M. Sc. Thesis

«Development of optimization algorithms for a smart grid community»

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ABSTRACT

The aim of this work is the development of an optimization model in order to minimize the cost of Leaf Community microgrid. This cost is a sum of energy cost and the maintenance cost of the Energy storage system. The developed objective function is constrained and the problem here is solved by using the method of genetic algorithms at Matlab. The genetic algorithm decides about the transportation of the energy from or to the ESS and it calculates an optimum cost. The optimization time horizon is 24 h ahead, thus the prediction of energy production and consumption was necessary. This was achieved by using neural networks. In order to verify the performance of the developed optimization model, some scenarios were tested evaluated. This study concludes that a management of a microgrid can achieve energy and money savings.

Contents

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NOMENCLATURE

E_0^{pur} : energy purchased from subsystem (0) – POD at time t, (kWh)
E_1^{pur} : energy purchased from subsystem (0) and has passed the transformer in order to be consumed at subsystem 1 and specifically at Leaf Working at time t, (kWh)
E_2^{pur} : energy purchased from subsystem (0) and has passed the transformer in order to be consumed at subsystem 2 and specifically at Leaf farm at time t, (kWh)
E_0^{sell} : energy sell to the subsystem (0) – POD at time t, (kWh)
E_{10}^{sell} : energy sell from subsystem (1) to subsystem (0) at time t, (kWh)
E_{30}^{sell} : energy sell from subsystem (3) to subsystem (0) at time t, (kWh)
$E_{Demand}^1\ (t)$: Energy demanded at Leaf Working at time t, (kWh), **predicted from the algorithm developed**
$E_1^{pur}\ (t)$: energy purchased from subsystem (0) and has passed the transformer in order to be consumed at subsystem 1 and specifically at Leaf Working at time t, (kWh)
$E_{11}^{use}\ (t)$: energy generated from PV plants (subsystem (1)) and can be used directly from Leaf Working (subsystem (1)) in order to cover its need at time (t), (kWh)
$E_{31}^{use}\ (t)$: energy generated from hydroelectric station (subsystem (3)) and can be used directly from Leaf Working (subsystem (1)) in order to cover its need at time (t), (kWh)
$E_{21}^{ESS}(t)$: energy stored at ESS (subsystem (2)) and can be used from Leaf Working (subsystem (1)) after feeding the Leaf farm (subsystem (2)) at time (t), (kWh)
$E_2^{ESS}(t-1)$: energy stored at the ESS (subsystem (2)) at time (t-1), (kWh)
$\mathrm{E}_{Demand}^2\ (\mathrm{t})$: Energy demanded at Leaf farm at time t, (kWh), **predicted from the algorithm developed**
$\mathrm{E}_2^{pur}\ (\mathrm{t})$: energy purchased from subsystem (0) and has passed the transformer in order to be consumed at subsystem 2 and specifically at Leaf farm at time t, (kWh)
$\mathrm{E}_{12}^{use}\ (\mathrm{t})$: energy generated from PV plants (subsystem (1)) and can be used directly from Leaf farm (subsystem (2)) in order to cover its need at time (t), (kWh)
$\mathrm{E}_{32}^{use}\ (\mathrm{t})$: energy generated from hydroelectric station (subsystem (3)) and can be used directly from Leaf farm (subsystem (2)) in order to cover its need at time (t), (kWh)
$\mathrm{E}_{22}^{ESS}(\mathrm{t})$: energy stored at ESS (subsystem (2)) and can be used from Leaf farm (subsystem (2)), (kWh)
$E_2^{ESS}(t-1)$: energy stored at ESS (subsystem (2)) at time (t-1), (kWh)
$\mathrm{E}_2^{ESS}(\mathrm{t})$: energy stored at ESS at time t, (kWh)
$\mathrm{E}_{0,ESS}^{pur}(\mathrm{t}-1)$: energy purchased from POD at time (t-1) in order to charge the batteries, (kWh)
$\mathrm{E}_{12}^{ESS}(\mathrm{t}-1)$: energy generated from PV plants (subsystem (1)) and goes for store at ESS (subsystem (2)) at time (t-1), (kWh)
$\mathrm{E}_{32}^{ESS}(\mathrm{t}-1)$: energy generated from hydroelectric station (subsystem (3)) and goes for store at ESS (subsystem (2)) at time (t-1), (kWh)
$\mathrm{E}_{ESS,Leaf farm}^2\ (\mathrm{t}-1)$: energy taken from ESS in order to cover Leaf's farm demands at time (t-1), (kWh)

$\mathrm{E}^{1}_{ESS,Polo\_2}(\mathrm{t}-1)$: energy taken from ESS after feeding Leaf farm, in order to cover demands at Leaf Working at time (t-1), (kWh)
${E_2^{ESS}}_{max}$: maximum energy can be stored at ESS, (kWh)
${E_2^{ESS}}_{min}$: minimum energy can be stored at ESS, (kWh)
$SOC(t)$**:** the state of battery charge at time t
SOC_{min} : the allowable minimum state of battery charge
$SOD(t)$**:** the state of battery discharge at time t
SOD_{max} : the allowable maximum state of battery discharge
$E_{PV}^{gen}(t)$: energy generated from PV plants at time t, (kWh), **predicted from the algorithm developed**
$E_{10}^{sell}(t)$: energy generated at subsystem (1) – PV plants and goes for sell to subsystem (0) – POD at time t, (kWh)
$E_{12}^{ESS}(t)$: energy generated at subsystem (1) – PV plants and goes for store at subsystem (2) – ESS at time t, (kWh)
$E_{11}^{use}(t)$: energy generated at subsystem (1) – PV plants and goes directly for use at subsystem (1) – Leaf Working at time t, (kWh)
$E_{12}^{use}(t)$: energy generated at subsystem (1) – PV plants and goes directly for use at subsystem (2) – Leaf farm at time t, (kWh)
$E_{hydro}^{gen}(t)$: energy generated from hydroelectric at time t, (kWh), **predicted from the algorithm developed**
$E_{30}^{sell}(t)$: energy generated at subsystem (3) – hydroelectric station and goes for sell to subsystem (0) – POD at time t, (kWh)
$E_{32}^{ESS}(t)$: energy generated at subsystem (3) – hydroelectric station and goes for store at subsystem (2) – ESS at time t, (kWh)
$E_{31}^{use}(t)$: energy generated at subsystem (3) – hydroelectric station and goes directly for use at subsystem (1) – Leaf Working at time t, (kWh)
$E_{32}^{use}(t)$: energy generated at subsystem (3) – hydroelectric station and goes directly for use at subsystem (2) – Leaf farm at time t, (kWh)
n_1: the efficiency of the transformer connected at line POD – Leaf Working
n_2: the efficiency of the transformer connected at line POD – Leaf farm
n_3: the efficiency of the inverter connected after the ESS at subsystem (2)

1 INTRODUCTION

Electricity is vital to the modern way of life, as it is used by industries, businesses, homes and transportation. This form of energy is produced by electrical power systems and has many advantages as it is clean, its transportation from the production to the consumption points is easily and its utility is really flexible. The electrical power systems should satisfy the needs of consumers by supplying the proper amount of electricity. The voltage and the frequency must be stable even though the demand is not.

Furthermore, it is important the electricity's cost being accessible to the majority of the population, while its production and use must pollute as less as possible the environment. Regarding these two topics, many researchers analyzed at their studies different ways that decrease the emissions to the environment by promoting the renewable energy sources, while economical models developed through intelligent applications such as neural networks and optimization methods, show the need of managing the energy in order to achieve a cost as minimum as possible.

Thus, economic, technology and environmental incentives are changing the face of electricity generation and transmission and centralized generating facilities are giving way to smaller, more distributed energy resources (DER). [1] The technical advantages of distributed generation units include power quality and reliability as well as energy management and efficiency. It also offers economical advantages in terms of reducing capital investment for construction of power systems since distribution of generation units eliminates the need for having extensive transmission systems. [2]

The growing deployment of DER units, mostly these on small scale which combine power and heat plants and renewable energy resources based on distributed generation units, has led to the development of microgrids, which are described below. [3]

The microgrid approach promotes: [4]

- a highly efficient energy delivery and supply system based on co-locating DER and loads
- a secure and reliable power supply configuration with service differentiations based on customer technology preference and power quality desires, and
- an energy delivery structure that has sufficient power generation and balancing sources to operate independent from the main grid in an autonomous manner during power outages or an energy crisis.

2 MICROGRIDS

Microgrids are small scale supply networks designed to provide electrical and heat load for a small community, such as a housing estate, a suburban locality, an academic or a public community, an industrial site or a commercial area.
The microgrid (MG) concept assumes a conjunction of power generation plants (distributed generators (DG) – renewable energy sources), energy storage units (distributed storage (DS) - batteries) and units of energy consumption (buildings), operating in low voltages, while it could be operating either on grid connected mode either on island mode interacting with the main grid. The electrical connection point of the microgrid to the utility system, at the low-voltage bus of the substation transformer, constitutes the microgrid point of common coupling (PCC). A typical microgrid structyre is presented at Figure 2.1. [5]

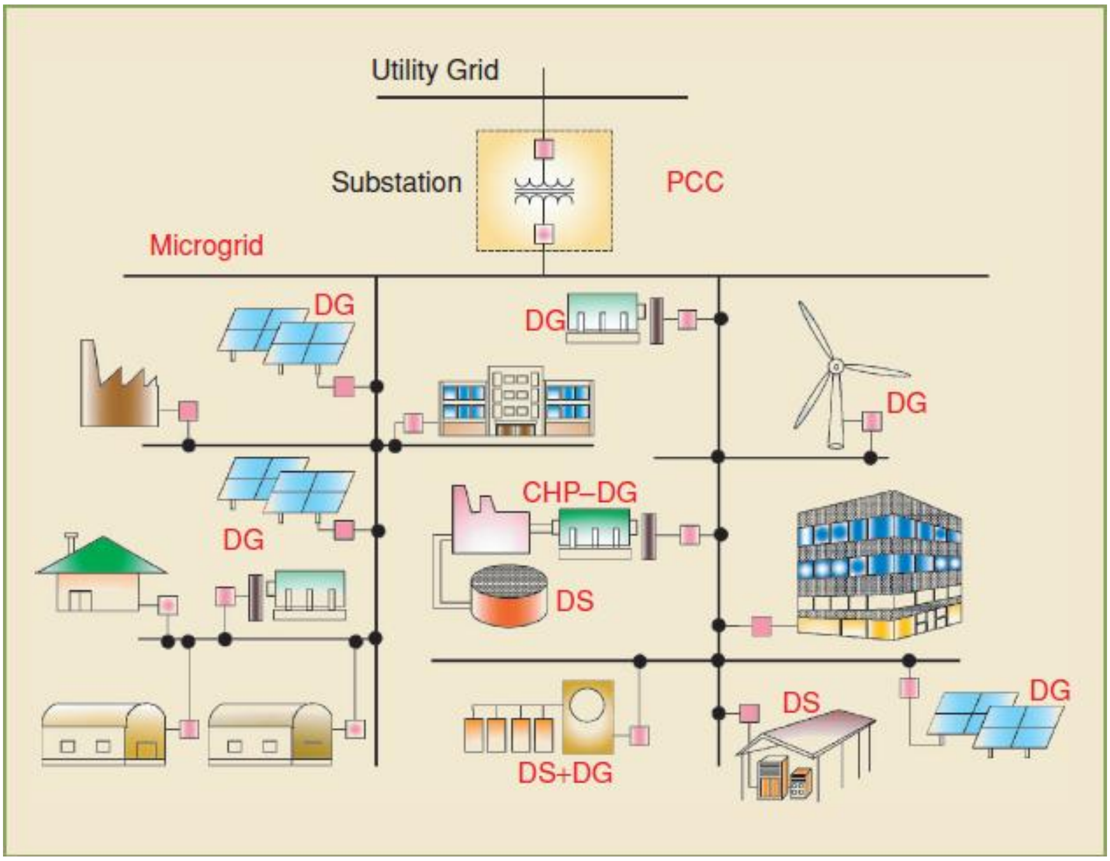


Figure 2.1: Typical microgrid structure including loads and DER units [5]

In grid-connected mode, the microgrid either draws or supplies power from or to the main grid, depending on the generation and load with suitable market policies. On the other hand, microgrid can operate independent when a power quality event in the main grid occurs. [6]

In the case that microgrid is connected to the main grid, it behaves as a controllable load or source, while operating under island mode it should face a number of issues that are described below.

2.1 Issues operating under island mode

In case of a fault on the main grid, the microgrid should disconnect and operating independently facing the followings. [7]

- Voltage and frequency management

Microgrid's voltage and frequency are determined by the grid when they are connected. Under a situation of disconnections, the values of these parameters should be adjusted, otherwise if frequency's value be too small, the load may be temporarily shaded.

- Balance between supply and demand

When there is a power flow from the grid to the microgrid or the opposite before disconnection, then secondary control actions must be followed in order to balance generation and consumption in island mode to ensure initial balance after a sudden fluctuation in load or generation.

- Power quality

Operating under island mode, microgrid should maintain a sufficient power quality, supplying an adequate reactive energy in order to decrease voltage sags. Additional, the storage system should be capable of reacting immediately and exchange large amounts of real or reactive power.

- Microsources issues

Most microsources like turbines or fuel cells delay to response to secondary voltage and frequency implements. For that reason, the intermediate storage units and microsources with built-in battery banks are going to offer the advantages like spinning reserves.

- Communication among Microgrid Components

The implementation of communication infrastructure linking the microgrid components is another aspect considered when selecting the control approach on an islanded microgrid. [7]

2.2 Technology requirements in a microgrid

Island mode operation of a microgrid requires variety technology systems in order to isolate from the grid and operate itself. The technology needed either on island mode operation either on grid connected is: [8]

- Distributed generation (GD)
- Islanding and Bi-Directional inverters
- Smart meters
- Distribution automation
- Substation automation
- Microgrid control systems
- Smart transfer switches
- Advanced energy storage

2.3 Distributed generation (DG)

Distributed generation refers to power generation at the point of consumption by electric power generators in small scale (1kW – 50MW). Distributed generator technologies includes combined heat and power (CHP), fuel cells, mini wind turbines, PV systems, micro-turbines, single-phase and three-phase induction generators, synchronous generators driven by IC engines or small hydro. [9] Most of the emerging technologies mentioned before, require an inverter interface in order to convert the energy into grid – compatible ac power. In order to be ensured a smooth operation for the microgrid control systems must be installed on the electrical power line. [5], [9]
At the following Table 2.1, the interfacing and power flow control options of the most common power generators are summarized.

Table 2.1: Typical characteristics of common DG [5], [9]

Characteristics	Solar	Wind	Microhydro	Diesel	CHP
Availability	Geographical location dependent	Geographical location dependent	Geographical location dependent	Any time	Dependent on source
Output power	DC	AC	AC	AC	AC
Gas emission	None	None	None	High	Dependent on source
Control	Uncontrollable	Uncontrollable	Uncontrollable	Controllable	Dependent on source
Typical interface	Power electronic converter (DC-DC-AC)	Power electronic converter (AC-DC-AC)	Synchronous or induction generator	None	Synchronous generator
Power flow control	MPPT[1] & DC link voltage control	MPPT, pitch & torque control	Controllable	Controllable	AVR[2] & governor

[1] MPPT: Maximum power point tracking
[2] AVR: Automatic voltage regulation

In this study, the distributed power generators are PV systems and a micro hydro. Therefore, some characteristics of those technologies are presented below at the followings sections.

2.3.1 Photovoltaic (PV) system

Photovoltaic systems exploit solar radiation in order to generate electric power. It is one of the common distributed generators which are preferred in a microgrid due to the enormous improvement of inverters. [10]

Some of the main advantages of a PV system are summarized below.

- Exploits a sustainable energy
- There are no environmental impacts
- Has a long life time
- Its operation is not noisy

Expect from advantages, there is also a list of disadvantages for these systems; some of them include the followings.

- Their installation is not economically advantageous
- They present low efficiency
- Their efficiency is depended on the weather

2.3.2 Micro hydroelectric system

Another distributed generator is the micro hydroelectric system, which is capable to produce electrical or mechanical energy by exploiting the energy of flowing water. Their efficiency is directly depended on the geographical location as well as the annual precipitation of the area. Moreover its generation is not stable due to uneven rainfalls. [10]

2.4 Energy Storage System (DS)

The energy storage devices like batteries, fly-wheels and super-capacitors, are one of the main technologies in a microgrid, through them the successful operation of the microgrid is ensured. They have to balance the energy demand with the generation and they take this responsibility in three necessary scenarios. [10]

1. They establish energy balance even thought the variation of loads, while distributed generators with low inertia are not able to be responded to these disturbances.

2. Provides ride-through capability when there are dynamic variations in intermittent energy sources and allows the DGs to operate as dispatchable units.
3. They provide the initial requirement energy when connections or disconnections are taking place with the main grid. [10]

2.5 Benefits of microgrid

Microgrid's development is very promising regarding the electric energy industry, because of the followings. [11]

- Environmental issues

The environmental impact of microsources is expected to be smaller than large conventional thermal power stations. Also, the main benefits of the microgrid in this topic are:

a) Physical proximity between consumers and microsources may help increase consumer awareness towards a more rational use of energy.

b) Reduction of gas emissions that may mitigate the alleged effects of climate change due to the creation of technical conditions to increase the connection of renewable energy resources at the low voltage level. This will be achieved by the use of these sources together with storage devices and their efficient coordinated control, both at a local level and at the microgrid level. In fact, RES are characterized by very low emissions and microturbines have also reduced impact due to close control of the combustion process. [11]

- Operation and investment issues

Reduction of both physical and electrical distance between generating units and loads may contribute to:

a) Improvements of reactive support of the whole system, thus enhancing the voltage profile
b) Reduction of transmission and distribution feeder overload
c) Reduction of transmission and distribution losses
d) Reduction/postponement of investments in the expansion of transmission and large-scale generation systems

- Quality of service

Improvement in power quality and reliability in particular is achieved due to:

a) Decentralization of supply
b) Better match of supply and demand
c) Reduction of the impact of large-scale transmission and generation outages.
d) Minimization of downtimes if microsources are allowed to operate autonomously, namely when there is a disturbance in the upstream distribution system, and enhancement of the restoration process through the black start function of microsources. [11]

- Cost saving

The following cost savings can be achieved in microgrids:

a) Utilization of waste heat in CHP[3] applications. Also, no substantial infrastructure is required for heat transmission since CHP sources are located close to customer loads.
b) Integration of several microsources combined into a microgrid allows sharing generated electricity among the customers, reducing the need to import/export power from/to the main grid through long feeders.

- Market issues

The following advantages can be attained: [11]

a) Possible development of market driven operation procedures of microgrids will lead to a significant reduction of market power exercised by established generation companies. The microgrid can be regarded as an aggregator for individual loads and microgeneration units, enabling them to participate in electricity markets.

b) Microgrids may be used to provide ancillary services.

c) Widespread application of modular microsources may contribute to a reduction in energy price in the power market with appropriate economic balance between network investment and DG utilization. Further price reduction may be achieved by optimizing microgeneration operation (e.g. generating power locally at expensive peak loads and purchasing power from the main grid when economically more attractive).

2.6 Disadvantages of microgrid

Conversely, several challenges and potential drawbacks face the development of microgrids as follows: [11]

[3] CHP: Combined heat and power

➢ <u>High costs of DER</u>

The high installation cost for microgrids is a big disadvantage that may be reduced if some form of subsidies from government bodies is obtained as a device to encourage investment, at least for a transitory period, given the current official environmental and carbon capture goals.

➢ <u>Technical difficulties</u>

These technical barriers are mostly related to the relative lack of experience and technical knowledge to operate and control a significant number of microsources. This aspect requires extensive real-time and off line research on issues such as management, protection and control of microgrids. Also, specific telecommunication in infrastructures and communication protocols need to be developed to help managing, operating and controlling the microgrids. In addition, economic implementation of seamless transition between operating modes is a major challenge since the currently available solutions are still quite expensive. [11]

➢ <u>Absence of standards</u>

Since this is a comparatively recent area, standards are not yet available for addressing power quality, operation and protection issues, for instance.

➢ <u>Administrative and legal barriers</u>

In some countries, there is a lack of legislation and regulations for the operation of microsources. Naturally, legislation and regulation for microgrid operation is more complex and will have serious implications regarding coordination with the distribution company on issues such as dispatch voltage/var control strategies, real time management, ancillary services provision, etc. [11]

2.7 Control and Management

According to the financial benefits of microgrid, owners have to opportunity to make prudent investment decisions and optimize energy assets in long term. Thus, a sound operation of microgrid is needed, especially to this that operates in island-mode. Therefore, appropriate control and management systems are required.

A principle of the energy management is presented schematically at Figure 2.2. [12]

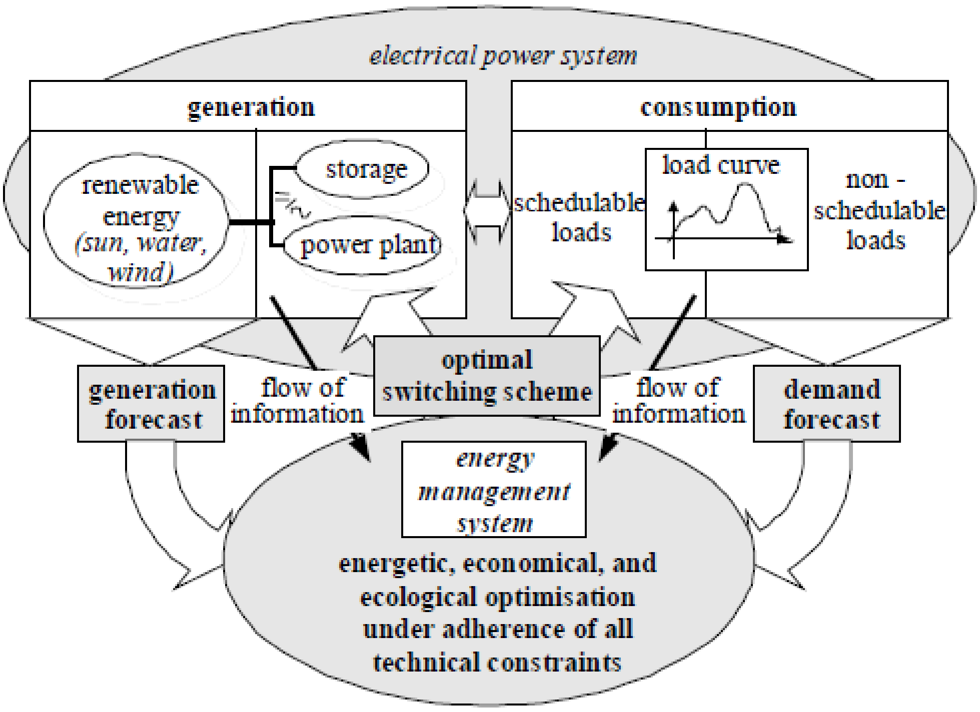


Figure 2.2: Principle of energy management [12]

The management of a microgrid requires an accurate model to describe the operation taking into account all the components of it. By developing detailed models, the achievements for the owners could be the followings:

- Reduce energy costs
- Optimize revenues
- Achieve net zero energy
- Minimize emissions
- Maintaining occupant satisfaction and comfort

Such these models are discrete and nonlinear in nature; hence optimization tools are needed, like dynamic programming, genetic algorithms, evolutionary computering, particle swarm optimization algorithms and simplex method. On the other hand, basic architectures and regulation techniques of microgrids are presented by Llaria et al., in order to study the islanding behaviour and mainly the different detection techniques and the inverters' control once islanded. [13]

2.8 Optimization of microgrids: State of the art

Several strategies have been reported in the literature related to the operation costs as well as minimizing emissions of microgrid. Havez et al., focus on the optimal design of a renewable energy based microgrid with the goal of minimizing the lifecycle cost, while taking into account environmental emissions. Four different cases were modeled at software HOMER, in order to compare and evaluate their economics, operational performance and environmental emissions. [14]

A simulation of a fuzzy logic energy management system for an autonomous polygeneration microgrid is presented by Kyriakarakos et al. The devices being managed at this work are the fuel cell, desalination unit and electrolyser unit. They develop a design tool based on TRNSYS 16, Matlab, GenOpt 2.0 and TRNOPT, while they used Particle Swarm Optimization (PSO) method. The results show that the fuzzy logic system utilizes the available energy in the system better and the components' sizes are, thus, considerably decreased. [15]

According to [16], the optimization of a small power system has important differences from the case of a large system and its traditional economic dispatch problem. In this study the researchers developed an optimization model which aims at reducing the fuel consumption rate of the system while constraining it to cover the local energy demand (both electrical and thermal) and provide a certain minimum reserve power.

Another work has been done by Faisal A. Mohamed et al., who present a non linear constrain multiobjective optimization problem in order to determine the optimal operating strategy and cost optimization scheme as well as the reduction of the emissions for a microgrid. [17] Furthermore, Faisal A. Mohamed et al., propose a cost function takes into account the costs of the emissions, NOx, SO_2, and CO_2, start up costs, as well as the operation and maintenance costs. The optimization is aimed at minimizing the cost function of the system while constraining it to meet the customer demand and safety of the system by using genetic algorithms. [18]

H.Z. Liang et al., use an improved genetic algorithm based method in order to minimize the microgrid's operational cost when it is isolated and maximize its revenue when it is connected to upstream network. [19]

Stadler et al, present the development of a web-based software as service approach for optimizing the selection and the operation of distributed energy resources equipment and running the Distributed Energy Resources Customer Adoption Model (DER-CAM). Given an individual microgrid's hourly energy requirements, available technologies and the economic environment, DER-CAM finds the economically or environmentally optimal combination of equipment to install and an optimal schedule to operate it. [20]

There are many optimization techniques that have been applied to many optimization problems. Some of them are mentioned before. This study focuses on the method of the genetic algorithms in order to modeling an existing microgrid in Italy and minimizes the energy cost for the owners.

3 OPTIMIZATION

Because of the complexity of many systems and products in engineering in order to improve and optimize them, efficient and systematic decision-making approaches are needed. This, leads to the development of optimization strategies.

Optimization as an idea is the procedure through mathematical equations that maximizes or minimizes a target of interest, by finding the best solution among a set of candidate solutions. This task requires the following elements: [21]

- An objective function: a reflection of a single quantity that needs to minimized or maximized. System's cost or efficiency could be the measure needed to optimize.
- Decision variables: the identification of the design parameters is a necessary step for the procedure. They reflect aspect of the problem that the decision maker has control over.
- Constrains: are actually the limitations of performance for the system.

3.1 Optimization procedure

The optimization procedure starts by finding the objective function in terms of the design variables and other problem parameters. The second step includes the identification of decision variables which are not stable during the process of optimization. Usually, a design problem involves many design parameters. The decision maker has to choose the sensitive ones during the formulation of the problem. The development procedure ends by setting the appropriate constrains. The constraints represent some functional relationships among the design variables and other design parameters satisfying certain physical phenomenon and certain resource limitations. [21]

These three steps should followed in order to develop an optimization model are presented schematically at Figure 3.1.

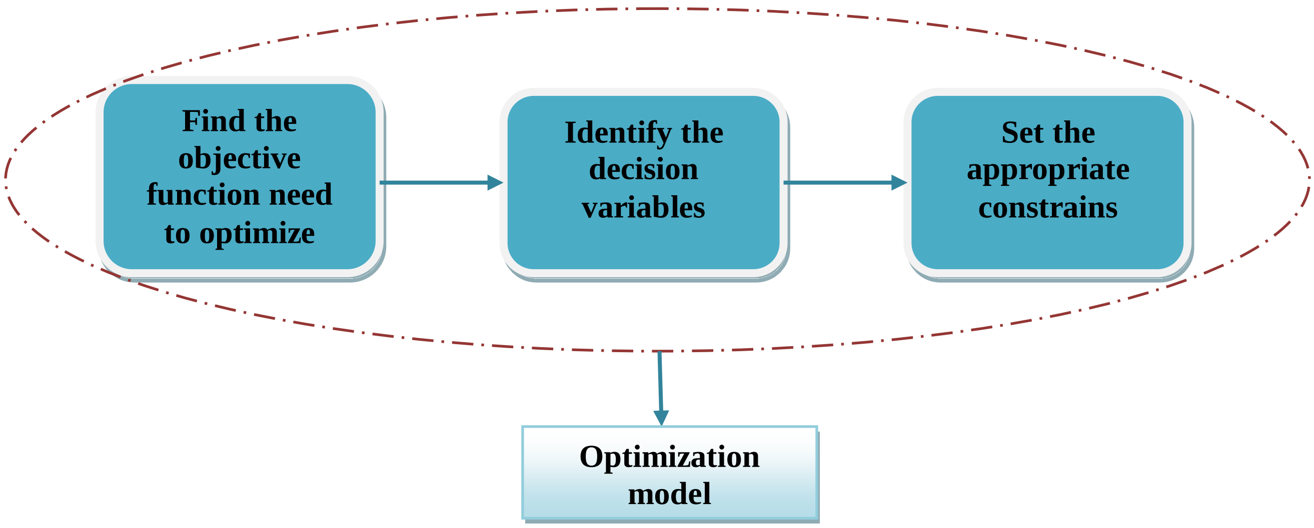


Figure 3.1: Optimization procedure

After all these were mentioned above, the formulation could be tested in order to be able to evaluate the optimization model.

3.2 General mathematical form of an optimization problem

A simple case of an optimization problem is to maximize or minimize a function (f) which is only dependent on design variables (x). This problem doesn't include any constrains. [22]

Furthermore, an advanced case is described by the following equations.

The objective function, **f(x)**, need to be minimized/maximized, might be subject to constrains:

- in the form of equality: $\mathbf{G_i(x) = 0}$, $(i=1,\ldots,m_e)$
- in the form of inequality: $\mathbf{G_i(x) \leq 0}$, $(i=m_e+1,\ldots,m)$
- in the form of parameter bounds: $\mathbf{x_i}^{(L)} \leq \mathbf{x_i} \leq \mathbf{x_i}^{(U)}$

f(x): the objective function
x: is the vector of length n design parameters
G(x): returns a vector of length "m" containing the values of the equality and inequality constraints evaluated at "x"
$x_i^{(L)}$: lower bound
$x_i^{(U)}$: upper bound
Lower and upper bounds are the minimum and the maximum limit respectively that decision maker estimates in order to enclose the best solution for the problem.

3.3 Optimization methods

Some numerical methods are used to optimization problems are: [23]

- **Linear programming**: studies the case in which the objective function “f” is linear and the design variables are specified using only linear equalities and inequalities.

- **Integer programming**: studies linear programs in which some or all variables are constrained to take on integer values.

- **Quadratic programming**: allows the objective function to have quadratic terms, while the set of design variables must be specified with linear equalities and inequalities

- **Nonlinear programming**: studies the general case in which the objective function or the constraints or both contain nonlinear parts.

- **Stochastic programming**: studies the case in which some of the constraints depend on random variables.

- **Dynamic programming**: studies the case in which the optimization strategy is based on splitting the problem into smaller sub-problems.

- **Combinatorial optimization**: is concerned with problems where the set of feasible solutions is discrete or can be reduced to a discrete one.

- **Infinite-dimensional optimization**: studies the case when the set of feasible solutions is a subset of an infinite-dimensional space, such as a space of functions.

- **Constraint satisfaction**: studies the case in which the objective function f is constant (this is used in artificial intelligence, particularly in automated reasoning).

As it was mentioned in the section of microgrids, there are many optimization methods that had been applied in this field, like dynamic programming, genetic algorithms etc. In this work, the optimization problem was developed based on genetic algorithms, which are described in the next chapter.

4 GENETIC ALGORITHMS

Genetic Algorithms (GA) are described first from Charles Darwin. They constitute a direct, parallel and stochastic method for global search, while they are part of the group of Evolutionary Algorithms (EA). They use techniques inspired of biology such as mutation, selection and recombination and they evaluate the target function to be optimized at some randomly selected points of the definition domain. [24]

The genetic algorithms are typically characterized by the following aspects:

1. The genetic code based on variable groups (artificial genetic strings) and not on variables themselves
2. They work with a set of potential solutions (population) instead of trying to improve a single solution.
3. They don't use information obtained directly from the object function, of its derivatives, or of any other auxiliary knowledge of the same one.
4. A global minimum can be found instead of a local minimum
5. They apply probabilistic transition rules, not deterministic. [25] , [26]

The method of genetic algorithm is a combination of the following concepts. [27]

- **Fitness function**: is the objective function that genetic is asked to minimize
- **Individuals**: sometimes is mentioned as *genenome* and the vector (number of design variables) entries of an individual as *genes*. An individual is any point that fitness function is applied.
- **Population**: is an array of individuals.
- **Generation**: is the new population produced arising at each iteration.
- **Diversity**: is the average distance between individuals in a population. High diversity refers to large distance, otherwise the diversity is low.
- **Parents and children**: next generation is produced by certain individuals of a current population called *parents*, while children refer to individuals of the new generation.

4.1 New generations by genetic algorithms

The evolution starts from a population of completely random individuals and occurs in generations. In each generation, the fitness of the whole population is evaluated, multiple individuals are stochastically selected from the current population and

modified (mutated or recombined) to form a new population. The new population is then used in the next iteration of the algorithm. [25], [28]
The procedure stops when one of the stopping criteria that described below is met.

Schematically, the method is described at Figure 4.1, while algorithmically the procedure includes the following steps: [29]

4.1.1 Algorithmically procedure steps

Step I: [Start]
Generate random population of chromosomes, that is, suitable solutions for the problem.

Step II: [Fitness]
Evaluate the fitness of each chromosome in the population.

Step III: [New population]
Create a new population by repeating following steps until the new population is complete. The creation includes:

a) Selection: Select two parent chromosomes from a population according to their fitness. Better the fitness, the bigger chance to be selected to be the parent.
b) Crossover: With a crossover probability, cross over the parents to form new offspring, that is, children. If no crossover was performed, offspring is the exact copy of parents.
c) Mutation: With a mutation probability, mutate new offspring at each locus.
d) Accepting: Place new offspring in the new population.

Step IV: [Replace]
Use new population for a further run of the algorithm.

Step V: [Test]
If the end condition is satisfied, stop, and return the best solution in current population.

Step VI [Loop]
Go to step 2.

These steps are shown at Figure 4.1, where a generation cycle is described.

