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Scuola di ingegneria

Dipartimento di Ingegneria Industriale DII

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ELECTRIC DISTRIBUTION NETWORK OPTIMAL RECONFIGURATION ALGORITHM TO CONTAIN OPERATIONAL COSTS

RELATORE: Prof. Massimiliano Coppo

LAUREANDO: *Alessandro Bresolin*

ID 1234280

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Abstract

The energy transition is probably the greatest challenge of our century. The greenhouse gas emissions of the global energy sector, mostly powered by fossil fuels, needs to be strongly reduced in order to reach the net zero emission by 2050 and stop the rising of global temperature at $+1.5\ °C$. In the report of the International Energy Agency "Net Zero by 2050 - A Roadmap for the Global Energy Sector" is stated that, in order to match the decarbonization objectives, the share of electricity in the total final consumption should raise from the 20% in 2020 to the 49% in 2050, involving sectors such as industry, transport and buildings. Another statement of this review involves the energy mix for electricity generation, which should rise its renewable generation penetration from the 29% in 2020 to the 88% in 2050. Both the electrification and the rising of renewable generation represent a hard challenge for the power system, which need to handle this great increase of distribution generation and electrical energy demand. This work leverages a metaheuristic method called Genetic Algorithm to minimize the operational cost of a distribution grid by considering three types of interventions: network reconfiguration, network expansion and generation shedding. This thesis aims to demonstrate the reliability and the advantages of this method in finding the best solutions among a large number of possibilities, giving the Distribution System Operators a powerful tool to evaluate the best interventions to take within a reasonable computational time.

Chapter 1

Introduction

1.1 Power system historical background

The first example of power system in history dates back to 1882, when Thomas A. Edison built, in Pearl Street (New York), the first lighting system, with 400 filament bulbs, powered at 110 volts in direct current [1].

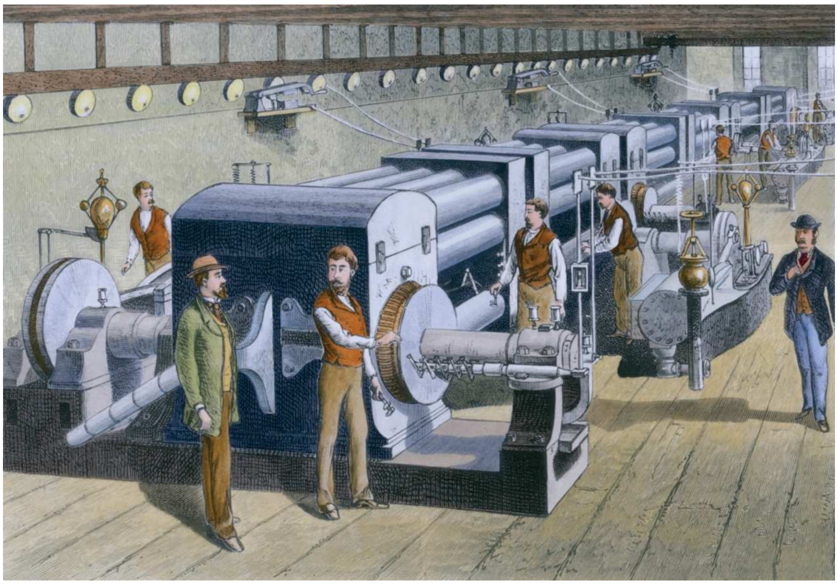

Figure 1.1: Pearl Street power station

This event marked the beginning of the era of electricity as an energetic vector, defining the basic concepts behind a power system: generation, transmission and consumption. The Pearl St. power system was also the first example of a commercial power system: the consumer doesn't buy the generator anymore, he buys electricity as a service. The cost of such service is determined through electricity meters, which calculate the consumption of each client. After the invention of the first electrical transformer in 1881 by Lucien Gaulard and John D. Gibbs, and the first alternator by Galileo Ferraris in 1884, the first alternate current power system was presented in Turin, demonstrating the great advantages of AC over DC, especially for long distances power transmission. Some years later, the so called "war of the currents" began between Westinghouse, supporting AC current, and Edison, supporting the DC current. In 1891, the first three-phase AC power system was presented by Oskar F. X. Miller, Michael Dolivo-Dobrowolsky and Charles E. L. Brown. This power system connected Lauffen with Frankfurt (175 km), delivering 240kW of power at 15kV and 40Hz, and confirming the supremacy of three-phase AC model over DC. From this date onward there was a great expansion of three-phase power system, with the construction of a 35MW power plant on the Niagara waterfall in 1897 (22kV) and, in Italy, the construction of the Paderno d'Adda 9MW power plant (13.5kV), which was the biggest one in Europe at the time [2].

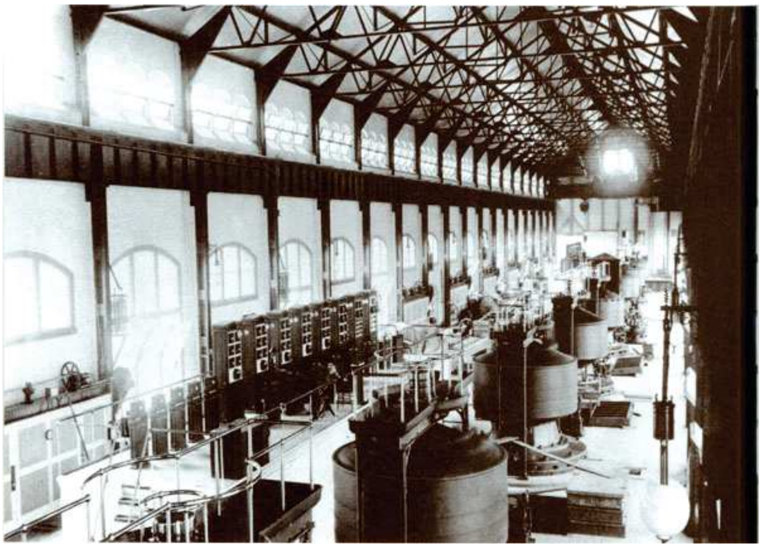

Figure 1.2: Westinghouse and Tesla power plant in Niagara waterfall

After the rise of the three-phase model, power systems significally grew up in number and power, beginning to be more and more interconnected to each other, leading to the necessity for a standardization of voltage levels and frequency.

1.2 Power system nowadays

The typical structure of the modern power system is composed by: generation, transmission and distribution (figure 1.1). The interconnection of those three guarantee the power supply to the consumers, ensuring them power quality and reliability all over the days of an year.

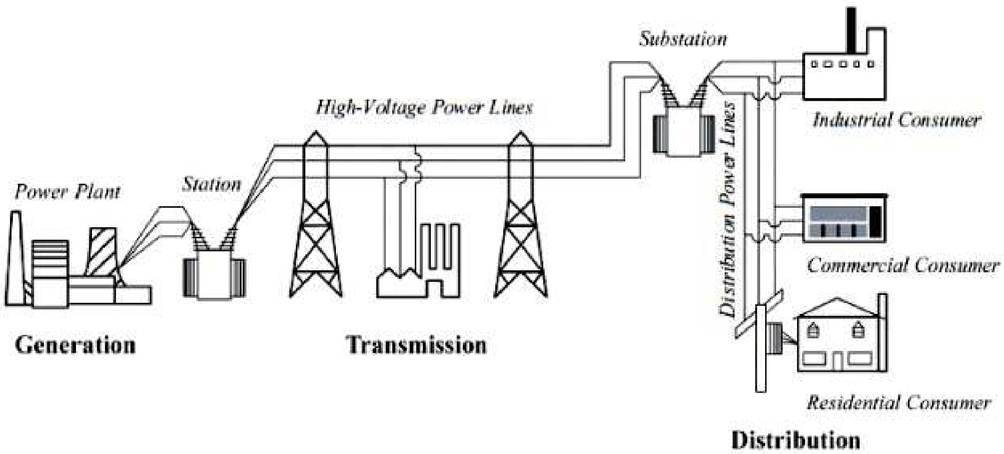

Figure 1.3: Structure of a modern power system

Generation

Power generation is responsible for producing the electrical power that will be delivered to the consumers through the transmission and distribution lines. The generation can be centralized, huge power plants directly connected to the transmission lines, or distributed, smaller power plants (generally renewable) connected to the distribution grid. An important aspect of the power generation is the installed capacity, which needs to be higher than the consumption in order to guarantee electricity supply to the loads, and also compensate for the energy losses in the transmission and distribution lines. In the last 30 years, the installed capacity grew up significantly (figure 1.3, to face the increasing demand of electricity.

The constant increase of electricity demand, distributed generators and renewable penetration is a great challenge in order to secure the correct functioning of a power system. For example, a wrong positioning or sizing of a distributed generator

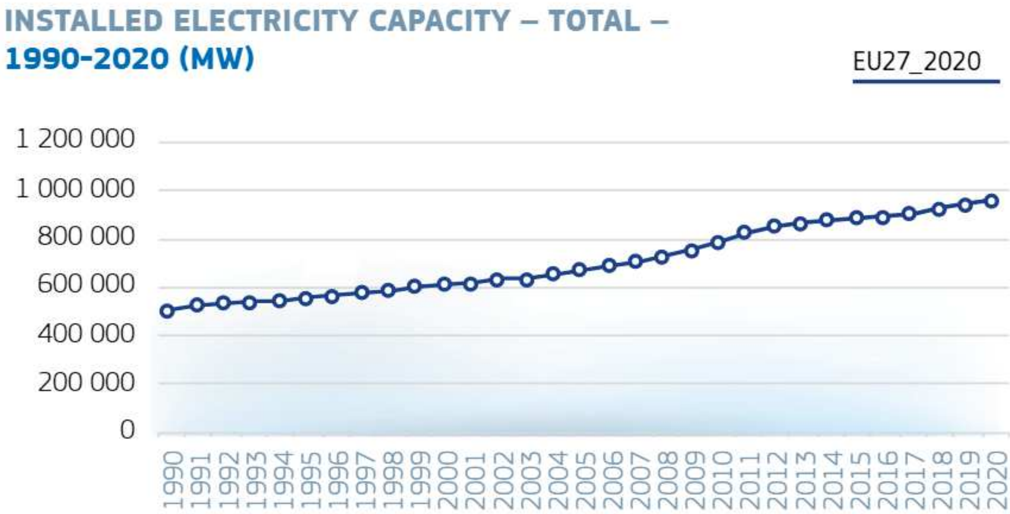

Figure 1.4: Capacity installed in Europe from 1990 to 2020

can lead to an increase of power losses [3] and decrease of voltage stability. For this reason, to increase the distributed generators penetration into the power system, an accurate planning is needed. Thus researchers are focusing on algorithms, like genetic algorithm or simulate annealing, to optimize their positioning in the power system [4].

Transmission

The transmission grid is the infrastructure that connects the centralized power plants to the distribution grid. Its structure is meshed and it operates at high voltage, in Italy between 380 and 220 kV, in order to transfer huge amounts of power, between 100 MW and 3000 MW per line, for long distances, with minimum power losses. This complex infrastructure is managed by the Transmission System Operator (TSO), whose role is to balance the offer from generators and the demand from loads in order to achieve the equilibrium in every instant of time. Another role of the TSO is to improve the connections of the national transmission grid and the connections between different nations, promote the integration of distributed generators, storage, prosumers and handle bidirectional power flows. The last role of TSO is to improve the resilience of the system in order to ensure power quality and service continuity to the consumers.

1.3 Distribution system

The distribution system is a radial grid which operates in medium (10kV, 15kV, 20kV) and low voltage (usually 380V) and connects the transmission system to the consumers. Traditionally the power system is not designed to be connected with generators, as it is for Transmission, and is organized with a vertically operated architecture [5] (figure 1.5):

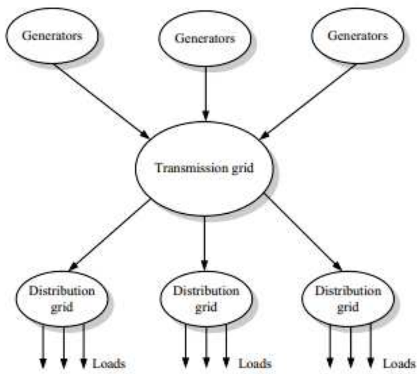

Figure 1.5: Traditional power system

The evolution of power system need to take in account the distributed generators and the issues connected to their integration with the power system (Figure 1.6):

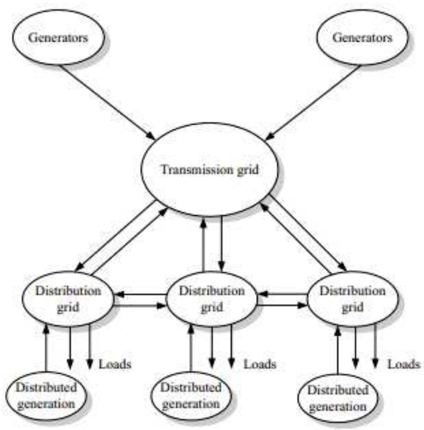

Figure 1.6: Present and future power system

The distributed generation is defined as: *Distributed generation is an electric power source connected directly to the distribution network or on the customer site of the meter* [6].

To better comprehend the capacity provided by distributed generators, they can be classified by rated power (P_n) as follows [6]:

- **Micro**: $1W < P_n < 5kW$
- **Small**: $5kW < P_n < 5MW$
- **Medium**: $5MW < P_n < 50MW$
- **Large**: $50MW < P_n < 300MW$

Those distributed generators have several advantage such as: emergency and standby services [7], stand alone applications [8] and environmental advantages, reducing the CO2 and other types of polluting emissions. The emergency and standby services are provided by distributed generators to the most sensitive loads which, in case of faults on the grid, can't be left without power supply; those loads are hospitals or industries which would have a significant economical damage from a supply interruption. Stand alone applications are particularly important in remote areas, where the infrastructure to link the loads to the power system is missing. The most known advantage of renewable distributed generation is its impact on reducing the polluting emissions of power generation, for example in Italy the reduction of CO2 emissions are up to 11.93% lower compared to the case with no renewable generation [9] as shown in figure 1.7:

	Without RE (tx 10^6)	With RE (tx 10^6)	Reduction (%)
Autumn	2.11	1.93	8.28
Winter	2.13	1.99	6.71
Spring	2.15	1.92	10.46
Summer	2.19	1.93	11.93

Figure 1.7: CO2 emissions with renewable generators

On the other hand, distributed generation, if not managed correctly, could be the cause several issues which will be discussed in the following paragraph.

1.4 Issues related to distributed generation and DSO role

As explained in the previous section, the integration of distributed generators with the distribution grid can be quite challenging. The distribution network is managed by the Distribution System Operator (DSO) which is defined by the European directive 2009/72/EC as: *DSO means a natural or legal person responsible for operating, ensuring the maintenance of and, if necessary, developing the distribution system in a given area and, where applicable, its interconnections with other systems and for ensuring the long-term ability of the system to meet reasonable demands for the distribution of electricity.* The traditional role of DSO is to deliver electricity in a reliable, secure and efficient way, by developing and maintaining the distribution network infrastructure. However the increasing penetration of renewables in the distribution grid pushes the DSOs to be more active in order to keep the grid adequate to the increasing demand and the issues could occur due to the distributed generation [10]. The main effect of such a change is that power flows in the distribution network, which, given the radial structure, were necessarily oriented downstream the primary substation (interface with the high voltage grid), may now flow in the opposite direction, according to the actual end-users' behaviour. The main issues the DSO has to face with are [11]:

- **Voltage control**: the presence of distributed generators can invert the power flow causing the rising of nodal voltages, making more difficult for DSOs to control node voltages.
- **Power quality**: the issues can be steady-state voltage rise, voltage flicker, frequency variations and harmonics.
- **Protection system**: there could be problems in automatic reclose of switches, difficulty in detecting short circuits and islanding problems.
- **Grid losses**: if not correctly positioned into the grid the distributed generator could increase the grid losses.

