Distributed Generation Impact Evaluation Using a Multi-objective Tabu Search

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Abstract— **Distribution networks paradigm is changing currently requiring improved methodologies and tools for network analysis and planning. A relevant issue is analyzing the impact of the Distributed Generation penetration in passive networks considering different operation scenarios. Studying DG optimal siting and sizing the planner can identify the network behavior in presence of DG. Many approaches for the optimal DG allocation problem successfully used multi-objective optimization techniques. So this paper contributes to the fundamental stage of multi-objective optimization of finding the Pareto optimal solutions set. It is proposed the application of a Multi-objective Tabu Search and it was verified a better performance comparing to the NSGA-II method.**

Keywords-distributed generation; medium voltage distribution networks; multiobjective optimization; optimal allocation; Tabu Search.

I. INTRODUCTION

Nowadays the electric power systems are facing a deep paradigm changing. In the specific case of the Distribution Networks (DNs), traditionally designed for passive operation, they must not only accommodate the Distributed Generation (DG), but they have to be conceived under a new perspective. Supported by innovative concepts of monitoring, control and communication, that new conception must allow a more active participation of the end consumers on the grid operation, allow a wide access of DG of different sizes and technologies, make the DN more flexible to incorporate new technologies, optimize the use of natural resources and mitigate environment impacts produced by the electric power systems [1]. It is recognized as desirable features for the planning methodologies and techniques, the ability to provide optimized solutions taking into account frequently conflicting interests, a number of restrictions from different natures and various operation scenarios [1], [2]. Thus, it is expected with this paper to contribute for the identification of the impacts on medium voltage DNs caused by DG penetration using a multi-objective optimization (MO) method based on the Tabu Search (TS) meta-heuristic [3], [4]. This is made looking for the optimal siting and sizing of DG units in a DN, considering a specific scenario and a set of technical objective functions.

Many works have been dealing with the DG optimal siting and sizing problem by means of MO tools, with a considerable number of them based on Genetic Algorithms (GAs). This is done in [5]-[7] considering cost-based objective functions. The MO approach was based on the ε-Constraint method to determinate the Pareto optimal solutions and a trade-off analysis for decision making was defined. In [8], [9] GA was applied to the MO method called Weighted Sum that assembles in one objective function many technical performance indexes by means of weighted factors. Methods like the ε-Constraint and the Weighted Sum are classified in [10] as naïve approaches to MO problems. They are GA conceived for a single-objective optimization problem and adapted to determine the optimal solutions set in a multi-objective problem. So no Pareto optimality concepts are aggregated on that class of techniques. Therefore, both ε-Constraint and Weighted Sum methods keep limitations concerning the important task of finding the Pareto optimal solution set. The ε-Constraint method performance can be reduced depending on the limit value chosen for the objective function considered as an inequality constraint. The Weighted Sum method requires the normalization of the objective functions and it is not possible to find the entire optimal solutions set if the Pareto front is not convex [11]. In order to overcome those limitations, methods defined in [10] as Pareto-based approaches demonstrate enhanced ability to determinate the Pareto optimal solutions set. This sort of methods was applied to the optimal DG allocation problem in [12] and [13] using techniques based on GA known as, respectively, NSGA method and its improved version the NSGA-II method. So the main focus of this paper is to contribute on that essential stage of the MO process still under investigation for the enounced problem: to find a high quality Pareto optimal solutions set in order to support the human decision making. That is pursued here by the proposal of evaluating the potential of the MO method based on TS for solving the defined problem. The meta-heuristic TS was already used in optimal allocation problem of devices in DN, including DG [14], but in a single-objective approach. In Section II the NSGA-II and the MO TS based method are presented, including some implementation details. In Section III is defined an approach for the optimal DG siting and sizing problem and a methodology to evaluate the impact of the DG penetration on DN using MO techniques. Results and discussions are presented in Section IV and conclusions in Section V.