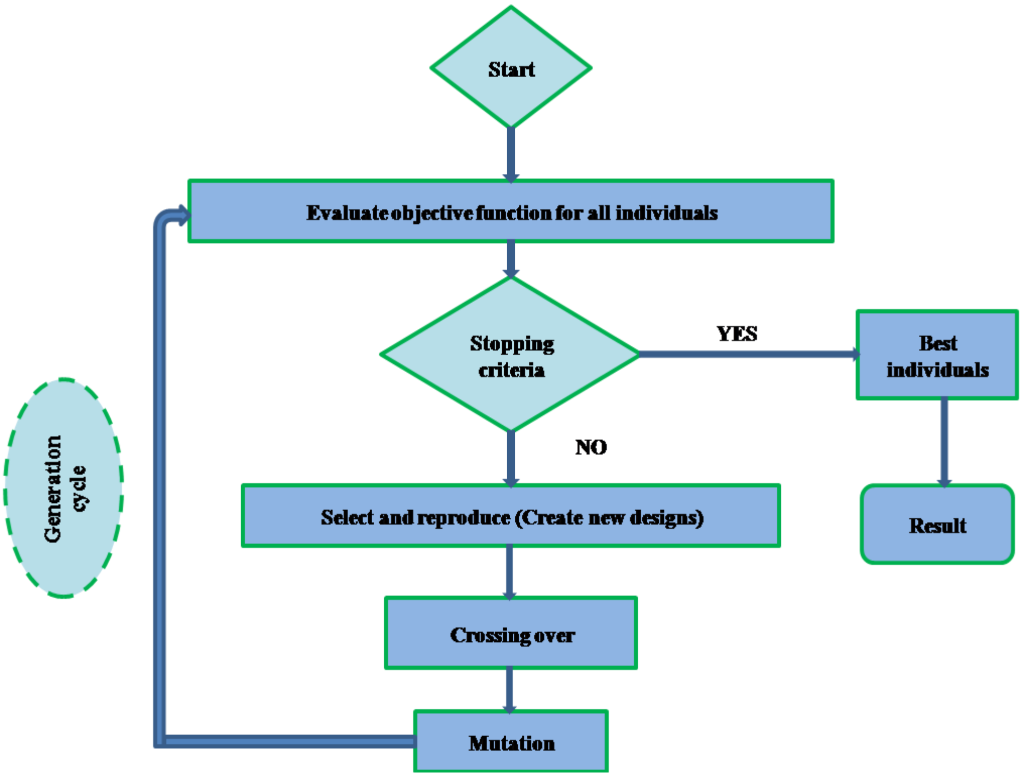


Figure 4.1: Genetic algorithms flow chart

4.2 Stopping criteria

The procedure stops when one of the stopping criteria set by the user is satisfied. A list of these follows below: [27]

1. Generations limit: specifies the maximum number of iterations the genetic algorithm will perform. The default is 100.
2. Time limit: specifies the maximum time in seconds the genetic algorithm runs before stopping.
3. Fitness limit: The algorithm stops if the best fitness value is less than or equal to the value of fitness limit.
4. Stall generations: The algorithm stops if there is no improvement in the best fitness value for the number of generations specified by stall generations.
5. Stall time: The algorithm stops if there is no improvement in the best fitness value for an interval of time in seconds specified by Stall time.

4.3 Selection Techniques in Genetic Algorithms (GAs)

Selection concerns the process of choosing the best individuals for the next generation; therefore it is an important function in genetic algorithms. The most common used techniques for selection of chromosomes are: roulette wheel, rank selection and steady state selection. [27]

4.3.1 Roulette wheel selection

Adding a roulette wheel selection, the parents are selected according to their fitness. In that way, better chromosomes, have more possibilities to be selected as parents in a generation cycle. It is the most common method for implementing fitness proportionate selection. Each individual is assigned a slice of circular roulette wheel, and the size of slice is proportional to the individual fitness of chromosomes, that is, bigger the value, larger the size of slice is. Roulette wheel selection in not successfully applicable in genetic algorithms, when there is a large difference between the fitness value of chromosomes. [29], [30]

4.3.2 Rank selection method

Rank selection method is characterized a slow technique, through her the population is ranked according to certain criteria and then every chromosome receives fitness value determined by this ranking. This method prevents quick convergence because the value of each individual is based on its rank rather than its absolute fitness. [29], [30]

4.3.3 Steady-state selection

This method is not preferable to select parents. The basic idea is that the majority of chromosomes should survive to next generation. In this case, GA's procedure is: [29]

1. A few chromosomes with the best fitness values are selected for generate a new offspring
2. Chromosomes with low fitness values are removed and replaced by the new offspring
3. The rest of population survives to new generation

4.4 Genetic Algorithms (GAs) Operators

Genetic algorithms (GAs) can be applied to any process control application for optimization of different parameters. Genetic algorithms (GAs) use various operators such as crossover and mutation for the proper selection of optimized value.

The appropriate crossover or mutation technique selected depends on the performance coding and the requirements of the current problem. Both processes are essential to the genetic algorithm. Crossover allows genetic algorithm to extract the best genes from different individuals and recombine them into potentially superior children. On the other hand, mutation is responsible of the possibility increasing that algorithm will generate individuals with better fitness values. [27]

4.5 Crossover

Crossover is the procedure that a child is formed by combining genes from a pair of individuals in the current generation. Crossover can be performed with binary encoding, permutation encoding, value encoding and tree encoding. [29], [31]

Binary encoding crossover

In binary encoding, the chromosomes may crossover at single point, two points, uniformly or arithmetically. In single point crossover, a single crossover point is selected and copied at the begging of the new offspring, while the rest includes data from the second parent. Two parents in this method give two new offsprings.

Uniform Crossover

In uniform crossover, data of the first parent's genes are copied to first offstring and second parent chromosome is assigned to the second offstring.

Arithmetic Crossover

In arithmetic crossover, crossover of chromosomes is performed by "AND" and "OR" operators to create new offsprings.

Permutation encoding crossover

Permutation crossover relates to one crossover point is selected, till this point the permutation is copied from the first parent, then the second parent is scanned and if the number is not yet in the offspring it is added.

Value encoding crossover

It can be performed at single point, two point, uniform and arithmetic representation as in binary encoding technique.

Tree encoding crossover

In this type of crossover, one point of crossover is selected in both parent tree chromosomes, which are divided at this point. The parts of tree below crossover point are exactly exchanged to produce new offstrings.

4.6 Mutation

Crossover procedure followed by mutation which is playing the role of recovering genetic information while it produces new genetic structures in the population by modifying randomly some of its blocks. Mutation gives to genetic algorithm the opportunity to achieve a global minimum and escape from the trap of a local one.
Like crossover, mutation can also be performed for all types of encoding techniques. [29], [32]

5 ARTIFICIAL NEURAL NETWORKS

According to the optimization theory presented on chapter 4, important steps for the development are the identification of the proper design variables and the constrains that describe and limit the system wanted to be optimized. This actually refers to a predictive model that describes the behavior of the system under specific conditions.

According to the literature, in the case of micrograids, an optimization model should take in concern the energy balance, ("energy generated" – "energy consumed"), of a time horizon in the future, in order to decide the energy flux in an optimum way.

For that reason, the prediction of some parameters is necessary in order to develop an efficient decision maker model. One of the most common methods used to predict is the method of Artificial Neural Networks (ANN).

5.1 Neural Networks - Theory

Neural networks relate to computational models, inspired by biological nervous systems. They are composed by elements operating parallel, while they are capable of machine learning and pattern recognition. Generally, they are presented as systems of interconnected nodes called "neurons". The connections between elements are these that determine the network function. [33]

Neural networks are trained or adjusted in order to a particular input leads to a specific target (output). Network's function as a machine learning is presented at Figure 5.1. [33]

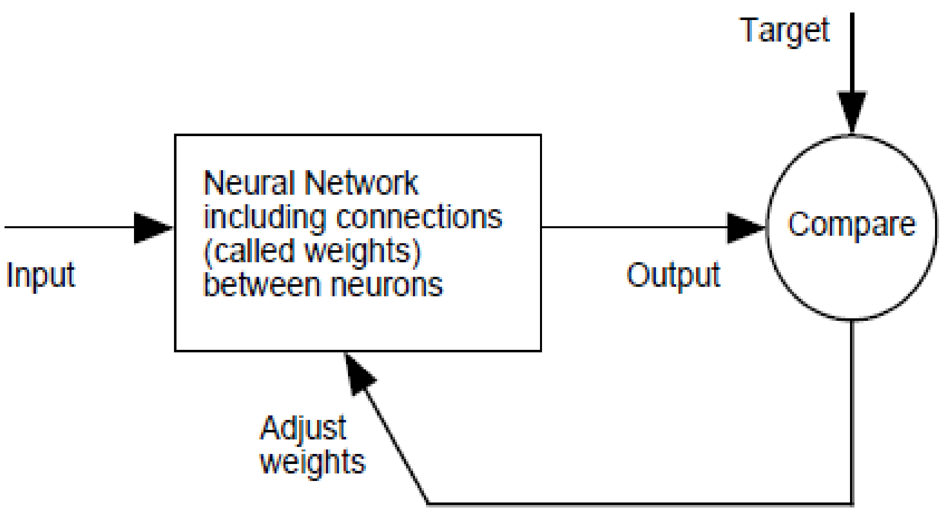


Figure 5.1: Neural networks as machine learning

They classified as two basically categories, feed forward and current networks, which are divided to other categories according to the structure or the operation of the network. The classification is shown at Figure 5.2. [34]

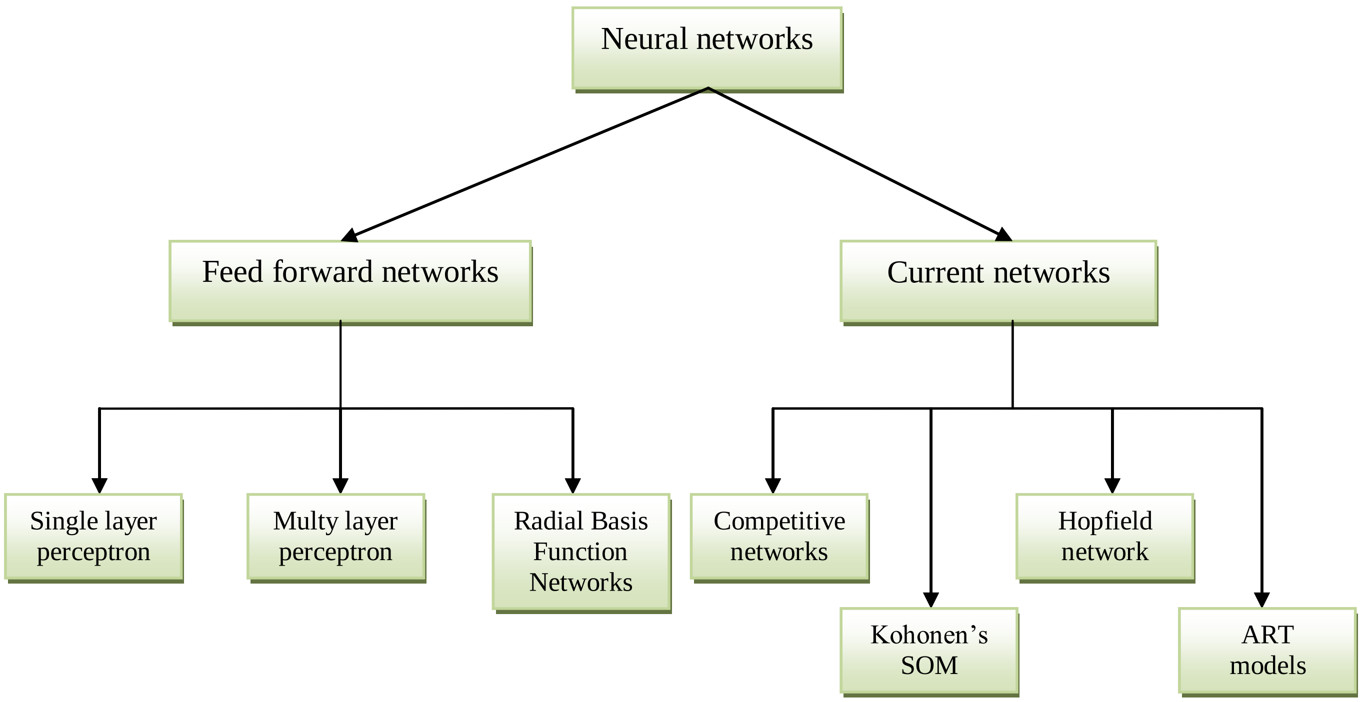


Figure 5.2: A taxonomy of neural networks architectures [34]

5.2 Characteristics of neural networks

A neural network is characterized by the following elements:

- The architecture of the model
- The training / learning method
- The activation function
- The generalization ability

5.2.1 Architecture of neural networks

The architecture describes the connections between the neurons. It consists of three groups, an input layer, an output layer and generally, one or more hidden layers in-between. Through neurons at input layer, data are fed to neurons of hidden layer via synapses. Each neuron performs a weighted summation of the inputs, which then passes an activation function, also called the neuron function. The network output is formed by another weighted summation of the outputs of the neurons in the hidden layer. This summation on the output is called output layer. Between input and output layer may more than one hidden layer exist. [35]

To create a neural network that performs some specific task, it must choose how the layers are connected to one another and set the appropriate weights on the connections. The connections determine whether it is possible for one unit to influence another. The weights specify the strength of the influence.

Basically, networks are classified to several types depending to their structure. The two most applied are the "Feed forward" networks and the "Recurrent" network. [35], [36]

Feed forward networks:

These networks allow the information flow only in one way along the connections, starting from the input layer, passing though hidden layers and ending at output layer. A feed forward network is presented at Figure 5.3. [35]

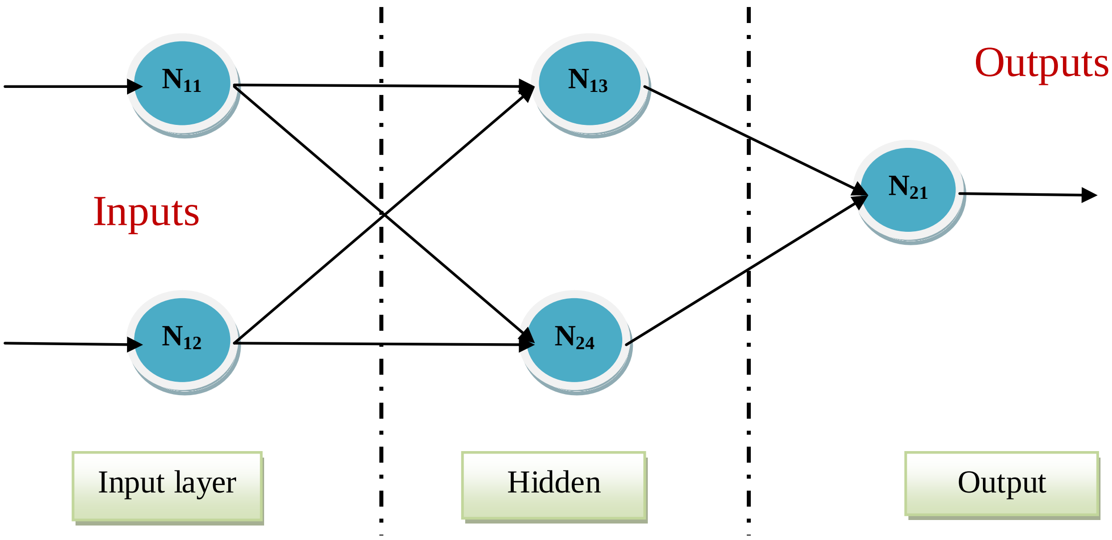


Figure 5.3: Feed forward network structure

Recurrent networks

This form of architecture allows the information flows on both ways and not only in directs one, by introducing loops. A typical structure of a recurrent network is presented below. [35], [36]

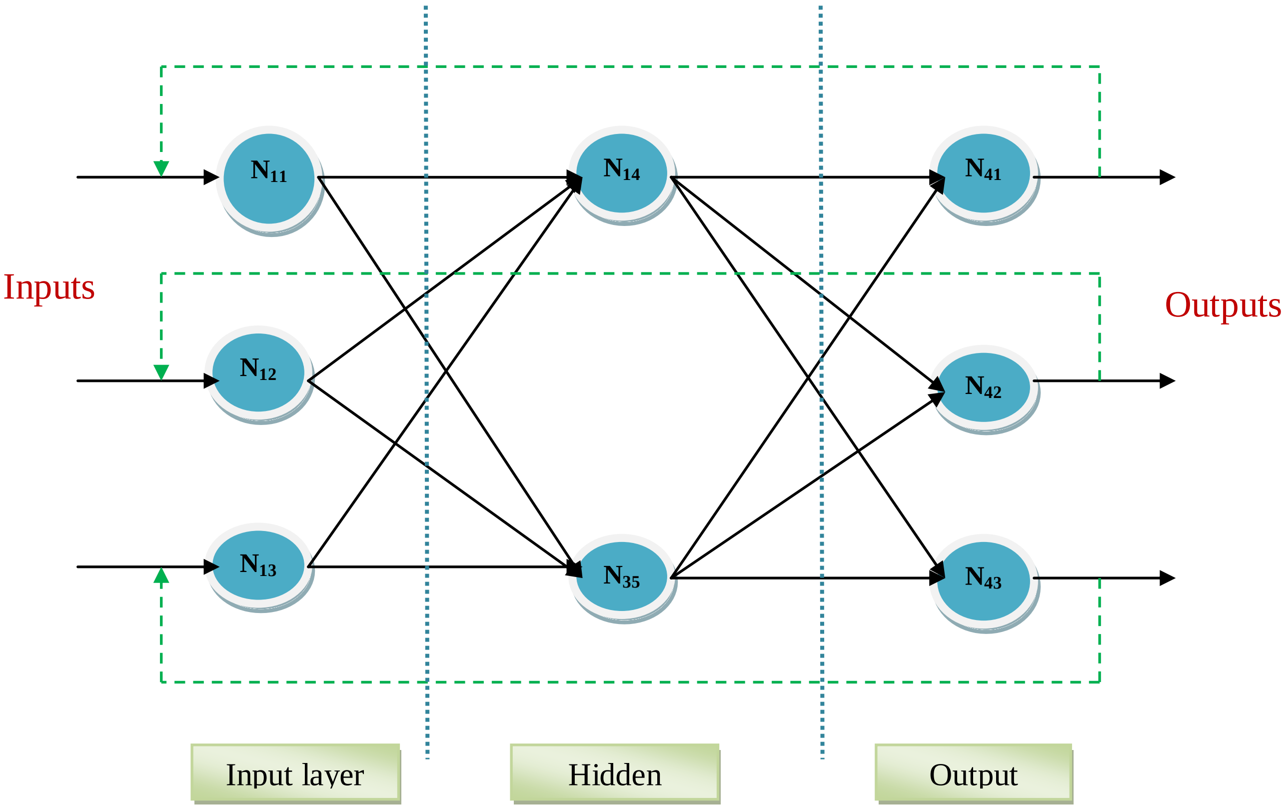


Figure 5.4: Recurrent network structure

5.2.2 Training / learning method

In order to train successfully the network, learning methods have been developed, that they determine the behavior of the model. A good training / learning algorithm must to converge quickly with no significant errors and be capable to generalize under unknown situations that must be solved. [33]

Three types of training methods are detected:

1. The supervised method
2. The unsupervised method
3. The reinforced method

5.2.2.1 Supervised learning

Applying this method, couples of inputs and outputs are used in order to train the algorithm. During the training procedure a teacher is supposed to be present, when the outputs are comparing with the values calculated by the network. By this comparison the error is determined and it could be used to change network parameters in order to improve the performance. A common form of supervised learning is the backpropagation, which it is often used for train feed forward networks. [33], [35]

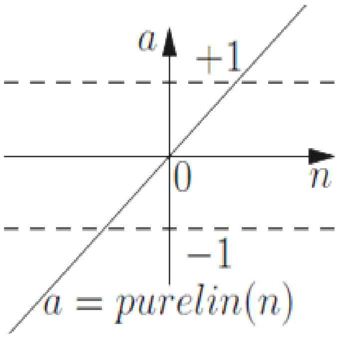


Figure 5.6: Linear transfer function

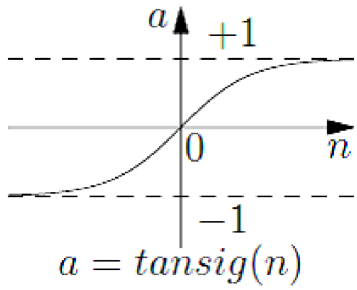


Figure 5.5: Sigmoid transfer function

5.2.2.2 Unsupervised learning

Output targets are not included in this method. Therefore the learning is unsupervised and the network is asked to discover and adapt to features in the inputs patterns by its own.

5.2.2.3 Reinforced learning

In this learning method, the error is not known as in supervised learning. Although, there is a teacher informs the network if the output is correct or incorrect. A reward is given for a correct answer and a penalty for a wrong one.

5.3 Activation function

The behavior of an ANN depends on both the weights and the input-output function (activation function) that is specified for the units. The activation function scales the output of the neural network into proper ranges. This function might be one of the followings: [37]

- linear (Figure 5.6)
- threshold
- sigmoid (Figure 5.5)

For **linear units**, the output activity is proportional to the total weighted output.

For **threshold unit**, the output is set at one of two levels, depending on whether the total input is greater than or less than some threshold value.

For **sigmoid units**, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but all three must be considered rough approximations.

Neural networks in the last section use the sigmoid activation function. The sigmoid activation function is the default choice for the **feed forward networks**.

5.3.1 Generalization ability

Generalization ability refers to the capacity of a network to response successfully to unknown input vector in relation to the vectors were used for the training procedure. Generalization is might be the most important characteristic of a neural network, as at many problems where neural networks are applied, is difficult to identify all the conditions might happen. [33]

5.4 Feed forward backpropagation neural networks

Feed forward backpropagation networks are the neural structures that feed the information to one direct way, while they trained by a supervised learning method, the backpropagation algorithm. Backpropagation was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. [35], [38]

The backpropagation algorithm is the most computationally straightforward algorithm for training the multilayer perceptron. This technique is employed as a mean of reducing error in the network's classification, by initially calculating this error and then propagating it back for reduction. [38]

Inputs are propagated to the first layer of hidden units, whose output is calculated and propagated to the next hidden later. This process is repeated until the output layer is reached. Each output layer unit calculates the activation, from the sum of weighted inputs from previous layers. The error on the initial output is computed and propagated back to the first hidden layer, where the weight matrix is updated. This process is repeated until the error is minimized as far as possible.

5.5 Develop an artificial neural network model

The procedure of development an artificial neural network model consists of the followings:

1. <u>Select the variables</u>: the first step includes the selection of the variables.

2. <u>Training, testing and validation tests</u>: data set is divided to three sets, one for training, one for testing and one for validation. The training test is the largest and is used to learn patterns present in the data. The testing set is used to evaluate the generalization ability, while the validation set is used in order to check the performance of the network.

3. Neural network architecture: this step concerns the definition of the network's structure including the number of the hidden layers and the number of neurons at each layer.

4. Evaluation criteria: different indicators can be calculated in order to estimate the error. The most common used is the root mean square error.

5. Network's training: the objective to training is to find a set of weights between neurons that determine the global minimum of error function.

5.6 Applications of neural networks

The applications of neural networks are not limited. They have been used for a wide variety of applications in many domains. Some of them are included below: [39]

- Data validation
- Energy management
- Airline security control
- Industrial process control
- Medical models
- Sales forecasting
- Environmental pollution
- Weather forecasting
- Energy forecasting
- Indoor quality conditions of building

Based on their applications to weather and energy forecasting, they used in this work in order to predict the energy loads for the Leaf Community microgrid.

6 LEAF COMMUNITY

The Leaf Community, the "community of clean energy" was conceived by the Loccioni group in order to develop solutions in the fields of automation, quality measurement and assurance and network infrastructure. It is situated in Angeli di Rosora, Ancona, in Italy and it is shown at the following Figure 6.1.

Figure 6.1: Leaf Community (Google earth)

The Leaf Community is composed by buildings as domains of energy consumption, renewable energy sources as domains of energy production, an energy storage system and it is connected with the main electricity grid. According to theory, Leaf Community represents a microgrid which is shown at Figure 6.2.

Figure 6.2: Leaf Community

The aim of the present work is to describe the optimization and control procedure for the operation of the microgrid with the objective to minimize the cost of energy for the microgrid users.

The electrical microgrid will be developed in two consecutive steps, where the second will be an extension of the first one. The first step includes an industrial building named “Leaf Working”, where PV systems are installed on the roof, an office building named “Leaf farm” and a hydroelectric station named “Leaf Water 4”. Furthermore, Leaf Community includes an energy storage system (ESS). All these are connected among each other and with the main grid - Energy National Network (ENEL). The microgrid at the first step is presented below at Figure 6.3.

Figure 6.3: Microgrid at step 1

The second step is actually an extension of the existing microgrid. The new components will be a building called “Leaf lab” for industrial use and a residential building called “Foresteria ex Paolucci”. These will be the new domains of energy consumption at Leaf Community, while extra energy will be generated by installed photovoltaic systems and two extra microhydroelectric stations named “Leaf Water 1” and “Leaf Water 2”.

6.1 Leaf Working

Leaf working consists of two buildings, one that is used as an industrial space named “SUMMA” and one office named “AEA”. The total area covered by “Leaf Working” is 5,600 m^2, while the total volume is 26.5 m^3. For heating, they use 5 gas boilers and for cooling air conditioning with one ground water electric heat pump and one cooling unit. Into office areas they have terminal fan coils, while into the industrial space, the laboratory and the conference room HVAC systems are operated.

6.2 Leaf farm

Leaf farm (Figure 6.4) includes an office building which covers an area of 280 m^2 and an annex building which is used occasionally covering 115 m^2. At this area, a electric heat pump is used for heating and cooling.

Figure 6.4: Leaf farm

6.3 PV plants

Two different types of photovoltaic systems are installed on the roofs of “AEA” and “SUMMA”, the two buildings constitute the “Leaf Working” area. This PV plant is called “Leaf Roof Angeli” and its operation started from the 8th of November 2010. The total power produced is 148.179 kWp and it is connected to “Leaf Working” with autoconsumption.

At AEA, the model of the PV system is SL-Solyndra 001-182. The inclination of them is 0^o and they have south orientation. The total power generated in this section is 112 kW.
SUMMA subfield includes two models of PV systems, which are SL-Solyndra 001-182 and HS-115 Heliosphera. The first one, has the same inclination and orientation as this at AEA while the second one has an inclination of 5º and their orientation is Southwest (108º). The total power can be generated from these types of PV systems is 10.2 kW and 25.8 kW respectively.
All these are presented schematically at

Figure 6.5, where the different characteristics of the PV system are shown at each section.

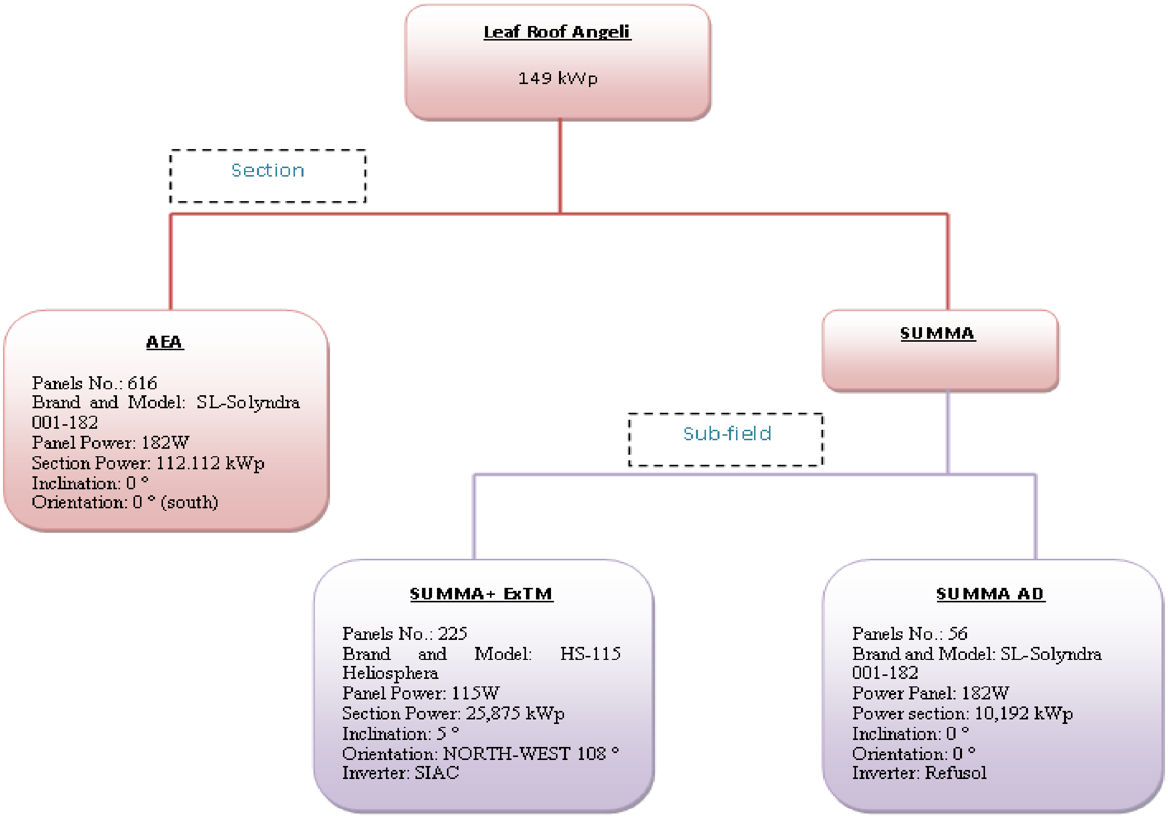


Figure 6.5: Leaf Roof Angeli and PV plants characteristics

6.4 Hydroelectric Station

Hydroelectric Station (Figure 6.6) is a cochlear hydroelectric flowing water plant called “Leaf Water 4”, along the river Esino. This plant operates from the 1st of March 2013. The total power that can be generated is 49.4kW and it was designed considering a hydraulic net jump 1580 mm, flow rate of 4,000 L/s and a rotation speed 21.5 rpm.

Figure 6.6: Hydroelectric station

6.5 Energy storage system (ESS)

The energy storage system of Leaf Community consists of Samsung SDI lithium-ion batteries (Figure 6.7) and has a roundtrip efficiency of 95.5%. The maximum power which can be stored is 224kW, while an inverter along the line connecting ESS with Leaf farm consumes 7kW, every time ESS is charged or discharged. In the case of discharging ESS, the energy charged is used firstly from Leaf farm and then is distributed to other buildings, while the energy stored can be sold to the main grid.

Figure 6.7: Lithium-ion batteries

Depending on the state of charge, the life time of ESS and the cycle cost was given and they are presented at Table 6.1.

Table 6.1: ESS's swing range and cycle cost

No Scenario	Swing range	Cycle life (EOL 80%)	Cycle-Cost [€/kWh]
1	0%-100%	6000	0.22
2	25%-100%	8400	0.21
3	0%-75%	12700	0.14
4	50%-100%	11600	0.23
5	0%-50%	36100	0.07
6	75%-100%	49500	0.11
7	50%-75%	30400	0.17
8	25%-50%	76100	0.07
9	0%-25%	139000	0.04

In this section all the components of the Leaf Community microgrid were described. The scope of this work is to develop a genetic algorithm that will be capable of optimizing the operation cost of Leaf Community considering the costs of selling energy, producing energy and storing energy.

7 MODELING THE MICROGRID

The optimization horizon time is set 24h ahead and for that reason, the first step of modeling the microgrid at Matlab was the prediction of the irradiance, the energy consumed and generated 24 hours ahead. This was achieved by using the method of neural networks and specifically by creating feed forward backpropagation networks at Matlab. The procedure followed is described below for the different components of the microgrid.

7.1 ANN as a prediction method – State of the art

Artificial neural networks are applicable as it was mentioned to the theory in many fields. Regarding, environmental issues, K. Gobakis, D. Kolokotsa et al., developed a model for urban heat island prediction using and testing different structures of neural network such as Elman, feed forward and cascade network. [40]

Environmentally, another important topic is the capability of networks on predicting the external conditions. Solar irradiance constitutes important information in many fields. For this reason, to know how it varies in a certain period is really necessary in many applications, such as atmospheric energy-balance studies, analysis of the thermal load on buildings, planning of the operations of renewable energy power plants, meteorology, agricultural sciences and also for some environmental impact analysis. [41]

Many researchers estimated the irradiance by using artificial neural networks. (Mohandes et al,) applied ANN techniques to predict GSR using weather data from 41 stations in Saudi Arabia. Data from 31 stations was used to train the networks and the remaining data was used for testing. Wenkian et al. estimated the monthly mean values of tilted global solar irradiation in 133 meteorological stations in Yunnan Province, China, and studied the ratio between global radiation on tilted surfaces and those on horizontal surfaces based on data estimated at these stations. Robledo and Soler assessed the Perez model for hourly diffuse vertical solar irradiation for various orientations (N, E, S, W) in Madrid and adapted this model to their local conditions improving its performance. Li et al. presented an approach to estimate the vertical outdoor illuminance from sky luminance data and solar geometry in Hong Kong based on Kittler and Perez models. [42]

The most common type of neural networks that was used to predict the solar irradiance is the Multilayer Preceptor. It consists of 3 types of layers, an input layer, an output layer and a hidden layer(s) and the adaption algorithm is the backpropagation. [41], [42], [43], [44]

As mentioned previously, the prediction of solar irradiance and environmental conditions generally, can be used in many research fields. This work focuses on the energy load prediction from renewable energy sources such as photovoltaics and hydroelectric systems. Adel Mellit et al., present an application of neural networks in which they use climate parameters such as irradiance and air temperature in order to predict the power generated by a PV plant at Trieste in Italy. [45] Regarding their results, it is obvious that the irradiance, the air temperature and the module temperature seem to be various parameters for the network's training. Another application is this presented by S.I Sulaiman et al., who predict the output power of a grid connected PV system by using a backpropagation neural network with one hidden layer. Their model uses as inputs the irradiance, the wind speed and the ambient temperature, while the output is the PV's power. [46]

Furthermore, the type of the neural network that is going to used for the power generated prediction is important. This topic is presented by S. Premrudeepreechacharn and N. Patanapirom, who examine two types of neural networks and specifically a backpropagation neural network and a radial basis function neural network. Their results show that both of the neural networks work well but the backpropagation network needs less information for training. [47]

The energy load prediction of the hydroelectric system aims to provide to the users information about the potentially available energy at a given time in the future. In the literature there are several studies which examine load forecasting of hydroelectric stations using neural networks.

