A Fast and Scalable Genetic Algorithm-Based Approach for Planning of Microgrids in Distribution Networks

Preprint

Abhijeet Sahua,[1,2] Kumar Utkarsh,[1] and Fei Ding[1]

1 National Renewable Energy Laboratory
2 Texas A&M University

Presented at the IEEE Power and Energy Society General Meeting
Denver, Colorado
July 17–21, 2022

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-5D00-80846
July 2022

A Fast and Scalable Genetic Algorithm-Based Approach for Planning of Microgrids in Distribution Networks

Preprint

Abhijeet Sahua,[1,2] Kumar Utkarsh,[1] and Fei Ding[1]

1 National Renewable Energy Laboratory
2 Texas A&M University

Suggested Citation
Sahua, Abhijeet, Kumar Utkarsh, and Fei Ding. 2022. *A Fast and Scalable Genetic Algorithm-Based Approach for Planning of Microgrids in Distribution Networks: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5D00-80846. https://www.nrel.gov/docs/fy22osti/80846.pdf.

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-5D00-80846
July 2022

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
303-275-3000 • www.nrel.gov

NOTICE

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office Agreement Number 37770. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government.

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

U.S. Department of Energy (DOE) reports produced after 1991 and a growing number of pre-1991 documents are available free via www.OSTI.gov.

Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

NREL prints on paper that contains recycled content.

A Fast and Scalable Genetic Algorithm-Based Approach for Planning of Microgrids in Distribution Networks

Abhijeet Sahu[a,b], Kumar Utkarsh[a], Fei Ding[a]

[a]National Renewable Energy Laboratory, Golden, CO, [b]Texas A&M University, Texas

***Abstract*—As a result of climate change, extreme weather events are occurring more frequently and with increasing impact. This trend poses a significant challenge for distribution utilities and system operators to ensure that there is uninterrupted power supply to critical loads in their networks; thus, the level of proactive preparation of the distribution system to be able to handle severe impacts of extreme weather events represents the system's resilience. One method that distribution system planners can use to prepare for future extreme events is to plan multiple microgrids which can use local generation as much as possible to supply critical loads. But partitioning an existing distribution system such that multiple feasible islands are planned and which are capable of supporting critical loads is still challenging for distribution systems—first, because of the size of the network graph partitioning problem and, second, because of the difficulty in properly formulating the desired attributes of such islands or microgrids. Therefore, this paper presents a genetic algorithm-based approach that facilitates incorporating multiple objectives for grid partitioning by formulating two types of problems—node allocation and edge elimination—and it considers multiple topological and resilience-enhancing objectives. The performance of the proposed genetic algorithm-based approach is numerically evaluated on multiple test systems as well as on a real distribution feeder in Colorado, United States.**

Keywords–edge elimination, genetic algorithm, microgrid, multi-objective optimization

I. Introduction

Historically, distribution system planners have performed studies related to distribution grid partitioning based on capacitor bank controllability, post-fault island formation, market supply and demand mismatch, etc. These methods are targeted toward specific solutions, such as determining capacitor bank set points, or fault-specific islanding, or islanding based on generation/load balance. Such segregated problems avoid scalability issues related to large systems because their goals are confined to a specific easily-solvable objective.

There have been many studies exploring network partitioning for different objectives. Network partitioning approaches are used in [1] for distribution system state estimation that leverages a post-order traversal algorithm considering radial topology structure and phasor measurement unit configuration. Graph partitioning is considered in [2] for capacitor control in a distribution feeder with a focus on voltage spread reduction and loss minimization. In [3], the shortest path-based Dijkstra algorithm is used for flexible island partitioning against distribution grid failures. In [4], a metric-based approach for grid partitioning with validation in a regional distribution network in Anhui Province, China, is presented that aggregates multiple graph-based metrics as objective. These techniques, however, cannot handle multiple-objective based network partitioning. A *k-means* clustering method for optimal partitioning into service areas is proposed considering the geographic information and administrative boundaries [5]. The major weakness is finding an optimal k as well as the high chance of obtaining local optima. Moreover, this method is highly sensitive to the feature considered in the adjacency matrix for computing the Laplacian.

