An Ordering Procedure for Admissible Network Configurations to Regularize DFR Optimization Problems in Smart Grids

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Abstract: The power loss reduction is one of the main targets for any electrical energy distribution company. In this paper the problem of the joint optimization of both topology and network parameters in a real Smart Grid is faced. A portion of the Italian electric distribution network managed by the ACEA Distribuzione S.p.A. located in Rome is considered. It includes about 1200 user loads, 70 km of Medium Voltage (MV) lines, 6 feeders, a Thyristor Voltage Regulator (TVR) and 6 distributed energy sources (5 generator sets and 1 photovoltaic plant). The power factor correction (PFC) is performed tuning the 5 generator sets and setting the state of the breakers in order to perform the distributed feeder reconfiguration (DFR). The joint PFC and DFR problem is faced by considering a suited objective function and by adopting a genetic algorithm. In this paper we present a heuristic method to compare the graphs of two admissible topologies, such that similar graphs are characterized by close active power loss values. This criterion is used to define a suited ordering of the list of admissible configurations, aiming to improve the continuity of the fitness function to the variation of the configurations parameter. Tests are performed by feeding the simulation environment with real data concerning dissipated and generated active and reactive power values. Preliminary results are very interesting, showing that, for the considered real network, the proposed ordering criteria for admissible network configurations can facilitate the optimization process.

1 INTRODUCTION

The wide diffusion of Distributed Generation (DG) represents a possible development of modern electrical distribution systems that can evolve towards Smart Grids (SG). It can be stated that a SG is a new generation electrical network where smartness, dynamicity, safety and reliability are achieved through the use of Information and Communication Technologies (ICT) (Dahu, 2011). Recently, electrical distribution networks have grown quickly and the backbones of the existing infrastructures have been built when DG was not considered at all. As a consequence, electric power is distributed to the final user through a unidirectional transportation infrastructure. This configuration implies a considerable transportation consumption due to the long distance between producers and consumers. The main problems concerning actual networks are listed below:

- losses due to long distance between producers and users
- management of energetic flows
- inefficient use of DG related to renewable energy generators
- lag in the reaction time in case of blackout
- incomplete and inaccurate knowledge on the instantaneous status of the infrastructure

In order to overcome these drawbacks, a large number of sensors must be installed on the network to obtain a complete information on the instantaneous status of the infrastructure. This information can be used as input of an optimization control algorithm capable of determining in real time the best network configuration able to satisfy the instantaneous power request and to drive suitable actuators, optimizing a given objective function.

The number of DG units in electrical distribution networks has been increasing very fast in the last few years (Singh et al., 2011). Technologies used for DG applications could include non-renewable energy resources, such as internal combustion engines, com-

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bined cycles, combustion turbines as well as microturbines and renewable energy resources, for example photovoltaic and wind turbines.

Another important degree of freedom that can be used to minimize active power loss in distribution feeders is offered by the opportunity to perform the distribution feeders reconfiguration (DFR). This operation consists in switching a certain number of breakers, altering the topological structure of the network considering the topological contraints. Therefore, the DFR problem can be conceptualized as the task of choosing the status of network breakers resulting in the configuration with minimal power losses, while all the system constraints are satisfied. The main drawback of DFR is that it results in a complex nonlinear combinatorial problem, since the status of the switches is non-differentiable. This discontinuous behaviour makes the optimization problem related to DFR very hard to solve. In recent years, many researchers have proposed interesting solutions. Probably the first contribution in this direction can be found in (Merlin and Back, 1975), where a branch and bound type optimization technique is used in order to find the minimal loss operating configuration, for the distribution system, at a specific load condition. After this work, a few different techniques are proposed by many researchers (Civanlar et al., 1988), (Carreno et al., 2008). In recent years, new heuristic algorithms are proposed in the literature with good results. Probably, the first attempt to use genetic algorithms (GAs) to solve the DFR problem with minimal losses can be found in (Nara et al., 1992). Since then, a great number of publications based on evolutionary algorithms are proposed in the literature (Storti et al., 2013a), (Possemato et al., 2013). Recently, GA is also used to solve the DFR problem with DG (Chandramohan et al., 2010), (Storti et al., 2013b). One of the main difficulties for solving the DFR problem using evolutionary algorithms is the radiality constraint. A solution to this problem is proposed in (Storti et al., 2014) where a cooperation with *ACEA Distribuzione S.p.A.* is engaged with the aim to design a control strategy for the SG under development in the west area of Rome. The authors conclude that the DFR is a challenging problem do to high non linearity of the objective function. For this reason, in this paper we propose an heuristic method based on the Hamming distance between network configurations, to improve the regularity of the objective function. The rest of the paper is organized as follows: in section 2 we present the main characteristics of the SG under analysis, in section 3 we formulate the DFR optimization problem, then in section 4 we describe an ordering criteria for the network configurations. Finally, in section 5 we report the results obtained by applying the proposed ordering heuristic to the set of admissible configurations together with a GA. Moreover, we compare results of the genetic optimization of network topology and DGs parameters for the ACEA SG, in the cases of unordered (Storti et al., 2014) and ordered configurations.

