Dynamic Multi-objective Planning for Distribution Systems with Distributed Generation

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***Abstract*—When planning the expansion and operation of distribution systems (DS), utilities face a complex combination of technical and regulatory constraints, which must be considered together with the influence that investment decisions today have on the behavior of the DS along the planning horizon. We present a novel methodology for the multi-stage expansion and operation of a DS, considering a broad set of expansion options, such as the installation or repowering of substations and feeders, variations of the network topology, as well as the installation of distributed generators of various technologies and capacities. The problem is posed as a multi-objective optimization with two objectives: the cost of the energy delivered and the reliability of the network. The problem is solved with an evolutionary algorithm that finds a broad set of non-dominated solutions.**

***Index Terms*—Distributed generation, distribution system planning, multi-objective optimization, multi-stage planning, radial distribution systems.**

I. Introduction

Planning the expansion and operation of distribution systems (DS) is essential for distribution utilities as they need to cope with a growing demand, and keep the network operation within given standards of quality and reliability, while achieving the greatest possible economic benefit. Therefore, the utilities must determine the right capacity, location and timing to install new elements, as well as to perform reinforcements and network reconfigurations. Given the technical constraints of the DS, its planning easily grows out of hand and finding an optimal solution for a given horizon becomes a difficult task.

Due to its relevance, the planning problem has received extensive attention. Recent proposals [1] have considered the load growth in a long-term time horizon, highlighting the importance of a multi-stage methodology to accommodate the gradual increase of the load at minimum cost for the operator. Further, there are other relevant objectives when DSs planning, such as loss reduction, reliability improvement, among others. This leads to multi-objective methodologies, seeking for a trade-off between the different objectives [2].

To tackle the DS planning problem we propose a multi-objective model built in a multi-stage fashion. By considering multiple stages in a single model we are able to explicitly consider the influence that decisions made at any stage have at later stages, affecting the total cost over the planning horizon. This issue is critical as the future conditions of the DS are directly affected by the investment decisions made today, and vice versa. For instance, the demand growth occurs at different times and in different geographical locations, forcing decision on the DS to be made at earlier stages to respond adequately. Additionally, our methodology heavily relies on graph-theoretic tools and load flow analysis, allowing the explicit analysis of radial topologies, commonly found in DSs [3].

Furthermore, as Distributed Generation (DG) has become an integral part of DSs [4], its optimal location and impact are explicitly considered in our methodology. We also consider the availability of primary energy resources in the DS operation area, a feature that limits both the candidate DG technologies and the nodes on which these can be connected to the DS.

II. Dynamic Multiobjective Planning Model

A multi-objective optimization problem is defined by a set of n decision variables, a set of k objective functions, and a set of m constraints [5],

$$y = \min \boldsymbol{f}(\bar{x}) = \min\ [f_1(\bar{x}), f_2(\bar{x}), ..., f_k(\bar{x})] \tag{1}$$

$$\text{s.a. } \boldsymbol{e}(\bar{x}) = (e_1(\bar{x}), e_2(\bar{x}), ..., e_m(\bar{x})) \leq 0,\ \forall \bar{x} \in X, \tag{2}$$

$$\bar{y} = (y_1, y_2, ..., y_n) \in Y,\ y_i = f_i(\bar{x}), \tag{3}$$

where $\bar{x}$ is the decision vector and X is the decision space, $\bar{y}$ is the objective vector and Y is the objective space. The constraints $\boldsymbol{e}(\bar{x}) \leq 0$ determine the set of feasible solutions S,

$$S = \{\bar{x} \in X \mid \boldsymbol{e}(\bar{x}) \leq 0\}. \tag{4}$$

We consider a distribution utility that aims to minimize its capital and operating costs, but at the same time tries to maximize the DS reliability. Therefore, we adopt as objectives the equivalent annual cost of delivered energy to customers, and the expected not-supplied energy (ENS). These two objectives are conflictive, and cannot be optimized simultaneously, hence we adopt the concept of non-dominated solutions.

A decision vector $\bar{x} \in S$ is said to be non-dominated with respect to a set $A \subseteq S$ iff $\nexists a \in A\colon a \succ \bar{x}$, that is, if no other solution in the set A provides a better value for all the objective functions than $\bar{x}$. Therefore $\bar{x}$ is said to be Pareto optimal iff $\bar{x}$ is non-dominated with respect to S. In other words, $\bar{x}$ is optimal in the sense that it cannot by improved in any objective without causing a degradation in at least another objective. The set of all the Pareto-optimal solutions is called the Pareto-optimal set and the corresponding objective vectors form the Pareto-optimal front [5].

