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# Multi-objective evolutionary particle swarm optimization in the assessment of the impact of distributed generation

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ABSTRACT

This paper proposes a multi-objective approach to a distribution network planning process that deals with the challenges derived from the integration of Distributed Generation (DG). The proposal consists of a multi-objective version of the well-known Evolutionary Particle Swarm Optimization method (MEPSO). A broad performance comparison is made between the MEPSO and other multi-objective optimization meta-heuristics, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and a Multi-objective Tabu Search (MOTS), using two distribution networks in a given DG penetration scenario. Although the three methods proved to be applicable in distribution system planning, the MEPSO algorithm has presented promising attributes and a constant and high level performance when compared to other methods.


## 1. Introduction

Distribution networks with a significant level of penetration of Distributed Generation (DG) can no longer be treated as a marginal phenomenon. The impact of the location of DG at system level must be evaluated; utilities should develop policies and regulators must permit the application of these policies in a fair and justified way.

Evaluating the impact of adding new DG units is clearly a multiple criteria problem: it must address issues, such as system power losses, short circuit levels, system reliability, environmental concerns, and electricity markets [1]. One solution is to identify zones or areas of the system where the combination of various forms of impact is somehow 'equivalent' in terms of trade-off among attributes. The zone encompassing the Pareto Front of the set of all feasible solutions is one important zone. This identification may enable the creation of an 'impact index' and eventually, a system of prices/penalties/rewards for investors who wish to place DG in any location in the network.

In order to achieve this, an efficient optimization tool is needed that is capable of dealing with multiple criteria problems, as well as with the complexity added by the integration of DG in the planning of distribution systems. Many methodologies based on multi-objective optimization (MO) meta-heuristics are presented in an attempt to overcome the difficulties that traditional planning tools have in adequately incorporating all of these new challenges. A common MO approach to the DG integration problem is the optimal allocation of generation units using classic MO techniques, such as the Weighted Sum and the $\varepsilon$-Constraint, with Evolutionary Algorithms (EA) [2–6]. Since the $\varepsilon$-Constraint and Weighted Sum methods present well-known limitations [7] and with the development of a considerable number of efficient MO methods, other techniques can be applied to the DG planning problem. In [8], a similar problem formulation from [6] is solved using the NSGA method, although with changes in the objectives and considering the time-varying load and generation. More recently, the second generation methods based on EA, such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [9] and the Strength Pareto Evolutionary Algorithm 2 (SPEA2), have been increasingly used in DG integration problems as reported in [10]. For instance, in [11], the NSGA-II method is used to optimize DG allocation, and in [12], it is compared with a Multi-objective Tabu Search method (MOTS) [13] to assess the impact of the DG. The SPEA2 method is applied to analyze the opportunities for distribution planning stemming from active Distributed Energy Resources (DER) management in [14]. The SPEA2 is also the MO tool for the planning framework for the integration of stochastic and controllable DER on a distribution level proposed by Alarcon-Rodriguez et al. [15]. Therefore, it

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is clear that the use of the EA-based MO methods prevails despite the existence of various multi-objective versions of popular single-objective meta-heuristics [7].

Hence, the contribution of this paper is applying MO to the new paradigm of distribution network planning, focusing on the methods used to define the Pareto optimal set. An original extension of the Evolutionary Particle Swarm Optimization (EPSO) method is proposed for the MO, which is called MEPSO. The aim is to exploit EPSO improvements in performance that have been verified in single-objective optimization [16]. Additionally, a broad performance comparison is done among the following methods with distinct features: the new MEPSO algorithm, the widely used NSGA-II, and the Tabu Search based MOTS. The results demonstrated the high level of the qualitative and quantitative performances of the MEPSO method.

Section 2 gives basic concepts on MO and the MEPSO algorithm is presented in detail. The methodology, problem formulation, and the MO metrics used to compare the performance are described in Section 3. The results are presented in Section 4 with a brief example of an MO analysis of two distribution networks as well as a detailed comparison of the performance of the methods. An additional discussion of the results is conducted in Section 5, and the conclusions are drawn in Section 6.

## 2. Proposed method: MEPSO

Before introducing the MEPSO method, an overall presentation of MO main concepts is given [7,17]. An MO problem consists of simultaneously optimizing a set of objectives that are subject to constraints. There is a set of optimal solutions that are known as the Pareto optimal set. For a final solution, the decision maker must state its preferences either prior to, after, or even during the search for the Pareto optimal set. In terms of dominance, a solution of the Pareto optimal set is not dominated by any other solution, and for this reason, it is also called a non-dominated solution. The Pareto optimal set mapped on the objective function space is known as the Pareto Front (PF). There are advantages with the MO [17], such as the clear distinction between the roles of the planners and decision makers, or the provision of a set of solutions submitted to decision makers whose preferences cannot always be represented mathematically. This kind of structure also makes the problem modeling more realistic.

The MEPSO structure can generally be seen as a hybrid of the EPSO and NSGA-II mechanisms. It exploits EPSO gains in terms of performance. This is verified in the single-objective optimization when compared with other meta-heuristics [16,18,19], which is obtained mainly by combining the Particle Swarm Optimization (PSO) scheme and movement rule with Evolutionary Strategies (ES). The general structure of the EPSO [18,20] is the following: replication where each particle is replicated $r$ times (in the basic model each particle is cloned once or $r = 1$ [20]); mutation: each replica has its weights mutated; reproduction: each particle, among the original ones plus the mutated replicas, generates offspring according to the EPSO's particle movement rule. This step can be seen as recombination in terms of Evolutionary Algorithms [18]. Afterwards, there is evaluation where the offspring has its fitness evaluated; and selection: in the basic model [20], this consists of preserving the best and discarding the worst, considering the offspring of both an original particle and its replica.

Hence, based on the basic EPSO algorithm, the replication and mutation procedures were fully preserved in the MEPSO approach. Nevertheless, the personal and global best assignment was strongly changed in the reproduction of the MEPSO. The evaluation and selection steps were also adapted to deal with multiple objectives. Therefore, the MEPSO inherited a number of improvements from the NSGA-II method [9], such as the Fast Non-dominated Sorting (FNS) procedure, the crowding distance metric, the crowded-comparison operator for selection and elitism.

