Pareto-Based Multi-Stage and Multi-Objective Planning of DG Enhanced Distribution System

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***Abstract*—The efficient planning of radial distribution feeders is important to ensure energy supply to load demands as suitable quality of the service is provided. This planning is usually separated into two decision-making stages, i.e., design of topology infrastructure and protection system shaping. Moreover, these stages are performed pursuing the achievement of multiple objectives such as costs minimization and reliability maximization. In consequence, a multi-stage and multi-objective optimization problem arises. In this paper, an efficient Pareto-based approach is proposed to solve the aforementioned kind of optimization. Infrastructure preparation considers possible interconnections between loads and installation of Distributed Generation (DG). Furthermore, the shaping of protection system considers the amount of devices as their efficient placement in the feeder. DG have been largely considered as an alternative to increase the operation performance of distribution systems (DSs), besides its merely function to provide energy. On the other hand, Non-Dominated Sorting Genetic Algorithm (NSGA-II) is implemented to solve each stage of the planning. Finally, simulations are applied on a 33-nodes test feeder with available sources to install DG.**

***Index Terms*—distribution system planning, multi-objective optimization, multi-stage optimization, evolutionary algorithm, optimum reclosers placement, optimal reconfiguration, Pareto-optimal solutions**

I. Introduction

In most real world optimization problems the solution must to be found considering multiple objectives instead of one. Whereas these objectives are often in conflict, a trade-off relation among them arises. I.e., it is necessary to sacrifice the performance of one or more objectives to enhance the other ones. Besides, when the decision making process is related, but not limited, to systems planning, it is possible that several planning stages should be performed. Thus, optimal procedures are required for each stage. Moreover, it is possible to realize a single solving process that considers all necessary variables. Nevertheless, both alternatives have non-desirable limitations and assumptions. In the first case, when passing through stages it is necessary to choose a definite solution, or say a global optimum, hard task when we talk about multi-objective optimization. A wrong selection may lead to biased results. In the second case, considering all possible variables is an endless task, and when realized, results an extremely widespread landscape, which may hinder or limit the exploration over the search space. In the same way, a large number of function evaluations must to be realized, demanding a prohibitive amount of computational resources and slowing down the algorithm. In consequence, we will focus on the first alternative, proposing an approach to avoid biased solutions when passing through stages.

To the best of our knowledge, multi-stage optimization jointly with multi-objective decision making has not been elucidated in the literature. We introduce a novel approach, namely Prime-Pareto, to attain efficient solutions of this kind of problems. Here, we address the complexity when planning the attendance of energy demands, pursuing appropriate relia- bility indices and minimizing investment. Identified stages of this planning comprehend infrastructure outline and protection system shaping.

In accordance with the literature, optimal planning of distribution systems (DS) toward suitable reliability performance, is a complex problem because its optimization stages are described by non-linear and non-differentiable objective functions, as well as combinatorial solutions. Traditionally, the planning has been treated as a problem of a single objective function where investments and available resources are used in a single instant of time [1]–[3]. The radial feeders are normally provided with alternate routes of power supply to ensure backup connections that minimize the impact of permanent faults and to prevent unserved load during scheduled interruption [4]. In [5] is presented a Pareto multi-objective optimization to determine the amount and location of protective devices, minimizing both total costs and reliability indices such as SAIFI and SAIDI. Authors in [6] and [7] include Distributed Generation (DG) penetration on a loop feeder while achieving the optimal placement of reclosers. They minimize SAIFI and SAIDI applying Evolutionary Algorithms (EAs).

This paper is organized as follows. Section II shows in detail the proposed approach for DS planning. Section III describes the formulation of objective functions and constraints of the problem. Section IV describes the optimization method. Section V shows the test system used and the numerical results obtained with the proposed methodology. Finally, Section VI presents the conclusions.

II. Proposed Approach

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To characterize a Multi-Stage Optimization Problem (MSOP), without loss of generality, let us consider the decision-making involved in the planning of DSs; primarily composed by topology outline, sizing of the protection system and placement of reclosers. Thus, this planning can be divided into two stages: i) Topology outline; and ii) Protection system shaping. In first, physical infrastructure of distribution feeder is designed in accordance to the geographical position of load points. Here, several elements with their main characteristics are selected in a reasonably basis, e.g., connection branches are chosen according to type of conductor, length, tower type, among others. Moreover, important elements such as substa- tions and DG power plants are also determined. In the second phase, protection system is designed on the selected network configuration resulted in the first stage. This decision-making considers the sizing of the protection system together with the efficient placement of protective devices toward the feeder reliability enhancement. In Fig. 1 the scheme characterizes the general process of a multi-stage decision making.

