Optimal Planning of Recloser-Based Protection Systems on DG Enhanced Distribution Systems

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Abstract

Protection systems planning is essential to enhance the reliability of radial distribution feeders. This planning must consider the amount of devices as their efficient placement in the feeder. Moreover, distributed generation (DG) has been largely considered as an alternative to increase the operation performance of distribution systems, besides its merely function to provide energy. Protective devices, such as reclosers, allow DG to operate in island mode decreasing the non-supplied energy (ENS). This paper addresses efficient placement of normally open reclosers (NORs) and normally closed reclosers (NCRs) in addition to the appropriate quantity of these devices. Efficient planning of NORs is attained by minimizing active power losses and ENS applying the aggregating function approach together with a genetic algorithm (GA). The economic theory of the firm, together with evolutionary algorithms, is used to derive the optimal planning of NCRs. A single-objective optimization problem is developed in order to minimize ENS. Furthermore, GA and differential evolution (DE) are implemented to solve the decision-making problem. Additionally, a multiobjective optimization is defined to reduce SAIDI, SAIFI, and costs. This approach yields optimal planning of NCRs by applying revised non-dominated sorting genetic algorithm (NSGA-II) and non-dominated sorting differential evolution (NSDE). Finally, simulations are developed on a real test feeder in two cases: without DG and with 6 MW penetration of distributed sources.

To my parents, my brother and all my family. For being the mainstay in all that I am, for your teachings in both academy and life, and for your inconditional love and support.

To my advisor and co-advisor, for your tips, guidance and support in all this process.

To my friends and colleagues, for advices, and both good and bad moments.

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Chapter 1

Introduction

The main purpose of the planning stage and operation of a power distribution system is to satisfy the energy demand as economically as possible, ensuring acceptable indices of quality and continuity of the service [2]. Nevertheless, previous objectives are in conflict whereas the enhancement of reliability indices requires large investments. Therefore, most of the time, the network operator (NOp) designs a distribution system (DS) attaining the basic requirements of reliability and quality that are established in the regulation.

Currently, given the smart grid concept, automated operation improves the reliability indices on distribution feeders. That is, there is a reduction in indices such as SAIFI, SAIDI, CAIDI, ASAI, among others. The automation allows the NOp to manage, control, and operate efficiently available resources on the system, such that suitable operation is given automatically (i.e., without manual intervention). In addition, it is essential to optimize the feeder operation taking into account the benefits obtained by the islanded operation of distributed generation (DG) when a fault event arises in the system.

From a technical perspective, the reliability indices can be enhanced with the use of protective devices (e.g., fuses and reclosers) and disconnectors, which allow automation in the system. Considering that the acquisition of these devices involves an economic cost, it is necessary to size these schemes by minimizing investment and maximizing the improvement of the reliability indices. In this sense, the number and location of devices in the system are critical variables to accomplish preceding objectives. Here, we focus on recloser-based protection systems, which function under two schemes: i) normally open reclosers (NORs), located at the open tie points of the feeder ensuring a backup supply when the main source is not available; ii) normally closed reclosers (NCRs), located within the DS providing capability to isolate a fault section and realizing self-healing of the grid. Thus, the protection system planning is divided into two stages; to be precise we consider the determination of efficient open tie points and the optimal amount along with suitable location of reclosers within a feeder.

According to the literature, the optimal placement of devices in a DS is a complex problem. This decision making has been addressed by several authors. Research progress in this area can be divided in terms of the generation profile within a feeder, i.e., feeders with or without DG. In the case of non-DG feeders, a Pareto multiobjective optimization is presented in [2], based on ant colony system (ACS), which minimizes both total costs and reliability indices such as SAIFI and SAIDI. A non-linear programming approach, along with a genetic algorithm (GA), is proposed by da Silva et al. [3]. This approach identifies the position of reclosers on a radial feeder considering the minimization of SAIFI. Moreover, these authors present a cost minimization problem solved with tabu search (TSA) and GA [4], [5]. Dehgani et al. [6] realize a compound index optimization such that SAIFI, SAIDI and MAIFIe are minimized by using GA. Moreover, Sohn et al. [7] introduce a linear binary programming which aims to minimize investment costs of reclosers. On the other hand, in the case of DG enhanced feeders, Wang et al. [8] implement ACS to minimize an index composed by SAIFI and SAIDI. In this line, Li et al. [9] change to multi-population GA to solve this index optimization problem. Pregelj et al. [10] include MAIFIe in the composite index and make use of GA to solve the decision making. Besides, Greatbanks et al. [11] and Khoshbakht et al. [12] optimize the placement of reclosers as well as DG within the feeder. These authors implement GA to reduce reliability indices and investment costs.

This paper provides an approach to find efficient open tie points on a DS. Here, a GA is applied in pursuance of both losses and ENS minimization taking into account technical and regulatory constraints. The outcome of this methodology is the suitable placement of NORs. On the other hand, we propose a methodology to achieve optimal sizing of a protection system on a DG enhanced distribution feeder, as well as efficient positioning of NCRs. To the best of our knowledge, efficient sizing, jointly with ideal location of protective devices, has not been yet considered in the literature.

We introduce a single-objective optimization problem (SOOP) based on economic theory. Here, cost minimization of non-supplied energy (ENS) is achieved by applying evolutionary algorithms (EAs). Moreover, we consider a Pareto-based multiobjective optimization to enhance SAIFI and SAIDI at the same time that investment costs are minimized. The output of this optimization is a set of efficient solutions, obtained with the application of multiobjective evolutionary algorithms (MOEAs), which provide the amount and position of NCRs in the feeder.

The remainder of this paper is organized as follows. In section II efficient planning methodologies of protection systems are proposed; where the open tie point, economic theory of the firm, and multiobjective optimization approaches are described. Optimization problems formulation is presented in Section III. Section IV presents the EAs and MOEAs to solve optimization problems. Here, the GA, differential evolution (DE), revised non-dominated sorting genetic algorithm (NSGA-II), and non-dominated sorting differential evolution (NSDE) are detailed. The test system is given in section V, and simulation results are provided in section VI. Finally, conclusions are drawn and future research is suggested.

Chapter 2

Proposed Approaches

As stated hereinbefore, the NOp decision-making concerning to planning of recloser-based protection systems is divided into placement of NORs and NCRs, determining the amount of these protection devices. In first place, the NORs placement is realized by minimizing NOp operational costs with reference to active power losses and ENS. Feasible areas are defined to install an open tie point that preserves feeder radiality and energy provision to all loads. On the other hand, NCRs settlement and quantification are effectuated from two perspectives. The first one corresponds to a single-objective optimization orientated to economic efficiency, whilst the second one concerns to a Pareto-based multiobjective optimization.

2.1 Optimal Open Tie Points

Open tie points in Radial DSs determine backup points (when fault events arise in a feeder), the amount of load, and the length of line-segments. These parameters establish operation indicators such as active power losses, voltage profile, elements loading, and quantity of fault events within a year. Thus, the efficient location of these open junctions enhances the operation parameters. Here, we focus on losses decrease and ENS reduction.

Consider the DS shown in Fig. 2.1.a, feeder 1 has ten load points, feeder 3 supplies six load points while the feeder 2 delivers energy for two load points. Assuming a scale drawing the feeder 1 is the longest, though feeder 2 is the shortest. It is presumable that if all load points demand the same energy feeder 1 has also the greater losses.

