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Integrating Several Subpopulation Tables with Node-Depth Encoding and Strength Pareto for Service Restoration in Large-scale Distribution Systems

D.S. Sanches, M.M. Gois, J.B.A. London Jr., A.C.B. Delbem

Abstract—Network reconfiguration for service restoration in distribution systems is a combinatorial complex optimization problem that usually involves multiple non-linear constraints and objectives functions. For large scale distribution systems, no exact algorithm has found adequate restoration plans in real-time. On the other hand, the combination of Multi-objective Evolutionary Algorithms (MOEAs) with the Node-Depth Encoding (NDE) has been able to efficiently generate adequate restoration plans for relatively large distribution systems (with thousands of buses and switches). The method called MEAN-NDS results from the combination of NDE with a technique of MOEA based on subpopulation tables and the MOEA called NSGA-II. In order to obtain a more efficient MOEA to treat service restoration problem in large scale distribution systems, this paper proposes a new method, which results from the combination of MEAN-NDS with the MOEA called SPEA-2. The idea is to improve the capacity of MEAN-NDS to explore both the search and objective spaces. Simulations results with distribution systems ranging from 632 to 1,277 switches, have shown that the proposed method found the configurations of lower switching operations, and explores the space of the objective solutions better than the MEAN-NDS, approximating better the Pareto-optimal front.

Index Terms—Multi-objective Evolutionary Algorithms, Node-Depth Encoding, Distribution Systems, Service Restoration

I. INTRODUCTION

Service Restoration (SR) problem emerges after the faulted areas has been identified and isolated and is usually solved by network reconfiguration procedures [1]. Network reconfiguration is the process of altering the topological structure of distribution systems (DSs) by opening or closing sectionalizing (normally-closed (NC)) and tie (normally-open-(NO)) switches.

When network reconfiguration is applied to SR problem, the main objectives are to minimize both the number of out-of-service areas and the number of switching operations (when not conflicting with these two objectives, minimize power losses) without violating the operational (limits for the node voltage, network loading, and substation loading) and radiality constraints. As a consequence, network reconfiguration for SR

problem is a multi-objective and multi constraint optimization problem. Due to the large number of switching elements, SR problem is highly combinatorial. Moreover, SR problem is nonlinear, since the equations governing the electrical systems are in general nonlinear, and non-differentiable, since a switch status change may result in crisp variations of the values in objectives and operational constraints. In fact network reconfiguration for SR problem belongs to the so called NP-Hard problems and there are no known methods to solve this type of problem exactly in a reasonable time [2].

Several meta-heuristics have been developed to design adequate SR plans [2], [3], [4], among them Multi-Objective Evolutionary Algorithms (MOEAs) are of interest to us. When applied to SR problems for large-scale Distribution System (DSs), the performance of MOEAs is dramatically affected by: the data structure used to represent computationally the electrical topology of the DSs. [4], [5], [6], [7]; and the genetic operators that are used, generally these operators do not generate radial configurations [6]. In order to overcome such a hurdle, the MOEAs proposed in [8], [7], [1] use the tree encoding named Node-Depth Encoding (NDE) [9] to represent computationally the electrical topology of the DSs. The properties of NDE that improve MOEAs performance to treat SR problems are discussed in details in [7] and will be summarized in section II.

The method proposed in [8] combines NDE with a modified version of the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) (NSDE hereafter). On the other side, the methodology proposed in [7], MoEA with Node-depth encoding named MEAN, uses NDE together with a technique of MOEA based on subpopulation tables, where each subpopulation stores the found solutions that better attend an objective or a constraint of the SR problem. The methodology proposed in [1], called MEAN-NDS, combines the best characteristics of both NSDE and MEAN in order to generate a new powerful MOEA to solve SR problem in large-scale DSs. The MEAN-NDS is based on the idea of subpopulation tables, as the MEAN methodology. However, new subpopulation tables, called non-dominated subpopulation tables, are added. These tables store the non-dominated solutions obtained during the generations. As the NSDE methodology, the non-dominated subpopulation tables use a non-dominance technique that ensures diversity among the solutions.