II. METHODS

Some basic concepts about MO are introduced in order to support the methods comprehension. The MO consists in minimize or maximize simultaneously a set of objectives subject to a number of constraints. The process of optimization in a multi-objective scenario occurs in two stages: the

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determination of the solution set, where all objective function values of each solution cannot be enhanced at the same time (this set is called Pareto optimal solutions or non-dominated solutions), and the human decision making whose criteria can be applied before, after or even during the optimization process. Distinctly of single-objective optimization, where just one optimal solution is determined, in a multi-objective context it is necessary to redefine *optimality*. In this sense, the concept of dominance is defined as: considering k objective functions and taking two solutions $\mathbf{x}$ and $\mathbf{y}$, it is said that $\mathbf{x}$ dominates $\mathbf{y}$ if $\mathbf{x}$ is better than $\mathbf{y}$ in at least one objective function $\mathbf{f}_i$ and it is not worst in any other objective function $\mathbf{f}_j$, where $i, j = 1, 2, \ldots, k$ and $i \neq j$ [12]. Then, in terms of dominance, a solution is a Pareto optimal if it is not dominated by any other solution.

The multi-objective Genetic Algorithm NSGA-II [15], used for performance comparison, is briefly presented. Furthermore, a detailed description of the TS-based approach to find the Pareto optimal set [3] is provided. The TS-based algorithm, named as Multi-objective TS (MOTS), is shown in Fig. 1.

A. *The NSGA-II Method*

The NSGA-II method is a multi-objective GA which combines solutions sorting mechanisms, elitism and the traditional genetic operators in order to find the non-dominated solutions set. The main strategies added to the NSGA-II technique, as an improvement with respect to its previous version, the NSGA method [16], are: the elitism, what guarantee the preservation of good solutions during the search process; the proceeding Fast Non-dominated Sort (FNS) where the population is sorted in different levels according to the Pareto dominance; and the proceeding Crowding Distance Assignment (CDA) stimulating the Pareto front diversity. So, after applying FNS and CDA, a mechanism called Crowded-Comparison Operator (CCO), that permits to compare two solutions and choose the best one, is applied. The first criterion for the choice is the dominance ranking and after is the diversity contribution. Then elitism is performed maintaining for the next generation the highest ranked solutions. Over the new population is applied the genetic operators of selection, based on CCO, recombination and mutation to generate an offspring population. Parent and offspring populations have the same size. So they are combined and the algorithm is repeated until the maximum generation number is reached. The detailed algorithm is presented in [15].

B. *The MOTS Method*

The TS algorithm is a heuristic neighborhood search in which optimal solution determination process is oriented using intelligent mechanisms. A basic single-objective TS algorithm is started defining an initial random and feasible solution, called seed. Then a set o neighbors is created using a predefined neighborhood structure. After determining the objective function value for each neighbor, a movement is executed from seed to the best solution among the neighbors solution. This move is performed even if it represents degradation in relation to the seed objective function. This strategy aims to avoid the search being trapped in a local optimal region. Nevertheless, this proceeding is not enough in avoiding cycling and driving the search to new regions. Hence the main strategy in the TS method is the Tabu List (TL).