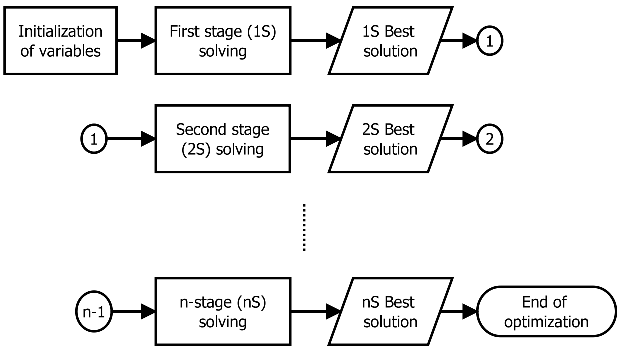

Figure 1. Flow diagram of multi-stage decision making.

Moreover, the aforementioned optimization stages are usually developed in a multi-objective basis. In Fig. 2, the continuous lines represent the initial topology of a DS, while the dashed lines represent the connection alternatives for new load points. In the first stage, the possible new load nodes in a system can be connected to the substation through different routes, therefore, design of the DS network is a combinatorial problem with technical and economic constraints. Finally, we must consider the availability of primary energy resources to locate and size DGs. This availability limits the area and the nodes to which DG can be connected.

In the second stage, the amount of protective devices in a DS can vary from any recloser to a few. Let us take two extreme hypothetical cases: 1) non branch has the capability to isolate a fault event; 2) each branch is able to isolate a fault event by the opening of a switch. If the reliability is the only objective of this decision-making problem, the ideal choice is the second case. Nevertheless, it is expected that a full reliable DS is likely to be very expensive, involving high costs that the Network Operator (NOp) is not willing to invest. Hence, the decision-making process must to be developed taking into account several objectives, such as high levels of reliability together with low costs.

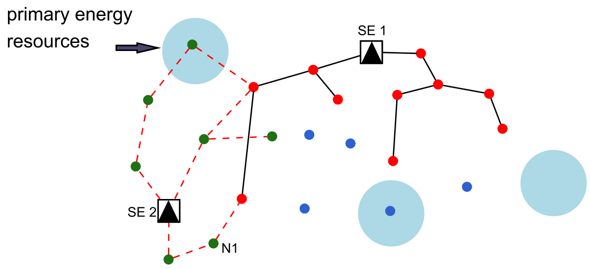

Figure 2. Topology decision making.

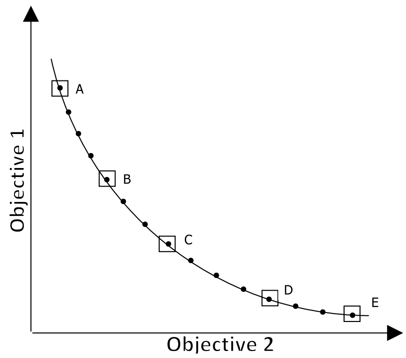

Figure 3. Two objectives Pareto-front.

The multi-objective optimization problem has n decision variables, M objective functions, as

$$max/min\ f(\bar{x}) = max/min\,[f_1(\bar{x}), f_2(\bar{x}),..., f_M(\bar{x})] \quad (1)$$

$$s.t.\ g(\bar{x}) = (g_1(\bar{x}), g_2(\bar{x}),..., g_J(\bar{x})) \geq 0 \quad (2)$$

$$h(\bar{x}) = (h_1(\bar{x}), h_2(\bar{x}),..., h_K(\bar{x})) = 0 \quad (3)$$

$$x_i^L \leq x_i \leq x_i^U = 0,\ i = 1,2,...,n, \quad (4)$$

where the last set of constraints determines lower and upper bounds for each decision variable. Besides, the problem is described by inequality and equality constraints.

As stated before, cascade optimization requires the outcome of a global optimum in each stage. Nevertheless, multi-objective optimization looks for compromises among objectives instead of finding a single solution. Therefore, the traditional optimality concept for a unique global optimal solution is improper to apply. Hence, we apply the optimality concept introduced by Vilfredo Pareto in 1896. In words, this notion can be defined as: if there is no feasible solution rather than $\vec{x}^*$ which improves one objective function without impairing the rest, then $\vec{x}^*$ is Pareto optimal. Formally, Coello et al. [8] define this notion as follows: a point $\vec{x}^* \in \Omega$ is Pareto-optimal if for every $\vec{x}^* \in \Omega$ and $\mathrm{M} = \{1,2,...,M\}$ either,

$$\forall (f_m \vec{x} = f_m(\vec{x}^*)), \quad (5)$$

or, there is at least one $m \in M$ such that

$$f_m \vec{x} > f_m(\vec{x}^*). \quad (6)$$

In Pareto approaches there is a set of trade-off solutions instead of a unique solution. In Fig. 3 is shown a generalized Pareto-front when minimizing two objectives. In this case, we highlight five solutions; A is an extreme solution that completely favors objective 2, E is an extreme solution that outperforms objective 1, and C is the most balanced solution within the optimal set.