This paper extend the principle of MEAN-NDS of aggrega-

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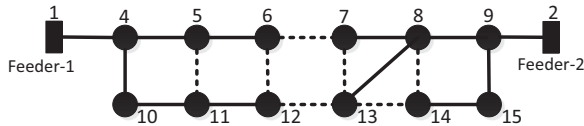
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tion other criteria to evaluate solutions by investigating additional types of subpopulation tables that benefit SR problems. In this sense, six new subpopulation tables are aggregated in the MEAN-NDS methodology. The first one is related to the non-dominated solutions based on the Strength-Pareto Evolutionary Algorithm 2 (SPEA2) [10]. The other five subpopulation tables are related to the required pair of switching operations. It is important to highlight that as the NSGA-II, the SPEA2 is a MOEA that searches for an approximated Pareto-optimal set based on elitism, i.e., the best solutions in the population are preserved to the next generation. Despite the similarities, these techniques differ in the way that they implement the elitism and in the strategy used to select the best solutions according to multiple objective functions. All those improvements (the new six subpopulation tables) are synthesized in a new methodology called MEA2N with subpopulation table related to solution STRength (MEA2N-STR). Section V presents some simulation results comparing the performance of both MEAN-NDS and MEA2N-STR.

II. NODE-DEPTH ENCODING

A graph G is a pair $(N(G), E(G))$, where $N(G)$ is a finite set of elements called nodes and $E(G)$ is a finite set of elements called edges. For DS network reconfiguration problems usually the DS is represented by a graph, where nodes represent the sectors¹; and the edges represent the sectionalizing- and tie-switches. The graph presented in Figure 1 can be seen as a DS with two feeders (each feeder is represented by one tree formed by the solid lines), where edges in solid lines represent NC sectionalizing switches and edges in dashed lines represent NO tie-switches.



$$T_1 = \begin{bmatrix} \text{depth} \\ \text{node} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 2 & 3 & 2 & 3 & 4 \\ 1 & 4 & 5 & 6 & 10 & 11 & 12 \end{bmatrix}$$

$$T_2 = \begin{bmatrix} \text{depth} \\ \text{node} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 2 & 3 & 2 & 3 & 3 \\ 2 & 9 & 15 & 14 & 8 & 7 & 13 \end{bmatrix}$$

Figure 1. Illustration of DS modeled by a graph and its corresponding NDE.

Nodes 1 and 2 in the graph are the root nodes of trees 1 and 2, respectively. These nodes correspond to sectors 1 and 2, which are, respectively, in substations 1 and 2. NDE is basically a representation of a graph tree in a linear list containing the tree nodes and their depths². It can be implemented by an array of pairs (n_x, d_x) , where n_x is the node label and d_x is the node depth in the tree. The order the pairs are disposed on the linear list is fundamental and can be obtained from a depth search algorithm [11], by inserting a pair (n_x, d_x) in

the list each time a node n_x is visited by the algorithm. This processing is off-line performed.

From NDE, two operators were developed to efficiently manipulate a forest producing a new one: the Preserve Ancestor Operator (PAO) and Change Ancestor Operator (CAO). Each operator performs modifications on the forest encoded by the NDE arrays that are equivalent to prune and graft a subtree of a forest generating a new forest. Both operators are computationally efficient, requiring $O(\sqrt{n})$ average time to construct a new NDE, where n is the number of graph nodes (each graph node corresponds to a DS sector). Additional information about the NDE and its operators applied to DS reconfiguration problems are described in [7].

NDE can improve the performance obtained by MOEAs in DS reconfiguration problems because of the following NDE properties: (i) The NDE through its operators produces exclusively feasible configurations, that is, radial configurations able to supply energy for the whole re-connectable system³; (ii) The NDE can generate significantly more feasible configurations in relation to other encoding in the same running time since its average-time complexity is $O(\sqrt{n})$; (iii) The NDE-based formulation also enables a more efficient forward-backward Sweep Load Flow Algorithm (SLFA) for DSs. Typically this kind of load flow applied to radial networks requires a routine to sort network buses into the Terminal-Substation Order (TSO) before calculating the bus voltages [12], [13], [14]. Fortunately, each configuration produced by NDE operators has the buses naturally arranged in the TSO. Thus, the SLFA can be significantly improved by NDE-based formulation.

