Active Power Losses Constrained Optimization in Smart Grids by Genetic Algorithms

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Abstract. In this paper the problem of the minimization of active power losses in a real Smart Grid located in the area of Rome is faced by defining and solving a suited multi-objective optimization problem. It is considered a portion of the *ACEA Distribuzione S.p.A.* network which presents backflow of active power for 20% of the annual operative time. The network taken into consideration includes about 100 nodes, 25 km of MV lines, three feeders and three distributed energy sources (two biogas generators and one photovoltaic plant). The grid has been accurately modeled and simulated in the phasor domain by Matlab/Simulink, relying on the SimPowerSystems ToolBox, following a Multi-Level Hierarchical and Modular approach. It is faced the problem of finding the optimal network parameters that minimize the total active power losses in the network, without violating operative constraints on voltages and currents. To this aim it is adopted a genetic algorithm, defining a suited fitness function. Tests have been performed by feeding the simulation environment with real data concerning dissipated and generated active and reactive power values. First results are encouraging and show that the proposed optimization technique can be adopted as the core of a hierarchical Smart Grid control system.

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). A rigorous definition of the term "Smart Grid" is somewhat difficult. In fact, due to the fast evolution of the technology, it is quite hard to mark out a sharp boundary including all the aspects associated with this terminology. A widely adopted definition states that a SG is an electrical network able to perform an intelligent integration of all the users connected to it (*i.e.* producers and consumers), with the purpose of distributing the electrical power in a safe,

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efficient and sustainable fashion. Tautly, 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 Communication Technologies (ICT) [4,7]. In fact, ICT can be considered an important support to the migration of traditional electrical infrastructure toward SG. Although the size of the actual electric networks has been improved in order to follow the always increasing power requests, this growth has been achieved without a global planning finalized to the optimization of the energy transportation. Moreover the backbones of the existing infrastructures have been built when the location of the main power users, such as industries, were much different from the actual configurations and when the DG was not even a theoretical concept. For these reasons distribution networks have been implemented in a hierarchic fashion. Electric power is distributed to the final user through an unidirectional transportation infrastructure. This configuration implies a considerable transportation consumption due to the long distance between producers and consumers. Finally, the available electric distribution infrastructures are inadequate to the future requirements. The main problems concerning actual networks are listed below:

- Losses due to long distance between producers and users
- Not optimal 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

As stated before, most of these problems can be solved by improving the actual infrastructures with the aid of ICT. More precisely a large number of sensors must be installed on the network in order to obtain a complete information on the instantaneous status of the infrastructure. This information can be used as the input of an optimization control algorithm capable to determine in real time the best network configuration in order to satisfy the instantaneous power request and to drive suitable actuators in order to achieve the optimal configuration. DGs can impact the bus voltage, line power flow, short-circuit current and power network reliability, so that it is very important in SG design and realization to be able to control DGs [3,5].

In the literature there is an increasing number of publications concerning the use of computational intelligence (CI) in SG [9,10]. Considering a SG as a complex, dynamic, nonlinear and stochastic system, CI can provide support for designing safer and more efficient control systems, in line with emerging technologies. From the point of view of the CI, the SG managing and control is a highly complex problem given the non-linearity and the dynamic of the system, as well as the heterogeneity of the elements that compose it (generators, transformers, transmission lines, time-variant loads, telecommunications system, market regulations). As well know, the main feature of control systems is the ability to run in real-time (unless the system is simulated). Neural and fuzzy approaches seems to be the main candidates, given the universality they offer to model any system. The distinction, considering a large-scale vision of a SG as a System of Systems (SoS), is between Distributed Local and Wide-Area Monitoring and Control. In the first case neural techniques are used for learning and tracing the system dynamics in order to implement operations such as constraints and operating points settings. Neural algorithms based on Multilayer Perceptron (MLP) and Radial Basis Functions (RBFs) allow to control elements such as turbine generators, solar and wind installations or transmission lines. Techniques known as Artificial Immune System (AIS) allow adaptive control strategies without the need for off-line learning. The ability to control a power system depends on the quality of sensors and the reliability of communication infrastructures. Errors and failures in these systems may easily cause incorrect control schemes with serious consequences. To this aim Swarm Intelligence techniques can be used to recover data from faulty sensors.