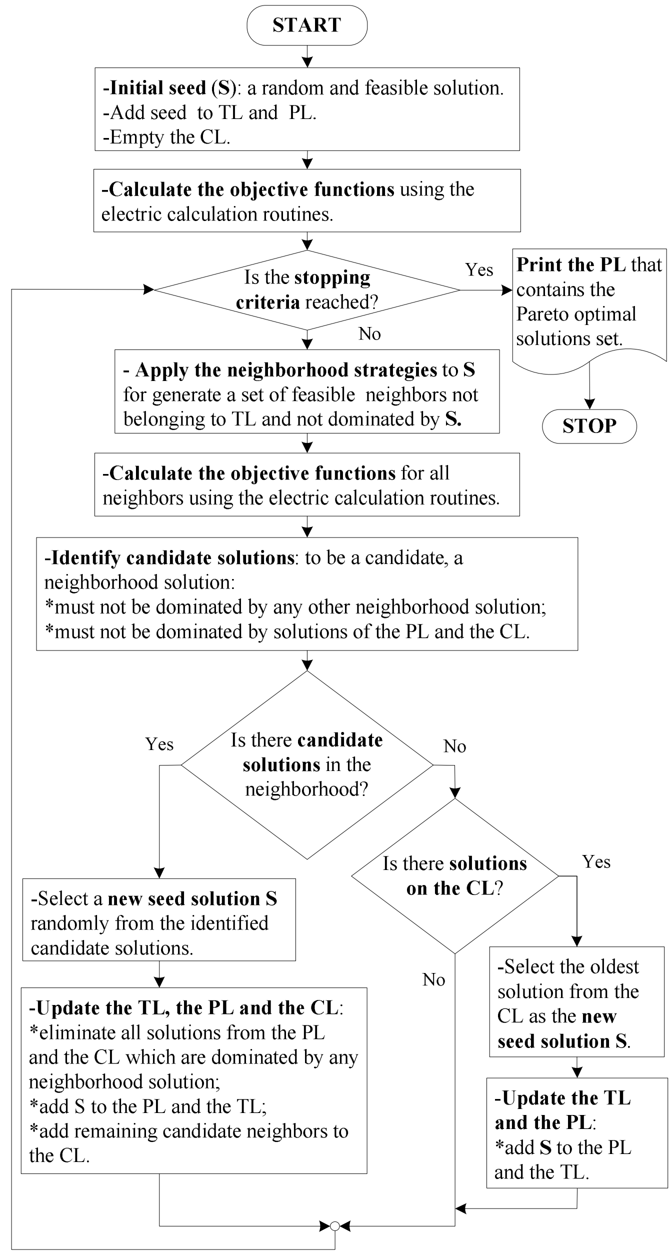

Fig. 1. The MOTS method algorithm [3].

This list registers the attributes or even the solutions from the n last movements in order to prohibit them in the search procedure for the next n iterations. The TL is updated in each iteration adding the last movement and excluding the oldest one in the list. The predefined value for n can be fixed or vary during the algorithm execution. Another mechanism, the aspiration criteria, tries to avoid the lost of good solutions whose attributes are prohibited by the TL: in the name of a desirable improvement on the best objective function value found, the prohibited attributes of a solution can be suspended and the movement admitted. Then a new seed is chosen and the algorithm is repeated until the stop criterion is satisfied. So MOTS is a MO approach proposed based on this basic algorithm. In MOTS the steps of the initial seed and the neighborhood generation can be similar to the basic TS algorithm. However, the stages of solutions selection and updating are considerably remodeled to consider the Pareto optimality concepts. Besides the TL, it is included the Pareto List (PL), keeping all the non-dominated solutions found, and the Candidate List (CL) in which are added the non-dominated solutions found in a iteration and not chosen as new seed solution. The MOTS algorithm is described in the Fig. 1, including some specific details of the problem discussed in this paper.

C. *Methods Implementation Details*

In this section are presented codification, neighborhood structure and stop criterion details. A configuration of DG units in the NSGA-II method, called chromosome, is defined using a vector where each position represents a node of DG connection. Buses with DG connected are identified in the vector by the generator type number, for instance, “1” or “2”. No DG connected is indicated by “0”.

It is shown in Fig. 2 a chromosome example for a 10-bus network. Two DG units were installed: a type “1” unit at the bus 806 and a type “2” generator at the bus 818.

Network nodes →	802	806	808	810	812	814	816	818	820	822
	0	**1**	**0**	**0**	**0**	**0**	**0**	**2**	**0**	**0**

Fig. 2. Codification example: NSGA-II method.

An equivalent codification model was defined for MOTS method: each vector position indicates an available DG unit and the value assumed in each position indicates the node where the generator is connected. The same example shown in Fig. 2 is presented according to this codification model in Fig. 3.

DG units →	1	2
	806	**818**

Fig. 3. Codification example: MOTS method.