To address the challenges in these techniques, a meta-heuristic, multi-objective-based genetic algorithm approach, known as the fast non-dominated sorting genetic algorithm (NSGA-2) [6], is adopted in this paper because of its fast convergence to near-global optimal results and its ability to deal with highly complex, nonlinear, and multidimensional optimization problems [7]. Though the spectral clustering [8] and the conventional genetic algorithm techniques might theoretically compute the partitions faster, they are effective usually only for single-objective problems. We further propose two solution methods—node allocation and edge elimination—and we evaluate the proposed methods for multiple topological and resilience objectives. This method ensures diversity in solutions that can assist system planners in appropriate distributed energy resource (DER) deployment. The major contributions of this paper are as follows: **a.** Formulate a node allocation and edge elimination-based, multi-objective, grid-partitioning problem. **b.** Incorporate the NSGA-2 algorithm to solve the problem for different scales of distribution feeders and compare its performance with other techniques. **c.** Validate the method for a real utility distribution feeder.

The paper is organized as follows. Section II provides a brief review of the genetic algorithm and its use in a distribution grid. Section III introduces the formulation of the node allocation and edge elimination-based microgrid formation problems. Finally, Section IV introduces the use cases and evaluates the performance of the proposed NSGA-2 technique.

II. Background

A genetic algorithm [9] is a meta-heuristic algorithm based on natural selection, with the algorithm initiating a random set of possible solutions, called a *population* of solutions. These solutions are evaluated based on a set of fitness functions, where the individuals having the best adaptation measure have higher chances of reproducing and generating new offspring. The generation process consists of *crossover* and/or *mutation* operators and it continues repeatedly until a global optimal solution is obtained. A crossover operator creates an offspring by combining parts of two parent solutions. The mutation operator is used to maintain genetic diversity from one generation of population to the next.

Genetic algorithm was first implemented in the distribution network as a loss-minimization reconfiguration problem [10], where the chromosomes consist of the sectionalizing switch statuses, and the fitness function is formulated as the total system losses and penalty value of voltage drop and current violations. An advanced genetic algorithm based on binary programming is proposed for maximizing the flexibility in network reconfiguration for determining the proper points to split an entire interconnected distribution network into microgrids [11].

A single fitness function cannot provide an optimal solution for multiple system-wide objectives; hence multi-objective genetic algorithms need to be explored. NSGA [6] has been found to efficiently solve constrained multi-objective problems. Therefore, this paper adopts NSGA-2 to solve the microgrid formation problem.

The algorithm for NSGA-2 (as given in Algorithm 1) primarily involves two steps: **a)** From the given population, P_t, at iteration t, the offspring solution, Q_t, is obtained using the selection, mutation, and crossover operations (Line 12-15). In the first step, using the union of P_t and Q_t, non-dominated sorting is performed to obtain solutions at different pareto-front levels (Line 2-3). Non-dominated sorting in multi-objective problems is a sorting done between two solutions, say X and Y, where X is considered to dominate Y if and only if there is no objective of X worse than that objective of Y and there is at least one objective of X better than that objective of Y. Further, pareto-front of a multi-objective problem is a set of non-dominated solutions, which are chosen as optimal if no individual objective can be improved without sacrificing at least one other objective. **b)** In the second step, while the next population set P_{t+1} is obtained by sequentially adding the elements in the obtained pareto fronts, starting with 1 until the condition $|P_{t+1}| + |F_i| \leqslant N$ is satisfied (where F_i is the solution in the i^{th} front, and N is the maximum size of the population), for the selection of the elements in F_i, crowding-distance computation using the fitness function in each front (Line 6) is performed to obtain diverse solutions (Line 5-9).

Algorithm 1 Pseudo-code for NSGA-2 [6]

```
1:  while termination criteria do
2:      R_t ← P_t ∪ Q_t
3:      F ← non_dominated_sorting(R_t)
4:      P_{t+1} ← φ; i ← 1
5:      while |P_{t+1}| + |F_i| ⩽ N do
6:          C_i ← crowd_sourcing_assignment(F_i)
7:          P_{t+1} ← P_t ∪ F_i
8:          i = i + 1
9:      end while
10:     F_i ← sort(F_i, C_i, desc)
11:     P_{t+1} ← P_{t+1} ∪ F_i[1 : (N − |P_{t+1}|)]
12:     Q_{t+1} ← selection(P_{t+1}, N)
13:     Q_{t+1} ← mutation(Q_{t+1})
14:     Q_{t+1} ← crossover(Q_{t+1})
15:     t ← t + 1
16: end while
```

III. Problem Formulation

This section presents the formulation of the multi-objective, grid partitioning problem considering topological and resilience metrics. The problem is formulated as a graph partitioning problem, where the distribution grid is considered as a graph, and each partition that can be obtained is considered as a subgraph. The graph partitioning problem can be solved using two methods. One method is based on allocating nodes to each partition. Using the genetic algorithm approach, the size of the solution or the chromosome with the node-based problem will be $m * n$, where m is the number of partitions, and n is the number of nodes. In the second method, which is based on eliminating edges, the size of the chromosome will be k, where k is the number of power lines or graph edges.

