Technical University of Crete

School of Environmental Engineering

“Development of DR energy management optimization at building and district level using GA and NN modeling power predictions”

Master thesis

by

Elisavet Tsekeri (2016057422)

Supervising committee:

Assoc. Prof. Dionysia Kolokotsa (Supervisor)

Prof. Konstantinos Kalaitzakis

Prof. George Karatzas

Abstract

In broad terms, Demand Response refers to the operational, regulatory and technical framework for inducing changes in the power demand of buildings or settlements during the day. Time of Use (ToU) pricing can be vital to leverage advancements in building or district energy management systems to shift loads, exploit storage capabilities, increase renewable energy penetration and ultimately relief stress from the grid. This is an important feature of the smart grid and a step closer to the necessary open and transparent market framework according to which energy consumption costs reflect actual costs of production, transmission, distribution, infrastructure maintenance and upgrade etc. In this paper Neural Network power predictions are performed and a genetic algorithm based framework for energy management in a group of buildings is developed and tested on real data.

According to the results ToU pricing could be exploited by the industry using ANN based day ahead prediction to perform load shifting and minimize associated costs.

Acknowledgement

Firstly, I wish to thank Prof. Dionysia Kolokotsa for her guidance and her support in the completion of this study. I would also like to thank Nick Kampelis for his contribution in the development of the survey and his overall instructions for technical matters. Moreover, I would like to thank my family and my friends for their support during my studies. Finally, I would like to thank the people of Loccioni, for all their instructions, and the cooperation we had.

The research is funded by the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie Grant Agreement SMART GEMS: SMART GRIDS ENERGY MANAGEMENT STAFF (Contract No 645677).

Contents

List of Figures

List of tables

1.Introduction

Scope: exploitation of day-ahead power predictions and unit energy pricing information for the optimization of power consumptions at building and district level.

Environmental serious challenges, put the environment in jeopardy, which has a significant impact to the society. To solve this serious worldwide problem, many approaches from researchers are created to develop new energy management methods concerning renewable and sustainable energy systems that will reduce the energy consumption and the carbon dioxide footprint.

Apart from the emissions, it is necessary to have a balance in electrical power between demand and response. It is a fact that the stability of the power is highly dependent on the frequency in the electricity grid. As long as the electricity generation and consumption is balanced, the frequency of the grid is not affected. Demand Response is a particular intelligent tactic to manage the electrical load of users. The continuous increase of energy demand created serious problems to the traditional grid in keeping the reliability in the load energy supply, since renewable energy sources intermittency and variations in consumption and others technology specific issues are linked to reliability and power quality problems. The main purpose of the grid is to keep perfect balance between the demand and the supply of energy every time.[1] Nowadays, the increasing of renewable sources, such as solar and wind power, created an uncertainty in their behavior because they are directly dependent on the weather conditions. Demand Response programs was the solution in storage services in order to manage the production and to resolve the uncertainty. [2]In other words, in an industry it is a substantial advantage if this equality is being ensured, due to the fact that if there is a gap between generated power and consumption, technical problems will be created to the network.[3] To achieve the balance in the network, a great variety of approaches to forecast the loads are used worldwide varying according to the time horizon. Obviously, no one can deny that the forecasting of electricity demand is a very difficult task using high advanced techniques for capacity planning and maintenance scheduling. To come across with the forecasting, several methods are used like fuzzy logic, statistic models and Artificial Neural Network. There is not a model or algorithm that is preferable from the others, and many times the researchers use them in parallel or in combination. [4]

Load prediction is important for microgrid to have Demand Response in order to have the ability to detect the demand and the supply in an industry, for ensuring the stability of the network.[5] A microgrid consists of renewable sources, energy storage and energy consumption, operating in low voltages. A microgrid can connect to the main grid, but also has the advantage to be independent in case of problem.[6] Apart from the benefit of independence, the operation of a microgrid is often linked to economic benefits. [7] The optimization is the brain in Energy Management Systems (EMS). The problem of the effective energy management can be reached by optimization-stimulation using Genetic Algorithms for multi-objective problems, minimizing the microgrid's operational costs. [8]

1.1 Aim and objectives

The aim of this work is to develop and evaluate a novel demand response approach for the management of distributed energy resources at building and district level using power prediction and optimization techniques

The objective of the thesis is presented below:

1.Create Artificial Neural Network models to conduct day ahead reliable prediction of power consumption using power and weather measurements.

2. Develop a multi objective GA optimization framework taking into account cost of energy and shifting of power loads.

3. Assess the implementation of the developed approach at building and district level.

1.1Methodology

The methodology followed consists of the following steps:

- Data collection from MyLeaf[1] smart monitoring platform, analysis and selection of test samples
- Definition of neural network input/output parameters and structure
- Training, testing and validation of neural network prediction models
- Development of Genetic Algorithm optimization approach
- Testing of Genetic Algorithm optimization at building and district level
- Sensitivity analysis
- Evaluation of results

[1] https://myleaf2.loccioni.com/beta/Account/LogOn

2.Literature Review

2.1Energy management systems

Energy management systems (EMSs) allow to monitor, to control and to analyze systems and equipment using sensors, switches and algorithms.[9] This system can be used to buildings, too. Building energy consumption can be reduced by efficient Building Energy Management Systems (BEMS). This system collects information concerning the operation of the building, using them to reduce building consumption and total energy cost.

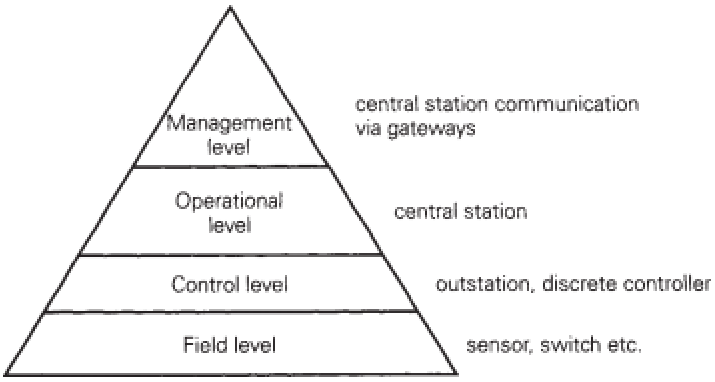


Figure 2.1 The levels of control in BEMS [10]

Figure 2.1 depicts the different levels of a BEMS from the field service, and becoming step by step more intelligent to the head management PC. This technology is a board concept of building control, having many characteristics. The BEMS differ from other control systems in the communication. To be more specific, in BEMS the processes and the functions of the building will be received and be controlled by a central operating unit. The advantage of the BEMS is that it has the opportunity to optimize the system. For example, the central and the operating unit will receive information about the temperature and the building occupancy. Having in mind this information, the BEMS will decide if it is necessary to lower the temperature in parts of the building where there are not occupied. In this way, building energy efficiency will be achieved. As far as their function is concerned, analogue or digital input signals inform the system, as temperature and humidity. Apart from these, inputs will include information about the equipment like pumps, fans and boilers, if this equipment operates or not. After that, analogue or digital outputs send to the central PC to control their settings, to switch them, as result to the thermal comfort.[11]

Moreover, there is a big variety of models that can be used, putting time input parameters as weather data and energy prices to improve building energy performance by saving energy or reducing peak demand.[12]

According to the IEA [13] using BEMS has advantages and disadvantages, too.

The main benefits are:

- improved energy efficiency
- monitor building status and improved environmental conditions
- Improved management of the building
- Remote monitoring and control of services and functions from a head PC
- Improved fire, security and other emergency procedures

The main drawbacks are:

- High cost for design and installation
- Operation and maintenance of BEMS maybe is higher than other simpler systems
- A skilled and professional operator is needed

It is significant to mention that energy management system is not only applicable to huge industries and establishments, but, it is equally beneficial and validated for houses as well to monitor energy consumption. Home Energy Management Systems (HEMS) are the technologies that have the ability to respond to alter conditions independently, even if there is no human intervention. To be more specific, these systems can shift the demand in response to the price of electricity without intervene to human comfort but optimizing the load peak.[14]

2.2 DR capabilities

The Management of Electricity Demand, known as Demand Side Management (DSM), is a methodology developed between the 1980s and 1990s in Canada and the USA by Electric Power Research Institute (EPRI), and then rapidly spread to Europe [15]. The DSM can be divided into two main parts, which are Energy Response and Demand Response (DR).

In the one hand, Energy Response aims to lowering power consumption and in the other hand DR is defined as changes in electrical consumption patterns in response to the price of electricity or other incentives during periods of critical system conditions or periods of high market power costs.[16]

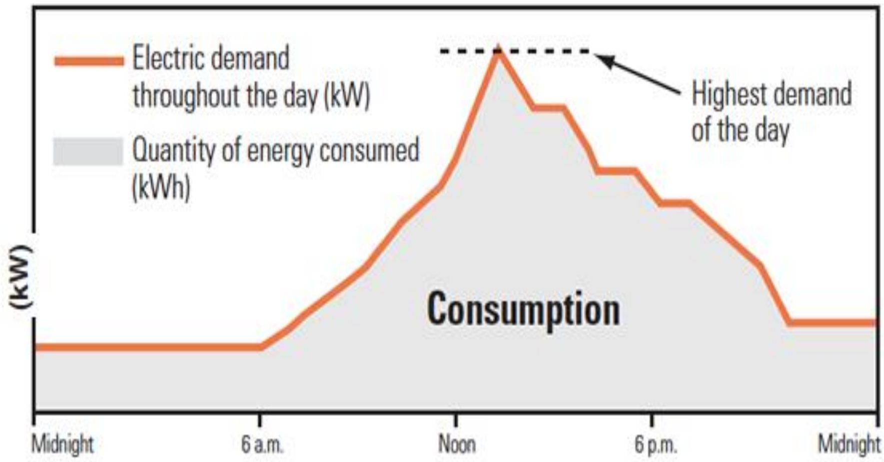


Figure 2.2: Power consumption during the day [16]

Figure 2.2 represents the Power consumption during the day. Is it obvious that during the day there is substantial difference in demand than in the night. Demand is a measure of the rate at which energy is consumed.

Demand Response consists of dependent program activities that have the ability to reduce the use of electricity of shift the use to another time period. DR programs can reduce or shift the electrical load when the price of electricity is high. In this way, DR can manage the electricity costs of a building and improve the reliability of the network.

Control strategies & techniques for DR

There is a big variety of strategies, concerning DR, that can be implemented using manual or automated systems. These control strategies concern air-conditioning, ventilation and lighting systems.[10]

Levels of Automation for DR

Manual DR: is a labor approach. In this case, turning off manually or change the comfort set point at each equipment.

Semi DR: Is a preprogrammed load shedding strategy that starts from a person using centralized control system.

Fully automated DR: In this case, there is not human intervention but Energy Management Systems are used in a home or in a commercial building.

Strategies that are based on HVAC systems differ from each other at the type of building, at the mechanical equipment, and at the EMSs. The best DR strategies are those which minimize the electricity demand, minimizing at the same time the negative impacts on the occupants of the building and on the processes, that they perform. Some of the main DR strategies are presented below:

HVAC systems

1. **Global temperature adjustment (GTA)**

This strategy allows to change easily the temperature points from one location. To be more specific, with this strategy control the temperature set point throughout the building. It is the most effective strategy of HVAC systems, due to the fact that it reduces the ventilation and the cooling load uniformly across to all zones of the building.

2. **Duct static pressure decrease (DSP)**

In this case, the fan power is reduced from the reduction of the duct static pressure setpoints that will bring saving power to the fan. The main drawback is that in the zones with less air flow, there is a reduction in ventilation rates below the desirable.

3. **Cooling valve limit**

This strategy reduces the cooling valve in order to limit the cooling load, without setting the cooling valve limit lower than the threshold of the chiller.

4. **Chilled water temperature increase**

In this strategy, there is a temperature increase of chilled water, helping reduce the cooling load and increase the chiller efficiency.

Lighting systems

5. **Zone switching**

The main role of this strategy is to switch all the luminaires in all zones, increasing/decreasing the cooling load and the heating load. The main drawback in this strategy is that it may annoy the employers of the building.

6. **Luminaire/ lamp switching**

Luminaire switching: In this case, a percentage of luminaires of the building is switched off.
Lamp switching: In the other case, a part of lamps in the luminaire is switched off.
The main disadvantage is that it may annoy the employers.

electromechanical equipment

7. **Fountain pumps**

The pums are used mainly for visual comfort, and they are situated in common place in the building. Switching off the fountain pumps can save energy without have effect on the thermal comfort of the occupant.

Benefits of DR

There is a majority of DR resource types as distributed generation, dispatchable load, storage and many other sources that can contribute to change the power system in the main grid. Moreover, DR programs use difficult mechanism to urge the consumers to reduce the demand for limiting the peak demand. [9] Demand Response is going to become a significant part of the system operations in the smart grid driven restructured power system and carbon dioxide reduction policies around the world in the near future. More specifically, DR systems have a big variety of advantages as shown below [15]:

- As it was presented before, the peak of load in an industry can be reduced by DR. In this way, an environmental benefit is being created for the society, reducing the carbon dioxide emissions
- Transmission System Operators take advantage of DR systems, due to the fact that the transmission of energy can be more reliable. Increased reliability of a network is a result of the reduction of the possibility of forced outages when the reserves of the systems are below of the desired level.
- DR encourage new technologies to take part in the network. Penetration of Renewable energy sources (RES) technologies such as solar, wind, geothermal and storage require DR as a significant resource in the management of the smart grid. For example, when there is a high speed of wind, the generation is substantial in operation. When the wind generation stops to work, economic problems will be created in the wind farm, making the period of payback high. Hence, the DR are useful to increase the demand in these periods.

Demand Response in HVAC systems is usually performed in individual building level. However, few studies, concerning the DR in district level have been done in order to evaluate the system's performance and their limitations are unclear in electricity pricing. Some researchers tried to bridge this gap. [17]

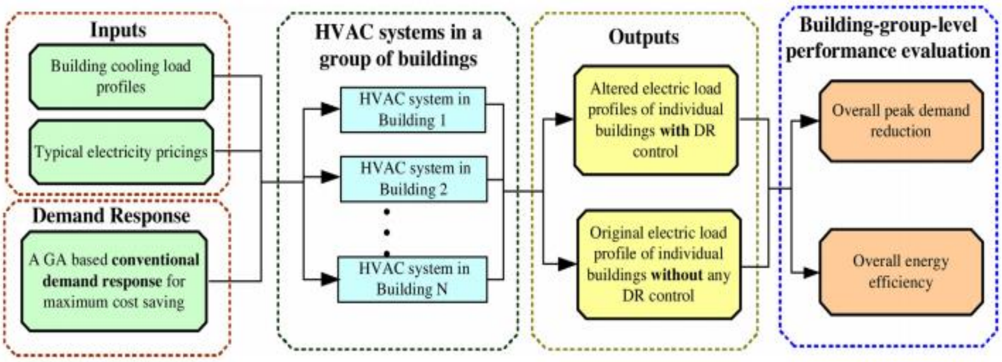


Figure 2.3 DR in group-level buildings [17]

Figure 2.3 illustrates the DR in district level. In [17] the researchers used Genetic Algorithms to optimize HVAC system in order to achieve the maximum energy efficiency without focusing in economic benefits of one building, but in s group level of buildings. To deal with this problem, typical energy prices and cooling loads of individual HVAC system were added as inputs, to obtain the total cooling load. Then, they compare the total load profile after the DR with the baseline case without DR. These comparisons are focused on the reduction of energy consumption in group level, helping the grid to relief.

2.3 Forecasting for DR

Load forecasting is important for reliable power system operation, and significantly affects the industry and the participants. The Energy Management System uses the historical data and other outputs like the weather to forecast the loads, and can be performed in different time scales. Subsequently, these data will be used later as inputs to the optimization. There is no single model or algorithm that is superior for all utilities and several load forecasting methods sometimes are used in parallel or combination.[18] There is a separation in load forecasting in terms of the planning horizon’s duration:

a) up to 1 day for short-term load forecasting (STLF),

b) 1 day to 1 year for medium-term load forecasting (MTLF), and

c)1±10 years for long-term load forecasting (LTLF).[19]

2.4 Theory of Artificial Neural Networks

In the literature, two methods have been recognized for load prediction, which are statistic models and Artificial intelligence models like artificial neural networks, fuzzy logic and hybrid systems. Artificial intelligence models have the ability to model the nonlinearity of the electricity demand variation and the complex relationship that exists between the load and the other parameters (like the weather, etc.) that have influence on it. [3]

Artificial Neural Network (ANN) is an attempt to approach the human brain using mathematical functions, providing the ability to perform calculations on high numbers of parallel streams. The architecture of ANN is based on biological neural network, which is found in the human brain. The main part of an ANN is a number of artificial neurons organized into human brain like structure

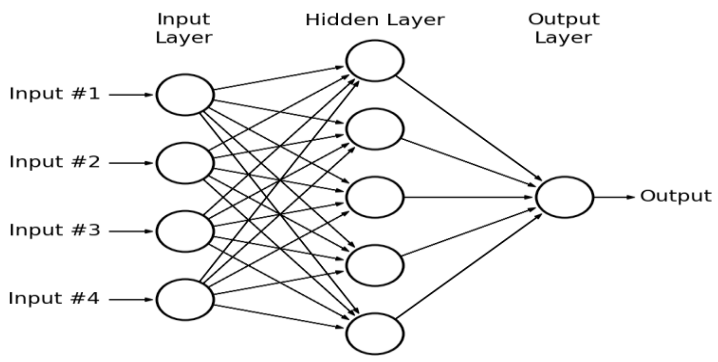


Figure 2.4.1: The structure of an Artificial Neural Network [20]

Figure 2.4.1 illustrates the structure of an Artificial Neural Network, which consists of many neurons. Each neuron has many inputs but only one output, and the connection between the neurons differs due to the weight factors. Two basic properties define the architecture of a network [20]:
1)the number of layers and
2)the connections between neurons
Apart from these, the learning algorithm is a significant property associated with the training and performance of the network.

Artificial Neural Networks (ANN) are artificial intelligence models widely used for forecasting providing high accuracy. There are two categories concerning the load forecasting. The first option treats the load pattern as a time-series signal and predicts the future load using the already mentioned time-series analysis techniques. In the second option, the load depends on weather variables as temperature and humidity and previous load patterns.[19]

Many techniques have been proposed during the last few decades regarding STLF. [21], develop a short-term load forecasting model based on ANN. to forecast the electrical loads of individual consumers (households). They collected anthropologic and structural data from 205 houses in Sweden and observed a significant correlation between the characteristic of consumers and their consumption. To train the STLF model, they use a tuple consisting of global variants (hour of day, day of week, temperature, etc.), house variants (number of occupants, number of school going children, wall types, etc.), and load value for that households. Each input corresponds to a neuron of first layer. The trainer associates weights with each neuron.

Hao Quan and Abbas Khosravi in [22], also use an ANN technique to forecast the load of renewable energy process concerning wind power, using day data as inputs and electrical load data as outputs from SG and New South Wales in Australia.

In [20], the researchers were interested in Urban Heat Island (UHI), that causes differences in thermal comfort between rural and urban settlements. In this case, an ANN was used to predict the air temperature in Athens for 1h and 24h prediction respectively. As inputs to the ANN were the date, the time, the temperature and the solar radiation. The performance of one to three hidden layers with 20-40 neurons each, using a variety of training functions were explored.

In [23], refers to the wind power forecasting. In this topic, researchers use a short-term load forecasting (STLF) model to forecast wind power up to 48 hours ahead in seven wind farms. To be more specific, historical data (as wind power data) were used to provide accurate wind forecasts with ANN.

In 1995, Kreider [24] used ANN without knowing the historic data of building's energy consumption. In this approach, the model provided an accurate method for predicting hourly energy use when only weather data is known. During the training of the network, actual measured data from a few past hours were used as inputs and a cyclical process was started. Finally, the error of this research was significant leading to conclusions for real measurements being necessary to improve network's efficiency.

In [25] used ANN to conduct forecasting in electric power systems. To start this approach, only historical load data were considered as inputs, without knowing the weather data. As outputs of the network was load forecasting for the next hour.

