A GOAL PROGRAMMING APPROACH FOR OPTIMAL ALLOCATION OF AUTOMATED SWITCHING DEVICES IN RELIABLE SMART GRIDS

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ABSTRACT

This paper presents a multi-objective mathematical model for optimal allocation of automated devices with protection and switching capabilities in distribution networks. A contingency simulation-based technique is used to model distribution reliability considering the protection system response to faults and the post-fault restoration, thus incorporating the most important actions that impact on performance of distribution systems. In addition to reliability criteria, the investment costs are also taken into account in determining number and locations of automated devices. Operational constraints of distribution systems, such as spare capacities and voltage profile play a critical role in the restoration procedure, since they impose limits in the post-fault reconfiguration of interconnected networks. In this paper restoration constraints are addressed by a linear power flow whose nodal-current equations are formulated as functions of geographical locations of the automated switches in a feeder. In order to establish the optimal trade-off between reliability improvements and investment costs, the Goal Programming approach is used and solutions obtained from a Branch and Bound-based method. A case study considering reliability optimization of real 743-buses distribution feeder is presented in order to evaluate solutions obtained in different scenarios of distribution generation penetration.

INTRODUCTION

Recent modernization of Electric Power Distribution Systems (EPDS) and the increasing demand for a high-quality energy supply are some factors that have driven the smart grid initiative. Among the features of a smart grid are the abilities to carry out fault isolation and self-reconfiguration in a fast and automated manner, so that the expected high level of reliability is attained. The ability to quickly and flexibly reconfigure an interconnected network is a key component of smart grid and is enabled by application of distribution automation [1]. This paper considers as Automated Switching Devices (ASDs) as those that incorporate protection and automatic switching capabilities. Currently, such functionalities are available in most modern electronic-controlled line reclosers [2]. Distribution automation have shown to be economically viable due to the emergence of a large number of manufactures and the development of new communication technologies [3].

Since network reconfiguration relies on a sequence of (potentially complex) switching actions, the number and locations of ASDs to be installed in a feeder must be selected in such a way that ensure the investment payback in terms of reliability improvement. For this purpose, optimal design of EPDS is a key factor in increasing the cost-effectiveness of distribution automation and consequently, in making feasible the smart-grid philosophy. From a reliability perspective, the role of overcurrent protection in limiting the impact of faults becomes just as important as restoration. Therefore protection design must also be addressed in the optimization framework.

Most previous studies related to the allocation of ASDs have not considered the effect of the protection system in modelling reliability of EPDS [3-7]. On the other hand, other studies have addressed this issue by optimal allocation of protective devices [8-10], but in conjunction with manually-operated switches and without considering constraints related to restoration. Thus, these approaches cannot ensure the effective application of switches in the system operations.

This paper proposes a multi-objective model for EPDS reliability optimization that considers the interrelated effects of the protection system response to faults and the post-fault restoration in determining number and locations of ASD. Protection and restoration are formulated independently, thus resulting in two Mixed-Integer Linear Programming (MILP) models. The protection model represents the effect of fault clearing carried out by ASDs and has as a result the component of the SAIFI index [11] related to the protection system response to faults. The restoration model provides the subtractive component of SAIFI which represents the impact of the fast load transfer performed by ASDs. Restoration is subject to constraints that ensure that operational limits of the system's components are not violated with topology reconfiguration. These include tie-points and generators capacities, voltage magnitudes and radial operation. To evaluate such parameters, a linear formulation of power flow equations is developed. The optimal level of reliability is determined as the trade-off between the reliability benefits provided by application of ASDs in protection and restoration of the network, and the costs of ASDs operation, acquisition and relocation. For this purpose, the optimization problem is stated as Goal Programming (GP) model [12] and solutions obtained from a Branch and Bound-based optimization package. The proposed model is applied to a 743-buses real distribution feeder and solutions evaluated under varying scenarios of operation, including increasing penetration of distribution generation.

PROPOSED MODEL

This section presents the analytical development of the MILP models that represent the effects of ASDs protection and restoration capabilities on the reliability of EPDS. Thereafter the models are aggregated and stated as the SAIFI goal function in a GP framework. It should be noted that in contrast to heuristic approaches [9, 10], MILP formulations guarantee convergence to the global optimum solution [13]. Also, efficient commercial solvers with large-scale capabilities are currently available which use exact algorithms, such as Branch and Bound to solve the MILP problems [14].

