the decision maker. Its general form is as follows: The original optimization model containing random variables can be abstractly represented as

$$\begin{cases} \max \overline{f} \\ s.t.\ PRO\{f(x,\xi) \geq \overline{f}\} \geq \alpha \\ PRO\{g_i(x,\xi) \leq 0\} \geq \beta \end{cases} \tag{13}$$

In this context, $x$ represents the decision variable, $\xi$ represents the random variable, and $f(x,\xi)$ is the objective function. $g_i(x,\xi)$ denotes the constraint, PRO{} denotes the probability that the event within the brackets occurs, and α and β are the confidence intervals for the objective function and the constraint, respectively. The constraints discussed in this paper include: (1) node voltage constraints; (2) current constraints; and (3) distributed generation output constraints.

## 4. An Improved NSGA-II Algorithm based on a Protection Strategy for the Global Pareto-Optimal Solution Set

A multi-objective genetic algorithm solves multi-objective optimization problems by finding the optimal solution that maximizes (or minimizes) each objective function as much as possible. A multi-objective optimization problem consists of three components: decision variables, objective functions, and constraints. The mathematical description is as follows:

$$\begin{cases} \min f(x) = [f_1(x), f_2(x), \dots, f_n(x)] \\ s.t.\ \ g(x) = [g_1(x), g_2(x), \dots, g_k(x)] \leq 0 \\ h(x) = [h_1(x), h_2(x), \dots, h_m(x)] = 0 \\ x = [x_1, x_2, \dots, x_d] \\ x_{j\_min} \leq x_j \leq x_{j\_max} \end{cases} \tag{14}$$

In this equation, f(x) is the objective function, h(x) is the equality constraint, g(x) is the inequality constraint, and d is the number of decision variables.

Srinivas and Deb proposed the NSGA series of algorithms[11] based on the fitness principle. To preserve elite individuals, the algorithm selects the next generation from a set of 2N individuals consisting of the offspring and their parents. The NSGA-II algorithm ranks individuals within the same non-dominant level by their crowding distance (selecting individuals with larger crowding distances). Given that power system problems involve multi-constraint, multi-variable input, higher demands are placed on algorithm performance. To prevent the algorithm from “premature convergence,” enhance its search capability, and accelerate the search speed, this paper proposes an improved NSGA-II algorithm based on a global Pareto-optimal solution set preservation strategy.

The steps of the improved NSGA-II algorithm are as follows:

(1) Initialize the algorithm parameters, randomly generate a population $Q_0$ containing N individuals, and define $Q_0$ as the set S of globally Pareto-optimal solutions.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202607_12(7).0006

(2) Perform selection, crossover, and mutation on the current i-th generation population $Q_i$ to obtain a subpopulation containing N individuals, denoted as $P_i$. Merge the subpopulation with the original population to obtain a doubled population $R_i$ containing 2N individuals.

(3) Sort the population Ri in non-dominance order based on fitness values and calculate the crowding degree of each individual; select the top N individuals to form the (i+1)th-generation population Qi+1.

(4) Add individuals from population Qi+1 that are not dominated by the global Pareto optimal solution set S to S, thereby updating S.

(5) Determine whether the maximum number of iterations has been reached; if so, proceed to (6); otherwise, proceed to (2).

(6) Output the global Pareto optimal solution set S as the optimal solution set, and the algorithm terminates.

## 5. Case Study Analysis

### 5.1 Basic Data

To verify the validity and rationality of this study, the model was implemented through programming on the MATLAB platform. The IEEE-33 node system was selected as the test case in this paper. Wind power was connected at nodes 10, 18, and 21, with rated active powers of 600 kW, 1,100 kW, and 1,000 kW, respectively. Both the PV active power output and the system's active and reactive power loads were predicted using a normal distribution, with a standard deviation set at 5% of the expected value. PV generation was connected at nodes 7, 16, and 33, with predicted maximum active power outputs of 500 kW, 900 kW, and 1,100 kW, respectively. In the NSGA-II algorithm, the population size is set to 100, the number of evolutionary generations is 50, the mutation probability is 0.02, and the crossover probability is 0.7. In the case study analysis, the individual with the highest distributed generation output within the Pareto set is selected for analysis. The system diagram is shown in Figure 1. [12-16]

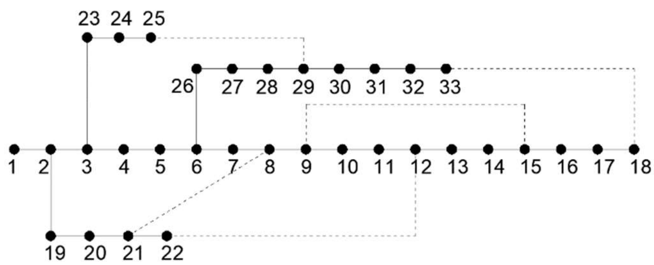


**Figure 1.** IEEE-33 node system diagram

### 5.2 Comparative Analysis of Optimization Results Across Multiple Scenarios

To account for the uncertainty in distributed generation output and the impact of network topology on both distributed generation output and active power losses, the following three scenarios are established for analysis.

CASE 1: Original network topology, with no distributed generation sources connected and no network restructuring considered; this scenario does not include an optimization process.

CASE 2: Original network structure with distributed generation sources connected; network restructuring is not considered. The active power output of each distributed generation source and active power network losses are optimized at confidence levels of 100% and 95%, respectively.