A. Node Allocation Problem

In the node based approach, the following objective functions are considered:

1) **Edge loss minimization:** Minimize the net loss of the edge values, which is equivalent to the net loss in the power line capacity when an edge is removed because of partitioning.
$$\min \quad F_1 = \sum_{e_{i,j} \in \mathbb{E}} pf_{ij} \cdot X_{ij} \tag{1}$$
where X_{ij} is a variable that decides whether the nodes i and j of the edge, $e_{i,j}$, belong to the same partition; and pf_{ij} indicates the real-power flow between buses.
2) **Similarly sized partitions:** Minimize the difference in the number of nodes in different partitions, to form similarly-sized partitions.
$$\min \quad F_2 = \sum_{i=1}^{P-1} \sum_{j=i+1}^{P} |n'_i - n'_j| \tag{2}$$
where n'_i and n'_j are the number of buses in the partitions, p_i and p_j, respectively. And P is the maximum number of partitions.
3) **Compact partitions:** Minimize the geographic spread of a partition to make the microgrids more geographically compact.
$$\begin{aligned} \min \quad & F_3 = \sum_{p=1}^{\mathrm{P}} \delta_p, \\ \text{where} \quad & \begin{aligned} \delta_p &= x_p^{\mathrm{U}} - x_p^{\mathrm{L}}, \quad \text{if } x_p^{\mathrm{U}} - x_p^{\mathrm{L}} > y_p^{\mathrm{U}} - y_p^{\mathrm{L}} \\ &= y_p^{\mathrm{U}} - y_p^{\mathrm{L}}, \quad \text{if } y_p^{\mathrm{U}} - y_p^{\mathrm{L}} > x_p^{\mathrm{U}} - x_p^{\mathrm{L}} \end{aligned} \end{aligned} \tag{3}$$
and (x_p^L,x_p^U) are the x-coordinate range, and (y_p^L,y_p^U) are the y-coordinate range in partition p.

The constraints considered for the node-based approach are:

1) A node cannot belong to more than one partition.
$$g_1 \equiv \sum_{p=1}^{\mathrm{z}} X_{ip} = 1; i = 1 \text{ to } n \tag{4}$$
where X_{ip} decides whether the node i belongs to the p^{th} partition.
2) There exist an upper and lower limit of the nodes within a partition.
$$g_2 \equiv n_p^{\min} \leqslant n_p \leqslant n_p^{\max}, \quad p = 1 \text{ to } P \tag{5}$$
3) The nodes within a partition need to be contiguous, which is incorporated based on the constraint that paths between all node pairs within a partition do not traverse through nodes in another partition. This constraint increases the computation time because enforcing contiguity constraints requires significant computation for larger graphs [12].

B. Edge Elimination Problem

In this approach, the decision variables are the edges that need to be removed from the existing grid to form the partition. The following objectives are considered:

1) **Edge loss minimization:** This is similar to (1), except X_{ij} is a variable that decides if an edge is eliminated.
2) **Similarly sized partitions:** This is similar to (2).
3) **Compact partitions:** This is similar to (3).

4) **Feasible islands:** A distribution system with switching devices has the capability to form multiple islands with geographically diverse DERs and loads, thereby improving its resilience against an event; therefore, the objective F_4 captures the number of feasible islands possible relative to the total number of asset nodes in the system.

$$F_4 = \frac{\max_{N_{sub}} \sum_{j\in\{1,..N_{sub}\}} A}{n(N)}$$
$$A = \left\{ \begin{array}{c} \left[\sum_{i\in N_j} \left(g_{ij} - l_{ij}^c\right)\right]_+ + \sum_{i\in N_j} \left[v_{\max} - v_{ij}\right]_+ \\ + \sum_{i\in N_j} \left[v_{ij} - v_{\min}\right]_+ \end{array} \right\} \tag{6}$$

where N_{sub} is the number of independent islands possible; N_j is the set of nodes in the island j; and g_{ij}, l_{ij}^c, and v_{ij} are the generation, critical load, and voltage at node i of island j.