In [26]researchers trained an ANN using recent load data to forecast a load with substantial accuracy, with no weather data input. In this process, they identified a load model with neural network that reflects the hourly load demand of Crete.

The authors [27] used ANN to examine the forecast of a 24h excess production of a microgrid in Loccioni Leaf Community. In the present paper, for prediction of PV and Hydro power different inputs were used in each case. In the first case, day of week, time of day, temperature and radiation were considered as inputs. In the second case, river water level and machine water level were the inputs for the network. Finally, an accurate prediction for different seasons was made using irradiance and temperature as inputs to the network.

In 2004 [28], M Beccali used ANN to forecast total electric consumption in an urban area of Palermo, in Italy. Load and weather data (as temperature, relative humidity, global solar radiation), from 2001 to 2004, were used as inputs to the network. The output of the forecast was the daily urban electric load profile. The results of the forecast, could provide a significant accuracy at so small a spatial scale as the suburban on2.5 Genetic Algorithm based optimization.

2.5 Genetic Algorithm based optimization

A Genetic Algorithm (GA) belongs to the larger class of evolutionary algorithms (EA), and tries to mimic the metaphor of natural biological evolution. Each and every genetic algorithm operate on a large population of potential solutions which follow the principle of survival of the most capable for solving the problem.[29]

Genetic algorithms (GA) differ from the traditional approaches of existing optimization techniques. The fitness function is evaluated for each solution, and the solutions are consequently ranked.[30] Firstly, a Genetic Algorithm codes the decision variable set describing a trial solution named string or ''chromosome'', and then uses a binary alphabet for the coding. After that, the GA evaluates the trial solution and computes a value of worth or "fitness" for the string. The new collection of solutions is known as ''population''. The new populations are created from the older. Every Genetic algorithm has the basic functions as shown below:

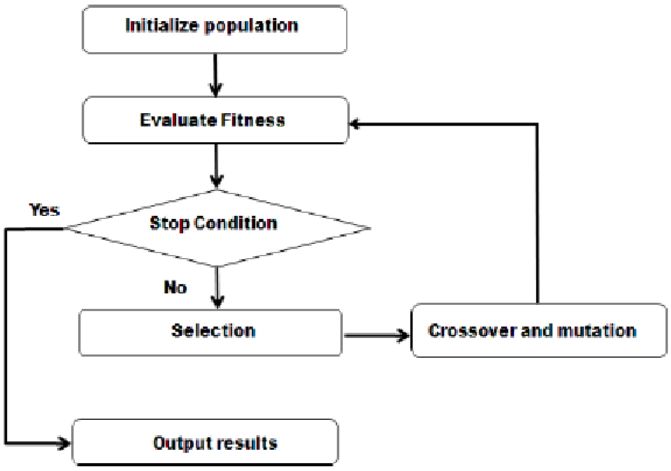


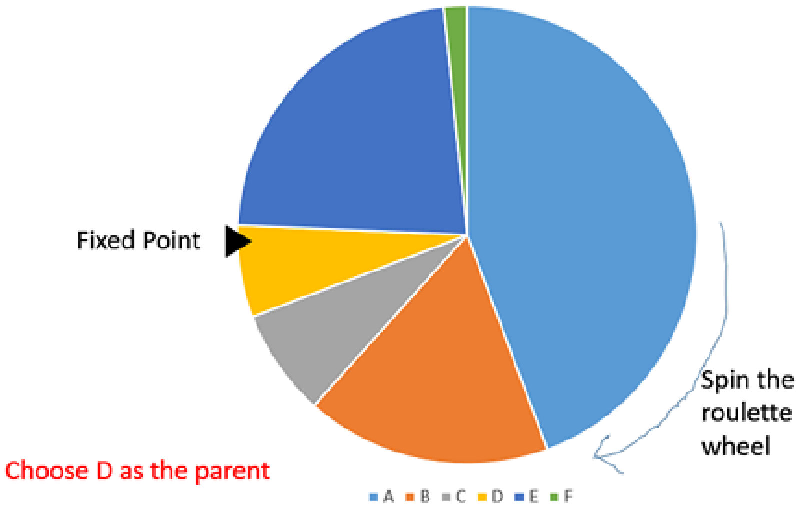
Figure 2.5.1 Genetic Algorithm flow chart [31]

These operators are necessary in order to optimize the fitness function, and find the optimal solution for the problem. The process is repeated until a termination criterion is satisfied.[32]

More specifically, ''selection'' is the function with witch the GA chooses the parents for the next generation. Selection determines the number or trials where an individual is chosen as a parent. This function is substantial in GA, since good parents drive to individuals that have ever better solutions.

Fitness Proportionate Selection: is the most common selection for parents' generation. In this case, each individual has the possibility to become a parent according to its fitness. In this way, fitter individuals have higher chance to mate and propagate their features to the next generation. In this case, there is a wheel which is separated into n pies and each individual gets a portion of the circle which is analogue with its Fitness Value.

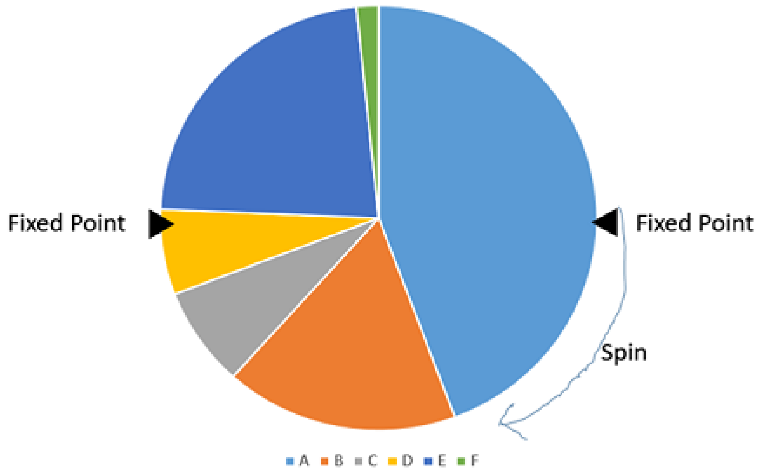
Roulette Wheel Selection: In this case, there is a circle of wheel as before. In the wheel there is a fixed point as the wheel is rotated. The region of the wheel which comes in front of the fixed point is chosen as the parent. For the second parent, the selection is repeated as before.



Chromosome	Fitness Value
A	8.2
B	3.2
C	1.4
D	1.2
E	4.2
F	0.3

Figure 2.5.2 Example of roulette wheel selection [2]

Stochastic Universal Sampling (SUS): This is similar as the roulette wheel selection. however instead of having one fixed point, we have many fixed points as shown in Figure 2.5.3.



Chromosome	Fitness Value
A	8.2
B	3.2
C	1.4
D	1.2
E	4.2
F	0.3

Figure 2.5.3 Example of *Stochastic Universal Sampling* [2]

[2] https://www.tutorialspoint.com/genetic_algorithms/genetic_algorithms_parent_selection.htm

The basic operation for producing new chromosomes in the GA is the function ''crossover''. In crossover, new individuals are produced by both parents' genetic material.[29]

One-point crossover: The simplest crossover is the as it is shown in the example below:

Figure 2.5.4 Example of one-point crossover [3]

Multi point crossover: is a generalization of the one-point crossover where the segments alter and swapped to get new off-springs.

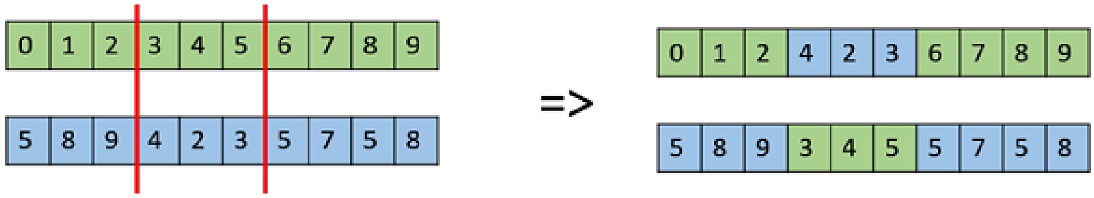


Figure 2.5.5 Example of multi-point crossover [3]

Uniform Crossover: In this case, a coin is flipped to decide where or not it will be included in the off-spring. Moreover, in this function the child can have more genetic material from one parent than the other.

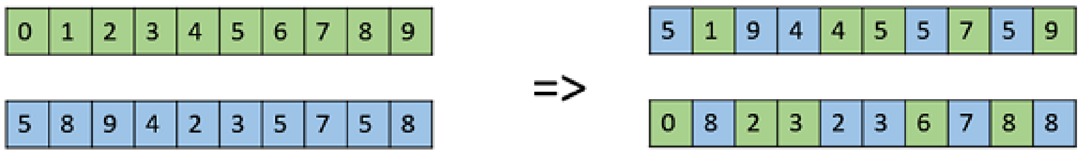


Figure 2.5.6 Example of uniform crossover [3]

Mutation is the operator that maintain the genetic diversity from one generation of chromosomes to another. In other words, this function helps the GA to make small random changes in the individual population to create mutation children, helping the GA to search a border space. There are many different functions of mutation as it is shown in Figure 2.5.6.

[3] https://www.tutorialspoint.com/genetic_algorithms/genetic_algorithms_crossover.htm

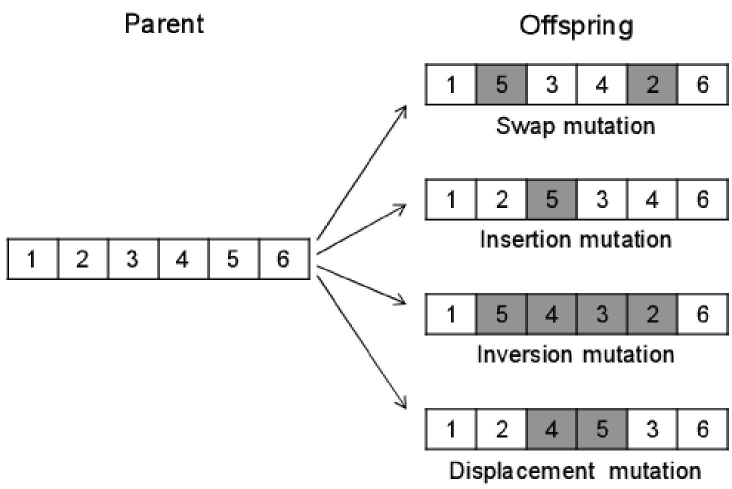


Figure 2.5.7 Example of mutation [29]

In literature, there is a significant variety of problems concerning energy management systems, in which optimization using genetic algorithms to solve constrained mixed integer (Nonlinear) programming (MINLP) problems, is preferred. This kind of problems often arise in the field of building and HVAC design.

In [30], Genetic algorithm was developed to control the HVAC loads with a hybrid-renewable generation and energy storage system. In this approach, the authors used historical hourly data for cooling loads, wind and PV penetration. In order to create the function, system energy cost, and system power were needed, too. Finally, they compared the results of minimization of GA with other methods and the optimization with GA demonstrated better efficiency.

In 2009, [33] Matti Polonen, used Genetic Algorithms to solve a single-objective optimization and a multi-optimization of life cycle cost of a house. In the first case, the goal is to minimize the difference between the investment cost for the construction (windows, insulation) with the ventilation heat recovery. In the second case, an optimization with GA was needed in two cost functions. The first function concerns the investment cost for the construction and the second concerns the annual space heating energy of the heating system.

In 2004, [6], an optimization problem was created in order to minimize the cost of Leaf Community microgrid, in Italy. The GA in the microgrid has significant benefits as the reduction of energy cost, the optimization of revenues, the minimization of carbon dioxide emissions, without changing user's thermal comfort.

In reference [32], the authors developed a GA model for a pipe network, due to the fact that the construction and the maintenance of pipelines for water supply cost millions of dollars every year. In this topic, the minimization of the cost is a result for a given layout of pipes and specific demands at the nodes.

M.H. Moradi and M. Abedini in [34], propose a Genetic Algorithm for optimal location and sizing of Distributed generation (DG) on distribution systems, in order to minimize the network power losses, and to improve the voltage regulation of the system operation and security constraints in radial distribution systems.

In [35], Jonathan A. Wright created a multi-objective GA in order to find the minimum pay-off between the HVAC system energy cost in a specific building and the thermal discomfort. Finally, the optimization of GA illustrates results with substantial accuracy.

3.Case study

3.1 Description of the Leaf Community

Leaf Community is situated in Angeli di Rosora at Italy and was established in 1968 by Enrico Loccioni. In this community, there is a combination of ideas, people and technology in order to develop measurements and control automatic systems for improving products and buildings quality, efficiency and sustainability. Figure 3.1.1 illustrates Leaf Community.

The main field of research are presented below:

- Energy: solutions and energy production from renewable sources
- Environment: Environmental monitoring
- Human care: Quality control solutions for human care
- Industry: Quality control solutions for industrial buildings
- Mobility: test and quality control systems for automotive components
- Train & Transport: solutions for transport and railways network
- Aerospace: Measure, automation and quality control solutions for aeronautic and aerospace processes, systems and components

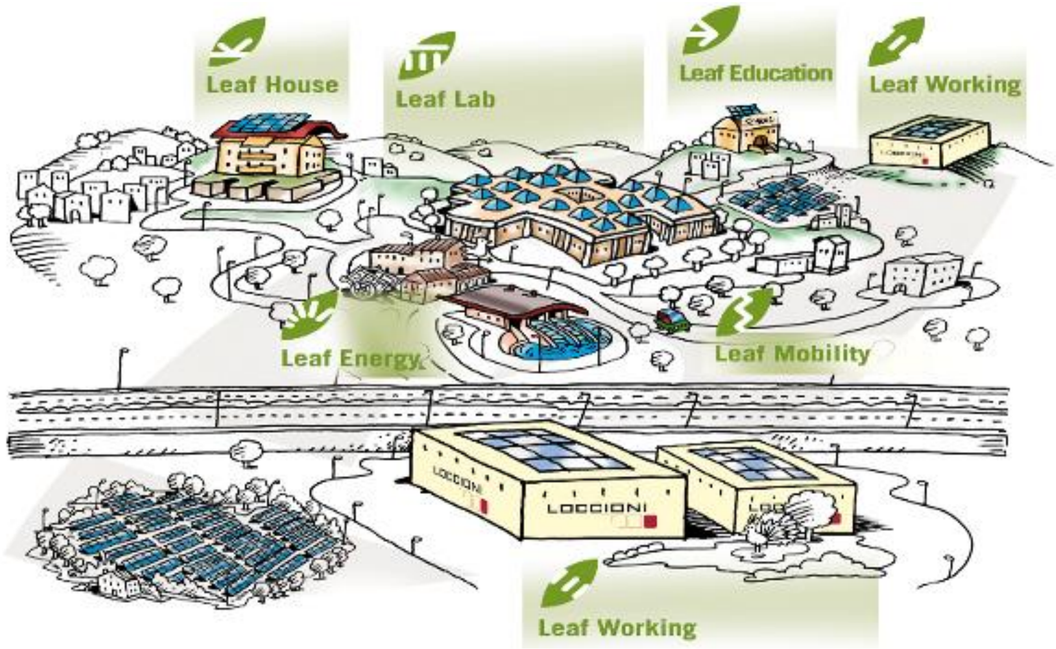


Figure 3.1.1: Leaf Community

Leaf Lab is an industrial building which is located in the Leaf Community. In Leaf Lab, there is reduction to minimum of energy needed, covering the demand for heating, cooling, ventilation and lighting due to the latest technology they are using. Leaf Lab is a Near-Zero Energy Building since it consists of passive systems, energy efficient technologies and renewable energy consumption. After this production, PV systems, heat pumps and thermal storage are used to optimize the HVAC system.[36]

Figure 3.1.2. Leaf Lab [36]

3.2 Data analysis

Power and weather data were collected from MyLeaf platform. In this platform the user has the opportunity to find measurements for every building of Loccioni. In this study, we decided to deal with the electrical consumption of 3 buildings: Loccioni L4 Leaf Lab, L5 Kite Lab and L2eL3. Figures 3.2.1 and 3.2.2 depict how we collected the data for each building.

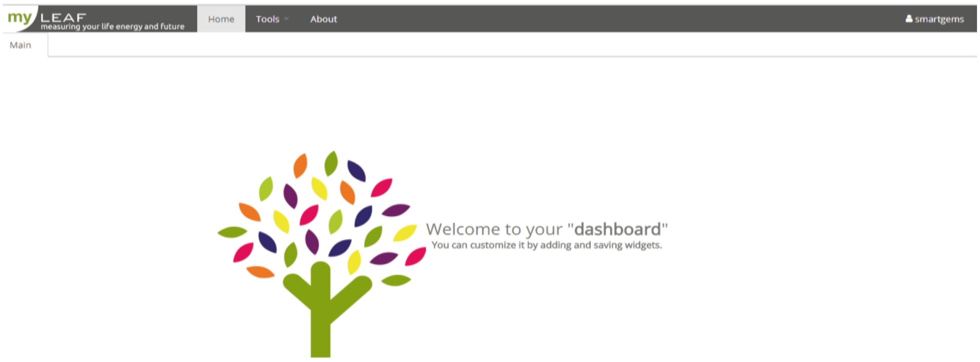


Figure 3.2.1: MyLeaf Platform

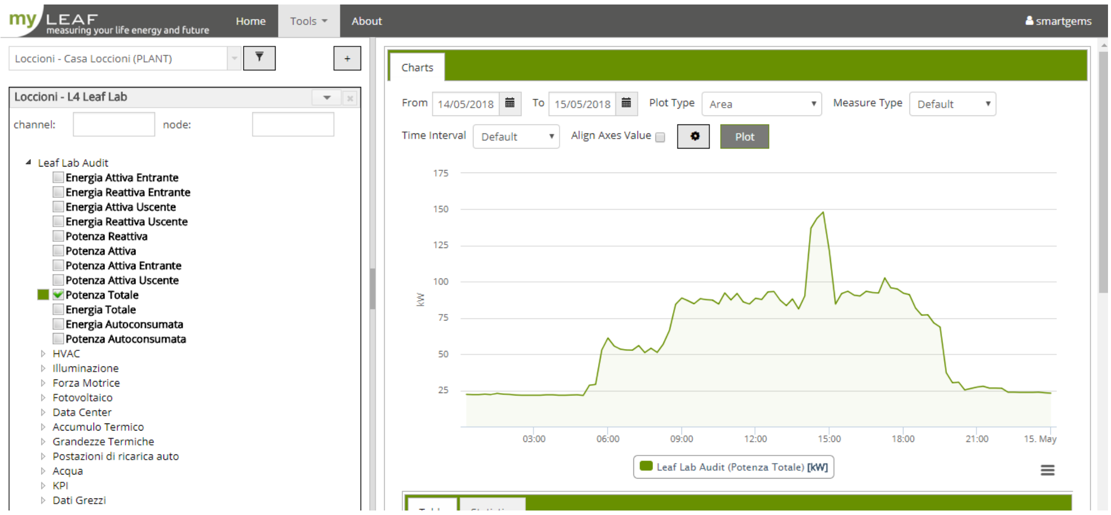


Figure 3.2.2: Power measurements

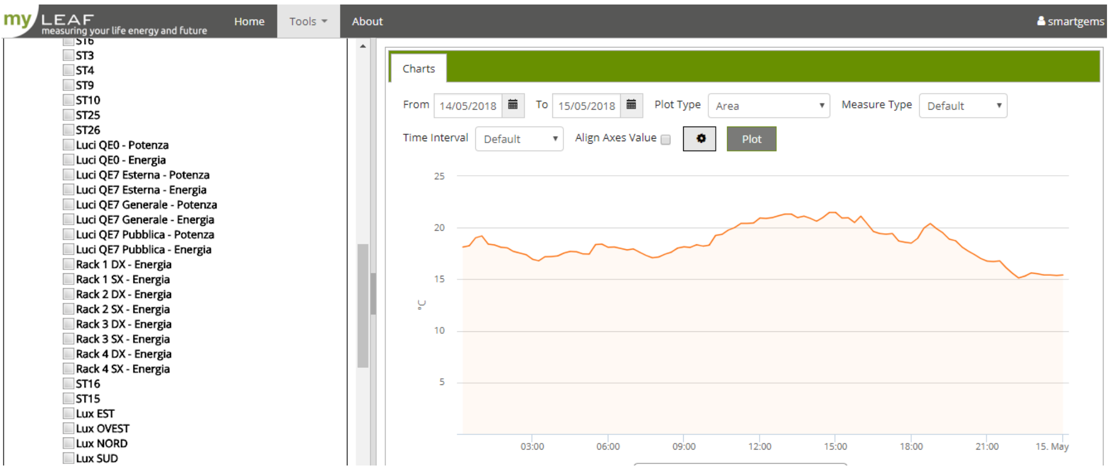


Figure 3.2.3: Weather measurements

From the platform, power and outside temperature were collected from 1/1/2017 to 1/3/2018, having measurements per 15 minutes. This is the first step of the study as the data are useful thereafter in the predictions with Artificial Neural Network.