In order to realize the cascade optimization, it would be possible to utilize every solution of the optimal set as an input of a subsequent stage. Nevertheless, although this process is less complex in comparison with the single solving process due to a more restricted search space, it is excessively time and resource consuming. In consequence, we propose the use of an efficient subset of solutions that compose the Pareto front, to function as inputs of the second stage in order to reduce complexity and optimization solving time.

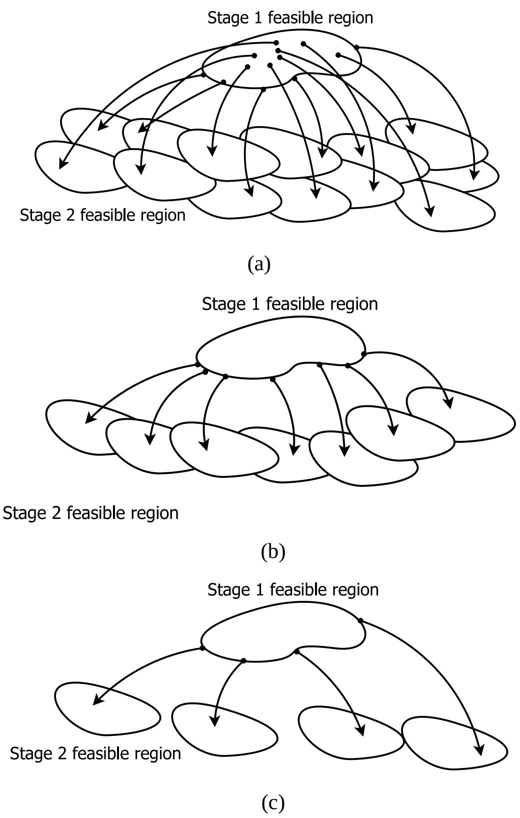

Figure 4. Feasible search spaces for distinct alternatives to solve Multi-Stage and Multi-Objective Optimization Problems (MSMOOPs). a) Single solving with all decision-making variables. b) Cascade solving with all efficient solutions .c) Cascade solving with efficient solutions subset.

Fig. 4 shows complexity (when exploring the search space) comparison among the different alternatives to solve a MSOP, stated hereinabove. Fig. 4a presents the feasible region when multi-stage decision making is realized with a single solving process that considers all required variables. Every solution in the feasible region 1 (alongside inner solutions) is associated with a feasible search space of second stage. Let G be the number of feasible solutions in first stage and P the number of average feasible solutions in every second stage search space. The entire landscape of this alternative is defined by the product GP. On the other hand, Fig. 4b shows the feasible region when multi-stage decision making is developed applying cascade optimization and using each solution of the optimal set as an input of the subsequent stage. Every efficient solution in feasible region 1 (located in the edge) is associated with a feasible search space of second stage. Let Q be the number of efficient solutions in first stage and P the number of average feasible solutions in every second stage search space. The entire landscape of this alternative is defined by the product QP. Since $Q \leq G$, then the entire search space in the second case is more delimited than the first case, scaled by the ratio Q/G. Finally, Fig. 4c describes the feasible region when multi-stage decision making is developed applying sequential optimization and using an efficient subset of solutions as inputs of the successive stage. As the second alternative, each subset solution in feasible region 1 (settled in the bound) is associated with a stage two feasible region. Let R be the size of efficient solutions subset in first stage and P the number of average feasible solutions in every second stage search space. The entire landscape of this alternative is defined by the product RP. Whereas $R \leq Q \leq G$, the entire search space in the proposed alternative is the less complex and more precise among the aforementioned alternatives. Here, the complexity of the search space is reduced by the ratio R/G.