5) **Path redundancy**: The higher the number of possible paths from DERs to loads, the higher the likelihood of ensuring power supply to such loads under varied damage scenarios of an event; this is used as another parameter, F_5 and it is defined as:

$$F_5 = \max \frac{\sum_{j\in N} \sum_{i\in N} 1/\sum_{k\in K} E\left(P_k(i,j)\right)}{n(N)^2/2\hat{E}\left(P_k(i,j)\right)} \tag{7}$$

where $P_k(i,j)$ is the k_{th} path from node i and j; and $E(P_k(i,j))$ and $\hat{E}(P_k(i,j))$ are the electrical distance of the path and the maximum electrical distance, respectively.

Both resilience metrics, *feasible islands (F_4)* and *path redundancy (F_5)*, are maximized in this edge elimination problem. The constraints considered are:

1) The number of partitions have an upper and lower limit:

$$g_1 \equiv P^{\min} \leqslant P \leqslant P^{\max} \tag{8}$$

where $[P^{\min}, P^{\max}]$ is the range of the number of partitions.

2) There exists a lower limit of the nodes within a partition:

$$g_2 \equiv n_p^{\min} \leqslant n_p, \quad p = 1 \text{ to } P \tag{9}$$

C. Solution Encoding

The solution for a graph partitioning problem can be obtained using either integer or binary encoding. In integer encoding, the nodes on the graph can be assigned integer numbers depending on the partition they belong to, which is appropriate for use in the node allocation problem. Binary encoding is used for the edge elimination problem, where the decision variables for an edge within a graph are binary, indicating lines where the system graph can be split. Because distribution grids are radial in nature, the difference between the number of edges and nodes is small; hence, formulating the problem as an edge elimination problem is computationally less expensive than the node allocation problem.

IV. Experimental Results

In this section, the NSGA-2 algorithm is used for both the node allocation and the edge elimination problems to formulate microgrids based on resilience and topological metrics, and the solution performance is evaluated on multiple distribution feeders.

Table I: NSGA-2 & problem attributes for the test feeders

Attributes	IEEE 13	IEEE 34	IEEE 123	SM Cozy
Number of nodes	16	37	123	623
Number of edges	15	36	126	629
Number of objectives	[1–4]	[1–4]	[1–4]	[1–4]
Number of constraints	3	3	3	3
Range of partitions	[2,16]	[3,37]	[4,123]	[5,623]
Minimum nodes within partition	3	4	6	[7,15]
Population size	[200–500]	[200–500]	[200–500]	[200–500]
Max no. of generations	1000	1000	1000	1000
Offspring generation	[10–40]	[10–40]	[10–40]	[10–40]
Crossover points	[10–40]	[10–40]	[10–40]	[10–40]
Crossover probability	0.9	0.9	0.9	0.9
Mutation probability	0.05	0.05	0.05	0.05

A. Use Cases

1) **IEEE 13 bus:** This is a small test feeder consisting of shunt capacitor banks, in-line transformers, and one substation voltage regulator consisting of three single-phase units connected in wye. Four DERs are added to this test feeder—at nodes 684, 645, 692, and 670—to study the grid partitioning.
2) **IEEE 34 bus:** This is a long and lightly loaded test feeder with a nominal voltage of 24.9 kV. It has two in-line regulators, an in-line transformer for voltage reduction to 4.16 kV, along with a few shunt capacitors. Five DERs are added to this test feeder—at nodes 836, 858, 826, 808, and 818—to study the grid partitioning.
3) **IEEE 123 bus:** This is a comprehensive feeder with unbalanced loading with all combinations of loads, four step-type voltage regulators, capacitor banks, and switching to provide alternate paths of power flow and to make the grid meshed. Six DERs are added to this test feeder—at nodes 35, 48, 64, 78, 95, and 108—to study the grid partitioning.
4) **A real distribution feeder in Colorado:** This feeder model is developed based on the information provided by our utility partner in Colorado. The data set contains two substations, each having 8 feeders. One feeder (named *SM Cozy*) is considered for grid partitioning in this paper. Along with 7 pre-existing generators, 10 utility-scale DERs and 10 behind-the-meter DERs are added to the primary and secondary circuits, respectively.