3.3 Model development

3.3.1 Power prediction using ANN

The first step of the optimization at building and district level was the prediction of electrical power 24h ahead. In this study, we decided to use Artificial Neural Network as it is the most preferable method concerning short-term load forecasting. It is known that the load depends on weather variables like humidity and temperature, and previous loads. For this reason, we decided to use day, time and external temperature as input and power as output from 1/5/2017 to 1/8/2017.

In order to have the power forecast, we should first create the structure of the ANN. The network consists of an input layer, which is the external temperature in our case. Apart from that, 3 hidden layers with 1 delay were used to connect the input layers with the output layers. However, weights were modified inside the network automatically. To build an Artificial Neural Network from the beginning, we had to use specific functions to create the net, to prepare the data and to train the model, as it is shown in Figure4.

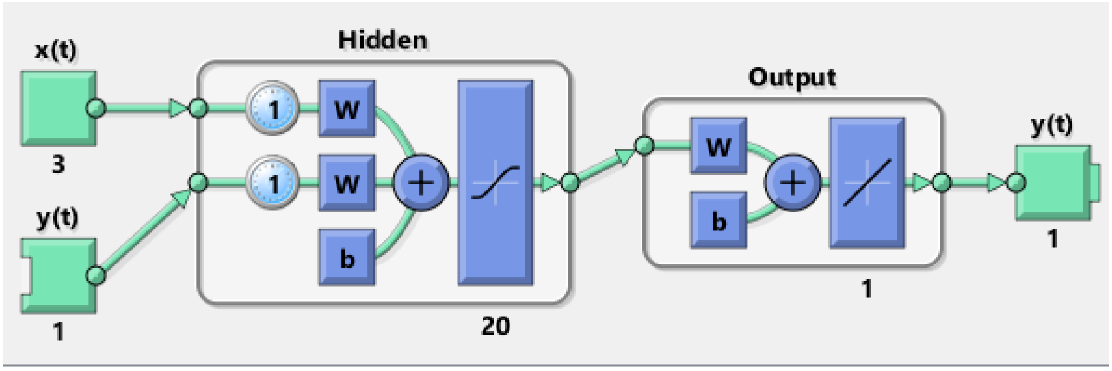


Figure 3.3.1.4: the structure of Artificial Neural Network in MATLAB

This Methology was tested many times changing the delays and the hidden layers before having the final output y(t). Moreover, this method was used firstly for the L4 Leaf Lab, the Kite Lab and the Education Lab and after that for district level, changing the inputs x(t) and the targets y(t). At the end of each process, we used main statistic indicators in order to test the reliably of the result, how close are the predicted values to the baseline values. More specifically, firstly Pearson test R (correlation coefficient) was used to analyze how strong is the relationship between the variables. The range is 0 to 1..(Kampelis et al. 2017) where:

- 1 indicates a strong positive relationship.
- -1 indicates a strong negative relationship.
- 0 indicates no relationship at all

To calculate this statistic indicator, ANN use this function as it is shown in eq.1:

$$R = \frac{n * \sum x_i * y_i - \sum x_i * \sum y_i}{\sqrt{n \sum x_i^2 * (\sum x_i^2)} * \sqrt{n \sum y_i^2 * (\sum y_i^2)}} \quad (1)$$

Apart from the R, two other statistic indicators where used to test the reliability of the network. Mean bias error (MBE) was the second indicator and it is calculated as it is shown in eq.2. MBE shows the direction of the error with positive and negative results.

$$MBE = \frac{\sum_{i=1}^{N} (P_i - O_i)}{N} \quad (2)$$

Finally, Mean Average Percentage Error (MAPE) was calculated too. This indicator shows the percentage of predictions that differ from the baseline.

$$\text{MAPE} = \frac{100}{N} * \sum_{i=1}^{N} \frac{O_i - P_i}{O_i} \quad (3)$$

Where

N: the number of samples

P_i: the predicted valueO_i: the baseline value

3.3.2 Optimization using Genetic Algorithms

Two optimization models have been created to minimize energy operating costs based on day-ahead hourly unit (kWh) energy prices. The first one concerns the optimization at one building and the second one the optimization at district level. Two criteria are used to evaluate the trade-off between the optimization of cost and load shifting. Load shifting is considered a competitive criterion as it is related with changes in the operation of systems in the building including HVAC, lighting, industrial loads etc. In other words, load shifting needs to be minimized to avoid significant intervention in the building's operation. Weighting coefficients are applied to both criteria to allow consideration of several alternatives depending on the decision maker's preferences. The optimization function displayed in eq.1 includes the criteria of the cost of energy $Cost_E$ and a penalty function which is related to load shifting. The two criteria are normalized based on theoretical estimates of maximum values as presented in equations 6 and 10.

$$f = \min\left(w_1 \frac{Cost_E}{Cost_{E_{max}}} + w_2 \frac{Load_{Shift}}{Load_{Shift\_max}}\right) (1)$$

3.3.2.1 Optimization in building level

3.3.2.1.1 Cost of electricity in L4 Leaf Lab

The first part of this function concerns the cost of electrical energy in one building (L4 Leaf Lab). Due to the fact that HVAC power consumption measurements are not available in the platform for all buildings, the total electrical power consumption of each building was taken into account. Hence, the $Cost_E$ denotes:

$$Cost_E = Cost_{E\_Lab} \ (2)$$

Where:

$Cost_{E\_Lab}$ is the daily energy operating costs of Lab building(€)

The calculation of $Cost_{E\_Lab}$ is presented below:

$Cost_{E\_Lab} = \sum_{h=1}^{24} X_{E\_Lab}^{h} * C_{E\_unit}^{h}$ (2.1)

where:

$C_{E\_unit}^{h}$ is the day-ahead hourly unit cost of energy (€/kWh)

$X_{E\_Lab}^{h}$ is the hourly average of total energy consumption (kWh)

In order to evaluate the results of the optimization we compare them with the baseline consumption as obtained by the Artificial Neural Network day ahead prediction model. In this case the cost of baseline (predicted) scenario is given by:

$$Cost_{E\_baseline} = \sum_{h=1}^{24} X_{E_{Lab_{baseline}}}^{h} * C_{E_{unit}}^{h} \ (3)$$

Where:

$X_{E_{Lab_{baseline}}}^{h}$: Baseline hourly average of total electrical power in kWh for each building based on day-ahead Neural Network based energy prediction.

Afterwards, we calculate the daily optimized energy consumption as:

$$E\_cons_{day\_ahead} = \sum\nolimits_{i=1}^{24} X_{E\_Lab}^{h} \ (4)$$

Also, we can calculate the daily baseline consumption as shown in eq.5:

$$E\_cons_{baseline} = \sum\nolimits_{i=1}^{24} X_{E_{Lab_{baseline}}}^{h} \ (5)$$

Finally, the criteria must be normalized. Obviously, the majority of problems have objective functions with different measure values units as Cost (€) and Load shifting (kW). For this reason, normalization is required in order to have values between [0,1] and be comparable. The criterion of cost was normalized, divided his value with the maximum daily cost ($Cost_{E_{max}}$) that each of the buildings is going to have.

3.3.2.1.2 Load shifting in L4 Leaf Lab

The second criterion of function (1) is $Load_{shift}$ It is a measure of deviation from the ideal (baseline) day ahead energy consumption profile. The concept behind this criterion is to integrate in the optimization a competitive criterion which reflects the fact that load shifting can be related to inconvenient changes in the way a building operates. Such inconvenience may be related to some form of intervention in the way HVAC, lights or industrial loads operate. Therefore, a penalty is introduced to account for this trade off. In eq.6, $Load_{Shift}$ is analyzed in the corresponding terms for L4 Leaf Lab building.

$$Load_{Shift} = Load_{Shift_{Lab}} (6)$$

where

$$Load_{Shift\_Lab} = \sum_{h=1}^{24} abs(X_{E\_Lab}^{h} - X_{E_{Lab_{baseline}}}^{h})(7)$$

Constraint below is applied to make sure there is no deviation in the total energy consumed every day by the building.

$$\sum_{h=1}^{24} X_{E_{Lab}}^{h} - \sum_{h=1}^{24} X_{E_{Lab_{baseline}}}^{h} = 0(8)$$

Finally, we follow the same procedure for the normalization of the second criterion. In this case, we divided his value with the maximum daily Loadshift ($Load_{Shift\_max}$)that the building may has.

In the objective function, each criterion is multiplied by the relative weight coefficient w_1 and w_2 which are constrained by eq. 9 and 10 below:

w_1+w_2 $= 1$ (9)

$w_1, w_2 \in [0,1]$ (10)

Exactly the same process was followed for L5 Kite Lab and L2eL3.

3.3.2.2 Optimization in Building group level

3.3.2.2.1 Cost of electricity in district level

The same methodology with 1.1 was used for the cost of electrical energy in district level. In this case, we deal with the power consumption of three buildings. In particular, we used data from L5 Kite Lab, L2eL3 and L4 Leaf Lab, that were taken from the platform, and the same procedure was started. Hence, the $Cost_E$ denotes:

$$Cost_E = Cost_{E\_Lab} + Cost_{E\_Kite} + Cost_{E_{\mathrm{EL2eL3}}} (13)$$

Where:

$Cost_{E\_Lab}$ is the daily energy operating costs of Lab building(€)

$Cost_{E\_Kite}$ is the daily energy operating costs of Kite building(€)

$Cost_{E\_\mathrm{EL2eL3}}$: is the daily energy operating costs of Leaf Education building (€)

Terms in eq.13 are calculated based on equations 13.1, 13.2, 13.3 as shown below:

$$Cost_{E\_Lab} = \sum_{h=1}^{24} X_{E\_Lab}^h * C_{E\_unit}^h \text{ (13.1)}$$

$$Cost_{E\_Kite} = \sum_{h=1}^{24} X_{E\_Kite}^h * C_{E\_unit}^h \text{ (13.2)}$$

$$Cost_{E\_\mathrm{L2eL3}} = \sum_{h=1}^{24} X_{E\_\mathrm{L2eL3}}^h * C_{E\_unit}^h \text{ (13.3)}$$

where:

$C_{E\_unit}^h$ is the day-ahead hourly unit cost of energy in each building (€/kWh)

X_E^h is the hourly average oftotal energy consumption in each building (kWh)

In order to evaluate the results of the optimization we compare them with the baseline consumption as obtained by the Artificial Neural Network day ahead prediction model. In this case the cost of baseline (predicted) scenario is given by:

$$Cost_{E\_baseline} = \sum_{h=1}^{72} X_{E_{baseline}}^{h} * C_{E_{unit}}^{h} \ (14)$$

$X_{E_{baseline}}^{h}$ *:* Baseline hourly average of total electrical power in kWh for all buildings based on day-ahead Neural Network based energy prediction.

Afterwards, we calculate the daily total optimized energy consumption as:

$$E\_cons_{day\_ahead} = \sum_{i=1}^{72} X_{E}^{h} \ (15)$$

Also, we can calculate the daily total baseline consumption as shown in eq.16:

$$E\_cons_{baseline} = \sum_{i=1}^{72} X_{E_{baseline}}^{h} \ (16)$$

As for the normalization in district level, the criterion of cost was divided with the maximum daily cost that the three building are going to have. So, we considered:

$$Cost_{E_{max}} = € \ (17)$$

3.3.2.2.2. Load shifting in district level

In this case, the second criterion concerns the Load$_{shift}$ of three buildings. Following the same approach, Load$_{shift}$ is calculated as it is shown in eq. 18:

$$Load_{Shift} = Load_{Shift\_Lab} + Load_{Shift\_Kite} + Load_{Shift_{\mathrm{L2eL3}}} (18)$$

where

$$Load_{Shift\_Lab} = \sum_{h=1}^{24} abs(X_{E\_Lab}^{h} - X_{E_{Lab_{baseline}}}^{h}) \ (19)$$

$$Load_{Shift\_Kite} = \sum_{h=1}^{24} abs(X_{E\_Kite}^{h} - X_{E_{Kite_{baseline}}}^{h}) \ (20)$$

and

$$Load_{Shift_{Education}} = \sum_{h=1}^{24} abs(X_{E\_\mathrm{L2eL3}}^{h} - X_{E_{\mathrm{L2eL3}_{baseline}}}^{h}) \ (21)$$

Constraints below are applied to make sure there is no deviation in the total energy consumed every day by each building:

$$\sum_{h=1}^{24} X_{E_{Lab}}^{h} - \sum_{h=1}^{24} X_{E_{Lab_{baseline}}}^{h} = 0 (22)$$

$$\sum_{h=1}^{24} X_{E_{Kite}}^{h} - \sum_{h=1}^{24} X_{E_{Kite_{baseline}}}^{h} = 0 \ (23)$$

$$\sum_{h=1}^{24} X_{E\_\mathrm{L2eL3}}^{h} - \sum_{h=1}^{24} X_{E_{\mathrm{L2eL3}_{baseline}}}^{h} = 0 \ (24)$$

As for the normalization, the criterion of $Load_{shift}$ was divided with the maximum daily $Load_{Shift\_max}$ that the three building are going to have.

Finally, the same group of weight coefficient are used as in eq. 9 and 10.

3.3.3 Sensitivity analysis

The two optimization models ended, giving the optimized hourly power consumption, minimizing the objective function. To test the final results, a sensitivity analysis was made in order to check their reliability. In other words, if we change some values, we will have different final results. Population size and other options of ga in Matlab as Tolerance fraction and migration fraction, $Cost_{E_{max}}$, and $Load_{Shift\_max}$ were the variables that were used and changed in order to test the sensitivity analysis.

4.Results

4.1 Artificial Neural Network

In this chapter there are presented the results of ANN for the summer, which is the first step of this study. The first case is L4 Leaf Lab building, whose predictions are shown below. For the forecast, data from 1/5/2017 to 1/8/2017 were used.

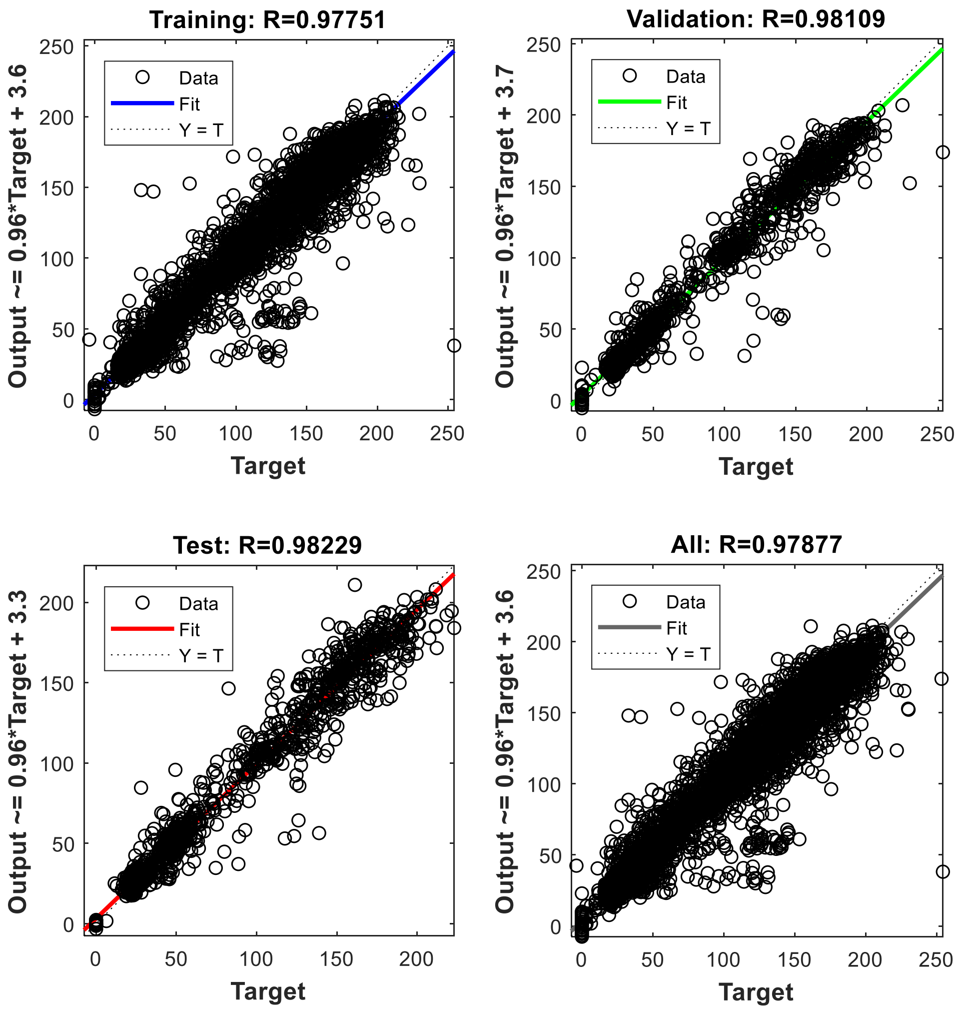


Figure 4.1: Prediction of electrical power with temperature and power input for L4 Leaf Lab

According to Figure 4.1 the forecast for the building is close to the real power consumption since the correlation coefficient R is 0.98.

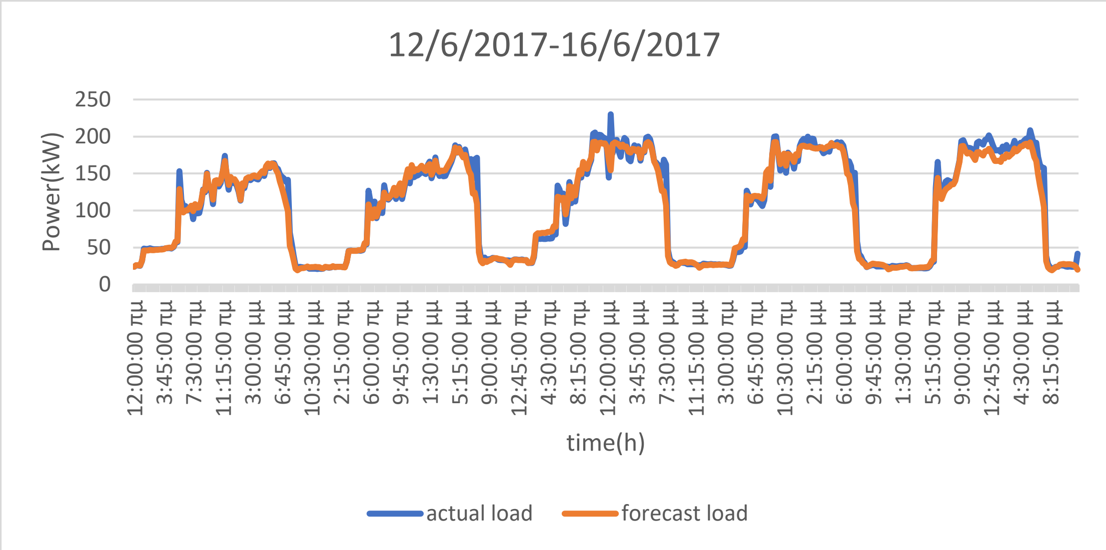


Figure 4.2: Plot with actual and predicted loads

Due to the fact that the chart of the results of ANN has a big variety of data, and it is not clear enough, we decided to depict a part of these predicted loads concerning one week of June and one day of July. Figure 4.2 depicts the load of power for 1 week (12/6/2017 to 16/6/2017), for actual and predicted load from ANN. In this plot, we can observe that there is not significant difference in the fluctuation of loads during the peak hours.