2 NETWORK SPECIFICATIONS

The portion of the network we consider in this paper is located in the west area of Rome. The entire SG is made up of:

- 5 feeders at 20 kV
- 1 feeder at 8.4 kV
- 2 High Voltage (HV) substations
- 76 Medium Voltage (MV) substations
- 5 generator sets (DGs)
- 1 photovoltaic generator (DG)
- 1 thyristor voltage regulator (TVR)
- 106 three-phase breakers
- 70 km of cables
- 1200 user loads

In each HV substation there is a transformer with 150 kV at the primary winding and 20 kV at the secondary winding (HV/MV transformer). The cables, the photovoltaic plant, the MV substations and the TVR are located in the MV portion of the network, whereas the user loads and the 5 generator sets are located in the LV portion of the network.

The TVR is a series voltage compensation device. It performs a bi-directional voltage regulation that maintains the system voltage within specified ranges. The bi-directional relation between the input and the output voltage is defined as follows:

$$V_{out} = V_{in} + N_{tap}\Delta V \quad N_{tap} \in \{0, \pm 1, \pm 2, \pm 3\} \quad (1)$$

where the values of V_{in} and V_{out} are expressed in kV and the ΔV is 0.1 kV. The voltage rated value of V_{in} is 8.4 kV. Each MV substation is equipped with 2 breakers (switches) that allow it to connect with the network in different ways. By changing the state of these switches it is possible to modify the topology of the network.

3 PROBLEM FORMULATION

In this paper, we consider the joint PFC and DFR problem for minimum active power losses, satisfying constraints on nodes voltage and branches current as well as system operating constraints.

3.1 Optimization Procedure

In this section we formulate the problem of active power losses minimization in SGs. It consists in finding the optimal network parameters and topological configuration that minimize the value of the total active power losses in the network, considering the constraints imposed on voltages and currents due to safety or quality of service issues. Consider an admissible set E of the network parameters and a suitable cost function $J : E \to \mathbb{R}$ that associates a real number to each element in E. Formally, the problem consists in minimizing the function J in E. Mathematically we can express the cost function J as follows:

$$J(\mathbf{k}) = \frac{P_{loss}(\mathbf{k})}{P_{gen}(\mathbf{k})} = \frac{P_{gen}(\mathbf{k}) - P_{load}}{P_{gen}(\mathbf{k})} \tag{2}$$

where $\mathbf{k}$ represents an instance of the network parameters, $P_{gen}(\mathbf{k})$ is the total power generated by all sources, P_{load} is the total power absorbed by the loads, and their difference $P_{loss}(\mathbf{k})$ represents the total losses in the network. Let's consider a generic SG characterized by n real parameters, m integer parameters and p nominal parameters. We can express the domain of the ordinal parameters as:

$$A' = \left\{ \mathbf{k}' \in \mathbb{R}^n \times \mathbb{Z}^m \;\; : \; \mathbf{k}'_{min} \leq \mathbf{k}' \leq \mathbf{k}'_{max} \right\} \tag{3}$$

in which $\mathbf{k}'_{min}$ and $\mathbf{k}'_{max}$ represent the vectors of the minimum and maximum values of the network ordinal parameters $\mathbf{k}'$. Concerning the nominal parameters, $\mathbf{k}''$, the domain is a set A'' of all possible admissible elements for such parameters:

$$A'' = \left\{ \mathbf{k}'' \in \mathbb{X}_1 \times \cdots \times \mathbb{X}_p \right\} \tag{4}$$

