Multi-objective Optimization of Microgrids Based on an Improved NSGA-II Algorithm: Postprint

Authors: Zhang Jun, Ren Hao, Liu Tingzhang

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Abstract

To address the multi-objective optimal operation problem of distributed generation in microgrids, an improved NSGA-II algorithm is proposed in response to the limitations of the traditional NSGA-II algorithm in approximation quality and computational efficiency, while considering the differences in individual similarity during the evolutionary process and the possibility of the algorithm becoming trapped in local optima. The new algorithm introduces an information entropy mechanism to enhance the operators, with crossover probability and mutation probability approximated by a decreasing function model and a Cauchy distribution model, respectively. The effectiveness of the proposed algorithm is validated through performance testing. Simulation experiments conducted on the IEEE 30-bus power system with integrated distributed generation demonstrate, through comparison with the conventional NSGA-II multi-objective optimization algorithm, the superiority of the improved algorithm in terms of enhanced convergence speed and improved optimization metrics.

Full Text

Preamble

Research on Multi-Objective Optimization of Micro-Grid Based on Improved NSGA-II Algorithm

Zhang Jun[1,2]†, Ren Hao[1,2], Liu Tingzhang[3]

[1]School of Automation Engineering, Shanghai University of Electric Power, Shanghai 200090, China
[2]Shanghai Key Laboratory of Power Station Automation Technology, Shanghai 200090, China

[3]School of Mechatronic Engineering & Automation, Shanghai University, Shanghai 200072, China

Abstract: In addressing the multi-objective optimal operation problem of distributed generation in micro-grids, this paper proposes an improved NSGA-II algorithm that targets the limitations of traditional NSGA-II algorithms in terms of approximation quality and computational efficiency. The new algorithm considers differences in individual similarity during the evolutionary process and the possibility of the algorithm falling into local optima. By introducing an information entropy mechanism to improve the operators, the crossover probability and mutation probability are approximated as a decreasing function model and a Cauchy distribution model, respectively. Algorithm performance tests demonstrate the effectiveness of the proposed approach. Simulation experiments using distributed generation integrated into the IEEE 30-bus power system show that the improved algorithm offers superior convergence speed and improved optimization metrics compared to the traditional NSGA-II multi-objective optimization algorithm.

Keywords: micro-grid; multi-objective optimization; information entropy; Pareto optimal solution set

0 Introduction

As natural resources become increasingly depleted and environmental protection gains prominence, distributed energy resources (DERs) have attracted growing attention as a flexible approach to utilizing dispersed energy sources. Unlike traditional fossil fuels such as coal and petroleum, distributed energy primarily includes solar, wind, tidal, geothermal, and biomass energy, characterized by wide distribution, low pollution, and suitability for small-scale utilization. Operating distribution networks in the form of micro-grids represents one solution to address the challenges of distributed energy dispatching, low utilization rates, and poor power quality. Consequently, multi-objective optimal operation of micro-grids that comprehensively considers economic, technical, and environmental indicators has become a hot research topic.

Existing multi-objective optimization algorithms handle multiple objectives mainly through two approaches: (a) converting sub-objectives into a single objective through weighting, which simplifies complex multi-objective problems but introduces significant subjectivity in weight calculation; and (b) employing Pareto non-dominated solution theory to obtain a Pareto optimal solution set from which the optimal solution is selected according to requirements. Modern optimization algorithms include genetic algorithms, particle swarm optimization, and similar approaches such as ant colony and bee colony algorithms. However, as research on these algorithms deepens, their limitations have gradually emerged. For instance, genetic algorithms tend to restrict the search space to local optima, while particle swarm optimization suffers from low search precision. In recent years, numerous studies have proposed improved algorithms based on fundamental methods to solve micro-grid optimization problems [1-7].

This paper investigates the constrained nonlinear multi-objective optimization problem of grid-connected micro-grids, using system economic and technical indicators as optimization objectives. By combining elite preservation and non-dominated sorting strategies, we propose an improved Non-dominated Sorting Genetic Algorithm (NSGAEN). Performance tests demonstrate the algorithm' s advantages in approximation quality and computational speed, and its feasibility is verified by solving the multi-objective optimization problem of distributed generation integrated into the IEEE 30-bus power system.

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1 Micro-Grid Model

The micro-grid structure is shown in [Figure 1: see original paper]. This micro-grid system consists of a solar power generation unit, wind power generation unit, micro gas turbine unit, and energy storage unit. The micro-grid power supply system can establish an accurate distributed generation power output characteristic model when economic and technical indicators are satisfied.