The distribution grids are partitioned by using NSGA-2 under the parameters and the details are given in Table I, and Fig. 1 presents the partition solution for the real distribution feeder in Colorado.

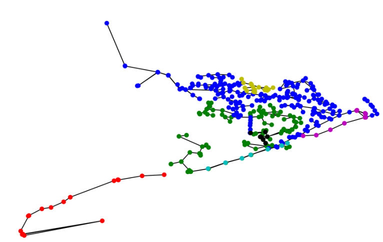


Figure 1: The partition solution of a Colorado feeder.

B. Node Allocation and Edge Elimination Comparison

Fig. 2 shows the computation time for the grid-partitioning problem using both the node allocation and edge elimination approaches solved using NSGA-2. The longer time taken to obtain the optimal solution in the case of the node allocation approach to the partitioning problem is because of the larger size of the chromosome ($m * n$, where m is the number of partitions, and n is the number of nodes), the increased computation overhead in satisfying the equality constraint in (4), and ensuring contiguous nodes within a partition.

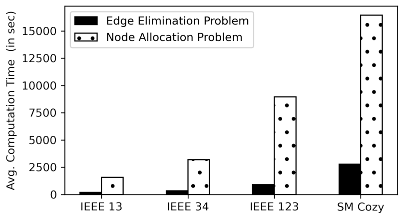


Figure 2: Computation time comparison of edge elimination and node allocation-based grid partition.

C. Comparison With Other techniques for graph partition

Here, we evaluate the NSGA-2-based grid partition with the conventional genetic algorithm technique and the graph spectral clustering technique. Spectral clustering is one of the fastest techniques to obtain the partitions because it considers only the system topology (Fig. 3); however, it is quite sensitive to the adjacency matrix (considered for computing the symmetric Laplacian matrix) and its eigenvectors (considered for k-means clustering for the partition). Incorporating multiple objectives for building the adjacency matrix can make the Laplacian ill formed, resulting in negative eigenvalues. The conventional genetic algorithm technique is relatively faster than NSGA-2, but it is feasible only for single fitness function-based problems.

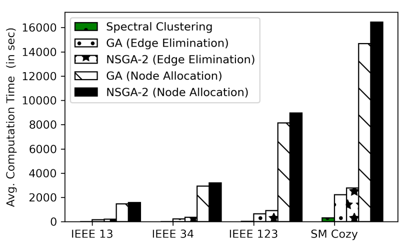


Figure 3: Comparison of NSGA-2 with genetic algorithm and spectral clustering technique.

D. Effect of Genetic Algorithm Parameters

Three common genetic algorithmic parameters are considered for the evaluation of computation time for different use cases: a) population size for each generation, b) crossover points in mutation, and c) offspring size in every generation. The time complexity of the NSGA-2 algorithm is $O(MN^2)$, where M is the number of objective functions, and N is the population size. Figs. 4(a) and 4(c) show the increase in computation time with increasing population and offspring size for different use cases. The number of crossover points in every generation did not affect the computation time (Fig. 4(b)). The algorithm can be sensitive to the increased number of crossover points, making it difficult to converge to an optimal solution; however, in certain cases—such as in the later stages of the genetic algorithm search process, when the population is homogeneous, or for a smaller population size—a larger number of crossover points can be beneficial [13].

E. Effect of Selection of Fitness Function

The impacts of the fitness function are evaluated based on two types of evaluation metrics: a) *objective-specific*, such as hypervolume (HV), generational distance (GD), and diversity index (DI); and b) *solution-specific*, such as electrical cohesive index (ECI) and cluster size index (CSI). Generational distrance computes the average euclidean distance in the objective space for each solution to the closest solution in the pareto front. For evaluating the hypervolume, reference points are considered instead of solutions in the pareto front. A higher hypervolume and lower generational distance indicates better solutions [14]. The diversity index computes the inter-solution euclidean distance among the solutions in the objective space. ECI measures the extent to which the buses within each cluster are electrically connected, formulated as:

$$ECI = \sum_{k=1}^{N_{sub}} \sum_{e_{i,j} \in S_k, e_{m,n} \in G} \frac{pf_{ij}}{pf_{mn}} \tag{10}$$

where N_{sub} is the number of partitions obtained from the solution, pf_{ij} is the real power flow in edges within each partition S_k, and pf_{mn} the real power flow in the original non-partitioned grid G. CSI measures the extent to which the cluster size deviates from the equally distributed cluster size with ideal partition p^*, i.e., $s^* = n/p^*$, where n is the number of buses. CSI is based on the shape of the log-normal distribution with the width parameter $\sigma = w\ ln(n)$ [15].

$$CSI = e^{\frac{-(ln(s) - ln(s^*))^2}{2\sigma^2}} \tag{11}$$

where s is the weighted average of the cluster size, and w is the penalty factor.