in which $\mathbb{X}_i$ is a generic nominal set with $i = 1, ..., p$. The overall domain A is defined as $A = A' \times A''$ and the parameters vector $\mathbf{k}$ is an element of such domain. Without loss of generality, we consider as possible to measure the voltages and the currents at all locations in the network. In order to be valid, a solution $\mathbf{k}$ must satisfy the constraints on voltages and currents defined below:

$$B = \left\{ \mathbf{k} \in \mathbb{R}^n \times \mathbb{Z}^m \times \mathbb{X}_1 \times \cdots \times \mathbb{X}_p : \\ V_{min_i} \leq V_i(\mathbf{k}) \leq V_{max_i}, i = 1, .., M \right\}$$

$$C = \left\{ \mathbf{k} \in \mathbb{R}^n \times \mathbb{Z}^m \times \mathbb{X}_1 \times \cdots \times \mathbb{X}_p : \\ |I_i(\mathbf{k})| \leq I_{max_i}, i = 1, .., R \right\}$$

where $V_i(\mathbf{k})$ is the voltage magnitude of node i for a fixed instance of parameters $\mathbf{k}$, M represents the number of nodes, V_{min_i}, V_{max_i} are the voltage limits for node i, while $|I_i(\mathbf{k})|$ represents the current magnitude of branch i for a particular instance of parameters $\mathbf{k}$, R the number of branches and I_{max_i} the current limit for branch i. The definitions given above allow to define the admissible set E as follows:

$$E = A \cap B \cap C \tag{5}$$

This formulation is an example of mixed-integer black box-based optimization problem because the optimization variables are integer and real. Moreover, it is not practically possible to derive expression (2) in closed form as a function of $\mathbf{k}$; for this reason we employ a GA (derivative free approach) as optimization algorithm. The constrained optimization problem is faced by defining the objective function as a convex combination of two competitive terms:

$$F(\mathbf{k}) = \alpha J(\mathbf{k}) + (1 - \alpha)\Gamma(\mathbf{k}) \tag{6}$$

where α is a real number in the range [0, 1] used to adjust the relative weight of the power losses term $J(\mathbf{k})$ over the constraints term $\Gamma(\mathbf{k})$. The function $\Gamma(\mathbf{k})$ is defined as follows:

$$\Gamma(\mathbf{k}) = (1 - \beta)\Gamma_I(\mathbf{k}) + \beta\Gamma_V(\mathbf{k}) \tag{7}$$

in which β is a real number in the range [0, 1] used to adjust the relative weight of the violation of current constraints $\Gamma_I(\mathbf{k})$ with respect to the term related to voltages violation $\Gamma_V(\mathbf{k})$. In this paper it is performed the minimization of $F(\mathbf{k})$ in A. Further details of the optimization procedure can be found in (Storti et al., 2013a).

3.2 Admissible Network Configurations

In order to perform the optimization procedure described in section 3.1, we introduce a suitable representation of the SG as a non oriented graph $\mathcal{G}\langle N, E\rangle$, in which N and E are the nodes and the edges of the real network, respectively. Let's define as $\hat{\mathcal{G}}\langle \hat{N}, \hat{E}\rangle$, the *reduced graph* of the network. The objective of this representation is to properly describe all the possible system reconfigurations satisfying the topology constraints. The reduced graph of the network $\hat{\mathcal{G}}\langle \hat{N}, \hat{E}\rangle$ doesn't contain all the information of the original network graph $\mathcal{G}\langle N, E\rangle$ because for our purposes we need only to know how different portions of the network can be electrically connected. As described in (Storti et al., 2014), the mapping of the real network in the simplified graph version is performed through two main steps:

- The nodes $\hat{N}$ of the simplified graph are used to model 2 different types of original nodes N. The first one represents nodes at 150kV providing the energy balance of the active and reactive power in the SG. In following sections we will refer to it as HV node. The second one can represent a single MV real substation eventually connected to loads, DGs and TVR, or a set of MV substations, powered by a single HV substation only (virtual MV). In both cases, we call this kind of nodes as MV node.

- Edges $\hat{E}$ of the reduced network graph are used to model the topology reconfiguration. The series of two switches, installed between two consecutive MV substations, are mapped into a single edge of the reduced graph $\hat{\mathcal{G}}$ (virtual breaker). Each edge is associated with a label representing its state i.e. close or open.

