Manuel Carlos dos Santos Sousa

Intelligent Forecasting of Electricity Consumption in Buildings, for Application in the Iberian Market of Electricity Bidding

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UNIVERSIDADE DO ALGARVE
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Masters in Electronics and Telecommunications Engineering

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Declaro ser o autor deste trabalho, que é original e inédito. Autores e trabalhos consultados estão devidamente citados no texto e constam da listagem de referências incluida.

Manuel Carlos dos Santos Sousa

(Manuel Carlos dos Santos Sousa)

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Resumo

O governo português, numa iniciativa conjunta com o governo espanhol, formou o Mercado Ibérico de Eletricidade ou MIBEL, que possibilita a qualquer consumidor do espaço ibérico, adquirir energia elétrica num regime de livre concorrência, a qualquer produtor ou comercializador de energia elétrica que atue em Portugal ou Espanha. Criou-se assim um mercado de energia muito competitivo, onde a energia elétrica é comprada e vendida ao preço do mercado. Como consequência, o risco assumido pelas empresas que produzem, vendem ou compram energia elétrica aumentou substancialmente, tornando-se difícil gerir uma empresa deste sector sem fazer qualquer tipo de análise estatística ou sem implementar técnicas e métodos de previsão. Daí a necessidade de estudar e desenvolver modelos de previsão para o consumo da energia elétrica.

Numa perspetiva de otimização das ofertas de compra de energia, em mercados organizados, atendendo às previsões das necessidades dos clientes e volatilidade dos contratos, o processo de compra revela-se uma atividade crucial. O trabalho desenvolvido presente neste relatório vem no seguimento desta necessidade identificada durante o periodo de estágio na empresa do Grupo Rolear, no departamento Rolear Viva responsável pela comercialização de electricidade e gás natural no mercado livre. Depois de um período de estudo aprofundado do funcionamento do setor, foram utilizados modelos de redes neuronais de função de base radial (RBFNN), em que a sua estrutura foi otimizada através do algoritmo genético multi-objectivo (MOGA). Os modelos foram idealizados para um horizonte de previsão de 24 e 48 horas, assentes em abordagens de consumos energéticos sazonais e anual, bem como utilizando variáveis exógenas que reflitam os hábitos diários e contributos atmosféricos no consumo de energia.

Palavras-chave: Redes Neuronais Artificiais, Função Base Radial, Previsão de Consumo Energético, MIBEL, Algoritmos Genéticos Multi-Objectivo.

Abstract

The Portuguese government, in a joint initiative with the Spanish government, formed the Iberian Electricity Market or MIBEL, which enables any Iberian consumer to acquire electricity in a free competition regime, to any producer in Portugal or Spain. This has created a very competitive energy market, where electricity is purchased and sold at the market price. Consequently, the risk assumed by the companies that produce, sell or purchase electric energy has increased substantially, making it difficult to manage a company in this sector without any statistical analysis or without implementing forecasting techniques and methods. Hence the need to study and develop forecast models for the consumption of electricity.

In a perspective of optimizing energy purchase offers, in organized markets, considering the prediction of consumers needs and contract volatility, the purchasing process proves to be a crucial activity. The work developed in this report is a possible answer to this need identified during the internship period at the Rolear Group company, in the Rolear Viva department responsible for the commercialization of electricity and natural gas in the free market. After a period of in-depth study of the sector's operation, radial basis function neural network models (RBFNN) were used, optimized through the multi-objective genetic algorithm (MOGA). The models were designed for a prediction horizon of 24 and 48 hours, based on seasonal and annual energy consumption approaches, as well as using exogenous variables that reflect the daily habits and atmospheric contributions in energy consumption.

Keywords: Artificial Neural Networks, Radial Basis Function, Energy Consumption Forecasting, MIBEL, Multi-Objective Genetic Algorithms.

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List of Abbreviations

MIBEL	Iberian electricity market
XBID	Cross-border intraday market project
EDP	Energias de Portugal
CEO	Chief executive officer
NES	National Electric System
ORP	Ordinary regime production
SRP	Special regime production
NTN	National transmission network
NDN	National distribution network
VHV	Very high voltage
HV	High voltage
MH	Medium voltage
SLV	Special low voltage
NLV	Normal low voltage
ERSE	Energy services regulatory authority
REN	Redes Energéticas Nacionais
LRES	Last resort energy supplier
DGEG	Directorate general for energy and geology
IMO	Iberian market operator
OMIP	Operator of the Iberian energy market (Portuguese pole)
OMIE	Operator of the Iberian energy market (Spanish pole)
DPC	Delivery point code
DNO	Distribution network operator
TNO	Transmission network operator
EB	Energy box
HAN	Home area network
ANN	Artificial neural network
RBF	Radial basis function
RBFNN	Radial basis function neural network

MOGA	Multi-objective genetic algorithm
GA	Genetic algorithm
NAR	Nonlinear autoregressive
NARX	Nonlinear autoregressive exogenous
PH	Prediction horizon

Chapter 1

Introduction

1.1 Internship motivations and goals

After a long academic journey that trained me with a solid scientific and technical knowledge in the field of electronics and telecommunications engineering, through the learning of methodologies and tools for solving problems in engineering, I decided to test myself, going out of the comfort zone of university environment, and approach a new experience in the field, by undergoing on an internship that could improve my capacities as a new professional in the business and grow as person.

This initiative had several main goals, that constantly motivated me to challenge myself. One of the main goals, and of course, the one that gives purpose to this work, is to complete my academic course, more specifically, to conclude the integrated master's degree in electronics and telecommunications engineering in the Faculty of Science and Technology of University of Algarve, but also, to seize the opportunity and make the most of my time in the company that embraced me. By taking advantage of the opportunity of an internship, it would be a great chance of being introduced to the field and to the job market, as well as, gain experience by working with direct contact with professionals, being a good test to my skills and to acquire new abilities that could serve me in the future.

In the scope of the report main topic, another motive that also captivated my curiosity, was the fact of being able to explore emerging fields related to artificial intelligent, such as machine learning, prediction algorithms or artificial neural networks and their methodologies. Having these subjects, such an increasing relevant role in nowadays different working areas, this could be an useful skill to possess, serving as preparation for what my professional future may bring.

The project developed during the internship was idealized with the purpose to fill a need, namely in the support of a task which reveals particularly relevant in the business of commercialization of electricity. This task, more specifically, is the process of purchasing electricity in the different Iberian electricity markets, where a good forecast in a short period of time proves to be a fundamental support for a favourable participation in the markets. With this aim in mind, a familiarization with the Iberian electricity markets and the National electricity system was carried out, in order to explore the use of methods based on artificial neural networks for different forecast periods and different consumption patterns during a year. The work developed furthermore is characterized by the capacity to be executed on the current state of the electrical system, but also able to adapt to the innovations that are currently being implemented in this sector.

1.2 Report scope

In chapter 2, a report of my experiences during the internship and how the work developed in this thesis fits in the needs of the company department is performed. In chapter 3, the constitution and hierarchy of the national electrical system structure is presented. In chapter 4, the different Iberian electricity markets and their specificities are explained. In chapter 5, is explained how the data availability flow is operated between the different agents in the national electrical system and the innovations in the sector. In chapter 6, is theoretically introduced the artificial neural networks concept, the training schemes applied and MOGA implementation. In chapter 7, the methodology, design and implementation used in the forecasting model using artificial neural networks is explained. In chapter 8, the results of the tests are presented and elaborated. In chapter 9, conclusions and future work are given.

Chapter 2

Rolear Internship

At the end of July of 2017, with the intention of completing the master's degree in electronic engineering and telecommunications and simultaneously acquire professional experience, I carried out an internship at the company Rolear, SA. This period was fruitful in learning and acquired skills, and this chapter reports in detail my experience during the internship.

2.1 The Rolear group

In May 1979, Rolear S.A. was founded in a small shop in Faro. This first company settled the foundations of what is now a major group of companies, all focused in different fields specializations, but at the same time working together in harmony, as a team and still characterized by the same values that marked the early beginnings since its foundation.