In this paper an analytical simulation technique [15] is used to model the sequence of events that succeed a contingency. By allowing calculation of the impact that the contingency has on each component of the system, the SAIFI index is expressed as a function of basic reliability parameters and binary variables that represent the feeder sections where ASDs are located.

Protection System Response Model

Overcurrent protection impacts on reliability by limiting the effect of faults, thus minimizing the number of interrupted customers. In formulating the protection system response it is assumed that proper coordination between ASDs is always attained, so that the device closest to the fault will operate. Consider Fig. 1 (a) which shows a representation of a feeder F1. At the substation node (CB1) the main feeder protection is performed by a set of relays. A fault occurrence at node *i* will cause operation of ASD1 located in section *jk*. In this case, the number of customers that will experience a sustained interruption is represented by N_j^*, i.e., the customers downstream from ASD1. The binary decision variables indicating the feeder sections where ASDs are installed are defined according to (1):

$$s_{jk} = \begin{cases} 0, \text{ ASD installed in section } jk. \\ 1, \text{ otherwise.} \end{cases} \quad (1)$$

Taking into account the binary variables (1) the impact of fault clearing by the protection system on the SAIFI index is expressed as:

$$f_P = \frac{1}{N_T} \sum_{i \in G} \lambda_i \sum_{\{jk\} \in U_i} N_j^* \overline{s_{jk}} \prod_{\{mn\} \in (U_i - U_j)} s_{mn}, \quad (2)$$

where λ_i is the permanent failure rate of node *i* (failures/year); N_T is the total number of customers on the feeder; *G* is the set of all feeder nodes and U_i is the set of sections that precede node *i* (sections upstream from node *i*) to node 1, which is defined as the feeder root node. The operator ($U_i - U_j$) denotes the complement of U_i in U_j, and results in a set of the elements of U_i that are not elements of U_j.

Equation (2) estimates the contribution to the SAIFI index of the permanent faults in node *i* when an ASD is installed in the circuit section *jk* (upstream from node *i*) and there are not ASDs installed in sections *mn* (between nodes *i* and *j*).

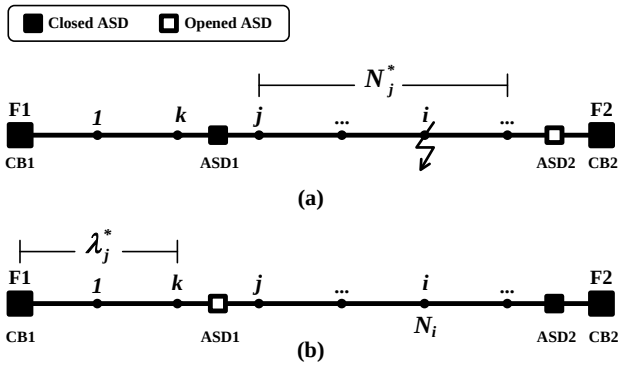

Figure 1. Analytical simulation of the protection system response to a faults (a) and load restoration (b).

Restoration Model

Restoration is the emergency action that follows the fault clearing by a protective device. It consists in a sequence of switching operations that result in a temporary configuration for the network. This state is maintained for the time necessary to repair the cause of the interruption. During this time, the interrupted load is transferred to an alternative feeder through a normally opened tie point. Restoration through ASDs is performed sufficiently fast to prevent degradation of sustained interruptions-related indices, such as SAIFI and SAIDI [11].

The restoration model formulation is described through Fig. 1 (b) that shows the post-fault state of feeder F1. For now it is assumed that restoration of all loads located between ASD1 and ASD2 does not violate any system constraints. In this case, for any faults occurring upstream from ASD1 (between nodes F1 and *k*), restoration of loads will be performed by opening ASD1 and by closing ASD2. A set of binary variables are defined in order to indicate feasibility of restoration of load point *i*:

$$r_i = \begin{cases} 1, \text{ feasible restoration of load point } i. \\ 0, \text{ otherwise.} \end{cases} \quad (3)$$

The topological modelling of the restoration process is mathematically expressed by (4):

$$f_R = \frac{1}{N_T} \sum_{i \in G} N_i \, r_i \sum_{\{jk\} \in U_i} \lambda_j^* \overline{s_{jk}} \prod_{\{mn\} \in (U_i - U_j)} s_{mn}, \quad (4)$$

where λ_j^* is the sum of permanent failure rates of nodes upstream from node *k* (failures/year); and N_i is the number of customers at the load point *i*.