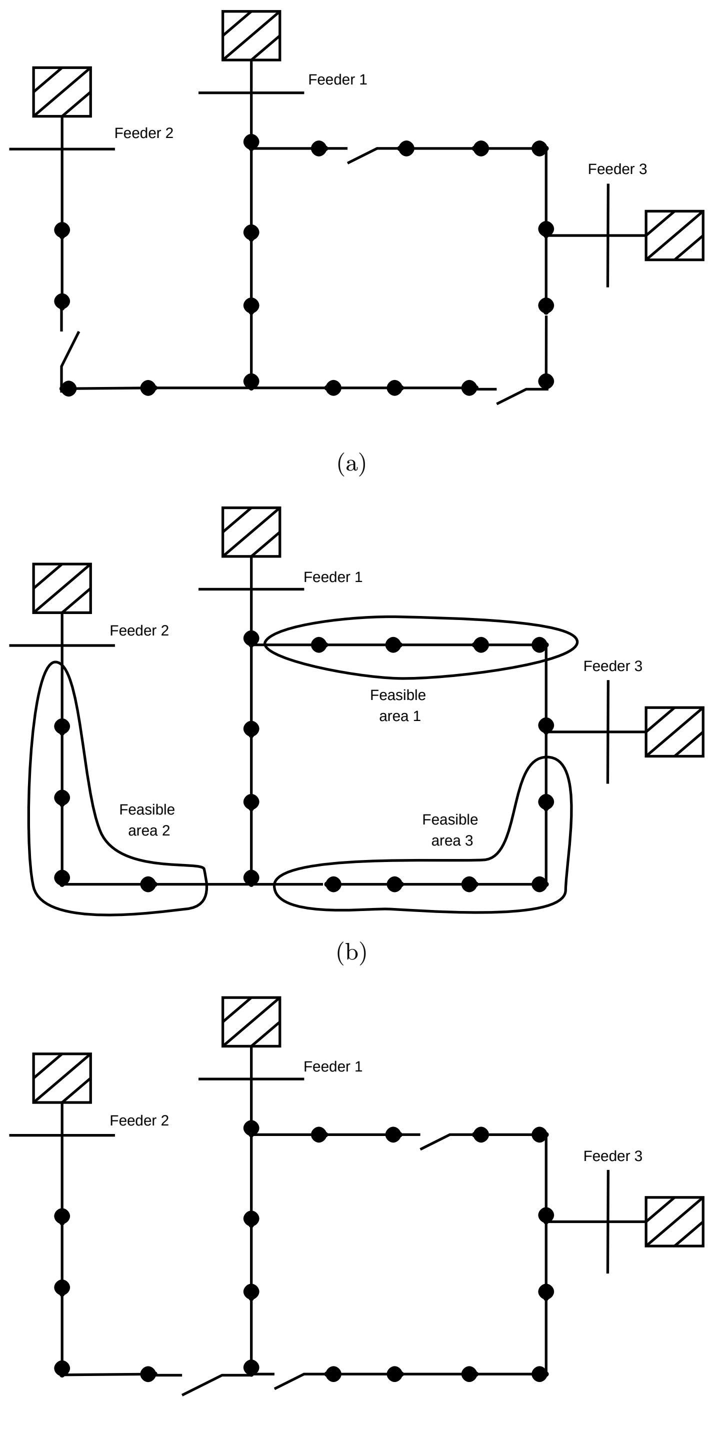


Figure 2.1: Hypothetical DSs for open tie points. a) DS with inefficient located NORs. b) Feasible areas prone of NOR installation. c) DS with efficient located NORs.

In this fashion, the open tie points can be reallocated in order to balance the load and length of feeders. As seen below, this problem is very similar to the placement of NCRs. Nonetheless, here new constraints arise, namely radiality preservation and attendance of all load points. For this purpose refer to Fig. 2.1.b where we propose the definition of feasible areas to install NORs. In these areas a switch is replaced by a line-segment, in consequence the extent of branches are prone to function as open tie points. In pursuance of meeting the above mentioned constraints, only one NOR must to be installed per feasible area.

The decision maker determines feasible areas providing a filter to the extent of the search space. This limitation reduces complexity and time exploration over the landscape. The entire search space of the reduced problem is equal to the product of feasible areas alternatives. In this hypothetical case the landscape size is 150 solutions. As long as the number of branches in a feeder increases, the search space is augmented. Besides, since the solutions are combinatorial, EAs stand as the main alternative to solve this optimization. Here, a GA is used to find efficient locations of NORs. Fig. 2.1.c shows a feasible output of this optimization, the obtained feeders are more load and length balanced than the base feeders (Fig. 2.1.a).

2.2 Economic Theory of the Firm

In this approach, efficient placement of NCRs is performed using EAs by minimizing the ENS of a radial feeder. On the other hand, we apply the economic theory of the firm concepts toward the optimal sizing of a protection system, i.e., the ideal number of devices is defined.

As Todaro states [13], from the point of view of a producer agent, the economic efficiency refers to "the use of production factors in combinations of low costs, consumption and expenditure allocation that maximize net benefits". Thus, in general terms, the producer agent problem is to maximize its profit by setting appropriate levels of production factors. The optimal producer level arises when the marginal benefits equal the marginal costs [14].

In a DS the decisions are taken by the NOp, which is analog to the producer agent in an economic system. For the NOp, in terms of the distribution automation system, the benefits come by decreasing ENS, and the production factors to achieve this reduction are reclosers. It is intuitive that the addition of a protective device causes an improvement in the reliability indices. That is, the greater the number of protective devices, the greater the system reliability.

To approximate the NOp to a producer agent, let **E** be the vector of the system ENS and **C** the vector of total costs (fixed costs plus variable costs), both depending on the amount of devices settled in the feeder.

$$\mathbf{E} = \{e_0,\ e_1,\ \cdots, e_n\}, \tag{2.1}$$

$$\mathbf{C} = \{c_0,\ c_1,\ \cdots, c_n\}. \tag{2.2}$$

Where e_0 is the ENS of the system without protection devices, c_0 is the total cost of zero protection devices (i.e., \$0), e_i is the ENS of the system with i protection devices located optimally, and c_i is the total cost of i protection devices. Considering that the NOp decision variable is the amount of protection devices, marginal values of ENS ($\dot{\mathbf{E}}$) and total costs ($\dot{\mathbf{C}}$) can be defined in function of i.

$$\dot{\mathbf{E}} = \{e_0 - e_1,\ \cdots, e_{n-1} - e_n\} = \{\triangle e_1,\ \cdots,\ \triangle e_n\}, \tag{2.3}$$

$$\dot{\mathbf{C}} = \{c_1 - c_0,\ \cdots, c_n - c_{n-1}\} = \{\triangle c_1,\ \cdots,\ \triangle c_n\}. \tag{2.4}$$

Thus, we define the marginal benefit $\dot{\mathbf{B}}$ of the NOp when the ENS of the system is decreased. In this case, π represents the monetary benefit of the NOp for each unit of energy delivered to consumers.

$$\dot{\mathbf{B}} = \pi \cdot \dot{\mathbf{E}} = \{\pi \cdot \triangle e_1, \pi \cdot\ \triangle e_2,\ \cdots,\ \pi \cdot \triangle e_n\}. \tag{2.5}$$

Consequently, the decision problem of the NOp has been approached to the firm maximization problem. Hence, the optimum number of protective devices in the DS is the one that meets the following marginality condition:

$$\dot{\mathbf{B}} = \pi \cdot \dot{\mathbf{E}} = \dot{\mathbf{C}}, \tag{2.6}$$

by solving (2.6), we must find the optimal number $\hat{i}$ of devices that satisfies:

$$\pi \cdot \triangle e_{\hat{i}} = \triangle c_{\hat{i}}. \tag{2.7}$$

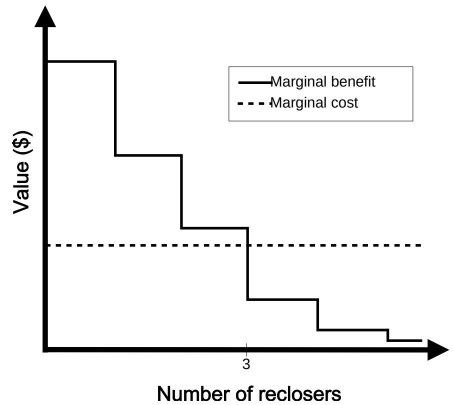


Figure 2.2: Marginal curves of hypothetical case.

Finally, the maximum profit $\hat{p}$ of the NOp is defined as:

$$\hat{p} = \sum_{i=1}^{\hat{i}} \pi \cdot (\triangle e_i) - c_{\hat{i}} \quad \xrightarrow{yields} \quad \hat{p} = \pi \cdot \left(e_0 - e_{\hat{i}}\right) - c_{\hat{i}}. \tag{2.8}$$

Consider the hypothetical case of Fig. 2.2, the marginal curves intersect each other when three reclosers are placed in the feeder, meeting the condition stated in (2.7). Thus, this is the protection system efficient size. This approach can be applied under a primary condition: the marginal benefit curve must to be degressive on its entire domain. Moreover, reclosers acquisition yields a constant marginal cost since there are no scale economies nor scale diseconomies.

2.3 Multiobjective Optimization

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. that is, it is necessary to sacrifice the performance of one or more objectives to enhance the other ones. Let us consider, in the context of this paper, the decision-making involved in the sizing of the protection system and the placement of NCRs. 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 NOp is not willing to invest. Hence, the NOp decision-making process must to be developed taking into account several objectives such as high levels of reliability together with low costs.