Figure 2.1 – Rolear group logo. [1]

In his early days, Rolear, S.A focused in the job market with innovative offers in customized engineering solutions, commercialization of electrical and electromechanical equipment, as well as technical assistance. The success of this first project, having its most impact mainly in Algarve, with leading pioneer investments in the representation of renowned brands, or in automation solutions for hydraulic oil systems, electricity and compressed air, dictated the continuous growth that enabled the constitution of Rolear Group. This resulted in the expansion of new business areas through creating and adding several specialized companies and brands, capable of keeping the same ability to be in edge of progress offering a wider range of solutions not only in Algarve region, but to all Portugal regions.

Currently the Rolear Group has his headquarters in Sitio do Areal Gordo, Faro, and is composed by 5 major branches:

- Rolear Mais, experts in the market of electrical, mechanical and electromechanical products and equipment for public and private spaces, as well as, representing several Portuguese and international leading brands. Also having 11 more shops spread throughout continental Portugal.

- Rolear.ON, is a company dedicated to both installation and maintenance services in industrial facilities, construction works infrastructures and landscaping.

- Rolegás, responsible for the supply of propane gas, installation projects and maintenance of gas grids.

- Academia Rolear, is a company focused on the training and teaching in technical and management areas.

- Rolear Viva, the most recent branch, created with purpose of providing natural gas and electricity in the liberalised energy market.

Having several departments specialized in such specific areas, makes Rolear Group present in the market in different ways, offering a wide range of solutions from product and equipment supply, to piped gas distribution, commercialization of natural gas and electricity, construction, infrastructures and landscaping to all sorts of technical installations, maintenance, technical support and training. All of this being supported by quality of products, but most of all, the know-how of a dynamic team of approximately 230 employees and the tradition of accurate working ethics for almost 40 years. [1]

2.2 Rolear.ON Internship

In the end of July 2017, the internship in Rolear Group officially started. The company in which the internship started was Rolear.ON, more especially, in the department of electricity and electrical panels, responsible for engineer and assemble electric panels, give assistance and maintenance to electrical systems and complete execution of electrical projects.

In this period, I was engaged in several works, that went from electric panels alarm modules programming and configuration, project external protection to air conditioner, luminaires control systems configuration, maintenance and assistance, implementation of cctv security systems, project security lock system for transformer substation, electrical surveys and orders, dimension or quantify electric cables and rails for different electrical systems, as well as, minimal maintenance works. It should also be noted the close monitoring of some works, that enabled a learning experience and captivated an interest such as in automation systems programming and assistance, electric panels assemble, complete projection of electrical systems and AutoCAD use for design, dimensioning and projection.

Alongside to this numerous works, I was involved in a main project which was the main subject of my master thesis. This project was a collaboration between Rolear.On and EasySensing – Intelligent Systems, Lda, a spin-off company of University of Algarve dedicated to intelligent control systems. The idea behind the partnership consisted in a concept for energy efficiency in buildings, namely hotel buildings, focused on energy monitoring using internet of things techniques and computational intelligence, for determination of the electricity consumption profile, and visualization of the relevant parameters. The optimization process would also involve a survey of habits and environment characteristics, that directly or indirectly, affect the energy consumption, finally resulting in proposals to optimize the consumption of those same behaviours, by ending or changing habits, or other relevant modifications.

Although the project had a promising start on an initial phase, slowly the process begin to gain some inertia in its development and failed to pass to the execution stage. Unexpectedly and not related to the project constraints, in the end of October 2017, an invitation appeared to enter the Rolear Viva department, ending my time at Rolear.ON. Despite having been such a short period of time, it was, above all, a rewarding period of professional relations, acquired experience and new knowledges, that in a way, prepared me for what was coming next.

2.3 Rolear Viva Internship

In the end of October 2017, due to the invitation of Group Rolear CEO, Engº António Parreira Afonso and the Rolear Viva chief department, Rui Santana, the internship proceeded at Rolear Viva department. The Rolear Viva department is the Rolear Group, most recent sector, responsible for the commercialization of electricity and natural gas in the liberalized energy market. In the scope of this business unit of Rolear, there is multiple and distinct operations essential to the activity functioning, from the participation in energy markets for supply, management of the operations of energy transportation and delivery, balance sheets and other direct activities with the final customers – contracting, management and billing.

During my internship period in this department, I dedicated myself to the knowledge of the energy commercialization activity - electricity and natural gas, familiarization of the energy markets and all its organization and procedures, as well as, the knowledge of the activities already existing in the company associated with the energy purchase forecast for the elaboration of offers. In a point of view of familiarization with the field and to follow the evolutions of the sector, I accompanied the chief department and my company guide, Rui Santana, at numerous meetings organized by EDP Distribuição, in which issues related to the electricity comercialization activity are presented and discussed, and also, an informative session organized by the OMIE, on a new intraday cross-border market (XBID), about to be implemented.

Following the change of department, became essential to reformulate the original concept of the thesis, that could adapt to the area of activity and that, in a way, could fill the existing needs. In this sense, the process of electrical energy purchase, that reveals a crucial process in the activity, became the main focus in the developing of this thesis. In a perspective of optimizing and technically assisting the procedure of energy purchase, in organized markets or by bilateral contracts, attending to the forecasts of the needs and characteristics of clients consumptions, a work was developed according to the guidance of Professor António Ruano.

This work is based on the application of algorithms of artificial neural networks for the consumption forecast of the clients list, defined by the specifications of the data availability flow, between the different identities belonging to the national electricity sector. The concept of this work not only meets the possibilities of application in the present state of the sector, as well as, to follow the modernization trends of electrical smart grids and smart meters. This developed work can thus be seen as, a support tool for the participation on the Iberian market of electricity, or MIBEL, being that, from the forecasts of consumption of each client, it is possible to quantify the necessary purchasing energy to supply the entire client portfolio, reflecting in the minimum deviations and losses possible.

It was on the basis of this ideology that the work for the thesis in question was developed. The following chapters will describe in detail the hierarchy of the electricity sector, how the method of data availability is conceived in an energy supplier point of view, and how organized electricity markets works. The algorithms of neural networks are sustained in the functioning of this activity, in the present, and looking at the innovations to be implemented in a near future. The methodology applied will also be explained in the following chapters.

In addition, during this period, on my own initiative, I took a training course at the Rolear Academy on "Photovoltaic systems - Selfcomsuption ", besides that, I acquired several skills at the level of Web applications development. This acquired knowledges, that arise as personal interests, soon became possibilities to explore, for the future development of the work exposed in the present thesis.

Chapter 3

National Electric System

In this chapter, a brief overview is made about the National electric sector, all its constituents and main parties involved, so that the reader can briefly understand the origin and evolution of the system, implemented hierarchy and the sequence of events from the production of the energy to its final customer consumption.

3.1 Background

Over the last 30 years, the national electric system (NES) has undergone a remarkable evolution from a structural, regulatory point of view and at the level of the properties of the assets involved. Previously, the national electric system had a vertically integrated structure in which a company, namely Electricidade de Portugal, EDP, encompassed all the different sectors from production to the relationship with the final customer. This type of vertical structure conditioned the electricity market, in the sense that there was no competition whatsoever in the business, acting based on a monopoly regime. In this business model, one company could own a set of captive clients who were limited in options, since they only had to stick to a single energy supplier and the services it provided.