Among the variety of techniques offered by CI the use of Genetic Algorithms (GA) seems to be a promising technique. In [6] an adaptive genetic algorithm is used to establish the best distributed generation siting and sizing on a distribution network, showing that the optimal siting and sizing of DG units can effectively reduce the network loss and improve the system voltage level. In [8] it is shown that GAs can deal well with the stochastic nature of the distribution grid and can be successfully used as an optimization method for solving the control problems. Beside theoretical studies it is important to have the opportunity to validate the designed optimization strategy on real data. Moving in this direction, a cooperation with *ACEA Distribuzione S.p.A.* [1] has been engaged with the aim to design a control strategy for the SG under development in the west area of Rome. The project concerning the upgrade of the actual network to up-to-date SG technology fulfils the requirements imposed by AEEG resolution 39/10 [2]. A complete simulator of the considered real network has been implemented; it is described in Sec. 2. In Sec. 3 the multi-objectives optimization problem is formulated and the use of a GA is proposed in order to solve it. In Sec. 4 it is shown how the proposed control strategy can be successfully used to modulate the power fed into the network by DGs in order to reduce active power losses taking into account suited constraints on voltages and currents levels, as well as the available working points of DGs. Finally, conclusions and works in progress are discussed in Sec. 5.

2 Network Simulation

The network under consideration is located in the west area of Rome. It is constituted of about 100 nodes and it is made up of:

– N.3 feeders at 20 kV
– N.2 transformers High Voltage/Middle Voltage (HV/MV)
– N.2 biogas generators
– N.1 photovoltaic generator
– 25 km of MV lines
– N.11 three phase breakers

The generators and the loads are driven by 2 inputs: Active Power (P) and Reactive Power (Q). The real behaviour of the SG can be simulated by means of P and Q yearly power profile. Moreover, in order to reproduce the possibility to supply each MV feeder from a different substation and therefore to change the topology of the network, a boundary switch (Breaker) is placed at the beginning and at the end of each line.

The proposed simulator has been implemented following a Multi-Level Hierarchical and Modular approach. The Multi-Level Hierarchical design improves, through the definition of suitable I/O interfaces, the readability of whole SG simulation model; the Modular approach allows to change, in a simple way, all the parameters of each component models. The structure of the SG simulator is implemented using the MatLab/Simulink SimPowerSystems ToolBox, which allows to rapidly and easily build models that simulate power systems. The SG simulation model is made up of 2 macro blocks: the Input Network and the Electrical Network. The interconnection of the blocks constituting the simulator are shown in Fig. 1. The first macro block, Input Network, is fed by the profiles of P and Q of all loads and generators coming from real measures. They have been saved in different *Excel* files, one for each feeder. These power profiles represent real data acquired with a time step of 1 hour. In the second macro block, Electrical Network, there are the HV, the MV and the LV networks, together with the State Breakers block, that, through several flags, sets the topology of the SG. In the HV network there are 2 transformers with 150 kV at the primary winding and 20 kV at the secondary winding; in the MV network the lines, the loads and the photovoltaic plant are modeled. In the LV network there are the two biogas generators. The lines are modeled using an equivalent model, given by MatLab/Simulink, based on lumped parameters modeling approach (Π model); the transformers are modeled using a block, also provided by MatLab/Simulink, called Three-Phase Transformer Inductance Matrix Type (Two Windings); the