Between the issues explained above, in this thesis the main focus will be on the power quality and the grid losses.

1.4.1 Power quality

The power quality represents the quality of the service provided by the DSO to the consumers. There are two main aspects of power quality: continuity of service, which means number and duration of interruptions, and quality of the voltage waveform. The factors that affect power quality can derive from distributor, for example during grid maintenance, from the consumers and from other causes like atmospheric events or damages caused by third parts. In Italy the quality of voltage waveform is regulated by the CEI 50160 standard which considers several categories of distortions, some of them will be discussed below.

Frequency variations the value of frequecy, according to the normative, has to be: $50Hz \pm 1\%$ for the 99,5% of the year and $50Hz + 4\%/-6\%$ in every instant of time of the year. Frequency variations (Figure 1.8) occur when generation and demand are unbalanced. The speed of the frequency variation is determined by the ratio between the synchronous and non synchronous generators (like PV generators), higher is the presence of non asynchronous generators, higher will be the the speed of frequency variation [12].

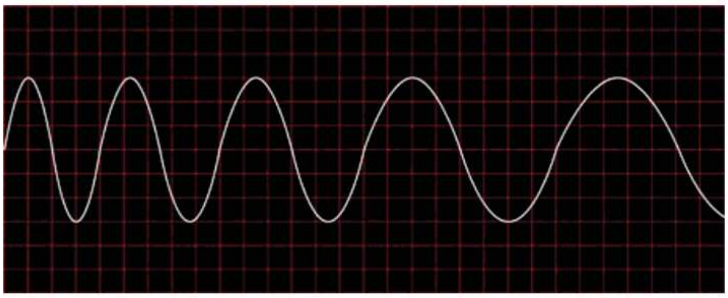

Figure 1.8: Frequency variation

Voltage under and overvoltages the voltage in each bus of the distribution grid should be, according to the normative, in the range of $U_n \pm 10\%$. The intermittent nature of distributed generators can cause an unbalance between generation and demand, leading to over/under voltages in some of the buses of the grid [13]. Over-voltages can be caused by an inversion of the power flow in areas of the distributed grid with a high penetration of renewable energy sources [14].

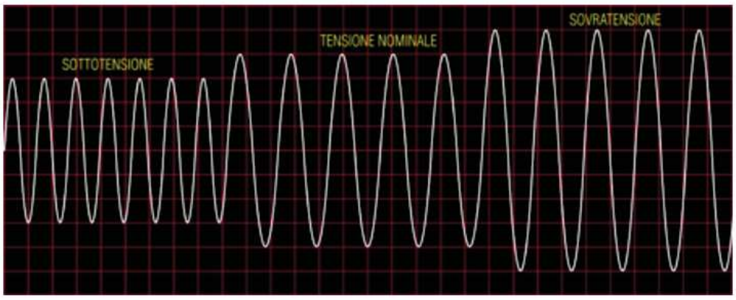

Figure 1.9: Under and over voltage

Voltage harmonics the voltage harmonics RMS, according to the normative, have to be under a certain percentage of the rated voltage, 6% for the 5^{th} harmonic and 5% for the 7^{th}, during the 95% of the year. Voltage harmonics are mainly cause by power electronics such as the inverters of PV power plants [15].

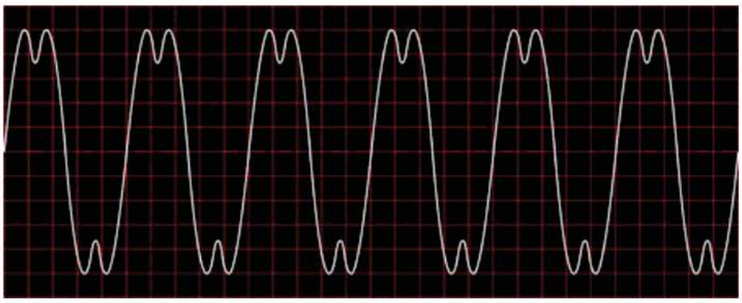

Figure 1.10: Voltage distorted by harmonics

1.4.2 Power quality: future role of DSO

As described in the previous paragraph, the distribution system operator is responsible for keeping the quality of the service compliant with the CEI 50160 standard. Today the DSO can operate only on the distribution grid infrastructure, in order to reduce the cost of losses and ensure power quality. The Clean Energy Package for all Europeans, states that DSOs should provide services, addressed to distributed generators, loads and storage, in a market-based way, when those services are cheaper than expanding the grid infrastructure [16]. One of those services could be the flexibility market, which is the possibility to change the consumption or production of the loads or generators in order to achieve the stability of the grid. On the other hand the loads or generators are remunerated for this service, and can compete in a liberalized flexibility market to provide this type of service [17].

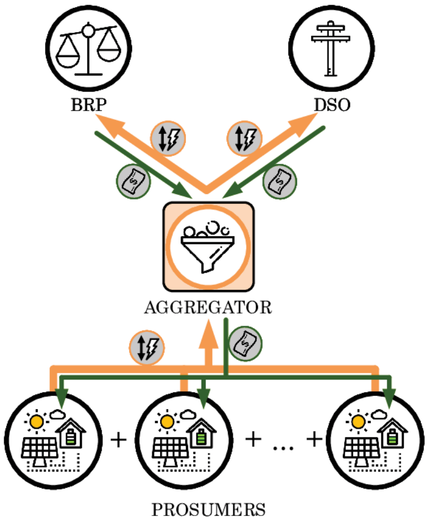

Figure 1.11: Flexibility market organization

Looking at Figure 1.11, an other actor is present alongside the DSO, which is the Balance Responsible Party (BRP). The BRP is responsible for the balancing of injection/withdrawal programs resulting from previous commercial interactions with the market at a specific node of the grid. Such a subject, therefore, could be interested in selecting flexibility services provided by an aggregator to adjust its physical position and guarantee the balance with the commercial one. The same dynamic can be envisioned for TSOs and DSOs that might purchase such service to keep the respective system portion in balance (i.e. equilibrium between demand and supply to avoid frequency deviations). Under this perspective, a pilot project by Terna (Italian TSO) has started back in 2018 (project UVAM), to allow aggregated resources (also connected to the distribution grid) to submit offers in the ancillary service market, to manage the transmission system. Currently, ARERA (the Italian energy authority) is evaluating the proposals by DSOs to begin pilot projects for activating local flexibility market platforms in order to enable DSOs to acquire those services from the distributed resources in order to manage their system portion more efficiently. It is clear that, in order to have an efficient flexibility market, a good co-operation between TSO and DSO is necessary to avoid possible conflicts between the services potentially purchased by them, which led to many research works focusing on the coordination schemes between TSO and DSO. In the near future, given the importance of the distributed resources connected at medium and low voltage levels, many researches point out that a common marketplace should be foreseen for both TSOs and DSOs to fulfill the respective requirements in terms of ancillary services. Even before discussing the market structure and the relative rules, however, it is of utmost importance that the DSOs can count on a higher controllability over the respective grid portion. This entails developing more advanced control algorithms that address the network regulation taking into account specific constraints that could potentially go beyond the mere technical operation. In this view, this thesis addresses the typically implemented methodologies for grid optimization in order to propose a procedure for the optimal reconfiguration of the distribution system in presence of distributed resources.

Chapter 2

DSO interventions optimization methods: state of the art

2.1 Problem overview

Nowadays distribution power networks are evolving to address the challenge of integrating distributed generators in a grids that were designed to be passive. The bidirectional power flows and uncertainties of the energy supply, caused by distributed generators (mostly renewable), make it necessary to modify the distribution grid to contain its operational costs, improving the power quality and system reliability. There are many ways to reduce operational costs of the distribution network, some of which are: network reconfiguration, network expansion and the curtailment of loads and generators [18].

- **network reconfiguration** which consists in changing the state of the network switches of the net in order to have a better topological configuration of the grid, reducing the power losses;
- **network expansion** which is the rewiring of existent lines, building new feeders or new substations;
- **curtailment of loads and generators** which consists in paying the loads for the electrical capacity they offer during curtailment periods and in paying the generators to produce less power than their rated one.

The problem of minimizing the operational costs of a distribution network can be solved in many ways. A naive approach to solve the problem could be through a "brute force" method which solves a problem through exhaustion, producing and evaluating every possible configuration of the grid, loads and generators, in order to find the global optimum.

Let us consider, as an example, the distribution network in figure 1.1 in which, for simplicity, we assume that all network buses can be potentially connected by changing the relative switch status and the load level at each bus can be changed with ten steps between maximum load and zero:

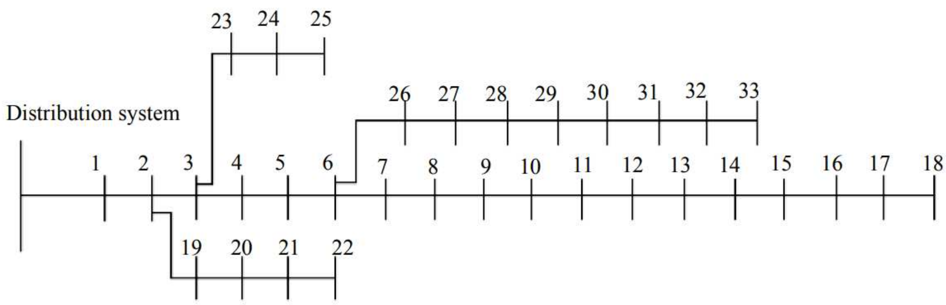

Figure 2.1: IEEE 33 bus distribution network

For the 33 bus grid we can calculate how many solutions a brute force method should should evaluate, in order to find the global optimum. The possible solutions for the network reconfiguration, considering that all 33 lines have a switch installed, are:

$$S_{NR} = 2^{33} \tag{2.1}$$

The possible solutions to rewire the lines of the grid, under the hypothesis of adding just one line in parallel to the existing one, are:

$$S_{rewire} = 33 \tag{2.2}$$

The possible solutions for the curtailment of the loads of the grid, with one load for each bus, ten levels of curtailment (levels = 10%, 20%, ... 100%) and a daily power consumption profile consisting of 24 hourly intervals, are:

$$S_{curtailment} = 10^{33 \cdot 24} \tag{2.3}$$

Therefore, the overall number of possible solutions that a brute force method should evaluate are:

$$S_{tot} = S_{NR} \cdot S_{rewire} \cdot S_{curtailment} = 33 \cdot 10^{33 \cdot 24} \cdot 2^{33} \tag{2.4}$$

Looking at the 2.4, the possible solutions are too many to be investigate with a brute force method, which is the reason why this method is not used for this kind for problems where the number of solutions is growing exponentially with the dimension of the problem (nodes, lines and loads). For this reason this kind of problems are usually solved though metaheuristic methods.

2.2 Metaheuristic methods

Metaheuristic methods are often used when the solution space is too broad to be feasibly explored by an exhaustive search. These methods aim to find a "good enough" solution, sometimes even the global best, that satisfies a given set of constraints, and reduce the search space by applying some general ideas derived from intuition. For instance, the genetic algorithm used in this thesis is based on the intuition that combining two good solutions may produce a better one. The optimization problem P could be defined as follows [19]:

$$P = (S, \Omega, f) \tag{2.5}$$

with S which is the search space over a finite set of predefined variables, Ω represent the constraints on the variables and f is the objective function to optimize. Usually the objective function has to be minimized, so the optimal solution s_{best} is defined as:

$$f(s_{best}) \leq f(s) \quad \forall s \in S \tag{2.6}$$

Using a metaheuristic method is important to have a balance between [20]:

- **intensification** that consists in improving the good solutions to get closer to the global optimum of the optimization problem;
- **diversification** that consists in a good exploration pattern to avoid getting stucked in a local optimum.

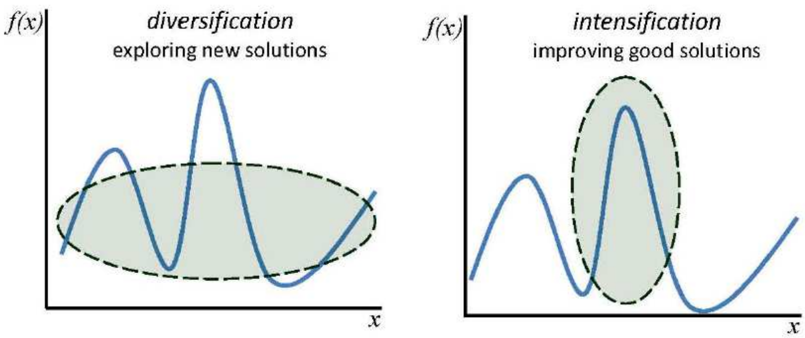

Figure 2.2: Diversification and intensification

For what concernes the distribution network problems, the most used meta-heuristic algorithmss are: genetic algorithm (GA), which is part of the category of the evolutionary algorithms, and from the category of the sworm based algorithms, the particle sworm optimization (PSO) and the ant colony search (ACS).