The MEPSO movement rule and the strategic parameters that are affected by mutation are presented in (1) and (2). Given the position of a particle $i$ in the iteration $k$, $\mathbf{X}_i^{(k)}$, the position in the iteration $(k+1)$ is the following:

$$\mathbf{X}_i^{(k+1)} = \mathbf{X}_i^{(k)} + \mathbf{V}_i^{(k+1)} \tag{1}$$

$$\mathbf{V}_i^{(k+1)} = w_{i1}^{*}\mathbf{V}_i^{(k)} + w_{i2}^{*}(\mathbf{Pb}_i - \mathbf{X}_i) + w_{i3}^{*}\mathbf{P}(\mathbf{Gb}_i^{*} - \mathbf{X}_i), \tag{2}$$

where the symbol "*" indicates the parameters that undergo mutation for the clone particles; $\mathbf{Pb}_i$ is the personal best or the best point found by particle $i$ from the beginning up to the current generation; $\mathbf{Gb}_i^{*}$ is the global best or the referential position in the swarm, communicated to the particle $i$, it is better in dominance or diversity at the current generation (differently from the EPSO method, the global best is not the same for all of the particles); $\mathbf{Gb}_i^{*} = \mathbf{Gb}_i + (w_{i4}^{*})N(0,1)$ is a position in the neighborhood of $\mathbf{Gb}_i$, where $N(0,1)$ is a random variable following a Gaussian distribution with zero mean and unitary variance; $\mathbf{V}_i^{(k)} = \mathbf{X}_i^{(k)} - \mathbf{X}_i^{(k-1)}$ is the velocity of particle $i$ in generation $k$; $w_{i1}$ is the weight of the inertia term (a new particle tends to move in the same direction as the previous movement); $w_{i2}$ is the weight of the memory term (the new particle is attracted to the $\mathbf{Pb}_i$ position); $w_{i3}$ is the weight of the cooperation or information exchange term (the new particle is attracted to the $\mathbf{Gb}$ position); $w_{i4}$ is the weight affecting dispersion around the best-so-far; $\mathbf{P}$ is a diagonal matrix with elements equal to 1 with a given communication probability $p$, or 0 with probability $(1 - p)$. Weights $w_{ik}$ are mutated for the replicated particles at each iteration according to $w_{ik}^{*} = w_{ik} + \sigma N(0,1)$, where $\sigma$ is an externally fixed learning parameter that controls the amplitude of mutations. The learning parameter $\sigma$ was set to 0.2 [18].

In [21], an MO PSO was proposed based on NSGA-II mechanisms. Differently from MEPSO, that approach does not incorporate EPSO's ES. The personal and global best assignment and elitism are also performed in a distinct manner.

The proposed MEPSO algorithm is presented here, where *IterMax* is the maximum number of iterations and *Npart* is the number of particles in the swarm, followed by a description of its main steps.

(i) Parameter and variable initialization;
(ii) FOR $k = 1$ to *IterMax*
(iii) Rank and sort the swarm based on the concept of dominance;
(iv) Update the Pareto List (PL), an external list that receives the non-dominated solutions;
(v) Assign the Global Best (Gb) to each particle of the swarm;
(vi) FOR $i = 1$ to *Npart*
(vii) Replicate the particle ($i$) producing the clone ($r$);
(viii) Execute on the clone ($r$): mutation of the strategic parameters;
(ix) Execute on both particle ($i$) and clone ($r$): reproduction using (1) and (2);
(x) Assign the Personal Best (Pb) to the particle ($i$) and the clone ($r$);
(xi) Add the clone ($r$) to the Replica List (RL) that retains the whole set of replicated particles;
(xii) END FOR
(xiii) Combine the original swarm with the RL;
(xiv) Perform Selection on the combined list of particles;
(xv) END FOR
(xvi) Print the PL and Pareto optimal set.

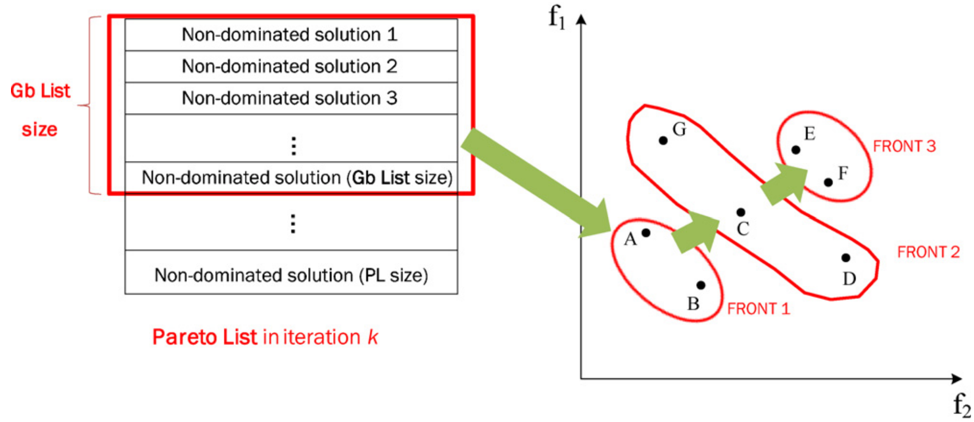


**Fig. 1.** Global best assignment procedure.

The MEPSO begins with an empty PL, the parameters are set and an initial swarm is randomly created.

The stopping criterion is checked. If this criterion is not satisfied, the swarm is ranked and sorted in different layers based on dominance using the FNS.

The PL is updated with the best ranked particles (non-dominated particles) in the swarm. This set of particles that will be added is compared with the current PL in order to avoid repeated and dominated particles.