A. Energy cost

The equivalent annual cost of the energy delivered to consumers in $[\$/kWh]$ is calculated, based on [6], to compare different expansion alternatives selected on the same project. The DS operation and expansion plan is valued considering the costs associated to the acquisition, installation, and maintenance of all the elements required for the DS operation and expansion along the planning horizon.

The energy costs are determined by the decisions taken at each of the stages in which the planning horizon is divided. The decision variables adopted for the problem are: *i)* installing a line in the branch (i,j) with a type-c conductor at stage t, $\bar{x}_{C_{ij,c,t}}$; *ii)* rewiring the line in branch (i,j) with a type-c conductor at stage t, $\bar{x}_{RL_{ij,c,t}}$; *iii)* installing a substation with capacity b at node i at stage t, $\bar{x}_{S_{i,b,t}}$; *iv)* repowering the substation in node i to capacity b at stage t, $\bar{x}_{RS_{i,b,t}}$; and *v)* installing a distributed generator at node i of technology g at stage t, $\bar{x}_{DG_{i,g,t}}$.

Based on these decisions, the objective function $\boldsymbol{f}_1(\bar{x})$ is the weighted average of the annualized total cost of the energy delivered by the DG units, $CTgd$, and the annualized total cost of the energy supplied by the main network, CTm,

$$\boldsymbol{f}_1(\bar{x}) = \frac{CTgd \cdot \sum_{t=1}^{T} Edg_t + CTm \cdot \sum_{t=1}^{T} Em_t}{\sum_{t=1}^{T} \left[Ed_t + Ep_t\right]}. \quad (5)$$

The weights are the energy delivered by the DG units, Edg_t, and the energy imported from the main network, Em_t; as a proportion of the total energy, including the actual energy demanded, Ed_t, and the energy losses in the DS, Ep_t. The cost terms are given by

$$CTgd = CMGD + D + CMR, \quad (6)$$

$$CTsist = G + Tr + D + CMR + CMSE, \quad (7)$$

where D and Tr are the charges for using the distribution and the transmission network, respectively, while G is the cost of generating the energy from the main network. Moreover, the average cost of network expansion CMR, the average cost of installing substations $CMSE$, and the average cost of installing GD units $CMGD$, are calculated as

$$CMR = \frac{\sum_{t=1}^{T} \left[R_{C_t}(\bar{x}_{C_{ij,c,t}}) + R_{RL_t}(\bar{x}_{RL_{ij,c,t}})\right]}{\sum_{t=1}^{T} \left[Ed_t + Ep_t\right]}, \quad (8)$$

$$CMSE = \frac{\sum_{t=1}^{T} \left[C_{S_t}(\bar{x}_{S_{i,b,t}}) + C_{RS_t}(\bar{x}_{RS_{i,b,t}})\right]}{\sum_{t=1}^{T} Es_t}, \quad (9)$$

$$CMGD = \frac{\sum_{t=1}^{T} KEgd_t(\bar{x}_{DG_{i,g,t}})}{\sum_{t=1}^{T} Egd_t(\bar{x}_{DG_{i,g,t}})}, \quad (10)$$

where the annual cost of installing new lines R_{C_t}, the annual cost of rewiring lines R_{RL_t}, the annual cost of installing substations C_{S_t}, and the annual cost of repowering substations C_{RS_t}, are functions of the decision variables at each stage t. The cost of the energy delivered by the DG units at stage t is denoted by $KEgd_t$. This cost and Egd_t depend on the power delivered by each of the DG units, which can be of different technologies and capacities.

We also point out that the decisions mentioned above depend on the expected peak demand in each load node i, at each stage t, which determine the required supply capacity in the DS.