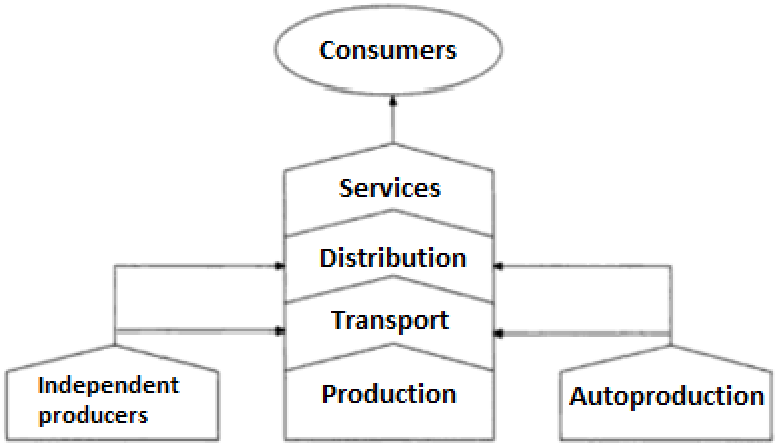

Figure 3.1 – National electric system structure in the early days. [2][3]

Over the years, inevitably, the structure of this sector has undergone deep changes. Currently, the national electricity system is based on a set of activities performed by different entities, ranging from the relations with the suppliers cycles of production and selling, until the final distribution phase and commercialization to the consumers. The changes led to the establishment of a more competitive electricity market once a liberalized regime has been implemented in detriment of a monopolistic regime. This restructuring is due to the progressive implementation of a liberalized market with the beginning of the XXI century, namely in the creation of a common market of electricity between Portugal and Spain, or MIBEL – Iberian Electricity Market, which began to be established in November 2001 and started its full activity in July 2007 [8][9].

The emergence of the MIBEL and its liberalized regime, culminated in the need to dismantle the vertical structure of the national electricity system, being in the genesis of the emergence of several new agents in different sectors, with the most notable cases being the production and commercialization sectors, this way reflecting in an increase of competition and giving consumers a more active role taking in count the possibility to select the service provider entity. As a consequence, the liberalization of the electricity market and the emergence of new agents in different crucial sectors, there was simultaneously, a growing clear need to regulate the various activities – quality service, for example. All these alterations made the national electricity system and the electricity market a business subject to regulation and therefore, more transparent, with better services and with a more balanced sectorial organization. [3]

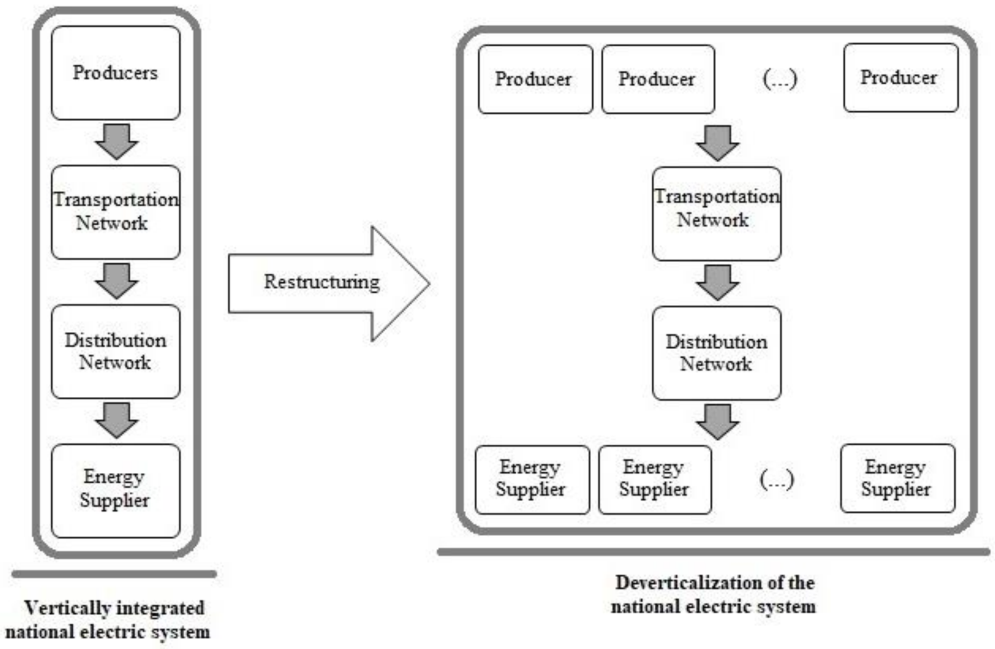

Figure 3.2 – Restructuration of the national electric system. [4]

3.2 NES value chain

The National Electricity System (NES) can now be synthesized through a value chain that integrates production, transportation, distribution, commercialization and in the end the final client, in which the production and commercialization activities practice their activities in an open competition regime, subject to obtaining the necessary licenses and approvals, while transportation and distribution activities operate by means of public concessions. All the different activities from the production to the commercialization in the value chain are subject to a regulation by a responsible entity, the Electricity Services Regulatory Entity (ERSE).

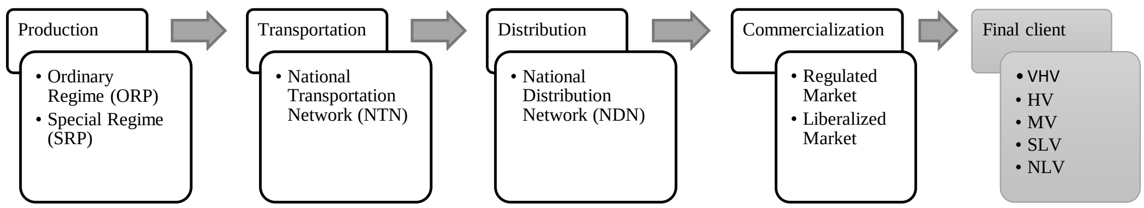

Figure 3.3 – National electric system value chain. [5]

3.2.1 Production

The production of electricity is a fully liberalized activity that operates on a market-based logic and under free competition regime, through the granting of a license. The electricity production is carried out under an ordinary regime (ORP) or under a special regime (SRP). The production in ordinary regime, relies on hydroelectric power plants or power plants that use non-renewable energy sources, mainly coal and natural gas. The production in special regime is based on production using renewable energy sources or cogeneration (combined production of electricity and steam). [6]

3.2.2 Transportation

The activity of transporting electricity, in very high voltage (150, 220 and 400 kV), is carried out through the National Transport Network (NTN), by means of a concession granted by the Portuguese State, under a public service regime and of exclusivity to REN, Redes Energéticas Nacionais. The concession includes the planning, construction, operation and maintenance of the NTN, also covering the planning and global technical management of the national electricity system to ensure the harmonized operation of the infrastructures that integrate it, as well as, the continuity of service and security of the electricity supply. The NTN is interconnected with the Spanish grid in several places, allowing electricity exchanges with Spain, either for security or for supply reasons. These links improve the security and stability of the grid and supply of electricity, as well as, facilitate the commercial exchanges of electrical energy between both national systems, contributing to the integration of markets.

3.2.3 Distribution

The distribution of electric energy is based on the National Distribution Network (NDN), which allows a regulated activity that consists of routing through the distribution networks of electricity between the National Transmission Network (NTN) substations and the end points consumption. NDN, like the NTN, is operated through an exclusive concession granted by the Portuguese State to the subsidiary of the EDP group, EDP Distribuição. In the case of low voltage networks, the activity is carried out under concession contracts signed through public tenders launched by the municipalities, which are attributed almost entirely to EDP Distribuição, with the exception of a few local companies.

3.2.4 Commercialization

The activity of commercialization of electricity is free but is subject to the attribution of a license by the competent administrative entity, Directorate General for Energy and Geology, DGEG, which clarifies the list of rights and duties in the perspective of a transparent exercise of the activity. In the course of their business, energy suppliers agents can freely purchase and sell electricity, with the right of access to the transmission and distribution networks, however, by paying regulated tariffs in order to have the right of access to the transmission and distribution networks. In Portugal, consumers can, under market conditions, freely choose their energy supplier with no additional costs. There are two types of energy supplier agents to operate in the national electricity market: energy suppliers in the regulated market and energy suppliers in the liberalized market. Regulated market energy supplier agents, also called last resort energy suppliers (LRES), aim to ensure the supply of electricity to all consumers with low voltage installations with contracted power equal to or less than 41.4kW (NLV), being subject to a system of regulated tariffs and prices and are usually the only ones to offer prices subject to the tariff regime fixed by ERSE, namely transitional tariffs. In continental Portugal, the commercialization of last resort in electricity is ensured by EDP Serviço Universal and by a group of small distributors that act locally.