As stated by Deb [15], a multiobjective optimization problem (MOOP) has a vector composed by objective functions which are to be minimized or maximized. Besides, a set of constraints describes the feasible region of solutions. On the other hand, Coello et al. [16] bring the words of Osyczka [17] to define the MOOP: "a vector of decision variables which satisfies constraints and optimizes a vector function whose elements represent the objective functions. These functions form a mathematical description of performance criteria which are usually in conflict with each other. Hence, the term *optimize* means finding such a solution which would give the values of all the objective functions acceptable to the decision maker". Generally speaking, a MOOP can be defined as follows [16]:

$$\begin{array}{ccc} \text{Min/Max} & f_u\left(x\right), & u = 1, 2, \ldots, M \\ \text{s.t.} & g_j\left(x\right) \geq 0, & j = 1, 2, \ldots, J \\ & h_k\left(x\right) = 0, & k = 1, 2, \ldots, K \\ & x_i^L \leq x_i \leq x_i^U, & i = 1, 2, \ldots, N \end{array} \tag{2.9}$$

This formulation contains a solution vector of N decision variables, where the last set of constraints determines the lower and upper bounds for each decision variable. Besides, the problem is described by J inequality and K equality constraints. Moreover, it is important to denote that despite is feasible to solve a mixed optimization problem (i.e., with objectives that requires to be minimized or maximized), it is better to use the duality principle in order to convert all maximization objectives into minimization objectives. Thus, the handling of the MOOP becomes less complex.

As reported by Deb [15], the aggregating function approach and the ε-constraint method have been the most popularly mechanisms to adequate a MOOP into a single-objective optimization problem. Thus, the traditional and widely studied methods to solve a SOOP can be applied. In first place, the aggregating function approach combines all the objectives into a single one using one or a set of arithmetical operations, such as addition, multiplication, among others [15]. Usually, a weighted sum of the objectives is carried out, where a set of weights must to be determined in order to state the importance of every objective. Evidently, the output of such optimization strategy has a strong dependency on the decision maker perspective, which chooses the weights. On the other hand, the ε-constraint method optimizes one objective while treats the rest as constraints by restraining each of them with predefined bounds. As in the aggregating function approach, the output of this optimization strategy depends on the decision maker point of view, which provides the boundary limits of each objective. However, whereas the outcome of above solution strategies depends on predefined values and the multiobjective decision-making is actually treated as a SOOP, a true multiobjective optimization technique is utilized. This technique is usually known as the Pareto approach.

Coello et al. [16] asserts that the Pareto approach look for compromises among objectives instead of finding a single solution. Therefore, it is improper to apply the traditional optimality concept for a unique global optimal solution. Vilfredo Pareto (in 1896) generalized a concept proposed by Edgeworth (in 1881) that is utilized as the notion of optimality for a multiobjective problem. In words, this notion can be defined as: if there is no feasible solution rather than $\overrightarrow{x}^*$ which improves one objective function without impairing the rest, then $\overrightarrow{x}^*$ is Pareto optimal. Formally, Coello et al. [16] define this notion as follows: A point $\overrightarrow{x}^* \in \Omega$ is Pareto optimal if for every $\overrightarrow{x} \in \Omega$ and $I = \{1,\ 2, \ldots, M\}$ either,

$$\forall_{u \in I} \left(f_u \left(\overrightarrow{x} \right) = f_u \left(\overrightarrow{x}^* \right) \right) \tag{2.10}$$

or, there is at least one $u \ \in$ I such that

$$f_u \left(\overrightarrow{x} \right) > f_u \left(\overrightarrow{x}^* \right). \tag{2.11}$$

As stated before, in the Pareto approach there is a set of trade-off solutions instead of a unique solution. The solutions that compose this set must to satisfy the Pareto optimality condition. Due to the Pareto optimal solutions are located in the bounds of the feasible outcome region; this bunch of results is called the Pareto front.

The task of finding the Pareto front is not easy. Specifically, the determination of an analytical expression of the bound that contains these points is often impossible to realize [15]. Nevertheless, there are such methods that provide the Pareto front as a result of heuristic search. The Pareto-based algorithms use the principle of dominance, which compares two feasible solutions on the basis of whether one dominates the other solution or not. Abraham et al., in [18], define the conditions that must be satisfied in order to x^1 dominates x^2:

1. The solution x^1 is no worse than x^2 in all objectives.
2. The solution x^1 is strictly better than x^2 in at least one objective.

The Pareto-based algorithms look for non-dominated solutions, i.e., solutions that satisfy the aforementioned conditions. When a significant sample of these solutions is attained it can be implied that a Pareto Optimal Set (POS) of solutions is achieved, which is the main purpose of this algorithm.

Let us consider, once again, the multiobjective decision-making involved in the sizing of the protection system and the placement of NCRs. This process, as seen below, is described by nonlinear objective functions and combinatorial solutions. Thus, it leads to a nonlinear combinatorial multiobjective problem (NCMOP). This kind of problem implies a high complexity level, besides the complexity of the Pareto approach application, since the solution techniques often do not have global optima convergence proofs. Thus, MOEAs are applied, which in general terms implement EAs together with the Pareto multiobjective approach.

In the literature a considerable number of authors have developed different MOEAs. Srinivas and Deb [19] present the non-dominated sorting genetic algorithm (NSGA). In [20], Horn et al. present the niched-Pareto genetic algorithm (NPGA). The multiobjective genetic algorithm (MOGA) is proposed by Fonseca and Fleming [21]. Zitzler and Thiele, in [22], introduce the strength Pareto evolutionary algorithm (SPEA). Finally, the Pareto archived evolution strategy is proposed by Knowles and Corne [23]. Moreover, there are enhanced versions of some MOEAs such as the NSGA-II [24], SPEA-II [25], and the revised version of the NPGA, proposed by Erickson et al. [26], called the NPGA-II.

Chapter 3

Problems Formulation

3.1 Optimal Open Tie Point

Since the configuration of DS tie points implies impacts on operation performance and robustness to failures, such indicators for both cases must to be considered. Here, active power losses and ENS determine the fitness of a feasible solution. Although this optimization can be treated as a MOOP, we utilize the aggregating function approach to convert the problem to a SOOP. To that end, active power losses are multiplied by its costs for the NOp and aggregated with the cost for the NOp when an energy unit is not delivered to consumers. Hence, the decision-making is related to costs minimization. This optimization has a non-linear and non-differentiable objective function, and combinatorial solutions. The optimal placement of NORs is characterized by the following optimization:

$$\begin{array}{ll} \min & \text{Losses cost} + \text{ENS cost} \\ \text{s.t.} & V_{\min} \leq V_v \leq V_{\max} \\ & I_{v,s} \leq I_{v,s}^{\max}, \end{array} \tag{3.1}$$

where,

$$\text{Losses cost} = \sum_{b=1}^{l} L_b \cdot \text{LF} \cdot 8760 \cdot (\text{G+T+D}) \tag{3.2}$$

$$\text{ENS cost} = \sum_{j=1}^{m} ACIT_j \cdot (Pd_j + Ps_j) \cdot \pi_j \tag{3.3}$$

Here, L_b are the active power losses of branch b, LF is the losses factor for the NOp, G is the energy generation cost, T is the transmission network usage fee, D is the distribution network usage fee, and l is the total amount of branches in the feeder. In the context of ENS cost, $ACIT_j$ is the average customer interruption time of the load point j, Pd_j and Ps_j are, respectively, the average amount of power disconnected and power shed at load point j, m is the total number of load points in the feeder. The constraints are related to operation limits. Voltage profile boundaries (V_{min}, V_{max}) are defined by regulatory standards, and the thermal boundary between nodes v and s ($I_{v,s}^{max}$) is defined by conductor capacity.

3.2 Economic Theory of the Firm

In order to characterize the marginal benefit and the marginal cost of the NOp for a specific feeder, it is essential to find the ENS of the system for different amount of reclosers placed suitably. Thus, another optimization problem emerges, namely the optimal placement of a certain quantity of protection devices in a DS. As stated in [2]- [10], this optimization is a complex problem since it is described by a non-linear and non-differentiable objective function, and combinatorial solutions. The optimal placement of NCRs is characterized by the following optimization:

$$\begin{array}{ll} \min & \sum_{j=1}^{m} ACIT_j^i \cdot \left(Pd_j^i + Ps_j^i\right) \\ \text{s.t.} & \text{Number of protection devices} = i. \end{array} \tag{3.4}$$

Where $ACIT_j^i$ 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.

The previous formulation indicates that for each i component of the vector $\mathbf{E}$ it is necessary to solve the aforementioned decision-making problem. Thus, this problem must be solved n times, i.e., until the information of the vector $\mathbf{E}$ is complete. Here, the only constraint is the number of devices in the system. On the other hand, when the ENS costs are not homogenous for all the m load points of the feeder, it is necessary to obtain directly the marginal benefit vector $\dot{\mathbf{B}}$. To that end, the optimization problem in (3.5) must be solved.

$$\begin{array}{ll} \min & \sum_{j=1}^{m} ACIT_j^i \cdot \left(Pd_j^i + Ps_j^i\right) \cdot \pi_j \\ \text{s.t.} & \text{Number of protection devices} = i. \end{array} \tag{3.5}$$

Where π_j is the average monetary benefit of the NOp for each unit of energy delivered to consumers belonging to the load point j.