III. SERVICE RESTORATION PROBLEM FORMULATION

The SR problem can be formalized as follows:

$$\begin{aligned} \text{Min. } & \phi(G), \gamma(G) \text{ and } \psi(G, G^0) \\ \text{s.a. } & \\ & Ax = b \\ & X(G) \leq 1 \\ & B(G) \leq 1 \\ & V(G) \leq 1 \\ & G \text{ is a forest,} \end{aligned} \quad (1)$$

where G is a spanning forest of the graph representing a system configuration [15] (each tree of the forest [15] corresponds to a feeder or to an out-of-service area, nodes correspond to sectors and edges to switches); $\phi(G)$ is the number of consumers that are out-of-service in a configuration G (considering only the reconnectable system); $\psi(G, G^0)$ is the number of switching operations to reach a given configuration G from the configuration just after the isolation of the fault G^0 ; $\gamma(G)$ are the power losses, in p.u., of configuration G ; A is the incidence matrix of G [16]; x is a vector of line current flow; b is a vector containing the load complex currents (constant) at buses with $b_i \leq 0$ or the injected complex currents at the buses with $b_i > 0$ (substation); $X(G)$ is called network loading

³The term "re-connectable system" means all areas having at least one switch (NC or NO) linking them to energized areas. Some out-of-service areas may not have any switch to re-connect them to the remaining energized areas.

¹A sector is a set of buses connected by lines without switches.

²The depth of a node is the length of the unique path from the root of the tree to the node.

of configuration G , that is, $X(G)$ is the highest ratio x_j/\bar{x}_j , where \bar{x}_j is the upper bound of current magnitude for each line current magnitude x_j on line j ; $B(G)$ is called substation loading of configuration G , that is, $B(G)$ is the highest ratio b_s/\bar{b}_s , where \bar{b}_s is the maximum current injection magnitude provided by a substation (s means a bus in a substation); $V(G)$ is called the maximal relative voltage drop of configuration G , that is, $V(G)$ is the highest value of $|v_s - v_k|/\delta$, where v_s is the node voltage magnitude at a substation bus s in pu and v_k the node voltage magnitude at network bus k in pu obtained from a SLFA for DSs, and δ is the maximum acceptable voltage drop (in this paper $\delta = 10\%$). Formulation of Equation 1 can be synthesized by considering:

- i*) Penalties for violated constraints $X(G)$, $B(G)$ and $V(G)$;
- ii*) The use of the NDE [7], i.e. an abstract data type [11] for graphs that can efficiently manipulate a network configuration (spanning forest) and guarantee that the performed modifications always produce a new configuration G that is also a spanning forest (a feasible configuration);
- iii*) The nodes are arranged in the TSO for each produced configuration G in order to solve $Ax = b$ using an efficient SLFA for DSs. The NDE stores nodes in the TSO;
- v*) $\phi(G) = 0$. The NDE always generates forests that correspond to networks without out-of-service consumers in the reconnectable system.

Equation 1 can be rewritten as follows:

$$\begin{aligned}
 \text{Min.} \quad & \psi(G, G^0), \gamma(G) \text{ and} \\
 & \omega_x X(G) + \omega_b B(G) + \omega_v V(G) \\
 \text{s.a.} \quad & \\
 & \text{Load flow calculated using the NDE,} \\
 & G \text{ is a forest generated by the NDE,}
 \end{aligned} \tag{2}$$

where ω_x , ω_b and ω_v are weights balancing among the network operational constraints. In this paper, these weights are set as follows:

$$\begin{aligned}
 \omega_x &= \begin{cases} 1, & \text{if, } X(G) > 1 \\ 0, & \text{otherwise;} \end{cases} \\
 \omega_b &= \begin{cases} 1, & \text{if, } B(G) > 1 \\ 0, & \text{otherwise;} \end{cases} \\
 \omega_v &= \begin{cases} 1, & \text{if, } V(G) > 1 \\ 0, & \text{otherwise.} \end{cases}
 \end{aligned}$$

IV. PROPOSED METHOD

Basically, MEA2N-STR combines the main aspects of the methods MEAN-NDS and the MOEA SPEA2. In the following all the subpopulation tables of both, the MEAN-NDS proposed in [1] and the MEA2N-STR, will be presented.