The Global Best (Gb) is assigned to each particle in the swarm. Since in the context of the MO there is no longer a unique Gb, this step was remodeled. Considering that the swarm is divided into different fronts after the FNS and the fronts are sorted into ascending order where the number "1" corresponds to the best one (formed by the non-dominated particles in the swarm), the particles belonging to front $f$ assume as the Gb a particle in the front $(f-1)$ chosen randomly. The particles in front 1 are the exception since for them the Gb is chosen randomly from a reduced set of the PL with a size that is predefined by the user. These candidate particles for Gb in PL correspond to the less crowded regions, they are given by crowding distance [9] to improve diversity. The global best assignment procedure is shown in Fig. 1.

Each particle of the swarm is replicated. Only the replicated particles have their strategic parameters from the EPSO movement equation mutated. The original and replicated particles then undergo recombination, which means that they execute movement according to (1) and (2).

After the movement, the Personal Best (Pb) is assigned: the Pb is the last non-dominated solution visited by the particle prior to the current iteration.

In the single-objective EPSO, the original particle is compared with its replicated particle after the movement step, and the best is chosen. Since this comparison is not trivial considering MO, the elitism procedure employed in [9] is used. The original and replicated particle sets are combined. The selection consists of composing the swarm of the next iteration using dominance rank as the first criterion and the crowding distance value for particles in the same front.

In this work, a traditional constraint handling approach was used that consists of penalizing the fitness functions of unfeasible solutions with a constant factor. If the penalization factor is adequately defined, it ensures that feasible solutions dominate the unfeasible ones and it does not affect the comparison between feasible solutions. Although it is simple, this idea inconveniently adds the need to set the penalty parameter for each fitness function. However, this constraint handling methodology is not a feature of the MEPSO, which easily admits the implementation of more sophisticated approaches, such as the approach proposed in [9]. This avoids the penalty parameter and introduces more sensitivity when ranking the unfeasible solutions. The penalization constraint handling was also applied in the NSGA-II and the MOTS in order to focus the performance comparison on the main structure of the methods.

## 3. The problem and the methodology

It is widely recognized and reported in the literature that high penetration of DG in distribution networks can be both beneficial and have negative consequences [1]. Both positive and negative impacts depend on various technical features, such as the technology used, the size of the units, the operation and control strategies used to deal with the DG, as well as the capacity and placement in the network. As mentioned in Section 1, there are a number of MO approaches that deal with these and many other complexities [10]. Generally, the aim is to investigate or propose ways of managing the impact of DG penetration with respect to regulation, costs and location, size, and the generation pattern of DG units. In terms of problem formulation, it is common to: define a set of technical or cost-based objectives, consider the dynamic nature of loads and generators in the planning period, and treat the DG position and generation or capacity as decision variables [2,4,6,10,22], although there are approaches that do not consider all of these elements mentioned.

This paper focuses on investigation of MO meta-heuristics performance. Therefore, a simplified model of the problem is assumed. It consists of studying the impact of the position and size of the generation units on network losses and short circuit levels. A fixed amount of DG units is defined. Furthermore, a single generation and load scenario is used to prepare the problem with discrete decision variables and a finite number of solutions in the search space.

Two radial distribution networks with different features are used: the IEEE-34 and IEEE-123 [23]. Both networks were adapted, excluding nodes and equipments, in order to create a scenario where only DG is used to ensure the network's adequacy. It is assumed that all loads are connected in wye and use the constant power model. A three-phase backward-forward sweep power flow method is used [24].

The DG units that will be allocated in the networks are defined in order to produce a similar penetration level in both grids: almost 50% of the rated load. Two synchronous generators are chosen for each network: a 200 kW generator and a 400 kW generator for the IEEE-123 network; as well as a 100 kW generator and a 200 kW generator for the IEEE-34 network.

The information about each network and the search space is summarized in Table 1. The substation node cannot receive a generator. The value chosen for the stopping criterion *MaxEvals*, which

**Table 1**
Summary of networks, tests and search space features.

| Network | Vs/s (pu) | Nodes (except S/S) | DG units | Solutions in the search space | *MaxEvals* |
|---|---|---|---|---|---|
| IEEE-123 | 1.0 | 113 | 2 | 12,656 | 5000 |
| IEEE-34 | 1.05 | 32 | 2 | 992 | 400 |

is the maximum number of evaluations of the objective functions, represent almost 40% of the search space size.

### 3.1. Problem formulation for the evaluation of impact of DG

The two objectives that will be minimized, real power loss and short circuit level, are represented through two indices [8], the *ILp* and the *ISC3*, in order to evaluate the influence of DG on the total real power losses in the network and to contribute to the DG impact evaluation concerning the network fault protection strategies. Voltage and capacity limits are considered as constraints in the model and the position and size of the DG units are the decision variables.

Both indices follow the distribution utility requirements in terms of DG unit connections. In some cases, losses and short-circuit impacts are the most important variables for connecting DG, especially for generation technologies connected to the network without power electronic interfaces that may eliminate generator's contribution to fault currents. The problem formulation is presented in (3).

$$\begin{aligned}
&Min\, ILp = \frac{Loss^{DG}}{Loss^{0}}\\
&Min\, ISC3 = \max_{i=1,NN}\left(\frac{I_{SC}abc_i^{DG}}{I_{SC}abc_i^{0}}\right)\\
&\text{s.t.}\quad \begin{cases}
P_i = \sum\limits_{j\in NC_i} P_{ij}(V_i, V_j, \theta_i, \theta_j) \quad i = 1, \ldots, NN\\
Q_i = \sum\limits_{j\in NC_i} Q_{ij}(V_i, V_j, \theta_i, \theta_j)\\
0.95\cdot V_N \le \left|V_i^{DG}\right| \le 1.05\cdot V_N\\
\left|I_k^{DG}\right| \le I_k^{max} \quad k = 1, \ldots, NB\\
n_i^{DG} \le 1\\
N_{network}^{DG} = N_{available}^{DG}
\end{cases}
\end{aligned} \tag{3}$$