Energy suppliers in the liberalized market, share a competition regime in the electricity market, where they are free to set their own energy prices according to the competition rules and the ERSE regulatory entity. Due to the healthy competitive environment created by this method of free competition, the liberalized energy market allows consumers to choose their electricity supplier, opting for a solution that is more appropriate to their needs. In the liberalized marketing market, several companies, including Rolear Viva, compete with each other to attract the largest number of clients.

The fact that an energy supplier agent belongs to the liberalized market does not necessarily mean that it practices prices lower than those of the regulated market. The difference in the two is that in the regulated market, the energy supplier is obliged to charge prices according to the tariffs defined by ERSE, while in the liberalized market the energy suppliers are free to choose their prices, as long as the regulated tariffs for access to electrical networks are covered [7]. The choice of energy supplier is at the discretion of the consumer who may opt for the free market or regulated market. According to the directive n.º 348/2017, published in November 2017 by the government, until 2020, a consumer is free to choose between the regulated market or liberalized market, but it is expected that from that date on, the regulated market will be extinguished and only the liberalized market will be implemented.

3.2.5 Final consumer

Depending on the needs and characteristics of the consumer type, a voltage level is assigned to them, in order to respond to their needs and match their dimensions. The following diagram shows the arrangement of the different voltage levels per customer:

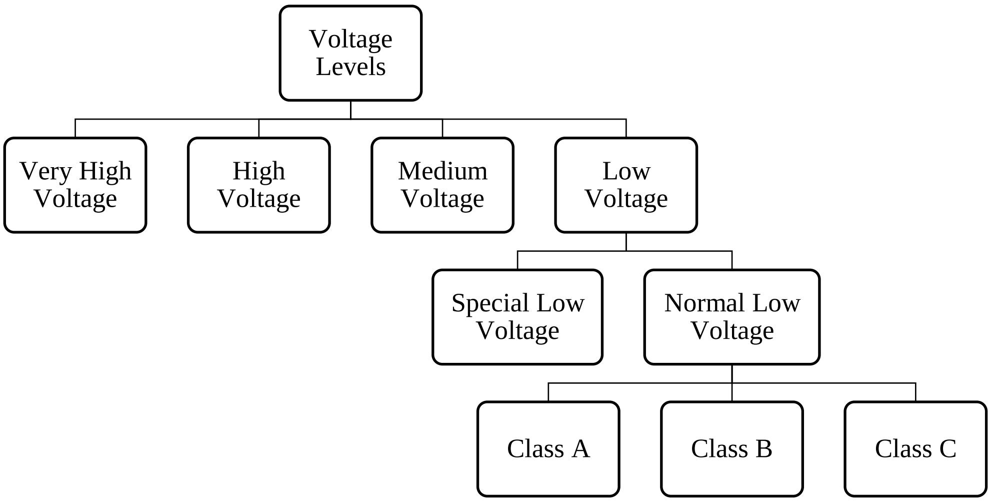

Figure 3.4 – Different voltage levels assigned to the customers.

- Very High Voltage (VHV): Facilities such as the automobile, railway, pulp and mining industries. Voltage between phases greater than 110kV;

- High Voltage (HV): Steel industry, large hospitals, pulp industry, plastics industry, fertilizer industry, energy services, etc. Voltage between phases greater than 45kV and equal to or greater than 110kV;

- Medium Voltage (MV): Automotive components, metallurgy, molds, vitrification, large hotel industry, etc. Voltage between phases greater than 1kV and equal to or less than 45kV;

- Low Voltage (LV): Residential customers, shops, offices and small businesses. Voltage between phases equal to or less than 1kV;
    - Special Low Voltage (SLV): Supply in LV with power superior to 41.4kW;
    - Normal Low Voltage (NLV): Supply in LV with power equal to or less than 41.4kW.

Clients of NLV level are further profiled according to consumption characteristics, based on contracted power and consumption of the previous twelve months. According to these characteristics three profiles are applied:

- Profile Class A for clients with contracted power exceeding 13.8kVA;
- Profile Class B for clients with contracted power equal to or less than 13.8kVA and annual consumption of the twelve months preceding the date greater than 7140kWh;
- Profile Class C for clients with contracted power equal to or less than 13.8kVA and annual consumption of the twelve months prior to the date equal to or less than 7140kWh.

Chapter 4

Iberian Electricity Market

In the previous chapter the National electric system, the different sectors and the main agents were introduced. In this chapter, we intend to explain the concept of the liberalized market, as well as to demonstrate and describe the operation and structure of the Iberian market of electricity, or MIBEL.

4.1 Liberalized market

As described in the previous chapter, what we now know as the electricity market is due to an accumulation of changes, made over a vast period of years. From this gradual evolution, the concept of liberalized market emerged. According to ERSE document [10], the liberalized market can be defined as follows:

"The market is considered liberalized when several operators can compete freely in prices and commercial conditions, observing the rules of competition, the general law and the applicable regulations. The transport and distribution - as natural monopolies - remain activities carried out under a public and exclusive service regime, being guaranteed the access of third parties to the networks in conditions of transparency and non-discrimination."

Consumer Guide of Electricity in the Liberalized Market, ERSE, 2010 [10]

Based on this characterization and the ideals of a free market, the understanding between the governments of Portugal and Spain arose so that in a cooperation process, they could create a common market of electricity. The result of this joint effort was the Iberian Electricity Market, or MIBEL. The MIBEL was created with the purpose of promoting the integration of the electric systems of the two countries, in which, electrical energy transactions are carried out and financial instruments are traded that refer to this same energy. [11] For all the parties involved, the MIBEL still had several benefits as objectives in its formation, and the following should be highlighted: [12]

- Benefit consumers of electricity from both countries;
- Structure the functioning of the liberalized market;
- Build a single reference price for the entire Iberian Peninsula;
- Provide free access to the market, in conditions of equality, transparency and objectivity;
- Favour the economic efficiency of companies in the electricity sector;
- Promote free competition between them.

With the formation of this common market between the two countries of the Iberian Peninsula, it became possible for any energy supplier to purchase electricity in a regime of free competition.

4.2 MIBEL operation

The organized markets of MIBEL operate based on an Iberian exchange market of electricity settled on a single market operator, the Iberian Market Operator (IMO), held in equal shares by entities of both signatory states, with two poles:

- OMIP - Operator of the Iberian Energy Market (Portuguese Pole): which is responsible of managing the forward markets;
- OMIE - Operator of the Iberian Energy Market (Spanish Pole): which is responsible for managing the daily and intraday markets.

The liberalization of the electricity sector added the existence of organized markets, which are constituted as negotiation platforms tendentially independent of the traditional agents that operate in the activities of production and commercialization of electricity. The energy suppliers can purchase electrical energy from various forms of contracting:

- Next day trading market (daily market), which is subdivided into two types, daily and intraday markets. It is in these markets that the various proposals of sale (production) and purchase (commercialization) of electricity for the day after the negotiation are presented;

- Futures market (forward market), where futures commitments for production and purchase of electricity are stipulated. The forward market may carry out physical liquidation (sale of energy) or financial liquidation.