Figure 1 shows an example of the representation of the network through the reduced graph $\hat{\mathcal{G}}\langle\hat{N},\hat{E}\rangle$.

Using the above notation we can introduce the following definitions:

Def. 1 (**Radial Topology Constraint**). *A network topology satisfies the Radial Topology Constraint iff each MV substation is fed by only one HV substation via only one path.*

Def. 2 (**Admissible Configuration**). *A reduced graph $\hat{\mathcal{G}}\langle\hat{N},\hat{E}\rangle$ satisfying the radial topology constraint is said to be an admissible configuration of the network.*

The graph representation $\hat{\mathcal{G}}\langle\hat{N},\hat{E}\rangle$ is used to perform an algorithm that executes an exhaustive search of all the admissible configurations of the network. The details of the automatic procedure are described in (Storti et al., 2014). The output of such procedure is a list of binary strings (admissible configurations) having length equals to the number of edges $\hat{E}$ of the reduced network graph. Each bit represents the state of the corresponding edge (breaker). The network topology is specified by an integer index, named N_{conf}, spanning the rows of the list of admissible configurations ordered according to the automatic procedure. During the optimization procedure, N_{conf} constitutes a nominal parameter to be optimized, so the objective function can change abruptly moving from a given configuration to the previous or the next one, making very challenging this optimization due to high discontinuities in the objective function. For this reason, in the following section, we present an heuristic method to compare the graphs of two admissible topologies, in terms of active power loss values through a purely topological analysis. This criterion is used to define a suited ordering of the list of admissible configurations, aiming to improve the continuity of the objective function to the variation of the N_{conf} parameter.

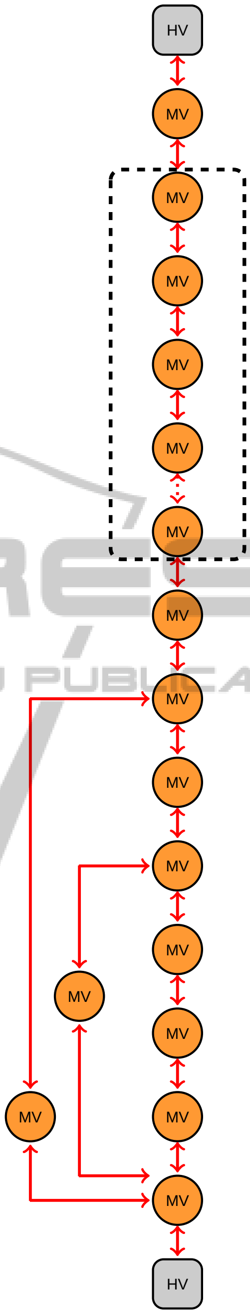

Figure 1: Example of the graph $\hat{\mathcal{G}}\langle\hat{N},\hat{E}\rangle$ of the simplified network. Orange circles indicate MV nodes, gray rectangles are HV nodes, dashed arrows represent open status edges. The dashed box highlights a portion of the network.

4 ORDERING HEURISTIC

In order to make effective any algorithm for solving the optimization problem described in section 3.1, we need an ordering heuristic of the admissible configurations to improve the 'regularity' of the objective function. In such a derivative free mixed integer context, it means reducing the variations of the objective function evaluated at an admissible configuration i from the objective values at $i-1$ and $i+1$, for $i = 2,3,\ldots,n-1$, where n indicates the number of the admissible configurations found as described in the previous section.

4.1 Graph Representation of Admissible Network Configurations

Each admissible configuration of the network is identified by a binary string of length equal to the number of virtual breakers of the reduced graph. Given a pair of configurations $\langle i, j\rangle$, we use the Hamming distance between the respective bit strings, $d_H(i, j)$, to quantify the dissimilarity between i and j. Let D be a square matrix of order n containing all the Hamming distances between admissible configurations, i.e. $d_{ij} = d_H(i, j)$ for $i, j = 1,\ldots,n$. Of course D is symmetric with zeros along the diagonal only. Let's define as $\mathcal{G}^{AC}$ the undirected graph of the admissible configurations represented by D, where each element d_{ij} of the matrix is the weight w_{ij} of the edge e_{ij} that connects nodes i and j of $\mathcal{G}^{AC}$. Let's denote by N^{AC} and E^{AC} the sets of nodes and edges of $\mathcal{G}^{AC}$, respectively. Figure 2 shows an example of the building process of $\mathcal{G}^{AC}$. The portion of the reduced graph considered in the example is highlighted within a dashed box in Figure 1. Opening the virtual breaker between nodes $\hat{N}_3$ and $\hat{N}_4$ represented by edge $\hat{E}_{3,4}$, we obtain the configuration [1 1 0 1], while disconnecting nodes $\hat{N}_2$ and $\hat{N}_3$ and reconnecting nodes $\hat{N}_3$ and $\hat{N}_4$ by opening the virtual breaker $\hat{E}_{2,3}$ and closing $\hat{E}_{3,4}$, the resulting configuration is [1 0 1 1]. The extracted configurations are two nodes of the graph $\mathcal{G}^{AC}$ at distance $d_H = 2$.