More specifically, for these 3 months we will focus in one day of the summer, which the daily temperature is significant high, in 21/7/2017, using the forecast data to the optimization later. Figure 4.3 represents the baseline and the predicted load in this day. As we can observe, the actual and the forecast load are very close during the day.

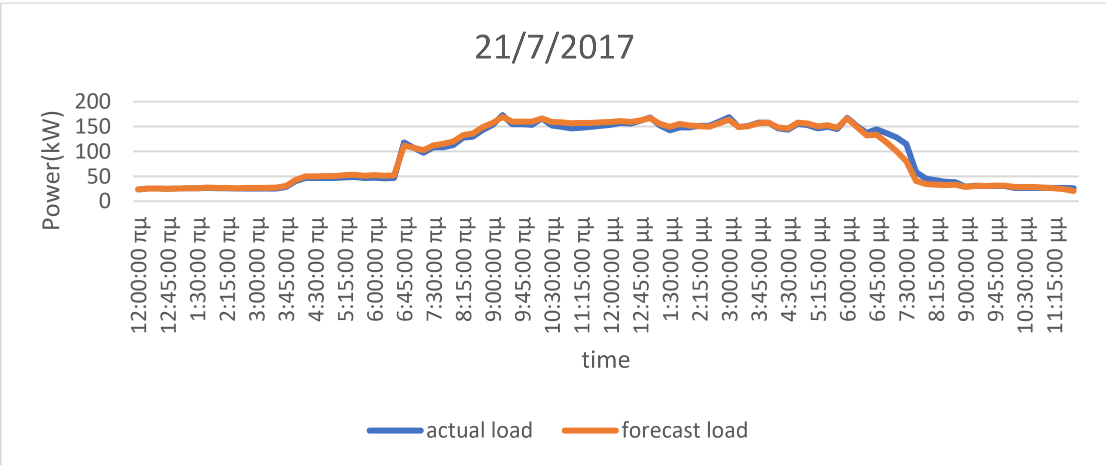


Figure 4.3 The prediction in 21/7/2017

Moreover, apart from the correlation coefficient R, we decided to calculate two other statistical indicators which are Mean Bias Error and Mean Average Predicted Error.

$$\text{Mean Bias Error (MBE)} = \frac{9091 - 9044}{96} = 0.49$$

$$\text{Mean Average Predicted Error (MAPE)} = \frac{1}{96} * \frac{|9044 - 9091|}{9044} = 0.005$$

$$=> \text{MAPE} = 0.005\%$$

MBE shows that we have managed to get a good approach since the value is only 0.49 and from bibliography it should be near zero. MAPE indicates that only the 0.005% of the predicted loads differ from the actual load in this day.

After the Leaf Lab, we should forecast the loads in L2 e L3 Angeli the same day as before (21/7/2017). The predictions are shown below in Figure 4.4, having the correlation coefficient R=0.97 which denotes good relationship between predicted and actual load.

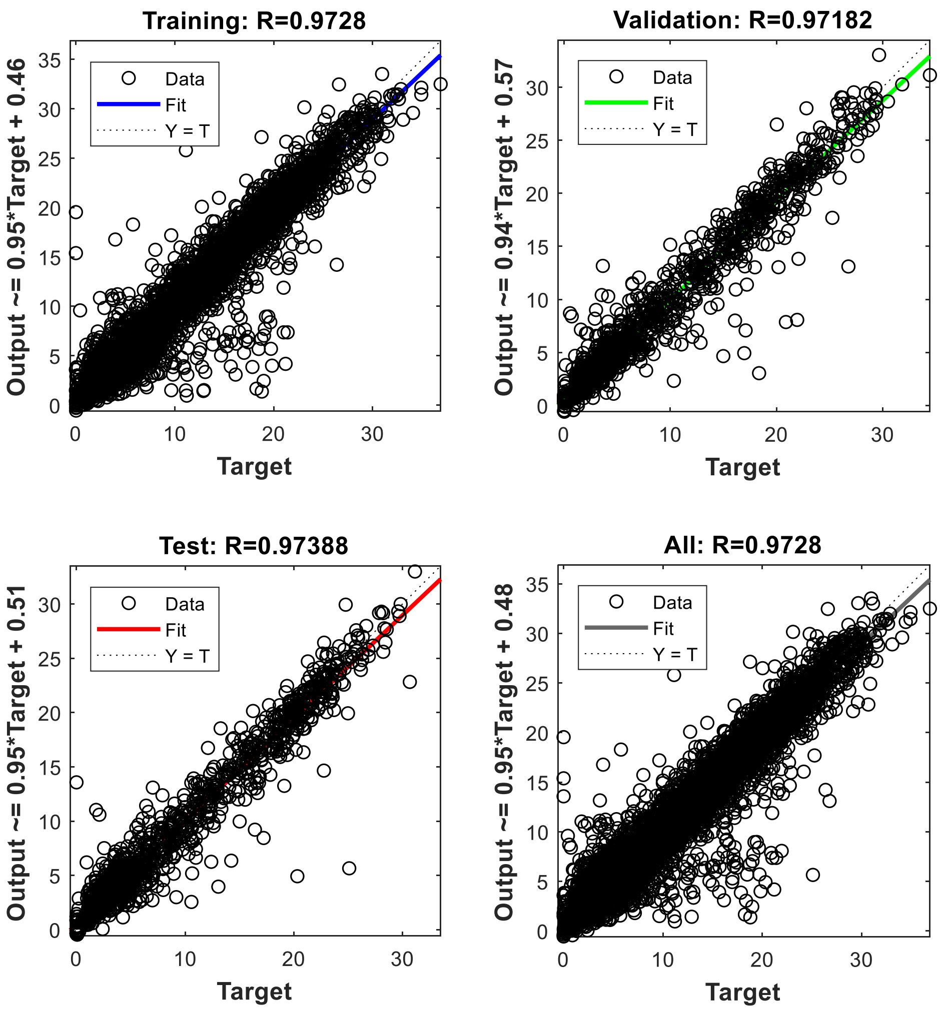


Figure 4.4: Prediction with temperature and power input for L2 e L3 Angeli

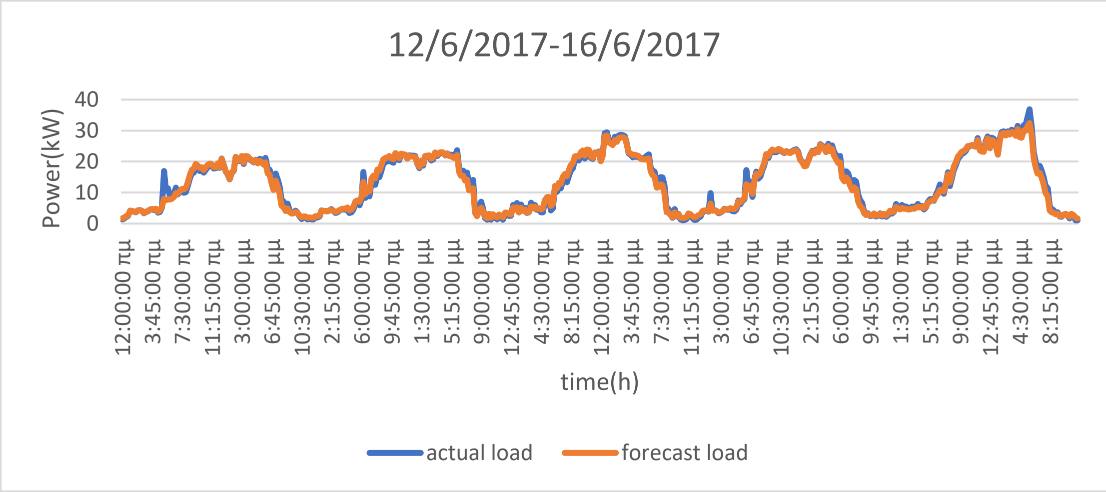


Figure 4.5: Plot with actual and predicted loads

As in the Figure 4.2, the same procedure was followed in Figure 4.5 for 12/6/2017 to 16/6/2017. In this figure, the actual and predicted load from ANN are depicted. In this plot, we can observe that there is not significant difference in the fluctuation of loads.

Apart from the 3 months, and in this case, we would like to focus to a specific day due to the fast that we will use this forecast later, in the optimization. Figure 4.6 illustrates the relationship between the data before and after the forecast.

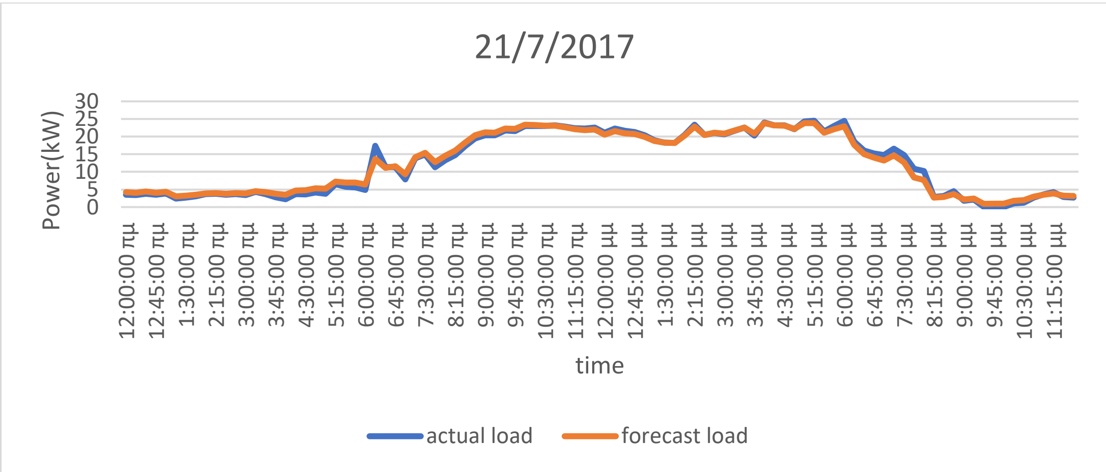


Figure 4.6 The prediction in L2 e L3 Angeli in 21/7/2017

Moreover, apart from the correlation coefficient R, we decided to calculate two other statistical indicators which are Mean Bias Error and Mean Average Predicted Error.

$$\text{Mean Bias Error (MBE)} = \frac{1215.5 - 1207.7}{96} = 0.08$$

$$\text{Mean Average Predicted Error (MAPE)} = \frac{100}{96} * \frac{\text{abs}(1207.7 - 1215.5)}{1215.5} = 0.007$$

$$\text{MAPE} = 0.007\%$$

MBE shows that we have managed to get a good approach since the value is only 0.48 and from bibliography it should be near zero. MAPE indicates that only the 0.007% of the predicted loads differ from the actual load in this day, in which is the difference is negligible.
After the L2 e L3 Angeli, we should forecast the loads in L5 Kite Lab the same day as before. The predictions are shown below in Figure 4.7, having the correlation coefficient R=0.98 which denotes good relationship between predicted and actual load.

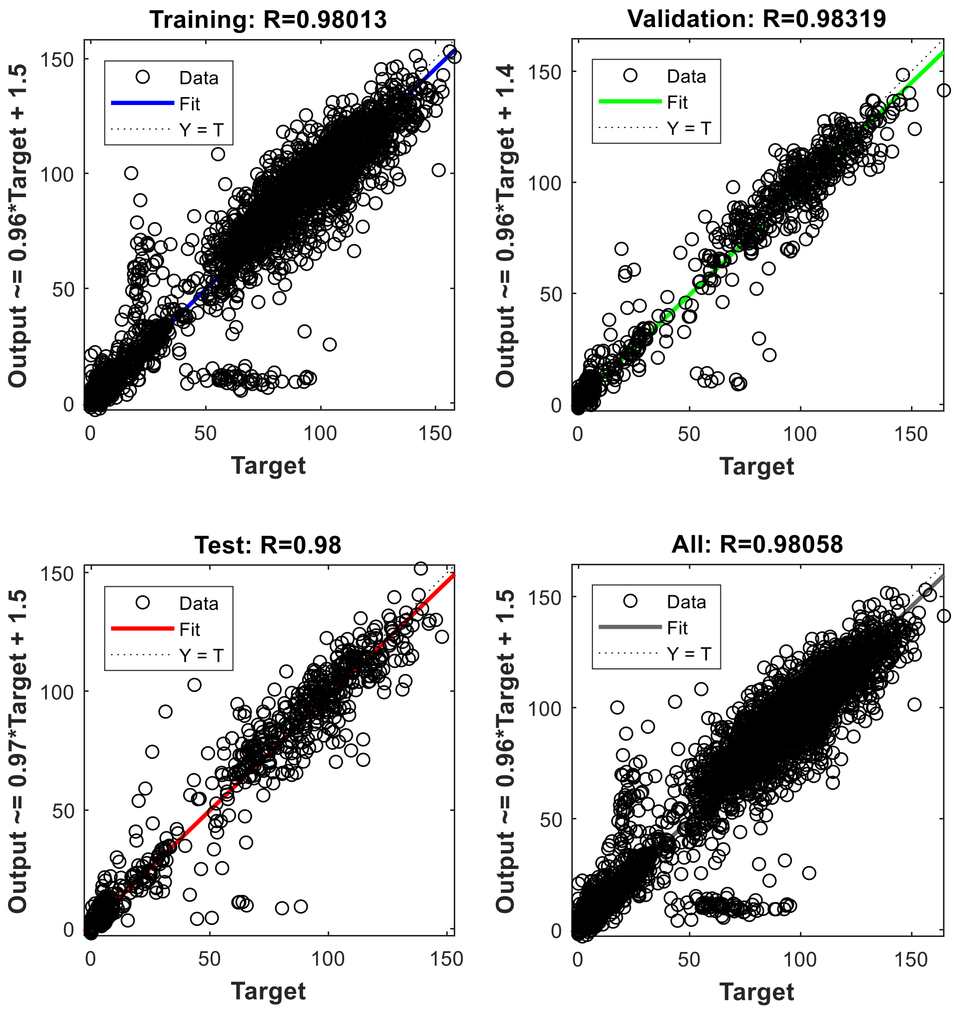


Figure 4.7: Prediction with temperature and power input for L5 Kite Lab

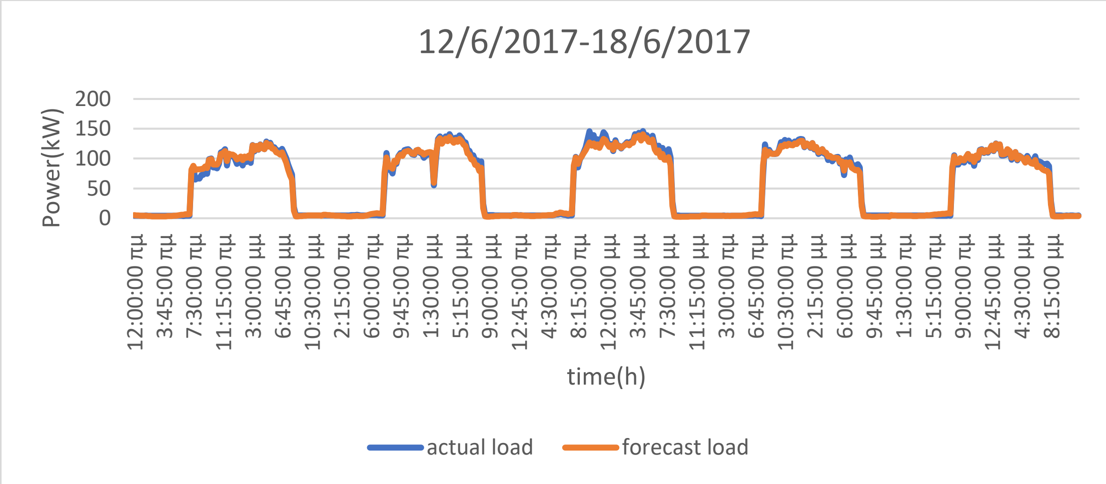


Figure 4.8: Plot with actual and predicted loads

As in the Figure 4.2 and in the Figure 4.5, the same procedure was followed in Figure 4.8 for 12/6/2017 to 16/6/2017. In this figure, the actual and predicted load from ANN are depicted. In this plot, we can observe that there is not significant difference in the fluctuation of loads.

Apart from the 3 months, and in this case, we would like also to focus to a specific day due to the fast that we will use this forecast later. Figure 4.9 depicts the relationship between the data before and after the forecast.

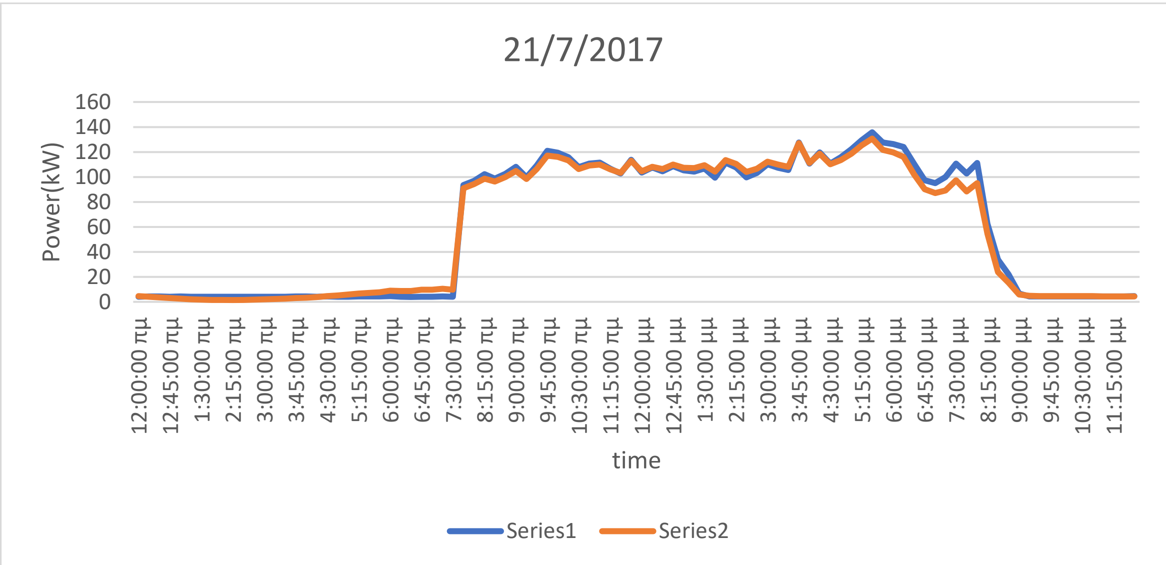


Figure 4.9 The prediction in L5 Kite Lab in 21/7/2017

$$\text{Mean Bias Error (MBE)} = \frac{5664.3 - 5785}{96} = -1.3$$

$$\text{Mean Average Predicted Error (MAPE)} = \frac{100}{96} * \frac{(5785 - 5664.3)}{5785} = 0.002 =>$$

$$\text{MAPE} = 0.002\%$$

The statistical indicators in this forecast are good, having in mind that the value of MBE should be near zero in the case of having good approach. The MAPE illustrates that only the 0.002% of the forecast differs from the baseline, and this is negligible difference.

The second step of this study is the forecast of loads using ANN for the winter. The predictions are shown below in Figure 4.10, having the correlation coefficient R=0.96 which denotes good relationship between predicted and actual load.