3.3 Multiobjective Optimization

As mentioned before, the addition of protective devices into a DS improves the reliability indices. In this case, we focus on SAIFI and SAIDI reduction. Nevertheless, improving these indices requires recloser investments, thus leading to conflictive objectives, desired condition to attain a set of efficient solutions for a decision-maker. In accordance with the standardized MOOP formulation (2.9), the multiobjective optimization of a recloser-based protection system planning is characterized by the following decision-making problem:

$$\begin{array}{cc} \min & \mathrm{SAIFI}\,(x)\,,\ \mathrm{SAIDI}\,(x)\,,\ \mathrm{Costs}\,(x) \\ \text{s.t.} & \mathrm{SAIFI}\,(x)\,,\ \mathrm{SAIDI}\,(x)\,,\ \mathrm{ENS}(x) \geq 0 \\ & x_i \in \{0,1\}\,, \end{array} \tag{3.6}$$

where,

$$\mathrm{SAIFI} = \frac{\sum_{j=1}^{m} ACIF_j \cdot C_j}{\sum_{j=1}^{m} C_j} \tag{3.7}$$

$$\mathrm{SAIDI} = \frac{\sum_{j=1}^{m} ACIT_j \cdot C_j}{\sum_{j=1}^{m} C_j} \tag{3.8}$$

$$\mathrm{Costs} = RC \cdot \left[\frac{r \cdot (1+r)^t}{(1+r)^t - 1} \right] \cdot Qr\ . \tag{3.9}$$

Here, $ACIF_j$ is the average customer interruption frequency of the load point j, C_j is the amount of customers in load point j. On the other hand, considered costs of reclosers are normalized with an annualization factor and include investment as operational costs. In (3.9), r is the discount rate for the NOp, t is the reclosers lifetime, Qr the quantity of reclosers placed, and RC the total costs of a single recloser (fixed costs plus variable costs). Constraints are related to physical and theoretical attainable values of reliability indices. Moreover, decision variables of the problem formulated above belong to binary domain.

Chapter 4

Case Study and Results

4.1 Case study

The proposed approach is tested on a 70-nodes and 8-laterals distribution feeder. This DS is derived from a real system that belongs to the North American utility PG&E (Fig. 4.1). This test system has been largely used in the literature to analyze the optimal placement of several elements in a feeder. In [1], authors propose this model to place capacitors optimally. Besides, a loop version is used together with DG penetration to achieve optimal placement of protective devices [8], [10].

Simulations are applied on the radial configuration of this distribution network considering two generation profiles: i) DG plants free feeder; ii) six DG plants each with 1 MW installed capacity. Moreover, the natural condition of the feeder is the absence of protection devices. Nevertheless, as seen below, the efficient placement of reclosers enhance the system reliability. The specific parameters of the system are presented in [1]; such as line-segments impedances, active and reactive load demands, length of branches, among others.

In pursuance of reliability assessments, it is necessary to define a fault model for each element in the feeder. Toward simplification solely line-segment faults are considered. We assume a line-segment failure rate of 0.22 outages per annum and per kilometer, and also three hours repair duration when a fault event arises in the system. Besides, a homogeneous monetary benefit π equal to 0.34 US$/KWh, and an annual equivalent cost of 2900 $US for each recloser in the feeder. Concerning to reclosers operation, we

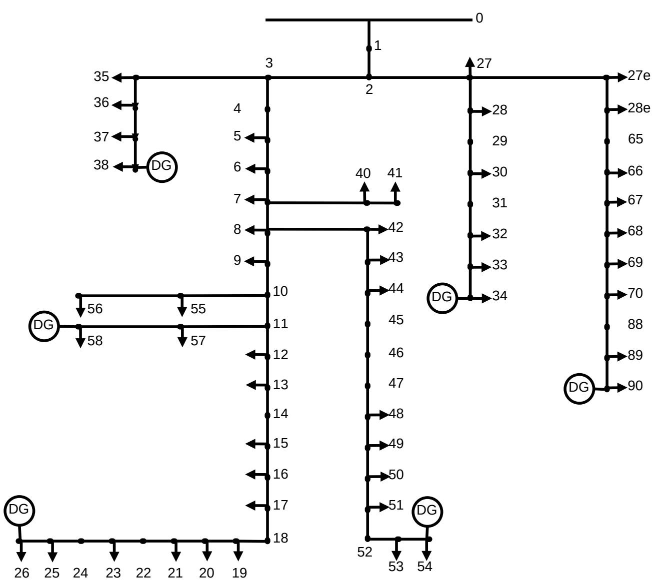


Figure 4.1: 70-nodes test feeder with DG penetration [1].

establish one minute as the switching time of these devices, and it is assumed that the nearest device to the fault location actuates to isolate the flawed area.

On the other hand, in consideration of open tie points simulation, we model a duplicate of the original feeder to use as supply backup. In this direction, the lateral terminals are defined as open unions to the new reflected feeder. that is, an end point is linked to its analogue through a NOR device, e.g., the busbar I.38 of the reflected circuit is the backup of busbar 38 in the original feeder. The proposed DSs are illustrated in Fig. 4.2. These feeders are considered with both generation profiles defined earlier.

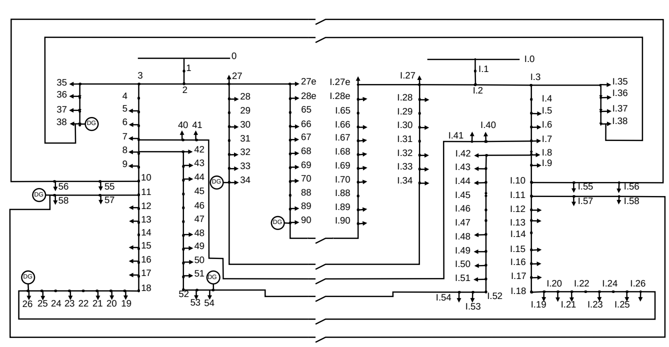


Figure 4.2: Backup-enriched DSs with mirrored version of 70-nodes test feeder with DG penetration [1].

4.2 Optimal Open Tie Point Results

Endeavoring for efficient placement of NORs in conjunction with radiality preservation and full load attendance, the set of branches prone to NOR installation are defined. The quantity of feasible areas equals the number of laterals. Each NOR placed on the backup-enriched DS (Fig. 4.2) is replaced by a line-segment configured with the parameters of neighboring lines. Thus, a set of eight feasible areas to install NORs are obtained. The parameters of these areas are detailed in Table 4.1.

In first place, the application of the GA by minimizing operation costs in a distribution feeder without DG, results in the original feeder configuration. that is, the NORs are located among the original DSs terminals. This outcome was foreseeable since the length and load were already balanced in the DS configuration of Fig. 4.2. Willfully, the case study for this approach was modeled using a mirrored version of the 70-nodes test feeder looking for this balance in order to verify the algorithm convergence.

Moreover, the approach appliance on DG-enhanced feeders leads to substantial results. At first, an exchange of loads and branches occurs between both feeders, reallocating NOR devices. Nonetheless, the most meaningful outcome is the DG balancing with the assignation of three power plants to each DS. These effects trigger losses reduction and reliability improvement. Hence, costs minimization is achieved by efficient placement of NORs designating terminal buses for each feeder. Hither, the original feeder is turned into a definitive DS with 3 MW installed capacity and 75 nodes. This result is shown in Fig. 4.3.

Table 4.1: Feasible areas of backup-enriched DS

Feasible area	Initial branch	End branch	Number of branches
1	10-55	I.10-I.55	5
2	11-57	I.11-I.57	5
3	11-12	I.11-I.12	31
4	27-28	I.27-I.28	15
5	27-27e	I.27-I.27e	23
6	3-35	I.3-I.35	9
7	7-40	I.7-I.40	5
8	8-42	I.8-I.42	27

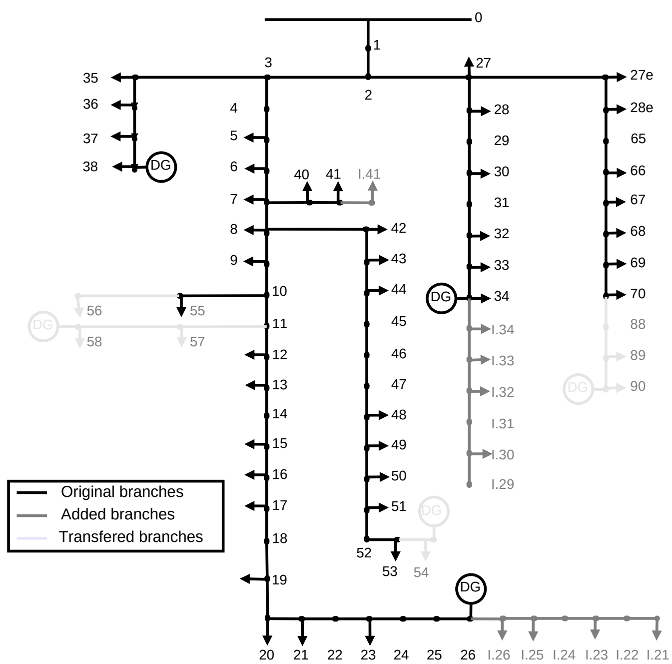


Figure 4.3: Radial feeder with efficient placement of NORs.