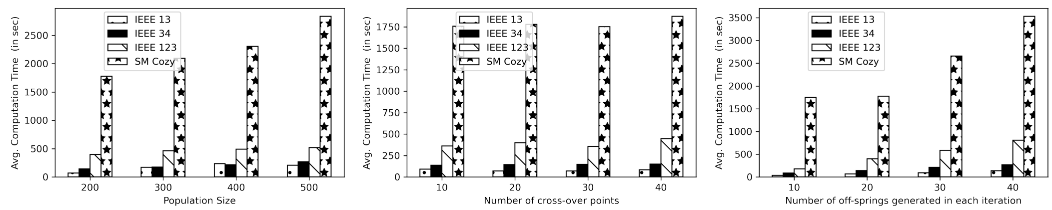
In Table II, column Obj is the total number of objectives considered. Sol is the average number of solutions obtained using NSGA-2. The rest of the columns are the evaluation metrics, averaged over all the experiments conducted with varying combinations of objective functions. The average number of solutions and the DI metric increases with increasing numbers of fitness functions, providing more options for grid partition but at the cost of a decrease in the HV and an increase in the GD metrics. The ECI metric is more than 0.85 for most scenarios, except the IEEE 123 case with consideration of four objective functions. Even the CSI metric reduces with an increase in fitness function; hence, it is crucial to identify ideal metrics to formulate the set of fitness functions in the problem.

Table II: Evaluation metrics for different distribution feeders. The scores reflect the average value, computed across every combination of the number of fitness functions selected.

Use Case	*Obj*	*Sol*	*HV*	*GD*	*DI*	*ECI*	*CSI*
IEEE 13	2	3	.019	2.7E-09	.57	.90	.269
	3	3	.003	1.2E-08	1.2	.89	.097
	4	5	0.0	3.9E-09	1.5	.89	.2
IEEE 34	2	37	.09	.0462	.32	.86	.15
	3	11	.05	.187	.78	.86	.063
	4	30	.01	.216	1.1	.87	.021
IEEE 123	2	57	.77	.26	.96	.90	.0092
	3	106	.61	.71	2.1	.87	4.9E-04
	4	200	.30	1.19	4.0	.79	5.5E-07
SM Cozy	2	35	.74	.41	1.4	.97	.067
	3	96	.44	0.73	2.5	.97	.011
	4	195	.033	1.13	3.7	.97	6.8E-05

F. Selection of Resilience Metrics

The feasible islands and path redundancy resilience metrics are evaluated based on their inclusion within the set of fitness



(a) (b) (c)

Figure 4: Effect of (a) population size, (b) number of crossover points, and (c) number of offspring in each generation.

functions. The scenarios shown in Table III are based on the inclusion of fitness functions F_4 and F_5 with the topology-based objectives F_1, F_2, and F_3. The resilience metric F_4 is better compared to F_5 on the basis of DI, but F_5 is relatively effective on the basis of the ECI and CSI metrics. The time to solve the problem for the IEEE 123 case including F_5 was approximately 10 hrs. Because the $path\ redundancy$ metric is computationally expensive, only the IEEE 13 and 34 cases are considered for the evaluation purpose.

Table III: Evaluation of the resilience metrics F_4 and F_5.

Use Case	Scenarios	Solns	DI	ECI	CSI
IEEE 13	with F_4	5	1.508	0.88	0.20
	with F_5	4	1.413	0.91	0.25
	with F_4 and F_5	10	1.058	0.89	0.1
IEEE 34	with F_4	33	1.087	0.87	0.02
	with F_5	35	0.91	0.90	0.01
	with F_4 and F_5	186	0.94	0.84	0.004

G. Improvisation with Parallelization

Incorporating multi-threading for evaluating the fitness of solutions in parallel reduced the computation time for obtaining the optimal solutions, as shown in Fig. 5; hence, with the usage of high-performance computing resources, NSGA-2 can be more effective and can obtain multiple optimal solutions even faster.