C.C. Nwobi-Okoye and A.C. Igboanugo have develop articial neural network models for predicting water levels at Kainji Dam, which supplies water to Nigeria's largest hydropower generation station. It involves taking of a ten-year record of the daily water levels at the dam from 2001 to 2010. The daily water level data were used to develope neural network models and an Autoregressive Integrated Moving Average (ARIMA) model to fit the daily water levels obtained in the year 2010. [48]

Abdulkadir, T. S. et al. have presented the modelling of reservoir variables of two hydropower dams along the River Niger (Kainji and Jebba dams) in Nigeria for energy generation using multilayer perceptron neural network. Total monthly historical data of Kainji and Jebba hydropower reservoirs' variables and energy generated were collected from Power Holding Company of Nigeria respectively for a period of (1970-2011) and (1984-2011) for the network training. [49]

Jorge O. et al. have analyzed in Buta Ranquil flow time series upstream reservoir and hydroelectric plant in order to model and predict daily fluctuations. They compare results obtained by using a three-layer artificial neural network (ANN), and an autoregressive (AR) model, using 18 years of data, of which the last 3 years are used for model validation by means of the root mean square error (RMSE), and measure of certainty. [50]

Another topic of this work is the prediction of the energy consumption from buildings. An approach for short – term load prediction in buildings is presented by Pedro A. Gonzalez and Jesus M. Zamarreno who predict the consumption based on a feedback neural network using as inputs the temperature, the measured load, the hour and the day in order to predict the load 24 hours ahead. It is understandable that the consumption in buildings and especially in office buildings is dependent from the outdoors conditions. [51]

Melek Yalcintas and Sedat Akkurt present a work that predicts the consumption by using neural networks trained by outdoors and indoors climate parameters. [52] Same applications are presented by Essam E. Khalil and Samy M. Morkos. Their study includes models for predicting weather conditions like solar radiation, temperature and wind speed which can be applied in energy consumption prediction. [53]

According to the literature that was mentioned above, artificial neural networks were used in order to predict the irradiance, the power generated by PV systems and the energy consumption for the Leaf Community. At the next sections, the work and the results above these topics are presented.

7.2 Predicting the power generated from PV systems

The method of artificial neural networks was used in order to predict the power generated from PV systems at "Leaf Working". It is common that PV systems use solar radiation in order to produce electrical energy. Therefore, couples of irradiance and power generated measurements were used in order to train a neural network at Matlab. Furthermore, it was asked to predict the irradiance separately, so in the future the forecast values will be used as inputs to the developed network in order to predict the power generated.

The procedure followed in order to predict the power produced from the PV plants is:

1. Collecting data of couples irradiance – power from earlier years
2. Development of a neural network in Matlab
3. Comparing the predicted with the measured power

All data were collected over the past 3 years from approximately 1/1/2011 to 24/05/2013. The time difference between the measurements is 15 minutes. After collecting the appropriate data, the first step for the development of the neural network, was their normalization. Normalization procedure before presenting the input data to the network is generally a good practice, since mixing variables with large magnitudes and small magnitudes will confuse the learning algorithm on the importance of each variable and may force it to finally reject the variable with the smaller magnitude.

A feed forward backapropagation neural network was developed which uses as inputs the measured irradiance one day before and as output the power generated now. The network predicts 24 hours ahead based on older values of irradiance. So in real world forecast values of irradiance can be used in order to predict the power. The hidden layers at this network are 3 which consist of 2, 2, and 1 neuron respectively. A one year long period data set was used to train the network while the rest of the data were used for validation by retraining the network every day. The prediction results are presented below:

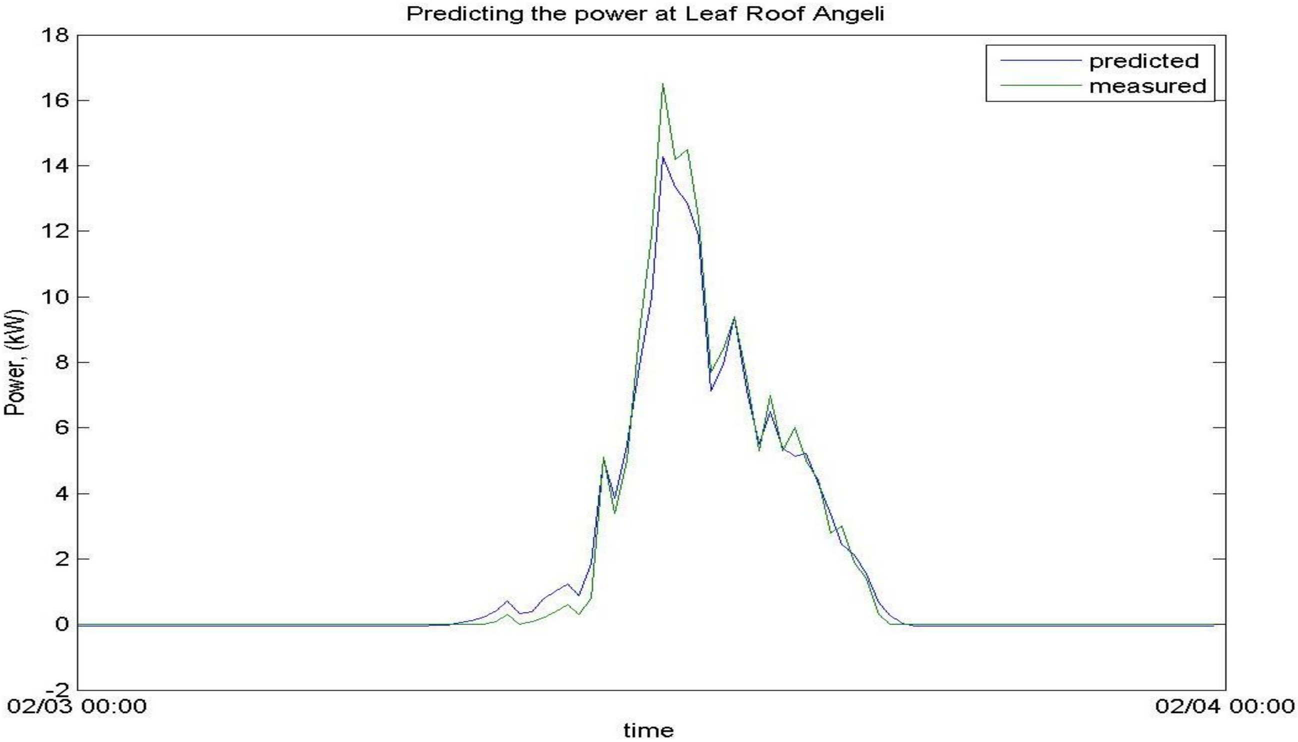


Figure 7.1: Comparison between the measured and the predicted generated power at Leaf Roof Angeli

Furthermore, applying the goodness of fit, the relationship between the measurements and the predicted values is shown at the following figure.

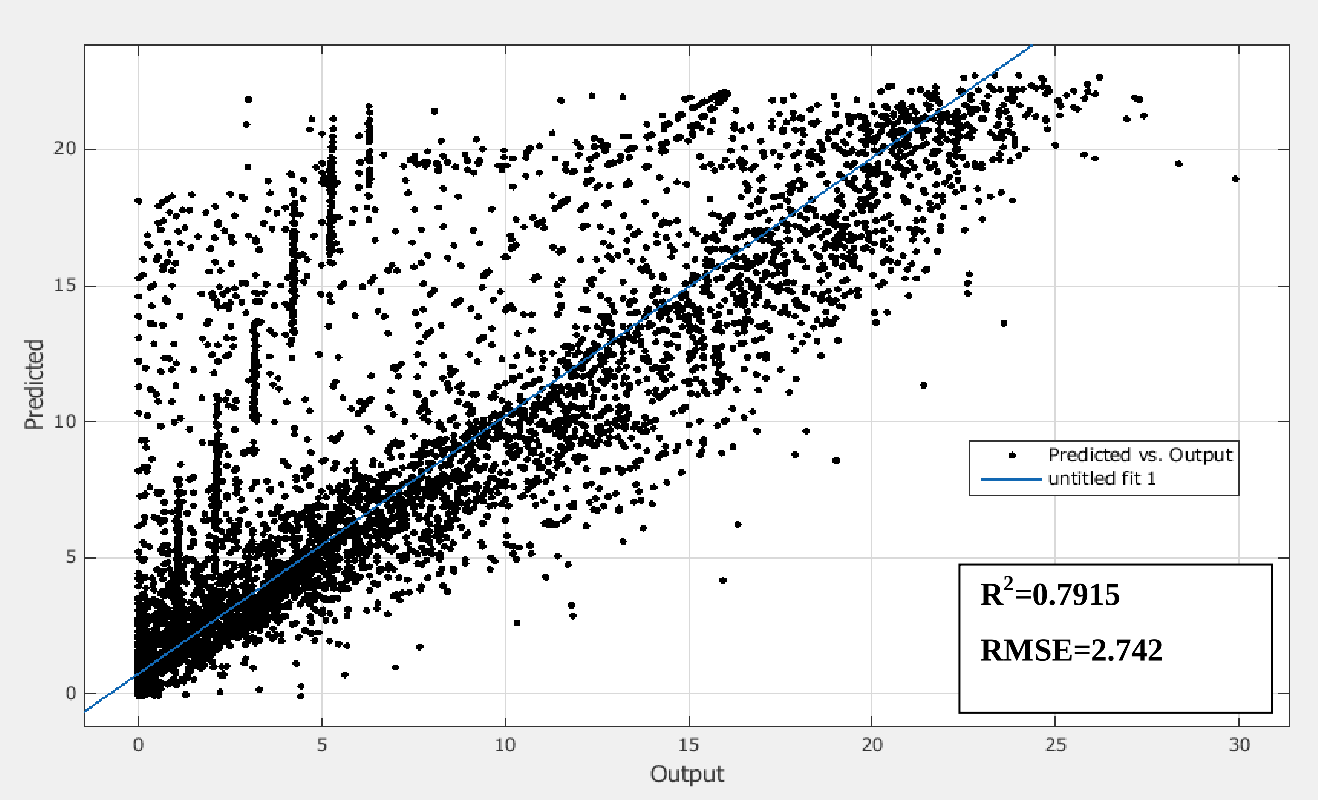


Figure 7.2: Relationship between predicted and measured generated power at Leaf Roof Angeli

According to the previous figures, it is obvious that a good relationship between measured and predicted power was achieved. Here, it must be mentioned that any negative values for power must be deleted.
So as a conclusion, if the irradiance can be forecasted with precision, the model can use it in order to predict the output power from the PV plants.

7.3 Predicting the irradiance by using ANN

The procedure followed was the same as before. A feed forward backpropagation network (Figure 7.3) was designed using 3 hidden layers applying 5, 3 and 2 neurons at each layer.

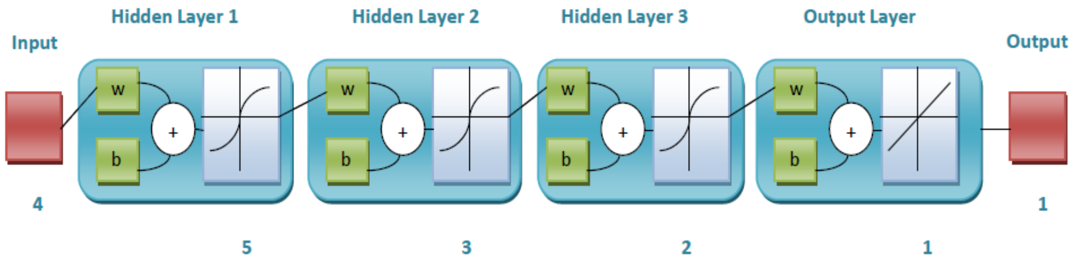


Figure 7.3: The feed forward network developed to predict irradiance

The goal is to predict the irradiance 24 hours ahead every 15 minutes. In order to achieve that a one year long period data set was used to train the network while the rest of the data were used for validation. As it was mentioned before the inputs consist of older data of irradiance (1,2,3 days before) and the output layer includes only the irradiance now. According to that the network can predict 24 hours ahead based on the measurements of the previous days.

7.3.1 Results of irradiance prediction

The developed model estimates the irradiance for the next 96 (96 quarters for one day) time steps. The network is retraining every day in order to achieve better prediction levels and the results are shown to the following figures.

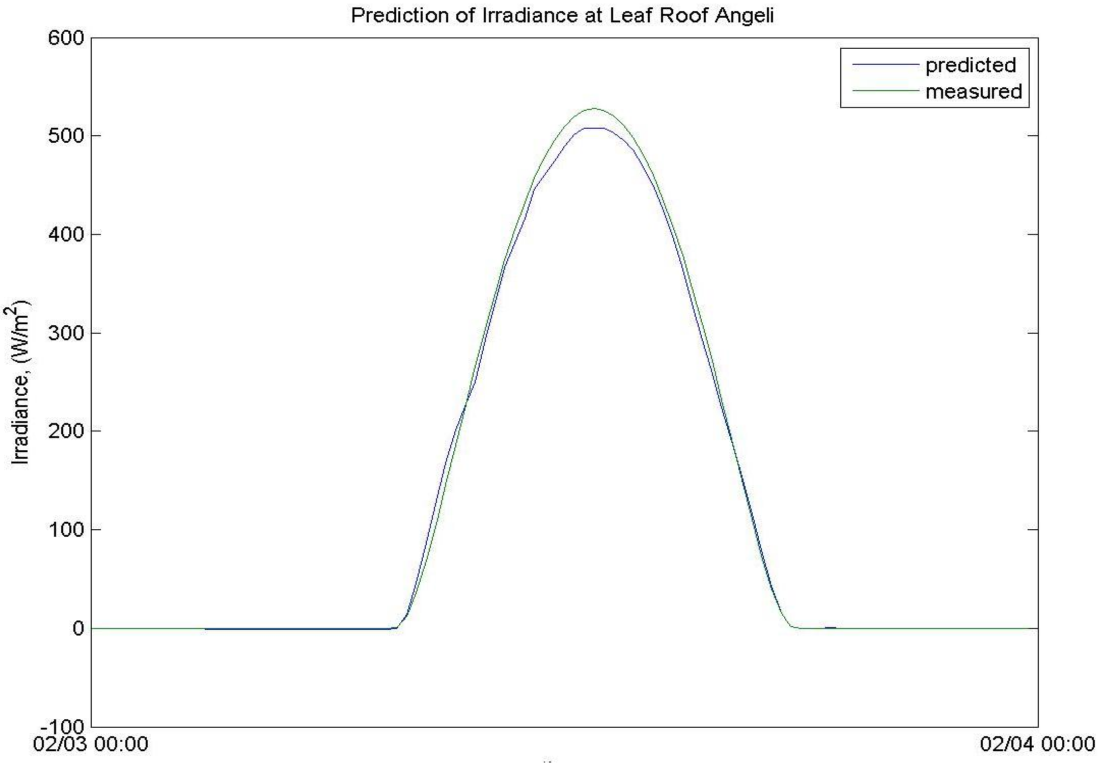


Figure 7.4: Comparison between predicted and measured values 24 hours ahead

At Matlab were also calculate the coefficient of determination and the root mean square error in order to show the relationship between the measurements and the predicted values by applying a linear model. The lower RMSE and the highest R^2, the more accurate is the estimation. The results are shown below.

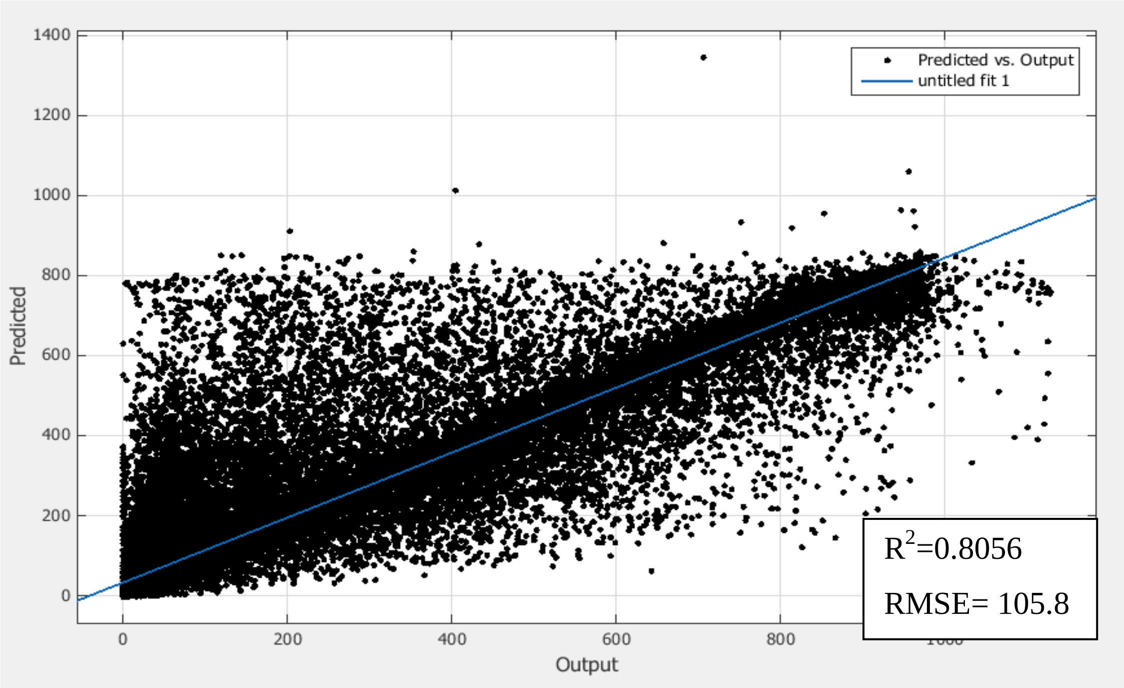


Figure 7.5: Relationship between predicted and measured irradiance

It is obvious from Figure 7.4 and Figure 7.5 above that the prediction curve follows the measurements good enough. Some peaks (minimum and maximum limits) diverge which is logical because irradiance is a parameter that depends on the cloudy index, a parameter that isn't measured at Leaf Community. For that reason, it was decided to calculate the irradiance at a clear and overcast sky using equations, in order to enclose the prediction results over a maximum (clear sky) and a minimum (overcast sky) limit.

7.3.2 Predicting the irradiance by using equations

7.3.2.1 Cloud Cover Index

It is known that the cloud cover index is an important parameter which directly affects the solar irradiance.

In order to generalize the prediction outputs, it was decided to calculate the solar irradiance through equations of both cases:

- Clear Sky
- Overcast Sky

The next step is the combination of neural networks' and equations' results in order to achieve the optimal prediction level considering the cloud cover index.

7.3.2.1.1 Clear Sky equations

To calculate the solar irradiance when the sky is clear, the following equations were used at Matlab.

Solar time

The first parameter that was calculated is the solar time which is based on the apparent motion of the sun as seen from a point on the surface of the earth, the deviation from local civil time being due to the nature of the orbit. Solar noon is the time when the sun reaches the highest point in the sky; it can differ from noon of local civil time by as much as one – quarter of an hour. [54] The difference between solar noon and noon of local civil time is called the equation of time E_t. It is a function of the time of year and can be approximated by:

$$E_t = 9.87\sin 2B - 7.53\cos B - 1.5\sin B \text{ (min)} \tag{7-1}$$

with

$$B = 360^o \times \frac{n-81}{364} \text{ for the nth day of year} \tag{7-2}$$

Solar time is defined by:

$$t_{sol} = t_{std} + \frac{L_{std} - L_{loc}}{15/h} + \frac{E_t}{60 \text{ min}/h} \tag{7-3}$$

Where:

t_{std} : the standard time (h)

L_{std} and L_{loc} : the longitudes (in degrees) of the time zone and the location respectively

Declination

Considering the point of view of the earth, one can say that the sun traverses, each day and in solar time one circular orbit around the earth. In general, this orbit does not lie in the plane of the equator; rather the line from sun to earth makes an angle δ relative to the equatorial plane. This angle is called the declination, and it is given by: [54]

$$\sin\delta = -\sin 23.45^o \cos\frac{360^o \times (n+10)}{365.25} \tag{7-4}$$

Where n = day of the year (with n=1 for January 1).

The declination is a crucial quantity for calculating incidence angles. The incidence angle of the sun on the earth's surface at a point is the angle between the normal of the surface at the point and the line from the point to the sun. It is called the zenith angle θ_s of the sun and it is given by:

$$\cos\theta_s = \cos\lambda \cos\delta \cos\omega + \sin\lambda \sin\delta \qquad (7\text{-}5)$$

Where

λ: latitude
ω: solar hour angle which is given by the following equation

$$\omega = \frac{(t_{sol} - 12h) \times 360^o}{24h} \qquad (7\text{-}6)$$

The relation between the angle hour ω, declination δ and the zenith angle θ_s is described by the following equation:

$$\sin\varphi_s = \frac{\cos\delta \sin\omega}{\sin\theta_s} \qquad (7\text{-}7)$$

Where φ_s is the angle from due to south.
Instead of the zenith angle many people employ the complement, called the solar altitude angle:

$$\text{Solar altitude angle} = 90^o - \theta_s \qquad (7\text{-}8)$$

Extraterrestrial Insolation

The solar irradiance outside the earth's atmosphere at normal incidence and at the mean sun – earth distance is called solar constant; its value is 1373 (W/m^2).
A good fit of extraterrestrial I_o is:

$$I_o = \left(1 + 0.033 \cos\frac{360^o \times n}{365.25}\right) \times 1373 \ \frac{W}{m^2} \qquad (7\text{-}9)$$

Clear Sky radiation

Solar radiation under clear skies can be represented with fairly good accuracy by simple models because the transparency of clear atmospheres does not vary all that much with time or location.

According to Hottel, the direct irradiance I_{dir} at normal incidence can be calculated from the extraterrestrial irradiance I_o and the zenith angle θ_s by a correlation with three coefficients [54]:

$$I_{dir} = I_o[a_o + a_1 \exp\left(-\frac{k}{\cos\theta_s}\right) \qquad (7\text{-}10)$$

The coefficients α_o, α_1 and k were calculated by the followed equations as a function of altitude A above sea level for 23 km visibility.

$$a_o = [0.4237 - 0.00821 \times (6.0 - A^2)] \qquad (7\text{-}11)$$

$$a_1 = [0.5055 - 0.00595 \times (6.5 - A^2)] \qquad (7\text{-}12)$$

$$k = [0.2711 - 0.01858 \times (2.5 - A^2)] \qquad (7\text{-}13)$$

For clear skies, the diffuse irradiance on a horizontal surface can be estimated from a relation due to Liu and Jordan (1960):

$$I_{dif} = (0.271 I_o - 0.2939 I_{dir})(\cos\theta_s) \qquad (7\text{-}14)$$

The horizontal irradiance is given by the following equation

$$I_{hor} = I_{dir}\cos\theta_s + I_{dif} \qquad (7\text{-}15)$$

Clear sky irradiance results

In order to estimate the direct, the diffuse and the horizontal irradiance for the Leaf Community, a Matlab code was created considering the equations above. It was given as inputs the date (year, month, day), the time (hours, timestep = 15 minutes), the latitude (L_{at}= 43.5^o), the longitude of the time zone (L_{std} = - 15^o) and the longitude of the location (L_{on} = - 13^o).
The function that was created could calculate the solar irradiance for all the year. The results for the Global horizontal irradiance, the direct irradiance and the diffuse irradiance under a clear sky are presented below.

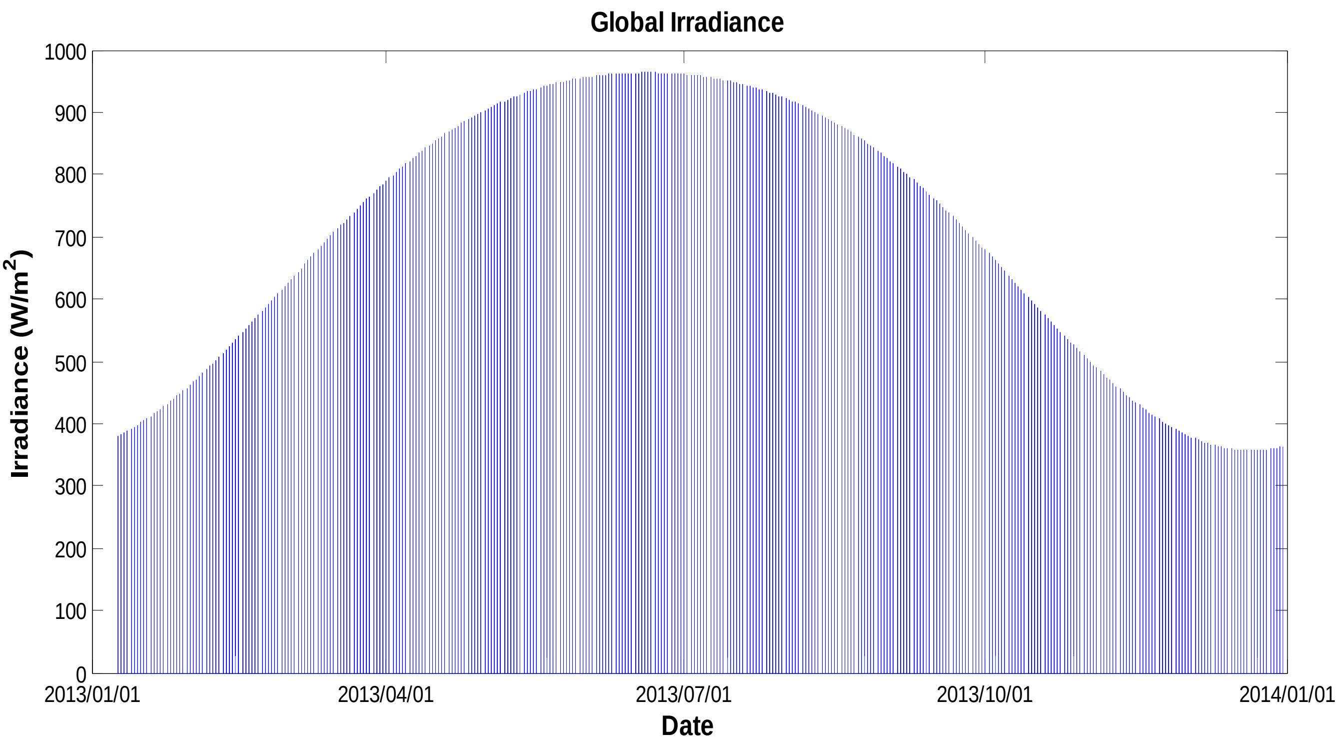


Figure 7.6: The horizontal irradiance under a clear sky for Leaf Community

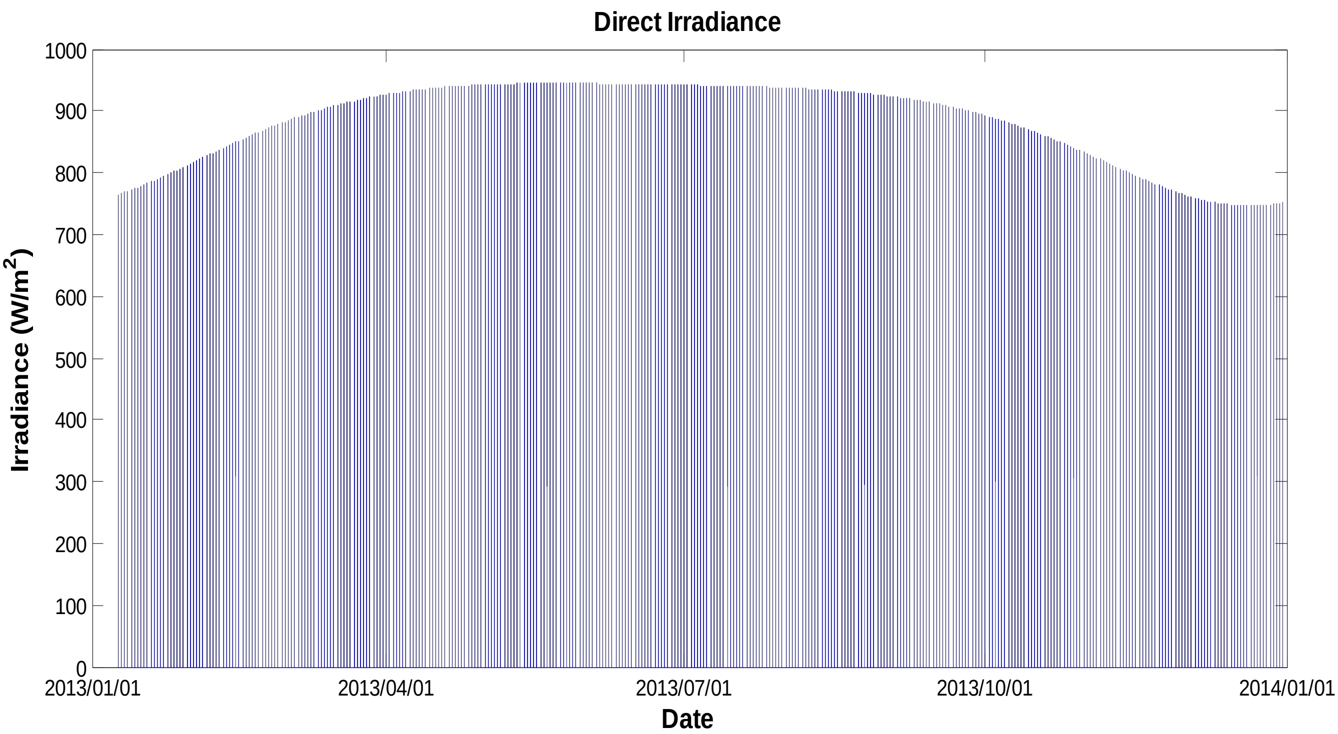


Figure 7.7: The direct irradiance under a clear sky for Leaf Community

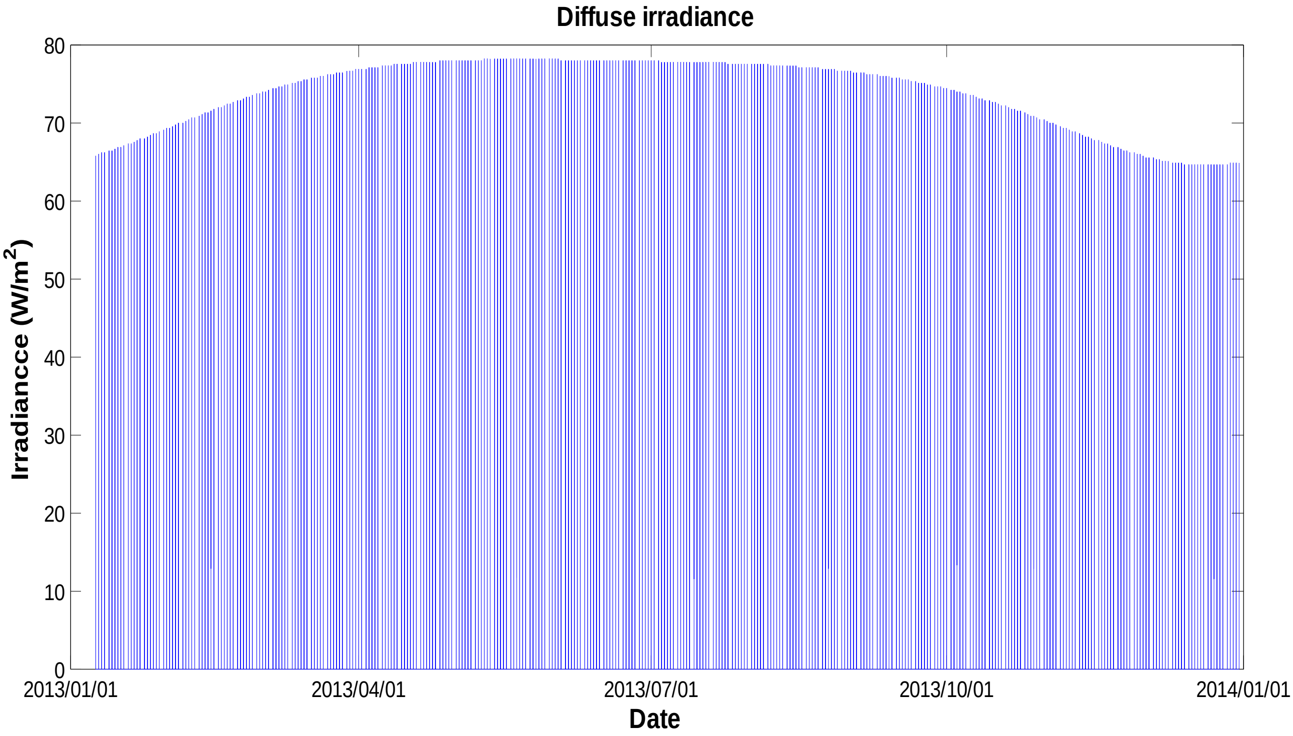


Figure 7.8: The diffuse irradiance under a clear sky for Leaf Community

These were the results considering a clear sky without any clouds. This irradiance represents the maximum irradiance limit. The next step is the calculation of the minimum irradiance limit considering an overcast sky. This work is presented at the next section.

Overcast sky equations

In order to calculate the irradiance under an overcast sky, different empirical models are used from many authors. In this study the Kasten and Czeplaks model is used. The Kasten and Czeplak article itself analyzed radiation correlations with cloud coverage and type. They determined that global hemispherical irradiance on a horizontal surface (GHI) as a function of cloud amount N (in eighths) is [55]:

$$\mathbf{G(N) = G(0)(1 - 0.75(N/8)^{\frac{3}{4}})} \qquad (7\text{-}16)$$

where G(0) is the clear sky solar GHI. The cloud amount N is mentioned 8 for an overcast sky and the results are presented below.

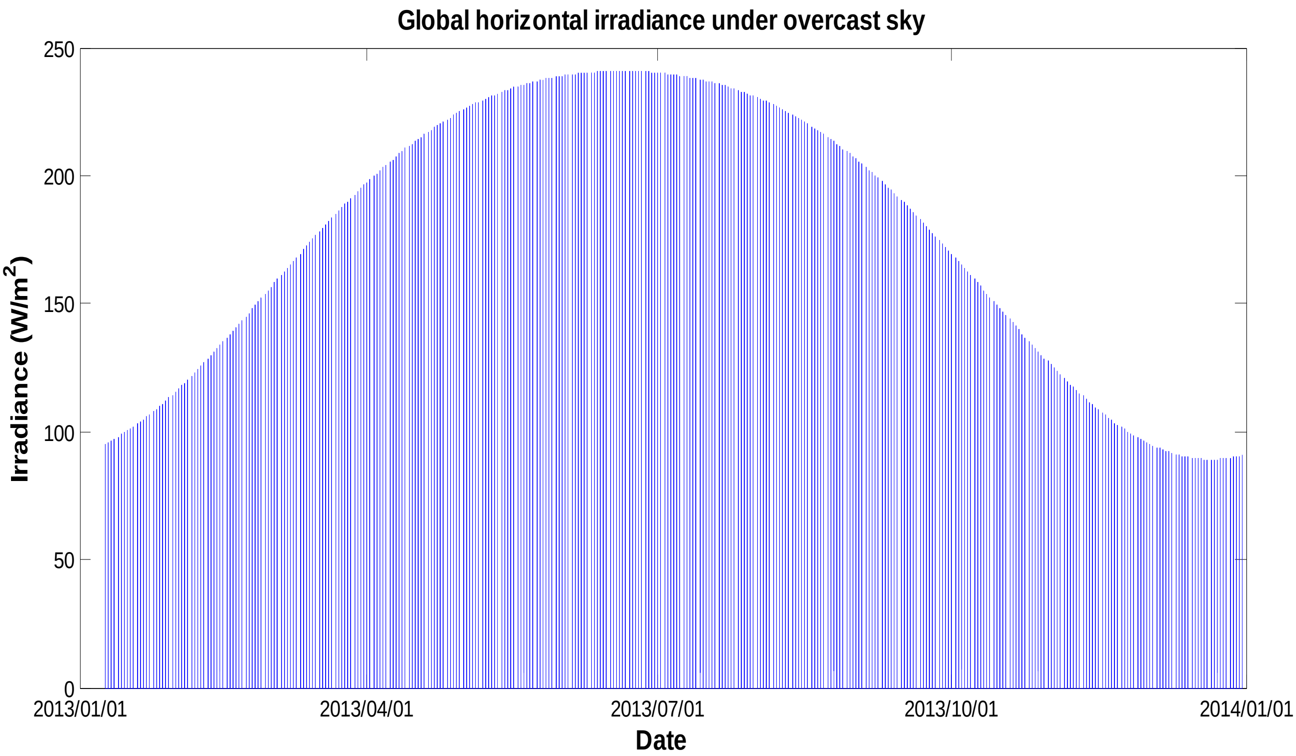


Figure 7.9: The horizontal irradiance under an overcast sky for the Leaf Community

It is understandable that under an overcast sky there is no direct irradiance. So the global horizontal irradiance under overcast sky is equal to the diffuse irradiance. These results above represent the minimum irradiance limits.
Hence, the predicted irradiance by using the neural network can now enclose to the maximum and the minimum limits in order to cut or ignored the values that are upper or lower respectively from that limits.