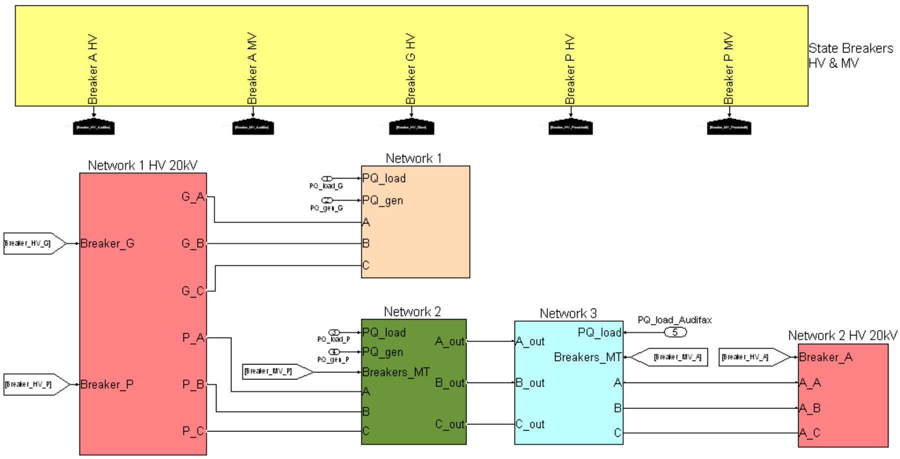

Fig. 1. Interconnection among simulator sub blocks

power driven loads and generators are modeled using the same custom block. This block is essentially a voltage controlled current source, with $I = (2P/V)^*$ where the value of P is read from the corresponding data file and the voltage V is measured at the three phase port of the block modeling the load (* represents the conjugate operator). The SimPowerSystem of MatLab/Simulink allows to use, for three phase network simulation, three solution methods: Continuous, Discrete and Phasor. Since the simulation sampling time is equal to one hour, it is possible to consider exhausted any transient response. For this reason the electrical network analysis has been carried out with the Phasor method.

3 Optimization Procedure

In this section it is described how the considered active power losses optimization problem can be formulated in terms of a multi-objective optimization problem and solved by adopting a suitable evolutionary computation approach. The faced problem consists in finding the optimal network parameters 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 a linear space K, an admissible set E and a cost function $J : E \rightarrow \mathbb{R}$ that associates a real number to each element in E. The problem consists in minimizing the function J in $E \subset \mathbb{R}^\nu$, where ν is the dimension of the space K. The admissible set E is defined through the inequality constraints $g_i(\mathbf{k}) \leq 0 \quad i = 1,..,m$, where m is the number of constraints of the problem. Without loss of generality it has been considered possible to measure the voltage $\mathbf{V}(\mathbf{k})$ and the current $\mathbf{I}(\mathbf{k})$ at all locations in the network in order to compute the cost function. In this paper it is assumed that it is possible to control both the active and the reactive power of each biogas generator in a given range though a couple of parameters. More precisely, the ratio k between the nominal power and the active power and the phase ϕ. Moreover it is assumed that the active power of the photovoltaic generator can be modulated in a given range. Summarizing, the dimension ν of the parameters vector $\mathbf{k} = \{k_1, k_2, k_3, \phi_1, \phi_2\}$ has been set equal to 5.

Let's define:

$$A = \left\{\mathbf{k} \subset \mathbb{R}^5 : 0.75 \leq k_1, k_2, k_3 \leq 1, -0.2 \leq \phi_1, \phi_2 \leq 0.45\right\} \tag{1}$$

$$B = \left\{\mathbf{k} \subset \mathbb{R}^5 : V_j(\mathbf{k}) - 1.1 V_{nom_j} \leq 0, \quad 0.9 V_{nom_j} - V_j(\mathbf{k}) \leq 0, j = 1,..,N\right\} \tag{2}$$

in which N represents the number of nodes of the network and V_{nom_j} is the nominal value of the voltage of the j-th node,

$$C = \left\{\mathbf{k} \subset \mathbb{R}^5 : |I_j(\mathbf{k})| - I_{max_j} \leq 0, j = 1,..,R\right\} \tag{3}$$

in which R represents the number of branches and I_{max_j} is the maximum current allowed in the j-th wire,

$$D = \left\{\mathbf{k} \subset \mathbb{R}^5 : k_1 < \cos(\phi_1), k_2 < \cos(\phi_2)\right\} \tag{4}$$

The set D has been defined analysing the Capability Curve of biogas generators that establishes safe operational limits. A capability curve is defined as a curve which shows boundaries of the area on the kW-kVar diagram within which a machine may be operated continuously.