where $Loss^{DG}$ is the real power for the network with a given DG configuration; $Loss^0$ is the total real power loss without DG; $I_{SC}abc_i^{DG}$ represents the three-phase fault current magnitude in node *i* for the network with a given DG configuration; $I_{SC}abc_i^{0}$ stands for the three-phase fault current magnitude in node *i* for the network without DG; *NN* is the number of nodes; $P_i$ and $Q_i$ are the net injection of real and reactive power, respectively, in node *i*; $P_{ij}$ and $Q_{ij}$ are, respectively, the real and reactive power flow in the *i*–*j* branch; $V_i$ and $\theta_i$ are, respectively, the voltage magnitude and angle in node *i*; $NC_i$ is the set of nodes connected to node *i*; $V_N$ is the nominal voltage; $V_i^{DG}$ is the voltage in node *i* for a given DG configuration; $I_k^{DG}$ is the current through the branch *k* for a given DG configuration; $I_k^{max}$ denotes the maximum rated current for branch *k*; *NB* represents the number of branches; $n_i^{DG}$ expresses the number of DG units connected to node *i*; $N_{network}^{DG}$ is the total number of DG units connected in the network; and $N_{available}^{DG}$ is the total number of DG units available.

This formulation guides distribution companies that own DG units, which is allowed in some places as an investment option [25], to take advantage of the connection by means of a tradeoff analysis. The study may also represent a situation where DG is not owned by the utility and the information provided aid to identify the impact on the technical performance of the network. This may encourage an incentive policy for DG connection. However, for a full impact analysis on the protection schemes, the results based on *ISC3* must be complemented with the modeling of all the equipments used in protection and their settings.

The coding of the NSGA-II and MOTS methods is detailed in [12]. The MEPSO coding is the same used for the MOTS, in which each particle is represented by a vector with a dimension that is equal to the number of DG units. Each position *j* of that vector assumes a discrete value that corresponds to the node where the DG unit *j* is connected. The MO methods applied to the problem stated in (3) will basically operate the coded vector and decode it to calculate the fitness functions, using the electrical calculation routines (the calculation of power flow and short-circuit currents) and check the feasibility. In terms of the MEPSO algorithm presented in Section 2, for instance, the data of the distribution networks and DG are inputs in initialization (step (i)), the decision variables are also encoded in vector $\mathbf{X}_i^{(k)}$ for each particle and the fitness functions of the initial swarm are calculated. Afterward, the stages that consist of decoding the vector of the decision variables for electrical calculations, assigning fitness function and checking constraint violation are performed during reproduction (step (ix)).

Occasionally, even the solutions that violate constraints may be relevant in the tradeoff analysis if the gain in some objective justifies the investment on making the solution feasible. It depends on the level of violation and the constraint violated. For this reason and also in order to assess the performance of the methods for a larger number of Pareto Fronts, the tests will be performed with and without the voltage and current constraints.

### 3.2. Evaluation of the performance of MO methods

In this work, the MO is classified as *a posteriori* decision making, which means that it is essential to determine a suitable Pareto optimal set beforehand. Ideally, the decision maker looks for the true Pareto Front (PF), which is not available due to the methods limitations or even to the nature of the problem.

Therefore, in order to evaluate an MO meta-heuristic performance, it is important to observe its ability to best represent the true PF with a finite number of solutions. The performance of the methods is generally evaluated using the graphics of the obtained Pareto Fronts and performance metrics, frequently presented using descriptive statistical measurements of central tendency and dispersion (such as mean and variance). In [13], for instance, graphics, the number of optimal solutions found and the extreme values of the fitness functions were used to compare the MOTS with the results reported in the literature. In [9,21] graphics and metrics, represented by mean and variance after ten runs of the algorithms, were used to summarize the performance of the methods. More information about MO meta-heuristic experimentation, such as other metrics or statistical testing, is provided in [7].

The key criteria for performance evaluation include the following: the convergence of the points obtained for the true PF, the uniform distribution of those points, and the exploration of the PF boundaries solutions, which means knowing the range of each objective [10]. A large number of metrics are proposed in the literature to quantify these criteria [7]. Two performance indices are used.

The Error Ratio (ER) metric [7] indicates the number of solutions in the obtained PF ($PF_{calc}$) that do not belong to the true PF ($PF_{true}$) in relation to the cardinality of $PF_{calc}$, as defined in (4).

$$\mathrm{ER} = \frac{\sum_{i=1}^{|PF_{calc}|} e_i}{|PF_{calc}|} \quad (4)$$

where $e_i$ is zero if the $i$th solution of $PF_{calc}$ belongs to $PF_{true}$ or $e_i$ is one if the $i$th solution of $PF_{calc}$ is not an element of $PF_{true}$. Then, the value of ER is between 0 and 1, where zero indicates a solution set where all of the solutions that are in $PF_{true}$.

Although the ER metric works as an indicator of how successful a method is in pushing its solution set to the real optimal set, the index alone cannot provide information for a complete performance analysis. It is possible, for instance, to find an optimal solution set composed of a small number of solutions with an ER that is equal to zero. As the analysts are also interested in finding as many solutions of the true PF as possible, another performance metric is proposed.

Eq. (5) defines the PF Ratio (PFR) metric which expresses the percentage of the $PF_{true}$ obtained.

$$\mathrm{PFR} = \frac{|PF_{calc} \cap PF_{true}|}{|PF_{true}|} \times 100 \quad (5)$$

For a comprehensive performance evaluation of a MO metaheuristic, it is noteworthy to measure the spread of the solutions in the PF obtained. An example of diversity metric is the $\Delta$ metric in [9], which measures how uniform the spreading of an obtained PF is and the distance from the extreme points of $PF_{calc}$ to the extreme $PF_{true}$ ones. Although the $\Delta$ metric may support important analysis on the diversity features of a method, it is not quite suitable for the problem proposed. It occurs in this case because the PF is a finite set with a fixed arrangement, which is not necessarily uniform. Thus, convergence may affect diversity, and the simple comparison among diversity metrics that are associated with the PFs obtained by different methods does not provide a definitive conclusion with regard to the methods' diversity features. Therefore, the diversity metric will not be presented since ER and PFR metrics provide a sound performance comparison of the performance of the methods.

Knowledge of the true PF is necessary to compute the ER and the PFR metrics. The problem size was conveniently chosen in order to calculate all of the possible combinations and define the true PF.