7.4 Predicting the power generated from the Hydroelectric station

In order to predict the power generated from the Hydroelectric Station 24 h ahead, another feedforward network was developed taking as inputs the time of the day in min, the river water level of the previous day, the machine water level of the previous day and the power generated during the previous day.

Because of the lack of the available measurements (measurements of 3 months) and their low quality due to unexpected stops of the plant, as it is shown at Figure 7.10 and Figure 7.11, it was necessary to correct them by using linear interpolation. The new data series are presented at Figure 7.12 and Figure 7.13.

The new data were used as the training set of the network and the comparison between the predicted power 24 h ahead and the real measurements is shown at Figure 7.14.

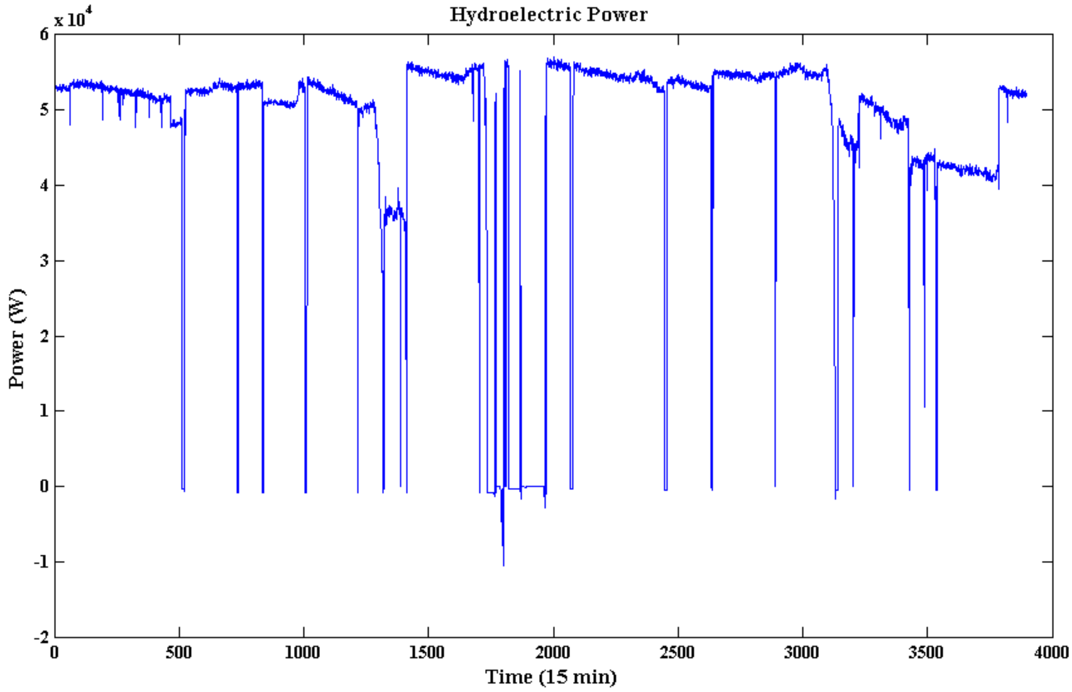


Figure 7.10: Available measurements of hydro power

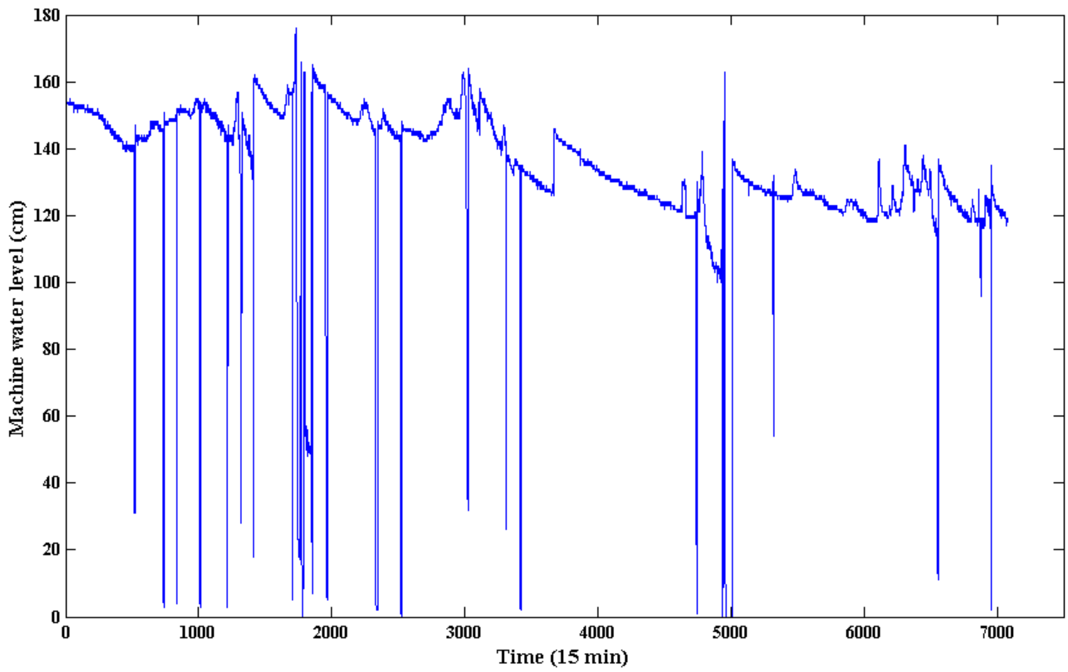


Figure 7.11: Available measurements of machine level

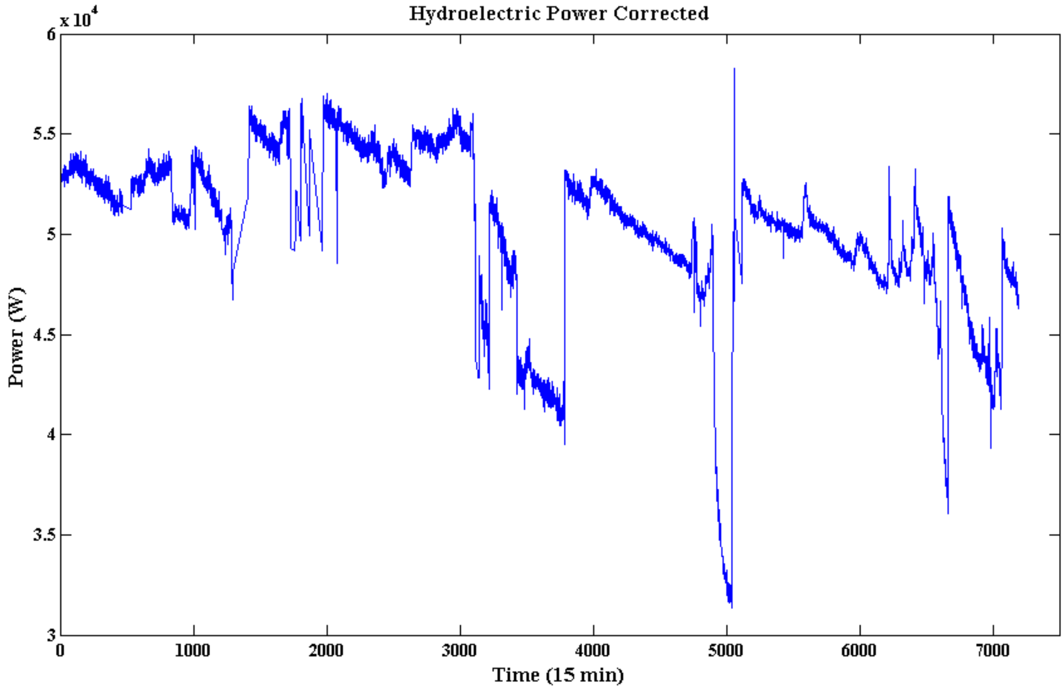


Figure 7.12: Data of hydro power after linear interpolation

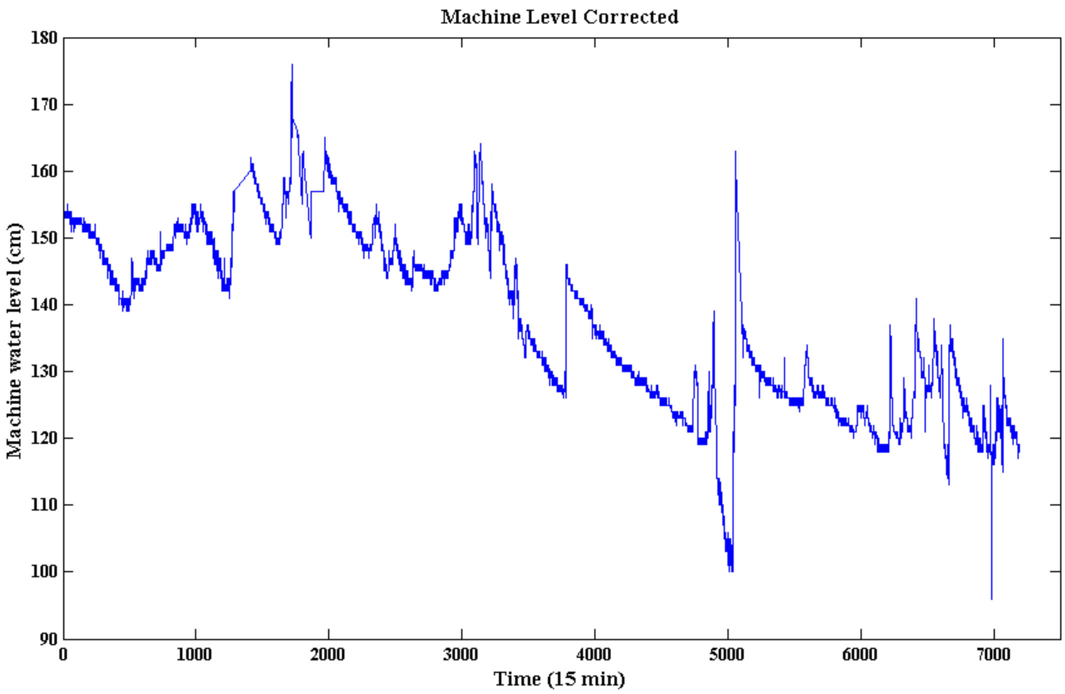


Figure 7.13: Data of machine water level after linear interpolation

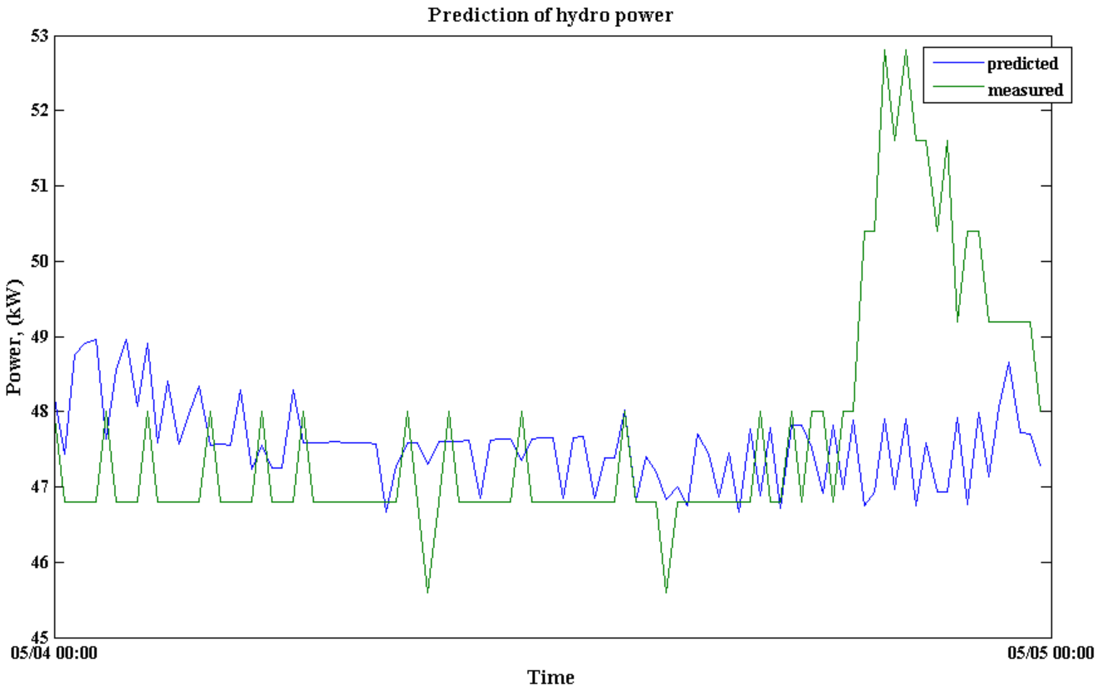


Figure 7.14: Comparison between the measured and the predicted generated power at Hydroelectric Station

According to Figure 7.14, it is obvious that the predicted power can't approach the real one. However, the hydroelectric station generates enough energy every quarter which means that Leaf Community could spent less money to ENE. For that reason it could not be deactivated from the optimization model. For that purpose, it was decided to use an average production of previous day for the next 24 hours. It is shown at Figure 7.12 that the difference comparing the next's day production with the previous one is too small that it is acceptable.

7.5 Predicting the energy consumed at Leaf Community with ANN

The prediction of energy consumption was performed by artificial neural networks (ANN) in Matlab. Regarding the energy consumption, two are the sections of interest, the "Leaf farm" and the "Leaf Working".
"Leaf farm" represents office buildings, while "Leaf Working" is an industrial space. The energy fluxes are shown at the following figure for both of them.

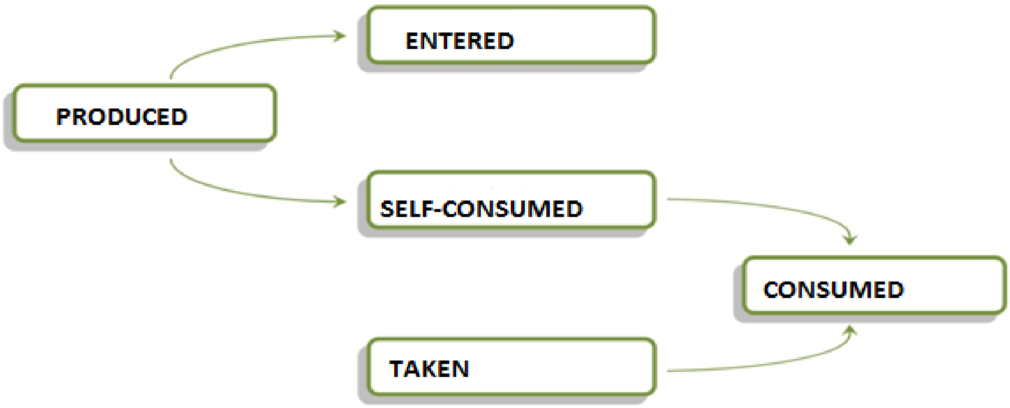


Figure 7.15: Energy fluxes at “Leaf farm” and “Leaf Working”

The goal here is to predict the *consumed energy*, which is a sum of the energy taken from the energy national network (ENEL) and the self consumed which represents the energy produced by the PVs minus the energy entered into ENEL.
The consumed energy is going to be predicted for the “Leaf farm” and the “Leaf Working” separately and the procedure followed for both of these sections includes the following steps:

1. Collecting data from earlier years
2. Preliminary data analysis
3. Determination of the inputs and the outputs
4. Development of a neural network in Matlab
5. Comparing the predicted with the measured energy consumption

Data collection

The first step before the development of the neural network was the collection of the data from earlier years. For this work, three years long period data approximately were collected for “Leaf farm” and “Leaf Working” respectively. Some of these data were used to train the algorithms developed while the rest of them were used for validation and testing.

Preliminary data analysis

Before the development of the prediction algorithms, a preliminary data analysis was necessary in order to understand the behavior of the energy consumption daily or weekly. That's why, the diagrams of the real measurements of energy consumption related to the time were designed. The weekly variation of "Leaf's farm" consumption is represented at Figure 7.16 and for "Leaf Working" at Figure 7.17.

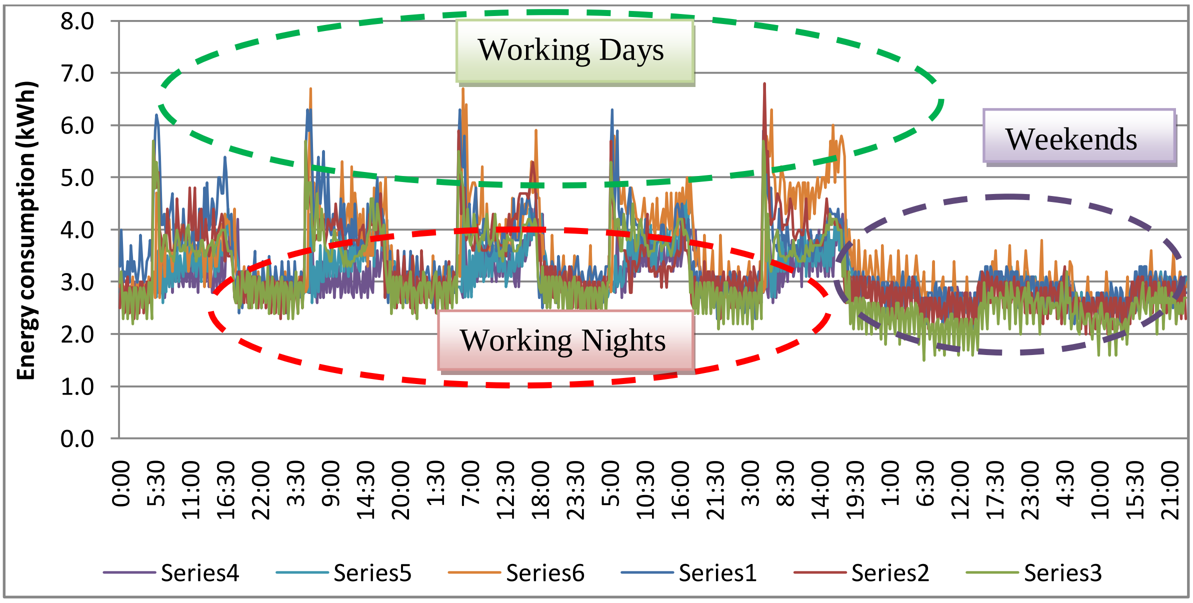


Figure 7.16: The weekly energy consumption for "Leaf farm" (7 weeks)

Observing the previous weekly diagram, it is understandable that in the mornings when the office buildings of "Leaf farm" are operated the consumption is greater than the nights when the lights are on. On the other hand, during the weekends it is obvious that the consumption is decreased, while during the night the consumed energy is lower than during the morning for weekend's days. This behavior was observed for 7 weeks. So it was assumed that the consumption behaves the same during the same days of the week.

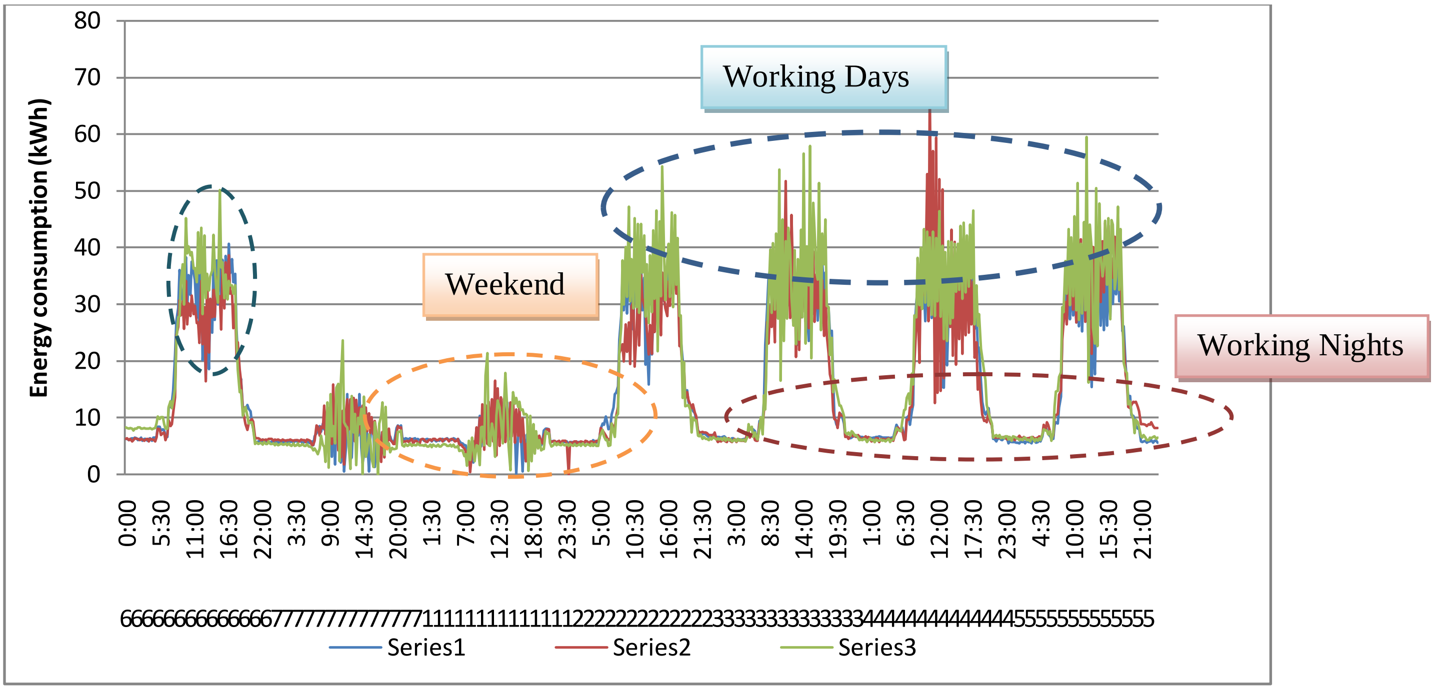


Figure 7.17: The weekly energy consumption for "Leaf Working" (3 weeks)

At "Leaf Working", which represents an industrial space, the energy's consumption variation follows the same behavior as it was analyzed before for "Leaf farm". For 3 continuous weeks as shown at Figure 7.17, during the days when the industrial is fully operated the consumption is greater than during the nights, while it is decreased early afternoon (*blue circle*). Also, during weekends it is observed that the consumed energy is lower, having higher consumption in the mornings.
In this case too, it was assumed that the consumption behaves the same during the same days of the week.

<u>Determination of inputs and outputs</u>

In order to predict the consumption at "Leaf farm" and "Leaf Working", it was decided that the appropriate parameters for the network's training are, the consumption of previous weeks because of the relationship was described previously, the day of the week for the same reason and the outdoors conditions of previous weeks. The irradiance was set as a parameter of outdoors conditions. The output parameter was set to be only the consumption for now.

7.5.1 Predicting the energy consumption at "Leaf farm"

A feed forward backpropagation network was developed to predict the consumption at Leaf farm consists of an input layer, 3 hidden layers with 4, 8 and 2 neurons in each layer and an output layer. As inputs were set the following parameters:

a) the time of the day,
b) the day of the week,
c) the irradiance now (in real world the forecast irradiance will be used)
d) the energy consumption 1 week before,
e) the energy consumption 2 weeks before,
f) the energy consumption 3 weeks before,
g) the energy consumption 4 weeks before and
h) the average energy consumption of the four previous weeks.

As output, was set the energy consumption at “Leaf farm” at the present time. Hence, the prediction horizon is 24 hours ahead. A year long period data set was used to train the network, while the rest of them were used for testing and validation by retraining the network every day.

The figure below shows the comparison between the predicted and the measured consumption at “Leaf farm”. It is important to mention that the holidays were ignored from the model in order to achieve better performance since the consumption now is based on older consumption measurements.

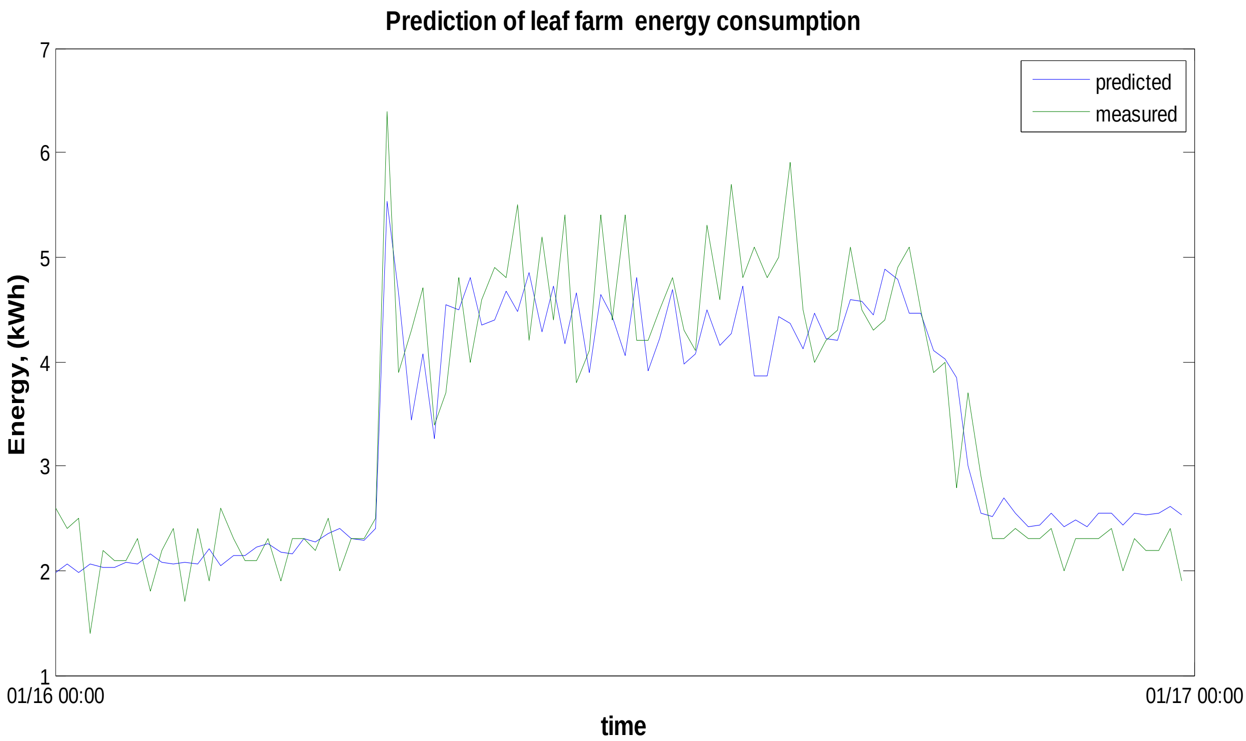


Figure 7.18: Comparison between the measured and the predicted energy consumption at “Leaf farm”

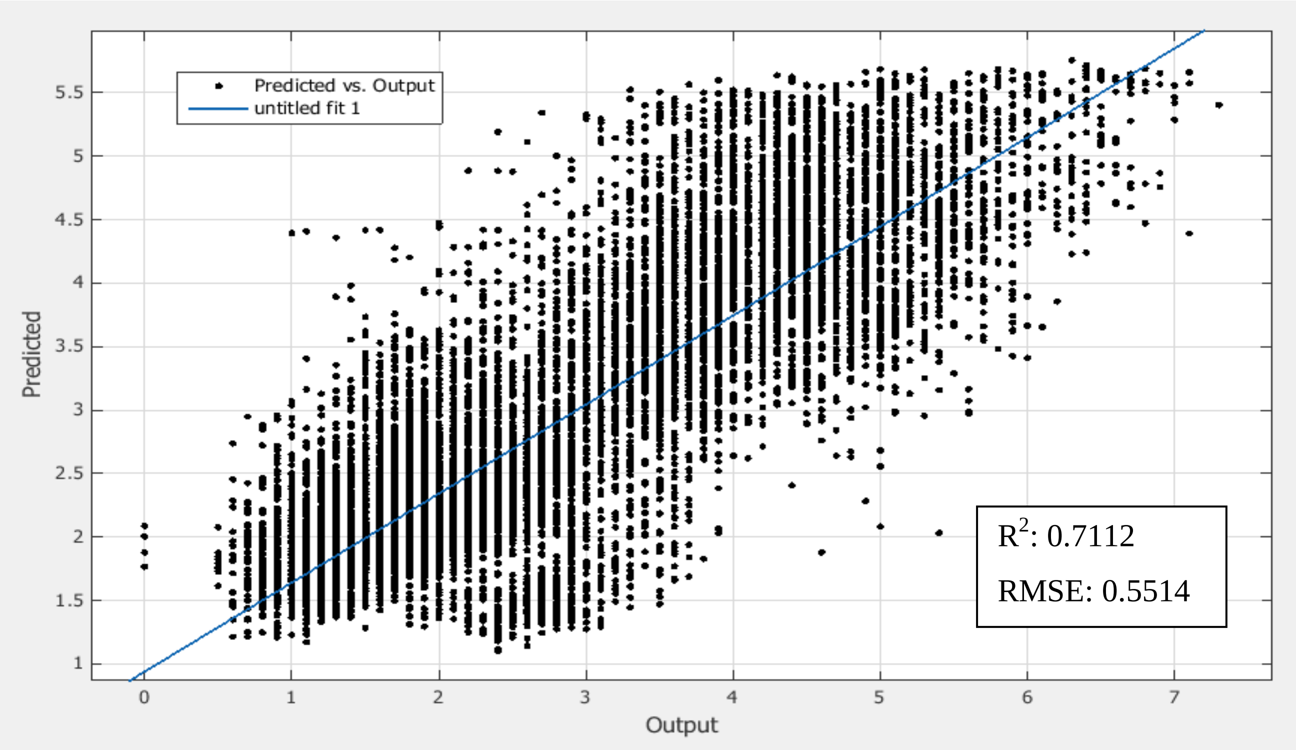


Figure 7.19: Relationship between predicted and measured energy consumption at “Leaf farm”

According to the figures above, the network can predict the energy consumption at “Leaf farm” satisfactorily. Because of the large consumption’s variation, some peaks cannot be predictable because the model is based on the energy consumption of previous weeks. Also, at this point it should be mentioned that any negative predicted values must be deleted.

7.5.2 Predicting the energy consumption at “Leaf Working”

The same network structure was developed also for the “Leaf Working” by setting the same parameters as inputs and output. In this case too, the algorithm predicts 24 hours ahead based on older weekly data. The training data were for duration of one year and the rest were used for testing and validation by retraining the network every day.

Likewise “Leaf farm”, the holidays were deleted from the model in order to not cause any confusion during the training. The results for “Leaf Working” are presented at the following figures.