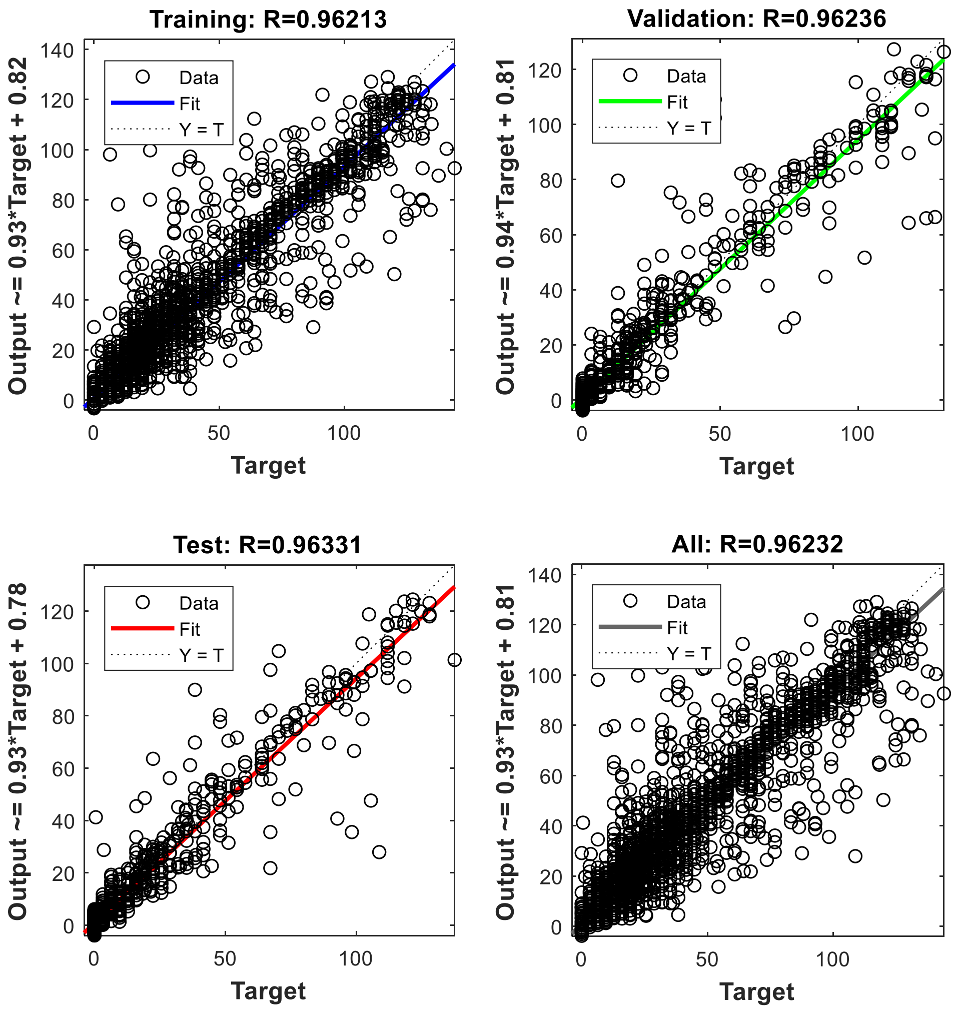


Figure 4.10: Prediction with temperature and power input for L4 Leaf Lab

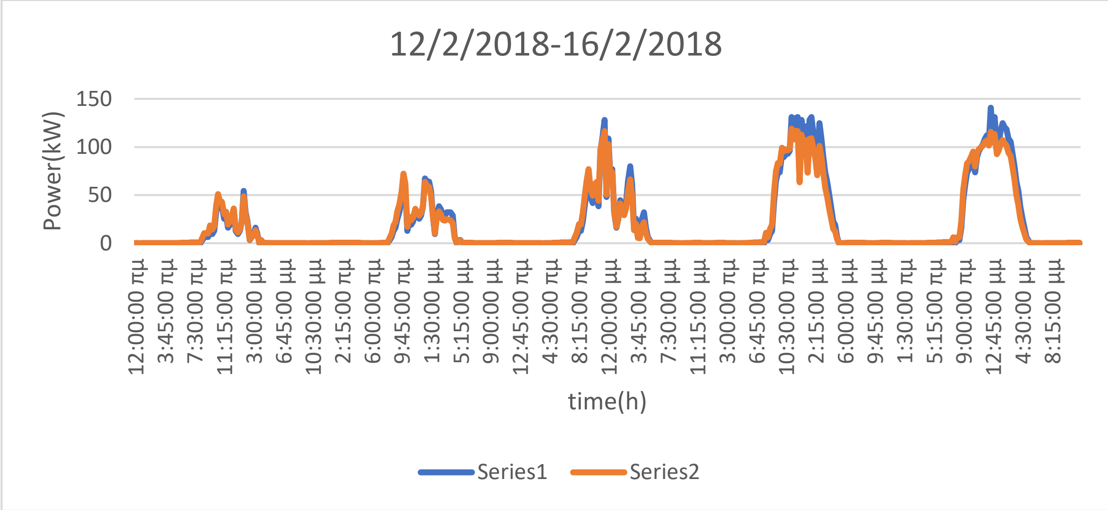


Figure 4.11: Plot with actual and predicted loads

Figure 4.11 depicts the load of power for 1 week (12/2/2018-16/2/2018), for actual and predicted load from ANN. In this plot, we can observe that there is not significant difference in the fluctuation of loads, apart from the peak hours in Thursday and Friday where the actual load is higher than the predicted load.

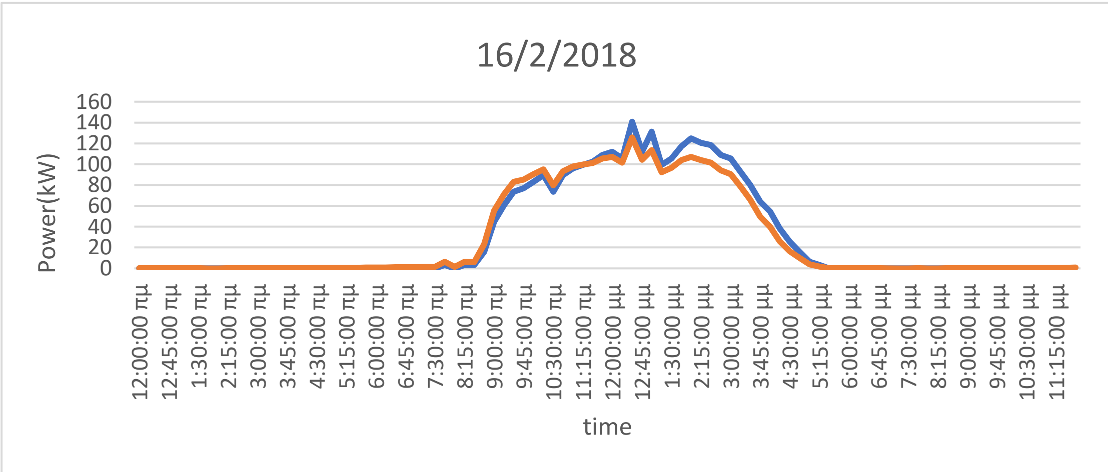


Figure 4.12 The prediction in L4 Leaf Lab in 16/2/2018

Apart from the 3 months, and in this case, we would like also to focus to 16/2/2018 due to the fast that we will use this forecast later. Figure 4.12 depicts the relationship between the actual data and the 24hour day ahead data. From this figure we can observe that there is not significant difference between the power data. Then, the statistical indicators were calculated as it shown below.

$$\text{Mean Bias Error (MBE)} = \frac{2754.9 - 2906.5}{96} = -1.58$$

$$\text{Mean Average Predicted Error (MAPE)} = \frac{100}{96} * \frac{\text{abs}(2906.5 - 2754.9)}{2906.5} = 0.05$$

$$\text{MAPE} = 0.05\%$$

The statistical indicators in this forecast are good, having in mind that the value of MBE should be near zero in the case of having good approach, and we have -1,58. The MAPE illustrates that only the 0.05% of the forecast differs from the baseline, and this is negligible difference.

After the L4 Leaf Lab, we should forecast the loads in L5 Kite Lab for the winter. The predictions are shown below in Figure 4.13, having the correlation coefficient R=0.98 which denotes good relationship between predicted and actual load.

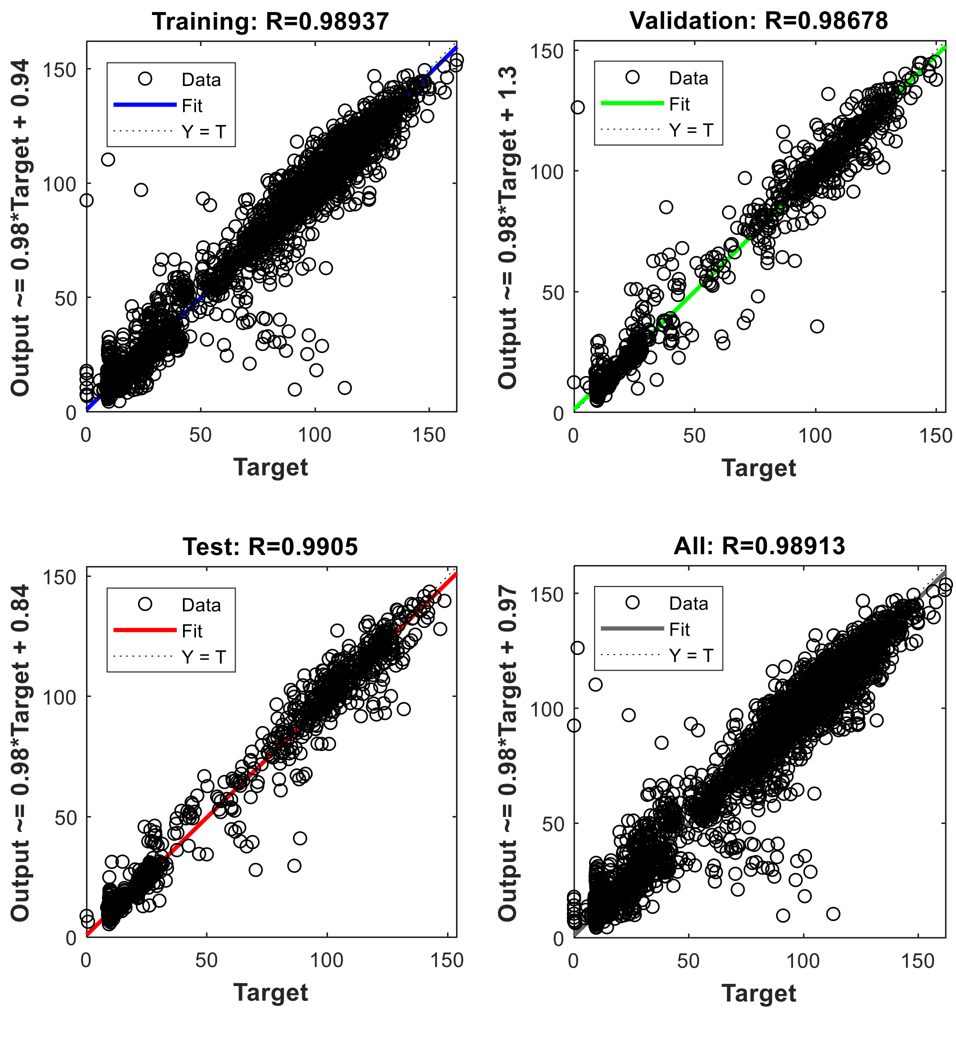


Figure 4.13: Prediction with temperature and power input for L5 Kite Lab

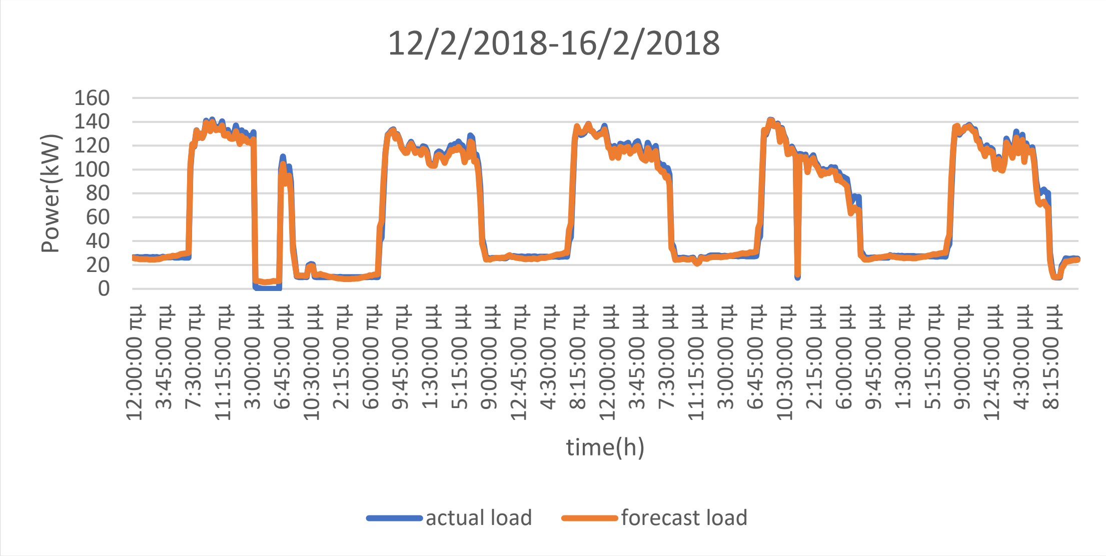


Figure 4.14: Plot with actual and predicted loads

Figure 4.14 depicts the load of power for 1 week (12/2/2018-16/2/2018), for actual and predicted load from ANN . In this plot, we can observe that there is not significant difference in the fluctuation of loads.

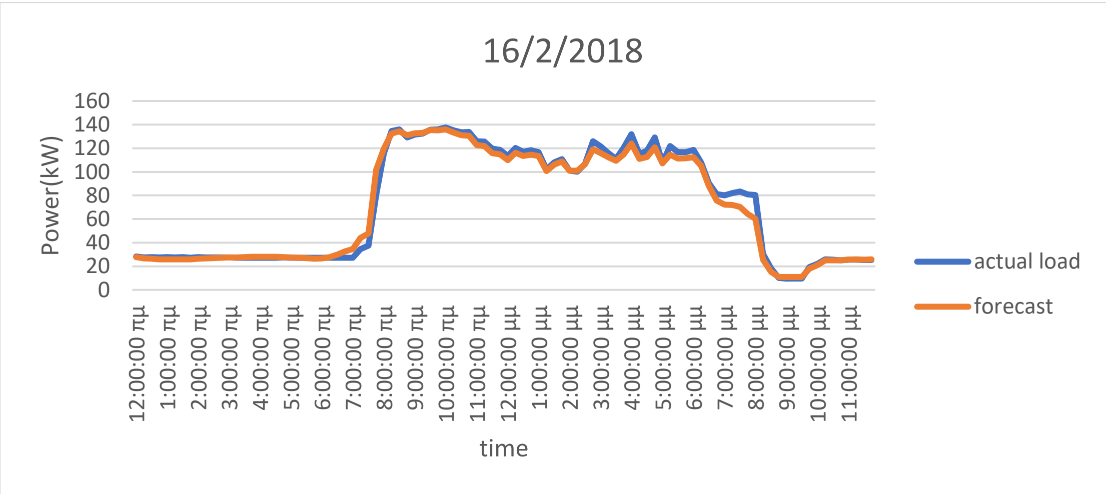


Figure 4.15 The prediction in L5 Kite Lab in 16/2/2018

We would like also to focus to 16/2/2018 due to the fast that it has very low temperature. Figure 4.12 depicts the relationship between the actual data and the 24hour day ahead data. From this figure we can observe that there is not significant difference between the power data. Then, the statistical indicators were calculated as it shown below.

$$\text{Mean Bias Error (MBE)} = \frac{6748.7 - 6905.5}{96} = -1.63$$

$$\text{Mean Average Predicted Error (MAPE)} = \frac{100}{96} * \frac{\text{abs}(6905.5 - 6748.7)}{6905.5} =>$$

$$\mathrm{MAPE} = 0.023\%$$

The statistical indicators in this forecast are very good, having in mind that the value of MBE should be near zero and in our case, is -1.63. The MAPE illustrates that only the 0.023% of the forecast differs from the baseline power, and this is negligible difference.

The final forecast concerns the loads in L2 e L3 Angeli the same period as before. The predictions are shown below in Figure 4.16, having the correlation coefficient R=0.92 which denotes good relationship between predicted and actual load.

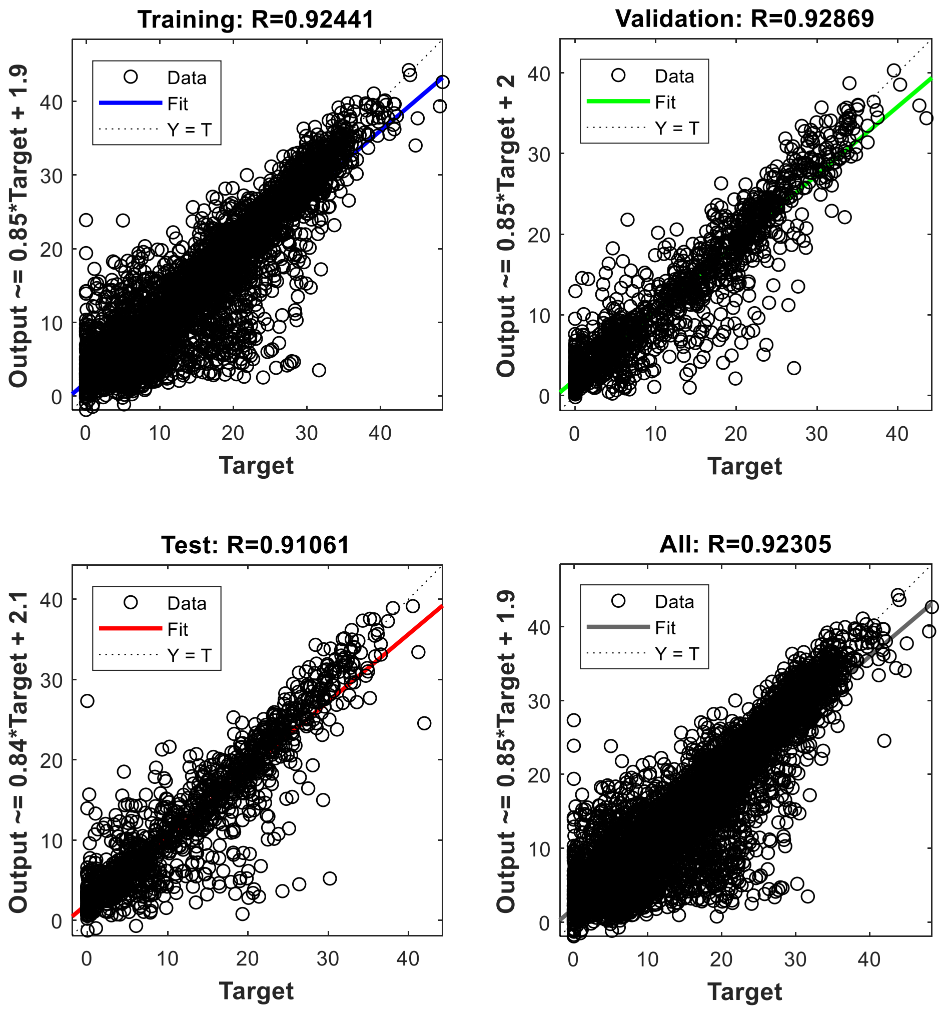


Figure 4.:16 Prediction with temperature and power input for L2 e L3 Angeli

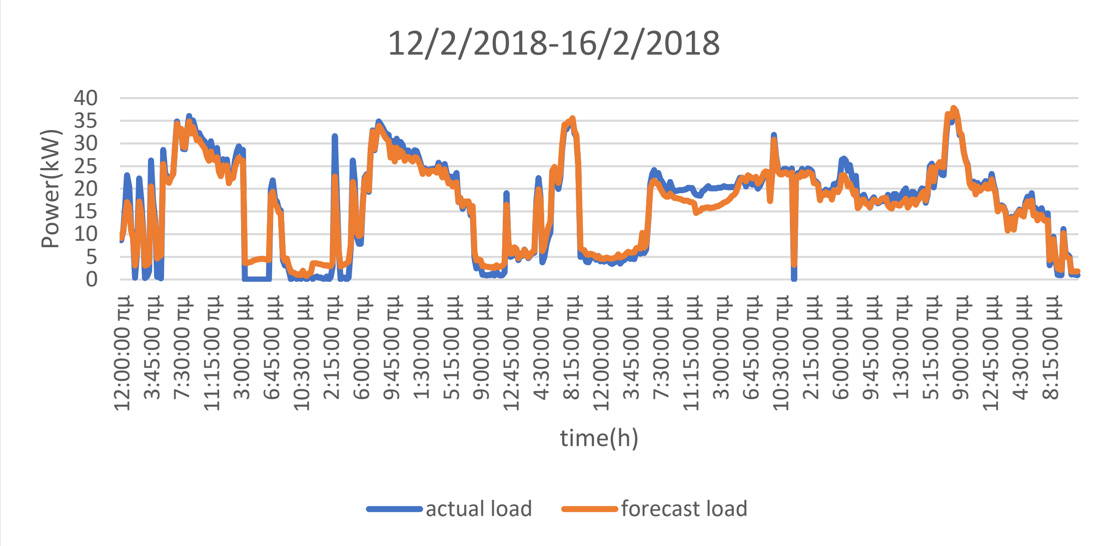


Figure 4.17: Plot with actual and predicted loads

Figure 4.17 depicts the load of power for 1 week (12/2/2018-16/2/2018), for actual and predicted load from ANN . In this plot, we can observe that there is not significant difference in the fluctuation of loads.