2.2.1 Genetic algorithm

Genetic algorithms are adaptive methods which cam be applied to a large variety of optimization problems. They are based on the principle of the evolution of populations according to the rules of natural selection, following the "survival of the fittest" as stated by the father of the evolutionary theory, Charles Darwin [21]. For the optimization problems of distribution networks, the genetic algorithm is used for network reconfiguration and rewiring [22], network expansion [23] and curtailment of loads and generators[24,25]. Genetic algorithm in distribution networks works as shown by the flowchart below:

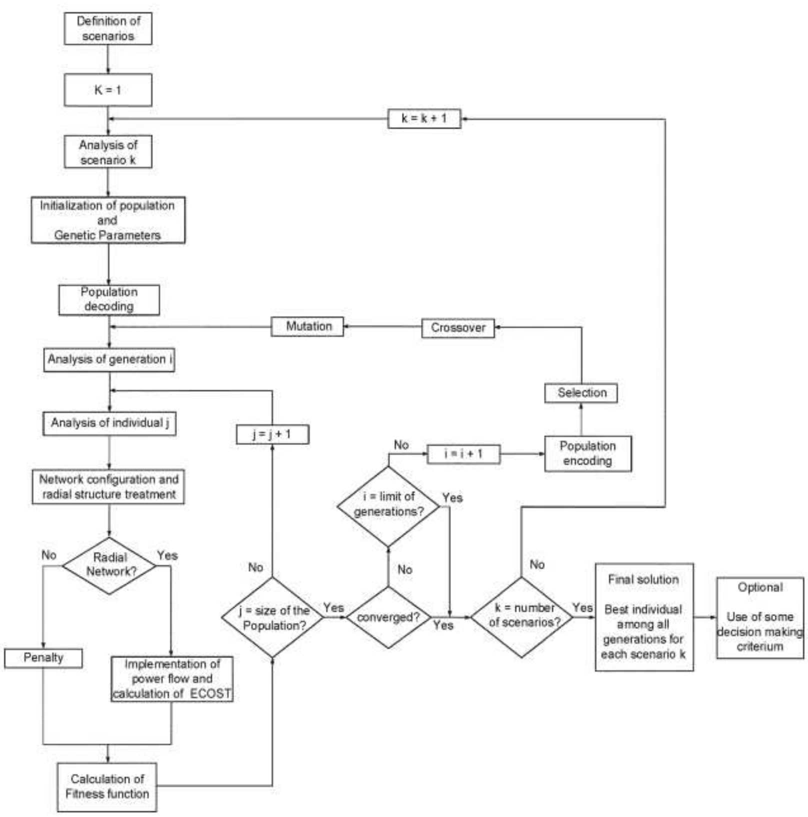

Figure 2.3: GA applied to electrical networks

After the initialization of the population, the genetic algorithm works with individuals, each one being a possible solution to the problem and, after the radiality check of the grid, a "fitness score" is given, which represents how good is the solution according to the objective function. The fitness score determines the probability of the individual to "survive" to the next generation and to become a parent. The next generation is built starting from two parents and using the two operators: crossover and mutation. The crossover is a single point crossover between the genes of the two parents as shown in figure 1.4:

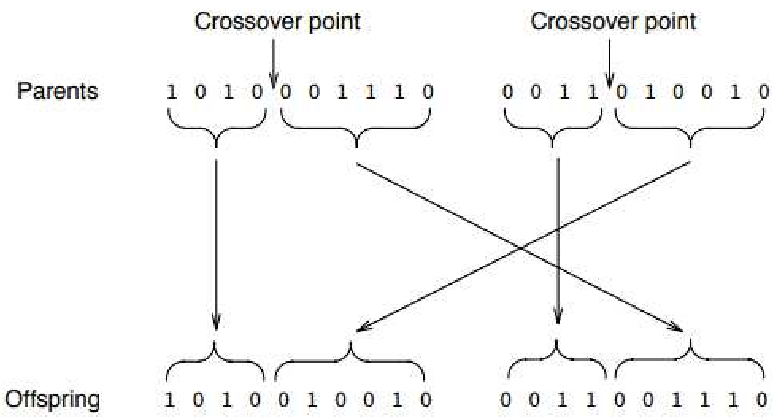

Figure 2.4: GA crossover

After the crossover, a mutation is performed on the child, by muting some randomly chosen genes as shown in figure 1.5:

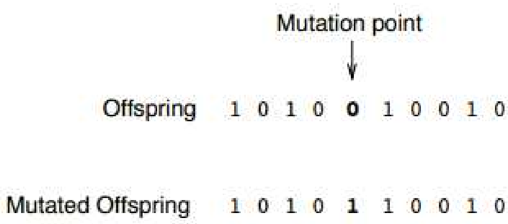

Figure 2.5: GA mutation

After the crossover and mutation a new generation is analyzed and new "fitting scores" are given to the individuals. This loop continues until a solution match some parameters (objectives) or when the algorithms reach a certain number of populations.

2.2.2 Particle sworm optimization

The particle sworm optimization is a method inspired by the movment of a flock of birds. Each member of the flock is represented as a particle, which is a possible solution of the optimization problem. In the distribution network optimiztion problems the PSO is used for network reconfiguration [26, 27], network expansion [28] and curtailment of loads and generators [29, 30]. The steps of the PSO algorithm for network reconfiguration are shown in the flowchart below:

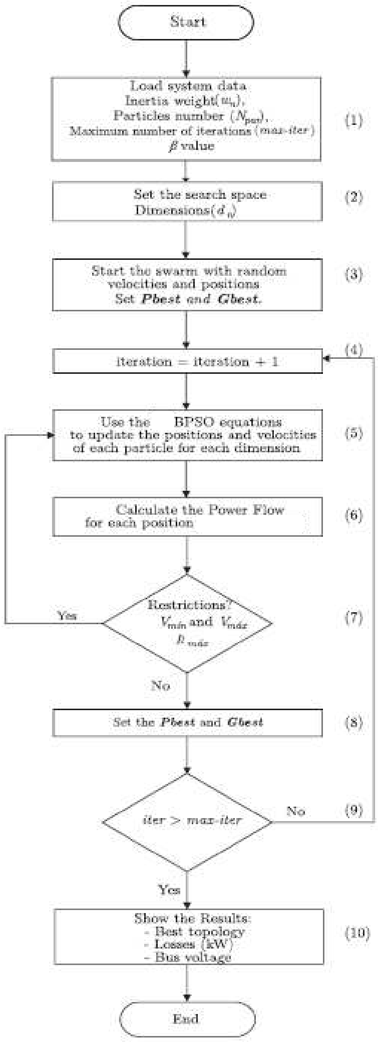

Figure 2.6: PSO applied to electrical networks

Each particle of the swarm can move in a multidimensional space and its movment is influenced by the best position of the other particles not only by its own best position. The objective function is defined as: $f : \mathbb{R}^D \to \mathbb{R}$; each particle can move, with a velocity, in a D-dimensional space and its coordinates x_i and velocities v_i are defined by a D-dimensional vector as follows:

$$x_i = [x_{i,1}, x_{i,2}, ..., x_{i,D}] \tag{2.7}$$

$$v_i = [v_{i,1}, v_{i,2}, ..., v_{i,D}] \tag{2.8}$$

Every particle has its personal best position $P_{B,i}$ and the sworm has its global best position G_B that are given by the fitness function. Both the best positions, personal and global, are updated as the particle moves in the space, always keeping the best ones during the iterations of the algorithm. The velocities and positions of each particle are updated every iteration **k** following the equations (1.9) and (1.10):

$$v_i^{k+1} = wv_i^k + c_1 r_1 (P_{B,i}^k - x_i^k) + c_2 r_2 (G_B^k - x_i^k) \tag{2.9}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{2.10}$$

where the parameter w is the inertia weight, c_1 and c_2 are the learning factors that control the influences of the individual and global bests and r_1 and r_2 are random numbers between 0 and 1. The algorithm converge when the maximum number of iteration is reached.

2.2.3 Ant colony search

The ant colony search method is inspired by the way the ants search for food. In nature, the ants are able to find the shortest path from the anthill to the food thanks to a "pheromone" that every ant release while looking for food. The pheromone is sensed by the other ants, that will be more likely to choose a path with higher pheromone (figure 1.7), which will be the shortest path; the more the shortest path is chosen, the more the trace of pheromone will intensify on that path, leading, after a certain amount of time, the ants to choose only the shortest path [31].

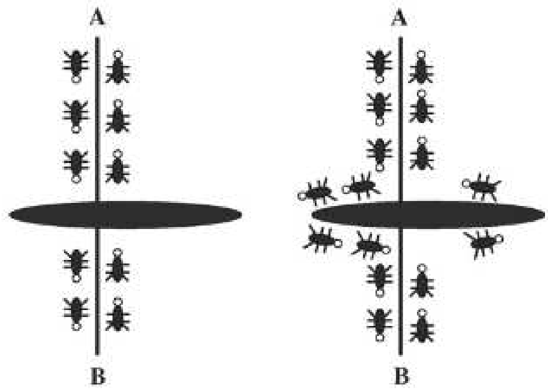

Figure 2.7: Ant choosing the right path to surpass an obstacle

The ant colony search is widely used to solve the distribution network optimization problems: network reconfiguration [32], network expansion [33] and load curtailment [34].

The ant colony search method applied to the reconfiguration of distribution network can be summarized on the flowchart below:

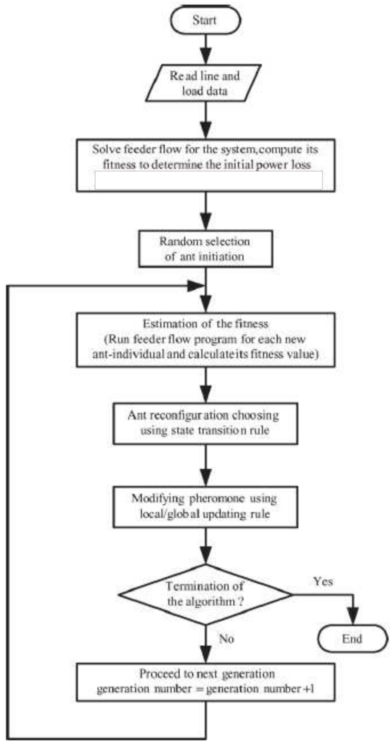

Figure 2.8: ACS applied to electrical networks

Each ant of the population is placed in a starting state and will move to the ending state using the state transition rule (1.11), which gives the probability $p_k(i,j)$ of the ant k to move from the node i to node j:

$$p_k(i,j) = \begin{cases} \dfrac{[\tau(i,j)][\eta(i,j)]^\beta}{\sum_{m \in J_k(i)} [\tau(i,m)][\eta(i,m)]^\beta} & if \;\; j \in J_k(i) \\ 0 & otherwise \end{cases} \tag{2.11}$$

where τ is the pheromone on the edge between i and j, η is the inverse of edge distance, $J_k(i)$ is the set of nodes that the ant k hasn't already visited, β is a parameter that define the importance of the pheromone respect to edge distance. While travelling through nodes the ant updates the pheromone with the local updating role (1.12):

$$\tau(i,j) = (1-\rho)\tau(i,j) + \rho\tau_0 \tag{2.12}$$

where τ_0 is the initial pheromone value and ρ is a parameter. Once the tour of every ant is completed, the global updating rule (1.13) is applied to the edge belonging to the best route of an ant:

$$\tau(i,j) = (1-\sigma)\tau(i,j) + \sigma\delta^{-1} \tag{2.13}$$

where δ is the distance of the globally best tour from the beginning of the trial and $\sigma \in [0,1]$ is the decay of pheromone. The algorithm ends when the maximum number of iterations is reached or when all the ants have selected the same path.

Chapter 3

Genetic algorithm implementation

In this thesis, a genetic algorithm will be designed for the management of a distribution network, including both the network reconfiguration and the users' power flow pattern change. The goal is to implement a procedure that could potentially support a DSO in the process of both planning structural changes to the specific grid portion and taking decisions referring the daily operation of such system. Hence, some interventions by the DSO will be implemented, using the genetic algorithm, in order to reduce the monetary operational cost of a distribution network while keeping its radiality, reliability and power quality constraints. The interventions proposed to achieve this goal are:

- **network reconfiguration**: changing the state of the network's switches;
- **network rewiring**: adding a parallel line to an already existing one;
- **building new feeders**: adding a new line that connects two already existing node of the network;
- **loads/generators curtailment**: each load or generator existing in the network could be curtailed by a percentage of its rated power.

All the interventions above, except for the network reconfiguration, have an investment cost, which will appear in the in the objective function of the genetic algorithm and represents the costs for the DSO. The reason for implementing all those intervention in one single algorithm, is to provide a single tool for the DSO, which is able to to evaluate different interventions, both for the short and the mid/long term.

3.1 Objective function

The objective function, is the sum of the costs of the four interventions and the cost of the lines' power losses:

$$C_{tot} = C_l[\sum_{i=1}^{24}\sum_{j=1}^{M} P_{l_{i,j}} + 2(\sum_{i=1}^{24}\sum_{j=1}^{L} \Delta P_{L_{i,j}} + \sum_{i=1}^{24}\sum_{j=1}^{G} \Delta P_{G_{i,j}}) + \sum_{i=1}^{24} P_{lt_i} + 24 \cdot P_0] + C_{nl} \cdot l_{nl} + C_{rl} \cdot l_{rl} \tag{3.1}$$

The best solution C_{best} of the problem will be:

$$C_{best} = \min\{C_{tot}\} \tag{3.2}$$

C_{best} is the best solution, between the solutions C_{tot}, which respects the constraints of the network.

3.2 Network constraints

Network constraints guarantee that a solution C_{tot} is feasible respect to the power quality standards and the radiality of the network. The power quality constraints, minimum and maximum voltage of nodes (2.3), lines' thermal rating (i.e. maximum current availability) (2.4) and transformer loading (2.5), are formally described by the equations below:

$$0.95 < v_n < 1.05 \quad for: \; n = 1, 2, ..., N \tag{3.3}$$

$$i_m < i_{m_{max}} \quad for: \; m = 1, 2, ..., M \tag{3.4}$$

$$S < S_n \tag{3.5}$$

3.3 Overview on Pandapower

The implementation of the genetic algorithm is made in the Python enviroment using Pandapower tool. Pandapower is an open source tool that allows to create electrical networks and their elements in order to perform power flows calculations and time based power flow calculations. In the following sections, the elements and modules used to implement the genetic algorithm will be described.

Bus

The buses are the nodes of the grid, the main parameters we can define for bus element are:

- **vn_kv**: nominal voltage of the bus, which is the reference for the per unit calculations;
- **geodata**: the coordinates of the bus in an x-y plane, mainly used for plotting the net;
- **max_vm_pu/min_vm_pu**: used for power flow calculations.

Line

The lines are the elements that connect the nodes of the grid to eachother. The main parameters that define line element are:

- **from_bus/to_bus**: the starting and ending buses of the line;
- **length**: the length of the line in km;
- **parallel**: number of lines in parallel;
- **max_i_ka**: the ampacity of the line;
- **r_ohm_per_km**: the resistance per kilometer;
- **x_ohm_per_km**: the reactance per kilometer;
- **c_nf_per_km**: the capacitance per km.

The lines are represented according to the π-equivalent model:

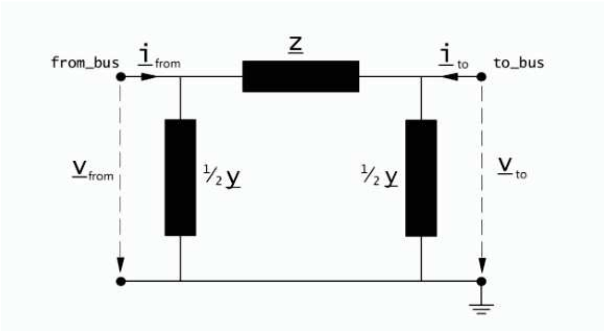

Figure 3.1: line π-equivalent model

The power flow results of the lines are defined as:

$$P_{from} = Re(\bar{v}_{from} \cdot \bar{i}^{*}_{from}) \tag{3.6}$$

$$Q_{from} = Im(\bar{v}_{from} \cdot \bar{i}^{*}_{from}) \tag{3.7}$$

$$P_{to} = Re(\bar{v}_{to} \cdot \bar{i}^{*}_{to}) \tag{3.8}$$

$$Q_{to} = Im(\bar{v}_{to} \cdot \bar{i}^{*}_{to}) \tag{3.9}$$

$$P_{loss} = P_{from} + P_{to} \tag{3.10}$$

$$Q_{loss} = Q_{from} + Q_{to} \tag{3.11}$$

Transformer

The two winding transformer element is described in Pandapower by the parameters below:

- **hv_bus**: high voltage bus
- **lv_bus**: low voltage bus
- **sn_mva**: rated apparent power

Transformers, by default, are represented according to the t-equivalent model:

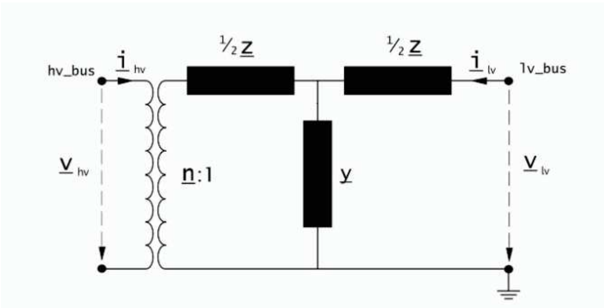

Figure 3.2: Transformer t-equivalent model

The results of the power flow of the transformer are described by the formulas:

$$P_{hv} = Re(\bar{v}_{hv} \cdot \bar{i}^*_{hv}) \tag{3.12}$$

$$Q_{hv} = Im(\bar{v}_{hv} \cdot \bar{i}^*_{hv}) \tag{3.13}$$

$$P_{lv} = Re(\bar{v}_{lv} \cdot \bar{i}^*_{lv}) \tag{3.14}$$

$$Q_{lv} = Im(\bar{v}_{lv} \cdot \bar{i}^*_{lv}) \tag{3.15}$$

$$P_{loss} = P_{hv} + P_{lv} \tag{3.16}$$

$$Q_{loss} = Q_{hv} + Q_{lv} \tag{3.17}$$

Switch, loads and static generators

Switches are the elements that allow to interrupt the electrical connection between two elements, its state is defined by the parameter "closed" which can be true or false and its position is defined by the element to interrupt. The loads and static generators have the parameter "bus" that defines their position in the network and their active and reactive power.