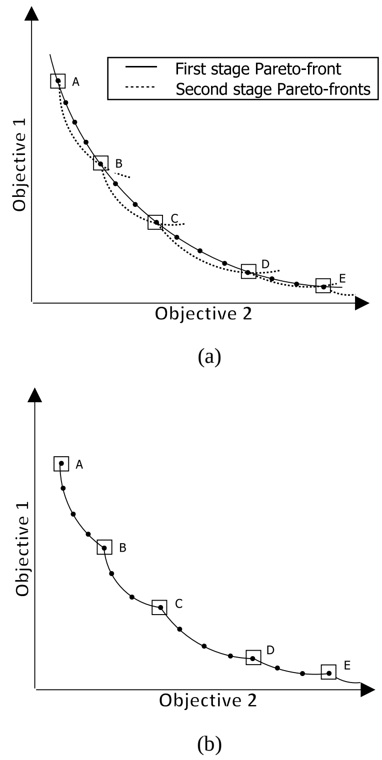

Figure 5. Pareto optimal sets. a) Second stage Pareto-fronts derived from first stage highlighted solutions. b) Prime-Pareto optimal set.

Applying the cascade optimization with efficient solution subset to the front of Fig. 3, the final stage outputs a new Pareto-optimal set composed by better solutions, which are located at the left-lower area of the first front of Fig. 5a. Willfully, we made highlighted solutions coincide with the intersection of both stages Pareto-fronts. To the right of these points it is presumable that solutions found in second stage will be worse than those of the first front. In consequence, it is necessary a new start point for second stage to find new better alternatives. It is essential to entirely cover the domain of the first front with the set of second fronts in order to maintain the objectives value range size. Besides, when meeting the above, the range expansion is likely to occur, a desirable effect for the decision maker.

In Fig. 5b is shown the Pareto-optimal set when filtering dominated alternatives of both realized stages. This Pareto- front is what we call a definitive set of efficient solutions because is the output of the last optimization stage. Since this set is the result of combining different fronts, we denominate it as the Prime-Pareto optimal set.

To obtain the Prime-Pareto optimal set for a multi-stage and multi-objective optimization problem, it is necessary to follow the scheme determined in Fig. 6. Here, we characterize the procedure for the first stage and a generalized form for subsequent stages.

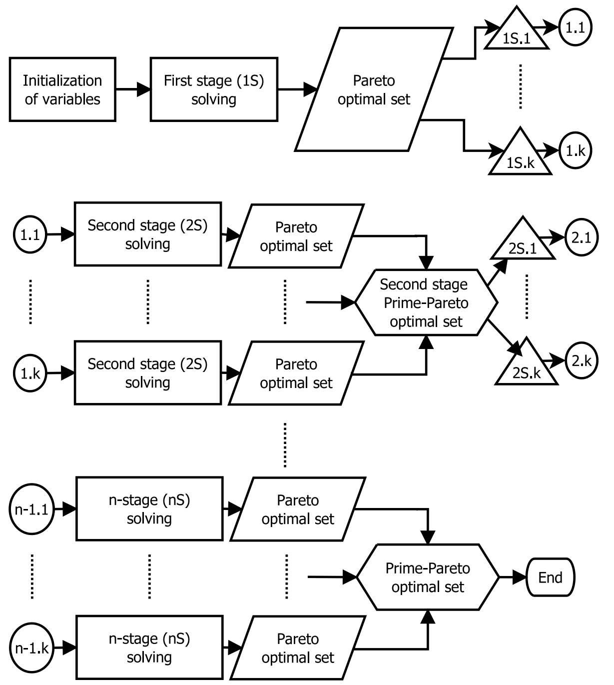

Figure 6. Flow diagram to solve MSMOP with Prime-Pareto approach.

III. Formulation

A. First Stage: Topology Outline

The majority of DSs operates with a radial topology for various technical reasons. Among the most important are, ease protections coordination, and reduction of DS short circuit currents. The conditions to obtain a DS network without branches that form a meshed grid, are based on [9]. To guarantee radiality conditions we define:

$$x_{ij} = \begin{cases} 1 & \textit{if the branch } (i,j) \textit{ is connected}, \forall ij \in \Omega_b \\ 0 & \textit{else} \end{cases}, \quad (7)$$

where, Ω_b is the total branches set and x_{ij} determines the subsets of Ω_b, which are Ω_{ab} and Ω_{ob}. The subset Ω_{ab} contains the active network branches needed to connect demand nodes and Ω_{ob} contains the open lines to ensure the DS radiality. The radiality conditions are:

$$\sum_{ij\in\Omega_{ab}} f_{ij} - \sum_{ji\in\Omega_{ab}} f_{ji} + p_{sb_i} + p_{DG_i} = d_i, \quad (8)$$

$$f_{ij} \le \vec{f}_{ij} \cdot x_{ij}, \quad \forall (i,j) \in \Omega_{ab}, \quad (9)$$

$$0 \le p_{sb_i} \le \vec{p}_{sb_i} = 0, \quad \forall (i) \in \Omega_{sb}, \quad (10)$$