Ten different and repeatable experiments are defined using ten distinct and fixed seeds for the random number generator. The performance metrics are applied to each solution set and at the end of the ten experiments they are also applied to the combined solution set, after proceeding with the elimination of repeated and dominated solutions.

## 4. Results

### 4.1. Evaluation of the impact of DG

This section presents an example of an evaluation of the impact of DG based on the technical performance indices, *ILp* and *ISC3*. The PF for both networks, with and without current and voltage constraints, are shown in Fig. 1.

The characteristics of each network, such as the voltage level and the length of branches, directly affect the relationship between *ILp* and *ISC3*. The urban IEEE-123 network does not present relevant conflict between objectives, as shown in Fig. 2. Despite the huge variation in *ILp*, the values for the *ISC3* do not change significantly. Thus, the decision making for the IEEE-123 network is straightforward and corresponds to choosing the solution with the minimum *ILp*. However, in accordance with Fig. 2, the rural IEEE-34 network presents an evident characteristic of conflict. In contrast to the IEEE-123, there is a variation in the *ISC3* index in the IEEE-34 network, due to the fault profile of this network. In fact, on the original condition the fault currents decrease considerably from S/S node to final nodes. With the connection of the DG units, especially those far from the S/S node, there is then a significant increase in the magnitude of the fault current at those points and, consequently, in the *ISC3* index.

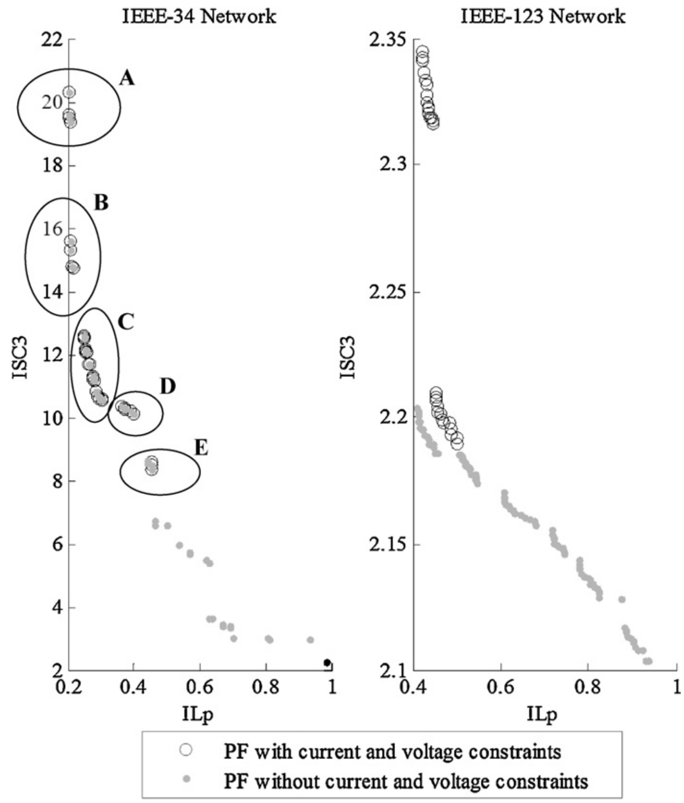


**Fig. 2.** Pareto Fronts for IEEE-34 and IEEE-123 networks with and without current and voltage constraints.

Based on the constrained PF of the IEEE-34 network, an impact study of DG penetration has been conducted, focusing on the position of the generators. The PF points were divided into five sets, as indicated in Fig. 2 (from A to E). This makes it possible to identify zones along the network with respect to the impact caused by the DG on the performance indices, as shown in Fig. 3. From the PF analysis, it can be observed that the network can be divided into two major parts: zone I, from S/S node to node 16, including node 18, and zone II that consists of the union of zones II(a) and II(b). In

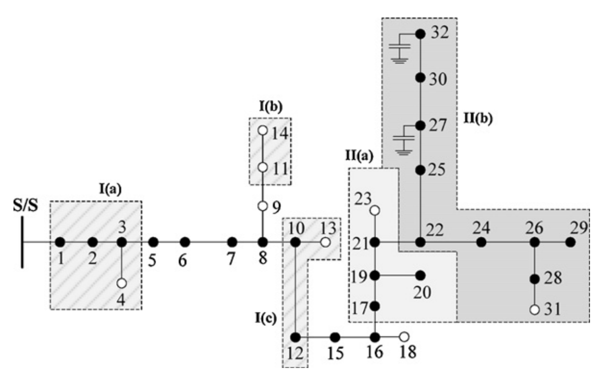


**Fig. 3.** Adapted IEEE-34 network with DG connections zones based on constrained PF.

**Table 2**
Cardinality of the true Pareto Front for different test cases.

| | IEEE-123 | | IEEE-34 | |
|---|---|---|---|---|
| | CONS | UNCONS | CONS | UNCONS |
| $\lvert PF_{true} \rvert$ | 29 | 91 | 52 | 76 |

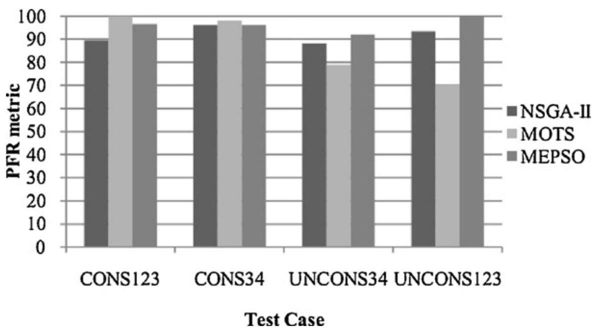


**Fig. 4.** PFR metric of combined solution set for each method for different problem formulations.

general, it can be seen that the allocation of DG units in each zone has opposite effects on the performance indices. For instance, the points of set A, with high *ISC3* and low *ILp*, have the two generators connected in zone II(b), where the major three-phase loads are concentrated. Whereas, E set, with low *ISC3* and high *ILp*, corresponds to the DG unit 1 connected in the I(c) area and the other generator in node 18. Therefore, they are both in zone I. The intermediate sets B, C, and D are the combined allocation of the two DG units in nodes inside zones II(a) and II(b), I(b) and II, I(a) and II(a), respectively.