1.1 Photovoltaic Cell Power Model

Grid-connected photovoltaic systems convert DC power generated by photovoltaic cells into AC power with the same frequency as the main grid through inverters. Since the output characteristics of photovoltaic cells are affected by illumination, temperature, and installation angle, the illumination intensity can be approximated as following a Beta distribution under maximum power tracking mode, with its probability density function given by [8]

$$f(S) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\left(\frac{S}{S_{\max}}\right)^{\alpha-1}\left(1-\frac{S}{S_{\max}}\right)^{\beta-1}$$

where S and $S_{\max}$ represent the actual and maximum illumination intensity during the period, respectively; α and β are shape parameters; μ and σ are the mean and variance of illumination intensity.

The photovoltaic cell power output model can be approximated as [9]

$$P_{PV} = P_{STC} \cdot \frac{G}{G_{STC}} \cdot [1 + k(T - T_{STC})]$$

where P_{STC} is the maximum power under standard test conditions (temperature 25°C, illumination intensity 1000 W/m^2); G_{STC} is the illumination intensity during testing; G is the actual illumination intensity; T is the battery test temperature; and T_{STC} is the standard test temperature.

1.2 Wind Power Generation Model

This paper employs a common doubly-fed asynchronous generator for wind turbines. In actual operation: when the real-time wind speed is below the cut-in speed, the output power is zero; when between cut-in and rated speed, output power follows a cubic function curve; when between rated and cut-out speed, the turbine outputs rated power; when above cut-out speed, the turbine shuts down for protection, yielding zero output. The relationship between turbine output power P_W and wind speed v is expressed as [10]

$$P_W = \begin{cases} 0, & v \leq v_{in} \text{ or } v \geq v_{out} \\ P_r \cdot \frac{v - v_{in}}{v_r - v_{in}}, & v_{in} < v \leq v_r \\ P_r, & v_r < v \leq v_{out} \end{cases}$$

where v_{in} is cut-in wind speed; v_{out} is cut-out wind speed; v_r is rated wind speed; and P_r is rated power at rated wind speed.

1.3 Micro Gas Turbine Model

Micro gas turbines are thermal power generation devices fueled by methane, natural gas, etc., primarily consisting of synchronous generators, gas turbines, conversion devices, and heating/cooling units. They offer convenient maintenance, long-duration operation, and exhaust heat that can be processed through lithium bromide refrigerators to meet cooling/heating loads, effectively improving energy utilization efficiency.

Using the American Capstone C600S micro-turbine as an example, when operating in combined cooling, heating, and power mode, its output power at time t is

$$P_{MT}(t) = \frac{V_{in}(t) \cdot \rho \cdot LHV}{3600} \cdot \eta_{MT}$$

where $V_{in}(t)$ is fuel intake flow rate; ρ is combustion gas density; LHV is fuel lower heating value; and η_{MT} is micro-turbine efficiency.

The heat recovery is

$$Q_{MT}(t) = V_{in}(t) \cdot \rho \cdot C_p \cdot (T_{ex} - T_{out})$$

where T_{ex} is exhaust temperature; T_{out} is steam outlet temperature; and C_p is combustion gas specific heat capacity.

2 Objective Functions for Distributed Generation Multi-Objective Planning

Based on the power output characteristics of each micro-source introduced above, a micro-grid multi-objective optimization model is established with the goals of improving power quality and economic benefits, considering both economic and technical indicators [11].

Economic Objective: Minimize investment cost and operating cost of distributed generation.

$$C = \sum_{i=1}^{N_{DG}} \left[\frac{r(1+r)^{n_i}}{(1+r)^{n_i} - 1} \cdot (C_{I,i} + C_{M,i}) \right]$$

where C represents the investment and operating cost of micro-sources; r is market discount rate; $C_{I,i}$ is installation cost at node i; $C_{M,i}$ is operating cost at node i; n_i is equipment expected service life (in years); N_{DG} is the number of grid branches; Y_i is 0 or 1, where $Y_i = 0$ indicates no distributed generation installed at the node and $Y_i = 1$ indicates installation.

Technical Objective: Minimize active power loss and node voltage deviation.

Active power loss:

$$P_{loss} = \sum_{k=1}^{N_l} G_{ij} \left[U_i^2 + U_j^2 - 2U_{iU} j \cos(\theta_i - \theta_j) \right]$$

Node voltage deviation:

$$\Delta U = \sum_{i=1}^{N_l} \left| U_i - U_{N,i} \right|$$

where P_{loss} is system active power loss; G_{ij} is branch ij conductance; U_i, U_j are voltage magnitudes at nodes i and j; θ_i, θ_j are voltage phase angles at nodes i and j; ΔU is load node voltage deviation; U_i is actual voltage at load node; $U_{N,i}$ is rated voltage at the node; and ΔU_{max} is the maximum allowable voltage difference.