Time series calculation

Pandapower's power flow solver, originally derived from PYPOWER, is based on Newton-Raphson method. PYPOWER operate on the bus-branch model of the grid, while Pandapower uses a element based model converting grid data into a tabular data structure, this allows Pandapower power flow solver to be significantly faster than others tools like PYPOWER. The algorithm presented in this thesis, implements the **time series calculation**, a Pandapower module, which consists in a loop that iterates over every time step, updating new data into the elements of the grid and returning the results of a power flow for each time step. The work principle of the time series is presented in the figure 2.3:

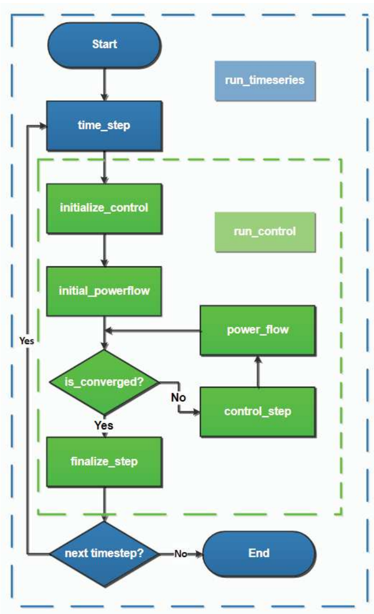

Figure 3.3: Time series

The time series model allows to implement loads and generation profiles in order to run the power flow considering demand and generation fluctuations during a day. To load the profiles into the time series, a CSV (comma separated value) file, containing the load and generation profiles, has to be red by the program. After the CSV is loaded into the time series, the model creates a data source, which is red by the "ConstControl". The ConstControl is a controller that takes the datas from the data source and write them into the net. In figure 2.3, the "initiate_control" step is when the controller changes the values of grid elements, after that the power flow is started and the loop continues for a determined number of iterations, which in our case is 24, one step for each hour of a day. The results of the time series' power flow are printed into a CSV file and saved in the computer's memory. The default printed results are the voltage of each node and the current of each line for every time step. Using the command "outputwriter" is possible to print other results like: power losses of lines and transformers and loading percent of transformers.

3.4 Algorithm description

As explained in the equation (2.2), the goal of the algorithm proposed is to minimize the cost function (2.1). To deal with such big amount of possible solutions, the genetic algorithm was chosen due to its simplicity to represent different ways to change network's topology and load/generation profiles at the same time, in addition to the fact that is a solid and well-known method to solve electrical engineering problems. The implementation of the genetic algorithm proposed in this thesis is explained by the following flowchart (figure 2.4):

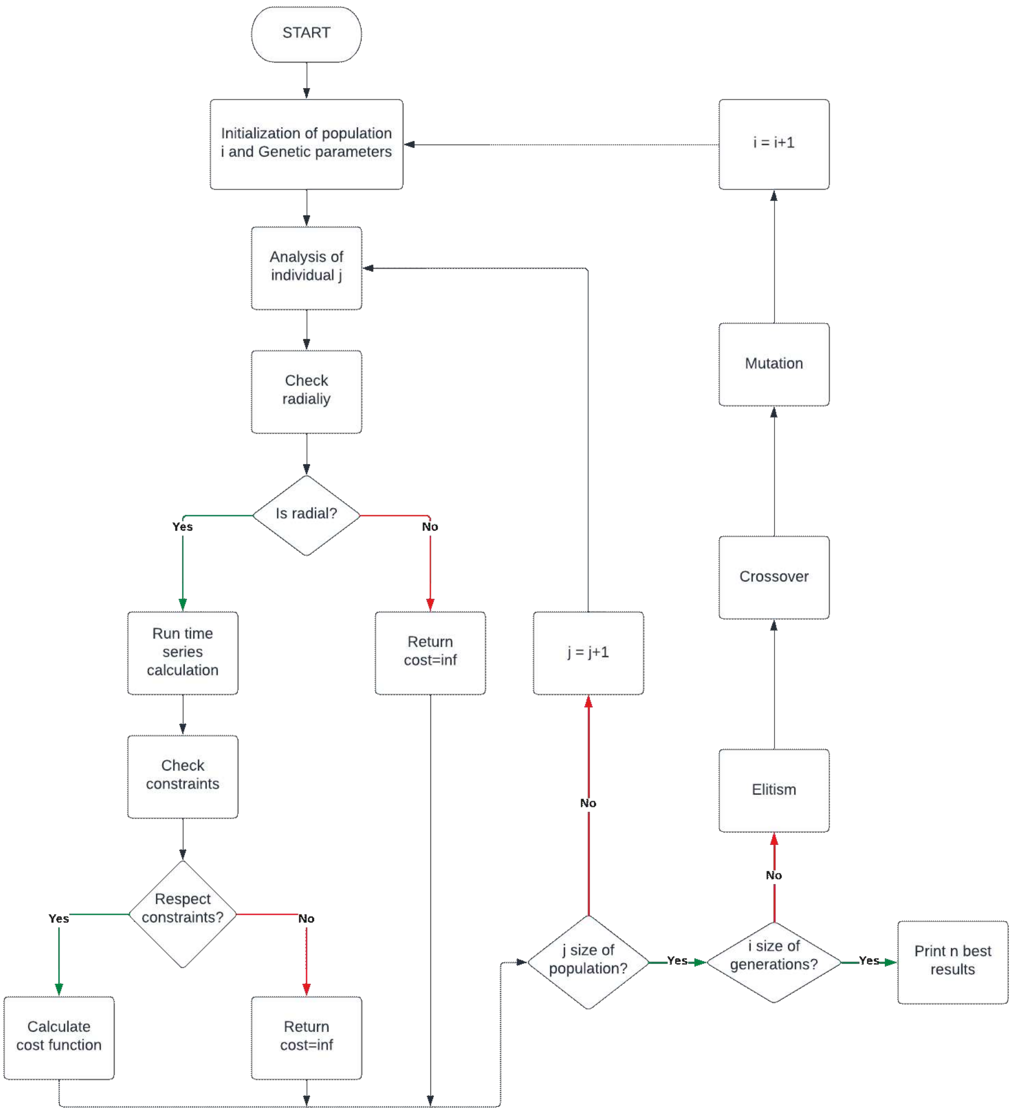

Figure 3.4: Proposed genetic algorithm

3.4.1 Generation 0

The first generation of solutions, the **generation 0**, is different from the following generations. A population of chromosomes (the possible solutions), with size **n_population**, is created randomly. The elements in each chromosome are:

- **state of switches**: a binary list of size equal to the number of switches, with 1 representing closed switch and 0 open switch;
- **rewired line**: an integer index of the line we want to rewire;
- **new line**: two integer indices representing the buses the new line is going to connect;
- **load curtailment**: a list of decimal indices, representing the fraction of power demanded, with size equal to the number of hours in a day (24);
- **distributed generators curtailment**: a list of decimal indices, representing the fraction of power generated, with size equal to the number of hours in a day (24).

The initialization of the population in generation 0 is shown by the pseudocode below:

Algorithm 1 Initialization of generation 0

```
for j in size population do
    network = analyzed_network
    switch_list = RandomInt(0:1, n_switch)  ▷ creates a list of random bits 0 and 1 of size n_switch
    idx = RandomInt(1:n_lines)  ▷ generates a random integer number between 1 and the number of lines in the grid
    (bus_in, bus_out) = (RandomInt(0:n_bus), RandomInt(0:n_bus))
    if bus_in = bus_out or (bus_in, bus_out) already existing line then
        (bus_in, bus_out) = (-1, -1))
    end if
    for i in k = n_loads + n_generators do
        curtailment(i) = RandomInt(1:10, k)*0.1  ▷ generates a list of random numbers from 0.1 to 1.0 of size 24
    end for
end for
```

3.4.2 Analysis of individual j and radiality check

Having the population i each element j in that population is analyzed. The parameters defined in Algorithm 1 are written on the analyzed network, creating a new network called: updated network. This operation with the parameters works as follows:

- **switch_list**: change the state of the switches according to this list;
- **idx**: add a line in parallel to the already existing one specified by the idx;
- **(bus_in, bus_out)**: if is different from (-1, -1), creates a new line that connects the two buses;

- **curtailment(i)**: multiply the load profile of the load i by the list curtailment(i);
- **curtailment(i + n_loads)**: multiply the generation profile of the generator i by the list curtailment(i).

After updating the network, the radiality of the network is verified. To do this, the net is converted in a NetworkX graph, through a Pandapower function, and than the function `nx.find_cycle()` returns: "True" if there are loops in the network and "False" if there aren't. The radiality check is performed before the check of the power quality constraints in order to save computational time, infact the radiality check is based only on the topology of the network and doesn't need to run the power flow as the other constraints. This allows to discard the non radial solution before running the time series calculation.

3.4.3 Run time series calculation and check constraints

After the time series, explained in paragraph 2.3, ran, the algorithm will print the results, for each time step, in a CSV file. Using the Pandas command `read_csv()` we can create a data frame and search for the values needed to check the constraints. From the data frame, are extracted: minimum value of voltage, maximum value of voltage, maximum value of current, maximum value of the transformer's loading. Those values are checked by the constraints in paragraph 2.2; if a constraint is violated the solution is unfeasible and infinite is given to the cost function.

3.4.4 Calculate cost function

To assign a cost function to each feasible solution the command `read_csv()` from paragraph 2.4.3 is again used. This time the following results are extracted from the data frame: active power losses of the lines, active and reactive power loss of the transformer. Those data are than used in the objective function, equation(2.1). The cost of the rewired line depends on the rewired line and is defined by its index `idx`. For the cost of the new line a function is created to find the distance between `bus_in, bus_out`, taking the geodata of the buses as input and returning the length of the line. In addition to the calculation of the cost function, is defined the `survive_probability` which is, for the solution j, being K the size of one population:

$$S_j = \frac{1}{C_{j_{tot}}} \tag{3.18}$$

$$P_{j_{survive}} = \frac{S_j}{\sum_{j=1}^{K} S_j} \tag{3.19}$$

This survive probability $P_{j_{survive}}$ will affect the chance of each solution to become a parent of the next generation.

3.4.5 Elitism

Elitism is the function that allows the best solutions to "survive" to the next generations preserving their chromosomes. The number of solutions that will be carried on in the next generation is defined by a parameter `n_elite`. So the `n_elite` best solutions of the generation i will be copied in the $i + 1$ generation, with their genes: `switch_list`, `idx`, `bus_in, bus_out`, `curtailment` and `cost`.

3.4.6 Crossover

The crossover operator give birth to the child of the next generation by mixing up the genes of two parents. The parents are selected by a function `select_parents` which does a weighted draw of two solution of the generation i and makes them the parents of the generation $i+1$. The weights are the `survive_probability` in the equation 2.19. After the selection of the parents a crossover between the two is performed as shown in the pseudocode below:

Algorithm 2 Crossover between two parents

```
gen1 = parent_1
gen2 = parent_2
for j in n_crossover do
    network = analyzed_network
    switch_list = shuffle(switch_list_gen1, switch_list_gen2) ▷ each bit of the switch_list has a 50% probability to be the one of gen1 or the one of gen2
    idx = Randomchoiche(idx_gen1, idx_gen2) ▷ randomly chooses the idx of gen1 or gen2
    (bus_in, bus_out) = (Randomchoiche((bus_in_gen1, bus_out_gen1), (bus_in_gen2, bus_out_gen2)) ▷ (bus_in, bus_out) has a 50% probability to be the one of gen1 or the one of gen2
    for i in k = n_loads + n_generators do
        curtailment(i) = shuffle(curtailment_i_gen1, curtailment_i_gen2) ▷ value of curtailment of each hour of each load and generator has 50% probability to be the one of gen1 or the one of gen2
    end for
end for
```

As shown in the Algorithm 2, the for loop that generates the children of the $i+1$ generation is performed for `n_crossover` times, which is a parameter that defines how mani children there will be in the following generation.

3.4.7 Mutation

The mutation operator takes as input one of the two parents or an elite child and changes their genes into a random number with a certain probability, otherwise it keeps the gene of the input. The solutions generated by the mutation become part of the $i + 1$ generation. The mutation of genes is explained BY the pseudocodes below:

Algorithm 3 Mutation of switches

```
for g in size(switch_list) do
    if random_number(0:1) < p_sw_mut then
        switch_list_input(g) = RandomInt(0:1)  ▷ the element g of the input switch_list is changed int a random 0 or 1
    end if
end for
```

Algorithm 4 Mutation of rewire and new lines

```
if random_number(0:1) < p_rewire_mut then
    idx_input = RandomInt(1:n_lines)    ▷ randomly changes the idx
end if
if random_number(0:1) < p_bus_mut then
    bus_in_input = RandomInt(1:n_bus)
end if
if random_number(0:1) < p_bus_mut then
    bus_out_input = RandomInt(1:n_bus)
end if
```

Algorithm 5 Mutation of curtailment

```
for i in k = n_loads + n_generators do
    for h in 24 do
        if random_number(0:1) < p_curtail_mut then
            curtailment_input(i, h) = RandomInt(1:10)*0.1    ▷ value of curtailment of each hour of each load and generator can change to another random value of curtailment
        end if
    end for
end for
```

Algorithm 6 Mutation

```
gen1 = parent_1
gen2 = parent_2
for j in n_mutation do
    network = analyzed_network
    if random_number(0:1) < p_elite then
        input = Randomchoiche(n_elite)    ▷ chooses a random elite solution
    else
        input = Randomchoiche(gen1, gen2)
    end if
    switch_list =Mutation of switches
    idx, bus_in, bus_out = Mutation of rewire and new lines
    curtailment = Mutation of curtailment
end for
```

As shown in the Algorithm 6 the mutation generates `n_crossover` solutions; the number of those solutions is given by:

$$n_{crossover} = n_{population} - n_{elite} - n_{crossover} \tag{3.20}$$

3.4.8 Hyperparameters

The hyperparameters are a very important aspect for the correct functioning of a genetic algorithm. They are the parameters that define how the operators, such as crossover and mutation, work and can heavily affect the performace of the algorithm [35]. The tuning of hyperparameters can be performed in different ways:

- **Experimental analysis**: consists in a searching for similar problems in the literature and implementing them into the algorithm, in order to evaluate the best choice of parameters, based on the quality of the solutions obtained;

- **Per algorithm basis**: a program is created to run the algorithm multiple times, with different values of hyperparameters, and the best solutions are printed with their set of hyperparameters. The drawback of this method is that requires a heavy computational power;

- **Optimization on budget**: is used to know how much improvement is expected from an set of hyperparameters in a given time. This is important to know since optimization is a very expensive process.