In both codification proposals the optimal DG siting problem is solved simultaneously with the optimal sizing problem.

The proceeding to generate the neighbor sets in the MOTS method is decisive for its performance. As said before, in [14] a single-objective TS method was applied to the optimal DG siting and sizing problem. It was used, in [14], a neighborhood structure considering as neighbor a solution obtained by a DG unit addition or elimination in relation to the configuration of the seed solution. This idea was adapted and in this work the neighborhood structure is defined as the change of one generator from its current connection bus to others within a limit defined by a parameter called *neighborhood_step*. A neighborhood generation example is illustrated in Fig. 4.

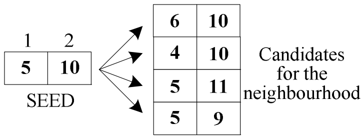

Fig. 4. Neighborhood generation considering two DG units (*neighborhood_step = 1*).

Due to the neighborhood criteria defined by MOTS, solutions dominated by the seed or prohibited by TL or unfeasible solutions are excluded of the generated neighborhood. When it is indicated the generator changing including a node with DG unit already installed, both generators exchange their positions. Therefore, the maximum number of neighbors generated by a seed is given by the expression (*2*DG units number*neighborhood_step*).

The stop criterion for the NSGA-II method was maximum number of generations. The MOTS execution is terminated when CL is empty and the algorithm cannot find any candidate solution [3].

III. TESTS METHODOLOGY

The electric network used was a modified version of the IEEE 34 Node Test Feeder [17]. This network has a long feeder, lightly loaded and the load concentrated far from the substation node [8], [18]. Some adaptations performed are indicated in the Fig. 5. The connection of DG units was restricted only to the three-phase nodes, indicated by black spots in Fig. 5. The white spots are single-phase nodes.

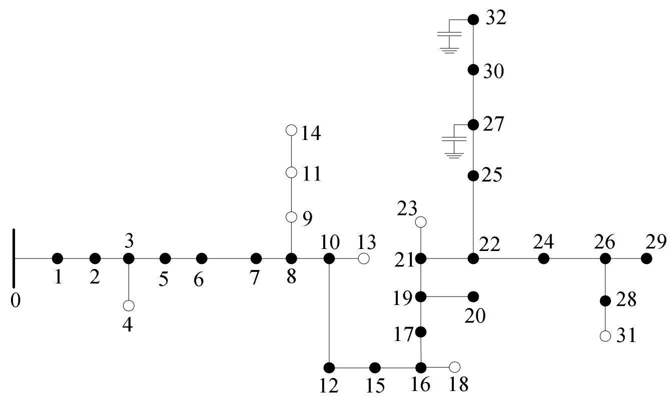

Fig. 5. Adapted IEEE 34 node test feeder [17].

The transformer connected between buses 832 and 888, in the original network, was removed as well as the bus corresponding to its secondary (888). The total distributed loads in a network segment was equally divided and concentrated at the extreme nodes of the segment.

Three technical indexes were defined:

1) Total Real Power Losses index (ILp) [12]: in (1) it is evaluated the DG impact over the real power losses by calculating the ratio between the network total real power loss for a DG configuration ($Loss^{DG}$) and the total real power loss without DG ($Loss^{0}$).

$$Min \quad ILp = \frac{Loss^{DG}}{Loss^{0}} \tag{1}$$

2) Three-Phase Short-Circuit Level index (ISC3) [12]: this index, defined in (2), contributes to the DG impacts evaluation concerning the network fault protection strategies.

$$Min \quad ISC3 = \max_{i=1,NN} \left(\frac{I_{SC}abc_i^{DG}}{I_{SC}abc_i^{0}} \right) \tag{2}$$

Where: $I_{SC}abc_i^{DG}$ represents three-phase fault current value in node i for a given DG configuration on the network; $I_{SC}abc_i^{0}$ represents three-phase fault current value in node i for the network without DG; NN is the number of nodes.