4.3 Economic Theory of the Firm Results

Based on the EAs, the marginal benefit of the NOp with efficient location of the protection devices is characterized. Simulation results for the original feeder (Fig. 4.1) with no DG penetration and the proposed algorithms are presented in Tables 4.2-4.3. In first place, the simulation results proves one of the key definitions related to the reliability of the system. That is, the higher the number of protective devices, the higher the system reliability. The ENS behaves as a decreasing function with respect to the amount of reclosers in the feeder. Furthermore, the DE algorithm shows better results and more consistency than the GA.

Figs. 4.4-4.5 show the curves of marginal benefits and costs for each EA. The behavior of the marginal benefit is degressive on its entire domain (in both GA and DE), an essential condition to apply the theory of the firm principle. In GA case four protection devices satisfy the optimality condition due to the intersection of both marginal benefit and cost curves at this point. On the other hand, in DE case three reclosers located at 8-9, 27-28 and 8-42, satisfy the optimality condition. Tables 4.2-4.3 show that the DE algorithm achieves better reliability indices, i.e., lower ENS in the

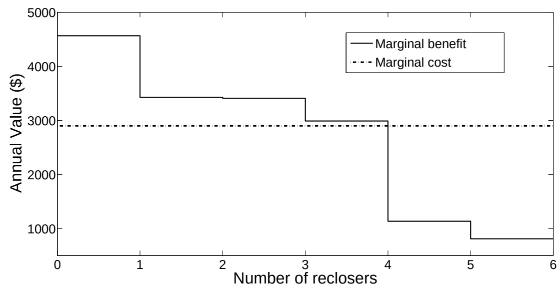


Figure 4.4: Marginal curves using GA on non-DG feeder.

feeder for a set of suitably placed reclosers. Based on Figs. 4.4-4.5, this result can be originated by obtaining the producer net benefit (2.8). In the GA case, although the size of the protection system is larger than the DE case, the producer net benefit ($2792) is lower than the obtained in the DE case ($3027).

Another important scenario to analyze is the penetration of DG in the feeder due to the important impacts that come with its implementation. DG has several benefits that are summarized in [27]. Focusing in the quality of distribution service, the improvement of reliability is feasible due to the possibility of DG to operate in "island mode" forming a micro-grid. Well positioned reclosers increment the operating time of a power plant whenever faults arise in any part of the system.

Hence, the total output and operation time of a DG power plant increase as the number of protective devices proliferates. Additionally, it is assumed that unintentional islanded operation is permitted. In consequence, the average outage time for a set of loads, within an isolated area and downstream of the fault, can be decreased with

Table 4.2: Efficient placement results using GA

i	E (MWh/y)	$\dot{B}$ ($/y)	Recloser positions (branches)
1	50,73	4566,2	8-9
2	40,65	3426,8	8-9, 27-28
3	30,62	3409,8	8-9, 2-27, 44-45
4	21,83	2989,0	8-9, 2-27e, 28-29, 8-42
5	18,49	1135,6	8-9, 27-28, 3-35, 42-43, 28e-65
6	16,11	809,4	8-9, 27-28, 27e-28e, 35-36, 42-43, 50-51

Table 4.3: Efficient placement results using DE

i	E (MWh/y)	$\dot{B}$ ($/y)	Recloser positions (branches)
1	50,73	4566,2	8-9
2	40,01	3642,5	8-9, 8-42
3	29,66	3519,0	8-9, 27-28, 8-42
4	21,25	2859,1	8-9, 27-28, 27e-28e, 8-42
5	17,59	1245,6	8-9, 27-28, 27e-28e, 35-36, 8-42
6	15,82	601,4	8-9, 27-28, 27e-28e, 35-36, 8-42, 50-51

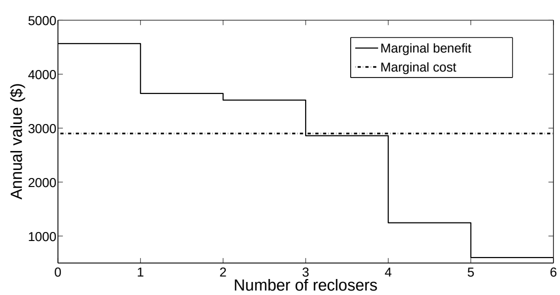


Figure 4.5: Marginal curves using DE on non-DG feeder.

Table 4.4: Efficient placement results using ga on dg enhanced feeder

i	E (MWh/y)	$\dot{B}$ ($/y)	Recloser positions (branches)
1	42,77	7270,6	8-9
2	31,56	3811,1	9-10, 44-45
3	24,22	2495,0	9-10, 2-27, 8-42
4	18,62	1905,0	8-9, 2-27e, 28-29, 43-44
5	15,75	976,7	10-11, 27-28, 35-36, 43-44, 28e-65

Table 4.5: Efficient placement results using de on dg enhanced feeder

i	E (MWh/y)	$\dot{B}$ ($/y)	Recloser positions (branches)
1	42,77	7270,6	8-9
2	30,87	4043,7	8-9, 42,43
3	23,00	2679,0	8-9, 2-27, 8-42
4	15,20	2652,0	14-15, 27e-28e, 45-46, 11-57
5	15,00	68,0	10-11, 2-27, 2-27e, 35-36, 44-45

the presence of DG. Tables 4.4-4.5 present the simulation results of both GA and DE applied on a DG enhanced feeder.

The behavior of the obtained results is very similar to the found before when analyzing the non-DG feeder. That is, the aggregation of protective devices enhances the system reliability, the reduction of ENS is a decreasing function, and the DE algorithm outperforms the GA process in terms of solution quality. Nonetheless, as expected, the ENS of the system is lower in this case. The mere penetration of DG, together with reclosers, reduces the unsupplied energy in about 17 percent.

When overlapping the results of the analyzed cases, some branches stand as crucial points to improve the system reliability. Especially, the line segments 8-9, 27e-28e, and 8-42 become critical locations since the addition of a recloser in any of these positions increase the system reliability significantly.

The marginal benefits and costs of the DG enhanced feeder for each EA are shown in Figs. 4.6-4.7. The function values of the curves decrease on its entire domain, thus the proposed approach is applicable. In both algorithms the intersection of the marginal functions is given when two protection devices are placed efficiently. The penetration of

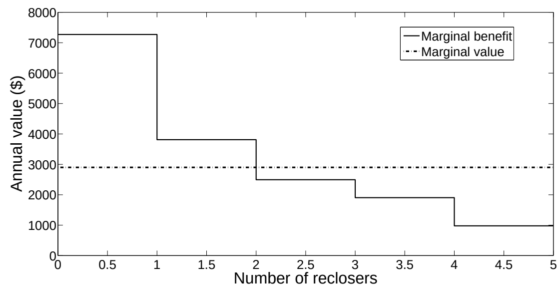


Figure 4.6: Marginal curves using GA on DG enhanced feeder.

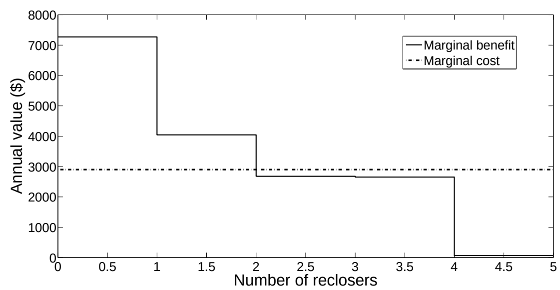


Figure 4.7: Marginal curves using DE on DG enhanced feeder.

DG in the feeder lowers required reclosers to enhance the reliability of the DS since the first device considerably increases the system reliability. This shows the premise that DG improves the ENS of the system when protective devices allow islanded operation.