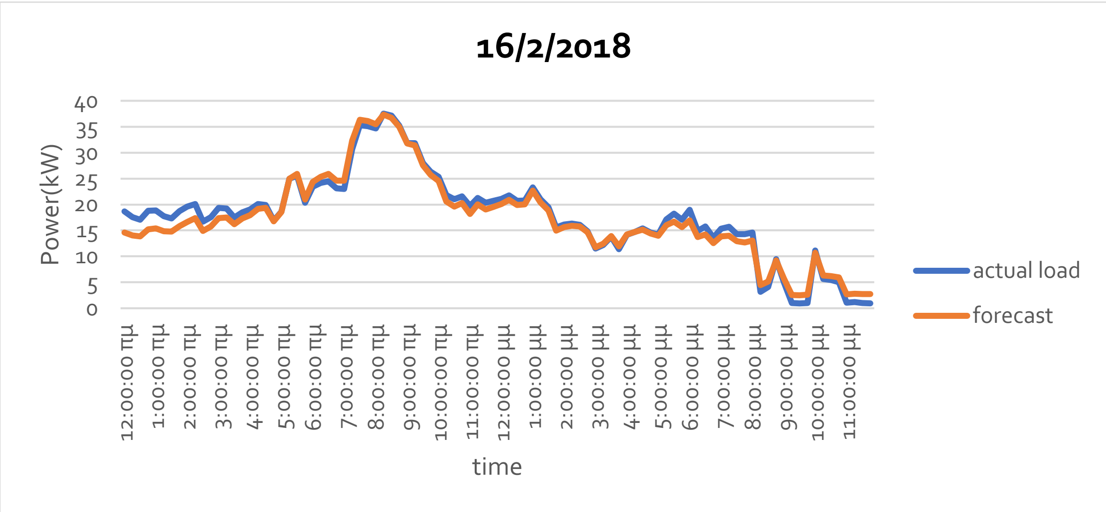


Figure 4.18: The prediction in L2 e L3 Angeli in 16/2/2018

We would like also to focus to 16/2/2018 due to the fast that it has very low temperature. Figure 4.18 depicts the relationship between the actual data and the 24hour day ahead data. From this figure we can observe that there is not significant difference between the power data. Then, the statistical indicators were calculated as it is shown below, showing the same result.

$$\text{Mean Bias Error (MBE)} = \frac{1654.9 - 1707.2}{96} = -0.54$$

$$\text{Mean Average Predicted Error (MAPE)} = \frac{100}{96} * \frac{\text{abs}(1707.2 - 1654.9)}{1707.2} => $$

$$\text{MAPE} = 0.03\%$$

The statistical indicators in this forecast are very good, having in mind that the value of MBE should be near zero and in our case, is -0.54. The MAPE illustrates that only the 0.03% of the forecast differs from the baseline power, and this is negligible difference.

Finally, all the forecast for each building concerning the summer and the winter will be used to the chapter 4.2.

4.2 Genetic Algorithms optimization

In this chapter there are presented in detail all results that concern each building and district level. To begin with the building level, for each of the three buildings the same Methology was followed. Firstly, one day of the summer and one day for the winter are set by using the daily predicted power values that are shown in chapter 4.1. Then, a flat energy price (0.07 €/kWh) was used to calculate the baseline cost. For the optimized cost were used data from AEA that were divided into two categories. The first one concerns the energy price during the peak period (0.0675 €/kWh), and the second one concerns the energy price during the off-peak period (0.0525 €/kWh), as it is shown in Figure 4.2.1.

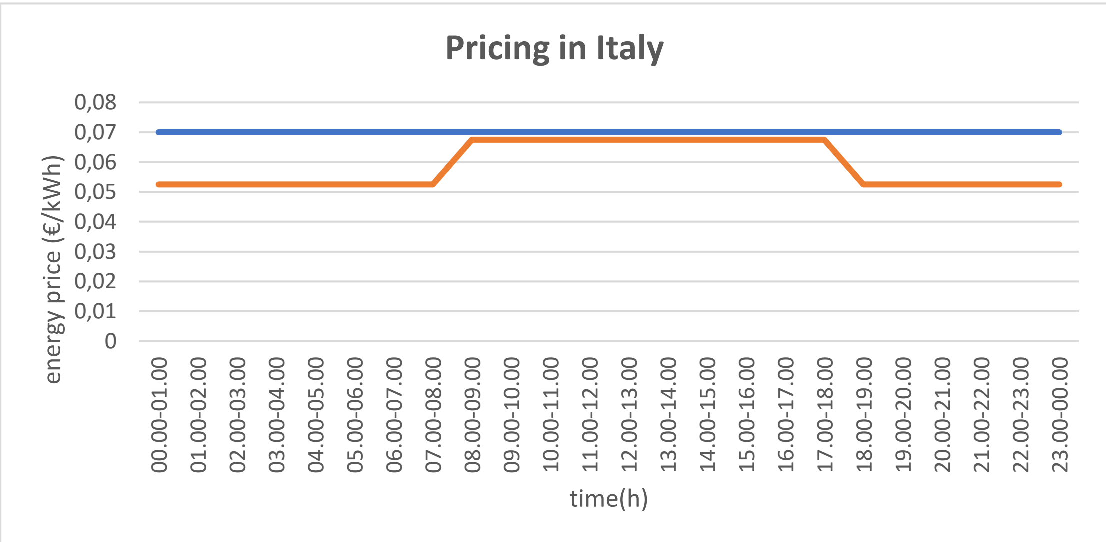


Figure 4.2.1: Energy pricing in Italy

According to the Figure 4.2.1 as peak hour, 07.00-18.00 was set. Apart from that, many weight coefficients were used in Genetic Algorithms, but only the results for the weight w1=0.5 and w2=0.5 will be represented in detail.

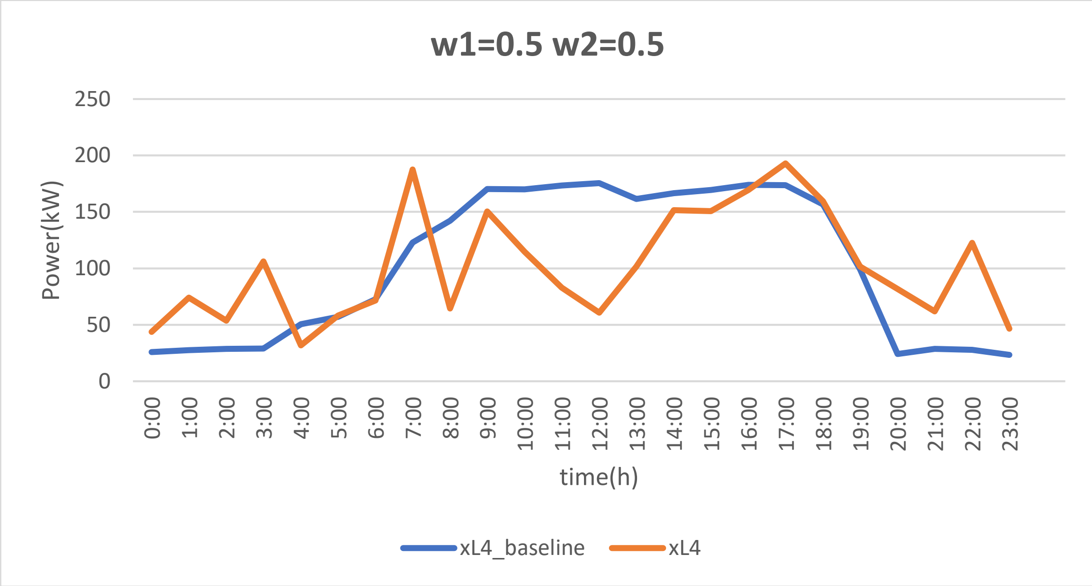


Figure 4.2.2: Optimized and baseline power (kW) in L4 Leaf Lab in the summer

The analysis of the results started with the building L4 Leaf Lab, concerning the summer period, as it is shown in Figure 4.2.2. This figure depicts the variance of power before and after the optimization during the day. We can observer that the variance of power has changed significantly, since we have not accumulated power during the peak hours (8.00-18.00). It should be mentioned that the total power has not been reduced, but only shifted.

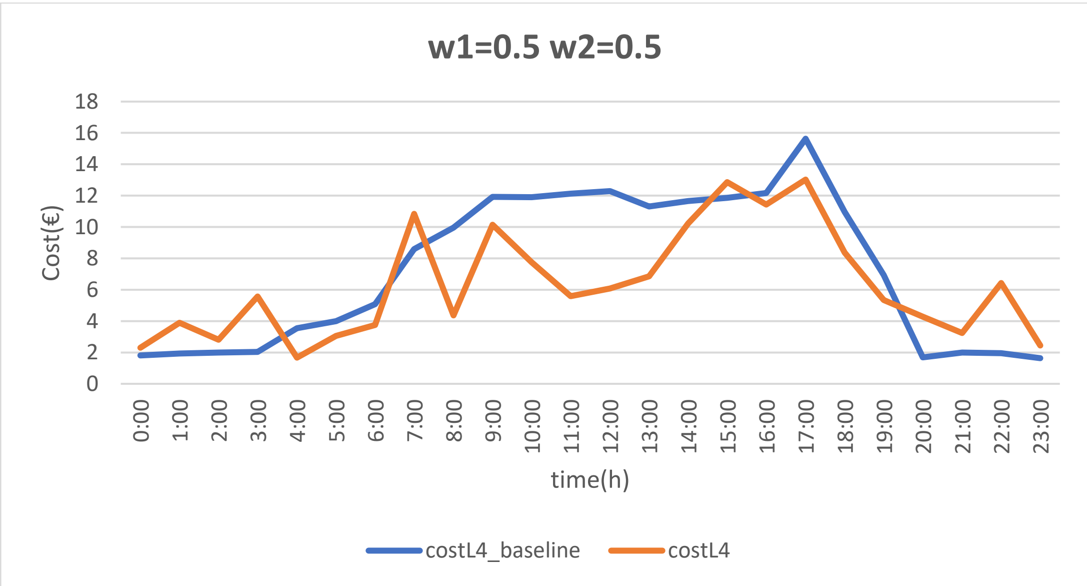


Figure 4.2.3: Optimized and baseline cost (€) in L4 Leaf Lab in the summer

Figure 4.2.3. illustrates the difference between the baseline cost that L4 Leaf Lab has during a summer day, and the optimized cost from the GA. We can notice that there is a substantial difference concerning the cost during the peak, especially in 11.00-13.00. Apart from that, the baseline daily cost is 174.90 € and the optimized daily cost is 147.40 €, achieving a reduction rate of 15.7%.

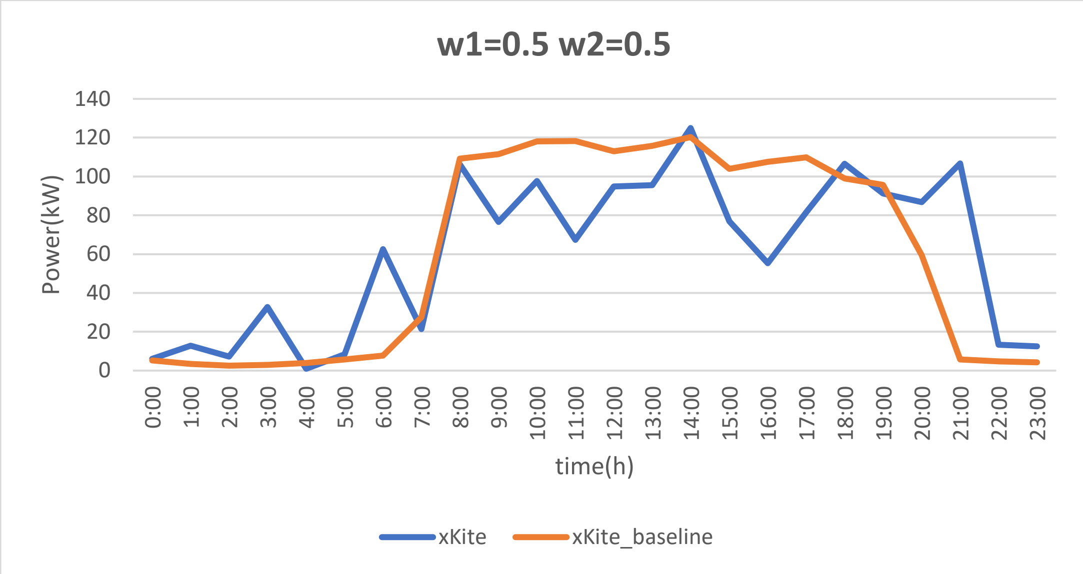


Figure 4.2.4: Optimized and baseline power (kW) in L5 Kite Lab in the summer

Figure 4.2.4 refers to the daily power in L5 Kite Lab during the summer. We can observe many changes to the variance of power before and after the optimization, as the power has shifted from the peak hours to the morning hours (2.00-7.00) and to the night, without reducing the total power consumption. In order not to lose energy in the morning, which may not be needed, an idea is to dispose of energy on batteries for future use.

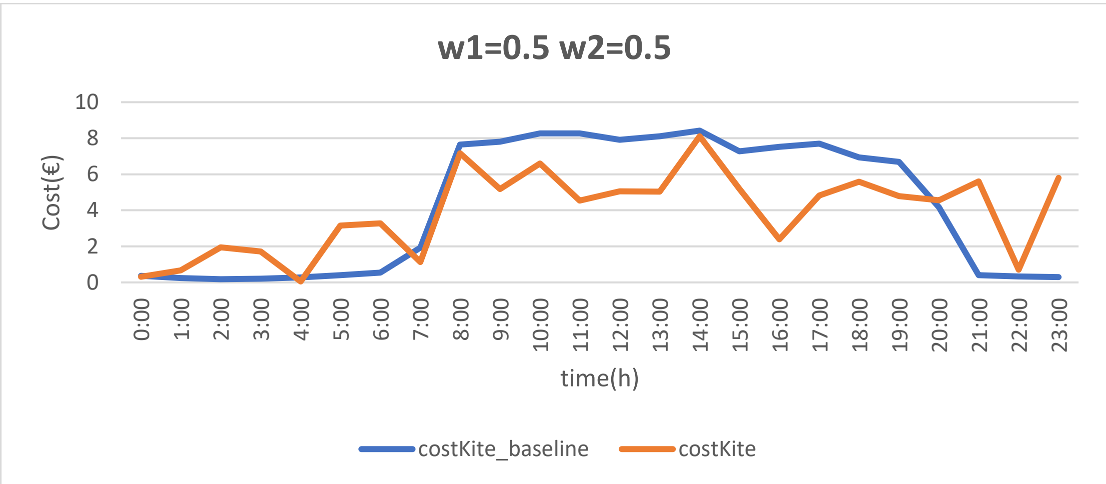


Figure 4.2.5: Optimized and baseline cost (€) in L5 Kite Lab in the summer

Figure 4.2.5. depicts the difference between the baseline cost that L5 Kite Lab has during a summer day, and the optimized cost from the GA. From this figure, we can notice that the optimized cost differs from the baseline, and the main advantage is the reduction of cost during the peak hours, when the energy cost is high. Although, there is an increase of the cost during the morning and the night when the energy cost is significant lower. To be more specific, in this case, the baseline cost is 101.9 € and the optimized total cost is 93 €, achieving a reduction rate of 8.7%.

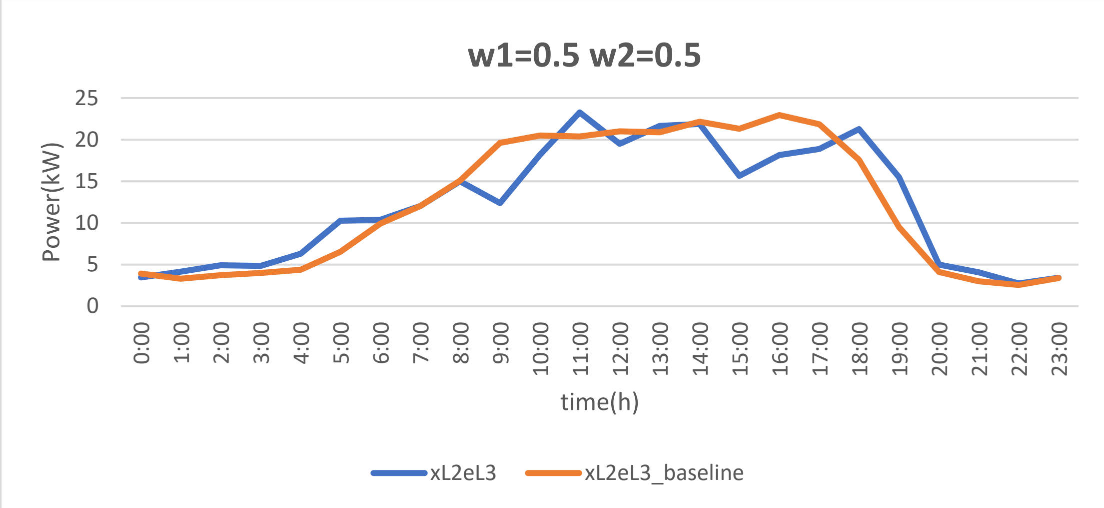


Figure 4.2.6: Optimized and baseline power (kW) in L2eL3 in the summer

Figure 4.2.6 refers to the daily power in L2eL3 during the summer. As we can see, the power consumption in this building is significant lower from L4 Leaf Lab and L5 Kite lab. Although the optimized power is close enough to the baseline power, we can observe some differences at the peak hours, concerning a small shift before and after the peak.

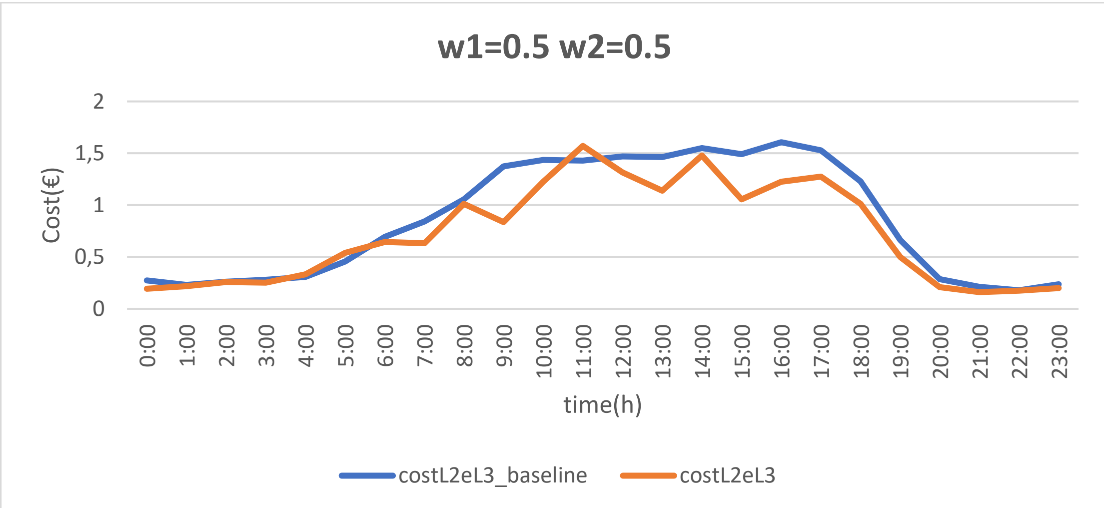


Figure 4.2.7: Optimized and baseline cost (€) in L2eL3 in the summer

Figure 4.2.7. illustrates the difference between the baseline cost that L2eL3 has during a summer day, and the optimized cost from the GA. It is a fact that we observe difference between the baseline and the optimized cost during 8.00-18.00, having in mind that in this building we do not have high price in the cost. In this case, the baseline daily cost is 20 € and the optimized daily cost is 17 €, achieving a reduction rate of 15%.

