

Abstract

This paper proposes an optimization problem to partition a distribution grid, such that multiple feasible islands are planned and are capable to support their critical loads independently. It leverage the use of a multi-objective Genetic Algorithm (GA) approach to solve the problem. The proposed work has following major steps:

- 1) Formulates the optimization problem as node allocation and edge elimination and solves using Non-Dominated Sorting GA approach.
- 2) Evaluates the performance of the proposed technique with other GA and spectral clustering methods for varying size of test systems.

Optimization Problem

Objectives :

- 1) Edge Loss Minimization
- 2) Similarly sized Partitions
- 3) Compact Partitions

$$\min F_1 = \sum_{e_{i,j} \in E} p_{f_{ij}} \cdot X_{ij}$$

$$\min F_2 = \sum_{i=1}^{P-1} \sum_{j=i+1}^P |n'_i - n'_j|$$

$$\min F_3 = \sum_{p=1}^P \delta_p,$$

where $\delta_p = \begin{cases} x_p^U - x_p^L, & \text{if } x_p^U - x_p^L > y_p^U - y_p^L \\ y_p^U - y_p^L, & \text{if } y_p^U - y_p^L > x_p^U - x_p^L \end{cases}$

- 4) Feasible Islands

$$F_4 = \frac{\max_{N_{sub}} \sum_{j \in \{1, \dots, N_{sub}\}} A}{n(N)}$$

$$A = \left\{ \left[\sum_{i \in N_j} (g_{ij} - l_{ij}) \right]_+ + \sum_{i \in N_j} [v_{max} - v_{ij}]_+ \right. \\ \left. + \sum_{i \in N_j} [v_{ij} - v_{min}]_+ \right\}$$

- 5) Path Redundancy

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

Constraints:

Edge Elimination problem:

- 1) Upper/Lower Bounds on partitions

$$g_1 \equiv P^{\min} \leq P \leq P^{\max}$$

- 2) Lower limit on no. of nodes in a partition

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

Node Allocation problem:

- 1) Node belongs to one partition

$$g_1 \equiv \sum_{p=1}^P X_{ip} = 1; \quad i = 1 \text{ to } n$$

- 2) Upper/Lower limits on nodes in a partition

$$g_2 \equiv n_p^{\min} \leq n_p \leq n_p^{\max}, \quad p = 1 \text{ to } P$$

- 3) Nodes within a partition need to be contiguous

Proposed Approach

Non-Dominated Sorting Genetic Algorithm

- Elitist Approach (considers the elite solutions in the next iteration).
- Provides a faster convergence to optimal pareto front.
- Maintains diversity in the non-dominated solution space.
- Parameter-independent in comparison to other Evolutionary Algorithms used for Multi-Objective optimal problems

NSGA-2 Algorithm and some terminology

Concept of Domination: A soln. X1 dominates X2 if:

- a) if $G_j(X1)$ is no worse than $G_j(X2)$, for all $j = 1, 2, \dots, m$ (m obj functions)
- b) if $G_j(X1)$ is strictly better than $G_j(X2)$ for at least one objective

Non-Dominated Solution Set: The set of solutions which are non-dominated.

EX: Say X1 and X2 are two solutions with two fitness G1 and G2 (min)

X1 = 2 G1 = 23 G2 = 45

X2 = 3 G1 = 34 G2 = 23

X1 and X2 are non-dominated solution set.

This solution set is also called the **Pareto Optimal Set**

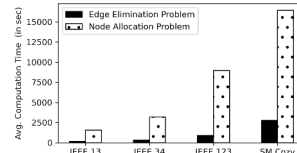
Now how to sort the solutions in the non-dominated set?

The idea is to segregate the solutions into multiple fronts, with the first one being the **Pareto Optimal Front**, which is F1 in the figure (since we try to minimize G1 and G2).

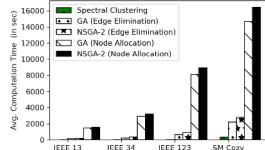


Numerical Results

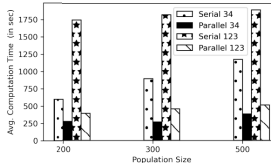
A. Comparison of Node Allocation & Edge Elimination Problem



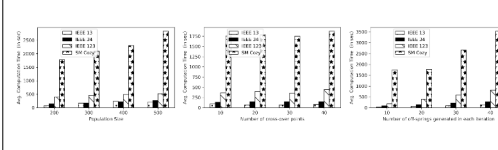
B. Comparison of NSGA-2 with other techniques



C. Improvement with Parallelization in solving NSGA-2



D. Genetic Algorithm Parameter Effects



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

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1: while termination criteria do
2:    $R_t \leftarrow P_t \cup Q_t$ 
3:    $F \leftarrow \text{non\_dominated\_sorting}(R_t)$ 
4:    $P_{t+1} \leftarrow \phi; i \leftarrow 1$ 
5:   while  $|P_{t+1}| + |F_i| \leq N$  do
6:      $C_i \leftarrow \text{crowd\_sourcing\_assignment}(F_i)$ 
7:      $P_{t+1} \leftarrow P_t \cup F_i$ 
8:      $i = i + 1$ 
9:   end while
10:   $F_i \leftarrow \text{sort}(F_i, C_i, \text{desc})$ 
11:   $P_{t+1} \leftarrow P_{t+1} \cup F_i[1 : (N - |P_{t+1}|)]$ 
12:   $Q_{t+1} \leftarrow \text{selection}(P_{t+1}, N)$ 
13:   $Q_{t+1} \leftarrow \text{mutation}(Q_{t+1})$ 
14:   $Q_{t+1} \leftarrow \text{crossover}(Q_{t+1})$ 
15:   $t \leftarrow t + 1$ 
16: end while
  
```

E. Evaluation of the algorithm based on the following metrics

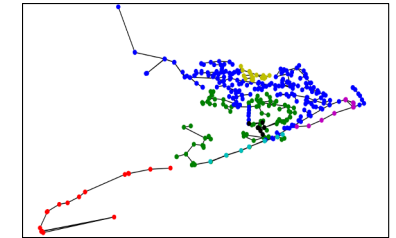
- Hypervolume (HV)
- Generation Distance (GD)
- Diversity Index(DI)
- Electrical Cohesive Index (ECI)
- Cluster Size Index (CSI)

Use Case	Obj	Sol	HV	GD	DI	ECI	CSI
IEEE 13	2	3	0.19	2.7E-09	57	90	269
	3	3	0.05	1.2E-08	12	89	097
	4	5	0.0	3.9E-09	15	89	2
IEEE 34	2	37	.09	.0462	32	86	13
	3	11	.05	.187	78	86	063
	4	30	0.1	.216	11	87	.021
IEEE 123	2	57	.77	.26	36	90	092
	3	106	.61	.71	21	87	4.9E-04
	4	200	.30	1.19	4.0	79	5.5E-07
SM Cozy	2	35	.74	.41	14	97	067
	3	96	.44	0.73	5.3	97	.011
	4	195	.033	1.13	3.7	97	6.8E-05

F. Effect of selection of Fitness Function

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

A sample solution for a real distribution feeder in Colorado



Conclusions

- 1) Edge Elimination Problems are easier to solve than Node-Allocation Problems based on the computation time.
- 2) NSGA-2 is preferred over spectral clustering and GA technique.
- 3) Proposed solution is validated for topological and resilience objectives.
- 4) Evaluated the method for different distribution grids & a real distribution feeder.
- 5) Parallelization capability in the meta-heuristic approach helps in reducing computation time.