B. Reliability

A radial SD is made of a set of components in series, including lines, cables, substations, nodes, switches, etc. A client connected to any node requires all components between itself and the point of supply to be available. Therefore, the principle of serial systems [7] for reliability assessment can be applied to radial DS. We consider the following parameters for the reliability analysis:

- Average failure rate λ_{St} in stage t,

$$\lambda_{St} = \sum\nolimits_{i \in NA(t)} \lambda_i + \sum\nolimits_{ij \in TA(t)} \lambda_c \cdot l_{ij}, \quad (11)$$

where λ_i is the failure rate (failures/year) of node i, and the set $NA(t)$ contains the active nodes at stage t. The average rate of failures per unit length (failures/km/year) of a line with a type-c conductor is denoted by λ_c, and l_{ij} is the length (km) of the line between nodes i and j. The set $TA(t)$ contains the active branch lines needed to connect active demand nodes at stage t. Thus, the failure rate of a line depends on the conductor type, and is approximately proportional to its length.

- Average annual outage time U_{St} (hours/year) in stage t,

$$U_{St} = \sum\nolimits_{i \in NA(t)} \lambda_i \sigma_i + \sum\nolimits_{ij \in TA(t)} \lambda_{ij} \sigma_{ij}, \quad (12)$$

where σ_i is the average outage time (hours/failure) at active node i, and σ_{ij} is the repair time of the line in branch (i,j).

We assume the protection scheme of a typical radial DS with a main breaker and isolators on the main feeder. To consider the DG units in the reliability assessment, we adapt the methodology in [8], considering the state of a DG unit as ideal, i.e. always available. If a fault occurs, the protections operate to isolate the fault, and the DG unit is connected to feed some loads (island operation) until the fault is repaired and the main supply is restored.

In summary, the average annual outage $U_{i,t}$ time at each demand node i at stage t depends on: the network configuration and the protective devices on the feeder along the supply route; island operation fed by DG; and the repair times of failed elements. The ENS of the system for the planning horizon further depends on the average demand $D_{p_{i,t}}$ in each node and stage t, and constitutes the second objective function

$$\boldsymbol{f}_2(\bar{x}) = \sum\nolimits_{t=1}^{T} ENS_t = \sum\nolimits_{t=1}^{T} \sum\nolimits_{i} (D_{p_{i,t}} \cdot U_{i,t}). \quad (13)$$

C. Constraints

The DS is considered as an expanded radial system, with several substations fed by a single primary source, and the network topology derived from each substation is treated as a single radial system. To achieve a multi-stage planning, the network topology of a given stage is used as a base to connect new nodes by means of Prim's algorithm.

We also consider a set of transfer nodes $NP(t)$, which do not have generation nor demand, but are used to connect two or more nodes, thus never being terminal nodes [3]. We define the variables $Y_{ij,t}$, equal to one if in stage t the branch line (i,j) is connected, and zero otherwise, for each $ij \in TA(t)$. The constraints to enforce radiality in the DS at every stage can be summarized as [3]

$$\sum_{ij \in TA(t)} Y_{ij,t} = n_{NA_t} - n_{SE_t} - \sum_{j \in NP(t)} (1 - y_{j,t}) \tag{14}$$

$$Y_{ij,t} \leq y_{j,t}, \quad \forall (i,j) \in TA(t),\ \forall j \in NP(t) \tag{15}$$

$$Y_{ji,t} \leq y_{j,t}, \quad \forall (j,i) \in TA(t),\ \forall j \in NP(t) \tag{16}$$

$$\sum\nolimits_{ij \in TA(t)} (Y_{ij,t}) + \sum\nolimits_{ji \in TA(t)} (Y_{ji,t}) \geq 2y_{j,t}\ , \tag{17}$$

where, $y_{j,t} \in \{0,1\} \forall j \in NP(t)$ is equal to 1 when the transfer node j is used at stage t. The number of active nodes in the system at stage t is $n_{NA_t} = |NA(t)|$, while the number of nodes with substations installed in stage t is $n_{SE_t} = |SE(t)|$, where the set $SE(t)$ contains the substations nodes.

Additionally, we included the generation capacity limits to evaluate the benefits of the power injection in the DS. We assume that during island operation a distributed generator must be able to deliver the active and reactive power demanded. Finally, the ampere capacity limits of the feeders I^{max}, the nominal capacity of substations S^{max}, and the node voltage profile V^{min} and V^{max}, are considered,

$$I_{ij,c,t} \leq I^{max}_{ij,c,t} \quad \forall (i,j) \in TA(t), \tag{18}$$

$$S_{i,t} \leq S^{max}_{i,t} \quad \forall i \in SE(t), \tag{19}$$

$$V^{min}_{i,t} \leq V_{i,t} \leq V^{max}_{i,t} \quad \forall i \in NA(t). \tag{20}$$

III. Evolutionary Algorithm

The DS planning problem is a mixed integer nonlinear multi-objective problem, for which metaheuristic algorithms can be designed to find a set of non-dominated solutions [5]. To solve the problem we make use of the *Improved Strength Pareto Evolutionary Algorithm* (SPEA2) [9].

