Distribution Network Fault Restoration Reconfiguration Based on POP NSGA- (Postprint)

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Date: 2018-06-27T00:00:00+00:00

Abstract

The fast non-dominated sorting genetic algorithm (NSGA-II) enables uniform distribution of individuals obtained during each evolutionary process, demonstrating favorable convergence and robustness. This paper analyzes the limitations of existing genetic algorithms (GA), applies NSGA-II to fault restoration reconfiguration in distribution networks, and proposes a Pareto Optimal Path (POP) approach to control selection operations. This approach not only expands the search space to avoid entrapment in local optima but also enables timely termination of evolution to reduce unnecessary computational overhead. Furthermore, this paper employs fuzzy set theory to determine the final solution for fault restoration reconfiguration, thereby adapting the NSGA-II algorithm to restoration reconfiguration problems. Case study results indicate that the POP NSGA-II algorithm exhibits superior optimization capability compared to both GA and standard NSGA-II algorithms, constituting a novel methodology for addressing distribution network fault restoration reconfiguration problems.

Full Text

Service Restoration Reconfiguration in Distribution Systems Based on Pareto Optimizing Path NSGA-II

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Abstract: The fast non-dominated sorting genetic algorithm (NSGA-II) can obtain uniformly distributed individuals in each evolutionary process and demonstrates excellent convergence and robustness. This paper analyzes the deficiencies of conventional genetic algorithms (GA) and applies NSGA-II to service restoration reconfiguration in distribution systems. A method controlling the selection operation through a Pareto Optimizing Path (POP) is proposed, which can expand the search region to avoid local optima while also stopping evolution appropriately to reduce unnecessary computation. Additionally, fuzzy set theory is employed to determine the final restoration solution, making NSGA-II suitable for restoration reconfiguration problems. Simulation results demonstrate that the POP NSGA-II algorithm possesses stronger optimization capability compared to both GA and standard NSGA-II, representing a novel approach for solving distribution network fault restoration reconfiguration problems.

Keywords: NSGA-II, service restoration reconfiguration in distribution systems, POP, fuzzy set theory, POP NSGA-II

1 Introduction

The objective of distribution network fault restoration reconfiguration is to restore power supply to non-fault outage areas after fault location and isolation by changing switch statuses. This process transfers loads from de-energized zones to normally operating branches while satisfying electrical constraints, thereby enhancing system self-healing capability and power supply reliability [1-2]. With the integration of distributed generation and increasing demands for power supply reliability, distribution network operation modes have become more variable, network complexity has grown, and influencing factors have multiplied. These trends increase both the probability of faults and the affected areas, directly impacting user safety, satisfaction, and the economic interests of utilities. As a critical smart grid function, fault restoration reconfiguration has become a research hotspot for minimizing losses to both users and utilities.

Fault restoration reconfiguration is a highly nonlinear, multi-objective, multi-constraint optimization problem that must simultaneously maximize restored load with minimal switching operations and line losses while satisfying network topology, line margins, and other electrical constraints [3-6]. Current solution methods primarily include heuristic search algorithms [7-9] and intelligent algorithms [10-12]. Among heuristic methods, Tabu Search (TS) [13] shows good performance, but to reduce computational burden, the tabu list length and forbidden set size must be limited. However, excessively small tabu lengths risk cyclic searches, while overly small tabu tables may fall into local optima. Among intelligent algorithms, Genetic Algorithm (GA) [14-16] is widely applied. Although numerous improved variants have emerged—such as Clone Genetic Algorithm (CGA) [17], Immune Genetic Algorithm (IGA), and simulated annealing hybrids—these still convert multi-objective problems into single-objective ones using weight factors (WF), making optimization results highly sensitive to WF selection and yielding unstable performance.

The fast non-dominated sorting genetic algorithm (NSGA-II) [19-21] coordinates relationships among objective functions by rapidly classifying populations into non-dominated fronts, distributing individuals uniformly across the objective space. Through selection, crossover, and mutation operations, NSGA-II identifies optimal solution sets where all objectives are optimized simultaneously. The algorithm uses non-dominated sorting ranks and crowding distance to evaluate individual quality, effectively avoiding the impact of weight settings on optimization results. This paper applies NSGA-II to distribution network fault restoration reconfiguration and improves the selection operation by proposing a Pareto Optimizing Path (POP) method. This approach accelerates convergence, expands the search area to avoid local optima, and accurately judges evolutionary progress to enable timely termination. Case studies validate the feasibility and effectiveness of this method, providing a new solution framework for distribution network fault restoration reconfiguration.