Apart from the optimization in each of 3 buildings, a new optimization model was developed for the group of buildings. To create the model, the baseline power consumption for each building was added, having the same pricing as before, and the results are presented below.

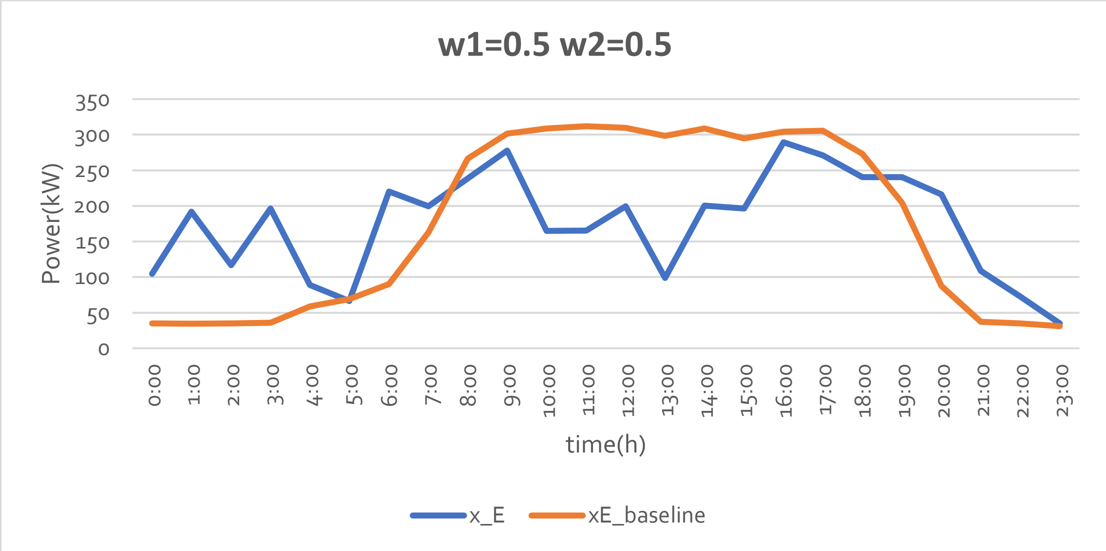


Figure 4.2.8: Optimized and baseline power (kW) in the group of buildings in the summer

To create Figure 4.2.8, the hourly power consumption was added for the three buildings. As we can observe, the optimized power differs enough from the baseline. According to the baseline power, there is high power consumption only in the peak period. In the other hand, the optimized power is uniformly distributed during the day. In the morning the power is high as it is closed to 200 kW and it may not be necessary. One idea is to it is to store this energy in batteries or to use it for charging electric cars.

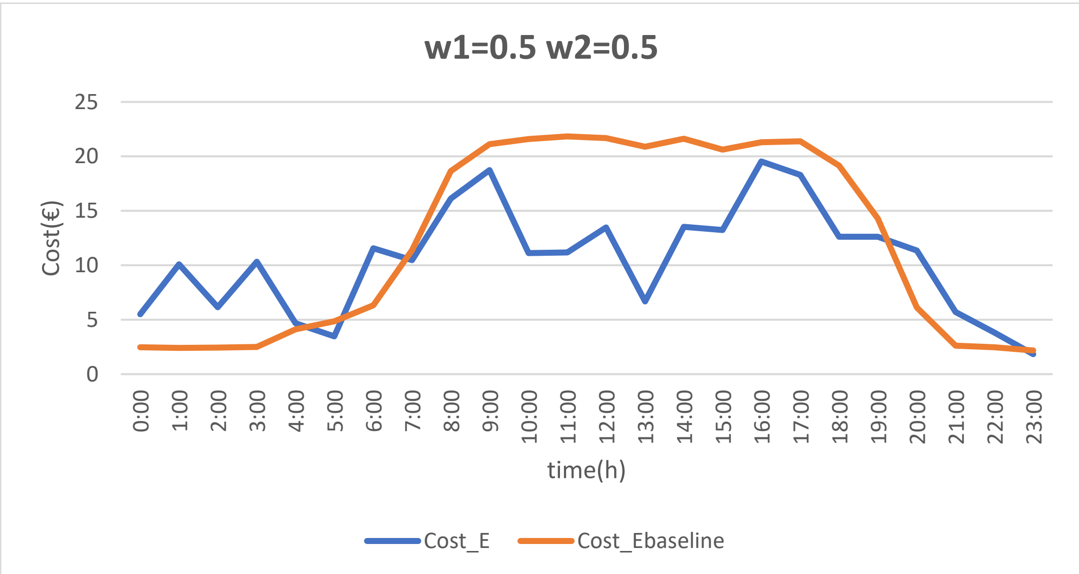


Figure 4.2.9: Optimized and baseline cost (€) in the group of buildings in the summer

The final figure for the summer is the figure 4.2.9 and depicts the total daily cost that the 3 buildings have, before and after the optimization. As we can notice, before the peak time and after the peak time the optimized cost is higher that the baseline. Although, during the peak period is significant reduced especially in 13.00 pm where the optimized cost is 6,7 € and the baseline cost is 20 €. Apart from that the total baseline cost in district level is 293 € and the total optimized cost is 252 €, achieving a reduction rate of 14%.

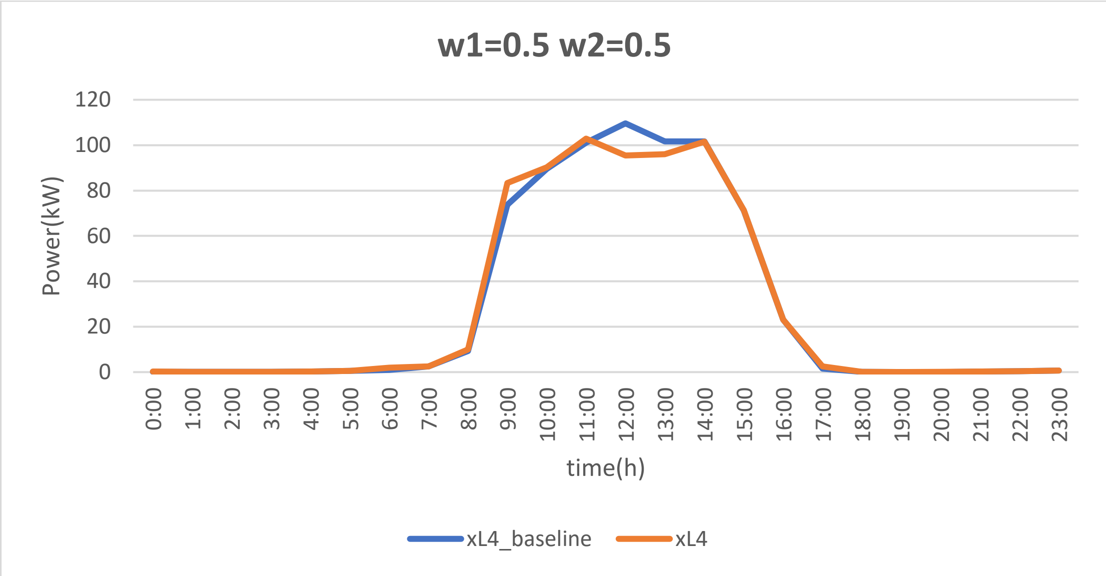


Figure 4.2.10: Optimized and baseline power (kW) in L4 Leaf Lab in the winter

The analysis of the winter results started with the building L4 Leaf Lab, as it is shown in Figure 4.2.10. Comparing this Figure, with Figure 4.2.2, it is obvious that the summer load is higher that the winter. Moreover, the variance of power before and after the optimization during the day does not differ, apart from 11.00-13.00 when the optimized power is higher than the baseline.

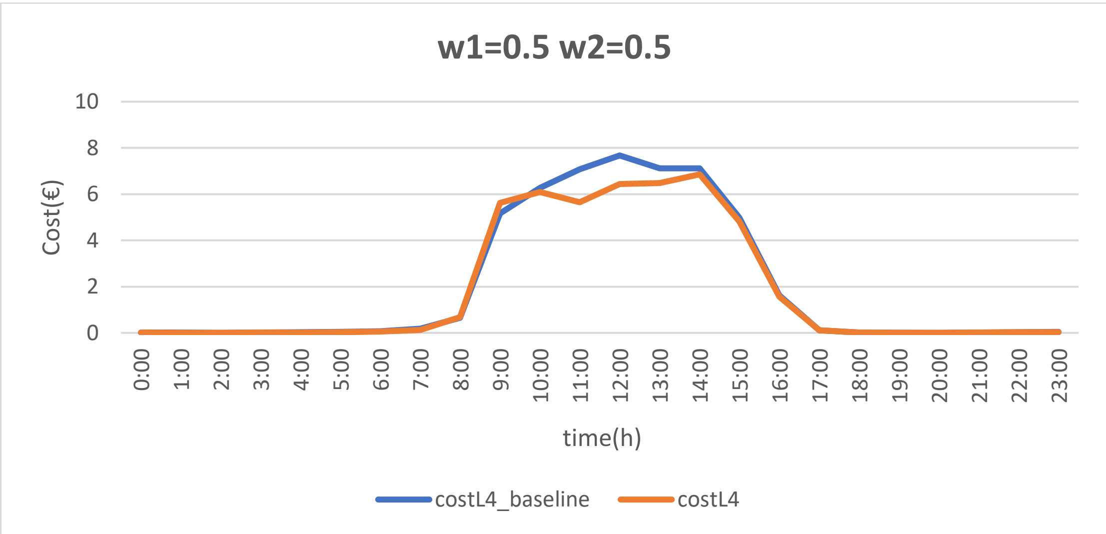


Figure 4.2.11: Optimized and baseline cost (€) in L4 Leaf Lab in the winter

Figure 4.2.11. illustrates the difference between the baseline cost that L4 Leaf Lab has during a winter day, and the optimized cost from the GA. We can notice that there is not difference during all day, apart from the peak period 10.00-14.00 where the

baseline cost is few higher than the optimized. Apart from that, the baseline daily cost is 48 € and the optimized daily cost is 44 €, achieving a reduction rate only 8%.

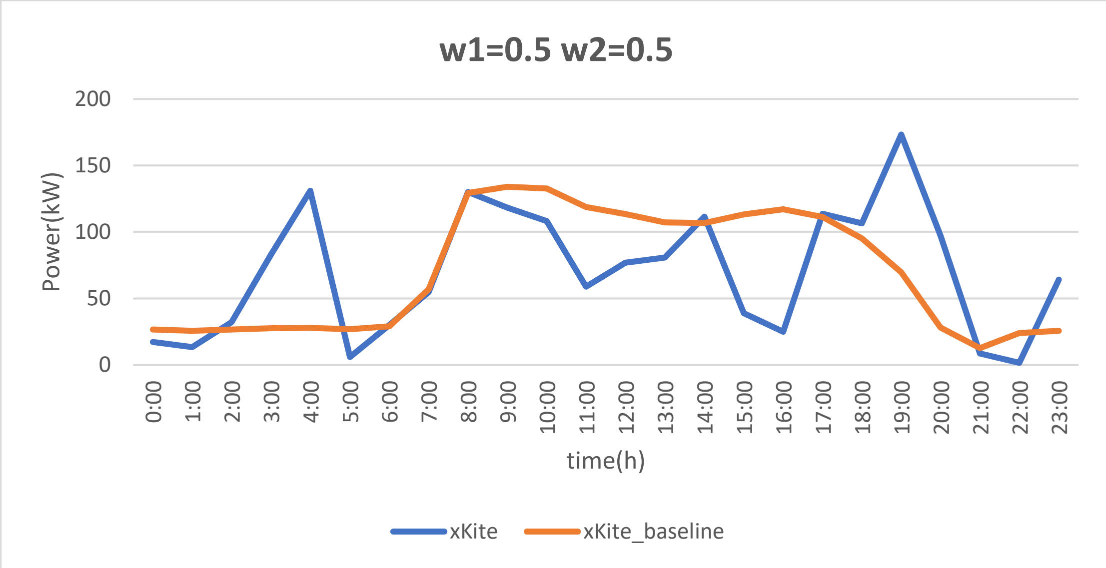


Figure 4.2.12: Optimized and baseline power (kW) in L5 Kite Lab in the winter

Figure 4.2.12 refers to the daily power in L5 Kite Lab during the winter. We can observe many changes to the variance of power before and after the optimization, especially in the morning, when in 3.00am and in 19.00pm the optimized power is higher than the baseline.

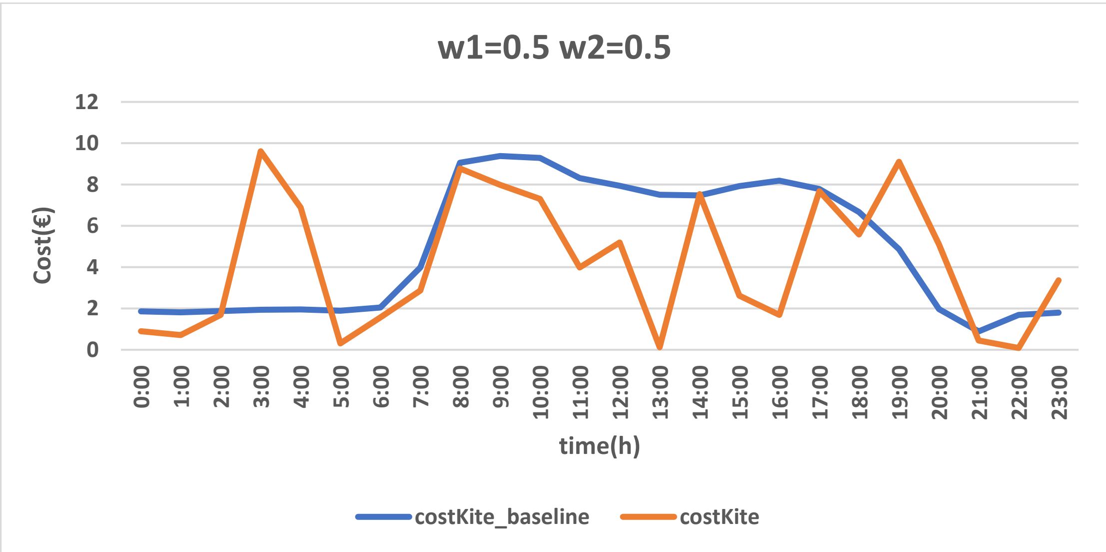


Figure 4.2.13: Optimized and baseline cost (€) in L5 Kite Lab in the winter

Figure 4.2.13. depicts the difference between the baseline cost that L5 Kite Lab has during a winter day, and the optimized cost from the GA. From this figure, we can notice that the optimized cost differs from the baseline, and the main advantage is the reduction of cost during the peak hours, when the energy cost is high. Moreover, the baseline daily cost is 118 € and the optimized daily cost is 101 €, achieving a reduction rate of 14,4%.

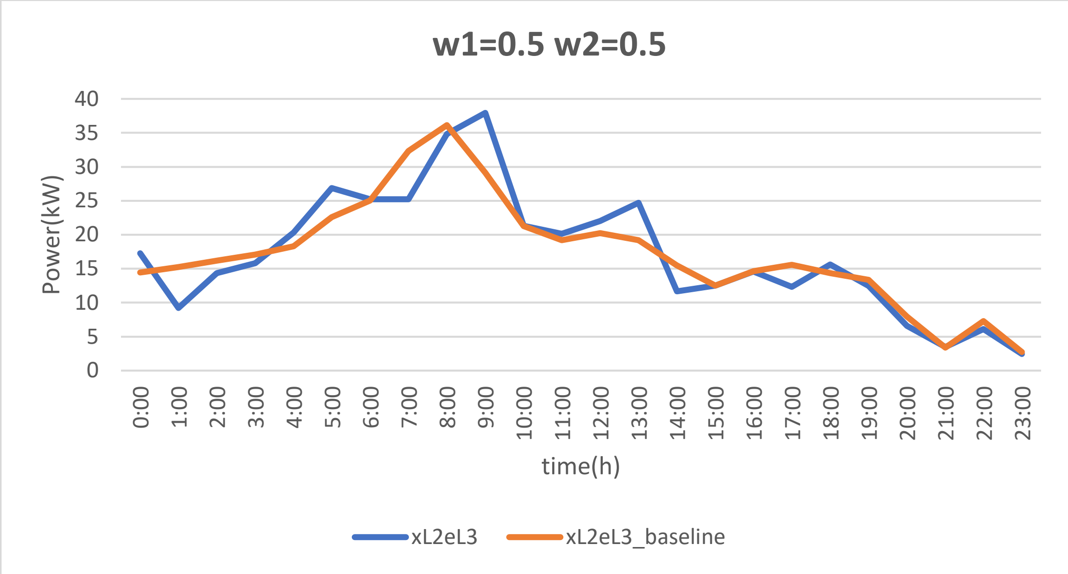


Figure 4.2.14: Optimized and baseline power (kW) in L2eL3 in the winter

As we can see in Figure 4.2.14, L2eL3 has lower power consumption than the other buildings. Apart from that, comparing the optimized and the baseline power we can notice that they are close enough during all day, except the peak hours 9.00am and 13.00pm when the optimized power is higher than the baseline.

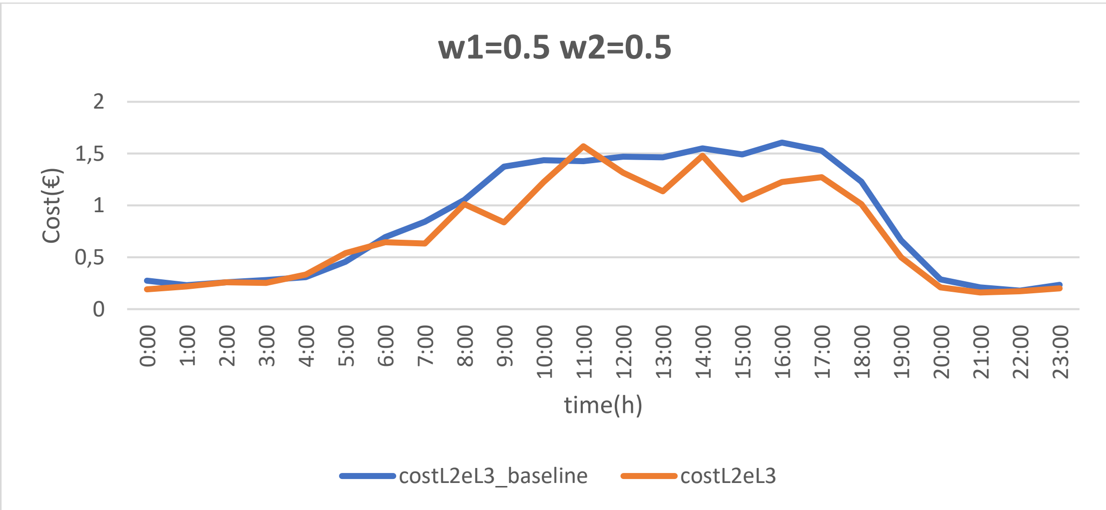


Figure 4.2.15: Optimized and baseline cost (€) in L2eL3 in the winter

Figure 4.2.15. illustrates the difference between the baseline cost that L2eL3 has during a winter day, and the optimized cost from the GA. Although in the case of peak period the baseline cost is lower than the baseline cost, during all the other day the optimized cost is lower than the baseline, due to the fact that we have different pricing. Also, the baseline daily cost is 28€ and the optimized daily cost is 24€, achieving a reduction rate of 14%.