3) Voltage Regulation index (IVR): in (3) is defined an index for evaluate the voltage deviations from the voltage of the reference node. It was considered the voltage of the phase with the worst voltage profile.

$$Min \quad IVR = \sum_{i=1}^{NN} \left| V_i^{DG} - V_n \right| \tag{3}$$

Where, V_i^{DG} is the voltage magnitude in node i for a given DG configuration on the network; V_n is the voltage magnitude in the substation node.

Power flow calculations were performed using a Backward-Forward Sweep algorithm [19]. The short-circuit currents were found using symmetrical components and the sequence impedance of network and generators are given in [8].

In order to analyze distinct scenarios of DG penetration, it was considered the availability of five synchronous generators whose generation technology can be, for instance, internal combustion engines. In Table I it is shown the rated power of each generation unit.

TABLE I. AVAILABLE DG UNITS

DG unit	Rated Power (kW)
1	100
2	150
3	200
4	300
5	400

Two DG penetration scenarios were defined: Scenario A with three DG units (1, 2 and 3) and penetration level corresponding to approximately 76% of the demand; and Scenario B with five DG units (1, 2, 3, 4 and 5) and a penetration level corresponding to approximately 195% of the demand. In both scenarios the generation and demand were considered at their rated values. The DG units operation was in unitary and constant power factor.

The methods performances are observed considering first two objective functions, ILp and ISC3, and after adding IVR. The parameters values adopted for NSGA-II method were: recombination rate = 0.7; mutation rate = 0.05; generation number = 200; population size = 500/1000/3000. The parameters values for MOTS method were: neighborhood_step = 10/18; TL size = 10/20. The parameters population size, neighborhood_step and TL size were varied depending on the test performed in such a way to obtain the best solution with the least processing time.

IV. RESULTS

Before proceeding with performance analysis of MOTS method, it is briefly presented some impact studies done using this methodology. In Fig. 6 are displayed the Pareto fronts for both scenarios considering two objective functions, ILp and ISC3. The major part of the Pareto optimal solutions obtained in scenario A is dominated by those found in scenario B, whose DG penetration level is higher. Nevertheless, the higher DG penetration in scenario B constraints the possibility of reducing the short-circuit level, since in scenario A was found better results on the ISC3 index.

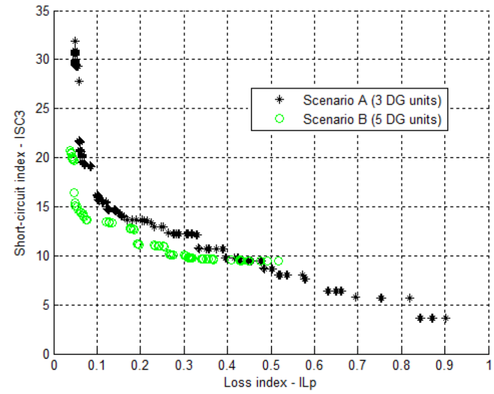

Fig. 6. Pareto fronts for scenarios A and B.

Results shown in Table II were obtained considering the three objective functions. It can be observed that the DG units connection near to the substation is beneficial to the short-circuit level. On the other hand, generators connected on buses far from the substation tend to reduce losses. Such observations are coherent with the network characteristics presented before.

TABLE II. DG IMPACT OVER THE NETWORK TECHNICAL INDEXES

Scenarios	Solution	DG units configuration	Nodes configuration	ILp	ISC3	IVR
Scenario A (3 DG units)	1	1-2-3	24-20-27	0.049	31.871	8.780
	506	1-2-3	3-2-1	0.903	3.598	11.797
Scenario B (5 DG units)	1	1-2-3-4-5	8-2-20-27-1	0.039	20.716	8.124
	1225	1-2-3-4-5	1-5-2-3-16	0.214	11.301	8.787
	1226	1-2-3-4-5	2-3-1-5-16	0.214	11.378	8.662
	1648	1-2-3-4-5	6-5-3-1-2	0.517	9.420	10.547

It can be realized either, from table II data, the limits for each technical criterion on different operation scenarios. If it is assumed the limits of voltage deviations as ±5% in relation to the nominal voltage, IVR values around 8.69 represent the voltage regulation limit. Thus, the intermediate solutions 1225 and 1226, included in Table II, demonstrate a situation where just exchanging the position of four generators may cause loss of voltage regulation. In the solution 1226 voltage regulation is possible on the contrary of the solution 1225, although both configurations keep a little difference between their respective ILp and ISC3 indexes.