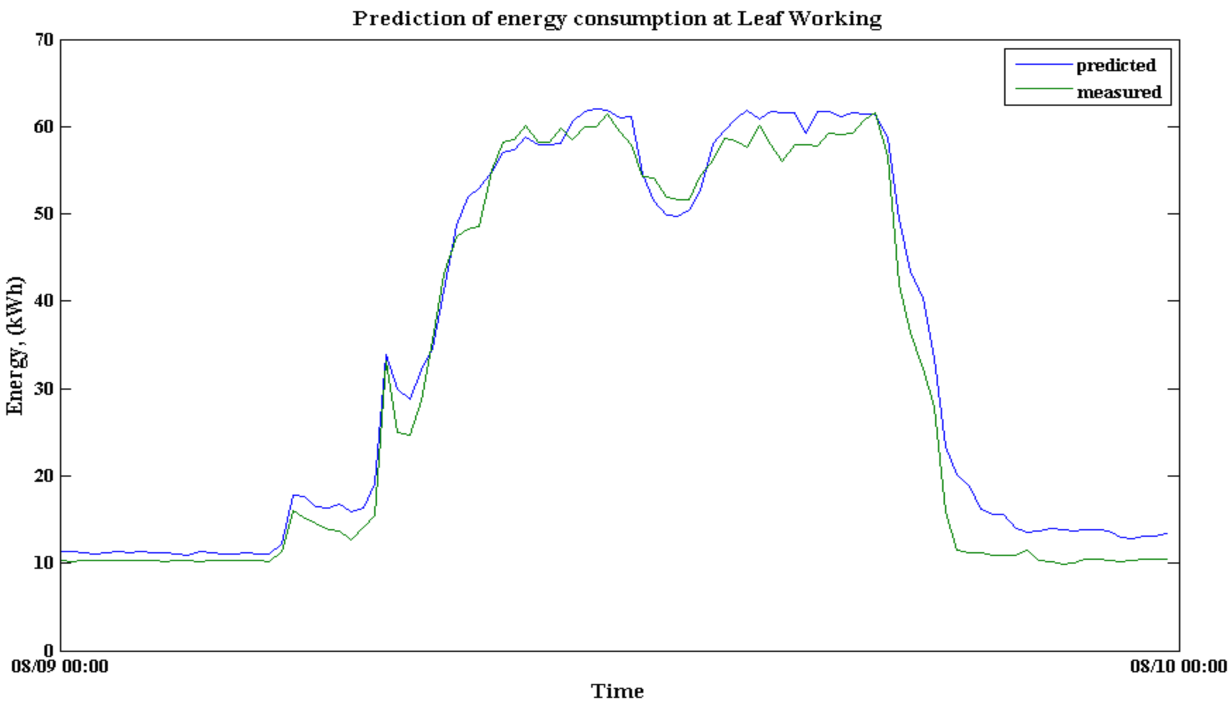


Figure 7.20: Comparison between the measured and the predicted energy consumption at “Leaf Working”

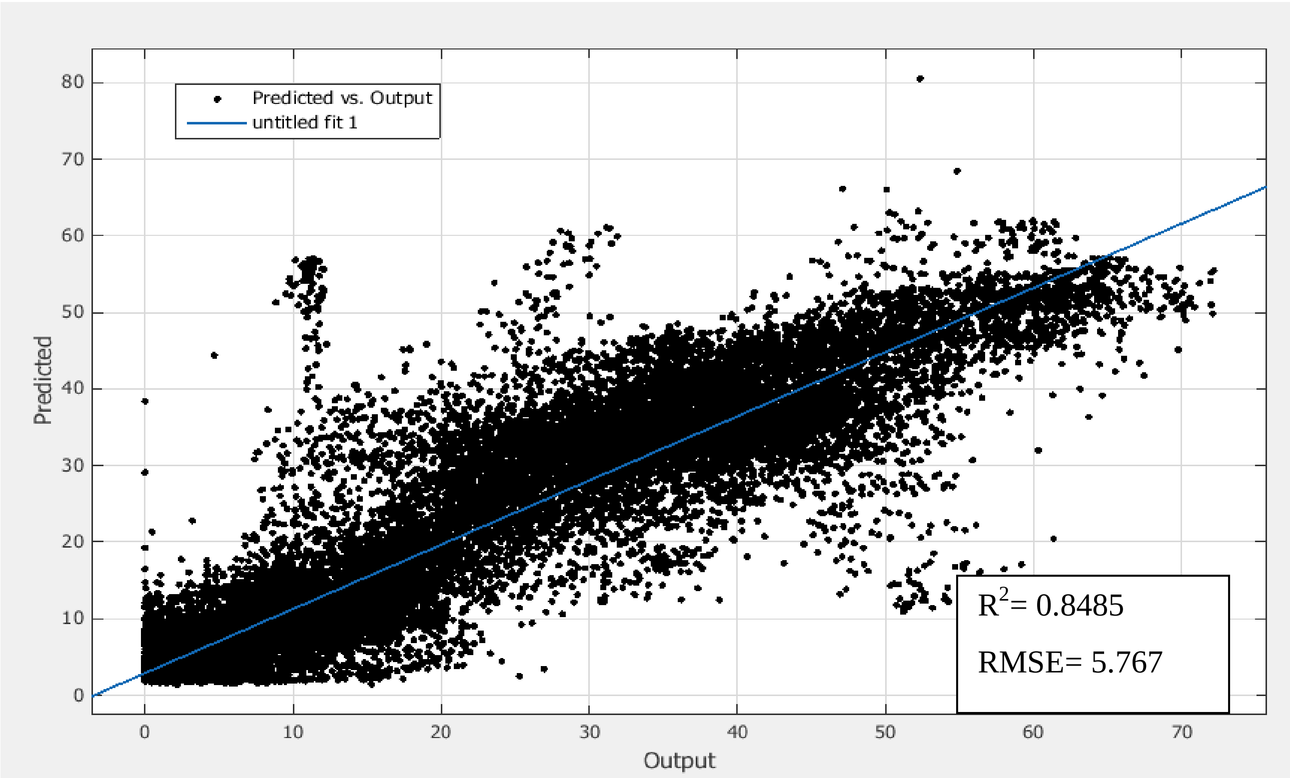


Figure 7.21: Relationship between predicted and measured energy consumption at “Leaf Working”

In this case, it is obvious from the figures that better results were achieved than those of “Leaf farm”. Looking the preliminary data analysis it is shown that the consumption at “Leaf Working” is more stable than the one at “Leaf farm” so the model can predict more accurately here.

At this stage, the first step of microgrid’s modeling has finished as it was achieved to predict the energy produced and generated 24h ahead by the method of artificial neural networks. In the case of hydroelectric station where the neural network is not capable to provide accurate forecast values because of the lack and the quality of the existing data, an average value of the production of the previous day will be used at the optimization algorithm which is presented below.

8 DEVELOPING THE OPTIMIZATION MODEL

The final object in this work is the development of an optimization model by using genetic algorithms in order to minimize the total cost for the microgrid of Leaf Community. In order to achieve that, the first necessary step was the study of energy routes inside the microcrid, including the National grid.

The microgrid of Leaf Community is shown at Figure 8.1. This figure shows the connections between buildings, energy producing plants and energy storage system, as well as the connection of all these with National energy grid (POD), including some inverters and transformers along the energy lines.

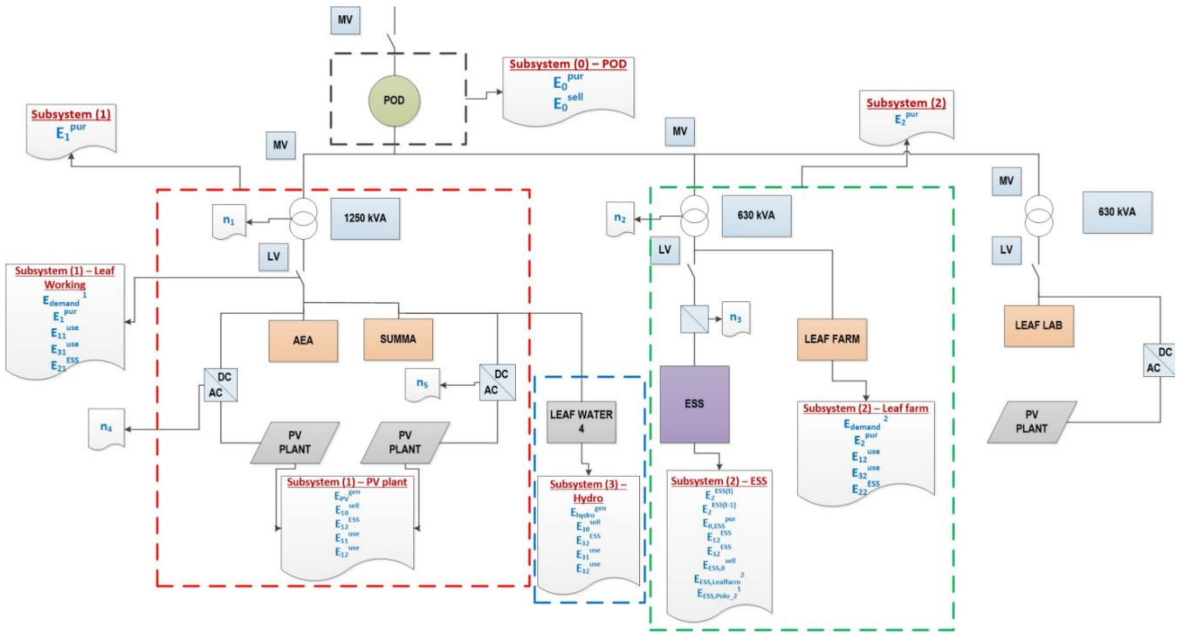


Figure 8.1: Leaf Community microgrid

As it was mentioned before, the goal of this work is to minimize the total cost of Leaf's community microgrid. This total cost must contain the cost of buying energy from ENEL in order to cover extra demands, the cost of selling energy produced to ENEL and of course the cost of using the energy storage system either for charging either for discharging. In order to develop the appropriate cost function which will be the objective function of the optimization, the microgrid was divided to 4 subsystems as it is shown at Figure 8.1.
Specifically the 4 subsystems are:

- Subsystem (0): Includes the POD's section
- Subsystem (1): Includes the Leaf's Working section with the PV plants
- Subsystem (2): Includes the Leaf's farm section with the ESS
- Subsystem (3): Includes the hydroelectric station

The main grid is connected with the microgrid by an electrical line with medium voltage (MV). Downstream the point of delivery (POD) there are two electrical lines where two transformers are placed, one for each line. The tension at the line on the left, as it is shown at Figure 8.1, is 1250kVA, while 630kVA are measured at the line on the right. These transformers convert the electrical power from medium to low voltage. The first one connects the POD with the “Leaf Working” building, the PV systems installed and the hydroelectric station, while the second one connects the POD with the Leaf farm and the ESS. Their efficiencies are 99% and 98% respectively.

8.1 Mathematical model

8.1.1 Developed cost function

The objective function must include the case of buying energy from main grid when it is necessary, the case of selling energy to National Network when it surpluses and the case of using the energy storage system in order to cover consumption demands or to store energy for future use. All these are included at the following equation (8-1).

$$C = \sum_{t=1}^{24}\left[E_0^{pur}(t) * C_0^{pur}(t) - E_0^{sell}(t) * C_0^{sell}(t)\right] + \sum_{t=1}^{24}\sum_{j=1}^{9} E_2^{ESS}(t)\text{Cycle cost}_j \qquad (8\text{-}1)$$

Where:

$E_0^{pur}(t)$: energy purchased to the grid at the time t , (kWh)
$C_0^{pur}(t)$: purchased price of the energy at the time t, (€ /kWh)
$E_0^{sell}(t)$: energy sold to the grid at the time t , (kWh)
$C_0^{sell}(t)$: selling price of the energy at the time t, (€ /kWh)
$E_2^{ESS}(t)$: energy charged/discharged from ESS at time t, (kWh)
$Cyclecost_j$: cost of each cycle dependent of the swing range of ESS (

Depending on the state of charge, the life time of ESS and the cycle cost was given and they are presented at Table 6.1.

Table 6.1), (€ /kWh)

Taking into account the description of the subsystems mentioned above, it is obvious that the appropriate constraints must be set in order to guide the genetic algorithm into deciding a true best solution.

8.1.2 Constraints

The constraints of the present optimization problem were set by looking the energy flows between the subsystems, which were presented above.

8.1.2.1 Subsystem (0), POD:

At this subsystem, the energy can be bought for immediate consumption at "Leaf farm" and/or at "Leaf Working" or can be sold from the subsystems 1 and 3. For subsystems 1 and 3, the energy that can be sold is the energy generated from the PV plants and the hydroelectric station respectively. When the microgrid needs to buy energy from Energy National Network the following constraint (8-2) must be respected:

$$E_0^{pur}(t) = n_1 E_1^{pur}(t) + n_2 E_2^{pur}(t) \tag{8-2}$$

While the demands of buildings are less than the energy generated, then Leaf Community can sell this extra energy to the main grid, considering the following energy balance (8-3).

$$E_0^{sell} = n_1 E_{10}^{sell} + n_1 E_{30}^{sell} \tag{8-3}$$

8.1.2.2 Subsystem (1), Leaf Working:

At this point of subsystem (2) the energy only is consumed in order to cover the needs of the buildings. Thus, the energy demanded will be covered from: i) subsystem (0) by buying energy, ii) by using energy generated from the PV plants, iii) by using energy generated from the hydroelectric station and iv) by using energy from the ESS. The equation for "Leaf's Working" energy balance is equation ((8-4):

$$E_{Demand}^{1}(t) = n_1 E_1^{pur}(t) + E_{11}^{use}(t) + E_{31}^{use}(t) + n_1 n_2 n_3 E_{21}^{ESS}(t) \tag{8-4}$$

$$E_{21}^{ESS}(t) = E_2^{ESS}(t-1) - E_{Demand}^{2}(t) - 7/4 \tag{8-5}$$

8.1.2.3 Subsystem (2), "Leaf farm":

The building of "Leaf farm" which is included at subsystem (2) can cover its needs by: i) buying energy from POD, ii) using energy generated by PV plants, iii) using energy generated by hydroelectric station and iv) using energy stored at ESS. Hence the energy demand at this point of the subsystem (2) is described by equation (8-6).

$$\mathrm{E}_{Demand}^{2}(\mathrm{t}) = \mathrm{n}_2\mathrm{E}_2^{pur}(\mathrm{t}) + \mathrm{n}_1\mathrm{n}_2\mathrm{E}_{12}^{use}(\mathrm{t})\mathrm{n}_1\mathrm{n}_2\mathrm{E}_{32}^{use}(\mathrm{t}) + \mathrm{n}_3\mathrm{E}_{22}^{ESS}(\mathrm{t}) \quad (8\text{-}6)$$

$$\mathrm{E}_{22}^{\mathrm{ESS}}(\mathrm{t}) = \mathrm{E}_{2}^{\mathrm{ESS}}(\mathrm{t}-1) - 7/4 \quad (8\text{-}7)$$

8.1.2.4 Subsystem (2), ESS:

At ESS point of subsystem (2), the energy ending up there to be stored, can origin from: i) PV plants and ii) hydroelectric station. Except from the case that the batteries are being charged, there are also cases when the batteries are being discharged. These are the following: a) cover the demands of "Leaf farm" and b) cover further demands if it is possible at Leaf Working. So, the energy at the ESS at time (t) is described by the equation (8-8) and equation (8-11) depending the charge or the discharge of the ESS:

<u>Charge the batteries:</u>

$$\mathrm{E}_2^{ESS}(\mathrm{t}) = \mathrm{E}_2^{\mathrm{ESS}}(\mathrm{t}-1) + \mathrm{E}_{12}^{ESS}(\mathrm{t}-1) + \mathrm{E}_{32}^{ESS}(\mathrm{t}-1) - 7/4 \quad (8\text{-}8)$$

$$\mathrm{E}_2^{\mathrm{ESS}}(\mathrm{t}) = (\mathrm{E}_2^{\mathrm{ESS}})_{\max} * \mathrm{SOC}(\mathrm{t}) \quad (8\text{-}9)$$

$$\mathrm{E}_2^{\mathrm{ESS}}{}_{\min} = \mathrm{SOC}_{\min}\ \mathrm{E}_2^{\mathrm{ESS}}{}_{\max} \quad (8\text{-}10)$$

<u>Discharge the batteries:</u>

$$\mathrm{E}_2^{ESS}(\mathrm{t}) = \mathrm{E}_2^{\mathrm{ESS}}(\mathrm{t}-1) - \mathrm{n}_3\mathrm{E}_{ESS,Leaffarm}^{2}(\mathrm{t}-1) - \mathrm{n}_1\mathrm{n}_2\mathrm{n}_3\mathrm{E}_{ESS,Polo_2}^{1}(\mathrm{t}-1) - 7/4 \quad (8\text{-}11)$$

$$\mathrm{E}_2^{\mathrm{ESS}}(\mathrm{t}) = (\mathrm{E}_2^{\mathrm{ESS}})_{\max} * (1 - \mathrm{SOD}(\mathrm{t})) \quad (8\text{-}12)$$

$$\mathrm{E}_2^{\mathrm{ESS}}{}_{\min} = (1 - \mathrm{SOD}_{\max})\mathrm{E}_2^{\mathrm{ESS}}{}_{\max} \quad (8\text{-}13)$$

For both cases (charge and discharge ESS):

$$E_{2}^{ESS}{}_{max} \leq E_{2}^{ESS}{}_{t} \leq E_{2}^{ESS}{}_{min} \quad (8\text{-}14)$$

8.1.2.5 Subsystem (1), PV plant:

The energy generated from PV plants at subsystem (1) can be: i) sold directly to POD, ii) stored at ESS, iii) used directly from "Leaf Working" and iv) used directly from "Leaf farm". So, the energy generated from PV plants has to be equation (8-15).

$$E_{PV}^{gen}(t) = n_1 E_{10}^{sell}(t) + n_1 n_2 n_3 E_{12}^{ESS}(t) - 7/4 + E_{11}^{use}(t) + n_1 n_2 E_{12}^{use}(t) \quad (8\text{-}15)$$

8.1.2.6 Subsystem (3) - Hydro Station:

Likewise PV plants, the energy generated from hydroelectric station can be: i) sold directly to POD, ii) stored at ESS, iii) used directly from "Leaf Working" and iv) used directly from "Leaf farm". The equation that describes all these is the equation (8-16):

$$E_{hydro}^{gen}(t) = n_1 E_{30}^{sell}(t) + n_1 n_2 n_3 E_{32}^{ESS}(t) - 7/4 + E_{31}^{use}(t) + n_1 n_2 E_{32}^{use}(t) \quad (8\text{-}16)$$

9 OPTIMIZATION MODEL AT MATLAB

The idea was to create a Matlab code that will prepare all the appropriate inputs and constrains for the genetic algorithm in order to optimize the cost function for the Leaf Community. The flow chart that describes the function of the developed algorithm is presented on Appendix A. So the developed code is really friendly to the user and flexible to any changes. The only thing that the user must do is to set a date, an initial state of energy storage system and the maximum energy purchased of the previous day.

The date must be set as year, month, day, hour, minutes and seconds, setting minutes as a function of ¼ of the hour. This is because all the date used in the model is measured every 15 minutes.

Two Matlab codes were developed, one named Prepare_all_inputs and one named Loccioni_cost_function_v2 for this work. More specifically, the work done at Matlab's environment is described below in detail.

9.1 Matlab code named "Prepare all inputs"

This Matlab script could be divided into five different sections. Firstly the appropriate data were saved in order to predict the consumption and the production of energy 24 hours ahead counting from the date set by the user and after some calculations and considering the constrains to the code ending with the optimization model using the genetic algorithms.

<u>Section 1:</u> This part of the script contains a code which finds and saves all the appropriate data in order to predict 24 hours ahead from the set date. More specifically, after loading the measurements of all domains of the microgrid (Leaf Working, Leaf farm, PV systems and Hydroelectric station) and the developed neural networks from the prediction work, it saves at new files only 96 values which are the predicted energy.

<u>Section 2:</u> At this point a variable named "Needs" is calculated. This variable constitutes of the difference between the energy consumed by Leaf farm and Polo_2 from the energy produced by the PV plants and the Hydroelectric station. The equation is:

$$\text{Needs} = (\text{PV\_production}) + (\text{Hydro\_production}) - (\text{Leaf\_farm\_consumption}) - (\text{Leaf Working\_consumption}) \quad (9\text{-}1)$$

The calculated "Needs" are 96 values and show every quarter the demands if there are any, of the microgrid for energy. If the result of the equation above is positive then means that there is extra energy at the microgrid can be sold or stored. When the result is negative, the buildings need more energy to cover their demands that can be bought from ENEL or given by discharging the ESS.

Section 3: This section substantially contains the constrains of using the ESS either for charging it either for discharging it. First of all, it should be mentioned here that positive energy from ESS means its discharging, while negative energy means charging it.

ESS_energy>0 ⇔ Energy discharged from ESS (9-2)

ESS_energy<0 ⇔ Energy charged to ESS (9-3)

The first constrain was set is the maximum energy storage value which is 224kWh. This constrain allows to charge the ESS until this value and not more. The second constrain regards the minimum energy of ESS that is the value of 0 kWh. The next two constrains concern the maximum and the minimum energy that can be charged or discharged from ESS every quarter which are respectively -56kWh (charge) and 56kWh (discharge). The last constrain requires, the energy discharged in order to be consumed from buildings to be less by 1.75 kWh which is the inverters consumption. The same requirement must be ensured when an amount of energy is going to be stored.

Section 4: At this point, the optimization model using genetic algorithm is developed using as an objective function, the function named Loccioni_cost_function_v2. This function will be described below.

The genetic algorithm calls the objective function that should be minimized and considering 96 variables (96 quarters per day) and the ESS's constrains finds the optimum cost for the microgrid. The operation of this method was described at the beginning of this report.

The options that can be changed by the user are the following parameters.

- Population type: The option "doubleVector" was chosen in order to solve the problem considering the constrains were set while the other options ignore them.
- Initial population range: As an initial population range, the range [-56, 56] was set which represents also the lower and the upper bound of ESS every quarter.
- Population size: It was set to the value of 200. It was shown by doing different tests that this size is enough to achieve an optimum result.

- Elite count: This parameter specifies how many individuals in the current generation are guaranteed to survive to the next generation. According to the tutorial this parameter can be calculated as 0.05*Population size and for that reason was set as 10.
- Generations: The number of iterations was chosen for this problem is 300.
- Stall generations: It was set to the value of 300.
- Plots: A variety of plots can be exported using genetic algorithms. For this problem it was chosen to plot the "best fitness" which is the optimum total cost, the "best individual" which represents the amount of energy charged or discharged from ESS for each variable and the distance between individuals at each generation.
- Display: In order to be informed at each iteration the option "iterative" was chosen.
- Evaluate fitness & constrain function: The option "In paraller" was chosen.

Section 5: This part includes the outputs of the genetic algorithm which are the variables named "x" and "fval". Variable x is actually the energy charged or discharged from ESS (considering the 1.75 kWh inverter's consumption) and as fval the total cost for Leaf.

9.2 Matlab code named "Loccioni_cost_function_v2"

It was mentioned before that the genetic algorithm uses as an objective function, the function named "Loccioni_cost_function_v2". Here, the structure of this function is described. First of all, the cycle cost (Table 1) considering all the swing ranges of ESS is loaded in order to calculate the cost of using the ESS. This cost is depending on the decision of the genetic algorithm which has as an output the transportation of the energy from or to the ESS. According to the swing range that includes at every time step this energy, the cost of battery is calculated by multiplying the energy charged/discharged with the respective cycle cost (€/kWh).

Other data that are loaded here are the purchase and the selling energy price. As selling energy price was set the constant value of 0.075 €/kWh, while the purchased price every quarter is presented at the following Table 9.1.

Table 9.1: The purchased price of energy at September

Date	Hour	PUN [€/MWh]	PUN + 4% loses [€/MWh]	taxes [€/MWh]	final purchase price [€/MWh]	final purchase price [€/kWh]
30/9/2013	1	57.94	60.26	85.28	145.54	0.15
30/9/2013	2	56.00	58.24	85.28	143.52	0.14
30/9/2013	3	50.36	52.38	85.28	137.66	0.14
30/9/2013	4	47.33	49.22	85.28	134.50	0.13
30/9/2013	5	50.35	52.37	85.28	137.65	0.14
30/9/2013	6	57.55	59.85	85.28	145.13	0.15
30/9/2013	7	62.83	65.34	85.28	150.62	0.15
30/9/2013	8	69.22	71.99	85.28	157.27	0.16
30/9/2013	9	81.41	84.66	85.28	169.94	0.17
30/9/2013	10	77.67	80.77	85.28	166.05	0.17
30/9/2013	11	77.66	80.77	85.28	166.05	0.17
30/9/2013	12	72.95	75.86	85.28	161.14	0.16
30/9/2013	13	62.85	65.36	85.28	150.64	0.15
30/9/2013	14	58.42	60.75	85.28	146.03	0.15
30/9/2013	15	63.85	66.40	85.28	151.68	0.15
30/9/2013	16	70.40	73.22	85.28	158.50	0.16
30/9/2013	17	70.33	73.14	85.28	158.42	0.16
30/9/2013	18	72.00	74.88	85.28	160.16	0.16
30/9/2013	19	73.72	76.67	85.28	161.95	0.16
30/9/2013	20	91.49	95.15	85.28	180.43	0.18
30/9/2013	21	84.10	87.46	85.28	172.74	0.17
30/9/2013	22	74.06	77.02	85.28	162.30	0.16
30/9/2013	23	67.56	70.26	85.28	155.54	0.16
30/9/2013	24	61.57	64.04	85.28	149.32	0.15

Graphically, the purchase price during the day is shown at the following figure.

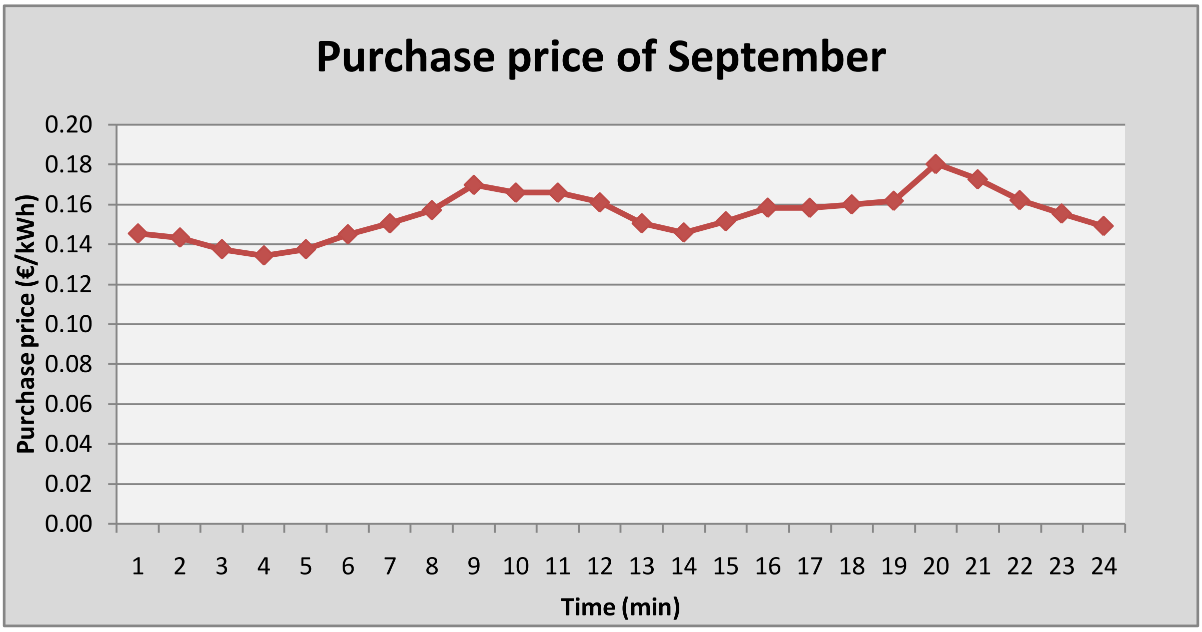


Figure 9.1: Purchase price of energy

An extra cost, required by the Italian law, is a payment of 10.76 €/kWh per month for the maximum energy purchased from ENEL. The user will provide the maximum energy purchased of the previous day (variable named max_energy) and by solving the last equation the algorithm will know if this cost must be included at the total cost of a specific day.

Except from these data mentioned above, this function receives as input the variable named "Battery" which is actually the variable x, the genetics' algorithm output. Considering the Battery for the next 96 quarters and the variable "Needs" (Production-Consumption), a new variable named "Grid power" is calculated.

The equation was written at Loccioni_cost_function_v2 is the following.

Grid power=Battery+Needs (9-4)

<u>If Grid power>0</u>: The energy can be sold to ENEL and the cost which in this case is a profit for Leaf Community is calculated by:

Cost of Grid_power=-Grid_power*sale price*0.99 (9-5)

The value 0.99 at the previous equation represents the efficiency of transformer of 1250 kVA.

If Grid power<0: More energy is needed in order to cover the demands of microgrid, so energy must be bought from ENEL.
The cost of grid is calculated by:

Cost of Grid_power=-Grid_power*purchased price/(0.99*0.98) (9-6)

The value 0.99 at the previous equation represents the efficiency of transformer of 1250 kVA, while the value 0.98 represents the efficiency of transformer of 630kVA.
After calculating the Cost of grid which will be either profit either payment to ENEL the total cost is calculated which includes this cost as well as the cost of Battery.
The final equation in this function is the following:

- ✓ If "-max_energy"> min (Grid_power) ⇔

Total_cost=Cost of Grid_power + Cost of ESS - min(Grid_power) * 10.76 (9-7)

- ✓ If "-max_energy"< min (Grid_power) ⇔

Total_cost=Cost of Grid_power + Cost of ESS (9-8)

Finally, a sum of these 96 values of total cost is calculated, which is actually the output "fval" of genetic algorithm.

At this point some results are presented below by setting different dates randomly and considering two cases, one that the hydroelectric station operates and one that it doesn't.

10 RESULTS

In this section some results are presented for different scenarios were chosen in order to test the developed genetic algorithm. The first four scenarios assume that the Hydroelectric station is not operated and at the last ones it entries into operation (using the available data of hydro).

10.1 Scenarios without Hydroelectric station

10.1.1 Scenario 1

The first scenario considers as date the 15^{th} of January 2013, when the Hydro station wasn't operate. As an initial battery state (BPS) was set the value 30 kWh, while the maximum energy purchased (max_energy) of the previous day was 40 kWh. The chosen plots are presented at Figure 10.1.

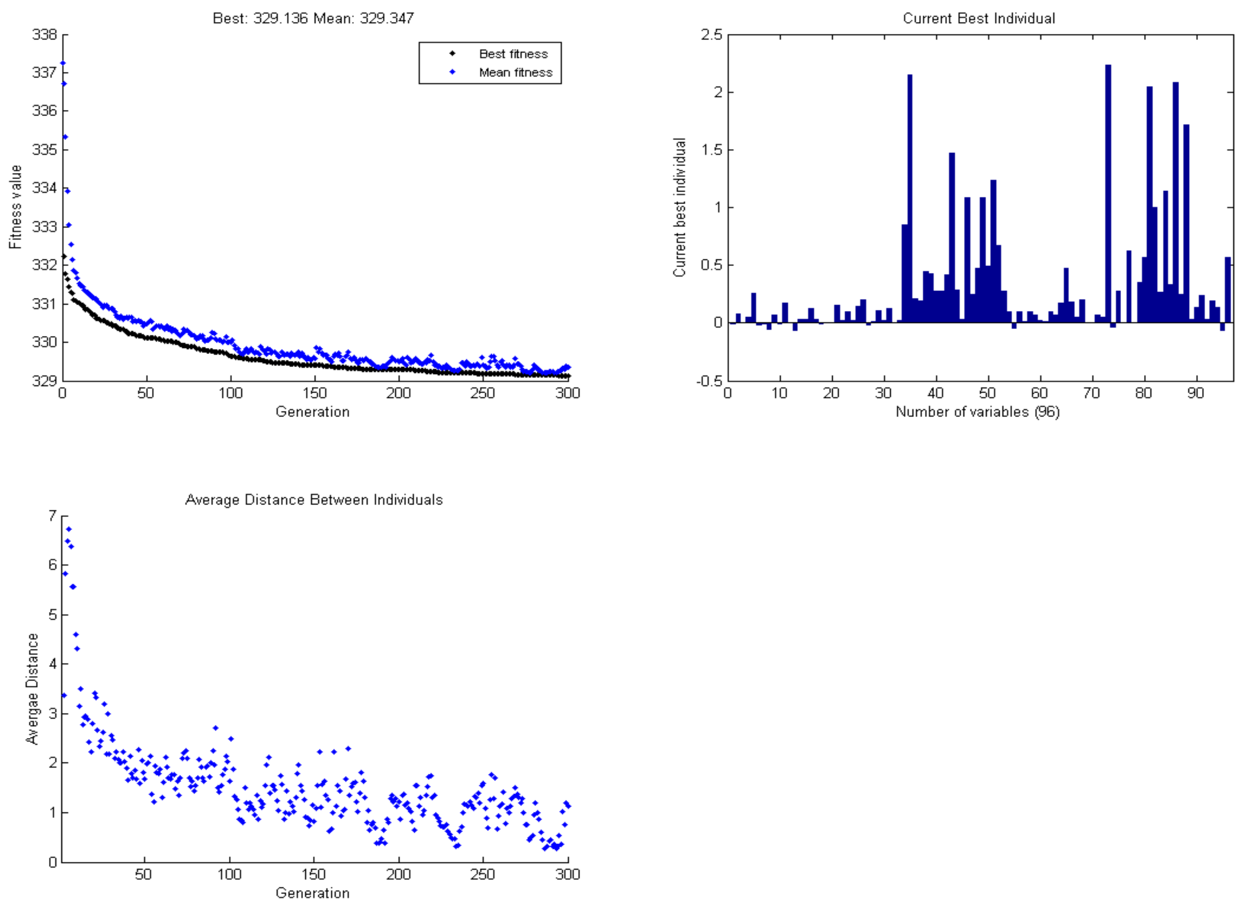


Figure 10.1: Plots of Best fitness, Current Best Individual and Average Distance (15/1/2013, BPS=30 kWh, max_energy=40kWh)

The optimum cost is 329 €, meaning that Leaf Community must pay mostly to Energy National Network in order to cover its needs. The figure of best individual shows the using of ESS during the day. Here, it must be mentioned that positive values of individuals mean discharging of ESS. The figure at the bottom shows the average distance between individuals which actually represents the diversity of the initial population that affects at the performance of the genetic algorithm. Generally, if the diversity is too high or too low the genetic might not perform well. Here, it is obvious that the distance does not reach extreme values, so it is considered that the performance is good.

Furthermore, some other results include the energy taken or sold from/to ENEL, the energy charged/discharged ESS after the consumption of inverter and their costs respectively during the chosen by the user day are presented at the figures below.