Within this segment of electricity contracts, but in another branch of MIBEL, there is also the non-organized market, characterized by the model of bilateral contracts. Bilateral contracts are a rigid model that guarantees the security of the price of electricity, since it is established by a physical contract and for a certain period. These types of contracts are permitted between all types of producers and other qualified agents and established the conditions under which energy suppliers and producers may sell energy previously acquired to other producers or external agents. One of the advantages of this model is the elimination of the risk associated with the price volatility in the stock market. [13][14]

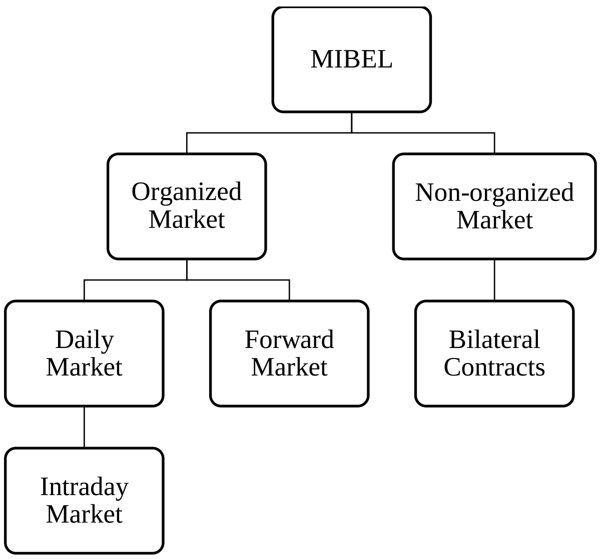

Figure 4.1 – Overall structure of the different Iberian electricity markets.

4.2.1 Daily market

The daily market of MIBEL is the platform where electricity is transacted for delivery on the day after the negotiation. This market is priced for each of the 24 hours of each day (it can still be 23 or 25 hours for the particular case of the summer time change or winter time change) and for each one of the 365 or 366 days of each year. Every day the daily market platform is active until 12:00, when, at the close of the session, electricity prices are presented for the following day. Before this deadline, the energy proposals of purchase and sale are made, which will be in the origin of the value of the prices of electricity for each hour. The participation in the market is performed through a simple computer system that uses the internet, which enables the simultaneous participation of a large group of agents and the management of a large number of offers for the purchase and sale of electricity in a short period of time, as well as the preparation of economic settlements. [15]

This market operates through the crossing of offers - of purchase and sale - by the various agents registered to operate in that market, each offer indicating the day and time to which it relates, the price and the corresponding amount of energy. The market price of electricity for each hour is found through a process, in which the price offers of sale (supply curve) are ordered in an increasing way, and the price offers of purchase (demand curve) are ordered in a decreasing way. The market price will correspond to the intersection of the supply and demand curves, resulting in the lowest price that ensures that the supply satisfies the demand. This process is based on an algorithm approved for all European markets, the EUPHEMIA algorithm. [15]

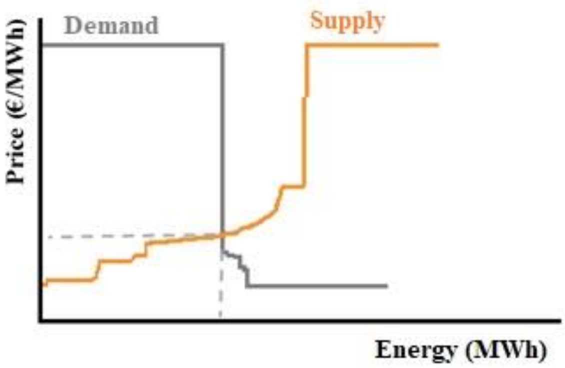

Figure 4.2 – The crossing of purchase and sale offers originates the market price of electricity. This method is based on the Euphemia algorithm. [16]

Regardless of the agents participating in the markets being in Spain or Portugal, the operation of the daily market implies that all buyers pay the same price and all sellers receive the same price, in what is called a single marginal price model. The operating rules of this organized market are specific to the market operator, OMIE.

In addition, since it is an Iberian market, constituted by Portugal and Spain, there may be circumstances where commercially available interconnection capacities between the two countries do not allow the cross-border flows of energy that cross-market offers would dictate. In case this occurs, the current market rules determine that the two market areas corresponding to Portugal and Spain are separated and that specific prices for each of the mentioned areas are found. The EUPHEMIA algorithm is then executed separately, in such a way that, a different price is defined for both countries. This mechanism is called market splitting or market separation. [15]

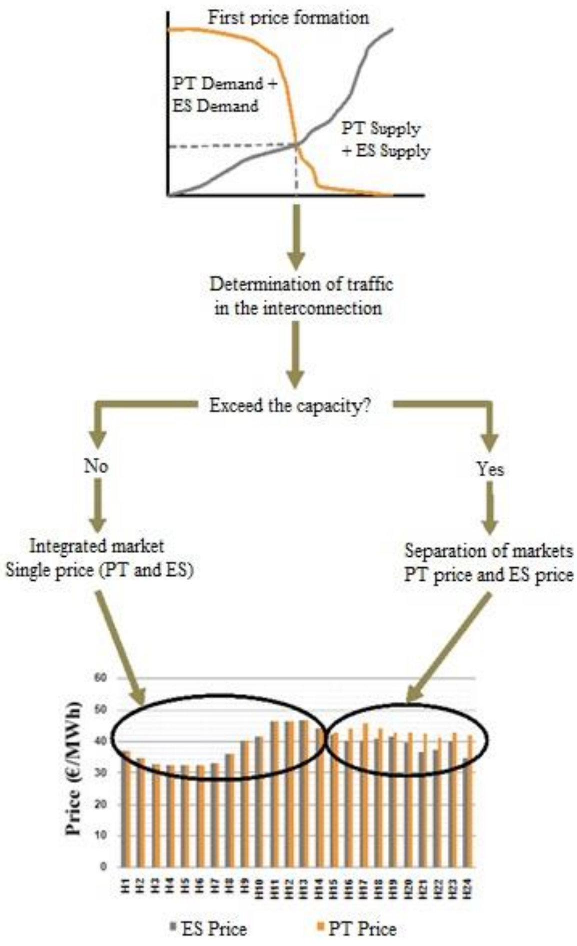

Figure 4.3 – Market splitting procedure. [16]

4.2.2 Intraday market

Complementary to the daily market, there is the intraday market (sometimes called the adjustment market), which daily, through several sessions, allows to make adjustments in the quantities transacted in the daily market. The intraday market is structured in six daily trading sessions, with an operating base similar to that described in the daily market, where the volume of energy and price per hour are determined by the intersection between supply and demand. The distribution of times per session is as follows [17][19]:

	1st Session	**2nd Session**	**3rd Session**	**4th Session**	**5th Session**	**6th Session**
Session opening	17:00	21:00	01:00	04:00	08:00	12:00
Session ending	18:45	21:45	01:45	04:45	08:45	12:45
Prices publication	20:45	23:45	03:45	06:45	10:45	14:45
Schedule horizon (time periods)	27 hours (21-24)	24 hours (0-24)	20 hours (5-24)	17 hours (8-24)	13 hours (12-24)	9 hours (16-24)

Table 4.1 – The different sessions available in the intraday market. [19]

- The first intraday session defines prices for the last 3 hours of the trading day and for the 24 hours of the day following the trading day;

- The second intraday session defines prices for the 24 hours the day after trading day;

- The third intraday session defines prices for the 20 hours between the hour 5 and the hour 24 of the day following the trading day;

- The fourth intraday session defines prices for the 17 hours between the hour 8 and the hour 24 of the day following the trading day;

- The fifth intraday session defines prices for the 13 hours between hour 12 and the hour 24 of the day following the trading day;

- The sixth intraday session defines prices for the 9 hours between hour 16 and the hour 24 of the day following the trading day.

The intraday market shares with the daily market the method of operation, based on the submission of offers, purchases and sales, by the various agents registered to act in the daily market, indicating each offer per session the day and hour, the corresponding price and quantity of energy. This type of market therefore gives a great versatility to the operation of the agents, allowing a very considerable degree of optimization, according to the needs of each agent, in a variety of time horizons and with the same guarantees in terms of transparency and possibilities of supervision which characterize the daily market.