4.2 Heuristic method for ordering the admissible configurations

In this subsection we present an heuristic method, based on $\mathcal{G}^{AC}$, used to order the admissible configurations of the network to avoid strong discontinuities between active power loss values of consecutive configurations. Then, in section 5 we will show how this method applied to a real electrical network actually makes less difficult to solve the optimization problem presented in section 3.1.
Given a configuration i, the objective function value $F(\mathbf{k})$ will depend on all the other parameters values in $\mathbf{k}$, i.e. on a set of virtually infinite combinations. However we need to associate with each configuration a unique scoring function, as an average estimate

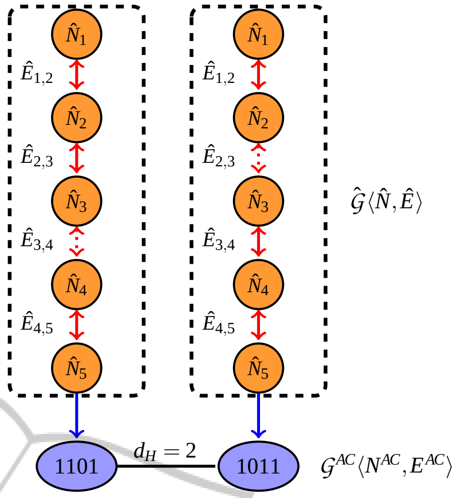

Figure 2: Building process of configurations graph $\mathcal{G}^{AC}$ of a portion of two instances of the reduced network graph $\hat{\mathcal{G}}\langle\hat{N},\hat{E}\rangle$.

of $F(\mathbf{k})$. To this aim, the following reference values of the real parameters are chosen for all configurations:

$$(\overline{k_j}) = (k_{j,min} + k_{j,max})/2, \qquad j = 1,\ldots,n \tag{8}$$

and for the integer parameters:

$$(\overline{k_h}) = [(k_{h,min} + k_{h,max})/2], \qquad h = 1,\ldots,m \tag{9}$$

in which the operator $[\cdot]$ indicates the round operation. For simplicity we will refer to $f(i)$ to indicate $F(\mathbf{k})|_{N_{conf}=i}$ and to $\overline{f}(i)$ to represent the fitness $f(i)$ computed in the reference values of the parameters expressed in (8) and (9).
Let W be the list of all possible values for the weights of the edges of graph $\mathcal{G}^{AC}$, ordered in ascending manner:

$$W = [w_1, w_2, \ldots, w_m]$$

Fixed a node i of $\mathcal{G}^{AC}$ and a weight $w_j \in W$, we define $(N_i^{AC})_{w_j}$ as the set of all nodes connected with i by edges with weight w_j. An estimate of the difference between $\overline{f}(i)$ at i-th node and the objective values associated with the nodes belonging to $(N_i^{AC})_{w_j}$, is given by the mean distance $(\Delta F_i)_{w_j}$ between $\overline{f}(i)$ and the fitness $\overline{f}(k)$, $\forall k \in (N_i^{AC})_{w_j}$. Indicating as $(\Delta\overline{f}_{i,k})_{w_j} = \left|\overline{f}(i) - \overline{f}(k)\right| / \overline{f}(i)$ the relative distance between the fitness $\overline{f}(i)$ and the fitness $\overline{f}(k)$, the mean distance can be mathematically expressed as:

$$(\Delta F_i)_{w_j} = \frac{\sum_{k=1}^{(l_i)_{w_j}} (\Delta\overline{f}_{i,k})_{w_j}}{(l_i)_{w_j}} \tag{10}$$