Equation (4) provides an estimate of the number of customers that are restored along a year, when sustained interruptions are resulting of permanent faults occurring upstream from node *j*. If an ASD is installed at section *jk* (upstream from nodes *i*) it will be able to perform isolation. If restoration of load point *i* is feasible, N_i customers are restored. Otherwise, $r_i = 0$ and the term of (4) respective to *i* will be equal to zero. The value

assumed by variable r_i depends on the constraints described in the following section.
It can be noted that (2) and (4) are non-linear due to the products of binary variables. Their linear forms are obtained by replacing each non-linear term by a new auxiliary variable and by adding two linear constraints. This linearization technique is described in detail in [7].

Restoration Constraints

The nonlinear nature of the restoration problem requires simplifications in the model's formulation, otherwise optimality cannot be ensured. In this paper a linear approximation of the power flow in the post-fault system is proposed. In part this assumption is justified by the fact that in emergency situations the operational requirements of the network are not strictly the same as in normal operation. Thus, some constraints such as voltage levels and overloads may be relaxed during the restoration process [16].
The formulation assumes a single-phase representation of the network, with admittances, voltages, currents and powers expressed in the per unit system (pu), in a common MVA base. Fig. 2 (a) shows a line section connecting nodes i and j, where V_i, V_j are the nodal voltages, I_{ij}, I_{ji} are the nodal currents and y_{ij} is the line admittance. The generalized node model shown in Fig. 2 (b) is used to represent loads, generators and tie points, the later through a Norton equivalent. The node model is characterized by a current injection (I_{ii}) and shunt admittance (y_{ii}). Assuming h as the neighbour node of i (not shown in Fig. 2) the nodal voltage equation for node i is expressed as:

$$-V_h y_{ih} + V_i\left(y_{ih} + y_{ii} + y_{ij}\right) - V_j y_{ij} - I_{ih} + I_{ii} - I_{ij} = 0. \quad (5)$$

Alternatively, in matrix form (5) becomes:

$$\mathbf{Y}_{bus} \cdot \mathbf{V}_{bus} + \mathbf{I}_{bus} = \mathbf{0}, \quad (6)$$

where $\mathbf{Y}_{bus}$, $\mathbf{V}_{bus}$ and $\mathbf{I}_{bus}$ are the bus admittance matrix, the nodal voltages and the nodal currents vectors, respectively.
The power flow (6) is straightforward, and does not contain information regarding ASDs locations. As shown in Fig 2 (a), allocation of an ASD in a section ij can be modelled as two controlled current sources that obey the relation (7):

$$I_{ji} = \begin{cases} \left(V_i - V_j\right) y_{ij}, & \text{if } s_{ij} = 0. \\ 0, & \text{if } s_{ij} = 1. \end{cases} \quad (7)$$

Thus, the power flow dependency with ASDs locations is imposed by the following constraints (8)-(10):

$$I_{ij} \le \left(V_i - V_j\right) y_{ij} + V_{max}\, y_{ij}\, s_{ij} \quad (8)$$

$$I_{ij} \ge \left(V_i - V_j\right) y_{ij} - V_{max}\, y_{ij}\, s_{ij} \quad (9)$$

$$I_{ij} - I_{ji} = 0. \quad (10)$$

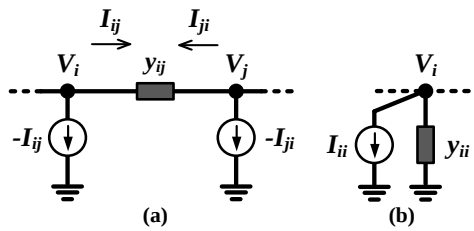

Figure 2. Line section model (a) and generic node model for loads, generators and tie-points (b).