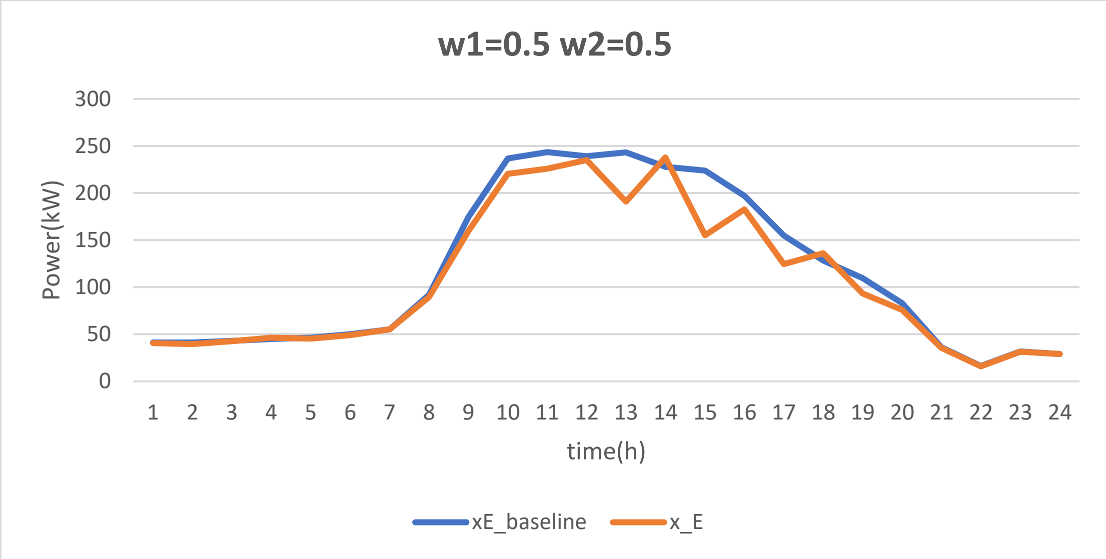


Figure 4.2.16: Optimized and baseline power (kW) in the group of buildings in the winter

To create Figure 4.2.16, the hourly power consumption was added for the three buildings. As we can observe, the optimized power differs from the baseline only in the peak period, during 10.00am-18.00pm where the optimized power is lower than the baseline.

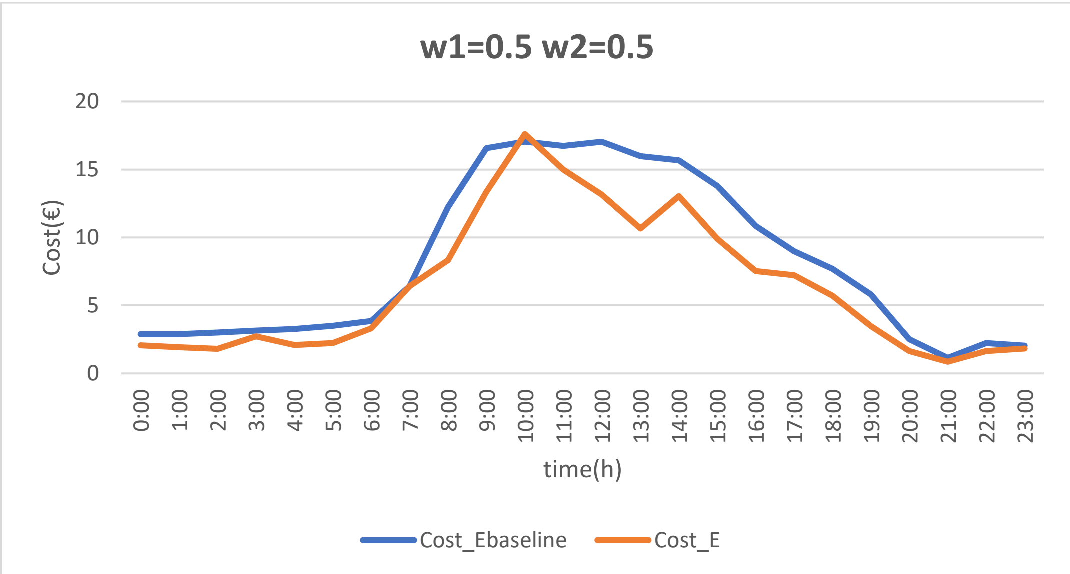


Figure 4.2.17: Optimized and baseline cost (€) in the group of buildings in the winter

Finally, figure 4.2.17 depicts the total daily cost that the 3 buildings have, before and after the optimization. As we can notice, during all day the optimized cost is higher than the baseline. Apart from that the total baseline cost in district level is 195 € and the total optimized cost is 153 €, achieving a reduction rate of 21%.

In table 4.2.1, are presented the results of optimization for each pair of weigh coefficient in building and district level, for the summer.

Weight coefficient	L4LeafLab cost(€)	L5KiteLab cost(€)	L2eL3 cost(€)	District level cost(€)
w1=0 w2=1	153.97	98.50	19.47	181.82
w1=0.1 w2=0.9	149.80	108.99	19.46	205.54
w1=0.2 w2=0.8	152.15	92.83	18.49	222.13
w1=0.3 w2=0.7	145.71	94.24	18.46	197.93
w1=0.4 w2=0.6	148.44	111.96	18.47	225,61
w1=0.5 w2=0.5	147.37	93.41	17.46	252.48
w1=0.6 w2=0.4	151.51	97.94	17.56	220.14
w1=0.7 w2=0.3	152.21	91.24	17.52	211.43
w1=0.8 w1=0.2	149.69	95.95	18.45	193.00
w1=0.9 w1=0.1	144.40	109.67	16.28	223.18
w1=1 w2=0	142.24	102.01	16.46	191.99

Table 4.2.1 Results of the optimization during the summer

According to Table 4.2.1, for L4 Leaf Lab the results for each case shows that the optimization is successful having in mind that the baseline cost is 174.90 € and the second maximum optimized cost is 152.21 € (the first maximum optimized cost is 153.97 € where the cost criterion has not been taken into account). Secondly, the optimization for L5Kite Lab showed that the genetic algorithm gain cost optimization in all the pair of weights apart from the case where the criterion of cost is w1=0.4. As for the previous buildings, as well for L2eL3, the optimized cost in each pair of weight is lower than the baseline cost which is 20 €. The last column represents the optimized cost in the group of buildings which is lower than the baseline cost (293 €). Comparing this column with the other, we can observe, that the optimization in the group of buildings achieve better results than each and every building, having lower optimized total cost in every pair of weight coefficient.

weight coefficient	L4LeafLab cost(€)	L5KiteLab cost(€)	L2eL3 cost(€)	District level Cost(€)
w1=0 w2=1	47.41	111.10	26.73	155.36
w1=0.1 w2=0.9	46.41	112.46	26.73	154.96
w1=0.2 w2=0.8	46.41	102.78	25.83	155.25
w1=0.3 w2=0.7	46.40	113.81	24.73	155.47
w1=0.4 w2=0.6	46.42	108.97	24.85	155.91
w1=0.5 w2=0.5	42.41	101.15	24.86	155.37
w1=0.6 w2=0.4	44.88	107.78	24.66	154.87
w1=0.7 w2=0.3	44.41	109.44	23.89	156.16
w1=0.8 w1=0.2	45.41	110.27	23.67	154.63
w1=0.9 w1=0.1	46.41	104.53	20.69	153.62
w1=1 w2=0	46.41	120.51	21.04	152.37

Table 4.2.2 Results of the optimization during the winter

In table 4.2.2, are presented the results of optimization for each pair of weigh coefficient in building and district level, for the winter. The results of L4 Leaf Lab, depict the optimized cost for all weights. As we can observe, in all cases, the optimized cost is lower than the baseline, which is 48€. Moreover, in L5 Kite Lab, the optimized cost is lower than the baseline (118€), apart from the last row where the criterion of Loadshift has not taken into account (120€). Secondly, the optimization for L2eL3 Lab showed that the genetic algorithm gain cost optimization in all the pair of weights, having in mind that the baseline cost in this building is 28 €. The last column represents the optimized cost in the group of buildings in the winter which is lower than the baseline cost (195 €). Comparing this column with the other, we can observe, that the optimization in the group of buildings achieve better results than each and every building, having lower optimized total cost in every pair of weight coefficient.

5. Conclusions and Future Prospects

The environment serious challenges that put the environment in jeopardy, made the researchers to investigate new approaches in order to develop new energy management systems that will be friendly to the environment, reducing the energy consumption and the carbon dioxide foot print.

In this study, buildings of Leaf Community in Loccioni are modelled in order to achieve an optimum operational cost for the industry.

The first step of this study was to predict the power consumption 24hours ahead in each of these buildings (L4 Leaf Lab, L5 Kite Lab, L2eL3) using Artificial Neural Network. This prediction is achieved for plenty of reasons using power and weather measurements of weather and day-time as inputs. The results showed that a significant approach was achieved during the summer and the winter period, tested with correlation coefficient R, and two other statistical indicators which are Mean Bias Error (MBE) and Mean Average Predicted Error (MAPE).

The second step was to create a cost function using the appropriate components and constraints. Thus, this function was used to develop an optimization approach using Genetic Algorithms in order to minimize the total cost in building level. Some pairs of weight coefficient were used in optimization to achieve many different results. The final results showed that the three buildings achieved lower cost without reducing the total daily power, in the summer and in the winter period.

Apart from the building level, exactly the same approach was followed to optimize the cost in the group of buildings having optimistic results for the industry. The results showed that the industry have better results and gain enough money every month, when the optimization is made in district level than in each building separately.

In conclusion, this study has significant possibilities for future research, that will benefit the industry and relief the stress from the grid.

While this thesis examines and evaluates a demand response approach at building and district level, using power prediction and optimization techniques, there are still possibilities for further study.

1. In this survey, power data were used from each building for the optimization. One step is to replace the electrical load with RES that the industry has already, as PV, when the energy pricing is high during the peak hours.

2. The priority of loads is a significant part of this study. During the peak hours, it is substantial to have priority in loads. To be more specific, in every building this priority changes, according to the necessities. Power data concern HVAC, lighting and the operation of the mechanical equipment. Thus, in every building it has to evaluate which loads must be present and which must be moved without causing any problems to the user.

3. In this study, we dealt with the prediction of data 24h ahead. In some cases where the power is not necessary, one idea is to it is to store this energy in batteries or to use it for charging electric cars, that the industry has already.

4. One idea is to connect this algorithm with a BEMS, that will have the ability to change the set point of HVAC when the energy pricing is high, taking into account the operation of the building and the user's thermal comfort.

Appendix A

Code of Artificial Neural Network

```
Aw=Aw'; %%temperature for input
B=B'; %%power for output
X=con2seq(Aw); %%accept big variety of data
T=con2seq(B);
net=narxnet(1,1,20); %%create Narx network
[Xs,Xi,Ai,Ts]=preparets(net,X,{},T); %%prepare the data
net=train(net,Xs,Ts,Xi,Ai); %basic train of the network
view (net); %%displays the image of the network
y=net(Xs,Xi,Ai);%%target y/load prediction
m=cell2mat(y); %%convert cell to double
%%upload date.xlx in column vector
datenumber=datenum(VarName1); %%convert datetime to double
figure(2) %%create a plot with date(x axis), m-T1(y axis)
plot(datenumber,abs(m));
datetick('x','dd-mm-yyyy');
hold on
plot(datenumber,abs(k));
hold off
```

Appendix B

Code for Genetic Algorithm

```
for i=1:11
 W1(i)=(i-1)/10
 W2(i)=1-((i-1)/10)
FitnessFunction = @(x)[W1(i)*(sum(Cost.*x(1,:))/450)+(W2(i)*sum(abs(x(1,:)-
xpredicted))/590)];
numberOfVariables=24
lb = []; % Lower bound
ub = []; % Upper bound
A = []; % No linear inequality constraints
b = []; % No linear inequality constraints
Aeq = []; % No linear equality constraints
beq = []; % No linear equality constraints
nonlcon = @unitdisk;
options =
optimoptions('ga','MigrationFraction',0.1,'MaxStallGenerations',150,'FunctionTolerance',1e-
1,'PopulationSize',150);
tic;
[x,fval]=ga(FitnessFunction,24,[],[],[],[],lb,ub,nonlcon,options);
toc;
```

```
for y = 1:24
    p(i, y) = abs(x(y)-xpredicted(y))
    c(i,y)=Cost(y).*x(y)'
    xxx(i,y)=x(y)
end
end
```

where

```
function [c,ceq] = unitdisk(x)

ceq=sum(x)-2272.753
;
c=[];
```

Bibliography

[1] Fera, M., Macchiaroli, R., Iannone, R., Miranda, S. & Riemma, S. Economic evaluation model for the energy Demand Response. *Energy* 112, 457–468 (2016).

[2] Aghajani, G. R., Shayanfar, H. A. & Shayeghi, H. Demand side management in a smart micro-grid in the presence of renewable generation and demand response. *Energy* 126**,** 622–637 (2017)

[3] Mordjaoui, M., Haddad, S., Medoued, A. & Laouafi, A. Electric load forecasting by using dynamic neural network. *Int. J. Hydrogen Energy* 42**,** 17655–17663 (2017).

[4] Zhou, Q., Guan, W. & Sun, W. Impact of demand response contracts on load forecasting in a smart grid environment. *IEEE Power Energy Soc. Gen. Meet.* 1–4 (2012). doi:10.1109/PESGM.2012.6345079

[5] Jin, M., Zhang, L. & Spanos, C. J. Power Prediction through Energy Consumption Pattern Recognition for Smart Buildings. (2015)

[6] Provata, E. *et al.* Development of optimization algorithms for the Leaf Community microgrid. *Renew. Energy* 74**,** 782–795 (2015).

[7] Mahat, P. *et al.* A micro-grid battery storage management. *2013 IEEE Power Energy Soc. Gen. Meet.* 1–5 (2013). doi:10.1109/PESMG.2013.6672497

[8] Palonen, M., Hasan, A. & Siren, K. A Genetic Algorithm For Optimization Of Building Envelope And Hvac System Parameters. *11th Int. IBPSA Conf. Build. Simul. 2009* 159–166 (2009).

[9] Siano, P. Demand response and smart grids - A survey. *Renew. Sustain. Energy Rev.* 30, 461–478 (2014).

[10] Motegi, N., Piette, M. A., Watson, D. S., Kiliccote, S. & Xu, P. Introduction to Commercial Building Control Strategies and Techniques for Demand Response. (2006).

[11] Phil Jones Mei, Building Energy Management Systems (BEMS), Energy in building and industry 29, 2011

[12] Ku, K. Building electric energy prediction modeling for BEMS using easily obtainable weather factors with Kriging model and data mining. 1–2 (2010).

[13] MOD, 2001. Building Energy Management Systems. Ministry of Defence: Defence Estates Design and Maintenance Guide 22

[14] Shakeri, M. *et al.* An intelligent system architecture in home energy management systems (HEMS) for efficient demand response in smart grid. *Energy Build.* 138**,** 154–164 (2017).

[15] Balijepalli, V. S. K. M., Pradhan, V., Khaparde, S. A. & Shereef, R. M. Review of demand response under smart grid paradigm. *2011 IEEE PES Int. Conf. Innov. Smart Grid Technol. ISGT India 2011* 236–243 (2011). doi:10.1109/ISET-India.2011.6145388

[16] Kutkut, N. Energy Management Through Peak Shaving and Demand Response :

By : Nasser Kutkut , PhD , DBA. 1–11

[17] Limei Shen, Zhengwei Li, Yongjun Sun, Performance evaluation of conventional demand response at building-group-level under different electricity pricings,2016, China

[18] Zhou, Q., Guan, W. & Sun, W. Impact of demand response contracts on load forecasting in a smart grid environment. *IEEE Power Energy Soc. Gen. Meet.* 1–4 (2012). doi:10.1109/PESGM.2012.6345079

[19] Alfares, H. K. & Nazeeruddin, M. Electric load forecasting: Literature survey and classification of methods. *Int. J. Syst. Sci.* 33**,** 23–34 (2002).

[20] Gobakis K, Kolokotsa D, Synnefa A, Saliari M, Giannopoulou K, Santamouris M. Development of a model for urban heat island prediction using neural network techniques. *Sustain Cities Soc*. 2011;1(2):104-115. doi:10.1016/j.scs.2011.05.001

[21] D'Oca, Simona Hong, Tianzhen Langevin, Jared, Renewable and Sustainable Energy Reviews, 731-742, (2017), doi:10.1016/j.rser.2017.08.019

[22] Quan, Hao, Srinivasan, Dipti, Khosravi, Abbas, Very short-term load forecasting of a distribution system with high PV penetration, Renewable Energy Journal, 142-148, (2017), doi: 10.1016/j.renene.2017.01.019

[23] Svensson, Morgan, Short-term wind power forecasting using artificial neural networks, Master's Thesis Journal, (2015)

[24] Wan, Sunny, Facility Power Usage Prediction with Artificial Neural Networks, Master's Theses and Project Reports Journal, (2009), June

[25] Mandal, JK, Application of recurrent neural network for short term load forecasting in electric power system, Neural Networks 1995, June2014, 2694–2698, doi:10.1109/ICNN.1995.487837

[26] Kalaitzakis, K, Sta, G, E Anagnostakis, Short-term load forecasting based on artificial neural networks parallel implementation, 2002

[27] Mavrigiannaki Angeliki, Kampelis Nikos, Kolokotsa Denia, Marchegiani Daniele, Standardi Laura, Isidori Daniela, Christalli Cristina, Development and testing of a micro-grid excess power production forecasting algorithms, Energy Procedia Journal, 2017, doi: 654-663, 10.1016/j.egypro.2017.09.583

[28] M. Beccali, M. Cellura, V. Lo Brano, A. Marvuglia, forecasting daily urban electric load profiles using artificial neural networks, Energy Conversion and Management 45 (2004) 2879–2900

[29] Chipperfield A, Fleming P, Pohlheim H, Genetic Algorithm Toolbox for use with MATLAB, Department of Automatic Journal, 1994, doi: 10.1243/0954405021519915

[30] Arabali A, Ghofrani M., Etezadi-Amoli M., Fadali M. S., Baghzouz Y., IEEE Transactions on Power Delivery Journal, 2013, 162-170, doi:10.1109/TPWRD.2012.2219598

[31] Abdeslam Ahmadi, Bouanani, Faissal El, Four Parallel Decoding Schemas of Product BlockCodes,2015, doi: 10.14738/tnc.23.229

[32] Simpson Angus R, G. Dandy, Graeme C, Murphy Laurence J, Genetic Algorithms Compared to Other Techniques for Pipe Optimization, 1994, 423-443, doi:10.1061/(ASCE)0733-9496(1994)120:4(423)

[33] Palonen Matti, Hasan Ala, Siren Kai, 11th International IBPSA Conference, Building Simulation 2009, 159-166

[34] Moradi, M. H. Abedini, International Journal of Electrical Power and Energy Systems, 2012, 66-74, doi: 10.1016/j.ijepes.2011.08.023

[35] Wright Jonathan A, Loosemore Heather A, Farmani Raziyeh, Optimization of building thermal design and control by multi-criterion genetic algorithm, Energy and Buildings, 2002, 959-972, doi: 10.1016/S0378-7788(02)00071-3

[36] Kampelis N, Gobakis K, Vagias, V, Kolokotsa D, Standardi L, Isidori D, Christalli C, Montagnino F. M, Paredes F, Muratore P, Venezia L, Dracou Kyprianou, Montenon A, Pyrgou, A. Karlessi Theoni, Santamouris Mat, Evaluation of the performance gap in industrial, residential & tertiary near-Zero energy buildings, Energy Buildings Journal, 2017, 58-73, doi: 10.1016/j.enbuild.2017.03.057