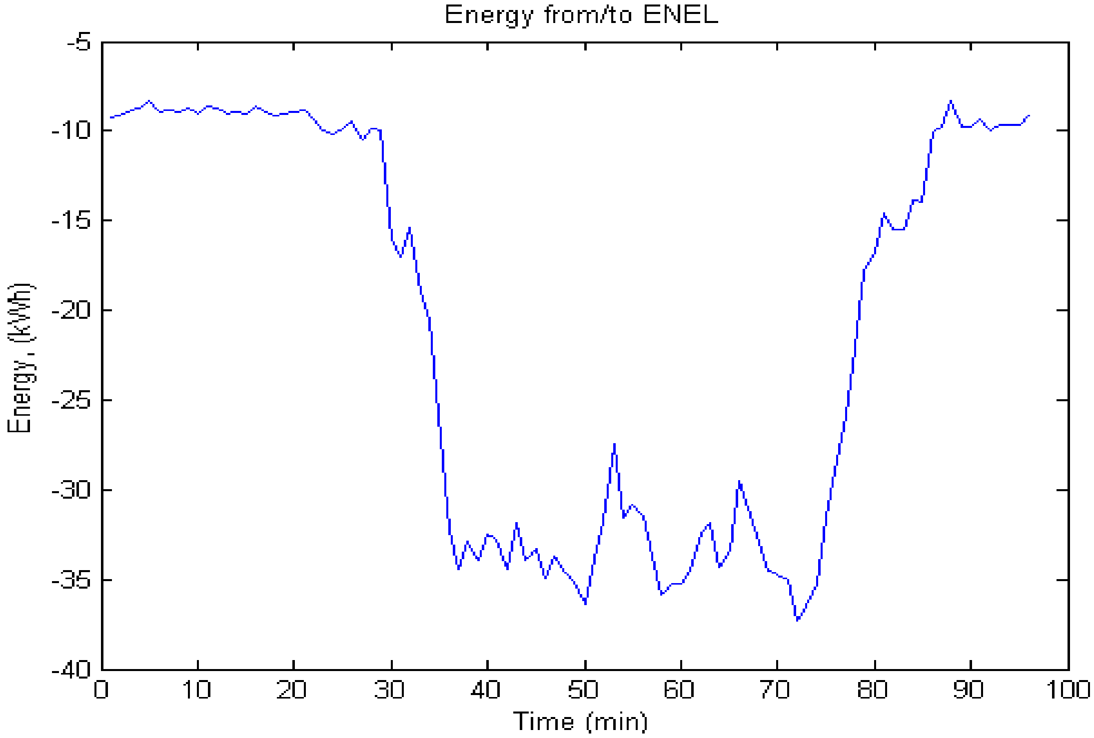


Figure 10.2: Energy from/to ENEL on 15th January 2013, considering BPS=30 kWh and max_energy=40 kWh

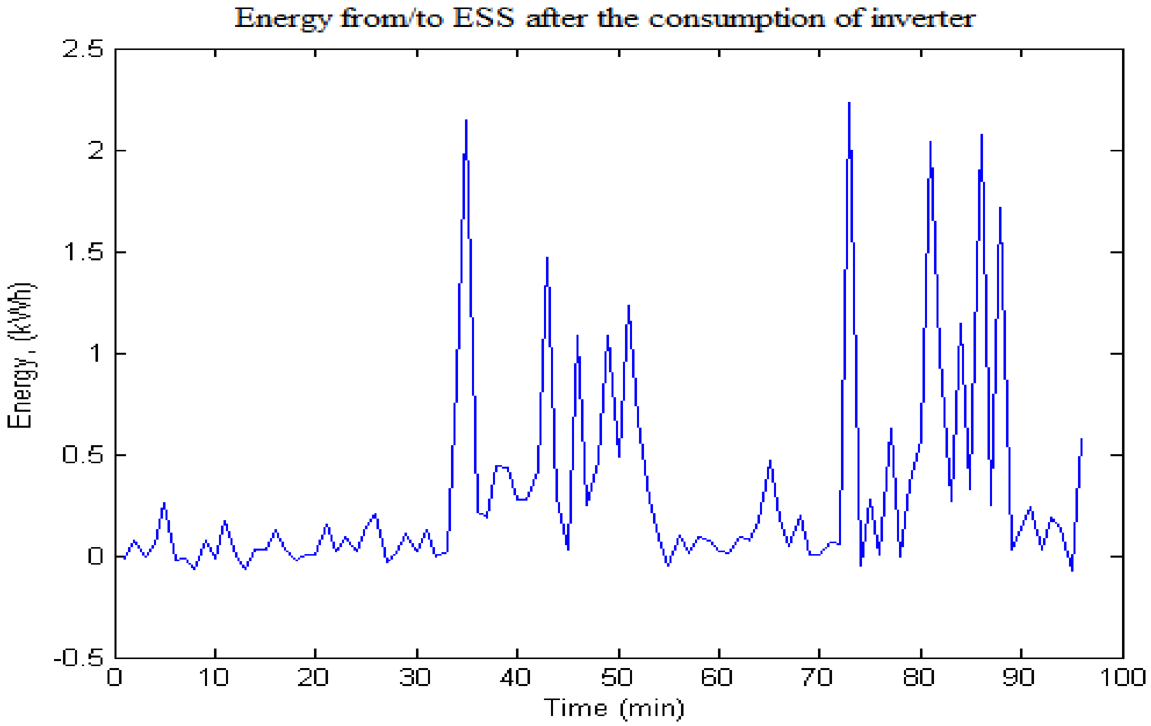


Figure 10.3: Energy charged/discharged at ESS on 15th January 2013, considering BPS=30 kWh and max_energy=40 kWh

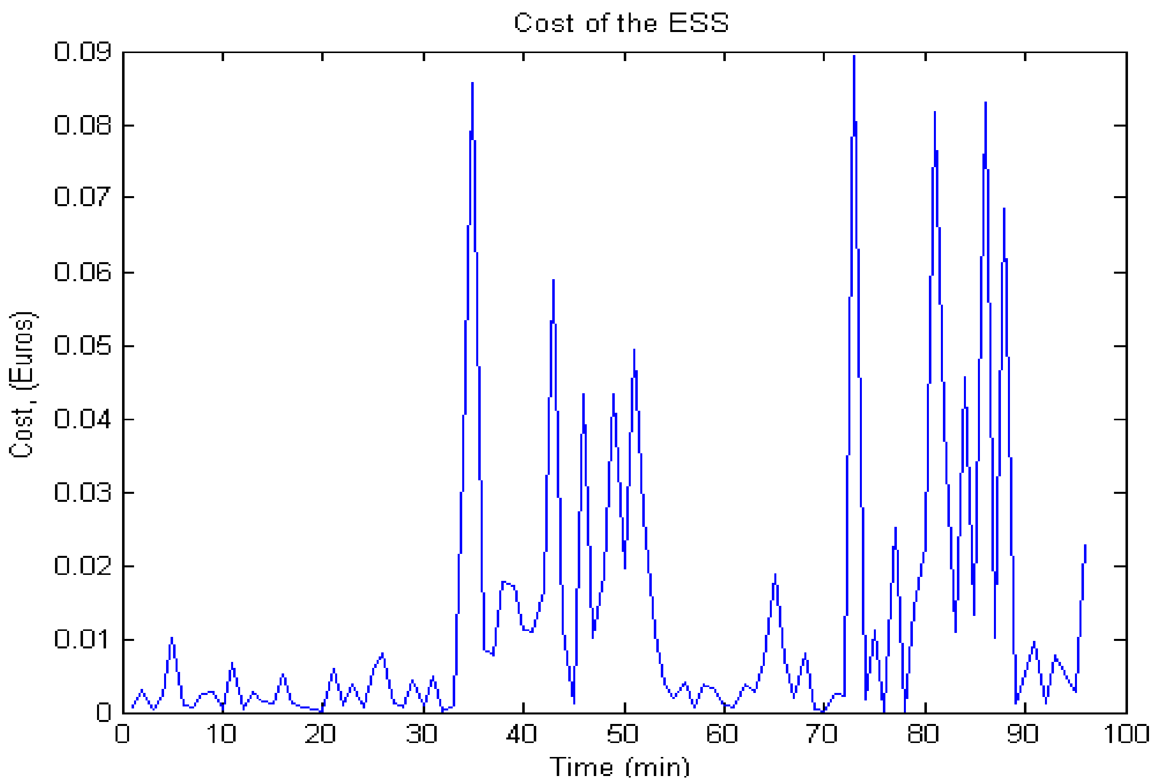


Figure 10.4: Cost of charging/discharging ESS on 15th January 2013, considering BPS=30 kWh and max_energy=40 kWh

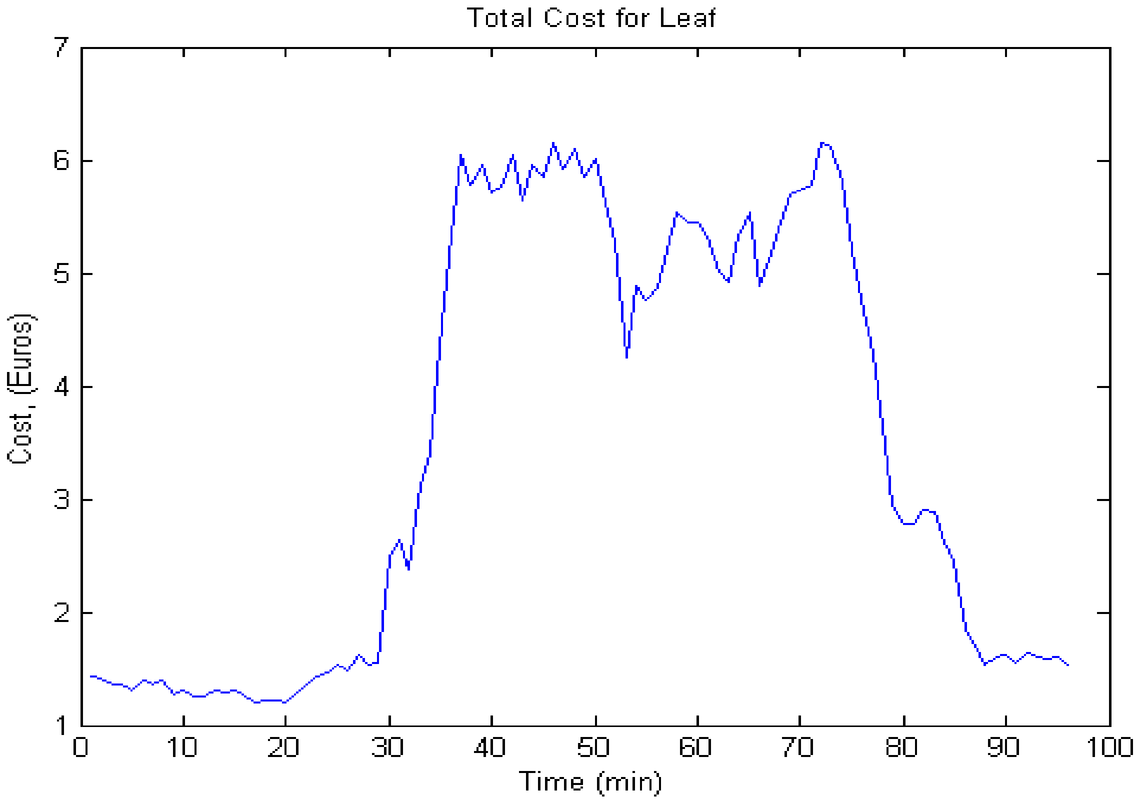


Figure 10.5: Total cost for Leaf Community on 15th January 2013, considering BPS= 30kWh and max_energy =40kWh

It is obvious at Figure 10.2 that during the 15th of January 2013, Leaf Community must buy energy all day in order to cover its demands, while a small amount of them are covered by using ESS (Figure 10.3). This management was decided by the genetic algorithm for this specific day, in order to achieve the optimum minimum total cost (Figure 10.5).

10.1.2 Scenario 2

The second scenario considers as date the 15th of January 2013, BPS=30kWh and max_energy= 10kWh. The optimum cost as it was calculated by genetic algorithm is 705 €. The results are shown at Figure 10.6.

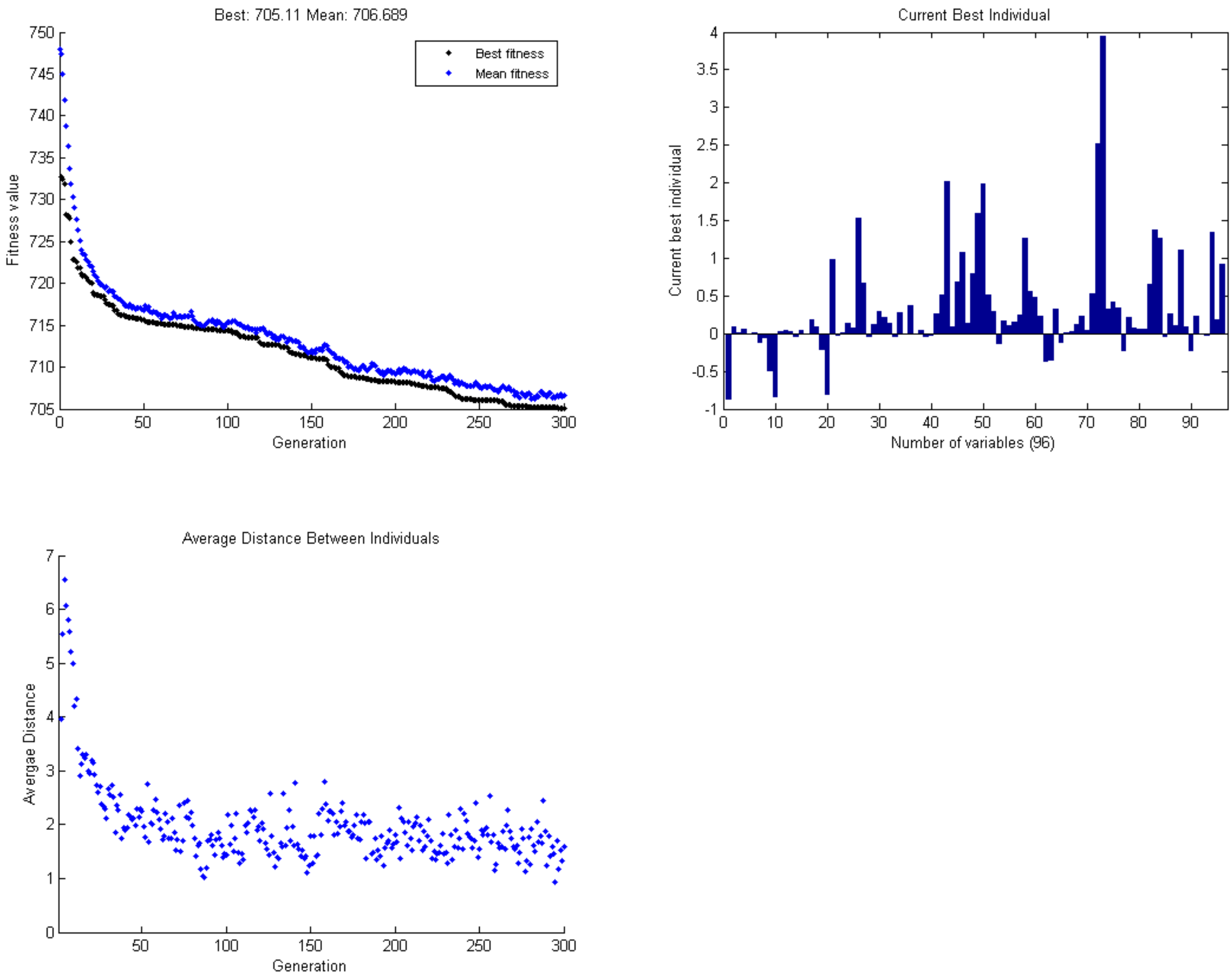


Figure 10.6: Plots of Best fitness, Current Best Individual and Average Distance (15/1/2013, BPS=30 kWh, max_energy=10kWh)

In this case, Leaf Community must pay much more money in relation to the first case because the maximum energy purchased of the previous day is lower than the present. So it pays the extra cost per month which is required by Italian law. However, the discharging of ESS (positive values – best individual) is more prominent now comparing the results of Figure 10.7 with those at Figure 10.2 and Leaf Community must

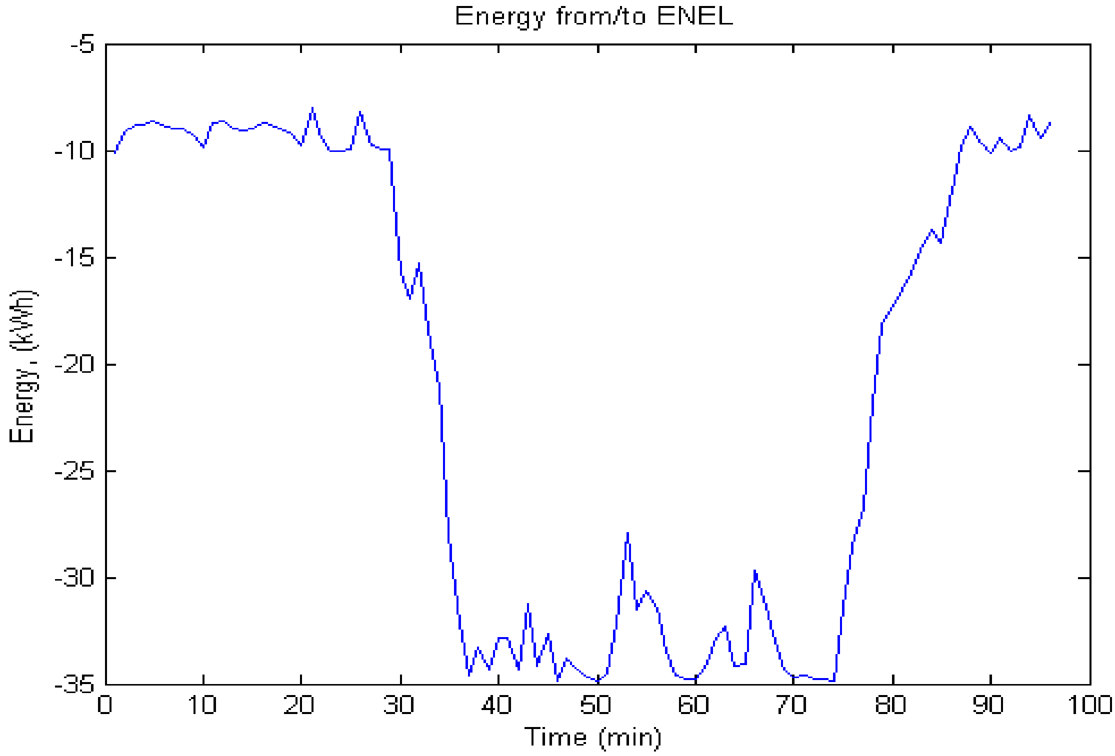


Figure 10.7: Energy from/to ENEL on 15th January 2013, considering BPS=30 kWh and max_energy=10 kWh

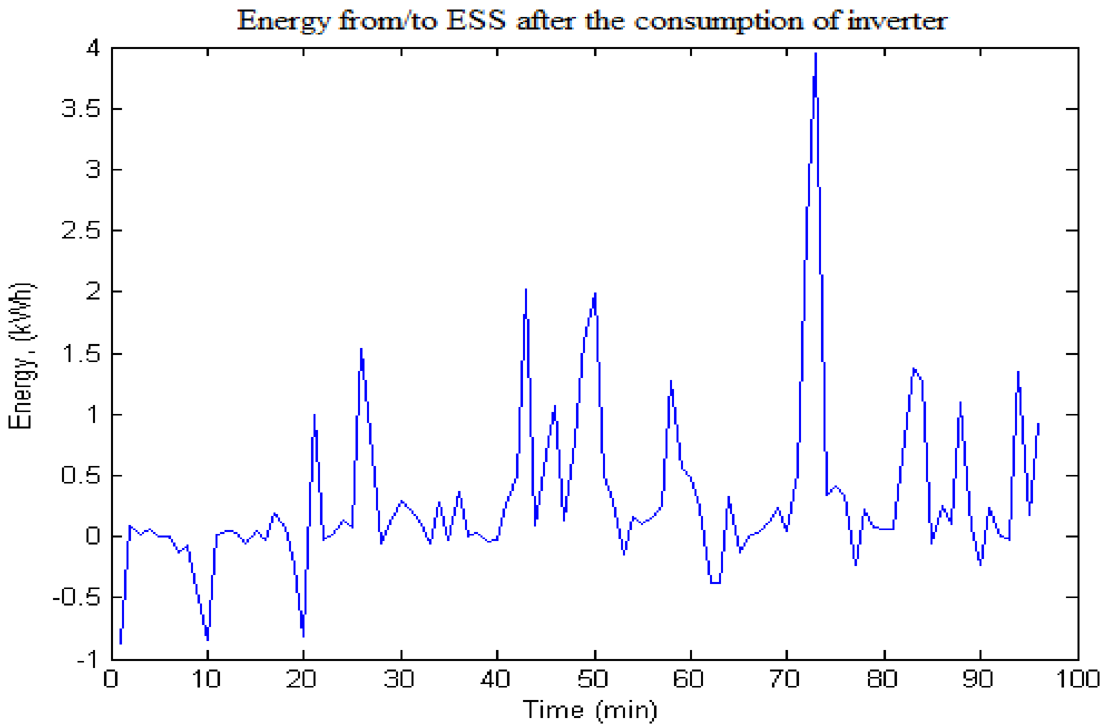


Figure 10.8: Energy charged/discharged at ESS on 15th January 2013, considering BPS=30 kWh and max_energy=10 kWh

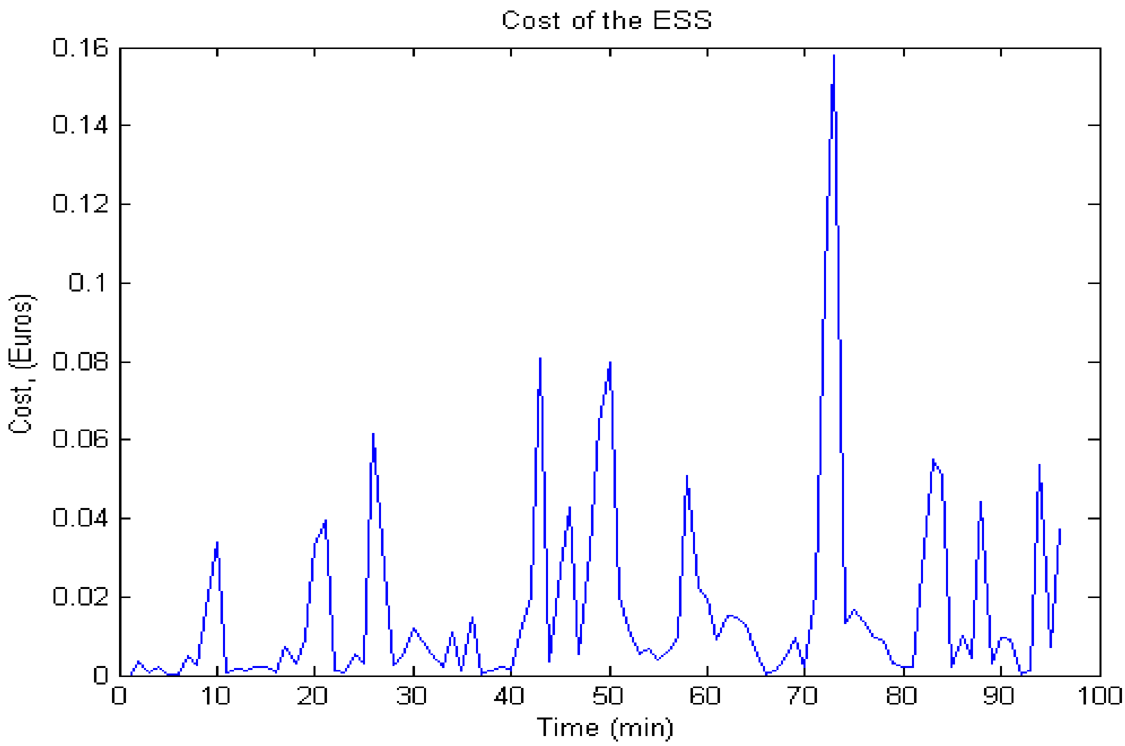


Figure 10.9: Cost of charging/discharging ESS on 15th January 2013, considering BPS=30 kWh and max_energy=10 kWh

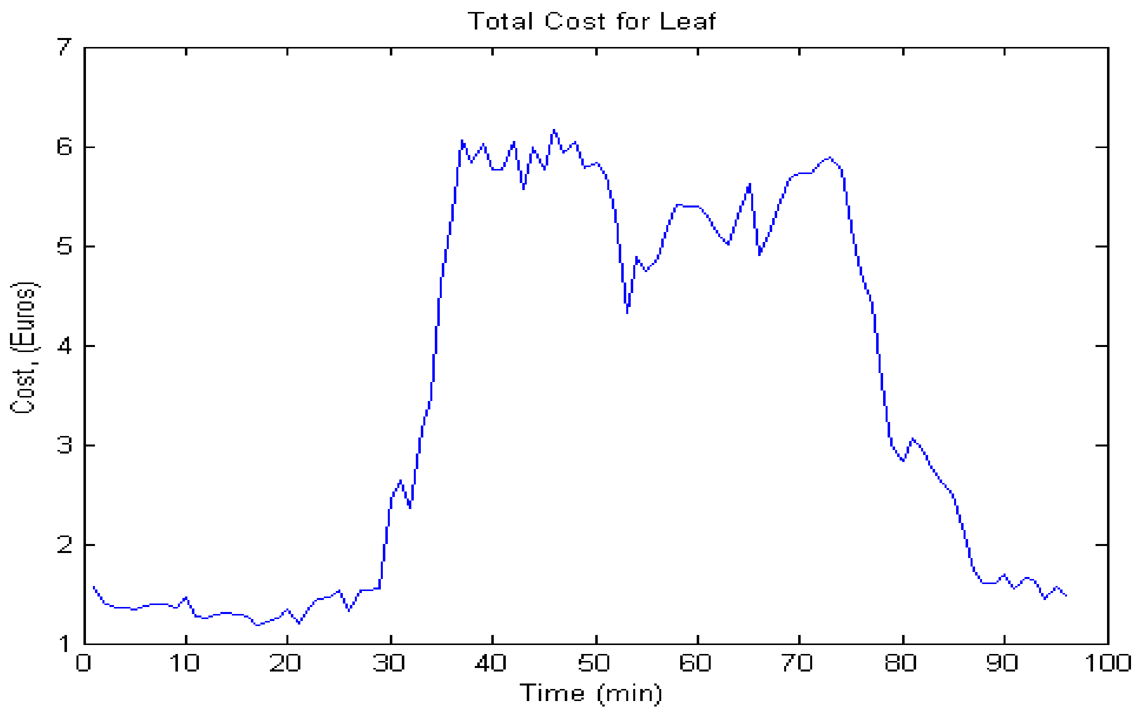


Figure 10.10: Total cost for Leaf Community on 15th January 2013, considering BPS= 30kWh and max_energy =10kWh

Comparing the energy taken from ENEL for those two scenarios described above (Figure 10.2, Figure 10.7) small differences are obvious during the 24 h of that day, but the maximum energy during that day is more than 10kWh that was set for the day before. Therefore, Leaf Community must pay 10.76 €/kWh for the maximum energy will be bought from ENEL. The algorithm decides to optimize the cost by using more the ESS and increasing its cost (Figure 10.9) in the second scenario because it takes into account the extra cost must be paid.

At these two scenarios were presented above, it was examined the behavior of genetic algorithm considering that the ESS contains an initial energy, while the parameter of interest, the maximum energy purchased of the previous day, was changed.

The next two following scenarios (scenario 3 and 4) consider that ESS is empty at the beginning of the day, while the maximum energy purchased of the previous day takes the same values as before (10kWh and 40kWh).

10.1.3 Scenario 3

A third scenario includes as date the 15th of January 2013, BPS=0 kWh and max_energy=40kWh. The optimum cost for Leaf Community is the amount of 334 €, which is also shown at Figure 10.11.

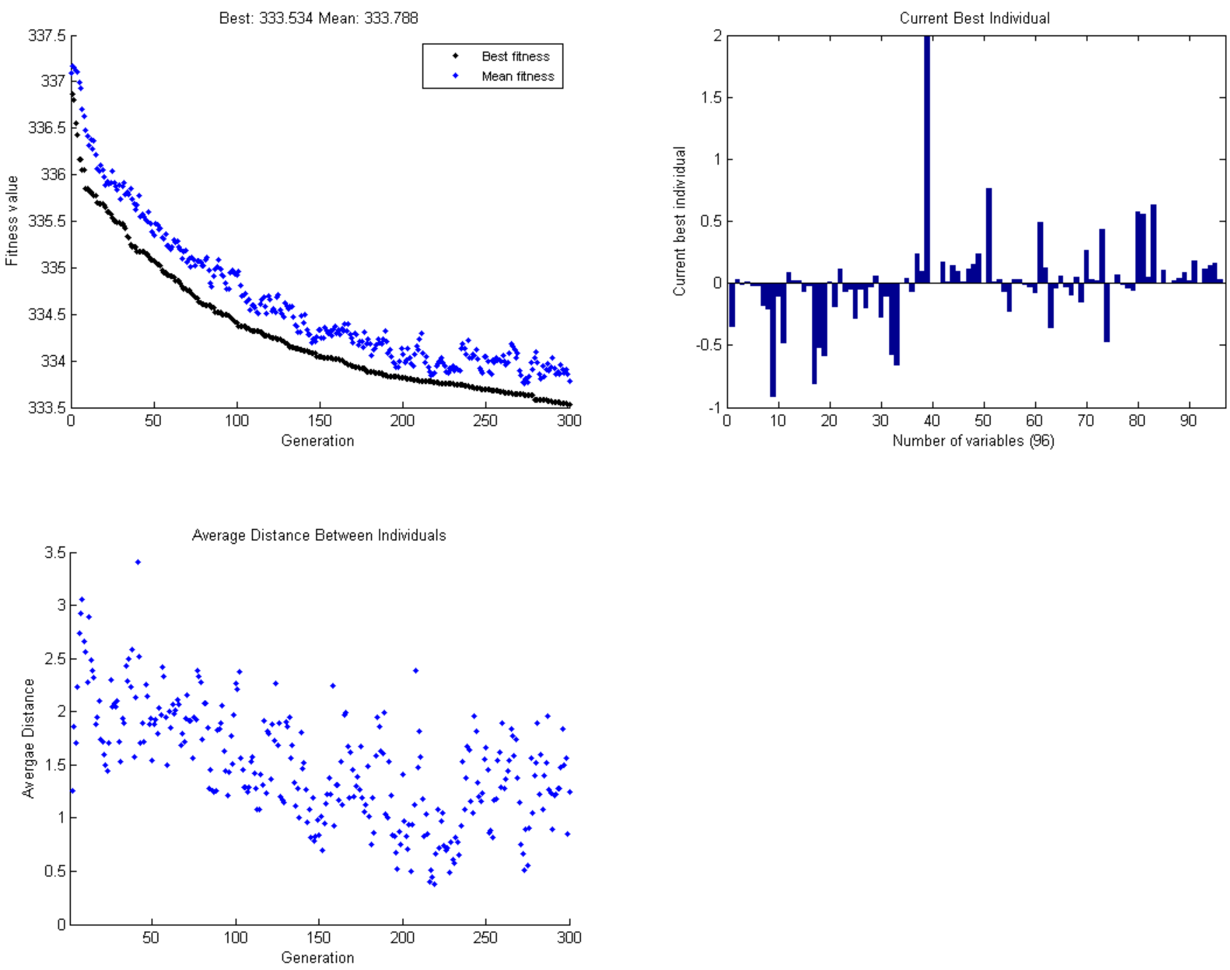


Figure 10.11: Plots of Best fitness, Current Best Individual and Average Distance (15/1/2013, BPS=0 kWh, max_energy=40kWh)

As it was mentioned before the total cost for Leaf Community in this case is 334 €. Comparing this result with scenario 1 (Total cost= 329€) the difference is not remarkable but it is obvious comparing the energy charged/discharged (Figure 10.3, Figure 10.13) the algorithm here decides charge more the ESS than previously at scenario 1.

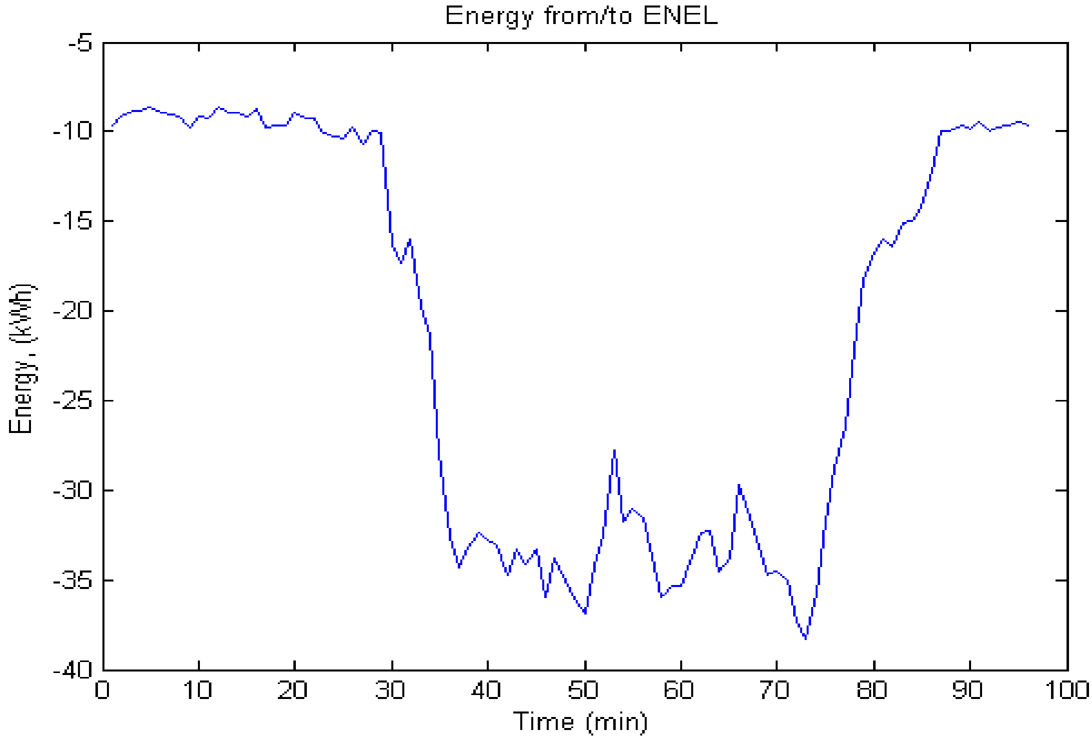


Figure 10.12: Energy from/to ENEL on 15th January 2013, considering BPS=0 kWh and max_energy=40 kWh

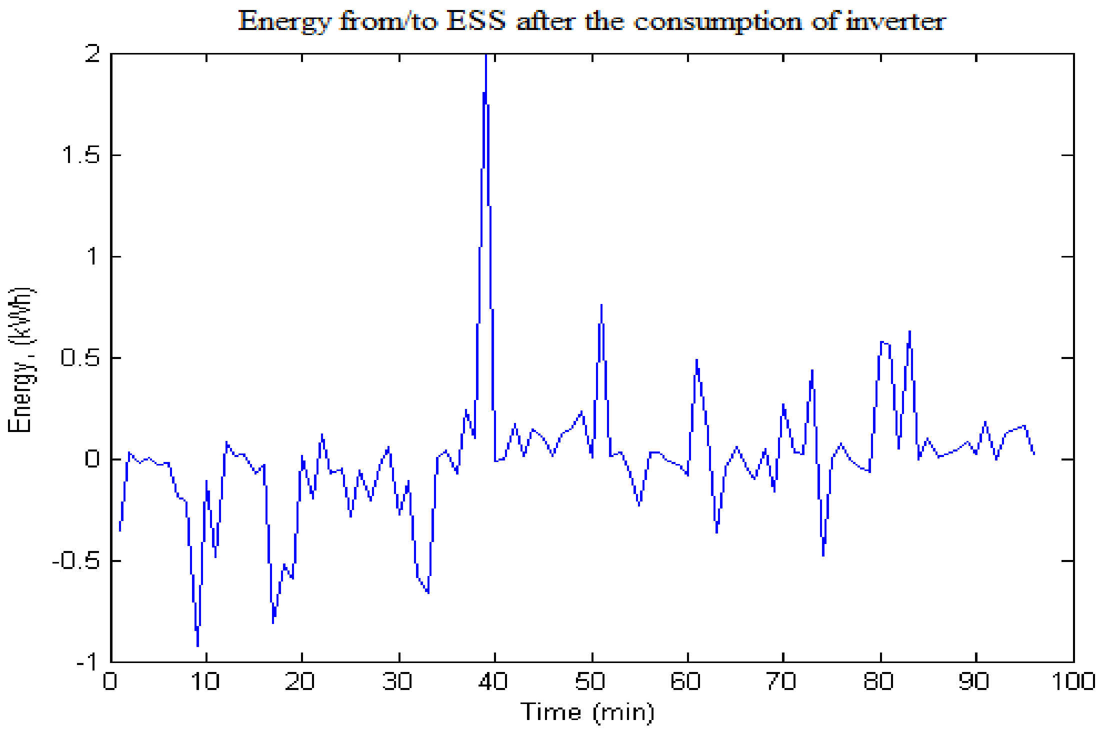


Figure 10.13: Energy charged/discharged at ESS on 15th January 2013, considering BPS=0 kWh and max_energy=40 kWh