$$0 \le p_{dg_i} \le \vec{p}_{dg_i} = 0, \quad \forall (i) \in \Omega_{dg}, \quad (11)$$

$$\textstyle\sum_{ij\in\Omega_{ab}} x_{ij} = nd - 1, \quad (12)$$

where, f_{ij} is the active power flow between nodes i and j, p_{sb_i} and p_{dg_i} are the active power supplied by the substation and distributed generators at node i, respectively. The active power demand at node i is denoted by d_i. The maximum active power limit of branches and substations are denoted by $\vec{f}_{ij}$ and $\vec{p}_{sb_i}$, respectively, and the number of nodes in the DS is denoted by $nd = |\Omega_n|$. Therefore, as proved in [3], the combination of the power balance constraint (8) and radial constraint (12), results that each load node is connected by a single path to the substation node.

Dijkstra's and Prim's algorithms, from graph theory, are used as auxiliary tools to conserve feasibility of individuals and ensure the radiality constraint fulfillment, using several expansion trees to find the efficient topology of a DS.

For the first stage evaluation, we consider two objective functions: minimizing the investment cost of DS expansion plus the costs of energy losses $f_1(\bar{x})$; and minimization of the expected value of non-supplied energy due to elements connectivity $f_2(\bar{x})$. In accordance with Eqs. (1)-(4), the multi-objective optimization of expansion and operation system planning is characterized by the following decision-making problem:

$$\min \quad \mathrm{ENS}(X_l, X_{sb}, X_{dg}), \mathrm{Costs}_{fs}(X_l, X_{sb}, X_{dg}) \quad (13)$$

$$\text{s.t.} \quad \mathrm{ENS}(X_l, X_{sb}, X_{dg}) \ge 0, \quad (14)$$

where,

$$\mathrm{Costs}_{fs} = (C_{dg} + C_e) \cdot \left[\frac{r \cdot (1+r)^t}{(1+r)^t - 1} \right] + C_{E_p} \quad (15)$$

$$\text{ENS} = \sum_{j=1}^{w} ACIT_j^i \cdot (P_{d\,j}^{\,i} + P_{s\,j}^{\,i}) \quad (16)$$

here X_l, X_{sb} and X_{dg} are decision variables to install lines, substations and DG power plants. We evaluate the total cost of DS expansion and reconfiguration with an annualization factor, including operational costs [10]. C_{dg} is the cost of DG install, C_e is the installed cost of lines and substations, and C_{E_p} is the losses annual cost. The elements lifetime and the discount rate are denoted by t and r, respectively. Moreover, $ACIT_j^i$ is the average customer interruption time of the load point j when i protection devices are installed in the feeder, Pd_j^i and Ps_j^i are, respectively, the average amount of power disconnected and power shed at load point j when i protection devices are installed in the feeder, w is the total number of load points in the feeder. In Eq. (16) the ENS is related to the average time of interruption for every user in the grid, and to shedding or disconnection of loads.

We assume the basic protection scheme of a typical radial distribution network with a main breaker and the absence of isolators on the main feeder. Considering DG as an active power source with no reactive power, leads to a potential increase in investment costs or the incorrect placement of DG due to poor selection of elements capacity of DS [11]. Therefore, we included the generation capacity limits to evaluate the impacts of power injections in DS.

The limits on the voltage profile $(V_i^{\min}, V_i^{\max})$ are defined by regulatory standards, and the thermal constraints $(I_{ij}^{\max})$ by elements capacities,

$$V_i^{\min} \le V_i \le V_i^{\max} \quad \forall i \in \Omega_n, \quad (17)$$

$$I_{ij} \le I_{ij}^{\max} \quad \forall (i,j) \in \Omega_b. \quad (18)$$

B. Second Stage: Shaping of Protection System

From a technical perspective, reliability indices in a distribution feeder are improved by using protective devices such as fuses and reclosers. The acquisition of these devices involves an economic cost. In consequence, the sizing of these schemes must consider the minimization of investment at the same time that reliability of the system is maximized. In this sense, the amount and location of devices in the system is a critical factor to be taken into account in order to accomplish preceding objectives.