where $(l_i)_{w_j}$ is the cardinality of $(N_i^{AC})_{w_j}$. If each node i of $\mathcal{G}^{AC}$ satisfies the following property:

$$(\Delta F_i)_{w_1} \leq (\Delta F_i)_{w_j}, \qquad j = 2,\ldots,m \tag{11}$$

we can deduce that, in mean, the active power loss of the network varies less between similar configurations than between dissimilar ones. Remember that with 'similar' we indicate similarity in terms of Hamming distance. We can extract the subgraph $\mathcal{G}^{AC}_{w_1} = \langle N^{AC}, E^{AC}_{w_1} \rangle$, whose set of edges $E^{AC}_{w_1}$ is defined as follows:

$$E^{AC}_{w_1} = \{e_{ij} \in E^{AC} \ \ s.t. \ \ w_{ij} = w_1, \\ \forall i, j = 1, 2, \ldots, n\} \tag{12}$$

The existence of an edge between a pair of nodes i and j of the graph $\mathcal{G}^{AC}_{w_1}$ should indicate that the configurations i and j have close active power losses. In the following section we will proof such property for the network under analysis.
To order the admissible configurations of the network we use the depth first traversal algorithm on $\mathcal{G}^{AC}_{w_1}$. The order in which the nodes are visited will be the new sequence of the indexes of the admissible configurations.

5 TESTS AND RESULTS

In this section we first empirically prove the property expressed in (11) for the network under consideration, then we compare the performances of GA when it is used to solve the optimization problem presented in section 3.1 for the considered electrical network, whether the configurations are ordered or unordered.

Following the notation introduced in section 3.1 and network specifications described in section 2, we can control the reactive power of the 5 generator sets through the phase parameters ϕ. Instead it is not possible to control the reactive power of the photovoltaic generator. Moreover it is possible to chose the N_{tap} value of the TVR and the configuration of the network selecting it from the set of admissible ones previously determined. The phases of the 5 generator sets $\phi_1, \phi_2, \phi_3, \phi_4, \phi_5$ will be spanned in a real given range specified by the capability functions of the corresponding generator sets. The tap N_{tap} of the TVR will be spanned in the discrete (normed) range defined in (1). Finally, according to the list of admissible configurations introduced in section 3.2, the network topology is specified by an index, N_{conf}, spanning the rows of such list. In particular, in the smart grid under consideration, the number of admissible configurations is 390. Summarizing, the candidate solution vector $\mathbf{k} = [\phi_1, \phi_2, \phi_3, \phi_4, \phi_5, N_{tap}, N_{conf}]$ will span the set defined below:

$$A = \{ \ \mathbf{k} \subset \mathbb{R}^5 \times \mathbb{Z} \times \mathbb{X} : \begin{array}{rcl} -0.2 \leq & \phi_1, \phi_2 & \leq 0.45 \\ -0.2 \leq & \phi_3 & \leq 0.55 \\ 0.0 \leq & \phi_4 & \leq 0.64 \\ -0.32 \leq & \phi_5 & \leq 0.45 \\ -3 \leq & N_{tap} & \leq 3 \\ & N_{conf} \in & \mathbb{X} \ \} \end{array}$$

in which $\mathbb{X} = \{conf_1, ..., conf_{390}\}$ is the set of indexes of all configurations. Moreover, in order to be valid, a solution $\mathbf{k}$ must satisfy the constraints on voltages and currents defined below:

$$B = \big\{ \mathbf{k} \subset \mathbb{R}^5 \times \mathbb{Z} \times \mathbb{X} : 0.9V_{nom_j} \leq V_j(\mathbf{k}) \leq 1.1V_{nom_j} \\ , j = 1, .., M \big\}$$

$$C = \big\{ \mathbf{k} \subset \mathbb{R}^5 \times \mathbb{Z} \times \mathbb{X} : |I_j(\mathbf{k})| \leq I_{max_j}, j = 1, .., R \big\}$$

in which M and R represent the total number of nodes and branches of the real network, respectively, whereas V_{nom_j} and I_{max_j} are the nominal value of the voltage of the j-th node and the maximum current allowed in the j-th wire, respectively.