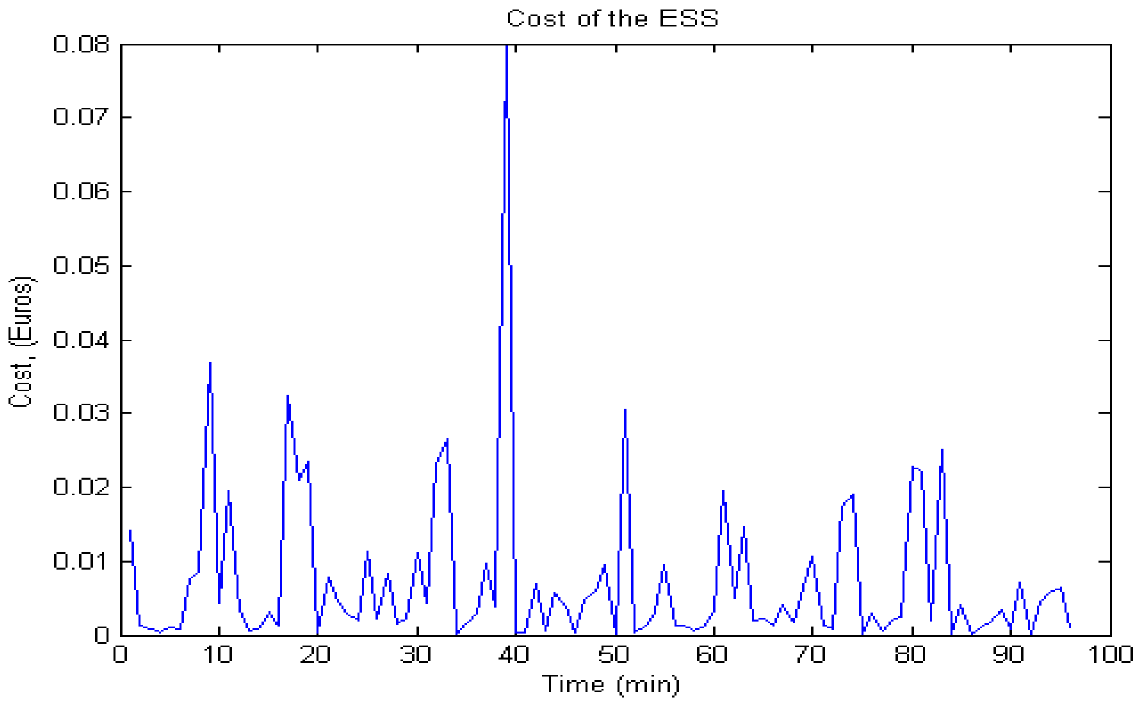


Figure 10.14: Cost of charging/discharging ESS on 15th January 2013, considering BPS=0 kWh and max_energy=40 kWh

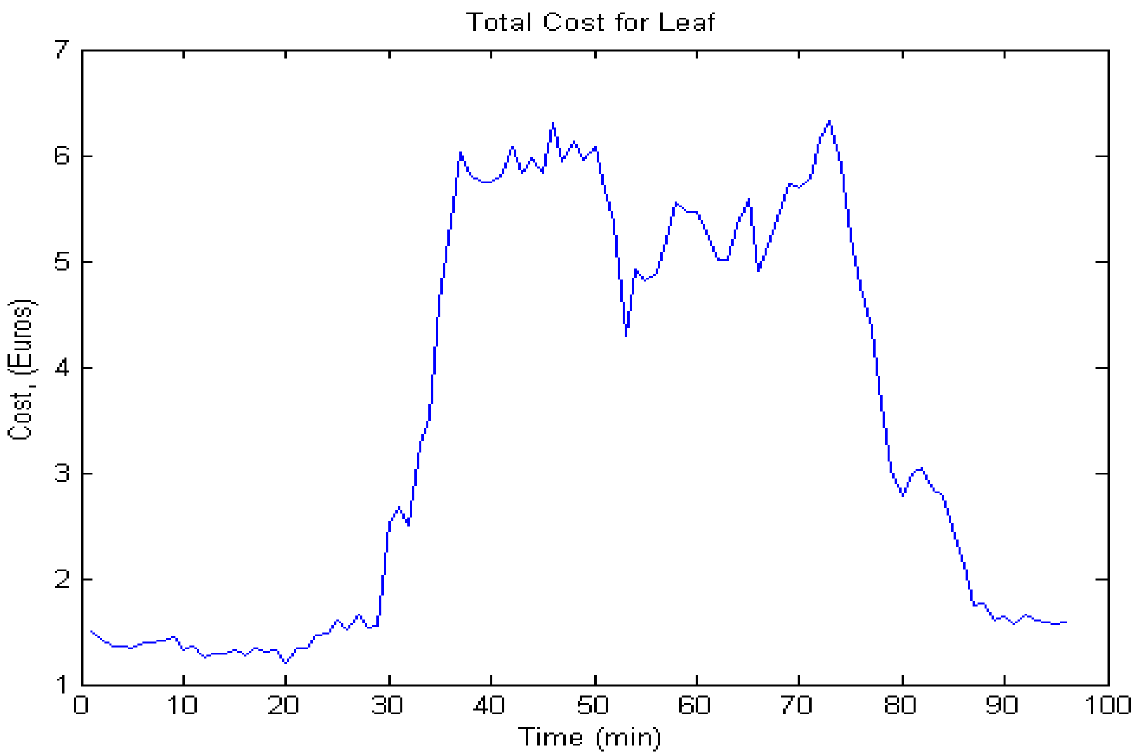


Figure 10.15: Total cost for Leaf Community on 15th January 2013, considering BPS=0kWh and max_energy =40kWh

10.1.4 Scenario 4

Considering an empty ESS for 15th of January 2013 and as maximum energy purchased of the previous day the value 10kWh, Leaf Community must pay 713 € (Figure 10.16).

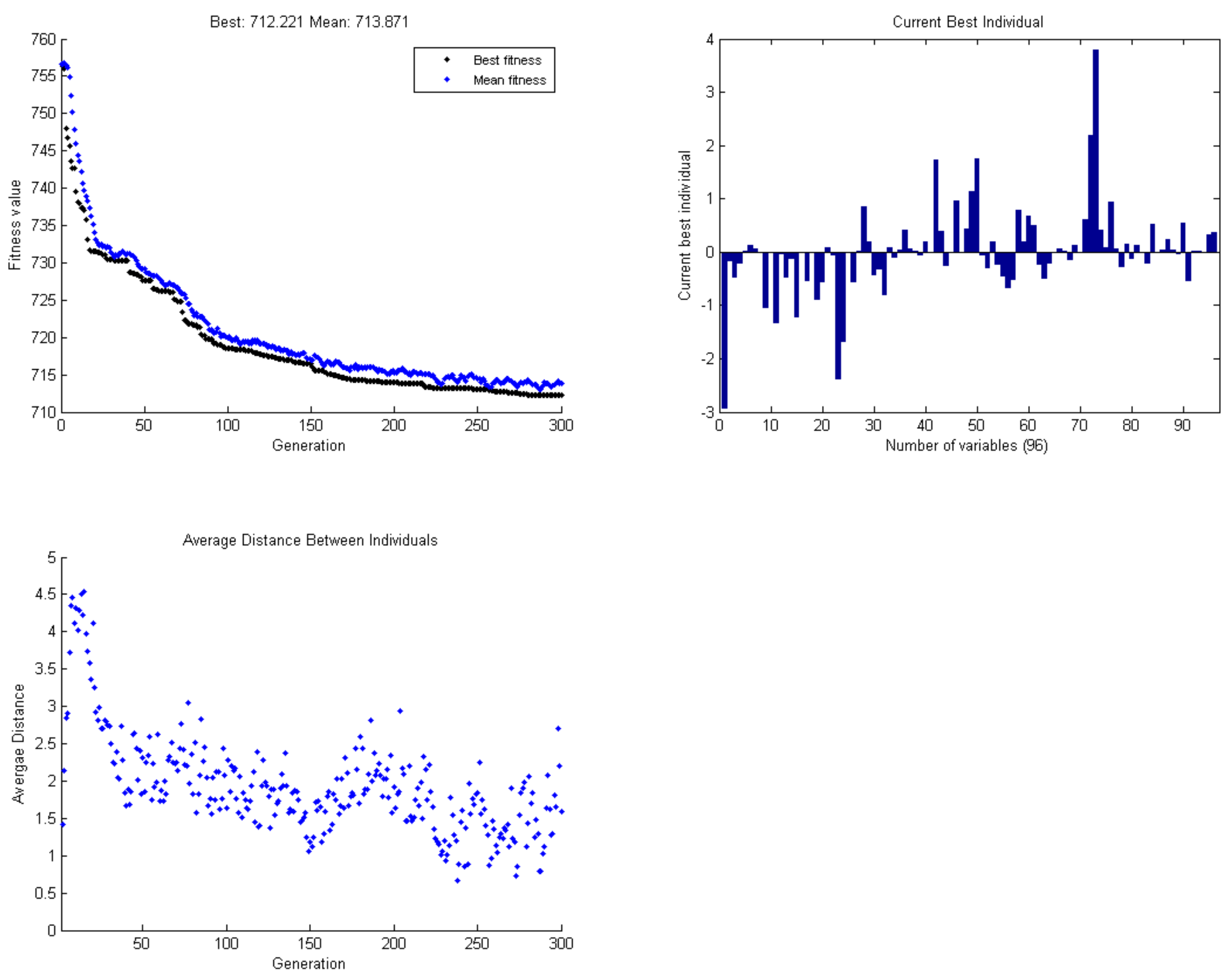


Figure 10.16: Plots of Best fitness, Current Best Individual and Average Distance (15/1/2013, BPS=0 kWh, max_energy=10kWh)

At scenario 2 where BPS= 30 kWh and the maximum energy purchased of the day before was the same as here, the total cost for the Leaf Community was 705 €, while here is 713 €. Here, the algorithm takes into account that ESS can't be use to cover some demands of Leaf Community like before at the start of the day and decides to charge it with small amounts of energy that can be used when the purchased price of energy from ENEL is not advantageous.

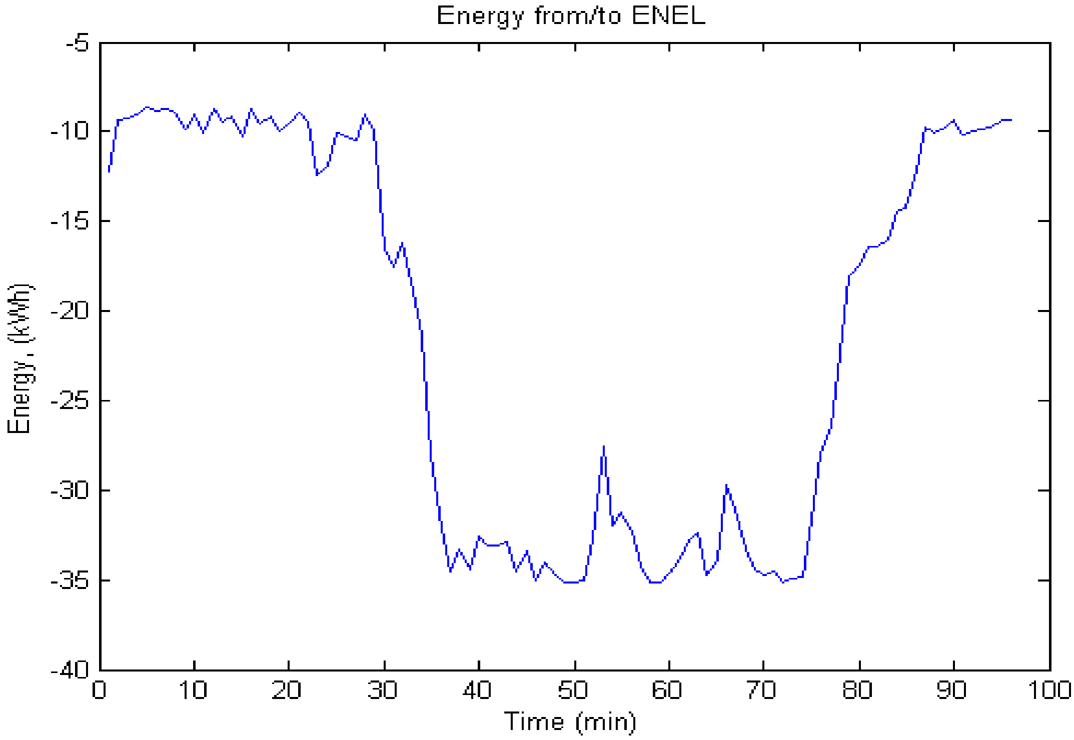


Figure 10.17: Energy from/to ENEL on 15th January 2013, considering BPS=0 kWh and max_energy=10 kWh

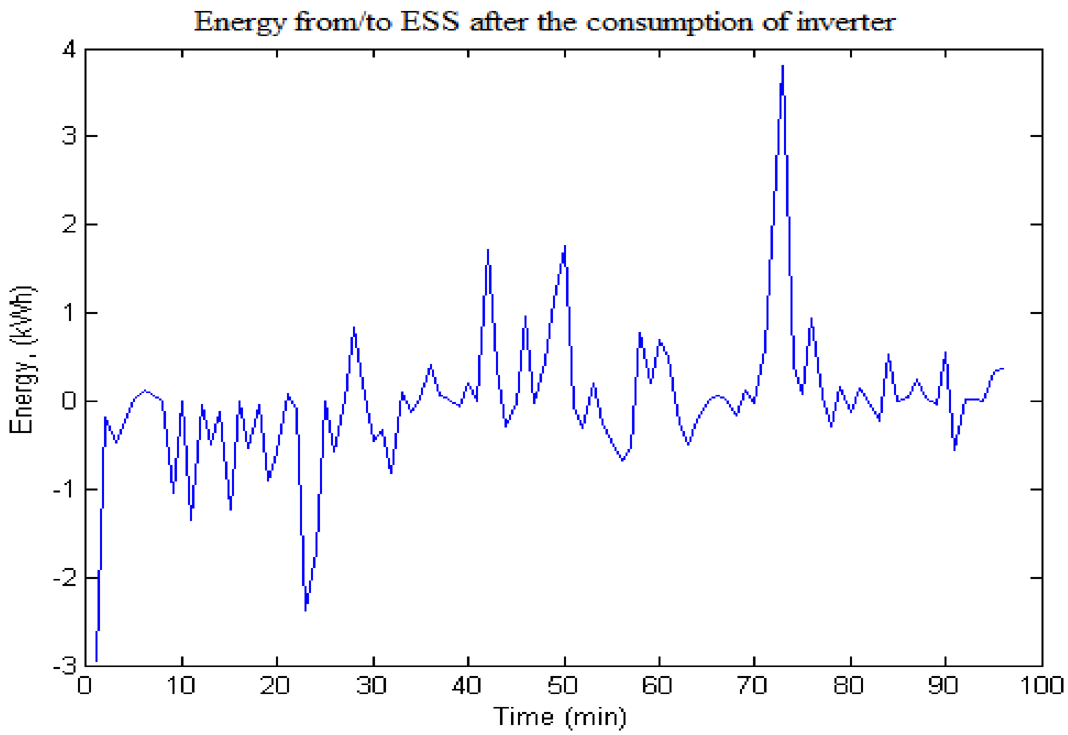


Figure 10.18: Energy charged/discharged at ESS on 15th January 2013, considering BPS=0 kWh and max_energy=10 kWh

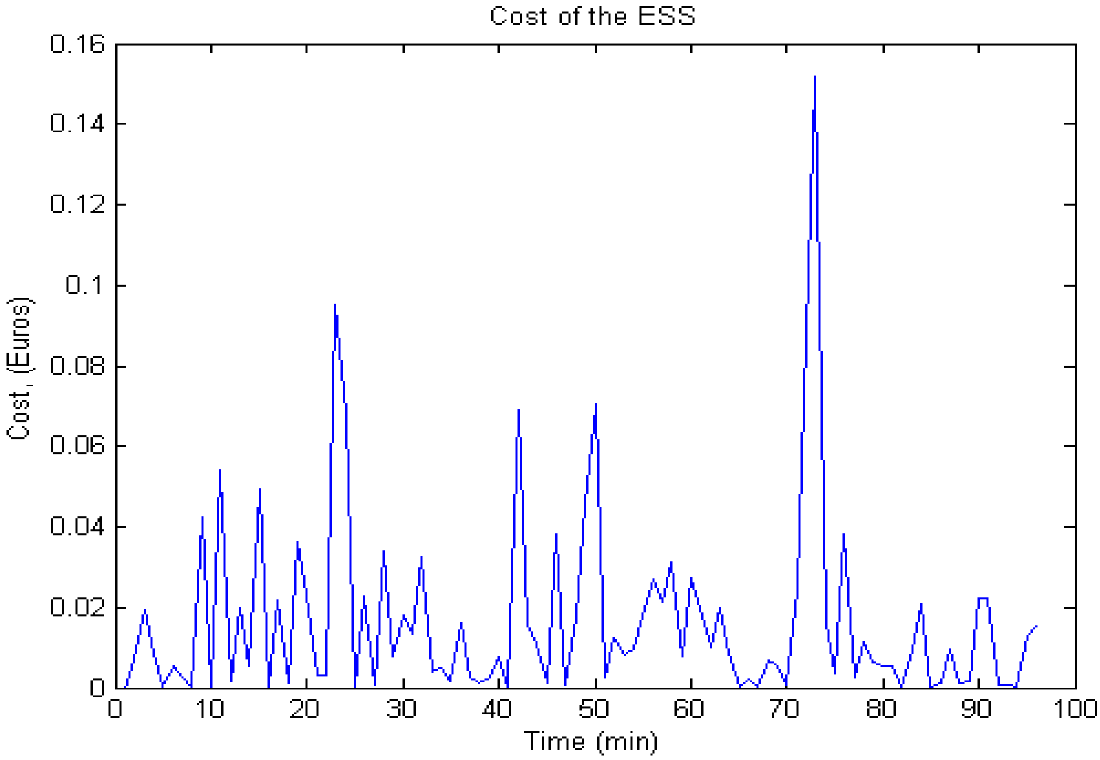


Figure 10.19: Cost of charging/discharging ESS on 15th January 2013, considering BPS=0 kWh and max_energy=10 kWh

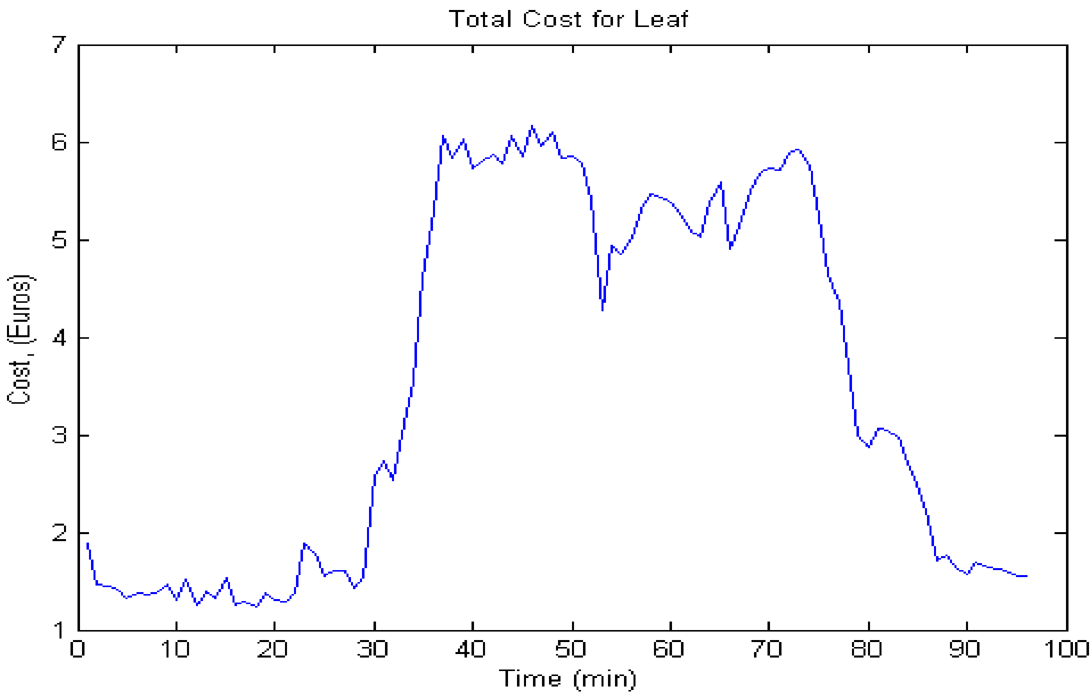


Figure 10.20: Total cost for Leaf Community on 15th January 2013, considering BPS=0kWh and max_energy =10kWh

10.2 Scenarios with Hydroelectric Station

Observing the available consumptions of “Leaf farm” and “Leaf Working”, it was noticed that demands could be covered from Hydroelectric’s production which produces more energy than needed during all the hours of the days. The remaining energy can be stored to ESS or sold to ENEL. For that reason, at scenario 5 and 6 the extra cost per month is not taking into account.

10.2.1 Scenario 5

The next two scenarios consider the operation of Hydroelectric station. Figure 10.21 shows the result by setting as date the 3rd of May 2013, BPS=30kWh and max_energy=10kWh.

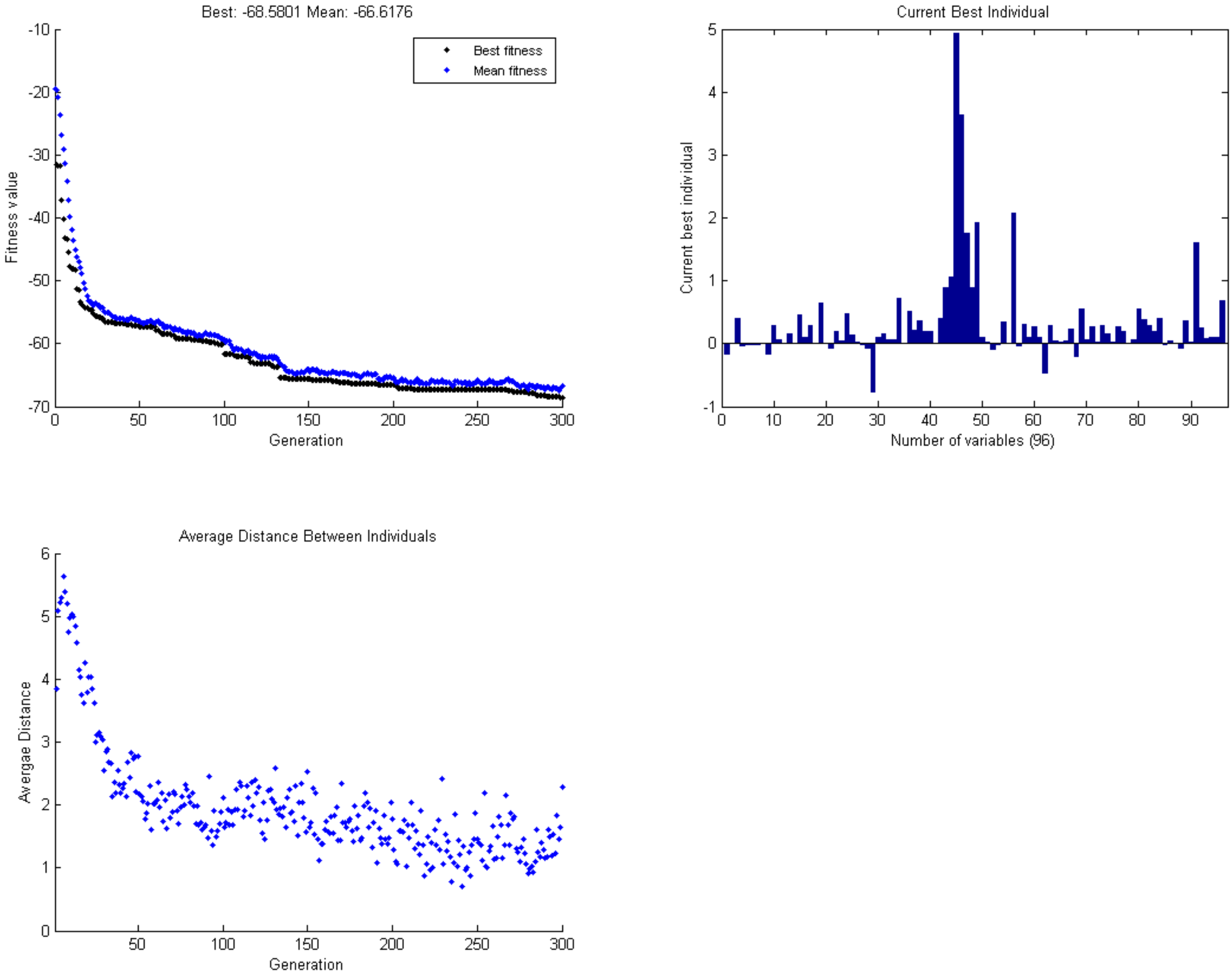


Figure 10.21: Plots of Best fitness, Current Best Individual and Average Distance (3/5/2013, BPS=30 kWh, max_energy=10kWh)

In this case, Leaf Community earns money and specifically 66 € by selling energy to the main grid (negative cost means profits). Except from selling energy, in this case the stored energy also used for covering the needs of Leaf Community (Figure 10.23), because the profits from selling are more than the cost of using the ESS.

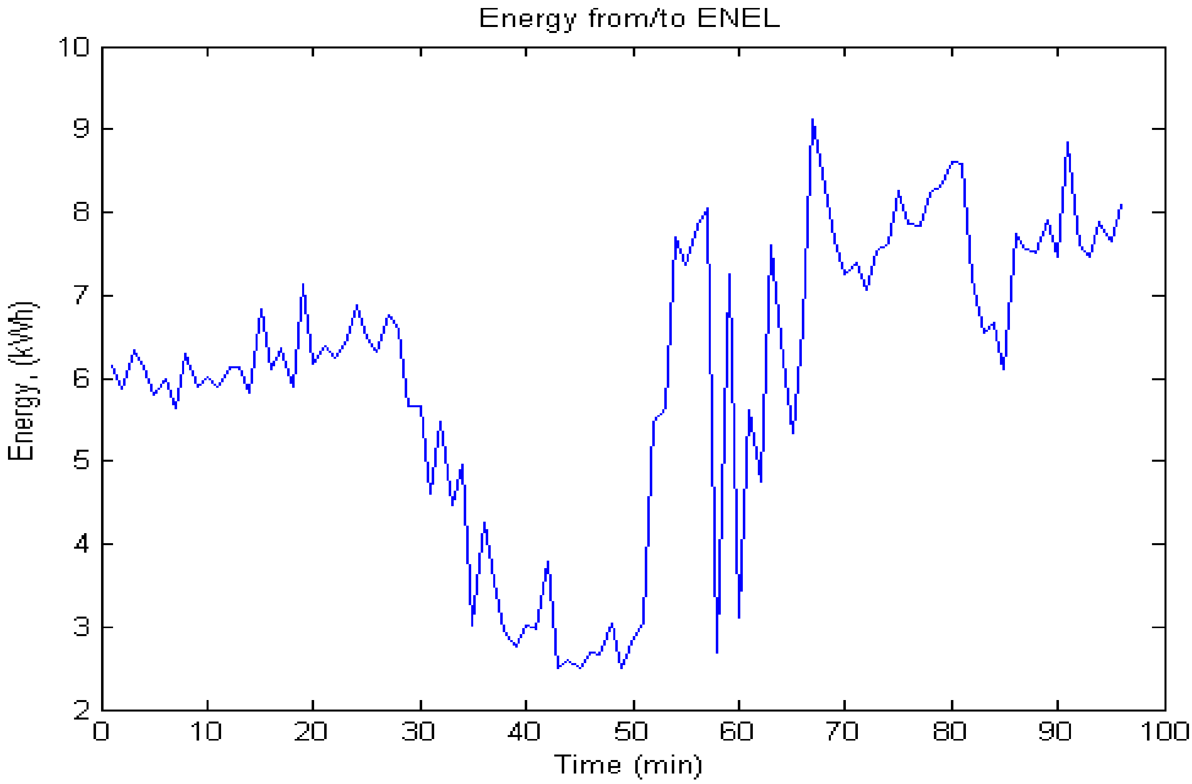


Figure 10.22: Energy from/to ENEL on 3th May 2013, considering BPS=30 kWh and max_energy=10 kWh

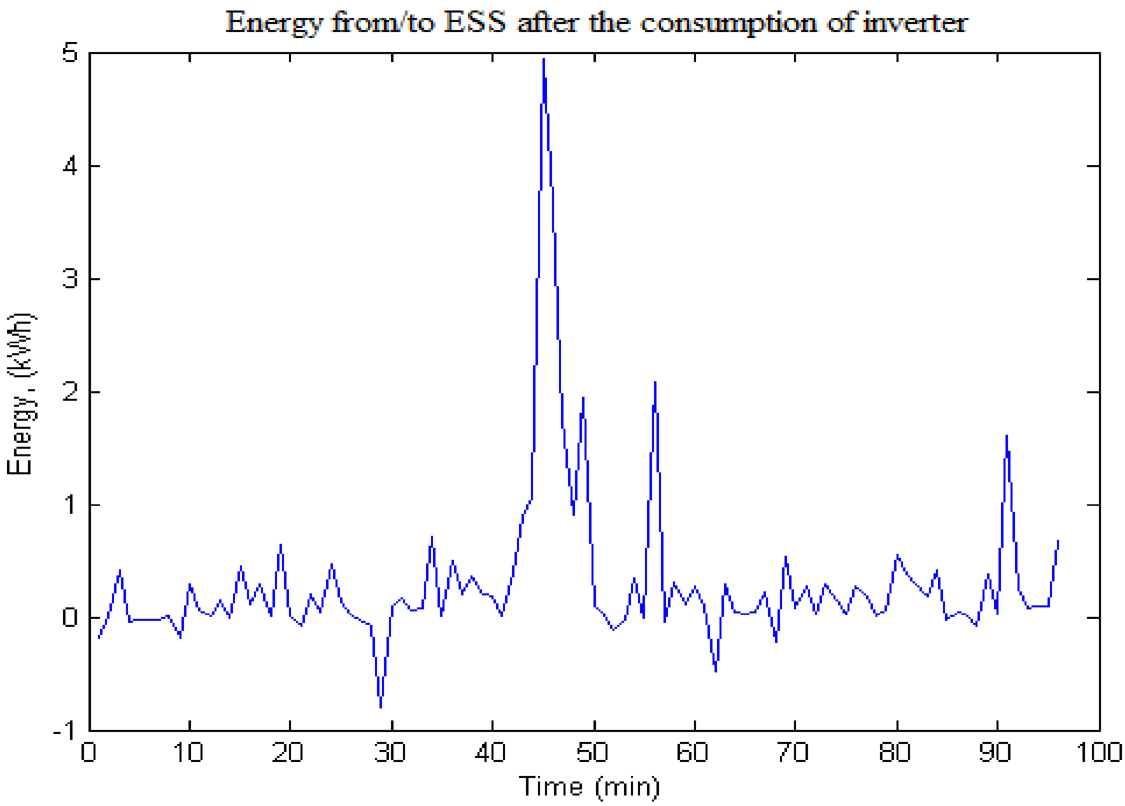


Figure 10.23: Energy charged/discharged at ESS on 3th May 2013, considering BPS=30 kWh and max_energy=10 kWh

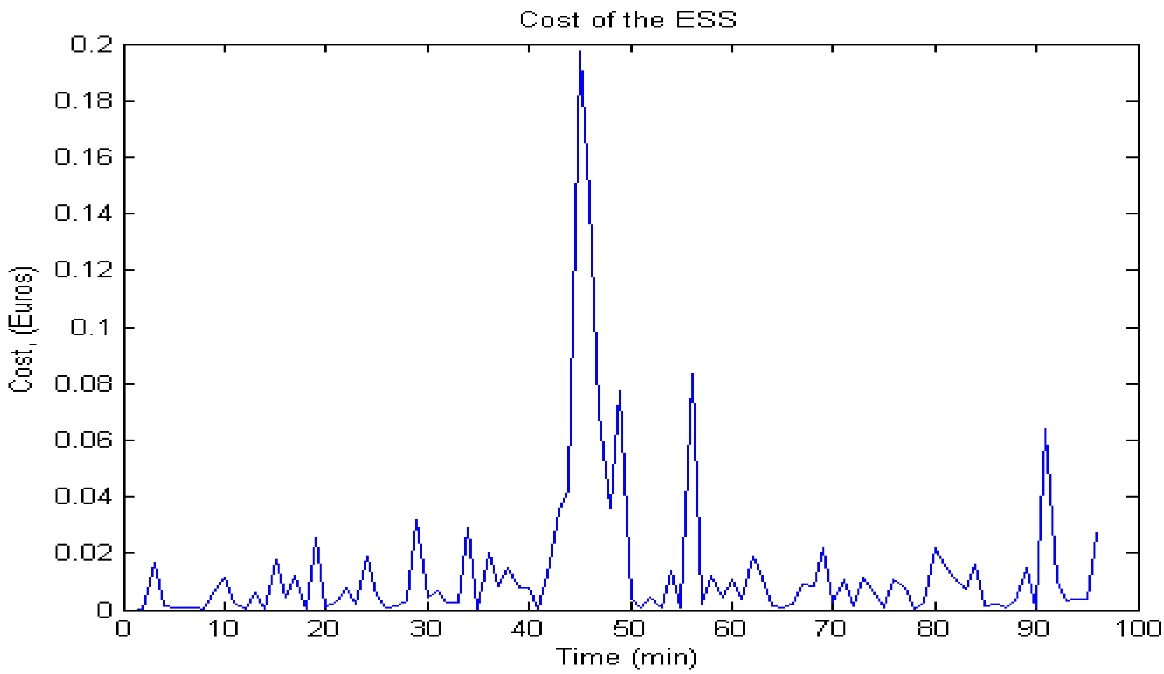


Figure 10.24: Cost of charging/discharging ESS on 3th May 2013, considering BPS=30 kWh and max_energy=10 kWh

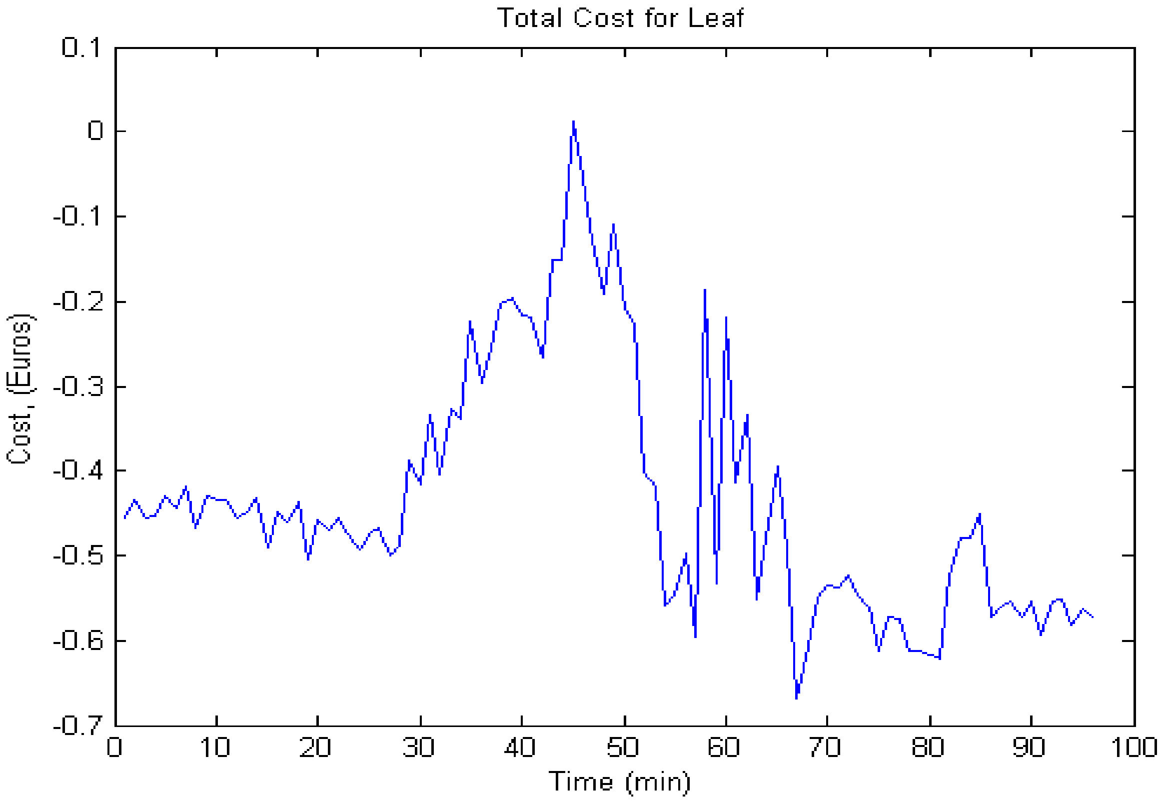


Figure 10.25: Total cost for Leaf Community on 3th May 2013, considering BPS=30kWh and max_energy =10kWh

10.2.2 Scenario 6

Considering that BPS is 0 kWh while the other inputs are the same, the profits are 58€ approximately, as Figure 10.26 shows below.