CASE 3: Network restructuring is considered. At confidence levels of 100% and 95%, the improved NSGA-II algorithm is used to determine the optimal network structure and the active power output of each distributed generation source.[17]

Table 1 shows a comparison of the optimization results across various scenarios.

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**Table 1.** Comparison of multi-scene optimization results

| Scenarios | Confidence Level | Power of Distributed Power Generation Nodes (kW) | | | | | | Total Power Absorption (kW) | Total power loss (kW) |
|---|---|---|---|---|---|---|---|---|---|
| | | $P_{10,WP}$ | $P_{18,WP}$ | $P_{21,WP}$ | $P_{7,PV}$ | $P_{16,PV}$ | $P_{33,PV}$ | | |
| 1 | - | - | - | - | - | - | - | 0 | 202.7 |
| 2 | 95% | 600 | 512.1 | 993 | 505.5 | 470.4 | 1053 | 4134 | 142.9 |
| | 100% | 596.9 | 666 | 1000 | 446.5 | 746.9 | 1100 | 4556 | 170.8 |
| 3 | 95% | 503.4 | 806.6 | 995 | 502.9 | 645.9 | 1043.7 | 4497.5 | 136.9 |
| | 100% | 560 | 1092 | 991 | 493 | 803 | 1058 | 4997 | 163.5 |

As shown in Table 1, the total network losses when accounting for the uncertainty of distributed generation are lower than those when such uncertainty is not taken into account. Specifically, at a confidence level of 100 per cent, total losses are reduced by 15.74 per cent; at a confidence level of 95 per cent, total losses are reduced by 29.5 per cent. This is because, by taking into account the uncertainty of distributed generation, the network is permitted, under certain probabilistic conditions, to deviate from the system's safe operation constraints; consequently, AC and DC distribution networks that account for the uncertainty of distributed generation can accommodate a greater output from distributed generation sources, thereby reducing the system's total network losses.

According to Table 1, the system that incorporates network restructuring accommodates more active power from distributed generation sources than the system that does not. Specifically, at a 100% confidence level, it accommodates 9.68% more active power from distributed generation sources; at a 95% confidence level, it accommodates 7.74% more. At the same confidence level, the active power output from wind power connected to Node 18 increased significantly, while the PV power absorbed by Node 16 increased slightly. At the same time, the wind power absorbed by Node 10 and the PV power absorbed by Node 7 also increased slightly; there were no significant changes in the output of distributed generation connected to Nodes 21 and 7. Therefore, the reconfiguration strategy plays a significant role in enhancing the absorption of distributed generation and reducing network losses.。

When accounting for the uncertainty of distributed generation sources, network reconfiguration results in lower network losses than a scenario without reconfiguration. Specifically, at a 100% confidence level, total losses are reduced by 4.27% (with switches 2-19, 10-11, 28-29, 21-22, and 16-17 disconnected); At a 95% confidence level, total losses are reduced by 4.2% (with switches 7–8, 10–11, 27–28, 12–22, and 17–18 disconnected). This is because the reconfigured network topology differs significantly from the original, resulting in substantial changes in the distribution of system power flows. The reconfigured network topologies are shown in Figures 2 and 3. [18]

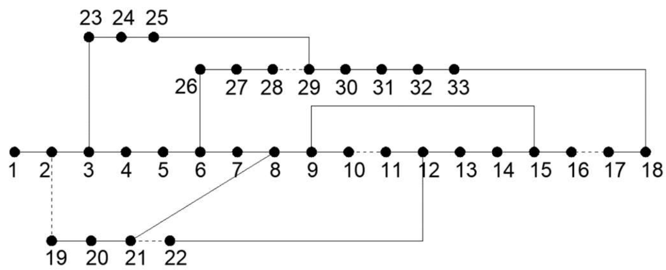


**Figure 2**. Reconfiguration system diagram with 100% confidence

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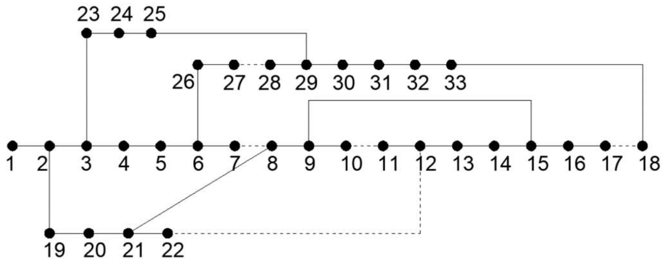


**Figure 3.** Reconfiguration system diagram with 95% confidence

The above results show that: (1) After integrating distributed generation, the active power network losses in the system are lower than those in the original network, regardless of whether network reconfiguration is considered. At the same confidence level, active power network losses are lower when network reconfiguration is considered than when it is not. (2) Systems that consider network reconfiguration can accommodate more active power from distributed generation than those that do not. [19]

## 6. Conclusion

When large-scale distributed generation sources are connected to the distribution grid, the dispatch center can employ distribution network reconfiguration techniques to maximize the integration of distributed generation output while ensuring the economic operation of the power system. This paper proposes a distribution network reconfiguration method that accounts for the uncertainty of distributed generation. Aiming to maximize the integration of distributed generation and minimize network losses, this method comprehensively considers safety constraints such as node voltage constraints, branch current constraints, and radial network constraints. It utilizes an improved NSGA-II algorithm to obtain optimal distribution network reconfiguration results and distributed generation output plans. Calculation results for the IEEE 33-node system indicate that restructuring the distribution network can effectively enhance the distribution grid’s capacity to accommodate distributed generation and reduce network losses, thereby providing robust guidance for control and regulation decisions made by distribution dispatch departments.

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