The set of hyperparameters to tune in this thesis are:

- **Population**: the amount of solutions (chromosome) created for each generation. Generally speaking higher is better, but increasing this parameter affects significally the computational time;

- **Number of generation**: defines the number of generation, once this number is reached the algorithm stops and print the best solution;

- **Number of elite**: the n best solutions of the generation i that are copied in the generation $i+1$. Higher this parameter is set, higher is the intensification (paragraph 1.2) of the algorithm and lower is the diversification;

- **Number of crossover and mutation**: the number of children generated by crossover and mutation, those two parameters increases the diversification;

- **Probability of mutation of the network elements**: defines the probability of each gene of mutating into a random other. Those parameter are indipendent from each other, meaning that there is one hyperparameter for swithch, rewiring, new line and curtailment mutations. Those hyperparameters affect the diversification, higher they are, higher is diversification.

In this thesis we decided to tune the hyperparameters trying different sets of them for multiple run of the algorithm. The hyperparameters which shown the best performances in terms of quality of the solution and convergence speed were chosen as the best. In the next chapter the set of hyperparameters used in each scenario will be provided.

Chapter 4

Case study applications

4.1 Case study presentation

To test the performances of the genetic algorithm proposed, a radial 33 nodes distribution grid, operating at the voltage of 20 kV is considered (Figure 4.1).

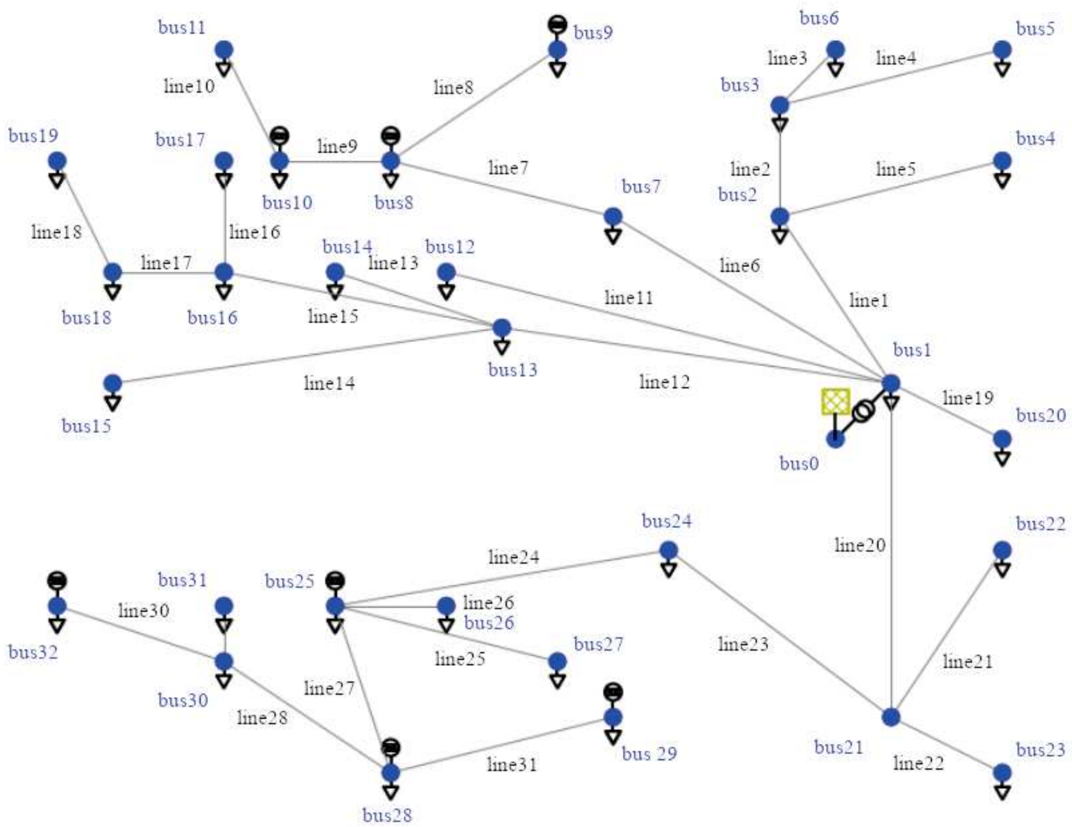

Figure 4.1: Distribution grid considered

The grid is equivalent to an existing distribution grid, operating in northern Italy, of which the topological and structural information are known. For what concerns the data of the generation and loads, their rated power is known and their profiles during time are hypothesized according to their typical behaviour. In particular, loads are defined by the rated contractual power and different user behaviour has been assigned based on the respective contractual power. Power consumption profiles are derived from average behaviour of industrial, residential and commercial users as discussed further in this section. Concerning generators, their rated power and distribution in the grid have been assumed in this work. The nodes of the grid have specific coordinates (table 4.1), in order to better resemble the real grid:

Node	**x [km]**	**y [km]**	**Node**	**x [km]**	**y [km]**
1	19	7	**18**	8	12
2	20	8	**19**	6	10
3	18	11	**20**	5	12
4	18	13	**21**	22	7
5	22	12	**22**	20	2
6	22	14	**23**	22	5
7	19	14	**24**	22	1
8	15	11	**25**	16	5
9	11	12	**26**	10	4
10	14	14	**27**	12	4
11	9	12	**28**	14	3
12	8	14	**29**	11	1
13	12	10	**30**	15	2
14	13	9	**31**	8	3
15	10	10	**32**	8	4
16	6	8	**33**	5	4
17	8	10			

Table 4.1: Nodes: topological informations

The characteristics of the lines are shown in the Table 4.2, each of them has its own type of line, which represents the cross section of the conductor and if it is an overhead line or a cable. The electric parameters for each type of line are explained in table 4.3.

Line	**From**	**To**	**Len [km]**	**Type**	**Line**	**From**	**To**	**Len [km]**	**Type**
Line1	2	3	3.8	AL_95	**Line16**	17	19	1	AL_35
Line2	3	4	1.7	AL_70	**Line17**	19	20	2.1	AL_35
Line3	4	7	1.5	AL_35	**Line18**	2	21	3.5	AL_120
Line4	4	6	2	AL_35	**Line19**	2	22	6	OH_95
Line5	3	5	2	AL_35	**Line20**	22	23	4	OH_70
Line6	2	8	4.2	AL_95	**Line21**	22	24	2	AL_35
Line7	8	9	3.5	AL_95	**Line22**	22	25	5	OH_95
Line8	9	10	3	AL_35	**Line23**	25	26	5	AL_120
Line9	9	11	1.6	AL_35	**Line24**	26	28	2	AL_70
Line10	11	12	2.45	AL_35	**Line25**	26	27	2.4	AL_95
Line11	2	13	4.1	AL_70	**Line26**	26	29	3.2	AL_70
Line12	2	14	7.2	AL_120	**Line27**	29	31	4.9	AL_35
Line13	14	15	2	AL_120	**Line28**	31	32	1.4	AL_35
Line14	14	16	3	AL_70	**Line29**	31	33	3.4	AL_35
Line14	14	17	3.8	AL_120	**Line30**	29	30	5.2	AL_70
Line15	17	18	2	AL_35					

Table 4.2: Lines: topologcal informations

Type	r [Ω/km]	x [Ω/km]	c [F]	g [S]	Imax [A]
AL_120	0.193	0.12	$2.3 \cdot 10^{-7}$	0	315
AL_95	0.268	0.13	$2.1 \cdot 10^{-7}$	0	265
AL_70	0.387	0.13	$1.8 \cdot 10^{-7}$	0	216
AL_35	0.727	0.14	$1.6 \cdot 10^{-7}$	0	153
OH_95	0.221	0.377	$1 \cdot 10^{-8}$	0	400
OH_70	0.3786	0.384	$9 \cdot 10^{-9}$	0	235

Table 4.3: Lines: electrical parameters

For what concerns the loads, they are subdivided in three different categories: residential (RES) in table 4.4, commercial (COM) in table 4.5 and industrial (IND) in table 4.6.

RES	Node	Pn [kW]	Qn [kVAr]	RES	Node	Pn [kW]	Qn [kVAr]
Load1	2	90	43.6	**Load33**	19	288	139.5
Load2	3	90	43.6	**Load36**	20	810	392.4
Load4	5	414	200.6	**Load38**	21	56.7	27.5
Load6	6	242.1	117.3	**Load39**	23	135	65.4
Load7	7	180	87.2	**Load40**	24	90	43.6
Load8	8	144	69.8	**Load42**	26	90	43.6
Load12	10	290	43.6	**Load45**	27	90	43.6
Load15	11	244	113.4	**Load48**	30	200	43.6
Load18	12	350.1	169.6	**Load51**	31	335	65.4
Load19	13	324	157	**Load52**	32	144	69.8
Load25	16	270	130.8	**Load55**	33	189	91.6
Load30	18	144	69.8				

Table 4.4: Residential loads

COM	**Node**	**Pn [kW]**	**Qn [kVAr]**	**COM**	**Node**	**Pn [kW]**	**Qn [kVAr]**
Load3	4	225	109	**Load31**	18	733.5	355.3
Load5	5	225	109	**Load34**	19	225	109
Load9	8	225	109	**Load37**	20	227	0
Load13	10	225	109	**Load41**	25	225	109
Load16	11	508.5	246.3	**Load43**	26	450	218
Load20	13	675	327	**Load49**	30	1387.5	573.2
Load23	15	508.5	246.3	**Load53**	32	225	109
Load26	16	225	109	**Load56**	33	508.5	246.3
Load28	17	225	109				

Table 4.5: Commercial loads

IND	**Node**	**Pn [kW]**	**Qn [kVAr]**	**IND**	**Node**	**Pn [kW]**	**Qn [kVAr]**
Load10	8	720	348.8	**Load29**	17	720	348.8
Load11	9	1440	697.5	**Load32**	18	360	174.4
Load14	10	360	174.4	**Load35**	19	360	174.4
Load17	11	916	0	**Load44**	26	3884	392.4
Load21	13	1080	523.1	**Load46**	28	550	0
Load22	14	360	174.4	**Load47**	29	720	348.8
Load24	15	360	174.4	**Load50**	30	1800	871.8
Load27	16	360	174.4	**Load54**	32	924	218

Table 4.6: Industrial loads

The generators, in the case study grid, are all photovoltaic static generators (table 4.7).

PV	Node	Pn [kW]	Qn [kVAr]	PV	Node	Pn [kW]	Qn [kVAr]
Gen1	9	4000	0	**Gen5**	29	2000	0
Gen2	10	2000	0	**Gen6**	30	2000	0
Gen3	11	2000	0	**Gen7**	33	2000	0
Gen4	26	2000	0				

Table 4.7: Photovoltaic generators

The load profiles are made considering the simultaneity factor, while the generation profile is made considering clear sky conditions, so the photovoltaic generators don't suffer of any shadowing effect. The data provided for the profiles, were given considering three typical days for each season: a working day, a Saturday and a Sunday. From those data the yearly typical day was created, by doing the weighted average of the given twelve days. The weighted average was performed considering that there are 65 working days per season, 13 Saturdays and 13 Sundays. The resulting profiles are shown in the figure 4.2 below.

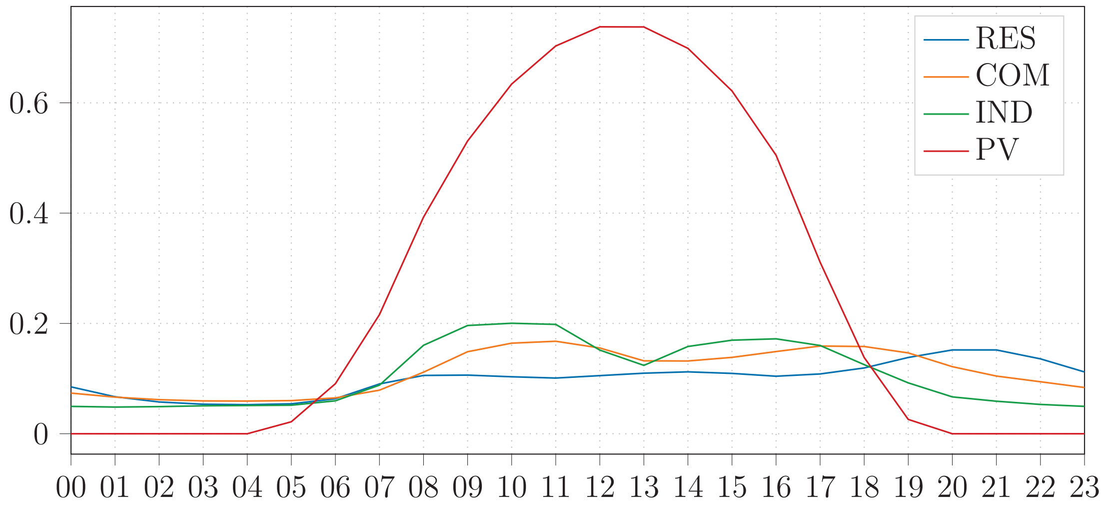

Figure 4.2: Yearly typical day load and generation profiles

As shown in figure 4.2 and in table 4.7, the grid has a high penetration of static generators which leads to overvoltages in some of the nodes of the grid.

4.2 Scenario 0: starting grid

In this scenario a power flow calculation, with a resolution of 24 instants of time, is performed to evaluate the daily cost of the considered network. The cost of the losses is set as the average between the PUN, single national price, in 2018 (61.3 €/MWh) and the PUN in 2019 (52.3 €/MWh), in order to have a price which is not influenced by the catastrophic events we experienced since 2020, first the COVID-19 pandemic and now, the war in Ukraine. The resulting PUN is: 56.8 €/MWh. The voltage constraints were set to ±5% of the rated voltage, in order to consider possible under or over voltages in the low voltage (BT) distribution grid. The costs of losses in this scenario are the sum of the power losses on the lines and the losses on the transformer, multiplied by the PUN (equation 4.1).

$$C_{tot} = PUN \cdot [\sum_{i=1}^{24}\sum_{j=1}^{M} P_{l_{i,j}} + \sum_{i=1}^{24} P_{lti} + 24 \cdot P_0] \tag{4.1}$$

The resulting cost of the network is: 231.9287 [€/day]. However, voltage constraints are violated in some nodes of the net, their maximum value during the day is shown in the table 4.8:

Node	**v_max [p.u.]**	**v_max - v_n [%]**
Node28	1.0567	5.67 %
Node29	1.0617	6.17 %
Node30	1.0667	6.67 %
Node31	1.0663	6.63 %
Node32	1.0747	7.47 %

Table 4.8: Nodes which violate constraints

The trend of nodal voltages is shown in figure 4.3, as was said before the overvoltages are clearly caused by photovoltaic generators, in fact the trend of the maximum nodal voltage in the net, follows the trend of the generation seen in figure 4.2.