4.2.3 Forward market

The forward market is a trading platform, which shares the same operating characteristics of MIBEL in daily markets but is distinguished by the establishment of electric energy purchase and sale contracts for a certain maturity in the future (week, month, trimester or year). In the scope of MIBEL and the agreements established for this market, the entity responsible for the management of the futures market is OMIP. In this way, OMIP offers the following instruments for the establishment of contracts [18]:

- Future Contracts: contract for the purchase or sale of energy for a certain time horizon, in which the buyer agrees to purchase electricity during the delivery period and the seller agrees to place the same electricity, at a price determined at the time of the transaction. Gains and losses resulting from price fluctuations during the negotiation phase in this type of contract are liquidated on a daily basis. According to OMIP, the most traded products in the futures market are Futures contracts.

- Forward contracts: a contract for the purchase or sale of energy for a certain time horizon, in which the buyer commits to purchase electricity during the delivery period and the seller agrees to place the same electricity, at a price determined at the time of the transaction. Contrary to the future contracts, in a Forward contract the gains and losses resulting from price fluctuations during the negotiation phase in this type of contract are liquidated on the days of physical or financial delivery.

- SWAP contracts: a contract in which a variable price position is exchanged for a fixed price position, or vice versa, depending on the direction of the exchange. Their function is to manage or take financial risk, not verifying the physical delivery of the product to which they refer, but only the liquidation of the corresponding margins.

Chapter 5

Data Availability

In this chapter, it is described how data availability and information flow is accomplished between the different agents of the sectors and the energy supplier agent. It is still addressed the topic of the smart meter, and what kind of benefits it will bring, not only to the customers but also to the entire electricity business.

5.1 Information flow

For an efficient functioning of the electricity sector, the exchange of information and the availability of data plays an essential role, among the various agents of the NES value of chain. For this reason, there are responsibilities in each one of the sectors that need to be accomplished, in terms of providing relevant data for the sectors that relate. Regarding the commercialization sector, there is a mandatory flow of information between the energy supplier agent, the distribution network operator (DNO) and the transmission network operator (TNO). This information becomes crucial, not only for billing purposes, but essentially to the management of the client portfolio or for the definition of strategies for the participation in MIBEL.

One of the factors with a major relevance in the ease of data acquisition, is about the existence or not of telemetering. Nowadays, telemetering with data consumption records, includes the totality of clients of the voltage level SLV, MV, HV and VHV, while, clients with voltage level NLV, do not have telemetering. In this case, estimates and average calculations according to a classification assigned are used, through records of the contracted power and the consumption of the last 12 months. This situation has been undergoing significant changes in recent years, due to technological innovations applied in the electrical grid, as we will see later in this chapter.

The data received by the energy supplier agent, comes with a mandatory daily and monthly frequency. Daily, it is possible to the energy supplier to receive consumption data referring to the previous day, but due to the particularity of the NLV client data daily available being based on estimates, there are monthly corrections of different levels sent, as actual real values are collected by the DNO. The energy supplier receives monthly 3 files in a period of nine months, namely one month after the consumption, three months after the consumption and nine months after the consumption. As these data files are received, they contain corrections and adjustments of the previous data files. Only nine months after the consumption, it is possible to the energy supplier to obtain the definitive data values of the complete client portfolio in that period.

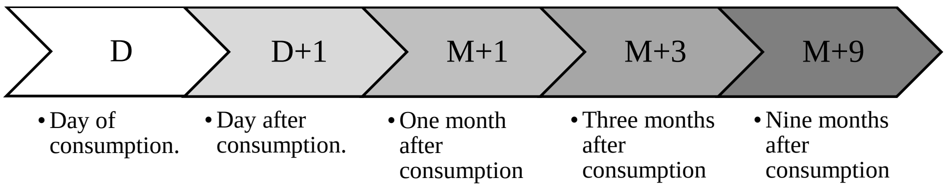

Figure 5.1 – Periodicity of the availability of data.

In the following points, the informations to be supplied by the DNO and the TNO to the energy supplier agent are explained in more detail, according to the type of information, as well as the periodicity of availability and its respective content.

5.1.1 Individual data by delivery point (DPC)

On a daily and monthly basis, by the part of the DNO, consumption data of each individual DPC, belonging to the client portfolio of the energy supplier, with a sampling period of 15 minutes, on the day after the consumption (D+1) and on the month after the consumption

(M+1) are made available. As said before, this data depends directly on the existence of telemetering, that is, in client of a mainly business sector, SLV, MV, HV and VHV, real data values are made available equivalent to the actual consumption. In the majority of domestic clients, the NLV, in which the telemetering functionality does not exist, the data available are based on estimates and averages calculated by historical records. The data referring the NLV clients are separated by classes: NLV A, NLV B and NLV C.

Data D+1, day after the consumption

Clients with telemetering: SLV, MV, HV, VHV

- Daily periodicity, on the day after consumption (D+1);
- Load diagram of one day of consumption, distributed in periods of 15 minutes, per DPC;
- Real data.

Clients without telemetering: NLV A, NLV B, NLV C

- Daily periodicity, on the day after consumption (D+1);
- Load diagram of one day of consumption, distributed in periods of 15 minutes, per NLV class;
- Data estimated by the DNO.

Data M+1, month after the consumption

Clients with telemetering: SLV, MV, HV, VHV

- Monthly periodicity, in the first month following the consumption (M+1);
- Load diagram of all the days of the month of consumption of the previous month, distributed in periods of 15 minutes, per DPC;
- Real Data.

Figure 5.2 – Periodicity and content type of the data made available by delivery point.

5.1.2 Data aggregated data by client portfolio

On a monthly basis, 3 types of consumption data are provided by the TNO: a consumption data file, corresponding to the previous month, M+1, also known as "Version 1", or V1, a consumption file corresponding to consumption three months before, referred to as "Version 2", or V2, and lastly, the consumption data file of nine months before, M+9, also designated as "Version 3", or V3. Each one of those file versions, corresponds to a correction of the previous version, and only Version 3 will contain definitive data. For SLV, MV, HV and

VHV clients, the data entered in versions V1, V2 and V3 do not differ in anything from their D+1 values, since the readings are real and do not change.

The reason behind this method, is due to the fact that in NLV installations, it is not always possible to obtain cyclic readings with the periodicity required by the availability of data, so it is necessary to use calculations to determine the estimated consumption. As the cycle readings are being performed, the data is being updated and this is being transposed into the various data corrections, in the form of file versions (V1, V2 and V3), received by the energy supplier agents.

As opposed to daily data, this monthly data is distributed by hour, for each day of the month, of the reference month. In addition to this data, there is also information on the recording of hourly and daily electricity prices, as well as information on the deviations, by default and in excess, per unit of energy (MWh) and currency unit (€), of operations of purchase of electricity in MIBEL in the previous month, by the energy supplier.

Data M+1, in the first month following the consumption (V1)

Clients aggregate: NLV A, NLV B, NLV C, SLV, MV, HV e VHV

- Monthly periodicity, in the first month following the consumption (M+1);
- Load diagram of all the days of the month of consumption of the previous month, distributed by hour, of the clients aggregate of the energy supplier;
- Estimated data based on average consumptions.

Data M+3, in the third month following the consumption (V2)

Clients aggregate: NLV A, NLV B, NLV C, SLV, MV, HV e VHV

- Monthly periodicity, in the third month following the consumption (M+3);
- Load diagram of all the days of the month of consumption of three months ago, distributed by hour, of the clients aggregate of the energy supplier;
- Data calculated on the basis of all the existing definitive consumptions, and in average consumptions for the remaining DPCs.

Dados M+9, in the ninth month following the consumption (V3)

Clients aggregate: NLV A, NLV B, NLV C, SLV, MV, HV e VHV

- Monthly periodicity, in the ninth month following the consumption (M+9);
- Load diagram of all the days of the month of consumption of nine months ago, distributed by hour, of the clients aggregate of the energy supplier;
- Data calculated on the basis of definitive consumptions.

Figure 5.3 - Periodicity and content type of the data made available for the complete client portfolio.