2 Mathematical Model for Distribution Network Fault Restoration Reconfiguration

Restoration reconfiguration must consider multiple objectives including restored power supply, switching operations, line losses, outage duration, and voltage distribution, along with constraints such as line capacity, network topology, branch currents, and node voltages. For clarity, this paper focuses on key objectives and constraints.

2.1 Objective Functions

The optimization aims to: (1) maximize power restoration to non-fault outage loads, (2) minimize switching operations, and (3) minimize line losses. The objective functions are formulated as:

max f (x) = max Q S
max f (x) = max P S
max f (x) = min |K - S |
max f (x) = min (P' ^{2} + Q' ^{2})r /U' ^{2}

where x represents the current network state related to all participating branch switches; S indicates the status of branch i ("0" for open, "1" for closed); P and Q are the rated active and reactive power at nodes connected to branch i; K is the initial switch status of branch i; P' , Q' , and U' are the active power, reactive power, and end-node voltage on branch i; r is the resistance of branch i; and n is the total number of branches participating in reconfiguration.

2.2 Constraints

The optimization is subject to: (1) line capacity constraints, where P' P' and Q' Q' for i = 1,2,···,n; (2) radial network operation constraint prohibiting loops; and (3) node voltage constraints, where U U U for i = 1,2,···,m, with m being the total number of nodes.

3 POP NSGA-II Algorithm for Fault Restoration Reconfiguration

3.1 Overview of NSGA-II

Unlike conventional GA, NSGA-II handles multi-objective problems through non-dominated sorting rather than weight factors. The algorithm calculates non-dominated sorting ranks and crowding distances to evaluate individuals, avoiding weight-related biases [20]. NSGA-II has been successfully applied to distribution network reconfiguration, reactive power optimization, and power system planning [21-23].

3.2 Algorithm Flow

The implementation steps for fault restoration reconfiguration are:

(1) **Encoding**: Binary encoding represents all participating switches, where "0" and "1" denote open and closed states, respectively.

(2) **Initial Population**: Randomly generate an initial population P of size N.

(3) **Objective Calculation**: Perform power flow calculations to obtain objective function values for each chromosome.

(4) **Non-dominated Sorting and Virtual Fitness Calculation**: Rank individuals and compute crowding distances.

(5) **Selection**: Employ elitist strategy to preserve superior parent individuals for the offspring generation, ensuring convergence toward Pareto optimal solutions while avoiding local crowding.

(6) **Crossover and Mutation**: Crossover preserves superior genes while mutation maintains population diversity. Normal mutation operators based on normal distribution are used.

(7) **Termination Check**: Stop if maximum iterations are reached or an optimal solution is found; otherwise, return to step (3).

3.3 Pareto Optimizing Path (POP)

POP contains two key pieces of information: Pareto Optimizing Tendency (T) and Chromosome Number in the Pareto optimal set F (CNum).

(1) Pareto Optimizing Tendency (T): At generation n, the elite strategy yields Pareto optimal set F representing the current best level. The tendency value at generation n+1 is defined as:

$T = T + 1$, if C^{1} C for any i,j

T , if $C^{1} = C$ for all i,j

where C^{1} is the i-th chromosome in F at generation n+1, C is the j-th chromosome in F at generation n, and denotes domination. $T = 0$. This tracks evolutionary direction by comparing consecutive F sets.

(2) Chromosome Number (CNum): Since NSGA-II produces an unknown number of optimal solutions, CNum changes also reflect evolutionary progress. The POP update is:

POP = POP + 1 if T = T and CNum changes
POP = POP + 1 if CNum is unchanged but F is updated

where C is the chromosome count in F at generation n. POP accurately reflects progress whenever offspring discover superior or equivalent-but-different individuals.

3.4 Virtual Fitness

Virtual fitness represents the local crowding distance between a point in objective space and its two adjacent points on the same front. For F(x) = (f (x), f (x), ···, f (x)), the crowding distance of point i equals half the perimeter of the rectangle formed by its neighbors i-1 and i+1 along each objective axis [Figure 1: see original paper].