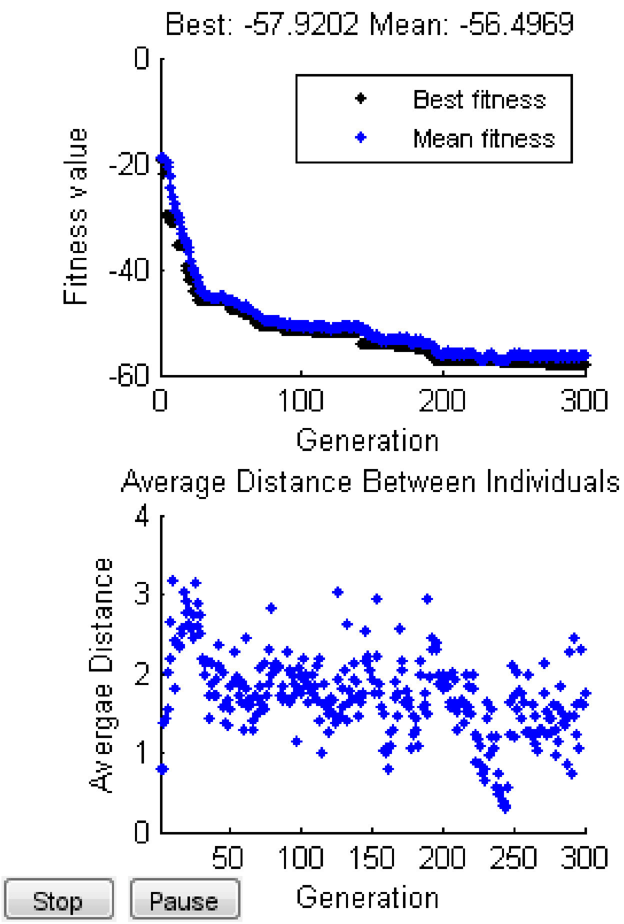


Figure 10.26: Plots of Best fitness, Current Best Individual and Average Distance (3/5/2013, BPS=0kWh, max_energy=10kWh)

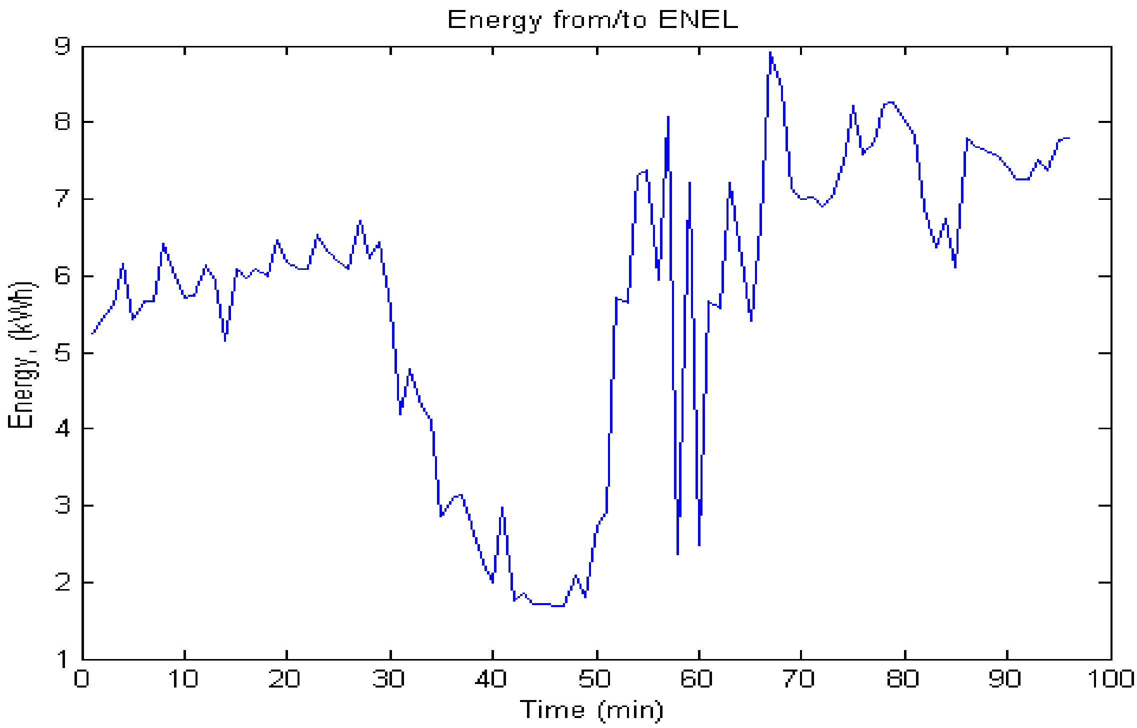


Figure 10.27: Energy from/to ENEL on 3th May 2013, considering BPS=0 kWh and max_energy=10 kWh

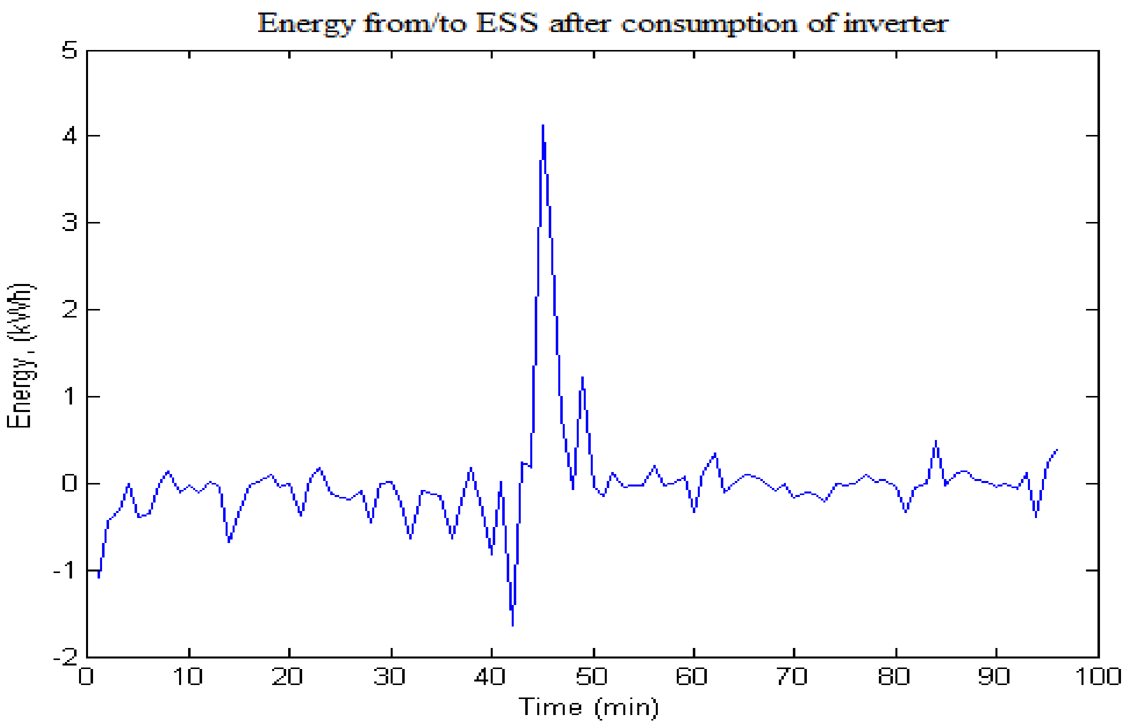


Figure 10.28: Energy charged/discharged at ESS on 3th May 2013, considering BPS=0 kWh and max_energy=10 kWh

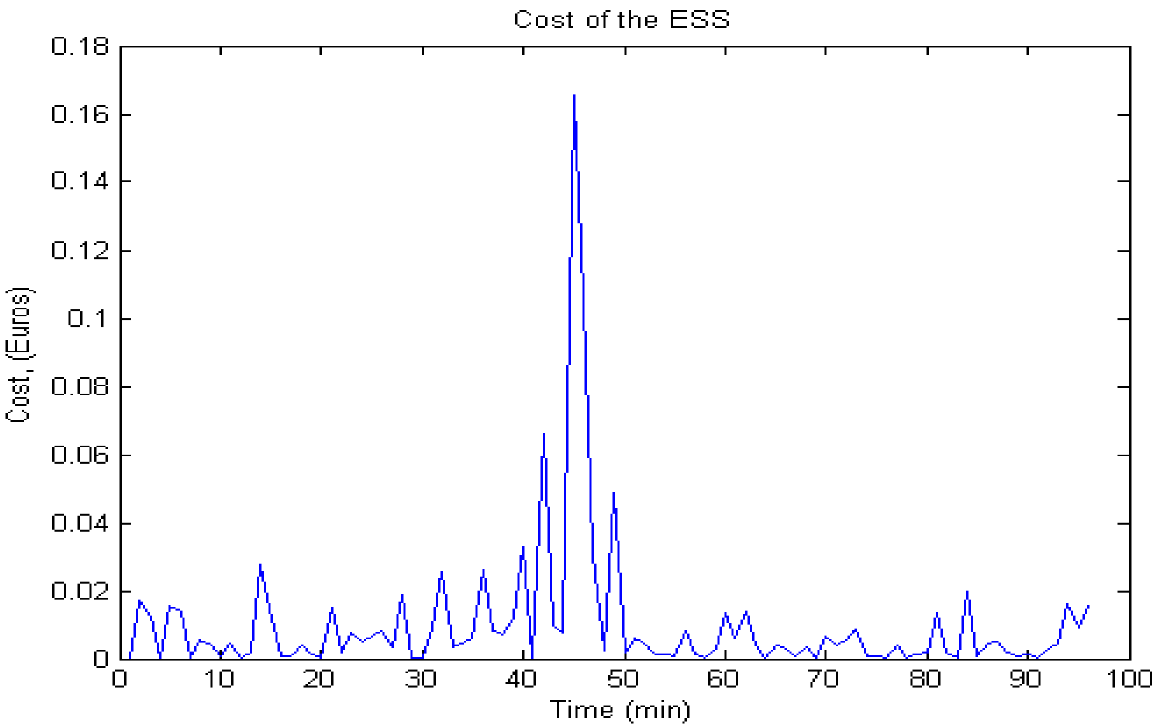


Figure 10.29: Cost of charging/discharging ESS on 3th May 2013, considering BPS=0 kWh and max_energy=10 kWh

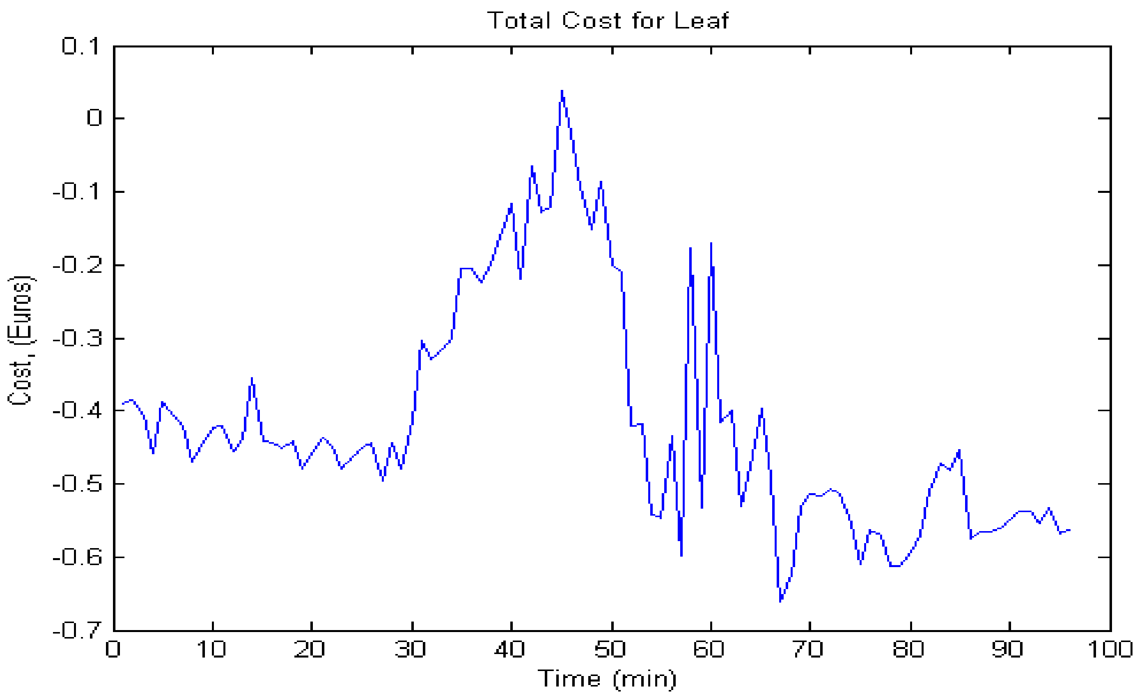


Figure 10.30: Total cost for Leaf Community on 3th May 2013, considering BPS=0kWh and max_energy =10kWh

The results from the last two scenarios where the Hydroelectric station is assumed that operates, show that Leaf Community earns money by selling energy either the initial battery state is zero either not. Also, it is obvious that the algorithm decides to sell the energy than charging a lot ESS in order to increase the profits.

The results from all scenarios examined, are gathered at Table 10.1 below and they are comparing with the costs given by genetic algorithm assuming that at Leaf Community microgrid hasn't an ESS.

Table 10.1: Totals results of the current optimization problem

	Hydro doesn't operate			**Hydro operates**		
	ESS	**No ESS**	**Difference**	**ESS**	**No ESS**	**Difference**
BPS=0 kWh &extra cost	713€	750€	37€	-	-	-
BPS=30kWh & extra cost	705€	750€	45€	-	-	-
BPS=0 kWh & no extra cost	334€	333.09€	-1€	-58€	-40€	18€
BPS=30kWh & no extra cost	329€	333.09€	4€	-66€	-40€	26€

According to Table 10.1, when hydroelectric station operates and Leaf Community has no ESS, the profits by selling energy are 40€. On the other hand, when the algorithm takes into account that energy could be charged or discharged from ESS, the profits are 58€ (BPS=0kWh) and 66€ (30kWh). Therefore, even though the use of ESS means cost for Leaf Community, decisions though the optimization model developed, could offer more money.

Same results are observed also in the case that hydroelectric station is not operated. The optimization model was developed in order to decide about the using of the energy of ESS in a way that minimizes the total cost. This was achieved looking and comparing the results above, while the difference is more obvious when Leaf must pay this extra cost required by the law for the maximum energy purchased.

11 CONCLUSIONS

This study focuses on the development of an optimization model for Leaf community microgrid that targets on the minimization of its total energy cost 24h ahead. The model was designed and solved by the method of genetic algorithms.

In order to optimize 24 hours ahead, it was needed to predict the energy produced by the generated units (PV systems and micro hydro) and the energy consumed by the buildings situated at Leaf Community ("Leaf farm" and "Leaf Working) setting as a time horizon 24 hours ahead. That was achieved by using artificial neural networks. The developed feed forward backpropagation algorithms are able to estimate the energy is going to be produced or consumed the next day.

Here, it must be mentioned that the networks were trained by using measurements of previous years and according to the results, it is presumed that larger sets of training data lead to the improvement of the algorithm's performance. Because of this, the energy generated from the hydroelectric plant wasn't predictable by applying this method. The available hydro data series was restricted and the network couldn't be trained successfully. On the other hand, the available data shows that hydro constitutes a domain of producing large amounts of energy and this could offer financial benefits to Leaf Community. For that reason, this plant couldn't be excluded from the optimization model and it was decided to use as predicted energy, an average energy of the previous day because the average difference is not remarkable.

The future values of energy for the generating and consumption points of the microgrid are known. However, the energy fluxes are affected also from the present in the microgrid of an ESS. The energy flows from or to ESS, are determined in this study by a genetic algorithm, which estimates the amounts of energy must be stored or discharged in order to minimize the total energy cost. So, the total energy cost constitutes the objective function that genetic algorithm is called to optimize.

The first job done was the definition of a mathematical formula that includes all the costs of energy in the microgrid. More specifically, the cost is required to optimize, contains the cost of energy must be bought in order to cover the demands if there are some, the profits of selling energy to the main grid and the cost of using the energy storage system either for charging either for discharging. The model was limited by setting the appropriate constrains that mainly are related to the energy storage system in order to avoid having an empty ESS or an unlimited energy flow to it.

In order to evaluate the developed model some scenarios were ran at Matlab that shows the influence of some parameters to the results. More specifically, the parameters were changed, were the amount of the initial battery state and the amount of the maximum energy purchased for the previous day considering that the hydroelectric station is not operated, while it is operated only BPS was changed taking the values 0kWh and 30kWh.

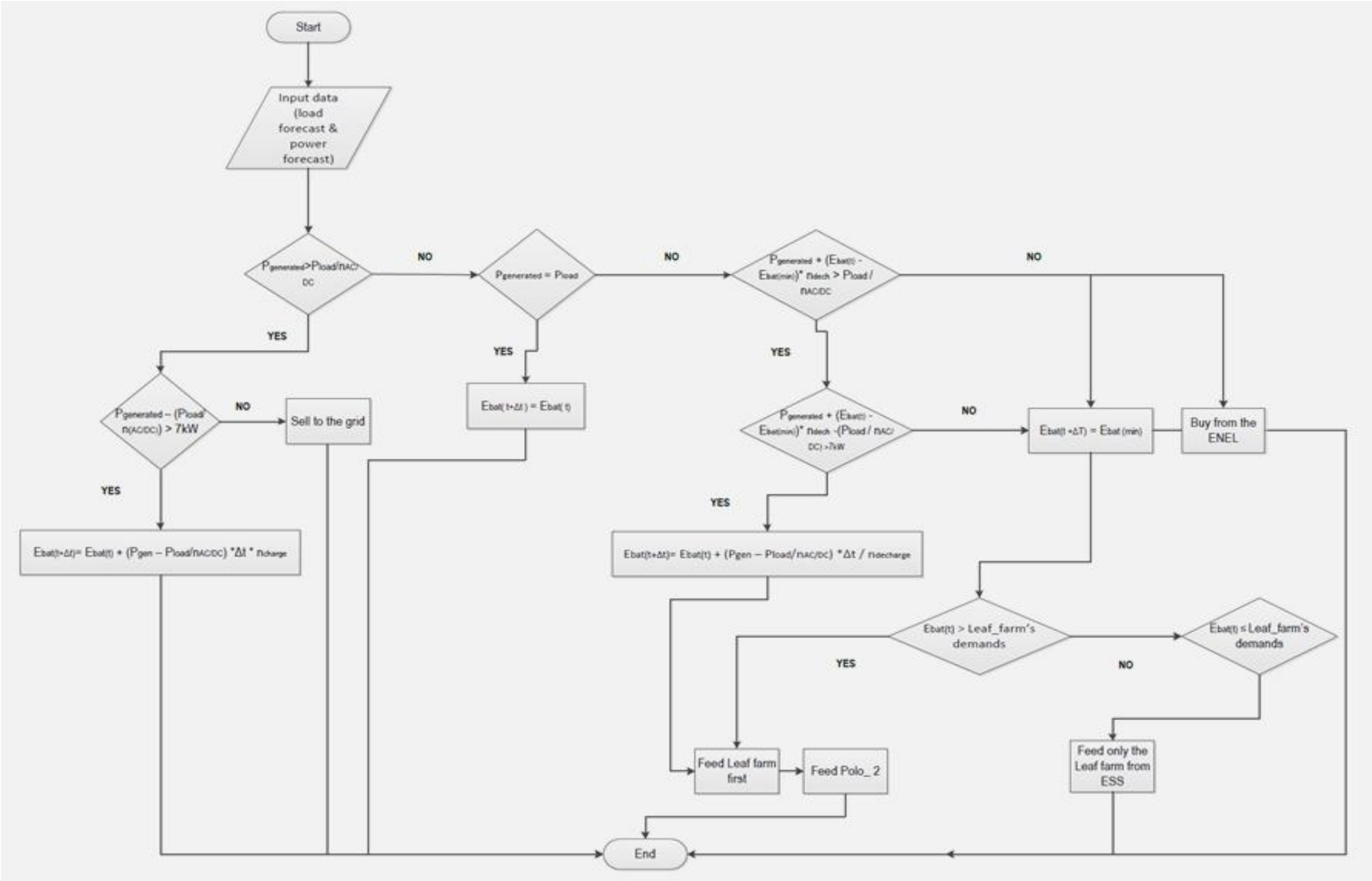
Assuming that the hydro plant doesn't operate, the results shows that Leaf Community can optimize the cost by adding the developed optimization model as it was found, it must pay more money in the case that there is no management plant for the energy storage system. The difference is more significant at the cases when Leaf Community must pay an extra cost per month required by the Italian law.

Except from these, the model obviously decides to use or store small amounts of energy to ESS and prefers to sell the energy generated to the main grid or use it at the consumption points of the microgrid. According to these scenarios, no profits are calculated for the Community, although it was achieved the minimization of the cost must be paid.

The last two scenarios consider that the hydroelectric plant is in operation. The results show that Leaf Community earns money by selling energy to ENEL, while the energy fluxes from or to ESS are not significant.

Finally, it could be mentioned that the hydroelectric station is an important source of earning money for the Leaf Community and its stability could offer except from money, energy that can be stored for future used.

Appendix A: Flow chart of genetics' algorithm function



12 REFERENCES

1. **LASSETER, Robert H.** Smart distribution: Coupled microgrids. *Proceedings of the IEEE.* 2011, 99.6: 1074-1082.

2. **Nikkhajoei, H. and Lasseter, R.H.** Distributed Generation Interface to the CERTS Microgrid. *Power Delivery, IEEE Transactions on* . July 2009, Vol. 24, 3, p. 1598:1608.

3. **Wang, X., Guerrero, J. M., Chen, Z., & Blaabjerg, F.** Distributed energy resources in grid interactive AC microgrids. *In: Power Electronics for Distributed Generation Systems (PEDG), 2010 2nd IEEE International Symposium on.* 2010, pp. 806-812.

4. **Driesen, J. and Katiraei, F.** Design for distributed energy resources. *Power and Energy Magazine, IEEE* . May-June 2008, Vol. 6, 3, pp. 30-40.

5. **Katiraei, F., Iravani, R., Hatziargyriou, N., Dimeas, A.** Microgrids management. *IEEE Power and Energy Magazine.* May 2008, Vol. 6, 3, pp. 54-65.

6. **Basak, P., Saha, A. K., Chowdhury, S., & Chowdhury, S. P.** Control techniques and modeling. *In: Universities Power Engineering Conference (UPEC), 2009 Proceedings of the 44th International.* 2009, pp. 1-5.

7. **PEDRASA, Michael Angelo and SPOONER, Ted.** A survey of techniques used to control microgrid generation and storage during island operation. *In: Proceedings of the Australian Universities Power Engineering Conference.* 2006.

8. **CEH, Ernie Hayden CISSP.** INTRODUCTION TO MICROGRIDS. 2013.

9. **N.W.A. Lidula, A.D. Rajapakse.** Microgrids research: A review of experimental microgrids and test systems. *Renewable and Sustainable Energy Reviews.* January 2011, Vol. 15, 1, pp. 186–202.

10. **Lubna Mariam, Malabika Basu, and Michael F. Conlon.** A Review of Existing Microgrid Architectures. *Journal of Engineering.* 2013, Vol. 2013.

11. **Madureira, André Guimarães.** *COORDINATED AND OPTIMIZED VOLTAGE MANAGEMENT OF DISTRIBUTION NETWORKS WITH MULTI-MICROGRIDS.* s.l. : Faculty of Engineering of University of Porto, 2010.

12. **Winkler, G., Meisenbach, C., Hable, M., & Meier, P.** Intelligent energy management of electrical power systems with distributed feeding on the basis of forecasts of demand and generation. *In: Electricity Distribution, 2001. Part 1: Contributions. CIRED. 16th International Conference and Exhibition on (IEE Conf. Publ No. 482). IET.* 2001, Vol. 4.

13. **A. Llaria, O. Curea, J. Jiménez, H. Camblong.** Survey on microgrids: unplanned islanding and related inverter control techniques. *Renewable Energy.* 2011, Vol. 36, pp. 2052-2061.

14. **O. Hafez, K. Bhattacharya.** Optimal planning and design of a renewable energy based supply system for microgrids. *Renewable Energy.* 2012, Vol. 45, pp. 7-15.

15. **G. Kyriakarakos, A.I. Dounis, K.G. Arvanitis, G. Papadakis.** A fuzzy logic energy management system for polygeneration microgrids. *Renewable Energy.* 2012, Vol. 41, pp. 315-327.

16. **C.A. Hernandez-Aramburo, T.C. Green, N. Mugniot.** Fuel consumption minimization of a microgrid. *Industry Applications, IEEE Transactions on.* 2005, Vol. 41, pp. 673-681.

17. **F.A. Mohamed, H.N. Koivo.** Microgrid online management and balancing using multiobjective optimization. *Power Tech, IEEE Lausanne.* 2007, pp. 639-644.

18. **Mohamed F.A., Koivo H.N.** Online management genetic algorithms of microgrid for residential application. *Energy Conversion and Management.* 2012, Vol. 64, pp. 562-568.

19. **H. Liang, H. Goo.** Unit commitment in microgrids by improved genetic algorithm. *IPEC.* 2010, pp. 842-847.

20. **M. Stadler, C. Marnay, N. DeForest, J. Eto, G. Cardoso, D. Klapp, J. Lai.** Web-based economic and environmental optimization of microgrids. *Innovative Smart Grid Technologies (ISGT), IEEE PES.* 2012, pp. 1-2.

21. **G. K. Smyth, A. H. El-shaarawi, and W. W. Piegorsch.** Optimization Optimization. *Encyclopedia of Environmetrics.* 2002, Vol. 3, pp. 1481–1487.

22. **Smyth, Gordon K.** Optimization. *Encyclopedia of Environmetrics.* 2002, Vol. 3, pp. 1481–1487.

23. **Kumar, D Nagesh.** *Classical and Advanced Techniques for optimization.* s.l. : Lecture notes.

24. **Charbonneau, P.** An introduction to genetic algorithms for numerical optimization. 2002.

25. **A.R. Simpson, G.C. Dandy, L.J. Murphy.** Genetic algorithms compared to other techniques for pipe optimization. *Journal of Water Resources Planning and Management.* 1994, Vol. 120, 4, pp. 423-443.

26. **Abdoun, O., & Abouchabaka, J.** A Comparative study of adaptive crossover operators for genetic algorithms to resolve the traveling salesman problem. 2012.

27. **Mathworks.** Global Optimization Toolbox User's Guide, Matlab. 2014.

28. **A. Rangel-Merino, J. López-Bonilla, R.L. y Miranda.** Optimization method based on genetic algorithms. *Apeiron.* 2005, Vol. 12, pp. 393-406.

29. **Rahul Malhotra, Narinder Singh, Yaduvir Singh.** Genetic Algorithms: Concepts, Design for Optimization of Process Controllers . *Computer and Information Science.* Vol. 4, 2, p. 39.

30. **Sivaraj, R., and T. Ravichandran.** A review of selection methods in genetic algorithm. *International journal of engineering science and technology.* 2011, Vol. 3, 5, pp. 3792-3797.

31. **MAGALHÃES-MENDES, JORGE. A.** Comparative Study of Crossover Operators for Genetic Algorithms to Solve the Job Shop Scheduling Problem. 2013, Vol. 12, 4, pp. 164-173.

32. **Abdoun, O., Abouchabaka, J., & Tajani, C.** Analyzing the Performance of Mutation Operators to Solve the Travelling Salesman Problem. *arXiv preprint arXiv:1203.3099.* 2012.

33. **Howard Demuth, Mark Beale.** Neural network toolbox for use with MATLAB. 1992-2002.

34. **M.W Gardner, S.R Dorling.** Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences. 1998, Vol. 32, 14-15, pp. 2627–2636.

35. **Daniel Svozil, Vladimir KvasniEka, JiE Pospichal.** Introduction to multi-layer feed-forward neural networks. 1997, Vol. 37, pp. 43-62 .

36. **Dheeraj S. Badde, Anil k. Gupta, Vinayak K. Patki.** Cascade and Feed Forward Back propagation Artificial Neural Network Models for Prediction of Compressive Strength of Ready Mix Concrete. pp. 1-6.

37. **Schmid, Michel D.** A neural network package for Octave. *User's Guide.* 2009, Version: 0.1.9.1.

38. **Zhen-Guo Che, Tzu-An Chiang, Zhen-Hua Che.** Feed-Forward Neural Networks Training: A comparison between genetic algorithm and back-propagation learning algorithm. 2011, Vol. 7, 10, pp. 5839–5850.

39. **V. Sharma, S. Rai, A. Dev.** A Comprehensive Study of Artificial Neural Networks. *International Journal of Advanced Research in Computer Science and Software Engineering.* 2012, Vol. 2, 10, pp. 278-284.

40. **K. Gobakis, D. Kolokotsa, A. Synnefa, M. Saliari, K. Giannopoulou, M. Santamouris.** Development of a model for urban heat island prediction using neural network techniques. *Sustainable Cities and Society.* 2011, Vol. 1, 2, pp. 104–115.

41. **Pavan, Adel Mellit & Alessandro Massi.** A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy. *Solar Energy.* 2010, Vol. 84, No.5, pp 807–821.

42. **Maitha H. Al Shamisi, Ali H. Assi and Hassan A. N. Hejase.** Using Matlab to Develop Artificial Neural Network Models for Predicting Global Solar Radiation in Al Ain City-UAE. [book auth.] Dr. Ali Assi (Ed.). *Engineering Education and Research using Matlab.* 2011.

43. **Christophe Paoli, Cyril Voyant, Marc Muselli, Marie-Laure Nivet.** Forecasting of preprocessed daily solar radiation time series using neural networks. *Solar Energy.* 2010, Vol. 84, pp 2146 - 2160.

44. **S. Seme, G. Štumberger and J. Pihler.** Predicting daily distribution of solar irradiation by neural networks . *International Conference on Renewable Energies and Power .* 2009.

45. **Adel Mellit, Alessandro Massi Pavan, and Soteris A. Kalogirou.** Application of Artificial Neural Networks for the Prediction of a 20-kWp Grid-Connected Photovoltaic Plant Power Output. *Soft Computing in Green and Renewable Energy Systems Studies in Fuzziness and Soft Computing Volume 269, 2011, pp 261-283.* s.l. : Springer, 2011.

46. **S.I Sulaiman, T.K Abdul Rahman, and I. Musirin.** Partial Evolutionary ANN for Output Prediction of a Grid-Connected Photovoltaic System. *International Journal of Computer and Electrical Engineering.* April 2009, Vol. Vol. 1, No. 1, pages 1793-8198.

47. **S. Premrudeepreechacharn, N. Patanapirom.** Solar-Array Modelling and Maximum Power Point Tracking Using Neural Networks. *IEEE Bologna Power Tech Conference.* 2003.

48. **C.C. Nwobi-Okoyea, A.C. Igboanugob.** Predicting Water Levels at Kainji Dam using Artificial Neural Networks. *Nigerian Journal of Technology (NIJOTECH).* 2013, Vol. 32, 1, pp. 129-136.

49. **Abdulkadir, T. S., Salami, A. W., Anwar, A. R. and Kareem, A. G.** Modelling of Hydropower Reservoir Variables for energy generation: Neural Network approach. *Ethiopian Journal of Environmental Studies and Management.* 2013, Vol. 6, 3.

50. **Jorge O. Pierini, Eduardo A. Gómez, & Luciano Telesca.** Prediction of water flows in Colorado River, Argentina. *Lat. Am. J. Aquat. Res.* 2012, Vol. 40, 4, pp. 872-880.

51. **Pedro A. Gonzalez, Jesus M.Zamarreno.** Prediction of hourly energy consumption in buildings based on a feedback artificial neural network. *Energy and Buildings.* 2005, Vol. 37, pp. 595–601.

52. **Akkurt, Melek Yalcintas and Sedat.** Artificial neural networks applications in building energy predictions and a case study for tropical climates. *International Journal of Energy Research.* 2005, Vol. 29, pp. 891–901.

53. **Morkos, Essam E. Khalil and Samy M.** On predicting Energy Consumption in Administrative Buildings: Neural Network Applications . *Aerospace Research Central.* 2012.

54. **Kreider, J.F., Curtis, P.S. & Rabl, A.** *Heating and Cooling of Buildings: Design for Efficiency Revised Se.* s.l. : USA: CRC Press Taylor & Francis Group., 2010.

55. **Myers, Daryl R.** *SOLAR RADIATION : Practical Modeling for Renewable Energy Applications.* s.l. : Taylor & Francis Group, 2013.

56. **Koivo, Heikki N.** Neural Networks: Basics using MATLAB, Neural Network Toolbox. 2008.