5.2 Smart meters

As mentioned previously, the fact that there are no telemetering conditions the quality of the data made available, since it is not always possible to the DNO to obtain cyclic readings at the frequency required by the availability of data, in which, alternatively, are used estimates using the historical records or the application of the annual consumption profiles. The fact that this happens, immediately conditions the energy supplier agent in the decision making, since the uncertainties generated by the estimates, lead to wrong decision making in the purchase of energy, in addition to conditioning the planning in the participation in the electricity markets.

In recent years, this situation has been changing with the gradual implementation of smart meters. Smart meters have emerged in recent years in Portugal, through the realization of intelligent electrical grids and energy efficiency projects, namely the InovGrid project, initiated in 2007, in Évora. The Smart Grid concept has revolutionized the way technical and commercial management of traditional electricity grids are conducted. This concept incorporates benefits of advanced communication and information technologies, in order to create an efficient network utilization and to provide real-time consumption information. [20]

This way, smart meters became a key element in the application of intelligent systems, since they act as the interface between the consumer and the rest of the electrical network, with the potential of, using the various sensors installed in the network, to be possible to feed information systems capable to manage and analyse large volumes of information. From the point of view, of the various users of the electricity network, among them the energy suppliers, this can be extremely useful regarding the possibility of managing and analysing big data systems, with a perspective to anticipate and predict consumption patterns, meaning a more efficient method for the participation in the electricity markets.

Currently, EDP Distribuição is in the process of replacing the conventional meters to smart meters, or Energy Box (EB). The EB's are equipped with an interface HAN (Home Area Network) external module, that allows the access of data not only to the clients using the devices, but also to energy supplier agents. The information available ranges from the active and reactive energy every 15 minutes, active and reactive energy per tariff every 15 minutes, max active power taken, instantaneous values of energy, voltage, active power, power factor and frequency, as well as the load diagram. Contractual information is also made available like the configured time cycle and the contracted limited power, with the available functionality of changing the contractual parameters through the communication with the EB. The distribution network operator, EDP Distribuição, is the owner of the devices, responsible for installing, maintaining and operating, while the energy supplier agent receives the data made available by the device and acts as an intermediary between the clients demands and needs, and the DNO respective operations.

Figure 5.4 – The smart meter, e-box, being installed by the EDP Distribuição. [21]

By the end of 2017, 1.3 million EB's were installed, and by the year 2020, the number is expected to increase until 3.4 millions corresponding to 60% of customers. Within the offer of new services to the energy suppliers, in addition to those already mentioned above, the following functionalities are included: [21][22]

- Consumer/production monitoring and energy efficiency services;
- New tariffs based on more granular consumption measures (hourly rates, prepaid);
- Improved billing service (without estimates, multipoint clients).

Chapter 6

ANN Theoretical Background

In the chapter 6, the reader is introduced to the general concepts of artificial neural networks (ANN) and a more focused explanation of a particular case of a neural network, a radial basis function neural network (RBFNN), used for the development of this work. The RBFNN training schemes, stopping criteria and the notion of multi objective genetic algorithms are also covered in this chapter.

6.1 Artificial Neural Network Concepts

The concept of artificial neural networks (ANN) was initially inspired by the operation of the brain and all its biological neuronal complexity. The basic component in a brain structure is the neuron. A neuron cell body is composed by a structure called dendrites connecting a nerve terminal, through a long axis called the axon. The nerve terminal is close to other neurons dendrites, forming junctions called synapses. These interconnections between neurons form a biological neural network circuitry. Neurons interact with each others by electrical signals, that propagate from the dendrites to the nerve terminal [23]. The figure 6.1 shows a biological neuron structure.

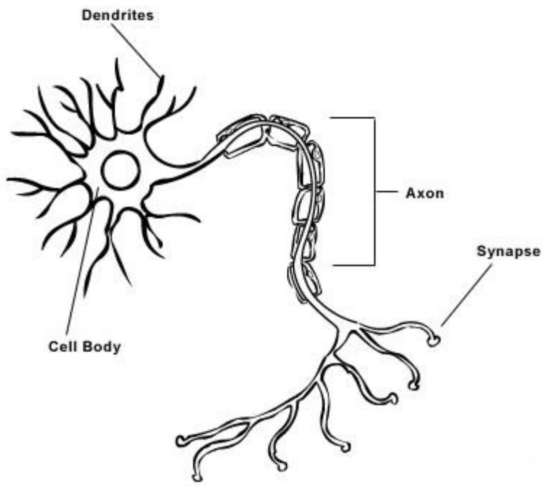

Figure 6.1 – Biological neuron. [24]

Taking inspiration from the brain functionality, the concept of mimifying in an analogous way the brain behaviour has emerged, through a mathematical model capable of computational processing that follows the operations of a neuron. This concept of artificial neural network is characterized as an high adaptivity capability system, capable of a very efficient computational model, able to learn from examples and to generalize others never executed before. This artificial system is capable of carrying out autonomous learning, as well as pattern recognition, trainable and not directly programmable, standing out in applications where the solution is hardly achieved in regular programs and models. [25]

Due to artificial neural networks modelling complexity, there are several factors to be considered in terms of network topology, learning algorithms and properties, that impact in a good neural network performance.

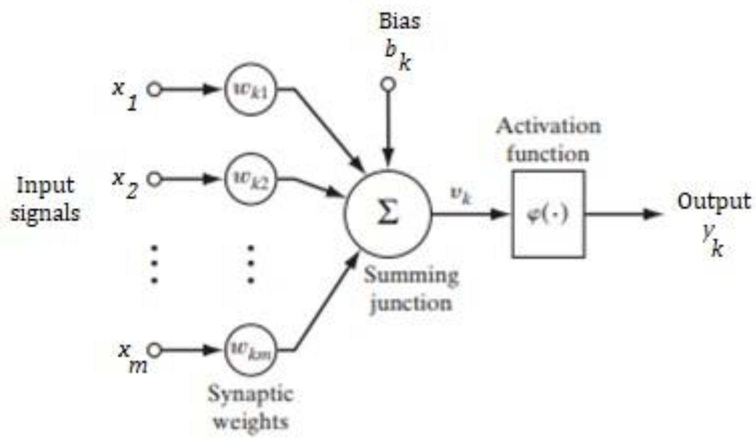

Figure 6.2 – Example of a neural network with x_m inputs, one neuron and one output. [26]

An artificial neural network can be shown in the figure above, composed by multiple inputs weighted and summed with an additional bias, connected with an activation function. In mathematical terms it can be described by equations 6.1, 6.2 and 6.3 with respect to neuron *k*, for *m* inputs: [26]

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \tag{6.1}$$

$$v_k = u_k + b_k \tag{6.2}$$

$$y_k = \varphi(v_k) \tag{6.3}$$

The input vector is defined by $x_1, x_2, \ldots, x_m$ and $\omega_{k1}, \omega_{k2}, \ldots, \omega_{km}$ are the synaptic weights of the neuron *k*. υ_k is the activation potential resulting from the sum of the terms $\omega_{kj} x_j$ and the bias b_k. Consequently, υ_k is denoted as net input and the argument of the activation function φ. Although an ANN could be composed by multiple neurons to handle multiple inputs, and multiple layers in the hidden layer, the concept is the same as explained before.

The activation function plays a relevant role, by the effect on the final output. Some of the most common activation function used in the different ANN are represented in the table 6.1:

Name	**Function**
Threshold function	$f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$

Piecewise-linear function	$\begin{cases} 1, & x \geq \frac{1}{2} \\ x + \frac{1}{2}, & -\frac{1}{2} < x < \frac{1}{2} \\ 0, & x \leq -\frac{1}{2} \end{cases}$
Linear function	$f(x) = x$
Sigmoid function	$f(x) = \frac{1}{1 + e^{-x}}$
Hyperbolic tangent function	$f(x) = \tanh x$
Gaussian function	$f_i\left(C_{i,k}, \sigma_i\right) = e^{\frac{\sum_{k=1}\left(c_{i,k} - x_k\right)^2}{2\sigma_i^2}}$

Table 6.1 – Most common activation functions. [23][25]

6.2 Radial Basis Function Neural Network

A radial basis function neural network (RBFNN) was introduced as a particular type of artificial neural network in the late eighties. RBFNN is composed by three layers. The first layer is the input layer, which connects the inputs to the network. The second layer is the hidden layer. Typically, in RBFNN, the network presents only one hidden layer, that can be composed by multiple neurons. Each neuron on the hidden layer contains a radial basis function as an activation function, hence the name radial basis function neural network. At last, comes the third layer, the output layer, usually composed by a single neuron, where the final result is outputted.