3.5 POP Selection Operator

The selection size S is dynamically determined based on POP. When POP remains unchanged for B consecutive generations, S increases with B (the count of stagnant generations) to expand search capability. When B reaches B without progress, evolution stops and the current F becomes the optimal solution set. The increased computation ΔM from POP selection is:

$\Delta M = (B - B)(B - B + 1)/4$

This is equivalent to additional $(B - B + 1)(B - B)/4$ evolutionary generations. Proper control of B and B ensures POP selection does not significantly increase computational burden while preventing premature convergence.

3.6 Similarity Crossover Operator

The Similarity Crossover (SC) operator compares gene differences between two parent chromosomes. When SC = 0 or SC = 1, SBX crossover produces offspring identical to parents, hindering evolution. The SC operator employs gene recombination: all parent genes are randomly permuted to generate offspring. When SC > 1, conventional crossover at certain points also yields identical offspring. Therefore, SC randomly selects crossover points to ensure effective evolution and accelerate convergence .

3.7 Determination of Optimal Solution

Since restoration reconfiguration requires a single final solution, fuzzy set theory is applied to select the best compromise from F [24]. The satisfaction degree h of each individual is:

$$h = 1 - (\quad (f \quad - f)/(f \quad - f \quad))/N$$

where N is the number of objectives, f is the objective value, and f , f are the maximum and minimum values of objective i in F . The individual with maximum h is selected as the optimal solution.

4 Case Study and Analysis

The test case is the PG&E 69-bus single-source distribution system [Figure 3: see original paper]. Solid lines 3-22 represent operational branches, while dashed lines 1, 2, 23, 24 are tie branches. Initially, all operational branches are closed and tie branches are open, with network parameters from [25]. Assuming a fault at nodes 10-11, downstream nodes 11-27 and 56-59 lose power. The optimization objectives are: (1) maximize restored active power f , (2) maximize restored reactive power f , and (3) minimize switching operations f . Constraints maintain radial topology and tie branch capacities.

Three algorithms are compared: Tabu Search Clonal Genetic Algorithm (TSCGA), conventional NSGA-II, and POP NSGA-II. Parameters: population size 100, maximum iterations 200, crossover probability 0.9, mutation probability 0.1, B = 5, B = 10. Tie branches 1, 2, 24 provide maximum active power of 350, 300, 250 kW and reactive power of 250, 200, 150 kvar, respectively. Each algorithm runs 100 times to account for randomness, with results averaged.

4.1 Algorithm Performance Comparison

Table 2 shows TSCGA results for various weight combinations (W). Stability represents the proportion of identical optimal solutions across 100 runs. TSCGA results favor objectives with higher weights, neglecting others, and exhibit poor stability due to weight sensitivity.

Table 2 shows that TSCGA cannot guarantee all objectives are optimized simultaneously, and its stability is significantly affected by weight allocation, resulting in high variability between runs.

Table 3 compares the three algorithms. POP NSGA-II produces more solutions in F than NSGA-II, providing more options for decision-makers. By improving evolutionary efficiency, POP NSGA-II reduces iterations, shortens computation time, and enhances solution stability and quality.

Table 4 presents single-run results. POP NSGA-II achieves better restoration with fewer switching operations (f = 6 vs. 7) and higher restored power (f = 703.8 kW vs. 695.8 kW, f = 484.1 kvar vs. 478.6 kvar).

[Figure 4: see original paper] illustrates the Pareto optimizing path for a single run with identical initial populations. In early generations, the similarity crossover operator drives efficient evolution toward Pareto optimality. During slow evolution phases, POP selection activates 11 times, increasing population size and search area to escape local optima and prevent premature convergence. The algorithm terminates at 45 iterations based on POP stagnation, while conventional NSGA-II becomes trapped twice with no progress for 15 consecutive generations.

5 Conclusion

This paper applies NSGA-II to distribution network fault restoration reconfiguration. The POP-controlled selection operation expands search area when evolution stagnates, reducing local convergence risk, while enabling timely termination to avoid unnecessary computation. Fuzzy set theory facilitates selection of the final solution from F , making NSGA-II fully applicable to restoration problems. The PG&E 69-bus case study demonstrates that POP NSGA-II outperforms conventional NSGA-II in both restoration effectiveness and the number of optimal solutions obtained.

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