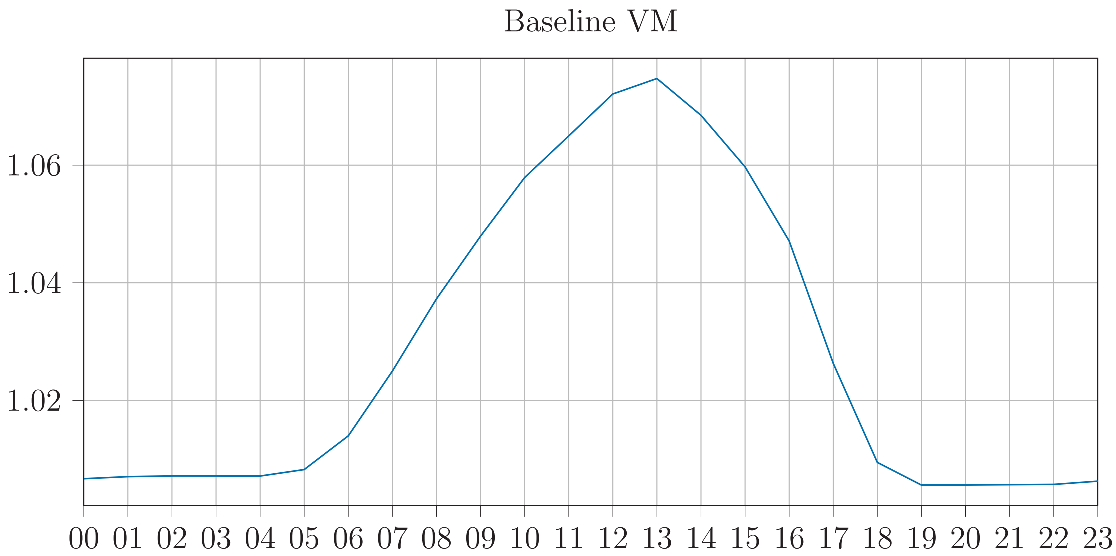

Figure 4.3: Maximum nodal voltage in the net for each hour

The trend of the nodal voltages which violate the constraints, are shown in figure 4.4.

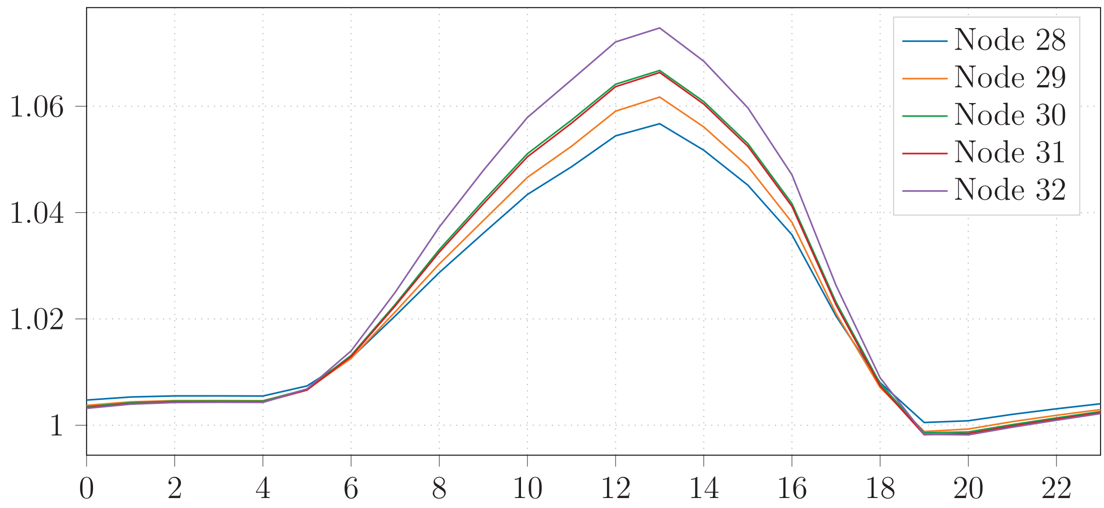

Figure 4.4: Nodal voltage trend for the nodes which violate constraints

In figure 4.5 the, total active power losses of the lines are shown for each hour of the day.

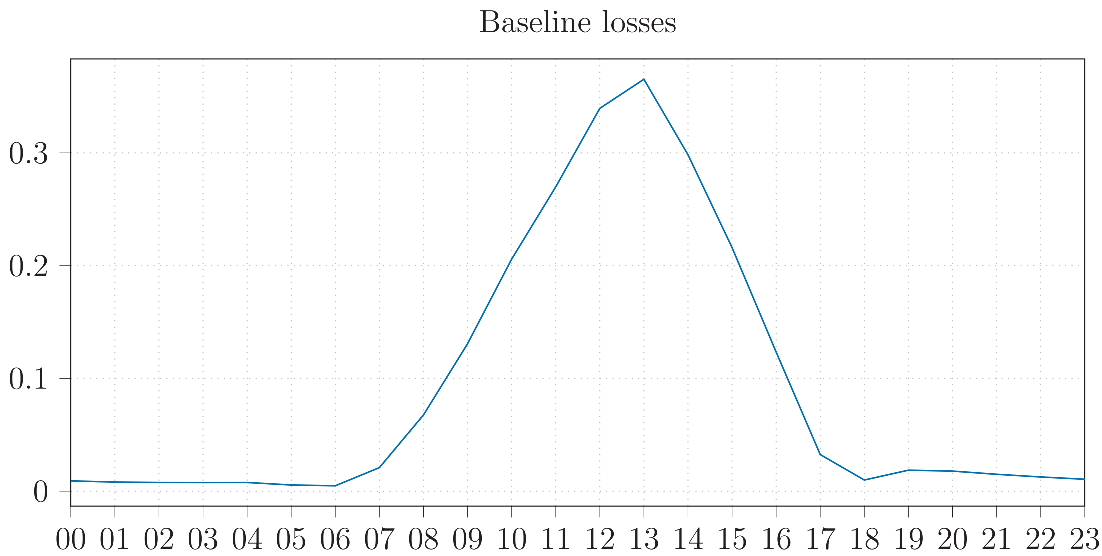

Figure 4.5: Line losses for each hour in MW

4.3 Scenario 1: network reconfiguration

In the first scenario, the reconfiguration intervention is considered. On the grid shown in figure 4.1, was hypothesized the presence of:

- 8 sectionalizing switches, which are normally closed
- 5 tie switches, which are normally opened
- 5 new lines

For what concerns the switches, their state and position is shown in table 4.9.

Switch	Line	State	Switch	Line	State
Sw1	2	Closed	**Sw8**	31	Closed
Sw2	7	Closed	**Sw9**	32	Opened
Sw3	14	Closed	**Sw10**	33	Opened
Sw4	15	Closed	**Sw11**	34	Opened
Sw5	24	Closed	**Sw12**	35	Opened
Sw6	27	Closed	**Sw13**	36	Opened
Sw7	28	Closed			

Table 4.9: Line switches

The positions and types of the added lines are shown in table 4.10.

Line	From	To	Len [km]	Type
Line32	3	9	3.9	AL_95
Line33	10	16	2.2	AL_95
Line34	15	32	4.1	AL_95
Line35	13	30	7.8	AL_95
Line36	21	29	5	AL_95

Table 4.10: Added lines: topologcal informations

The grid previously described, has a different structure from the one presented in figure 4.1, the grid considered for this scenario has the structure in figure 4.6.

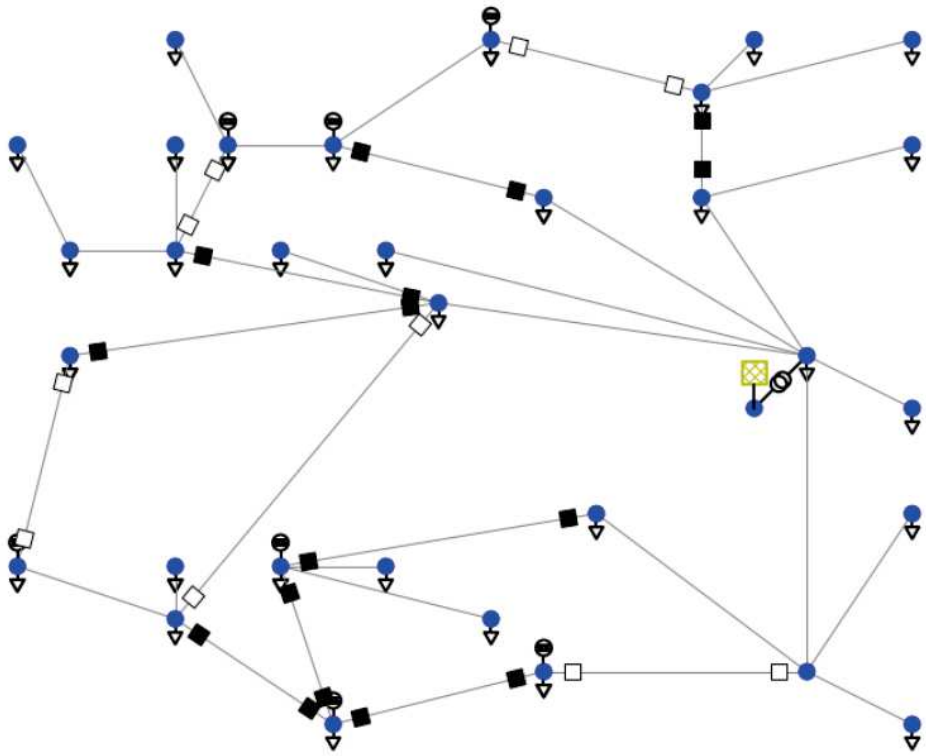

Figure 4.6: Grid considered in scenario 1

The white squares represent the normally opened tie switches, while the black squares represent the normally closed tie switches. The proposed genetic algorithm was run by changing only the state of the switches of the grid, with the hyperparameters shown in table 4.11.

Hyperparameters	Value
Population	50
Generations	30
p_sw_mut	0.1
Crossover number	20%
Elite number	2

Table 4.11: Hyperparameters for scenario 1

The plot in figure 4.7 displays the best solution produced by the genetic algorithm at each generation. The curve behaviour suggests that the proposed algorithm converges to a solution with cost 175.9846 €/day, whose details are reported in the table 4.12.

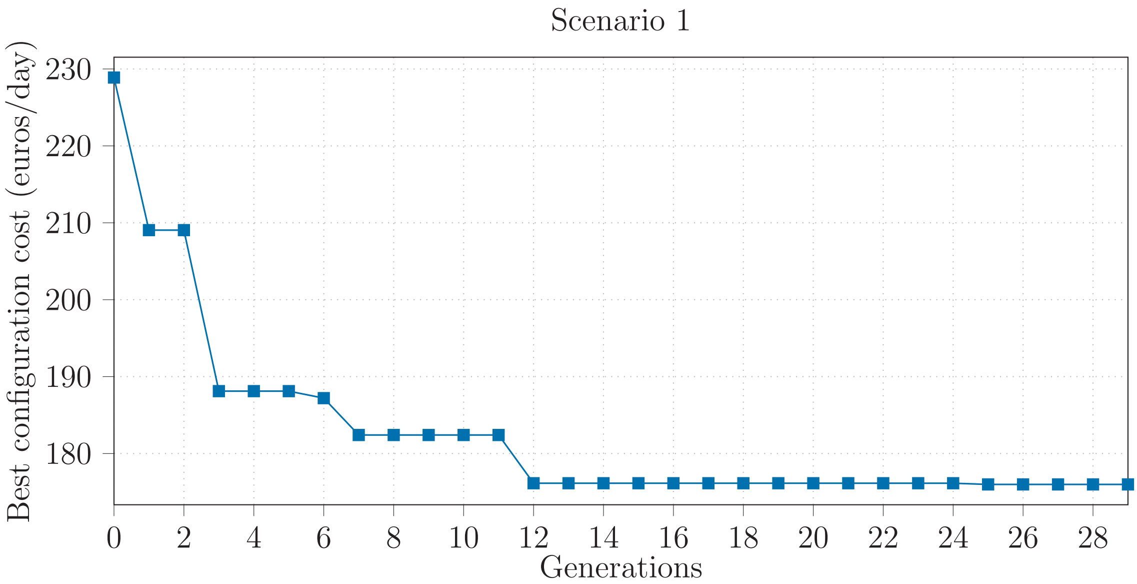

Figure 4.7: Convergence plot

Cost	**Value**
Scenario 0	231.9287 €/day
Scenario 1	175.9846 €/day
Improvement	-24.12 %
Computational time	1h 11min

Table 4.12: Genetic algorithm performances

The new configuration of the grid, found by the genetic algorithm, is shown in the figure 4.8 and table 4.13.

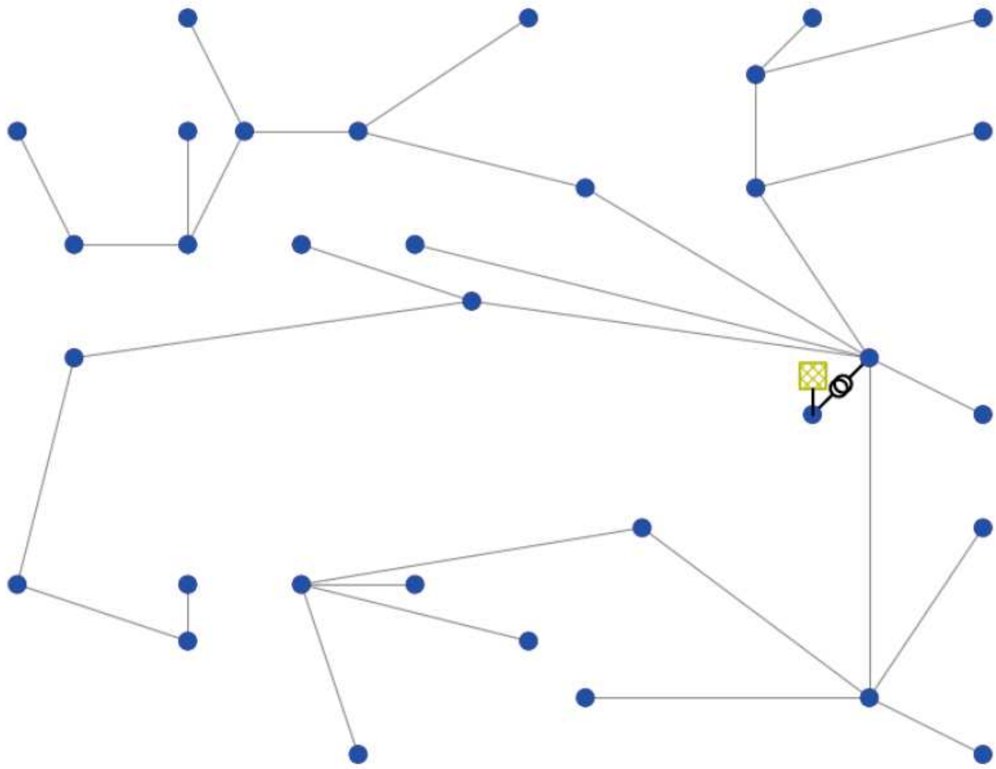

Figure 4.8: Best configuration for scenario 1

Switch	Line	State	Switch	Line	State
Sw1	2	Closed	**Sw8**	31	Opened
Sw2	7	Closed	**Sw9**	32	Opened
Sw3	14	Closed	**Sw10**	33	Closed
Sw4	15	Opened	**Sw11**	34	Closed
Sw5	24	Closed	**Sw12**	35	Opened
Sw6	27	Closed	**Sw13**	36	Closed
Sw7	28	Opened			

Table 4.13: Line switches

The reconfigured grid, respects all the power quality constraints, lowering the voltages of critical buses under the 5% of the grid's rated voltage. In figure 4.9, the comparison between the highest node voltage at each hour of the day of scenario 0 and scenario 1 is shown.