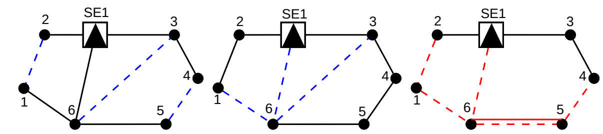
Algorithm 1: Pseudocode of SPEA2

Input: DS conditions and decision variables
$t \leftarrow 0, \quad Initialize(P_0, P'_0)$
while *not EndingCondition* (t, P'_t) **do**
  FitnessAssignment (P_t, P'_t)
  $P'_{t+1} \leftarrow$ EnvironmentalSelection $(P_t \cup P'_{t+1})$
  if $|P'_{t+1}| > N'$ **then**
    $P'_{t+1} \leftarrow$ Truncate (P'_{t+1})
    else $P'_{t+1} \leftarrow$ FillWithDominated (P'_t)
  Parents $\leftarrow$ SelectionTournament (P'_{t+1})
  Offspring $\leftarrow$ Crossover(Parents)
  $P_{t+1} \leftarrow$ Mutate(Offspring)
  $t \leftarrow t + 1$

SPEA2, illustrated in Algorithm 1, has a fixed population of P individuals, and uses elitism to store the non-dominated solutions of each generation in an external file P'. For the fitness assignment strategy, each individual in P and P' is given a strength value that represents the number of solutions it dominates, and a value of "raw fitness" determined by the strength of its dominators in both P and P'. Density information (a function of the distance to the k-th nearest solution) is incorporated to discriminate between individuals with similar raw fitness values.

TABLE I
Multistage Chromosome Structure

$c_{1,1}$	$\cdots$	$c_{1,TR}$	$b_{1,1}$	$\cdots$	$b_{1,S}$	$\frac{K_{g_{1,1}}}{g_{1,1}}$	$\cdots$	$\frac{K_{g_{1,GN}}}{g_{1,GN}}$
$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
$c_{T,1}$	$\cdots$	$c_{T,TR}$	$b_{T,1}$	$\cdots$	$b_{T,S}$	$\frac{K_{g_{T,1}}}{g_{T,1}}$	$\cdots$	$\frac{K_{g_{T,GN}}}{g_{T,GN}}$



(a) Father 1 (b) Father 2 (c) Offspring base

Fig. 1. Crossover Operator

A. Chromosome

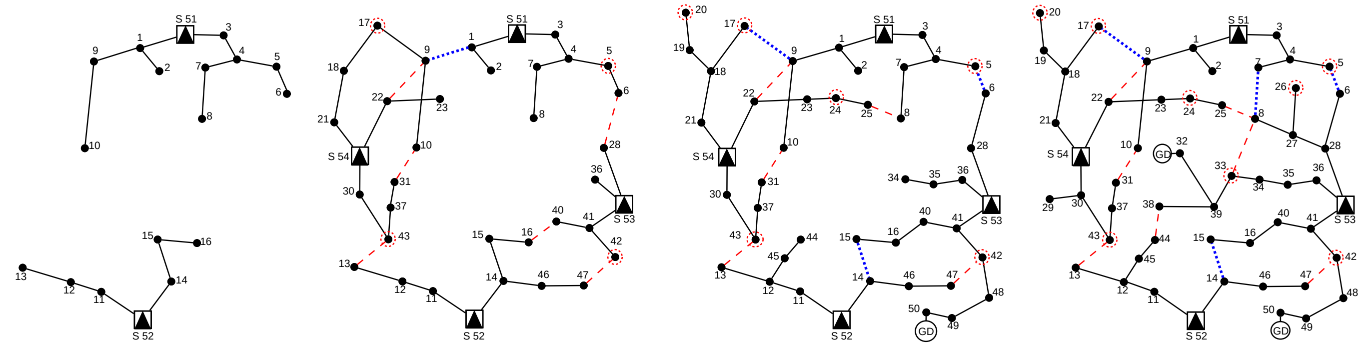
The chromosome encoding (in integers) is based on [10]. As shown in Table I, the chromosome has as many rows as stages in the planning horizon, and is divided into three sections.