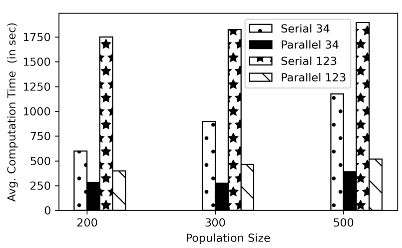


Figure 5: Effect of parallelizing the evaluation of solutions for different population sizes for the IEEE 34 and 123 cases.

V. Conclusion

Planning of microgrids in a distribution system, based on a meta-heuristic genetic algorithm approach, is proposed in this paper. The method works efficiently when the edge-elimination approach is considered rather than the node-allocation approach. and the former approach provides multiple diverse solutions that can provide more flexibility to the system planners for microgrid planning. The proposed method is validated with topological and resilience metrics for multiple test feeders and a real distribution feeder, and it allows for integration of multiple other reliability/resilience objectives as well. These objectives are currently being explored by the authors on several models of real distribution feeders and will be discussed in a future publication.

Acknowledgment

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office Agreement Number 37770. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting this article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

References

[1] P. Yuan, W. Zhang, and J. Chen, "A network partition approach for distributed three-phase state estimation of active distribution networks," in *2018 IEEE Power Energy Society General Meeting (PESGM)*, 2018, pp. 1–5.

[2] M. R. Kleinberg, K. Miu, N. Segal, H. Lehmann, and T. R. Figura, "A partitioning method for distributed capacitor control of electric power distribution systems," *IEEE Transactions on Power Systems*, vol. 29, no. 2, pp. 637–644, 2014.

[3] Y. Wu, Y. Xia, W. Hu, and L. Chen, "A two-step island partition strategy of active distribution system," in *2020 12th IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, 2020.

[4] D. Jinjin, Z. Hao, Z. Qian, L. Guoli, and L. Binbin, "Clusters partitioning of distribution network with distributed renewable generators," in *2017 IEEE 7th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER)*, 2017, pp. 1324–1328.

[5] Z. Li, Y. Lou, J. Liu, S. Liu, F. Yang, and Y. Fu, "Optimal partition of power distribution network service areas based on improved k-means algorithm," in *2014 International Conference on Power System Technology*, 2014, pp. 883–889.

[6] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: Nsga-ii," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.

[7] I. Mukherjee and P. K. Ray, "A review of optimization techniques in metal cutting processes," *Computers Industrial Engineering*, vol. 50, no. 1, pp. 15–34, 2006.

[8] B. J. Frey and D. Dueck, "Clustering by passing messages between data points," *Science*, vol. 315, no. 5814, pp. 972–976, 2007.

[9] K. Man, K. Tang, and S. Kwong, "Genetic algorithms: concepts and applications [in engineering design]," *IEEE Transactions on Industrial Electronics*, vol. 43, no. 5, pp. 519–534, 1996.

[10] K. Nara, A. Shiose, M. Kitagawa, and T. Ishihara, "Implementation of genetic algorithm for distribution systems loss minimum re-configuration," *IEEE Transactions on Power Systems*, vol. 7, no. 3, pp. 1044–1051, 1992.

[11] S. Zhang, D. Wang, X. Xu, and T. Zhao, "Optimal microgrid partition strategy of distribution generation based on advanced ga," in *2010 International Conference on Intelligent System Design and Engineering Application*, vol. 2, 2010, pp. 13–16.

[12] D. King, S. Jacobson, and E. Sewell, "Efficient geo-graph contiguity and hole algorithms for geographic zoning and dynamic plane graph partitioning," *Mathematical Programming*, vol. 149, no. 1-2, pp. 425–457, Jan. 2014.

[13] K. De Jong and W. Spears, *An Analysis of the Interacting Roles of Population Size and Crossover in Genetic Algorithms*, 10 2006, vol. 1, pp. 38–47.

[14] J. Blank and K. Deb, "Pymoo: Multi-objective optimization in python," *IEEE Access*, vol. 8, pp. 89 497–89 509, 2020.

[15] E. Cotilla-Sanchez, P. D. H. Hines, C. Barrows, S. Blumsack, and M. Patel, "Multi-attribute partitioning of power networks based on electrical distance," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4979–4987, 2013.