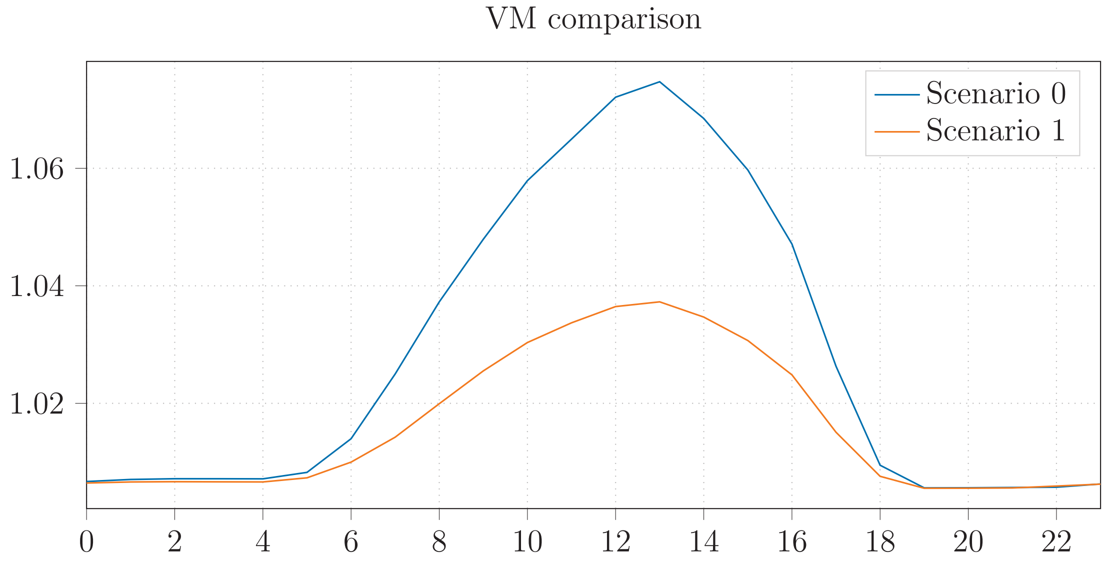

Figure 4.9: Maximum nodal voltage in the net for each hour

The same comparison shown in figure 4.9, is done in figure 4.10, considering the line losses at each hour of the day instead of the nodal voltages.

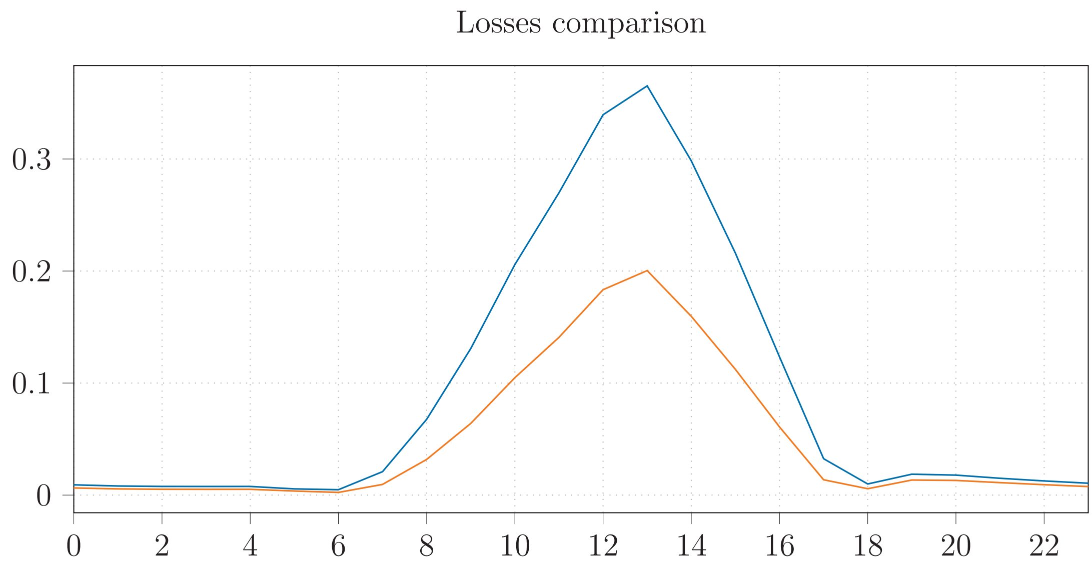

Figure 4.10: Line losses for each hour in MW

4.4 Scenario 2: grid expansion

In this scenario, a grid expansion intervention is considered. The grid is the same as the one in figure 4.1, with the presence of the eight sectionalizing switches presented in the paragraph 4.3. Two types of expansion grid interventions are considered:

- **line rewiring**: one of the existing lines of the grid is rewired by adding a line, of the same type, in parallel to it.
- **new line**: a new line is built between two existing nodes of the grid. The type of line is chosen from a group of four.

To evaluate the daily cost of the grid with the intervention, evaluating the actualized cost of rewiring a line and adding a new one is necessary. To do so, a document from Enel Distribuzione was used, in order to associate a cost to the construction of new lines (Table 4.14).

Section of line [mm^2]	**Cost [k€/km]**
AL_35	45
AL_70	48.5
AL_95	50
AL_120	55.5

Table 4.14: Cost of building a new line

Those costs, comprehend both the cost of the conductor and the cost of the infrastructure to place the conductors. For the rewired line, a cost of 1/5 of the ones shown in table 4.14 is considered, since the infrastructure is already present on the grid. To actualize the cost to a daily cost, a lifetime of 30 years was considered for both the rewired and the new lines.

The total daily cost in this scenario is calculated according to the equation below:

$$C_{tot} = PUN \cdot [\sum_{i=1}^{24}\sum_{j=1}^{M} P_{l_{i,j}} + \sum_{i=1}^{24} P_{lti} + 24 \cdot P_0] + C_{nl} \cdot l_{nl} + C_{rl} \cdot l_{rl} \tag{4.2}$$

To enhance convergence the nodes of the grid are subdivided by the branch where they belong. The four groups of nodes identified are shown in the table below:

Group	From node	To node
Group 1	2	6
Group 2	7	11
Group 3	12	19
Group 4	20	32

Table 4.15: Groups of nodes for the new line

The new line built by the algorithm, has always the starting bus and the ending bus taken from different groups. Another way used to help convergence is to open one switch at a time in order to reduce the amount of non radial solutions in each generation. The hyperparameters used in this scenario are shown in the table below:

Hyperparameters	Value
p_sw_mut	0.4
Population	100
Generations	10
p_newline_mut	0.5
p_rewiredline_mut	0.5
Crossover number	50%
Elite number	2

Table 4.16: Hyperparameters for scenario 2

The plot in figure 4.11 shows the best cost for each generation, while the table 4.17 shows the performances of the genetic algorithm for this scenario.

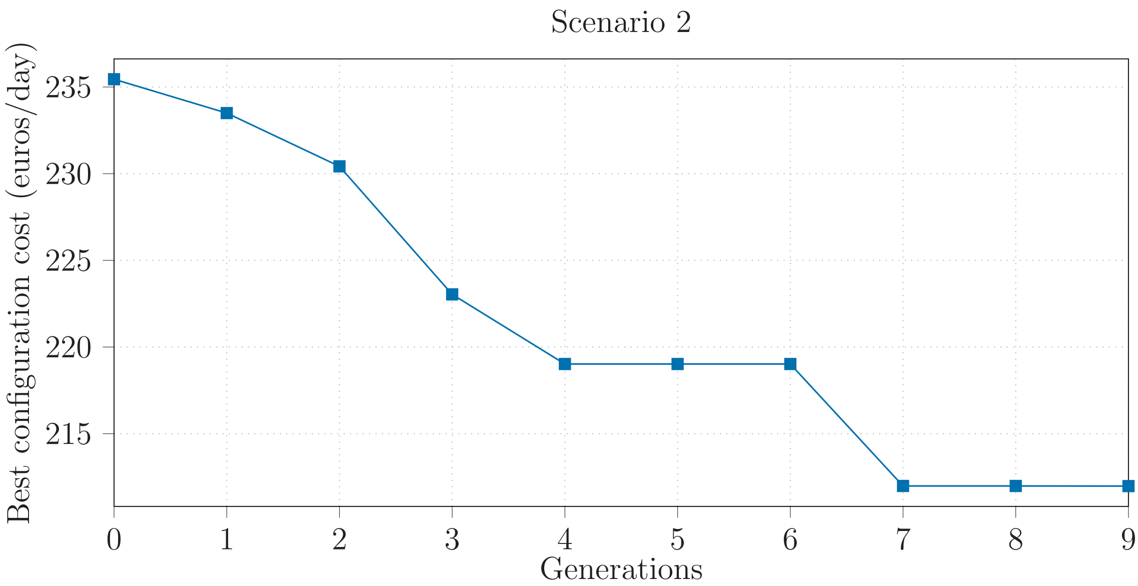

Figure 4.11: Convergence plot

Cost	Value
Scenario 0	231.9287 €/day
Scenario 2	211.9780 €/day
Improvement	-8.6 %
Computational time	0h 33min

Table 4.17: Genetic algorithm performances

The algorithm chose, as best solution, to upgrade the line 6 and to build a new line connecting the node 15 with the node 32. The sectionalizing switches are all closed, except for the switch 7 (Sw7) which was opened, disconnecting the line 28 from the grid (table 4.18).

The new configuration of the grid, according to the best solution, is the one shown in the figure 4.12.

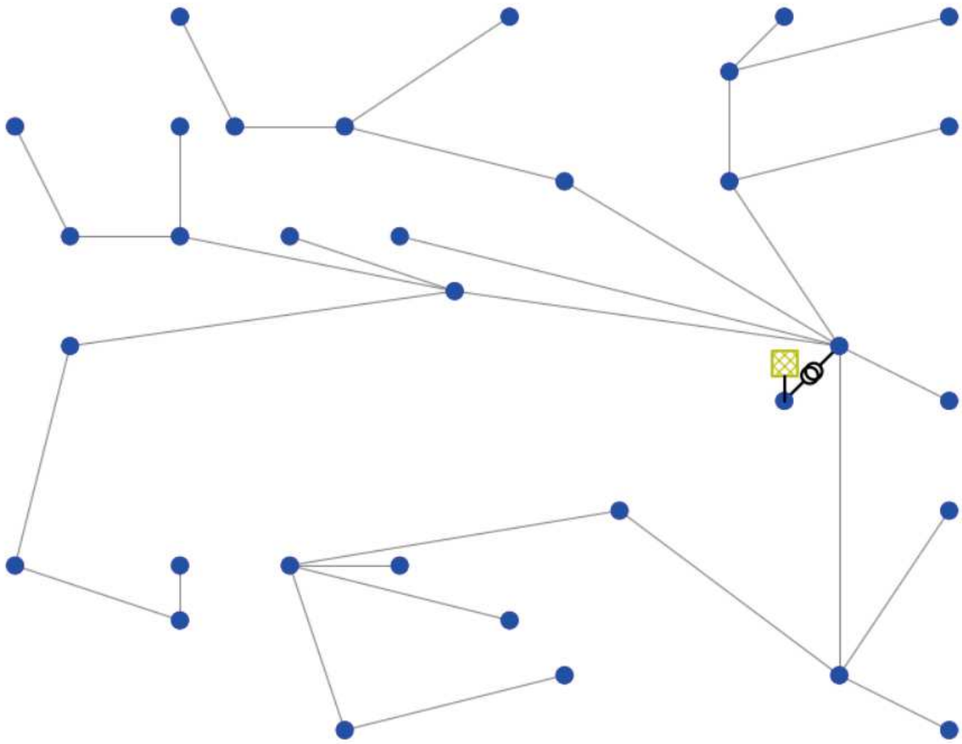

Figure 4.12: Best configuration for scenario 2

Changes	Info
Opened switch	Switch 7
New line	[15, 32]
Type	AL_35
Rewired line	6

Table 4.18: Grid expansion details

The best configuration of the grid lowered the operational costs by 8.6% and also respects all the constraints, lowering the critical voltages under the 5% permitted by the voltage constraints. In figure 4.13 is shown the improvement of the voltage profiles respect to the scenario 0 and in figure 4.14 is shown how the expansion of the grid lowered the line losses.

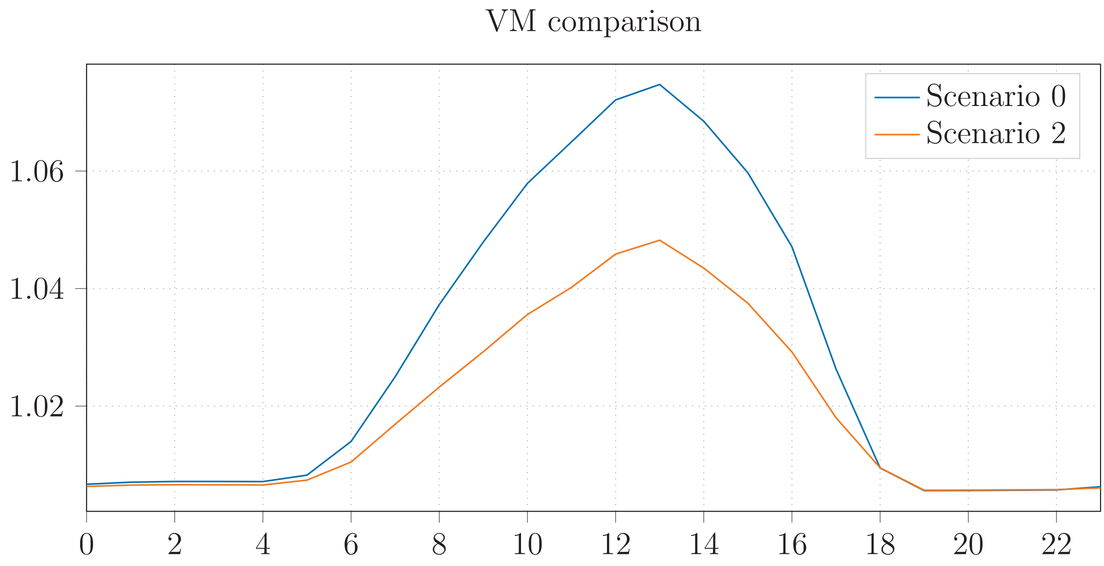

Figure 4.13: Maximum nodal voltage in the net for each hour

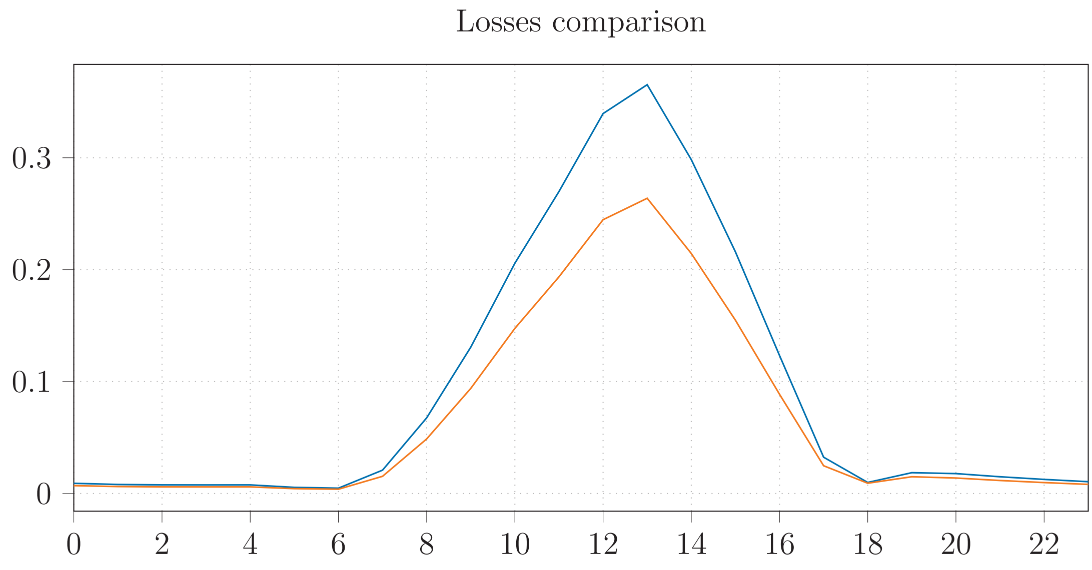

Figure 4.14: Line losses for each hour in MW

4.5 Scenario 3: generation curtailment

In the third and last scenario a generation curtailment intervention is considered to solve the overvoltage problem seen in scenario 0. As seen in figure 4.3, the critical overvoltages are present in the hours of the day between 10 and 15, for this reason that time span was taken in consideration for the curtailment of generators. The curtailment of the generated power was set at ten different levels between 10% and 100%, with 10% meaning that the generator produces only the 10% of its capability, and 100% meaning no power was curtailed. The cost for the flexibility service provided by the generators was set to be two times the PUN. The genetic algorithm takes into account all the generators of the grid (table 4.7). The hyperparameters used in this scenario are the ones shown in table 4.19.