### *4.2. Comparison of MO methods*

The number of optimal solutions for each network, with and without the constraints, is presented in Table 2. The comparison of the performance of the methods is initiated by the combination of solution sets from the ten experiments. Fig. 4 gives a general overview of the method's performance using the PFR metric. The voltage and current constrained problem is indicated by CONS and the unconstrained problem is indicated by UNCONS, both are followed by a number, 34 or 123, which refers to the distribution network.

The cases were organized in ascending order of PF cardinality. In two situations, the true PFs were found: using the MOTS method in CONS123 and using the MEPSO method in UNCONS123. In the first two test cases, the MOTS method showed the best performance. However, it presented the worst results in the last two cases with less than 80% of the true PF being determined. Furthermore, the MEPSO method had a constant trend in results, with all cases obtaining more than 90% of the true PF. The NSGA-II method presented a similar performance, but it did not find the true PF in any of the test cases and in two of them it determined less than 90% of the true PF. The other performance metrics and the results are shown in Tables 3 and 4.

**Table 3**
Summary of the results for CONS34 and CONS123 test cases.

| | CONS123 | | | CONS34 | | |
|---|---|---|---|---|---|---|
| | NSGA-II | MOTS | MEPSO | NSGA-II | MOTS | MEPSO |
| $\lvert PF_{calc} \rvert$ | 26 | 29 | 28 | 50 | 51 | 50 |
| DS[a] | – | – | – | – | – | – |
| ER | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| PFR | 89.6 | 100.0 | 96.6 | 96.2 | 98.1 | 96.2 |

[a] DS means dominated solutions in calculated PF.

**Table 4**
Summary of the results for UNCONS34 and UNCONS123 test cases.

| | UNCONS34 | | | UNCONS123 | | |
|---|---|---|---|---|---|---|
| | NSGA-II | MOTS | MEPSO | NSGA-II | MOTS | MEPSO |
| $\lvert PF_{calc} \rvert$ | 67 | 61 | 70 | 85 | 69 | 91 |
| DS[a] | – | 1 | – | – | 5 | – |
| ER | 0.0000 | 0.0164 | 0.0000 | 0.0000 | 0.0725 | 0.0000 |
| PFR | 88.2 | 78.9 | 92.1 | 93.4 | 70.3 | 100.0 |

[a] DS means dominated solutions in calculated PF.

The analysis of the convergence of the methods is complemented by observing the ER metric. This index represents how successful the exploration of the regions visited during the search was, even if the $PF_{true}$ was not completely defined. The NSGA-II and MEPSO methods yielded the best ER situation, which is zero, in all test cases. However, the MOTS had non-zero ER values in the last two test cases. In UNCONS123, for instance, around 7% of the $PF_{calc}$ were dominated by points belonging to the $PF_{true}$.

Another method analysis is performed on the solutions obtained in each one of the ten experiments. The PFR and ER metrics are explained for the best and worst test case performance of each method, based on the PFR results shown in Fig. 4. For the NSGA-II method, the best and worst test cases are CONS34 and UNCONS34, respectively; for the MOTS method they are CONS123 and UNCONS123, respectively; and for the MEPSO method UNCONS123 is the best test case and UNCONS34 is the worst case. In Fig. 5 the results of the ten experiments are summarized for the best test cases using boxplots. The lower side of the box is the first quartile; the upper side is the third quartile; and the red line inside is the second quartile or median. The whiskers represent the maximum and minimum obtained in the data series. A point is an outlier, drawn as a red cross, if it is larger than the 3rd quartile plus 1.5× *IQR* or smaller than the 1st quartile minus 1.5× *IQR*, where *IQR* is the interquartile range.

As shown in Fig. 5(a), the NSGA-II method presented the PFR metric as being below 30 in more than 75% of the experiments with the maximum PFR obtained being under 40. The MOTS method obtained better extreme PFR solutions than the NSGA-II and 75% of the experiments had a PFR metric higher than 35. The last method in Fig. 5(a), MEPSO, clearly achieved the best performance with the PFR metric being between 70 and 80 in all of the experiments, except the outlier with the PFR close to 60. This means that between 70% and 80% of the true PF was defined in each experiment. In Fig. 5(b), the methods with a better PFR performance generally found more true PF points amongst the PF points obtained, as expected. The NSGA-II method presented a larger ER metric for extreme points and a larger distance between them when compared to the other methods, with points concentrated around intermediate ER levels. The ER metric for the MOTS method in Fig. 5(b) oscillated around 0.3, without exceeding 0.5, and the MEPSO method presented an ER that was lower than 0.17 in 80% of the experiments.

The methods performance is represented for the worst test cases in Fig. 6. The PFR metric for the NSGA-II method, as seen in Fig. 6(a), had a similar result to those observed in Fig. 5(a). A clear performance decrease was verified in using the MOTS method with PFR varying between approximately 10 and 20. When compared with Fig. 5(a), MEPSO has also shown a drop in performance. However, it maintained larger extreme PFR values than the other methods and the major part of the experiments had PFR around 30. The ER metric behavior shown in Fig. 6(b) resembles that observed behavior in Fig. 5(b): NSGA-II has the most dispersed ER values; MOTS has all points lower than 0.5. The MEPSO method obtained an ER that was concentrated between 0.25 and 0.36 with three outliers.