4.4 Multiobjective Optimization Results

Based on the MOEAs, addressing minimization of SAIFI, SAIDI and reclosers investment costs, the optimal Pareto-front is characterized. Simulation results for the original feeder (Fig. 4.1) with both generation profiles, and the proposed algorithms, are presented in Figs 4.8-4.9. Due to the lack of space, we highlight three representative solutions of the Pareto set, which are presented in detail in Tables 4.6-4.7. A is an extreme solution that completely favors cost minimization, C is an extreme solution that outperforms reliability, and B is the most balanced solution within the optimal set. For instance, alternative A of the Pareto-front without DG in Fig. 4.8 presents high reliability indices but low costs. Meanwhile, alternative C shows greater reliability in contrasts with its excessive costs. Next, as seen in single-objective optimization,

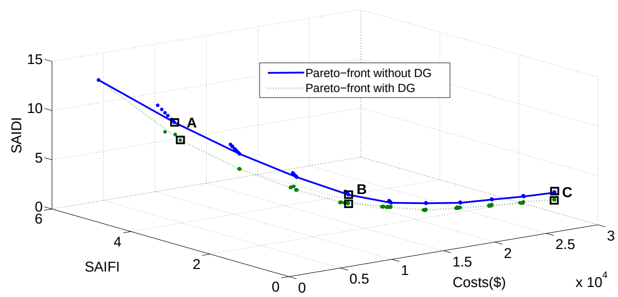


Figure 4.8: NSGA-II non-dominated set of solutions.

Table 4.6: Details of highlighted non-dominated solutions of NSGA-II

Solution		SAIDI	SAIFI	Costs($)	Recloser positions
No DG	A	10,98	3,66	2900	5-6
	B	4,54	1,51	11600	8-9, 27-28, 27e-28e, 42-43
	C	2,49	0,83	29000	3-4, 8-9, 11-12, 17-18, 27-28, 27e-28e, 35-36, 42-43, 44-45, 10-55
With DG	A	9,34	3,51	2900	7-8
	B	3,69	1,52	11600	8-9, 27-28, 27e-28e, 8-42
	C	1,75	0,83	29000	4-5, 8-9, 11-12, 19-20, 27-28, 27e-28e, 35-36, 8-42, 48-49, 67-68

DG penetration enhances system reliability. The Pareto set undergoes a displacement in direction of lesser SAIDI. This reduction reaches a 20 percent on average when compared with the non-DG feeder. In distinction of the curves, the steepest gradient takes place in the range of one to five reclosers. From this point, despite the addition of a recloser heightens reliability, robustness of the feeder increases slightly. Case in point, reliability variance of solution A in comparison with solution B is larger than the dissimilarity between alternatives B and C, even though fewer reclosers are included.

Apropos of results, algorithms feature the efficient placement of reclosers. Several branches are decisive to ameliorate system robustness. In depth, NCRs installation on 8-9, 27e-28e, and 27-28 upgrades system reliability to a high degree. Moreover, when a large number of devices are available, the installation of reclosers encourages the protection of large sections in the feeder. For instance, the section delimited by busbars 3 and 26 encompasses the majority of protective devices. Just after lateral

Table 4.7: Details of highlighted non-dominated solutions of NSDE

Solution		SAIDI	SAIFI	Costs($)	Recloser positions
	A	10,90	3,63	2900	6-7
No DG	B	4,79	1,59	11600	10-11, 27-28, 27e-28e, 42-43
	C	2,55	0,85	29000	3-4, 10-11, 11-12, 21-22, 27-28, 27e-28e, 35-36, 42-43, 44-45, 10-55
	A	9,90	3,66	2900	5-6
With DG	B	3,63	1,52	11600	8-9, 27-28, 27e-28e, 43-44
	C	1,79	0,83	29000	3-4, 8-9, 11-12, 18-19, 27-28, 27e-28e, 3-35, 8-42, 44-45, 67-68

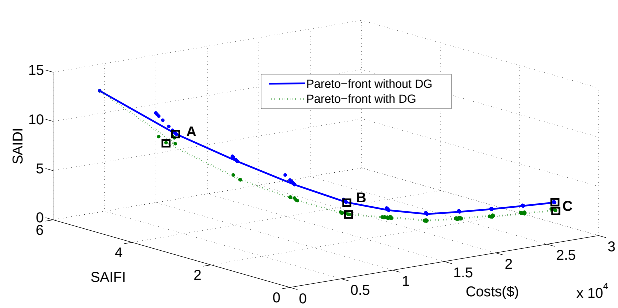
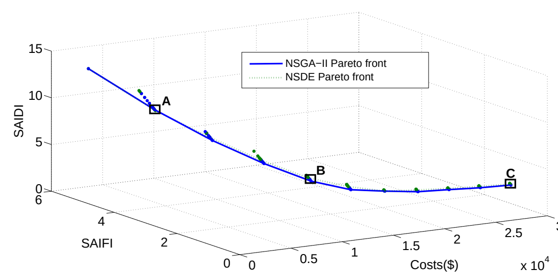
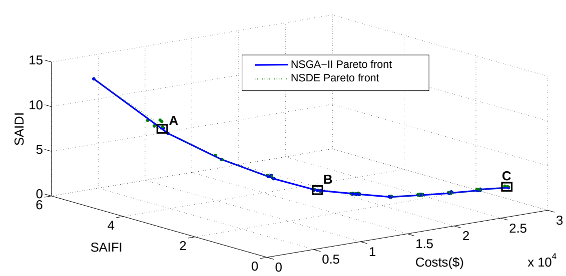


Figure 4.9: NSDE non-dominated set of solutions.



(a)



(b)

Figure 4.10: Comparison of non-dominated sets obtained with MOEAs. a) contrast of NSGA-II and NSDE on non-DG feeder. b) contrast of NSGA-II and NSDE on DG-enhanced feeder.

sections are equipped with reclosers, the main trunk of the feeder is segmented forming zones capable of isolation if a fault arises within these. Furthermore, DG penetration appeals reclosers placed nearby power plants for the sake of microgrids creation. To clarify, consider NSGA-II locations for ninth and tenth devices: i) when DG is included the ninth recloser is displaced from branch 44-45 to branch 48-49, reducing the size of the microgrid delimited by busbars 49 and 54, and discarding four branches that may augment fault probability in the interior of the microgrid; ii) When DG is considered the tenth recloser is relocated from a non-DG lateral to branch 67-68, allowing islanded operation of DG connected to node 90.

In the matter of algorithms comparison, a contrast examination between NSGA-II and NSDE is exposed in Fig. 4.10 for both generation profiles. In free DG feeder scenario the NSGA-II shows better results on account of the slight distance beneath NSDE curve. Alternatively in DG installed case, both MOEAs path passes through solutions separated by almost imperceptible distances. Therefore, this decision making evidences NSGA-II surpassing performance with respect to NSDE, which also achieves an efficient set of alternatives for NORs placement.

4.5 Integral Optimal Planning Results

As informed earlier, the protection system planning is divided into two stages: i) NORs placement, determining the length of line-segments, the demand of energy, and the terminals of the feeder; ii) NCRs placement, defining the positions and the amount of protective devices within the feeder. In optimal open tie point simulations we succeed on the original DS reshaping attaining laterals with new terminal busbars and balancing DG on feeders. Nevertheless, previous NORs placement was realized on the original feeder of Fig. 4.1. In contemplation of an integral planning of the protection system, NORs placement algorithms are implemented on the feeder reached as a result of the open tie point optimization with GA (Fig. 4.3). Forasmuch several algorithms have been compared, we adopt those that perform the better, i.e., DE and NSGA-II. Additionally, the integral planning is examined on a DG enhanced DS.

Fig. 4.11 shows the curves of marginal benefits and costs for DE algorithm, and Table 4.8 presents detailed results. The behavior of the marginal benefit decreases on its entire domain. In this case, two NCRs are proficient to enrich the system reliability preserving economic efficiency. Since the extent of new branches are connected to busbars 26 and 34, these laterals become critical for the system. Thus, installation of NCRs on branches 8-9 and 2-27 is consistent with the new system topology. In addition, the producer net benefit ($8309) is better than the obtained in the original feeder case ($5514). In the same way, expected ENS of the feeder is lower in this case.