In order to compare the NSGA-II method and MOTS method, their performances are summarized in Tables III and IV. It is evaluated the ability of each one on finding the Pareto front and how much time was needed. Moreover, the success of both algorithms on exploring all regions of the search space is analyzed verifying if there are solutions obtained by one of the methods dominated by any solution found by the other method.

TABLE III. COMPARED PERFORMANCE BETWEEN MOTS METHOD AND NSGA-II METHOD WITH TWO OBJECTIVE FUNCTIONS (ILP AND ISC3)

Method	Scenario A (3 DG units)			Scenario B (5 DG units)		
	Pareto set	*Solutions dominated by the other method*	*Time (s)*	*Pareto set*	*Solutions dominated by the other method*	*Time (s)*
MOTS	277	0	80	151	0	81
NSGA-II	275	0	737	151	0	846

TABLE IV. COMPARED PERFORMANCE BETWEEN MOTS METHOD AND NSGA-II METHOD WITH THREE OBJECTIVE FUNCTIONS (ILP, ISC3 AND IVR)

Method	Scenario A (3 DG units)			Scenario B (5 DG units)		
	Pareto set	*Solutions dominated by the other method*	*Time (s)*	*Pareto set*	*Solutions dominated by the other method*	*Time (s)*
MOTS	506	0	146	1648	0	1160
NSGA-II	505	0	1556	1644	1	5704

In just one test both methods found the same non-dominated solutions set. The MOTS method obtained more Pareto optimal solutions in the other three tests. In one case, scenario B for three objective functions, one solution of the NSGA-II is dominated by a solution obtained by MOTS. However, the more evident performance difference between both methods relied on the processing time. In the Fig. 7 graph, the time spent to find each non-dominated solutions set is presented.

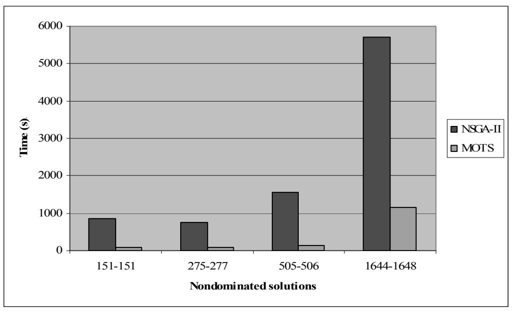

Fig. 7. Processing time for MOTS and NSGA-II method.

Especially when the Pareto front has many solutions, as in scenario B with three objective functions, the MOTS ability to find non-dominated solutions, maintaining the time saving feature, was well evidenced.

V. CONCLUSIONS

The MO methodology for the DG optimal siting and sizing problem exposed in this paper allows evaluating the DG impact penetration toward the medium voltage DN. The methodology has flexibility, permitting modification of models and objective functions and inclusion of others DG generation technologies. New scenarios can be easily added to the analysis. The MO can be completed by defining *a-posteriori* decision making processes. The results obtained can orientate investments, operation strategies and regulatory definitions.

This MO methodology must be supported by a reliable and efficient method to find the Pareto optimal set. The MOTS method, in this preliminary study was shown that it can be applied to the enounced problem presenting an efficient performance. Using NSGA-II as a reference method, MOTS presented a considerable superior result concerning the processing time, what is a desirable feature, especially in more complex analysis where time requirements become critical. Comparing the ability of each method to find the Pareto optimal set, the MOTS method demonstrated a small advantage over the NSGA-II. Nevertheless this result is not enough to make definitive conclusions, being necessary to investigate the methods behavior considering different networks and a more complete formulation of the problem.

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