Concomitant with Eqs. (1)-(4), the multi-objective optimization of a recloser based protection system planning is characterized by the following decision-making problem:

$$\min \quad \text{ENS}(X), \text{Costs}_{ss}(X) \quad (19)$$

$$\text{s.t.} \quad \text{ENS}(X) \ge 0, \quad (20)$$

$$x_i \in \{0,1\} \quad (21)$$

where,

$$\text{Costs}_{ss} = RC \cdot \left[\frac{r \cdot (1+r)^t}{(1+r)^t - 1} \right] \cdot i + \text{Costs}_{fs}. \quad (22)$$

For the network operator, reliability benefits arise when the Non-Supplied Energy (ENS) is decreased in feeders. To achieve this reduction it is necessary the use of reclosers, which are intended to be placed efficiently. A distribution system yields reliability indicators concomitant with failure and repair rates of the network elements, and the infrastructure topology. Moreover, it is plausible that the addition of a protective device encompasses the ENS improvement. Considered costs of reclosers are normalized with an annualization factor and include investment as operational costs.

Here, the only constraint is related to the physical and theoretical attainable values of ENS. Moreover, decision variables of the problem formulated above are the existence (or not existence) of a protective device in a branch. Thus, a "1" indicates the presence of a recloser on the associated line-segment; meanwhile, a "0" indicates an unprotected branch. The length of the decision-variables vector regards to the extent of branches prone of recloser installation while the index indicates an explicit branch.

IV. Evolutionary Algorithm

Algorithm 1 Fast non-dominated sort

foreach $p \in P$ **do**
  $S_p = \varnothing, n_p = 0$
  foreach $q \in P$ **do**
    if $p \prec q$ **then**
      $S_p = S_p \cup \{q\}$;
    else if $q \prec p$ **then**
      $n_p = n_p + 1$;
  end
  if $n_p = 0$ **then**
    $p_{rank} = 1,\ \mathrm{F}_1 = \mathrm{F}_1 \cup p$;
  $i = 1$
  while $\mathrm{F}_i \ne \varnothing$ **do**
    $Q \ne \varnothing$;
    foreach $p \in \mathrm{F}_i$ **do**
      foreach $q \in S_p$ **do**
        $n_q = n_q - 1$
        if $n_q = 0$ **then**
          $q_{rank} = i + 1, Q = Q \cup q$
      end
    end
    $i = i + 1, \mathrm{F}_i = Q$;
  end
end

Nondominated sorting genetic algorithm II (NSGA-II) is a multiobjective evolutionary algorithm (MOEA) which was proposed by Deb et al. [12]. NSGA-II shows some advantages in comparison with other MOEAs (e.g., Pareto-achieved evolution strategy and strength-Pareto EA). In this way, NSGA-II allows to find a diverse set of solutions, converging near the true Pareto-optimal set. Based on [12], we describe the NSGA-II algorithm in three parts: 1) Fast nondominated sorting approach; 2) Diversity preservation; and 3) Main loop.

The fast nondominated sorting approach allows to identify all individuals on the nondominated fronts. The Algorithm 1 outlines the steps of fast nondominated sorting.

First, for each solution $p \in P$, it is calculated the number of solutions (n_p) which dominate P, also it is conformed the set of solutions S_p that the solution P dominates. Now, for each solution P with n_p =0, the algorithm visits each member $q \in S_p$ and reduce its domination count by one. Then, if for any q the domination count becomes zero, it is located in a list $_Q$ conforming the second dominated front. Finally, this process continues until all fronts are identified.

Algorithm 2 Crowding distance assignment

Designate the size of the analyzed front: $l = |\mathrm{I}|$

foreach i **do**
  set $\mathrm{I}[i]_{\text{distance}} = 0$
end
foreach objective m **do**
  $\mathrm{I} = \mathrm{sort}(\mathrm{I}, m)$;
  $\mathrm{I}[1]_{\text{distance}} = \mathrm{I}[l]_{\text{distance}} = \infty$;
  for $i = 2\mathrm{to}(l-1)$ **do**
    $$\mathrm{I}[i]_{\text{distance}} = \mathrm{I}[i]_{\text{distance}} + \frac{\mathrm{I}[i+1]m - \mathrm{I}[i-1]m}{f_m^{\max} - f_m^{\min}}$$
  end
end

Second, the diversity preservation refers to maintain a good spread of solutions. To achieve this, it is defined two concepts: i) crowding distance; and ii) crowded comparison operator. Crowding distance serves as an estimate of nearness of neighbor solutions, which is useful to choose individuals among front members. The Algorithm 2 outlines the crowding distance computation of all solutions in a nondominated set I, where $\mathrm{I}[i]m$ refers to the m th objective function of the individual $i \in \mathrm{I}$, the parameters $f_m^{\max}$ and $f_m^{\min}$ are the maximum and minimum values of the m th objective function. On the other hand, the crowded comparison operator ($\prec_n$) guides the selection process at the various stages of the algorithm towards a uniformly spread-out Pareto-optimal front. The operator is defined by $i \prec_n j$ if $(i_{\text{rank}} < j_{\text{rank}})$ or $((i_{\text{rank}} = j_{\text{rank}})\text{-and-}(i_{\text{distance}} > j_{\text{distance}}))$ where i_{rank} is the nondomination rank and i_{distance} is the crowding distance.