The first section refers to the network topology and the number of genes is equal to the number of branches in the DS. When the branch is used, at each stage t, the corresponding gene takes an integer value that reflects the conductor type used, otherwise it is zero. The second section refers to substations, and the number of genes is equal to the number of substation nodes. The genes take an integer value that reflect the substation capacity, which is zero if no substation has been installed at the node. The third section, dedicated to DG decisions, has two sub-levels to consider the technology and capacity of the DG units, as shown in Table I. The number of genes is equal to the number of nodes that can hold DG units. In the first sub-level the gene is an integer value equal to the installed DG capacity, and in the second one it is equal to the DG technology type.

B. Crossover and Mutation Operators

The classical operators that randomly change the individuals are not efficient in this problem due to the radiality constraints, as they can easily transform feasible solutions into infeasible ones. We therefore introduce specific operators to tackle this problem.

For the crossover operator the Prim's and Dijkstra's algorithms, from graph theory, are used. We illustrate the operator in Fig. 1(a) and 1(b), where the continuous lines form a spanning tree from SE1, and the dotted lines are unused branches. To preserve the parents characteristics in their offspring, we create the adjacency matrix Am_t of the graph with branches that are part of the spanning tree in both parents. The continuous lines in Fig. 1(c) are the base of the spanning tree of the offspring, and represent the common branches in the spanning trees of both parents. Prim's algorithm uses Am_t along with radiality criteria to build the offspring network topology, adding branches to the base spanning tree to connect the load nodes. This procedure



(a) Initial state (b) Firts stage (c) Second stage (d) Third stage

Fig. 2. Radial distribution test system - Solution B

preserves some features of the parents at every stage. Dijkstra's algorithm is an auxiliary tool to identify the paths from each load node to each available substation, and to identify infeasible branches due to overloads in feeders or substations.

The mutation operator focuses on the chromosome's third section, considering the two sub-levels in this section. On two genes, both chosen at random, one of three actions is performed randomly: 1. Install or uninstall DG units; 2. Change randomly the installed capacity, when a DG unit is in place; 3. Change the technology randomly, according to resource availability, when a DG unit is already installed. These actions are applied to the genes from a random stage, greater than or equal to the stage when the node first becomes active.

IV. Numerical Results

The methodology is applied to a test system of 54 nodes (4 substations and 50 load nodes) and 64 branches operating under 13.4kV, depicted in Fig. 2 [11]. The main features of the test system and planning criteria are shown in Table II. We consider 5 different conductor types as options for the installation of new lines and the rewiring of existing ones. The test system, in Fig. 2, has two installed substations, S51 and S52, with a 2.5 MVA capacity, and 2 potential substations, S53 and S54. For expansion purposes, we allow the substations to have a final capacity of 2.5, 4 or 6 MVA. In Table III we depict the nodes selected as candidates for the installation of DG units, together with their respective potential DG technology and capacity, which are determined by the availability of primary energy resources at each node.

The proposed method provides a set of Pareto efficient

TABLE II
Test Feeder Assessment Information

Planning horizon	12 years
No. of stages / No. years per stage	3 (+ initial) / 4
No. nodes per stage	36; 47; 54
No. branches per stage	39; 51; 61
Total length of new branches per stage (km)	28.85; 11.75; 12.65
Nominal voltage	13.2 kV
Voltage regulation	±5%, ±10%
Installed load per stage (MVA)	9.85; 13.6; 16.7
Load factor / Loss factor	0.6967 / 0.4855
Demand annual growth rate	2.6%
Maximum loadability - Lines / Substations	70% / 100%

TABLE III
DG Technology and Stage by Each Node

Node		**5**	**17**	**20**	**24**	**26**	**32**	**33**	**42**	**43**	**50**
Activation stage		1	1	2	2	3	3	3	1	1	2
Technology	**Cap[MVA]**	**Potential technology at node**									
Hydro	2 / 4 / 5	✓		✓	✓	✓	✓	✓			✓
Gas turbine	1.5 / 2 / 3		✓	✓			✓	✓	✓	✓	
Wind	0.5 / 1 / 2			✓		✓	✓			✓	✓
Solar PV	0.5 / 1 / 2	✓	✓		✓				✓	✓	✓

solutions that represent the best compromise between the two objectives considered. Fig. 3 shows the evolution of the non-dominated solutions obtained with the proposed algorithm. Three solutions are displayed (panels A, B and C) in representative areas of the Pareto front, to illustrate the properties of the DS at each stage, and the different combinations of the proposed alternatives in each solution. The main features of these solutions are shown in Table IV. We now discuss these results.