Performing the analysis described in the previous section, we found that in the network under consideration there are only three different possible weights (i.e. Hamming distance values) associated with the edges of the graph of the admissible configurations $\mathcal{G}^{AC}$. In particular:

$$W = [2, 4, 6]$$

whereby we have to compute $(\Delta F_i)_2$, $(\Delta F_i)_4$, $(\Delta F_i)_6$ for $i = 1, 2, \ldots, 390$. The minimum weight belonging to W is $w_{min} = 2$, as we could expect, since in a real electrical network, a topology change implies, at least, closing a given breaker and opening another one. Thus, we have to check if the following two conditions are satisfied:

$$(\Delta F_i)_2 \leq (\Delta F_i)_4 \quad i = 1, \ldots, 390 \tag{13}$$

$$(\Delta F_i)_2 \leq (\Delta F_i)_6 \quad i = 1, \ldots, 390 \tag{14}$$

To compute the fitness value associated with each node of $\mathcal{G}^{AC}$, we have considered as input of the network model the power profile associated with the 1:00PM (one hour) of the 1-st of January.
Figure 3 shows the values of $(\Delta F_i)_2$, $(\Delta F_i)_4$, $(\Delta F_i)_6$ calculated for all nodes of $\mathcal{G}^{AC}$. It is possible to observe that, for most of nodes, relations (13) and (14) are satisfied. An accurate data analysis returns that over 97% of nodes (network configurations) satisfy these two relations.
It's important to point out that this result doesn't depend on the values initially assigned to fitness parameters $\overline{\phi_j}$ for $j = 1, \ldots, 5$ and $\overline{N_{tap}}$. In fact, the set of nodes satisfying relations (13) and (14) is the same for any set of admissible values initially assigned to these

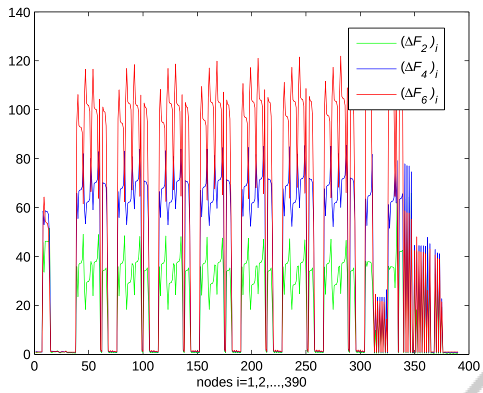

Figure 3: Mean distance between the fitness value associated with node i, $\bar{f}(i)$, and fitness values associated with all the adjacent nodes of the i-th node belonging to $(N_i^{AC})_2$, $(N_i^{AC})_4$, $(N_i^{AC})_6$ respectively, for $i = 1, 2, \ldots, 390$. The scale factor is equal to $\bar{f}(i)$.

parameters. Thus, we have empirically proven Equation (11), specifically that similar network configurations (i.e. nodes of graph $\mathcal{G}^{AC}$ connected by edges with small weights) correspond to close active power loss values. Note that we have verified this property only for the network under analysis.

At this point, as described in section 4.2, we can choose a depth first traversal of the sub graph $\mathcal{G}_2^{AC}\langle N^{AC}, E_2^{AC}\rangle$ to order the admissible configurations. It was verified that $\mathcal{G}_2^{AC}$ is a connected graph, with size, i.e. the number of its edges, equal to 4743. In particular, the *minimum degree* of $\mathcal{G}_2^{AC}$, i.e. the minimum number of edges incident to its nodes, is equal to 21. There are 90 nodes having this number of edges incident to them. The *maximum degree* of $\mathcal{G}_2^{AC}$ is 37 and only 20 nodes have this number of edges incident to them. In order to compare the effectiveness of this ordering heuristic technique in solving the proposed optimization problem, the execution of GA is repeated 6 times, whether the configurations are ordered or unordered. Different executions consider different sequences of indexes obtained through depth first traversal of $\mathcal{G}_2^{AC}$, starting from different root nodes.

To compare performances of GA, the algorithm parameter setting is chosen identical whether the configurations are ordered or unoredered (in the second case, we consider the initial ordering of the admissible configurations returned by the automatic procedure described in (Storti et al., 2014)). In particular, the number of individuals of a population is set to 20. The elite individuals are 2, i.e. only 2 individuals in the current generation are guaranteed to survive to the next generation. The crossover fraction parameter is 0.8. The mutation operator is applied to the remaining individuals. Furthermore, the α and β coefficients used in expressions (6) and (7) are set to 0.9 and 0.2, respectively.
The maximum number of iterations before the algorithm halts is 100, but GA can stop if the weighted average relative change in the fitness value over 50 iterations is less than or equal to 10^{-9}.