- 1) Tables associate to each objective and constraint:
 - a) T_1 - solutions with the lowest found $\gamma(G)$;
 - b) T_2 - solutions with the lowest found $V(G)$;
 - c) T_3 - solutions with the lowest found $X(G)$;
 - d) T_4 - solutions with the lowest found $B(G)$;

- e) T_5 - solutions with the lowest found values of an aggregation function, defined as follows:

$$f_{agg}(G) = \psi(G, G^0) + \gamma(G) + \omega_x X(G) + \omega_b B(G) + \omega_v V(G) \tag{3}$$

where $\psi(G, G^0)$, $\gamma(G)$, $X(G)$, $B(G)$, $V(G)$, ω_b , ω_v and ω_x were defined in Section III ⁴;

- 2) Tables for improving diversity in the space of objectives arranged by dominance ranking used by the NSGA-II [17]. Such strategy consists in dividing a set of M solutions into several fronts ($\mathcal{F}_1, \mathcal{F}_2, \dots, \mathcal{F}_k$) according to the degree of dominance of each solution. \mathcal{F}_1 front (called Pareto Front) contains the non-dominated solutions of the whole set M of found solutions. \mathcal{F}_2 contains non-dominated solutions of set $M \setminus \mathcal{F}_1$, \mathcal{F}_3 stores non-dominated solutions of $M \setminus (\mathcal{F}_1 \cup \mathcal{F}_2)$, and so on. There are three tables of this type:
 - a) Table T_6 - solutions from \mathcal{F}_1 ;
 - b) Table T_7 - solutions from \mathcal{F}_2 ;
 - c) Table T_8 - solutions from \mathcal{F}_3 .

All the tables presented up to know is common to both methodologies MEAN-NDS and MEA2N-STR. The next are the new tables that exist only in the proposed methodology MEA2N-STR.

- 3) Tables denoted T_{8+p} , with $p = 1, \dots, 5$: they store the solutions with at most p switching operation pair (after fault isolation), ranked (increasing order) according to the value of $V(G) + X(G)$. Solutions with similar value, considering precision 10^{-2} , are randomly ranked;
- 4) The Strength Pareto Table T_{14} : it is filled according to the number of solutions that each individual dominates. It is considered the best individual who dominates most solutions. If the size of the strength Pareto table exceeds a predefined limit, the worst individual is deleted.

The sizes of those tables and the number of generations are the parameters of MEA2N-STR:

- S_{T_i} is the size of the subpopulation table T_i indicating how many individuals can be stored in T_i , with $i = 1, \dots, 14$;
- G_{max} is the maximum number of individuals generated by the MEA2N-STR. It is also used as a criterion to stop the algorithm.

The reproduction operators used to generate new individuals are PAO and CAO (Section II). First a solution is selected from the subpopulation tables as follows: a subpopulation T_i is randomly chosen, then, an individual from it is randomly picked up. Next, PAO or CAO (according to a dynamic probability [7]) is applied to such individual, generating a new one, I_{new} . Subpopulation table T_i receives I_{new} if T_i is not full (since T_i has size bounded by S_{T_i}) or if I_{new} is better

⁴Note that all configurations generated by MEAN-NDS and MEA2N-STR are feasible, that is, they are radial networks able to supply energy for the whole re-connectable system.

(according to the criterion associated to T_i) than the worst solution in T_i , then replacing it.