Now, it is possible to define the admissible set E as follows:

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

The cost function J has been defined as follows:

$$J(\mathbf{k}) = \frac{P_{loss}(\mathbf{k})}{P_{gen}(\mathbf{k})} = \frac{P_{gen}(\mathbf{k}) - P_{load}}{P_{gen}(\mathbf{k})} \tag{6}$$

where $P_{gen}(\mathbf{k})$ 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.

Given a particular determination $\overline{\mathbf{k}}$ of the vector $\mathbf{k}$, the value returned by (6) is equal to the normalized total active power losses in the network, and can be considered as a measure of how well $\overline{\mathbf{k}}$ solves the optimization problem. Since it is not practically possible do derive expression (6) in closed form as a function of $\mathbf{k}$, in this paper a genetic algorithm (derivative free approach) has been employed. A GA is a search method based on the principles of natural selection and evolution which selects individuals with high adaptation to environmental conditions as candidates to survive and being part of the following generation of individuals. Moreover, satisfying constraints (5) and minimizing expression (6) are two conflicting objectives, since active power loss is minimized when the voltage across the line is high. Consequently, the constrained optimization problem can be faced by defining a multi-objective optimization, by relying on the following fitness function:

$$F(\mathbf{k}) = \alpha J(\mathbf{k}) + (1 - \alpha)\Gamma(\mathbf{k}) \tag{7}$$

where α is a coefficient between 0 and 1 and it is 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:

$$\Gamma(\mathbf{k}) = \beta\Gamma_{NLC}(\mathbf{k}) + (1 - \beta)\left[\gamma\Gamma_I(\mathbf{k}) + (1 - \gamma)\Gamma_V(\mathbf{k})\right] \tag{8}$$

in which β and γ are real numbers between 0 and 1. The function $\Gamma_V(\mathbf{k})$ is a measure of how much the constraints on voltages are violated, $\Gamma_I(\mathbf{k})$ evaluates the violation of the constraints on currents and $\Gamma_{NLC}(\mathbf{k})$ is a measure of the violation of the nonlinear constraints defined in (4). The parameter β is used to assign the relative weight of the nonlinear constraints violation with respect to the term measuring how much voltages and currents are far from the admissible range. In the same way, the γ parameter adjusts the relative weight of the violation of current constraints with respect to the term related to voltages violation.

4 Tests and Results

In order to test the effectiveness of the proposed optimization procedure, the first generation of the genetic algorithm has been generated in a random way, in the domain A of the network parameters defined in (1). This initialization does not necessarily guarantee the satisfaction of the constraints defined in (2), (3) and (4), considered in the definition of the chosen fitness function. In this way, it is possible to verify if the optimization algorithm is able to restore the network in a safe configuration satisfying all the constraints, possibly minimizing the total active power losses. For this test the behaviour of the control system has been simulated and validated in a single time sample (one hour). All the simulations have been realized using the Matlab Global Optimization Toolbox together with the developed network simulator.

Setting the nominal voltage for the low voltage lines (LV) to $V_{nom} = 400$ V and for the medium voltage lines (MV) to $V_{nom} = 20800$ V, the voltages constraints on the nodes of the network are expressed as follows:

$$360\ V < V_{LV} < 440\ V, \quad 18710\ V < V_{MV} < 22880\ V \tag{9}$$

Moreover, considering $I_{MAX} = 270$ A as the maximum allowed current in the network breakers and I as the current flowing in a given network branch, it is possible to define the currents constraints as follows:

$$|I| < 270\ A \tag{10}$$

Without loss of generality, voltages and currents have been measured only in some critical nodes and branches taken into consideration on the basis of the network topology. Four runs of the genetic algorithm have been done. The proposed solution represents the mean value of the results obtained in all the different simulations. The number of generations has been set to 55 and the number of individuals for each generation has been set to 10. A few comments can be made on the results showed in Fig. 2. First of all it should be noted that the GA produces 50 generations instead of 55 due to early convergence to a satisfying solution. In addition, it can be seen that the trend of the normalized voltage level remains almost constant into allowed ranges (Fig. 2 part (a)). Moreover the GA reduces the current level of the first and the second feeder (Fig. 2 parts (b) and (c)) approximately by 2% and 30% respectively. The decrease of the current level on the branches induces a reduction of the power loss as can be seen in Fig. 2 part (d). After 30 generations the trend of the power loss becomes almost stable and the overall decrease is approximately 2% of its original value. Looking at Fig. 3 it can be seen that the action performed by the GA is to increase the power contribution associated with all the DGs. In fact, the gains k_1, k_2 and k_3 of all generators and the power factors $\cos(\phi_1)$ and $\cos(\phi_2)$ of the two biogas generators tend to unity, trying to achieve the maximum injection of active power in the network (see Fig. 3 part (a), (b), (c), (d) and (e)), reducing in this way the power request from the main grid. Finally in Fig. 3 (f) it can be seen the trend of the fitness function, that decreases with the increasing of the

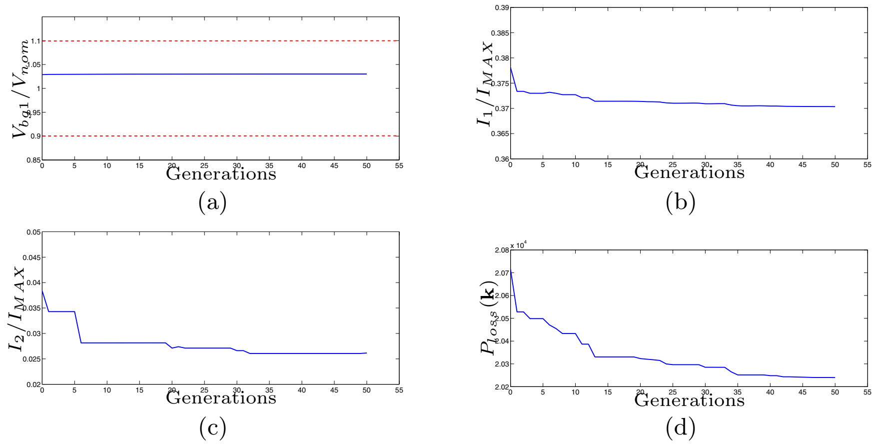

Fig. 2. Evolution of the normalized voltage and current levels and power losses versus GA generations