Hyperparameters	Value
Population	200
Generations	80
p_curt_mut	0.05
Crossover number	40%
Elite number	2

Table 4.19: Hyperparameters for scenario 3

The performances for the curtailment intervention are shown in the table below:

Cost	Value
Scenario 0	231.9287 €/day
Scenario 3	622.6656 €/day
Improvement	+168.47 %
Computational time	11h 53min

Table 4.20: Genetic algorithm performances

The best cost for each generation of the genetic algorithm is shown in the plot in figure 4.15.

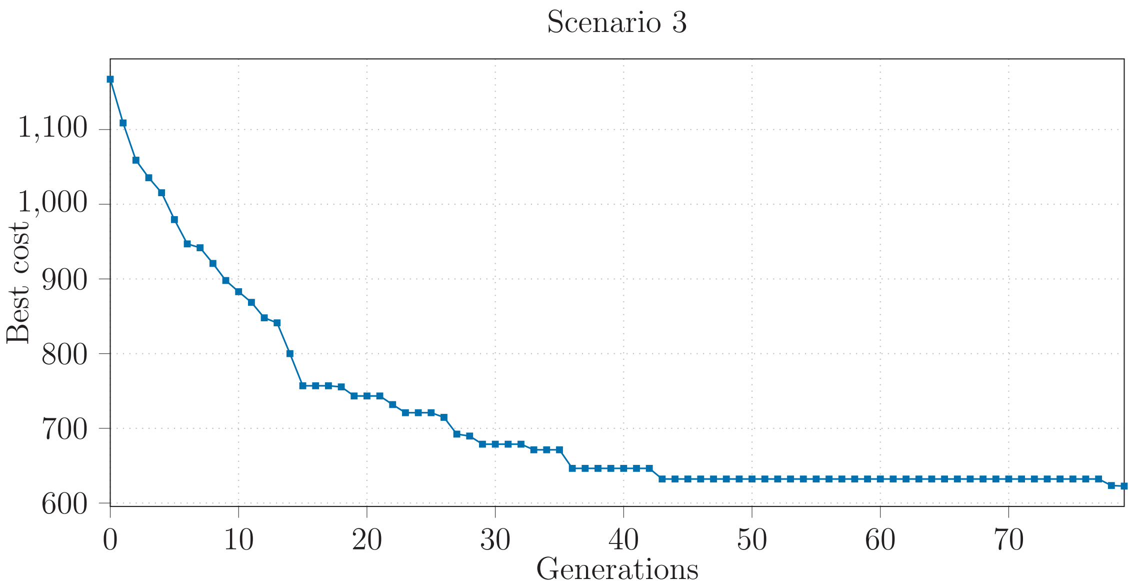

Figure 4.15: Convergence plot

The curtailment levels found for the best solution are shown in table 4.21, for each generator and each hour of the time span considered for the curtailment.

PV	**10:00**	**11:00**	**12:00**	**13:00**	**14:00**	**15:00**
Gen1	100%	100%	100%	100%	100%	100%
Gen2	100%	100%	100%	100%	100%	100%
Gen3	100%	100%	100%	100%	100%	100%
Gen4	100%	80%	100%	80%	100%	100%
Gen5	100%	100%	50%	60%	90%	70%
Gen6	100%	100%	100%	80%	90%	100%
Gen7	70%	60%	50%	60%	50%	80%

Table 4.21: Curtailment in the best solution

The new generation profiles, after the curtailed intervention, are shown one by one in the figure 4.16, while the overall generation profile, sum of all the generated power for each time step, is shown in the figure 4.17.

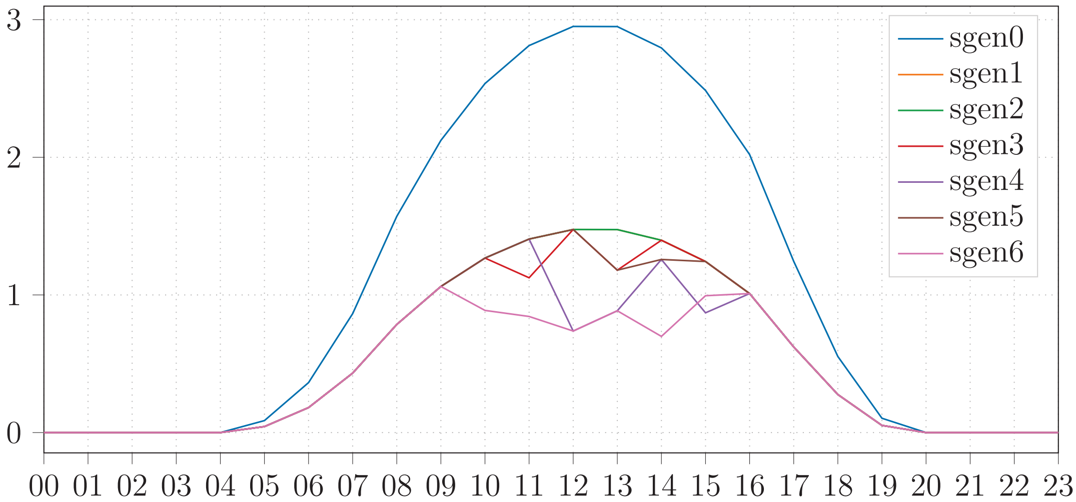

Figure 4.16: Curtailed generation profiles

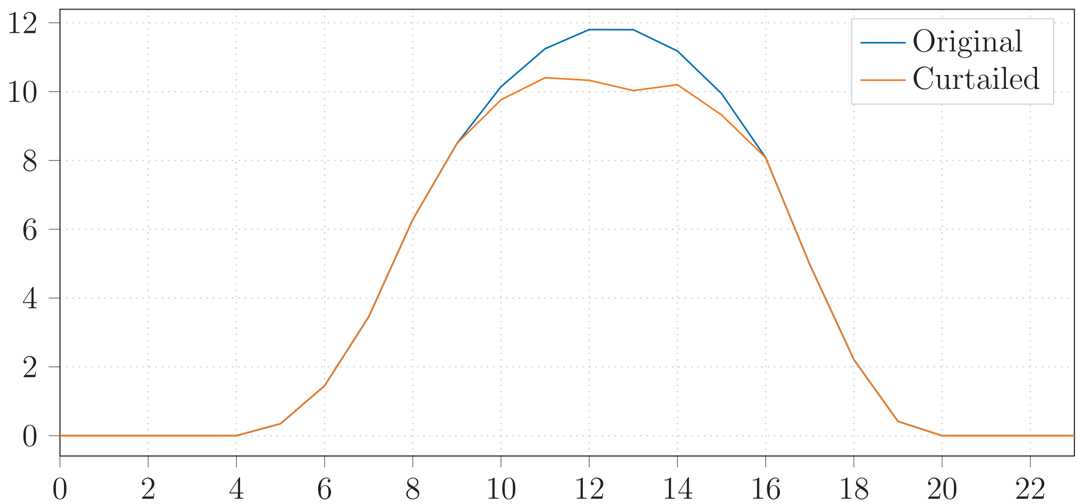

Figure 4.17: Sum of curtailed generation profiles

The voltage profile after the curtailment are shown in figure 4.18, while the line losses profile is shown in figure 4.19. As is possible to see, both the profiles are flattened in correspondence to the hours in which the curtailed was applied.

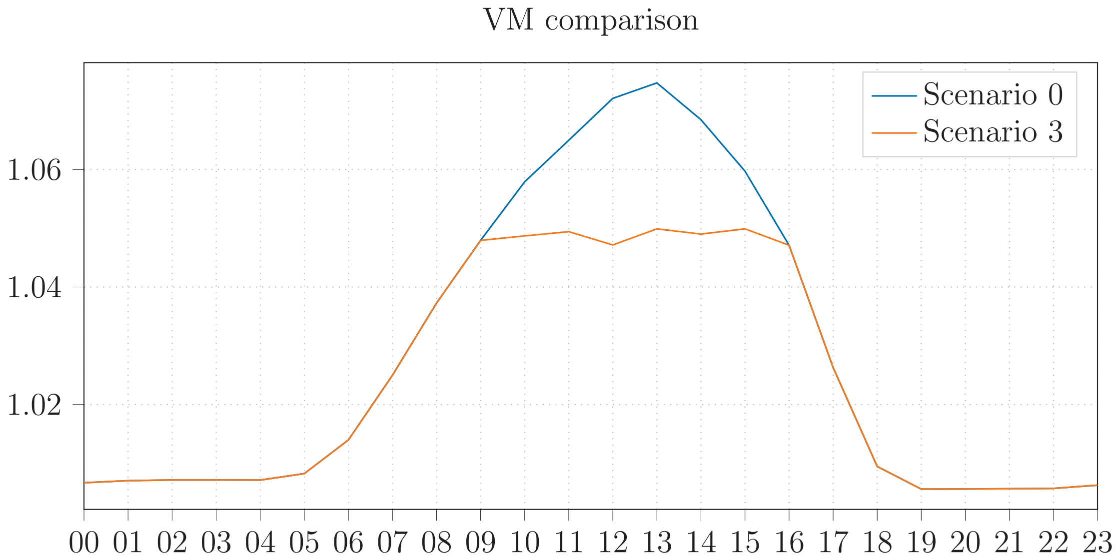

Figure 4.18: Maximum nodal voltage in the net for each hour

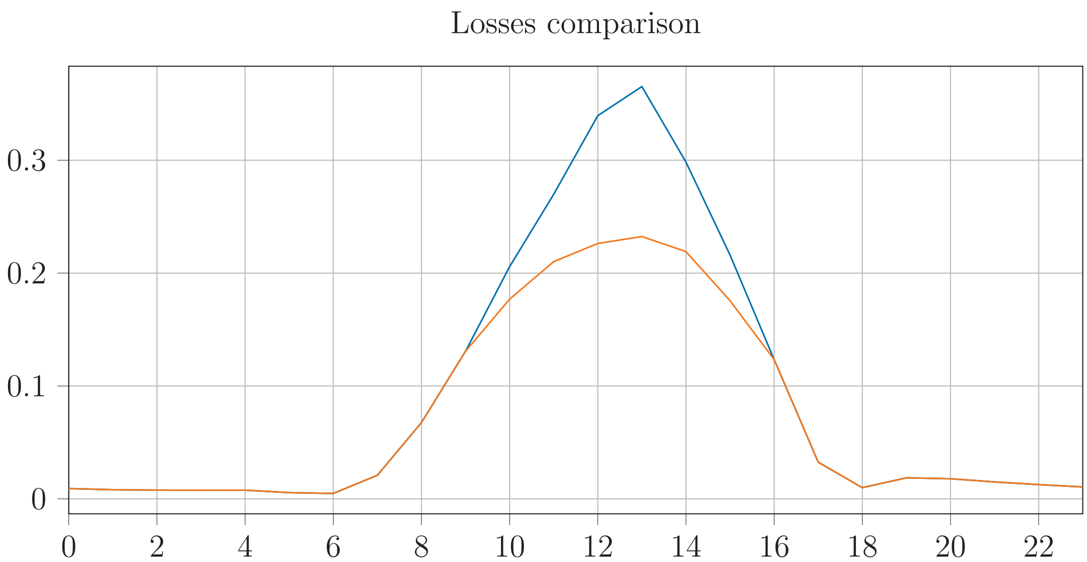

Figure 4.19: Line losses for each hour in MW

Conclusion

The goal of this thesis was to test the effectiveness of the genetic algorithm applied to different types of intervention that a Distribution System Operator could carry out, in order to reduce the grid's operational cost and respect the power quality constraints. Three scenarios were considered and applied to an existing grid in the North of Italy, which has a high penetration of photovoltaic distributed generators. This high penetration of generators caused overvoltages in some nodes of the grid for some hours of the day, so the algorithm not only had to reduce the operational costs, but also had to bring the critical voltages below the allowed limits. In the first scenario a network reconfiguration intervention was analyzed, by hypothesizing the presence of additional lines and switches. The result were a reduction of the operational cost by 24.12%, respecting the voltage constraints, in a computational time quite low: one hour and eleven minutes. The found solution shows the great economical convenience of reconfiguring a grid, thanks to the fact that is a nearly zero cost intervention, especially using an algorithm which can find the global best reconfiguration in an acceptable amount of time. In the second scenario a grid expansion intervention was considered, using the genetic algorithm to search the best type and position of a new line to build, the best existing line to rewire and the switch to open in order to keep the grid's radiality. The result showed a reduction of the operational cost by 8.4%, the nodes were all under the voltage limits and the computational time was only 33 minutes. The solution found for the second scenario shows that, even if the investment cost of building or rewiring new lines is quite large, the actual daily operational grid cost could be reduced, with the additional benefit of improving the grid's power quality. In the third scenario a flexibility service, provided by the distributed generators was considered, in order to lower the voltage of the critical nodes below the allowed limits. The solution found by the genetic algorithm was quite costly, in fact the cost of the service was nearly three times the operational cost of the grid. However the DSO could decide to sustain such high cost in particular situation like: during faults, maintenance of the grid or, more in general, in cases where there is a problem of islanding in some areas of the grid. The results of the three scenarios analyzed above are not meant to be compared to each other because the first and the third scenario are short term interventions, while the second scenario is a mid/long term intervention, since the construction of new infrastructures require years. Summing up the results analyzed above, the genetic algorithm proved to be a solid and flexible method to find the best interventions to adopt on a distribution grid, providing a valuable tool to the DSO to make the right decisions for increasing the efficiency of the grid, decreasing the costs, and improving the system power quality. As future works would be interesting to implement, at the same time, all the interventions proposed in this thesis, in order to evaluate the best mix between them. Another future work could be to consider: the load curtailment, the presence of storage in the grid (or the benefits of installing new storage), the effect of the vehicle to grid and reactive power management as an ancillary service offered by the consumers.

Ringraziamenti

Al termine del mio percorso di studi, è doveroso ringraziare tutti coloro che mi hanno supportato in questi anni.

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Nomenclature

$\Delta P_{G_{i,j}}$ amount of active power curtailed from generator j at time step i

$\Delta P_{L_{i,j}}$ amount of active power curtailed from load j at time step i

C_l cost of losses

C_{nl} actualized cost of the new line per km

C_{rl} actualized cost of the rewired line per km

G number of generators in the grid

i_m current flowing in the line m

$i_{m_{max}}$ ampacity of the line m

k parameter of curtailment costs

L number of loads in the grid

l_{nl} length of the new line

l_{rl} length of the rewired line

M number of lines in the grid

N number of nodes of the grid

P_0 iron losses for the transformer

$P_{l_{i,j}}$ active line power losses

P_{lt_i} active power losses for transformer at time step i

S_n rated power of the transformer

v_n voltage in p.u. of the node n

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