To illustrate the solutions generated by the proposed method, we show in Fig. 2 the DS topology evolution for Solution B from Table IV. As mentioned before, the DS expansion of each stage is based on the topology of the previous stage, considering network reconfigurations. The reconfiguration options can be seen in the figure as dotted lines, which represent non-operational (open) lines that allow changes in the DS topology

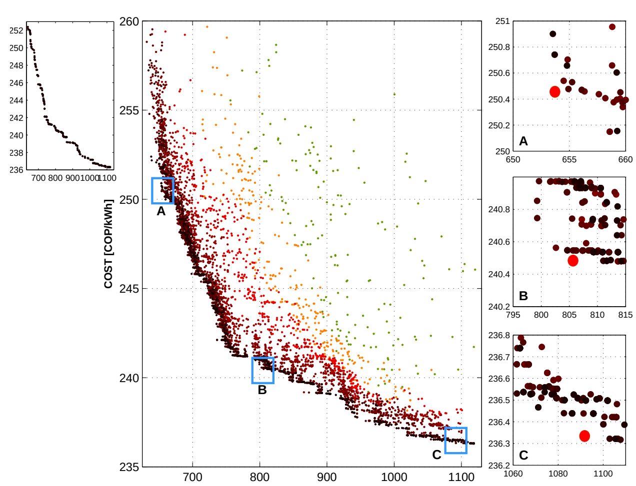


Fig. 3. Selected solutions in the Pareto frontier

TABLE IV
FEATURES OF SELECTED SOLUTIONS

	Sol. A	Sol. B	Sol. C
Annualized Cost [COP$/kWh]	250.43	240.49	236.34
ENS annual [MWh]	654.1	805.8	1092.3
New substations	2	2	1
Repowering of substations	0	1	2
Installed DG units / Total MVA	5 / 6.5	2 / 2.5	1 / 1
Energy losses in stage t_1	1.14%	1.24%	1.26%
Energy losses in stage t_2	1.37%	1.60%	2.58%
Energy losses in stage t_3	1.51%	1.75%	2.54%
Capacity[MVA] / Loading			
Substation S51	2.5 / 74.6%	2.5 / 94%	4 / 93.5%
Substation S52	2.5 / 80.7%	2.5 / 80.7%	4 / 94.9%
Substation S53	2.5 / 80.1%	2.5 / 91.6%	- - -
Substation S54	2.5 / 56.7%	4 / 79.8%	4 / 85.7%
Installed conductors			
Conductor type 1-2	92%	92%	94.1%
Conductor type 3-4	8%	8%	5.9%
Conductor type 5	0%	0%	0%

to achieve an improved performance. Despite the costs that open lines represent, the solutions are non-dominated in relation to the objective functions, meaning that it is better to maintain these open lines to allow for future reconfigurations, since it minimizes the overall cost of investment and operation of the DS, including the cost of energy losses.

The results show that the installation of DG rapidly increases the cost of the energy delivered to the customers. Hence, a higher percentage of DG penetration means a higher energy cost [kWh]. However, with each new DG unit installed it is possible to meet a larger load in isolation, greatly reducing the expected amount of ENS in the event of faults. Fig. 4 shows the relationship between ENS and DG installed capacity, with the total cost of energy as a reference (the curves result from a polynomial interpolation of the solutions obtained). At the curves' junction point, the GD penetration level reaches 22%, with a reduction in the ENS of 21.3%, and a cost increase of 1.71% respect to the lowest cost obtained. Beyond the junction point, a GD penetration level of 56% is reached, although this only represents an additional reduction of 14.7% in the ENS, and an additional increase in the total cost of 5.79%. This implies a decrease in the benefit obtained from installing GD units, as the positive impacts on the ENS also decrease. These results enable us to determine the marginal benefit that a DG project has in any given scenario.