Meanwhile, Fig. 4.12 illustrates non-dominated solutions located in the POS by applying NSGA-II, and Table 4.9 expose depth information for highlighted solutions. Regarding to the curve, the most prominent slope takes place in the range of one to six reclosers. From this point, the addition of a recloser marginally increases reliability on the feeder. Thus, considering limited resources, solutions composed by more than six NCRs are not prone to be chosen. Nevertheless, with limitless capital each branch of the feeder may be protected. Hence, MOEAs do not provide a unique solution; instead we have a POS that provide several efficient solutions that meets the decision

Table 4.8: Efficient placement results using de on dg-enhanced feeder

i	E (MWh/y)	$\dot{B}$ ($/y)	Recloser positions (branches)
1	47.48	8062.7	8-9
2	29.70	6047.1	8-9, 2-27
3	23.19	2212.0	8-9, 2-27, 35-36
4	19.48	1261.0	8-9, 2-27e, 27-28,8-42
5	16.15	1132.6	8-9, 27-28, 27e-28e, 35-36, 8-42

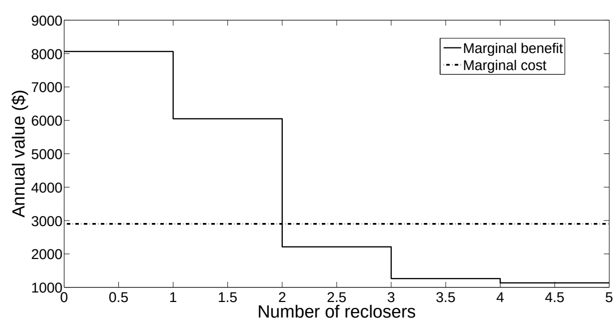


Figure 4.11: Marginal curves using DE on efficient DG-enhanced feeder.

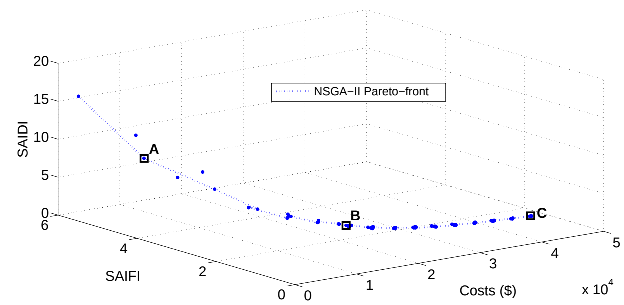


Figure 4.12: NSGA-II non-dominated set of solutions on efficient DG-enhanced feeder.

Table 4.9: Details of highlighted non-dominated solutions of NSGA-II

Solution	**SAIDI**	SAIFI	**Costs($)**	**Recloser positions**
A	9.71	4.27	2900	5-6
B	3.09	1.59	17400	3-4, 10-11, 21-22, 30-31, 35-36, 44-45
C	1.59	0.83	43500	3-4, 6-7, 8-9, 10-11, 14-15, 23-24, 2-27, 27e-28e, 30-31, 33-34, 3-35, 7-40, 42-43, 44-45, 10-55

maker requirements. As the NCRs location on the original feeder, the outcome of this simulation shows an important feature, i.e., with abundant reclosers the optimization encourages the protection of large sections in the DS, segmenting the main trunk of the feeder.

Chapter 5

Concluding Remarks

Novel approaches to optimize planning and operation of a DS are proposed. Methodologies are used to determine the amount of reclosers in a feeder and their efficient location. The PG&E 70-nodes radial feeder is successfully tested with programmed algorithms in DigSilent software, achieving efficient solutions of sizing and placement of protective devices.

Operational costs minimization, in consideration of active power losses and ENS, is developed in pursuance of NORs suitable placement. This optimization determines feeder backup terminals, which provide alternate supply to load demands when a fault event arises within the system. A mirrored version of the PG&E test feeder is modeled to shape a backup-enriched DS which verifies algorithm performance.

Optimal sizing and settlement of NCRs rely on the economic theory of the firm and EAs. This novel approach shows an incentive for the NOp to invest in quality service enhancement at the same time that maximizes its profit. Here, DE shows better results and more consistency than the GA. Moreover, a multiobjective optimization is proposed to find a Pareto optimal set of solutions toward SAIFI, SAIDI, and costs minimization. NSGA-II and NSDE are effectively implemented to attain an efficient set of alternatives, exposing better performance of NSGA-II.

Simulation results show the importance of both protective devices and DG to enhance reliability in radial distribution feeders. Reclosers are located nearby DG power plants to allow islanded operation, thus increasing functioning time and energy delivery. Additionally, when several reclosers are available, lengthy sections of the feeder are segmented into small areas increasing self-healing freedom degrees.

In future research, allocation of fuses and disconnectors may be included as decision variables whereas these devices are also critical in protection systems. Likewise, existent DSs can be modeled to analyze feasible real world implementation.

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Appendix A

Evolutionary Algorithms

Traditional analytical approaches, such as linear and non-linear programming, are unsuitable to solve the above detailed optimization problems. In consequence, EAs and MOEAs are implemented. The operation of these algorithms relies in a stochastic search through the feasible region of solutions, approaching to an efficient alternative as the number of iterations of the process increase. An algorithm that is said to be evolutionary is composed by three phases; selection, recombination, and mutation of individuals [28]. Moreover, a feasible solution is described by a chromosome. In consequence, it is necessary to define the generalized form of this gene arrangement. The existence (or not existence) of a protective device in a branch constitutes a decision variable described in terms of binary domain. Here, a "1" indicates the existence of a recloser on the associated line-segment, while a "0" indicates an unprotected branch. The length of the chromosome regards to the total amount of branches susceptible of recloser installation, while the index indicate an explicit branch.

A.1 Genetic Algorithm

GA is a population-based and stochastic search algorithm which was introduced by John Holland in the early seventies [28]. The operating principle of the algorithm is similar to the evolutive process in nature. that is, each component of the society has a fitness level that indicates its adaptation to the environment. It is presumable that the better the fitness, the greater the chances of an individual to inherit its genes to the next generation. Hence, as the number of generations increase better solutions are achieved. Algorithm 1 shows in detail the steps carried out to realize the GA.

It is necessary to create a random initial population composed by *NP* chromosomes. The population size influences the GA performance. A small population size may not provide a sufficient variety of solutions, which may hinder or limit the exploration over the search space. Thus, by a premature convergence, suboptimal solutions may arise. On the other hand, a large population produces a large number of function evaluations demanding a prohibitive amount of computational resources and slowing down the algorithm. Moreover, the termination criterion is related to the number of generations to be evaluated, i.e., setting G_{max} to a high value would cause the same effect on the algorithm as a large population size. Additionally, a small number of generations will not allow the society to evolve, leading also to suboptimal solutions. In this case NP and G_{max} are settled to one hundred, both providing a suitable combination of speed and reliability. The fitness of each chromosome is related to the system ENS, thus, a reliability assessment of the DS must to be realized. With full information of the population fitness, the following steps are performed: i) selection: a tournament mechanism is utilized by randomly choosing three individuals and comparing their fitness, such that the chromosome with the lowest fitness is selected as a possible parent of the next generation; ii) crossover: the genetic material recombination of two parents is developed with a multipoint scheme where two random points (n_1 and n_2) indicate the intervals of each parent inherited to the new chromosome; iii) mutation: the switch mutation process is applied, which is characterized by a position exchange between two randomized genes. For further information concerning to the GA, we refer the reader to [28] where different schemes for every step are detailed.

A.2 Differential Evolution

As well as GA, DE is a population-based and heuristic search algorithm which was proposed by Storn and Price in 1996 [29]. The functioning of the algorithm is very similar to the GA, i.e., the selection is based on fitness comparisons but crossover and mutation present slight differences. Algorithm 2 shows in detail the pseudo-code of DE.

The DE algorithm requires the creation of a random initial population composed by NP chromosomes. As mentioned in the GA algorithm, the population size and

Initialization of population: $X_G = \{X_{1,G}, \ldots, X_{NP,G}\}$
for $G = 1$ *to* G_{max} **do**
  Reliability assessment: fitness assignment for each individual.
  for $i = 1$ *to* NP **do**
    $f(X_{i,G}) = ENS(X_{i,G})$
  end
  Selection: find the parents of next population P_G.
  for $i = 1$ *to* $NP/2$ **do**
    if $f(X_{r1,G}) \leq f(X_{r2,G})$ & $f(X_{r1,G}) \leq f(X_{r3,G})$ **then**
      $P_{i,G} = X_{r1,G}$
    else if $f(X_{r1,G}) \leq f(X_{r2,G})$ & $f(X_{r1,G}) \leq f(X_{r3,G})$ **then**
      $P_{i,G} = X_{r1,G}$
    else
      $P_{i,G} = X_{r1,G}$
  end
  Crossover: generate the next population X_{G+1}.
  for $i = 1$ *to* NP **do**
    $x_{j,i,G+1} = p_{j,r4,G}$ for $n_1 + 1 \leq j \leq n_1 + n_2 - 1$ $x_{j,i,G+1} = p_{j,r5,G}$ otherwise
  end
  Mutation: make stochastic changes in X_{G+1}.
  for $i = 1$ *to* NP **do**
    if $mr_i \geq$ *probability of mutation*
    then
      $a_1 = x_{r6,i,G+1}, \qquad a_2 = x_{r7,i,G+1}$
      $x_{r6,i,G+1} = a_2, \qquad x_{r7,i,G+1} = a_1$
  end
end