Constraints include inequality and equality constraints. Equality constraints are system power flow equations:

$$\begin{cases} P_{Gi} + P_{DG,i} - P_{Li} - U_i \sum_{j=1}^{n} U_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) = 0 \\ Q_{Gi} - Q_{Li} - U_i \sum_{j=1}^{n} U_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) = 0 \end{cases}$$

Inequality constraints include:

$$\begin{cases} P_{DG,i}^{min} \leq P_{DG,i} \leq P_{DG,i}^{max} \\ Q_{DG,i}^{min} \leq Q_{DG,i} \leq Q_{DG,i}^{max} \\ V_i^{min} \leq V_i \leq V_i^{max} \\ \sum P_{DG} \leq P_{DG}^{max} \end{cases}$$

where $P_{DG,i}$ and $Q_{DG,i}$ are active and reactive power of distributed generation i; $P_{DG,i}^{min}$, $P_{DG,i}^{max}$, $Q_{DG,i}^{min}$, $Q_{DG,i}^{max}$ are upper and lower limits of active and reactive power; V_i is line voltage at node i; and $\sum P_{DG}$ is total active power of distributed generation connected to the distribution network with P_{DG}^{max} as the maximum allowable capacity.

3 Improved NSGA-II Algorithm

3.1 Traditional NSGA-II Algorithm

Pareto theory employs elite preservation strategies to retain individuals generated through non-dominated sorting. Using crowding distance sorting avoids the difficulty of presetting parameters, reducing computational complexity and improving efficiency [12]. The main process of NSGA-II is shown in [Figure 2: see original paper].

The NSGA-II algorithm proceeds as follows:

a) Randomly generate an initial population P_0, perform non-dominated sorting, then select elite individuals for crossover and mutation to obtain new population Q_0. Set $t = 0$.

b) Combine parent and offspring populations ($R_t = P_t \cup Q_t$), perform fast non-dominated sorting on R_t to obtain non-dominated fronts $F_1, F_2, ...$.

c) Perform crowding distance sorting on the non-dominated fronts from step b), select the best individuals to form new population P_{t+1}.

d) Perform replication, crossover, and mutation on P_{t+1} to form new population Q_{t+1}.

e) If termination conditions are met, end the loop; otherwise, set $t = t + 1$ and return to step b).

The crowding distance sorting mechanism of NSGA-II has limitations. During evolution, individuals at higher ranks with larger crowding distances are more likely to be preserved [13]. However, crowding distance does not consistently reflect solution density, causing some non-dominated individuals with large crowding distances and high solution density to be retained. This may lead the algorithm into local optima and yield unevenly distributed optimal solutions. To address this, we introduce an information entropy mechanism to enhance local search capability.

3.2 Information Entropy-Based NSGA-II Algorithm

Information entropy, a concept from information theory, describes the uncertainty of an information source and characterizes the probability of specific information occurrence. The population information entropy [14] is defined as:

$$E = -\sum_{i=1}^{N} \frac{m_i}{N} \log \frac{m_i}{N}$$

where N is population size; m_i is the number of individuals in subset P_i; the optimization objectives are divided into N equal intervals in the feasible solution space; m represents the number of individuals in the same range. When $m = 1$, E reaches its minimum value of 0; when $m = N$, E reaches its maximum value of $\log N$.

After introducing the information entropy mechanism, the crossover and mutation probabilities become:

$$\begin{cases} P_c = a_1 - a_2 \cdot \frac{m}{N} \\ P_m = a_3 - a_4 \cdot \frac{m}{N} \end{cases}$$

where a_1 and a_2 are constants between 0 and 1. Equation (13) shows that smaller m yields larger genetic probability and richer population structure, while larger m yields smaller genetic probability and more stable population. Information entropy reflects the uniformity of individual distribution in the solution space; using it to improve crossover and mutation probabilities across generations enhances convergence accuracy and computational efficiency.