Finally, the NSGA-II main loop is described. NSGA-II starts creating an initial population P_0, which is sorted based on the nondomination. In this way, to each solution is assigned a fitness equal to its nondomination level (1 is the best level). Then, binary tournament selection, recombination, and mutation operators, are used to create an offspring population Q_0 with N individuals. Next, the Algorithm 3 outlines the main loop steps of NSGA-II. First, a combined population $R_t = P_t \cup Q_t$ is created. Then, the population R_t is sorted according to nondomination. Now, solutions belonging to the best nondominated set F_1 are the best solutions in the combined population and are prioritized above than any other solution in the combined population. If the size of F_1 is smaller than N, we choose all population members F_1 and the remaining members are chosen from subsequent nondominated fronts in the order of their ranking. This procedure is continued until the size of P_{t+1} is equal to N. However, the individuals of last front are chosen using the crowded comparison operator. Finally, the new population P_{t+1} is used for selection, crossover, and mutation (Make-new-population (P_{t+1})) to create a new population Q_{t+1}.

Algorithm 3 NSGA-II Algorithm

$R_t = P_t \cup Q_t$;
$\mathrm{F} = \mathrm{Fast-nondominated-sort}(R_t)$
$P_{t+1} = \varnothing$ and $i = 1$;
repeat
  Crowding-distance-assignment F_i;
  $R_{t+1} = P_{t+1} \cup \mathrm{F}_i$, $i = i + 1$;
until $|P_{t+1}| + |\mathrm{F}_i| \leq N$;
Sort$(\mathrm{F}_i, \prec_n)$;
$P_{t+1} = P_{t+1} \cup \mathrm{F}_i[1:(N - |P_{t+1}|)]$;
$Q_{t+1} = \mathrm{Make-new-population}(P_{t+1})$
$t = t + 1$;

V. CASE STUDY

The radial network used for this analysis is the 33-nodes radial DS shown in Fig. 7. The main characteristics of the system are: 12.66 kV voltage profile, 32 line-segments, 5 tie-lines, and a total demand of 3715 kW plus 2300 kVAR. We refer the reader to [13] for more details on the 33-nodes radial DS modeling.

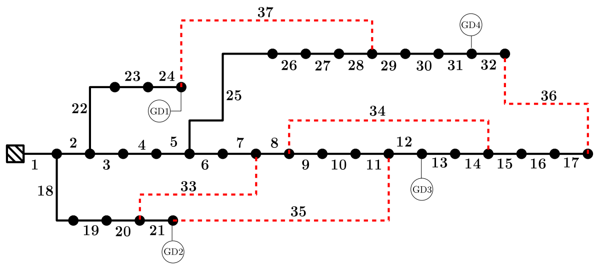

Figure 7. 33-bus radial distribution system.

A. Stage 1 Results

In the first stage, the proposed method provides a set of Pareto efficient solutions (Fig. 8) that represent the evolution of the non-dominated solutions obtained with the NSGA-II algorithm. Five solutions are displayed (panels S1 to S5) to illustrate the properties of the DS, with different combinations of the proposed alternatives in each solution. The main features of these solutions are shown in Table I.

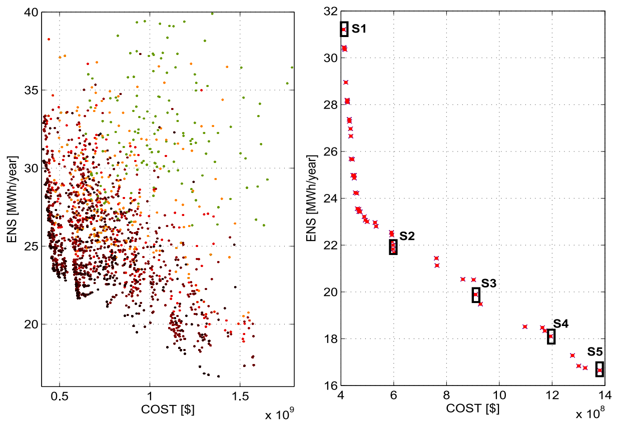

Figure 8. First stage Pareto-front.

TABLE I. OPTIMAL SOLUTION IN THE STAGE 1.