All performed tests consider the same states of the network to seed GA. More precisely, a fixed initial population is considered for all of the executions of the GA when the admissible configurations are ordered and unordered. It should be noted that the random initialization does not necessarily ensure the satisfaction of the constraints considered in the definition of the chosen fitness function. Results of the simulations are shown in Table 1. It compares the mean value of the number of generations created (#*gen*), the fitness percentage reduction (%F reduct.) and the reduction of active power loss of the network (*Ploss* reduct.), whether the configurations are ordered or unordered (Storti et al., 2014). More precisely, last two indicators consider the reduction of the fitness value and actual active power loss between the optimal solution and the best individual of the initial population. Moreover, Figures 4 (a)-(b)-(c) show the mean value of the number of generations, the mean percentage reduction of fitness value and the mean reduction of power loss and the respective standard deviation in both cases of ordered and unordered list of configurations.

Table 1: Mean number of generations (# *gen*) produced by GA to return the optimal solution, mean percentage reduction of the fitness value (%F reduct.), mean reduction of the active power loss (P_{loss}) whether the admissible configurations are ordered or unordered.

	ordered conf.	unordered conf.
# *gen*	73	67
%F reduct.	0.023	0.022
P_{loss} reduct. $[W]$	1096.97	1088.34

We can note that the mean number of generations of GA when the configurations are ordered is larger than in the unordered case. This is due to greater headway made by GA during the search process of the optimal solution, in the first case. This allows to have, on average, an higher reduction of the fitness value, as well as of the total active power loss, from the initial state of the considered network. As we expected, the power loss reduction is not very high, but considering that all the tests simulate only one hour of one day and projecting this power loss reduction to the whole network over time, the savings could become interesting in the regular operating condition of the real network in which the value of the power loss

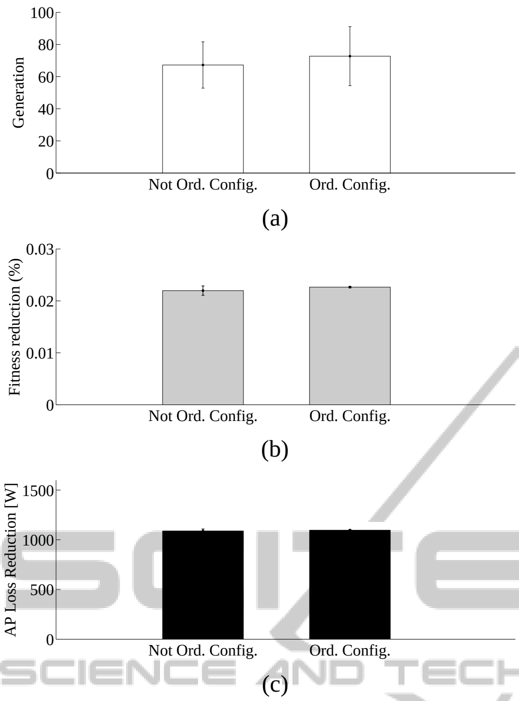

Figure 4: Mean value of the number of generations (a), the mean percentage reduction fitness value (b) and the mean reduction of active power loss (c) with the respective standard deviation for ordered and unordered list of configurations.

becomes considerable.

6 CONCLUSIONS

In this paper an improvement of the control system described in (Storti et al., 2013a), (Possemato et al., 2013), (Storti et al., 2013b) and (Storti et al., 2014) is presented. We propose an heuristic method to compare admissible network topologies and a criteria to order the list of such topologies aiming to improve the continuity of the objective function to the variation of the configuration parameter. We execute some tests on the SG sited in the west area of Rome realized by *ACEA Distribuzione S.p.A.*. Results show that, for the network under analysis, the proposed ordering procedure makes the joint PFC and DFR optimization problem simpler to cope with a plain genetic algorithm. In future works we intend to verify the criteria in a more complex network and at different time intervals. Moreover, by exploiting the property described by Equations 13 and 14, it is possible to redefine more suitable mutation and crossover operators to furtherly improve the convergence of the GA during the evolutionary process.

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