It is important to highlight that T_6 , T_7 , T_8 and T_{14} are related to non-dominance and must be fulfilled according to the corresponding dominance ranking. It is also important to highlight that two criteria are used by MEA2N-STR to evaluate dominance: *i*) number of switching operations ($\psi(G, G^0)$) and *ii*) the aggregation function $f_{agg}(G)$ (Equation 3).

V. TEST RESULTS

In order to compare the methodologies MEAN-NDS and MEA2N-STR for SR problem, two systems were used. The first one is the fairly large DS of Sao Carlos city in Brazil, System 1 hereafter. The second one, named System 2, is composed of two System 1 interconnected by 13 NO new additional switches (for more details about the Systems, see [7]). These DSs have the following general characteristics:

System 1: 3,860 buses, 532 sectors, 632 switches (509 NC and 123 NO switches), 3 substations and 23 feeders;

System 2: 7,720 buses, 1,064 sectors, 1,277 switches (1,018 NC and 259 NO switches), 6 substations and 46 feeders.

The tests were performed using a Core 2 Quad 2.4GHz, 8G RAM, with Linux Operating System Ubuntu 10.04 version, and gcc-4.4 as the C the language compiler.

The parameters utilized in the simulations were:

- MEAN-NDS: $S_{T1, \dots, T5} = 5$, $S_{T6} = 20$, $S_{T7} = 40$ and $S_{T8} = 20$, and $G_{max} = 100.000$;
- MEA2N-STR: $S_{T1, \dots, T5} = 5$, $S_{T6} = 20$, $S_{T7} = 40$, $S_{T8} = 20$, $S_{T9, \dots, T14} = 5$, and $G_{max} = 100.000$.

In this paper the two methods are going to search by SR plans which restore the entire out-of-service area (full restoration cases) respecting the radiality and all the operational constraints (voltage drop, substation and network loading). On the other hand, those methods can find SR plans with less switching operations if: (i) some non-significant violations of operational constraints are accepted; and (ii) load curtailment is applied.

A. Single fault in System 1

It is simulated a fault in the largest feeder of System 1 that interrupts the service for the whole feeder. Table I show the average and standard deviation values of the best solutions found by those methodologies over 100 trials (1,000 evaluations for each trial). The number of switching operations presented in this table is those necessary to full restoration after the isolation of the faulted areas. The solutions found by MEA2N-STR are better since they have average number of switching operation for full restoration around 6 while the solutions found by MEAN-NDS have that average number around 8.

Figure 2 illustrates that MEA2N-STR for System 1 is able to evolve individuals near to the Pareto Front.

B. Single fault in System 2

It is simulated a fault in the largest feeder of System 2 that interrupts the service for the whole feeder. Table II

Table I
SIMULATION RESULTS - SINGLE FAULT IN SYSTEM 1

	MEAN-NDS		MEA2N-STR	
	Average	SD*	Average	SD*
Total Amount of Power Losses (KW)	353.37	33.96	382.94	35.69
Maximum Voltage Ratio (%)	3.83	0.84	4.42	0.90
Maximum Network Loading (%)	82.78	5.51	82.54	5.83
Maximum Substation Loading (%)	52.96	2.18	53.95	2.02
Switching Operations	8	2.78	6	1.85
Running Time (sec.)	8.89	1.07	16.77	1.10

*Standard Deviation

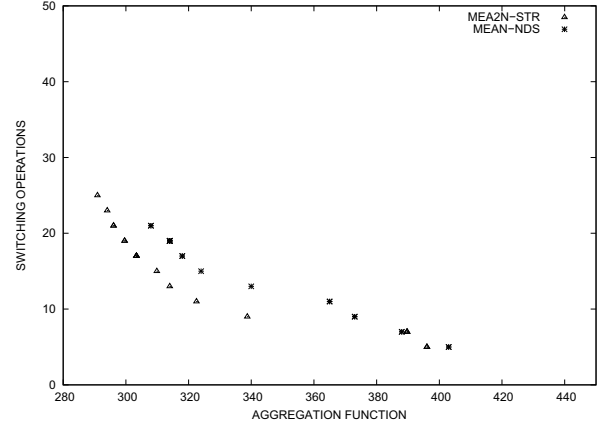


Figure 2. Pareto front obtained from System 1.

show the average and standard deviation values of the best solutions found by those methodologies over 100 trials (1,000 evaluations for each trial). The number of switching operations presented in this table is those necessary to full restoration after the isolation of the faulted areas. The solutions found by MEA2N-STR are better since they have average number of switching operation for full restoration around 9 while the solutions found by MEAN-NDS have that average number around 13.