Regarding the DG placement, we note that there are demand nodes that do not receive the benefits of DG under island operation, and therefore their reliability indices do not improve (e.g. nodes associated with the S52 substation). These results are a direct consequence of the availability of primary energy resources for DG, which is a crucial input for the algorithm. This information constraints both the location and the capacity of the DG units to be installed, thus affecting the system operation, as well as its ability to achieve a higher service availability.

Regarding the thermal capacity constraints, we find that conductors with the highest current capacity should be used when the GD penetration level increases, as this results in

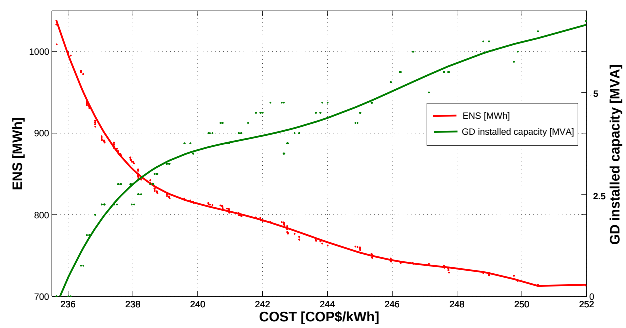


Fig. 4. GD installed capacity vs ENS

lower energy losses. Similarly, installing a higher DG capacity allows for substations with a lower capacity (or less loaded substations), as shown in Table IV, increasing the substations' lifetime. Finally, in Solution C higher capacity and more loaded substations are installed, compared to Solutions A and B. In this case, the DS has three substations only, and longer feeders than those obtained for Solutions A and B. Such longer feeders must deliver a higher load, causing higher energy losses. Due to the optimal dimensioning and placement of the network elements, along with the network topology optimization at each stage, the solutions found with the method show significantly lower energy losses than those found in current DSs, typically between 3% and 6% [12].

REFERENCES

[1] E. Naderi, H. Seifi, and M. Sepasian, "A dynamic approach for distribution system planning considering distributed generation," *Power Delivery, IEEE Transactions on*, vol. 27, no. 3, pp. 1313–1322, 2012.

[2] A. Soroudi and M. Ehsan, "A distribution network expansion planning model considering distributed generation options and techo-economical issues," *Energy*, vol. 35, no. 8, pp. 3364–3374, 2010.

[3] M. Lavorato, J. Franco, M. Rider, and R. Romero, "Imposing radiality constraints in distribution system optimization problems," *Power Systems, IEEE Transactions on*, vol. 27, no. 1, pp. 172–180, 2012.

[4] K. Zou, A. Agalgaonkar, K. Muttaqi, and S. Perera, "Distribution system planning with incorporating DG reactive capability and system uncertainties," *Sustainable Energy, IEEE Transactions on*, vol. 3, no. 1, pp. 112–123, 2012.

[5] E. Zitzler, "Evolutionary Algorithms for Multiobjective Optimization: Methods and Applications," Ph.D. dissertation, ETH Zurich, 1999.

[6] M. Velasquez, C. Tautiva, and A. Cadena, "Technical and economic assessment of distributed generation to increase energy coverage in rural areas," in *Transmission and Distribution: Latin America Conference and Exposition (T&D LA), IEEE/PES*, 2012.

[7] R. Billinton and R. Allan, *Reliability Evaluation of Engineering Systems: Concepts and Techniques*. Pitman Books, 1983.

[8] C. Tautiva, F. Rodríguez, and A. Cadena, "Optimal placement of distributed generation on distribution networks," in *Universities Power Engineering Conference*, 2009.

[9] E. Zitzler, M. Laumanns, and L. Thiele, "Spea2: Improving the strength pareto evolutionary algorithm for multiobjective optimization," *Evolutionary Methods for Design, Optimisation and Control with Application to Industrial Problems*, 2002.

[10] V. Martins and C. Borges, "Active distribution network integrated planning incorporating distributed generation and load response uncertainties," *Power Systems, IEEE Transactions on*, vol. 26, no. 4, pp. 2164–2172, 2011.

[11] V. Miranda, J. V. Ranito, and L. Proenca, "Genetic algorithms in optimal multistage distribution network planning," *Power Systems, IEEE Transactions on*, vol. 9, no. 4, pp. 1927–1933, 1994.

[12] C. dos Santos, "Determination of electric power losses in distribution systems," in *Transmission Distribution Conference and Exposition: Latin America, 2006. TDC '06. IEEE/PES*, 2006, pp. 1–5.