Where V_{max} is the maximum allowable system voltage.
In addition to (8)-(10), constraints (11)-(17) are considered as criteria for restoration feasibility.
Current capabilities of ASDs:

$$I_{ij} \le I_{ij}^{max}\, \overline{s_{ij}} \quad (11)$$

$$I_{ij} \ge -I_{ij}^{max}\, \overline{s_{ij}} \quad (12)$$

where I_{ij}^{max} is current-carrying capability of the ASD in section ij.
Allowable voltage range:

$$V_i \ge V_{min}\, r_i \quad (13)$$

$$V_i \le V_{max}\, r_i, \quad (14)$$

where V_{min} is the minimum allowable system voltage.
Capacity limits of tie points and distributed generators:

$$-I_i \le I_i^{max}\, r_i \quad (15)$$

$$-I_i \ge 0, \quad (16)$$

where I_i^{max} is the current capability of a tie-point or distributed generator at node i.
Radial topology of the post-reconfiguration network:

$$\sum_{\{ij\} \in P_{kl}} \left(1 - s_{ij}\right) - r_k - r_l + 1 \ge 0,\ k \ne l. \quad (17)$$

Where P_{kl} is the set of feeder sections in the path between tie-nodes k and l.

ASD Costs Model

Economic criteria must be aggregated to limit the utility costs to improve reliability. The costs model considers the possible existence of ASDs previously installed on the feeder. Thus, the required cost for improving reliability is the sum of the costs for ASDs operation, relocation and acquisition, expressed as:

$$f_C = \left(c_{ac} + c_{op}\right) \sum_{\{ij\} \in G} \left(1 - s_{ij}\right) + c_{re} \sum_{\{ij\} \in S} s_{ij} - c_{ac} \left|S\right| \quad (18)$$

where c_{ac}, c_{op} and c_{re} are the unit costs of ASDs acquisition, operation and relocation, respectively (US$); S is the set of sections where the existing ASDs are installed; and $|S|$ is the number of elements of set S.

Goal Programming Formulation

Goal Programming is based on the concept of meeting a number of objectives in order to get as close as possible of their goals. Goals are selected so that they cannot be reached simultaneously. The function to be minimized is the weighted sum of the deviations in relation to their respective goals [12]. The proposed GP model is given by (19).

$$\begin{aligned} \min \quad & \delta_R + \delta_C \\ s.t. \quad & f_P - f_R - \delta_R = g_R \\ & f_C - \delta_C = g_C \\ & \mathbf{s}, \mathbf{r}, \mathbf{I}, \mathbf{V} \in C_r . \end{aligned} \tag{19}$$

Where δ_R and δ_C are the deviations from the objectives (2), (4) and (18) in relation to their respective goals g_R and g_C; **s**, **r**, **I** and **V** are the model's decision variables; and C_r is the set of constraints (6), (8)-(17).

In this paper, the goal g_R is selected as the difference between the minimum and the maximum possible values of (2) and (4), respectively. In selecting the cost's goal it is important to foresee a base (minimum) value to account for the operation costs of ASDs. An incremental value may be set in order to accomplish specific reliability targets.

CASE STUDY

The proposed model was evaluated considering a distribution feeder of the CELESC distribution utility (SC, Brazil). The feeder referred to as F1 operates at 13.8 kV and has 746 nodes, total line length of 24.9 km and peak demand of 6.81 MVA. Fig. 3 shows a Google Earth view of F1, where locations of existing ASDs are indicated by S1-S6. Node F2 is a tie point with a neighbour feeder that has 3262 kW of spare capacity. In order to provide a more direct assessment, a permanent failure rate (λ) equal to 0.2 failures/year and the number of 50 customers (N) were considered for all load points. Voltage levels were considered acceptable within the range from V_{min} = 0.93 pu to V_{max} = 1.05 pu. Costs of ASDs operation, relocation and acquisition were assumed as equal to c_{op} = US$ 5.412, c_{re} = US$ 1.250 and c_{ac} = US$ 25.000, respectively [8].