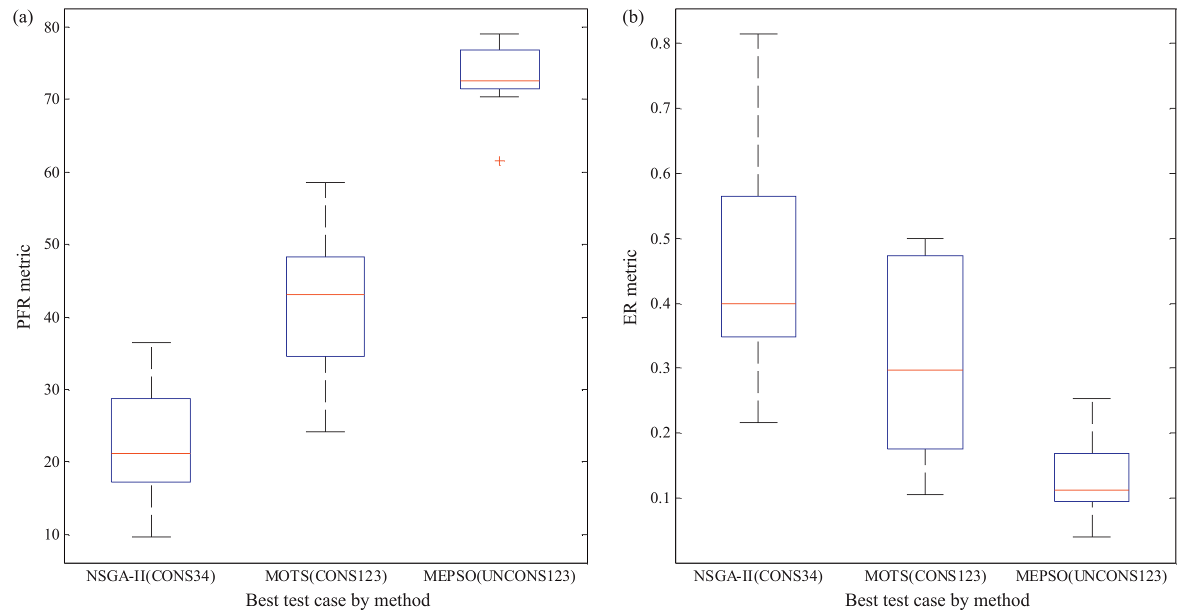


**Fig. 5.** Detailed performance for general best test cases considering the three methods.

## 5. Discussions and remarks

With regard to Fig. 4 and Tables 3 and 4, the MEPSO method showed a constant and high performance. The MEPSO always presented the best ER condition; its PFR metric results were always over 90 and it found the true PF for the UNCONS123 test case, where the PF cardinality was the highest. The MEPSO method also demonstrated a stable behavior with less sensitivity to PF changes when compared with the other methods. The NSGA-II method performance was similar to the MEPSO with ER always being equal to zero and PFR being greater than 88. However, NSGA-II had more variation in its PFR and was not better than the MEPSO in any test case. Only MOTS showed a clear trend in reducing the PFR as the PF cardinality increased: despite finding the true PF in the first test case, it was the worst performance for the UNCONS123 with almost 70% of the true PF being defined. The main reason for this situation is the method structure inherited from the Tabu Search. Unlike NSGA-II and MEPSO, in MOTS the movement during the search is made from just one solution to another called the seed. The neighborhood of the seed is explored and candidate solutions for the Pareto optimal set are preserved on the Candidate List (CL). However, just one solution is sent to the PL per iteration. This means that in $N$ iterations, there will be $N$ or fewer solutions in the PL. Then, if the user wants to define PF in a single run as much as possible, it is necessary to permit the execution of MOTS until the CL is emptied, which may cost a significant number of iterations.

Since CL retains non-dominated solutions that were not taken as seed solution, another option is combining the PL and the CL when

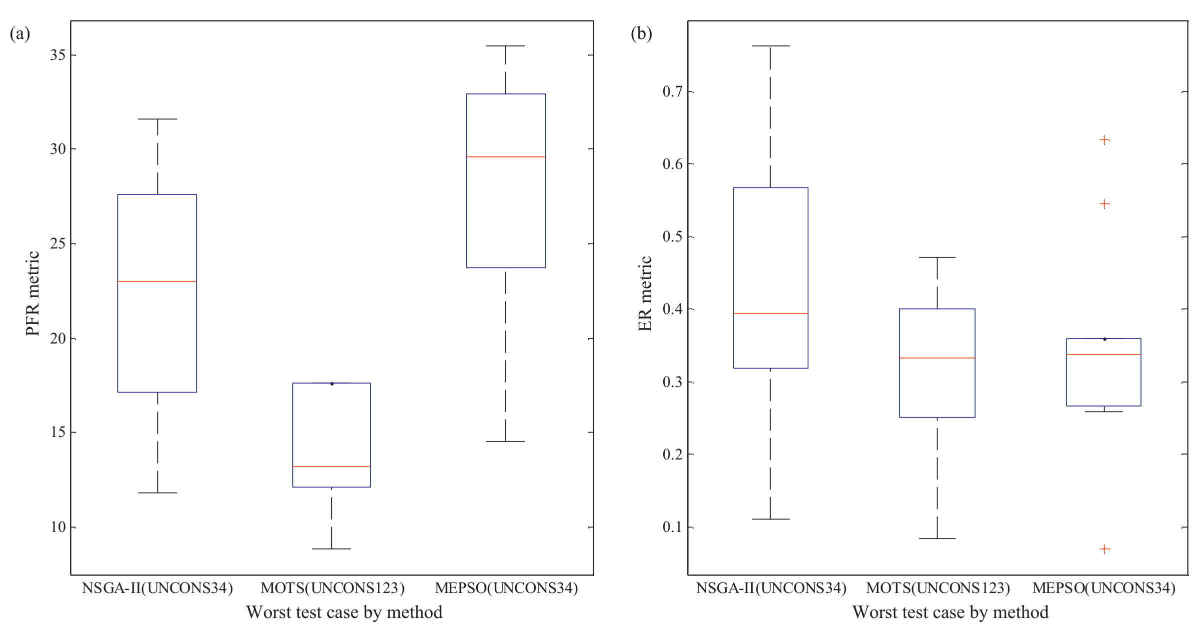


**Fig. 6.** Detailed performance for general worst test cases considering the three methods.

the MOTS execution is interrupted. This is performed for the test cases of Fig. 4 and a remarkable improvement can be seen in the MOTS' performance. The true PF was found in the first three test cases. Nevertheless, the behavior of the MOTS in the UNCONS123 test case deserved attention because the MOTS performance was the worst among the other methods. Although it had a PFR that was higher than 90, the MOTS in UNCONS123 was the only method that presented an ER other than zero (0.0562). This is caused by the poor exploration of the CL solution neighborhoods and may represent a decrease in the MOTS' performance as the PF cardinality increases, even when combining the PL and the CL.