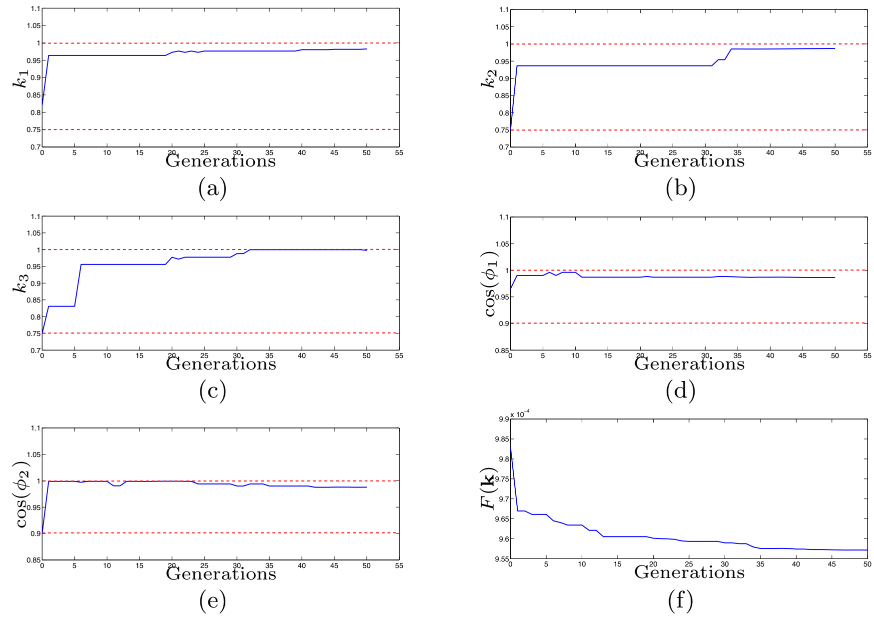

Fig. 3. Evolution of GA parameters and fitness function versus GA generations

numbers of generations. Comparing Table 1 and 2 it is possible to figure out the percentage of active power absorbed (AAP), capacitive reactive power (CRP), active power generated (GAP) and inductive reactive power (IRP) generated by the loads, distributed generators, network and balance nodes in the initial and final configuration of the network. Some relevant comments can be made about

Table 1. Percentage of the distribution of power in the Loads, Distributed Generators, Network and at the Balance Nodes in the initial configuration

	Loads	Distributed Generators	Balance Nodes	Network
AAP	0,9955	0,0000	0,0000	0,0045
GAP	0,0000	0,1467	0,8533	0,0000
IRP	0.9914	0.0086	0,0000	0,0000
CRP	0,0000	0,0000	0,7266	0,2734

Table 2. Percentage of the distribution of power in the Loads, Distributed Generators, Network and at the Balance Nodes in the final configuration

	Loads	Distributed Generators	Balance Nodes	Network
AAP	0,9956	0,0000	0,0000	0,0044
GAP	0,0000	0,1717	0,8283	0,0000
IRP	1,0000	0,0000	0,0000	0,0000
CRP	0,0000	0,0161	0,7077	0,2762

the absorbed and generated active power in both conditions. In the non controlled configuration the active power is generated by 15% from DGs and 85% from balance nodes, while the network absorbs about 0.45%. In the optimized configuration, the active power is generated by 17% from DGs and 83% from balance nodes, while the network absorbs about 0.44%. Although the reduction of power dissipation of the network is small, it can be seen an increase in active power generated by the DGs, so it can be concluded that the evolutionary optimization procedure tries to minimize the total losses by decreasing the power requests from the main grid (balance nodes), while increasing the power fraction produced by DGs which, in the considered network, are closest to loads. Consequently, the distribution paths on the network from power sources to loads are shortened, decreasing the total active power dissipated on electrical lines. Moreover, in the initial configuration the DGs deliver inductive reactive power, while, at the end of the simulation, they deliver capacitive reactive power; this is a further aspect that helps to reduce the power losses on the overall network.

5 Conclusions

In this paper it has been proposed a control system able to reduce power losses in the *ACEA Distribuzione S.p.A.* SG in the west aera of Rome by modulating the DGs active and reactive powers, while considering suitable constraints on voltages and currents imposed by safety and quality of service issues. Moreover the constraints imposed by safe operational limits established by the Capability Curve of biogas generators have been considered. The network has been accurately modelled and simulated relying on the MatLab/Simulink SimPowerSystems ToolBox, which allows to rapidly and easily build models to simulate power systems. The optimization problem has been faced as a multi-objective one, since power losses minimization and constraints satisfaction are conflicting objectives. Since it is not practically possible to derive in closed form the expression of the power losses in terms of system parameters, a derivative free optimization procedure based on a genetic algorithm has been adopted. First results show that the proposed control strategy is able to reduce power losses and to achieve admissible voltage and current levels according to predefined constraints. Future works will concern on evaluating different derivative free optimization techniques, such as Particle Swarm Optimization. Moreover, a Thyristor Voltage Regulator (TVR) and Li-Po Energy Storage System (ESS) will be soon installed in the considered electrical network. An advanced control system able to deal with these two new components is currently under study.

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