Tests were performed considering reliability optimization in 5 scenarios of the feeder operation. For comparison purposes, the original arrangement of ASDs previously installed on the feeder will be referred to as the base case. Table 1 presents the results obtained from the evaluation of the base case and the solutions from the proposed model. It includes for each scenario, the level of DG penetration (P_{DG}), the goal value of the cost objective (g_C), the SAIFI index value ($f_P - f_R$), the percent reduction of SAIFI in relation to the base case (ΔSAIFI), the value of the cost function (Cost), the percent difference between the cost function and its goal (ΔCost) and the number of ASDs that solutions have determined to be acquired (n_{ac}), to operated (n_{op}) and to be relocated (n_{re}).

Figure 3. Google Earth view of the test feeder F1.

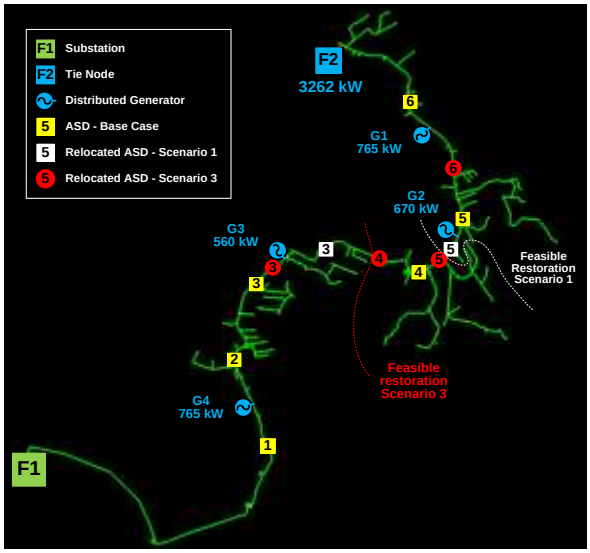

Figure 4. ASDs locations for the base case, scenarios 1 and 3.

From Table I it can be seen that the same values were used for the cost goals in scenarios 1-4. Scenario 1 reproduces the same operation conditions of the base case. Nevertheless, it has resulted in a reduction of 13% in the SAIFI, at the negligible additional cost of US$ 2.500 for relocation of two ASDs. From scenario 1 to 2, the improvement on reliability is most due to the increased load transfer capability of the system provided by generator G1. In scenarios 3 and 4 the system is still constrained in capacity and reliability improves with generation penetration without increasing costs. The penetration of 42.3% is sufficient to eliminate load transfer constraints, thus reliability no longer improves. A change in solutions from scenario 4 to 5 was obtained by increasing the cost goal for the last scenario.

Fig. 4 shows locations of ASDs for the base case and solutions from scenarios 1 and 3. The boundaries of the system whose loads can be restored through load transfer are also shown, indicated as feasible restoration areas. It can be noted that in both scenarios solutions have determined relocation of an ASD in a section very close

Table I. Base case and solutions from the proposed model.

Scenario	P_{DG} (%)	g_C (US$)	SAIFI (1/yr)	ΔSAIFI (%)	Cost (US$)	ΔCost (%)	n_{ac}	n_{re}	n_{op}
Base Case	-	-	3.76	-	32472	-	-	-	6
1	-	32472	3.27	-13.03	34972	+7.70	-	2	6
2	11.7 (G1)	32472	2.89	-23.14	34972	+7.70	-	2	6
3	22.0 (G1, G2)	32472	2.32	-38.30	37472	+15.40	-	4	6
4	42.3 (G1-G4)	32472	2.18	-42.02	37472	+15.40	-	4	6
5	42.3 (G1-G4)	38966	2.03	-46.01	39972	+2.58	-	6	6

to the boundary, so the number of loads that are passive for restoration is expanded.

In the tests cases presented in this paper, solutions were obtained by using the Gurobi Optimizer [14] optimization package, provided on-line through the NEOS-Server for Optimization [17]. For all cases, optimal solutions were found in time intervals of less than 0.2 s, with the control parameters of the algorithm all maintained as default values.

CONCLUSIONS

This paper presented a Goal Programming model for allocation of ASD in EPDS. Its main features are to account for the effects of protection and restoration capabilities ASD on the network reliability, also considering load transfer constraints. Tests have shown that the model is effective in optimizing reliability and that the formulation in a goal programming structure is suitable in integrating the associated costs. Future works should address some issues regarding normalization of the objectives and goals to avoid incommensurability. Such questions were not dealt in this paper due to space limitations.

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