The purpose of the results shown in Figs. 5 and 6 is to compare the best and worst test case performance for each method. The NSGA-II generally presented an irregular PFR performance, especially for the CONS34 test case. This variation is more evident considering the ER metric that shows a huge variation throughout the experiments and is the highest value found among the methods. Although the general NSGA-II performance for the CONS34 test case may indicate the ability to explore different regions of the search space on each experiment, the huge ER and the fact that the true PF was not found in any test case indicate difficulty in local exploration. When compared with NSGA-II and MEPSO, the MOTS method performance was intermediate for CONS123 and low for UNCONS123, where the PFR was never higher than 20 in any experiment. This was caused by the already mentioned MOTS structure as it does not allow for intense PF exploration with a reduced number of iterations. Despite the variations in ER, the metric was always smaller than 0.5, demonstrating that more than 50% of the found PF corresponds to solutions from the true PF. It is a desirable behavior, but it may have limited importance if the number of solutions defined is small. The combination of the CL with the PL affected this ER behavior negatively. Finally, the MEPSO best and worst PFR performance test cases were generally better than the other methods. The MEPSO's high performance in the UNCONS123 test case with constant and high level metrics results was remarkable.

There are qualitative aspects concerning the methods that are ignored or not explicitly perceived in the analysis of the performance metrics. As MO meta-heuristics do not guarantee the convergence to the optimal solution set, one strategy to overcome this limitation is to consider as a final solution the combination of the results obtained in a number of algorithm runs, as illustrated in Fig. 4. Thus, the MEPSO and NSGA-II methods have desirable attributes for this purpose: both methods have a fast convergence, which can be exploited making many algorithm runs with a reduced number of iterations. In contrast, the MOTS method has a slower convergence because it explores the neighborhood of each candidate solution. If an interruption is needed before the CL is emptied, it is possible to combine the remaining CL solutions with the PL in the final solution set. However, if the exploration of all candidate solutions is wanted for a better local search, all of the CL solutions must be taken as seed, which costs a high number of iterations.

Another important issue to consider when dealing with meta-heuristics is how the results are affected by the parameter tuning for a method. Since it is not the objective of this paper to conduct a detailed study on the sensibility of each method to its parameters, the discussion on this topic is specific to the problem being analyzed. Some methods parameters were fixed for all of the tests whereas others were changed according to the size of the search space. For NSGA-II, the mutation and recombination probability were fixed at 0.05 and 0.7, respectively. The tournament size was 2 and the population size was changed depending on the network. In MEPSO only the number of particles varied. The factor used for stochastic star communication for the global best position [18] was 0.2, and the list size to choose the global best was 5. The MOTS's fixed parameter was the TL size of 10. The neighborhood size and the parameter *step i* [13], which is used to generate the neighborhood solutions, were defined according to the network.

**Table 5**
Parameters set for each network.

| Method | Parameters | IEEE-34 | IEEE-123 |
|---|---|---|---|
| NSGA-II | Population size | 50 | 250 |
| MOTS | Neighborhood size and *stepi* | 20 and 18 | 200 and 60 |
| MEPSO | Number of particles | 20 | 50 |

The parameters values adjusted for each network are shown in Table 5. The results obtained for the three methods are strongly dependent on the values defined for those parameters. For MOTS and NSGA-II, the parameters are different from those used in the literature [9,13] because of the discrete problem formulation and the need to find the true Pareto optimal solutions with a reduced number of objective function evaluations. For the MOTS method, the parameter tuning is a more difficult task because two values have to be set together. It is important to stress that the performance of the MEPSO is sensible to the probability $p$ of the stochastic star communication, such as the EPSO. However the tuning of $p$ seems to be strongly dependent on the characteristics of the problem and it does not seem to be related to the settings of the other parameters [18].

## 6. Conclusions

The expected challenge for the years to come will be combining AI techniques in order to solve complex power system problems, essentially considering the most recent trends, such as DG, Smart Grids and Microgrids. This paper presented a broad comparison of the MO methods based on different meta-heuristics. A new approach for a multi-objective EPSO, called MEPSO was also introduced. From the quantitative and qualitative analysis, MEPSO presented satisfactory performance. The MOTS method performance was remarkable when the PL and the CL were combined. However, even in this case, the reduction of the performance was maintained for the test case with the highest PF cardinality (UNCONS123), which may indicate a loss in performance for problems with increased size and complexity. Additionally, the MOTS required more effort for parameter tuning than the other methods. The NSGA-II performance does not seem to be affected by the problem changes, but it generally shows a less efficient convergence to the true PF, with the highest ER per experiment. In the MEPSO method, not only can the performance be highlighted, especially for test case UNCONS123, but its stable behavior must also be noted, like in Fig. 4. The MEPSO shown fine convergence features to the true PF with intense exploration of the visited regions of the search space, as seen through the performance metrics in Figs. 5 and 6. Furthermore, it presented parameter tuning similar the NSGA-II and more user-friendly than the MOTS.

The proposed approach successfully combined some of the MO strategies from the NSGA-II with the EPSO algorithm. The comparison with NSGA-II may indicate the improvement in convergence provided by the influence of the EPSO movement equation. Therefore, the MEPSO may represent an important tool for MO-based methodologies to evaluate the impact of DG.

Based on these initial results for MEPSO and the methodology to evaluate MO meta-heuristics, many studies are being performed in order to investigate other important issues, such as the method's performance in problem formulations with continuous decision variables, the influence of other method parameters and codification in performance, and methodology improvements as testing with a higher number of experiments. In terms of the application of the method to the proposed problem, improvements are being developed in order to take advantage of MEPSO performance in studies of the impact of DG related to its location in the network.

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