In the initial evolutionary stage, population individuals have low similarity. Increasing crossover probability accelerates evolution while decreasing mutation probability reduces computational burden. In the middle stage, appropriately increasing mutation probability effectively prevents the algorithm from falling into local optima. In the final stage, as individual similarity increases, reducing both crossover and mutation probabilities enables gradual convergence. Based on these principles, crossover probability is approximated as a decreasing function model over evolutionary generations, while mutation probability is approximated as a Cauchy distribution model:

$$\begin{cases} P_c'' = a_3 \cos^2\left(\frac{\pi t}{2T}\right) \\ P_m'' = \frac{a_4}{1+2\left(\frac{t-T/2}{a_5}\right)^2} \end{cases}$$

where t is current generation; T is total generations; a_3 is a constant between 0 and 1; and a_5 is a scale parameter greater than 0. The final crossover and mutation probabilities for the improved algorithm are:

$$\begin{cases} P_c^{final} = (1-a_1)\cdot a_3\cos^2\left(\frac{\pi t}{2T}\right) \\ P_m^{final} = (1-a_2)\cdot \frac{a_4}{1+2\left(\frac{t-T/2}{a_5}\right)^2} \end{cases}$$

The improved algorithm steps are shown in [Figure 3: see original paper].

3.3 Algorithm Testing

Multi-objective optimization test functions ZDT1 and ZDT6 from were selected to evaluate algorithm performance. Each test function ran 50 times with averages taken, using Approximation (AP) and Running Time (TM, in seconds) as evaluation metrics. Comparison of test data in and Pareto fronts in [Figure 4: see original paper] and [Figure 5: see original paper] demonstrates that the improved NSGAEN algorithm based on information entropy mechanism achieves better convergence and speed than traditional NSGA-II, with its optimal solution set closer to the true Pareto front.

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4 Case Study

A hybrid micro-grid simulation system shown in [Figure 6: see original paper] was selected for analysis. The distributed generation units integrated into this micro-grid include wind turbines, photovoltaic cells, and micro gas turbines. Experimental voltage and current data for distributed generation in the micro-grid model are provided by photovoltaic simulators, doubly-fed wind power simulators, and gas turbine simulators, collected through a data acquisition system interfaced with the micro-grid energy control and management software for data communication.

Since wind power (WT) and photovoltaic power (PV) have no fuel costs or pollution, only operation and maintenance costs are considered. Micro gas turbines (MT) must account for generation costs, environmental treatment costs, and operation and maintenance costs, as detailed in .

A micro-grid with 5 MW installed capacity integrated into the IEEE 30-bus system shown in [Figure 7: see original paper] serves as the case study. This system contains 6 generators and 4 transformers, with a per-unit root node voltage of 1.0 and base power of 100 MVA. All source nodes are treated as PV nodes and load nodes as PQ nodes. Population size is set to 100 and evolution generations to 300. [Figure 8: see original paper] and [Figure 9: see original paper] show the Pareto optimal solution sets for node voltage deviation, line active power loss, and economic cost when the algorithm evolves to 300 generations.

The Pareto fronts obtained from experimental results reveal a trade-off relationship between node voltage deviation, line active power loss, and investment/operation costs. Lower investment/operation costs correspond to higher line losses and node voltage deviation. The improved NSGAEN algorithm demonstrates better economic performance than NSGA-II under the same technical indicators. Designers can select appropriate solutions from the population' s non-dominated solution space based on actual requirements and site conditions to reasonably balance economic and technical objectives, effectively avoiding inefficiencies from blind selection.

Convergence analysis uses system node voltage deviation and line active power loss as metrics. and compare optimization results for selected nodes and branches, while [Figure 10: see original paper] and [Figure 11: see original paper] compare convergence characteristics of these two parameters under both algorithms. Comparisons show that for selected nodes and branches, both node voltage deviation and line active power loss are improved under the optimized algorithm. Both algorithms exhibit high node voltage deviation and line active power loss in the initial evolutionary stage. As evolution progresses, traditional NSGA-II converges to optimal node voltage deviation and line active power loss at generations 110 and 100, respectively, while the improved NSGAEN algorithm achieves optimal convergence at generations 80 and 70. The improved algorithm demonstrates faster convergence with both node voltage deviation and line active power loss smaller than those of traditional NSGA-II.

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5 Conclusion

Aiming at the limitations of NSGA-II algorithm in convergence and computational speed when solving micro-grid multi-objective optimization problems, this paper presents the following contributions:

a) An improved NSGAEN algorithm is proposed by modifying the crossover and mutation operators based on information entropy mechanism. Performance testing using ZDT1 and ZDT6 test functions validates the algorithm' s effectiveness.

b) A multi-objective mathematical model is established according to the structure and operational characteristics of micro-grids. Applying NSGAEN to multi-objective optimization of distributed generation demonstrates that the proposed algorithm effectively improves convergence characteristics and operational efficiency compared to the original NSGA-II, further verifying its feasibility for solving complex micro-grid multi-objective optimization problems.

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Note: Figure translations are in progress. See original paper for figures.