Algorithm 1: GA algorithm

Initialization of population: $X_G = \{X_{1,G}, \ldots, X_{NP,G}\}$
for $G = 1$ *to* G_{max} **do**
  Mutation: build the donor set V_G
  for $i = 1$ *to* NP **do**
    $V_{i,G} = X_{r1,G} + (X_{r2,G} \bigoplus X_{r3,G})$
  end
  Crossover: generate the trial set U_G
  for $i = 1$ *to* NP **do**
    $u_{j,i,G} = v_{j,i,G}$ for $n_1 + 1 \leq j \leq n_1 + n_2 - 1$
    $u_{j,i,G} = x_{j,i,G}$ otherwise
  end
  Reliability assessment: fitness assignment for each solution
  for $i = 1$ *to* NP **do**
    $f(X_{i,G}) = ENS(X_{i,G})$
    $f(U_{i,G}) = ENS(U_{i,G})$
  end
  Selection: find the next population X_{G+1}
  for $i = 1$ *to* NP **do**
    $X_{i,G+1} = X_{i,G}$ if $f(X_{i,G}) \leq f(U_{i,G})$
    $X_{i,G+1} = U_{i,G}$ otherwise
  end
end

Algorithm 2: DE algorithm

the horizon of generations must to be chosen commensurate to the complexity of the problem. The GA configuration is also apposite for DE algorithm.

Algorithm steps are reorganized additionally to the minor variations made with respect to the GA. The arrangement and details of the algorithm are given as: i) mutation: a difference function is applied to three random individuals creating a new chromosome known as donor vector. The mutation scheme is composed by binary arithmetic, i.e., OR and XOR functions are used due to the chromosomes binary nature; ii) crossover: the recombination of two vectors is settled with a multipoint scheme where two random indices (n_1 and n_2) determine the sections of each vector inherited to the new chromosome referred as trial vector; iii) selection: the fitness of the trial vector and the chromosome of the population, that served as a parent in the crossover, are compared. The individual with the lowest ENS remains for the next generation. Supplementary information of DE algorithm is detailed in [29] where different alternatives to apply the mutation function are furnished.

A.3 Revised Non-dominated Sorting Genetic Algorithm

NSGA-II is a MOEA which was proposed by Deb et al. in [24]. This algorithm allows finding a diverse set of solutions converging near the true Pareto-optimal set. Based on [24], the NSGA-II algorithm is described in three parts: 1) main loop; 2) fast non-dominated sorting; and 3) diversity preservation.

NSGA-II starts creating an initial population X_0 with NP individuals, which are sorted based on their non-domination level. In this way, to each solution is assigned a fitness equal to its non-domination rank (the lower, the better). Then, GA operators are used to create an offspring population Y_0 with NP chromosomes. When random populations are obtained, the combined population $Z_G = X_{G-1} \cup Y_{G-1}$ is created. This population is sorted according to non-domination level in order to obtain the next generation individuals. The elements of lower non-dominated sets principally conform next generation. that is, solutions belonging to the non-dominated set $\mathcal{F}_1$ are prioritized above than any other solution in the combined population. If the size of $\mathcal{F}_1$ is smaller than NP, we choose all population members of $\mathcal{F}_1$ and the remaining members are chosen from subsequent non-dominated fronts in the order of their ranking. This procedure continues until the fulfillment of X_{G+1} is completed. However, the individual of last required front are chosen using the crowding distance assignment. Finally, the population X_{G+1} is used alongside selection, crossover, and mutation in order to create a new offspring population Y_{G+1}. Here, the population size and number of generations are configured likewise EAs.

The core of this MOEA relies on the fast non-dominated sorting approach, which is described in the Algorithm 4. This approach allows assigning all individuals to non-dominated fronts. First, for each solution $p \in X_G$, it is calculated the number of solutions (n_p) which dominate p, also it is conformed the set of solutions S_p that solution p dominates. Realize that here are applied the dominance conditions stated by Deb et al. [24]. Afterward, for each solution p with $n_p = 0$, each member $q \in S_p$ reduce its domination count by one. If for any q the domination count becomes zero, the individual is located in an auxiliary list $\mathcal{F}_{aux}$ that is assigned to the subsequent non-dominated front. Finally, this process continues until all fronts are identified.

For MOEAs is very important the diversity of solutions in the non-dominated set, i.e., is better a set with scattered solutions. In this case, the diversity preservation is achieved by the crowding distance assignment detailed in Algorithm 5. This process serves as an estimate of nearness of neighbor solutions, useful when individuals of the same front must to be discarded. For a non-dominated set $\mathcal{F}$, f_m^i refers to the mth objective function of the individual $i \in \mathcal{F}$, and the parameters f_m^l and f_m^1 are the maximum and minimum values of the mth objective function.

A.4 Non-dominated Sorting Differential Evolution

As well as NSGA-II, NSDE is a MOEA that looks toward an efficient set of solutions preserving diversity and nearness to the true Pareto-optimal set. This approach was proposed by Iorio et al. [30]. The functioning of this process is identical to described in Algorithm 3 with one exception, the mutation step uses the differential operator defined in Algorithm 2.

Initialization of population: $X_0 = \{X_{1,0}, \ldots, X_{NP,0}\}$
Reliability assessment: fitness assignment for each solution.
for $i = 1$ *to* NP **do**
    $f_1 (X_{i,G}) = SAIFI (X_{i,G})$
    $f_2 (X_{i,G}) = SAIDI (X_{i,G})$
    $f_3 (X_{i,G}) = Costs (X_{i,G})$
end
Fast non-dominated sort: Algorithm 4 appliance on X_0.
Selection: find the parents of offspring population Y_0.
Crossover: create the offspring population Y_0.
Mutation: make stochastic changes in Y_0.
for $G = 1$ *to* G_{max} **do**
    Combine populations: $Z_G = X_{G-1} \cup Y_{G-1}$
    Reliability assessment: fitness assignment for each solution of Z_G.
    Fast non-dominated sort: Algorithm 4 appliance on Z_G.
    Creation of next population: X_{G+1}
    $X_{G+1} = \emptyset$, $i = 1$;
    while $|X_{G+1}| + |\mathcal{F}_\mathbf{i}| \leq N$ **do**
        Crowding distance assignment: Algorithm 5 appliance on $\mathcal{F}_\mathbf{i}$.
        $X_{G+1} = X_{G+1} \cup \mathcal{F}_i$;
        $i = i + 1$;
    end
    Descendant sorting of $\mathcal{F}_\mathbf{i}$ according to crowding distance.
    $X_{G+1} = X_{G+1} \cup \mathcal{F}_i [1 : (N - |X_{G+1}|)]$;
    Creation of next offspring population: Y_{G+1}
    Y_{G+1} = selection, crossover and mutation from X_{G+1}
end

Algorithm 3: NSGA-II Algorithm

```
foreach p ∈ X_G do
    S_p = ∅, n_p = 0 ;
    foreach q ∈ X_G do
        if p ≺ q then
            S_p = S_p ∪ {q};
        else if q ≺ p then
            n_p = n_p + 1;
    end
    if n_p = 0 then
        𝓕_1 = 𝓕_1 ∪ p;
    i = 1;
    while 𝓕_i ≠ ∅ do
        𝓕_aux ≠ ∅;
        foreach p ∈ 𝓕_i do
            foreach q ∈ S_p do
                n_q = n_q − 1;
                if n_q = 0 then
                    𝓕_aux = 𝓕_aux ∪ q;
            end
        end
        i = i + 1, 𝓕_i = 𝓕_aux
    end
end
```

Algorithm 4: Fast nondominated sort

Designate the size of the analyzed front: $l = |\mathcal{F}|$

foreach $p \in \mathcal{F}$ **do**

  $\mathcal{F}(i)_{distance} = p_{distance} = 0;$

  foreach *objective* m **do**

    $\mathcal{F} = sort\,(\mathcal{F}, m)$

    $\mathcal{F}(1)_{distance} = \mathcal{F}(l)_{distance} = \infty;$

    for $i = 2$ *to* $(l-1)$ **do**

      $\mathcal{F}(i)_{distance} = \mathcal{F}(i)_{distance} + \frac{f_m^{i+1} - f_m^{i-1}}{f_m^l - f_m^1}$

    end

  end

end

Algorithm 5: Crowding distance assignment