Table II
SIMULATION RESULTS - SINGLE FAULT IN SYSTEM 2

	MEAN-NDS		MEA2N-STR	
	Average	SD*	Average	SD*
Total Amount of Power Losses (kW)	626.24	44.53	638.33	32.79
Maximum Voltage Ratio (%)	3.83	0.85	3.90	0.86
Maximum Network Loading (%)	84.27	7.74	76.04	7.61
Maximum Substation Loading (%)	54.89	1.76	54.19	1.19
Switching Operations	13	9.53	9	2.52
Running Time (sec.)	8.46	0.59	17.40	1.11

*Standard Deviation

Figure 3 illustrates that MEA2N-STR for System 2 is able to evolve individuals near to the Pareto Front. Both test problems (System 1 and 2) show MEA2N-STR gets to approximate the Pareto optimal set while preserving a diverse, evenly-distributed set of nondominated solutions.

VI. CONCLUSION

This paper have presented a new MOEA using NDE to solve SR problem in large-scale DSs (i.e., DSs with thousands of buses and switches).

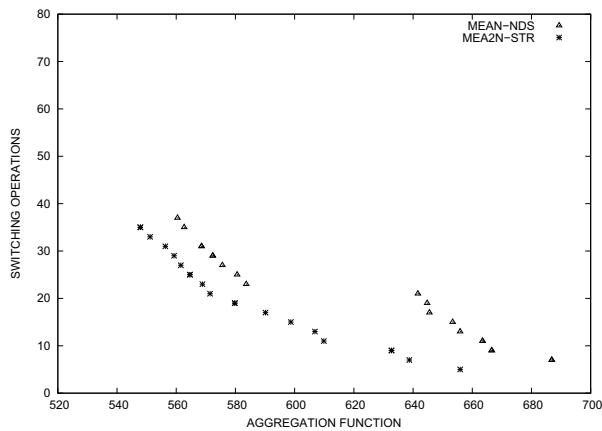


Figure 3. Pareto front obtained from System 2.

This paper extends the principle of MEAN-NDS [1] of aggregation other criteria to evaluate solutions by investigating additional types of subpopulation tables that benefit SR problems. The proposed methodology, called MEA2N-STR, aggregated six new subpopulation tables into the MEAN-NDS methodology. The first one is related to the non-dominated solutions based on the Strength-Pareto Evolutionary Algorithm 2 (SPEA2) and the others are related to the required pair of switching operations. In this paper both methodologies, MEAN-NDS and MEA2N-STR, were applied to two DSs. The results have demonstrated that they enabled SR in large-scale DSs and solutions were found where: energy was restored to the entire out-of-service area, the operational constraints were satisfied, and a reduced number of switching operations was obtained. Moreover, from the relatively low running time required to elaborate restoration plans for the tested systems, we can conclude that those methodologies can elaborate adequate SR plans for large-scale DSs.

Statistical analyses performed in this paper have shown the MEA2N-STR performs better than the MEAN-NDS for SR problem, since the SR plans obtained by MEA2N-STR presented average number of switching operations smaller than those obtained by MEAN-NDS. It is important to highlight that the percentage of switching operation reduction obtained by MEA2N-STR increases with the size of the System. Other simulation results have demonstrated that this characteristic maintains to larger DSs. It is also important to highlight that the analysis of the results, according to metrics used to compare MOEAs [18], show that the MEA2N-STR outperforms MEAN-NDS for both tested Systems in terms of approximating the Pareto optimal set while preserving a diverse, evenly-distributed set of non-dominated solutions.

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