Solution	Lines switched out	Total kW losses	Worst voltage	GD capacity
Base case	33-34-35-36-37	211.22	0.9038	0
Sol. S1	7-9-14-25-32	140	0.932	0
Sol. S2	9-14-26-32-33	96	0.967	G2 1MW
Sol. S3	7-10-14-27-36	102	0.955	G4 1.25MW
Sol. S4	6-10-1427-36	186	0.935	G1 2MW
Sol. S5	6-11-26-34-36	220	0.964	G2/G4 2.5MW

The topology optimization, in the first stage, is strongly influenced by the power losses when DG is installed. The Pareto front show that the great leaps in the expansion and reconfiguration costs are mainly due to DG installation. Despite optimizing the location and size of DG, a high percentage of penetration, as seen in the solution S5, increases the losses level due to the restricted feeder capacity. However, the ENS reduction is not significant in this stage because of the adopted protection scheme for the network design in normal operation. The ENS is obtained by connectivity analysis, therefore, the algorithm refers to topology optimization uniquely when active elements are installed, e.g., DG.

B. Stage 2 Results

Based on the first stage results and formulation presented earlier, the multi-objective optimization of protection system, for each starting topology, is applied through the NSGA-II. As expected, a new set of better solution arises by minimizing ENS when reclosers are efficiently placed. These results are presented in Fig. 9. Here, a bunch of four fronts is attained in order to cover the entire domain of the main front obtained in the first stage.

From the simulations outcome, it is verified a significant premise associated to the reliability of the system. That is, the higher the number of protective devices, the higher the system reliability. Suitably placed reclosers boost the operating time of a power plant whenever faults arise in any part of the system. Henceforth, the overall output and operation time of a DG power plant increase as the number of protective devices proliferates.

In Table II are presented in detail the most common efficient places of reclosers for each obtained optimal set. A number of branches stand as critical points to ameliorate the system reliability. Particularly, the line-segments 2, 18, and 37 become decisive locations since the addition of a recloser in any of these positions increase the system reliability considerably. Finally, by combining the bunch of second stage Pareto-fronts, it is derived the Prime-Pareto optimal set presented in the right side of Fig. 9, which provides better solutions than the reached in the first stage.

VI. CONCLUDING REMARKS

A novel approach to solve multi-stage and multi-objective optimization problems is proposed. The methodology is used to determine the efficient planning of an electrical distribution system. This planning considers infrastructure outlining, and protection system shaping. The approach relies on Pareto optimality concepts and evolutionary algorithms. The 33-nodes radial feeder is successfully tested with NSGA-II, programmed in DigSilent software. An initial Pareto front is achieved with infrastructure outlining. The expansion and reconfiguration problem of DSs require the determination of branches. We use restrictions and graph theory techniques to keep radiality of the system while peak demand is supplied.

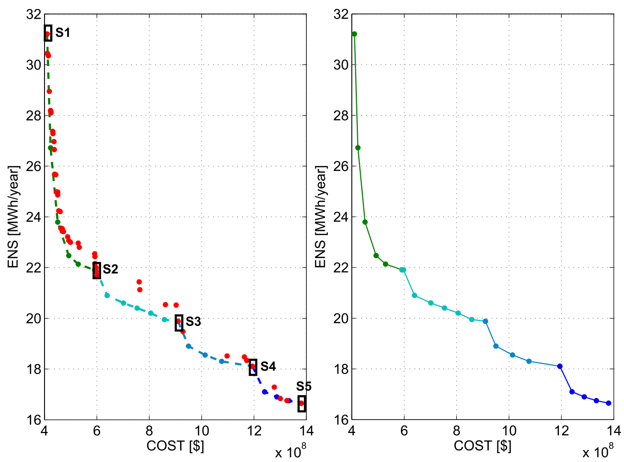

Figure 9. Second stage Pareto-fronts and Prime-Pareto optimal set.

TABLE II. EFFICIENT PLACEMENT RESULTS USING GENETIC ALGORITHM.

Pareto front	Starting point	Recloser positions (branches)
Front 1	Sol. S1	2-18-34-35-37
Front 2	Sol. S2	5-18-34-35-37
Front 3	Sol. S3	2-18-22-33-37
Front 4	Sol. S4	2-18-33-35-37

The methodology to determine the amount of reclosers and their efficient location within a feeder, include reliability assessments to characterize ENS. On the other hand, investment and operation costs are combined into a single objective that conflict with reliability performance objective. This behavior befit with a multi-objective optimization problem that may be solved with MOEA ́s.

Simulation results show the importance of both topology and protection systems planning to enhance the reliability in radial distribution feeders. The proposed solving scheme leads to the Prime-Pareto optimal set concept which may become a generalized method to elucidate multi-stage and multi-objective optimization problems.

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