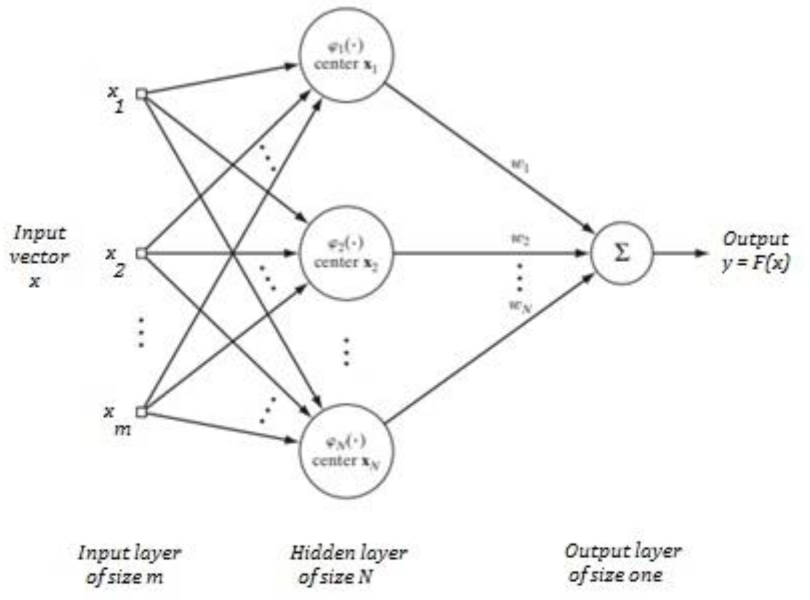

Figure 6.3 - Example of a RBF neural network with x_m inputs and N neurons. [26]

The hidden layer is formed by a neuron set, each one represented by a radial basis function, given by:

$$\varphi_i(x) = \gamma(|c_i - x|) \qquad (6.4)$$

The i^{th} input data point c_i defines the centre of the radial-basis function, and the vector x is the signal (pattern) applied to the input layer. Unlike other types of ANN, like the multilayer perceptron, the links connecting the source nodes to the hidden units are direct connections with no weights.

Although, there are several radial basis functions possible, the most widely used and also on this report, is the Gaussian function, using the Euclidean norm, which can be written as:

$$\varphi_i(x, c_i, \sigma_i) = e^{\frac{\|x-c_i\|_2^2}{2\sigma_i^2}} \qquad (6.5)$$

Where σ_i and c_i are the width and center of the i^{th} Gaussian function, respectively. The output of a RBFNN can be expressed as:

$$y(x) = b + \sum_{i=1}^{n} w_i \varphi_i(x, c_i, \sigma_i) \tag{6.6}$$

Where w_i is the i^{th} linear weight, n is the number of hidden neurons, and b is the bias. [26][27]

6.3 RBFNN Training Schemes

One of the most enthusiastic features regarding the artificial systems, is the ability to learn and adapt through changes in the environment. In ANN, learning becomes the process of updating the inner properties of the system, in response to external stimulation, with the goal to achieve a specific task. This learning ability can be achieved by a training method, that consists of presenting to the network training examples, similar to the way we learn from experience. This procedure can involve from network architecture modifications, to adjusting the weight connections between layers and nodes, or even changes in the neurons properties, in order to adapt to the given training examples [4]. There are three classes of major methods for RBF training and are going to be explained in the following sections. This section follows close the section 2.2.1 in [23].

6.3.1 Fixed centers selected at random

Initially, the RBFNN were considered as interpolators, capable of forcing the function to pass exactly for every point in the training data. This scheme had its problems due to need of enlargement of the data set, meaning an increase of complexity, usually originating badly conditioned networks. In order to avoid this problem, the RBFNN began to be considered as an approximator, which simplified the procedure by allowing a considerable decrease of the number of basis function needed and making possible the functions base centers not match the data points. The simplest way to determine the functions base centers is, by choosing them randomly, in the range of the training set. The Gaussian standard deviation, in this method, is usually given by:

$$\sigma = \frac{d_{max}}{\sqrt{2n}} \tag{6.7}$$

Where d_{max} is the maximum Euclidean distance between the centres and n is the number of centres. This avoids the condition of the base functions to be too picky or too flat. The linear weights can be obtained by:

$$\hat{w} = \Phi^{+} t \tag{6.8}$$

Where Φ^{+} is the pseudo-inverse outputs matrix of the hidden neurons, with dimension $Q \times n$, being Q the number of training patterns. The t vector is the desired output of the network, with $Q \times 1$ dimension.

6.3.2 Self-organized selection of centers

The problem with the previous described training method is related to the need of a large training set in order to achieve an acceptable performance. As an alternative an hybrid training process could be used involving a two-step method: A self-organized learning step, to determine the locations of the centres of the radial basis functions, and a supervised learning step, to determine the linear output weights.

In the first step, for grouping the data in a homogenous manner, the most popular method is the k-means clustering algorithm [28]. This algorithm iterates by placing the centers into regions were significant number of examples are grouped, stopping the iterations until there are no significant alterations of the centres. The problem with this algorithm that it only can get to a local optimum solution, that depends on the centers initialization values. To solve this limitation several other algorithms have been proposed based on a measure that weights a variation on a group. One of them is the k-means adaptive clustering, allowing to converge to an optimum result, or close to it, without depending on initial centre values [29]. In relation to the standard deviations or spreads, they can be calculated using equation 6.7 or using other heuristics such as:

- K-nearest neighbours: considering k (a user-defined percentage of the total number of centres) centres nearest the centre $\boldsymbol{C}_i$.

$$\sigma = \frac{\sum_{j=1}^{k} \left\| C_i - C_j \right\|}{k\sqrt{2}} \tag{6.9}$$

- Nearest neighbours: Considering *k* the nearest neighbour of centre *i*. *Q* is an application-defined parameter.

$$\sigma = Q \frac{\| C_k - C_i \|}{\sqrt{2}} \tag{6.10}$$

- Empirical standard deviation: where n is the train pattern number associated to the *i* group;

$$\sigma = \sum_{j=1}^{n} \sqrt{\frac{\left\| C_{j,i} - x_j \right\|^2}{n}} \tag{6.11}$$

- Maximum distance between patterns: where m is the train pattern number.

$$\sigma = \frac{max_{i,j=1\ldots m} \left\| x_i - x_j \right\|}{2\sqrt{2}} \tag{6.12}$$

6.3.3 Supervised selection of RBFNN parameters

In this learning scheme, all the RBF network parameters: spread, σ , centres, *C* and linear weights, *w*, are obtained with a supervised learning process computed using error-correction algorithms. The error is calculated as the sum of the squared differences between the net output and the desired output, being back propagated through the hidden neurons to update the weights of the connections. This process is repeated until a convergence in a minimum error solution is verified. The error back-propagation (BP) algorithm is the best known learning algorithm for performing this operation. The BP algorithm implements the steepest descent method and uses a methodology based on the update of parameters, expressed like the equation below:

$$w[k+1] = w[k] - \eta g[k] \tag{6.13}$$

In equation 6.13, w is the vector that correspond to the model parameters, n is the learning rate and g is the gradient vector. Usually, the error criterion is applied by minimizing the sum of the square of the errors between the target and the actual output, expressed in equations 6.14 and 6.15 using the gradient vector, mathematically expressed in above equation 6.16.

$$e[k] = t[k] - y[k] \tag{6.14}$$

$$E = \frac{1}{2} e^t e = \frac{1}{2} \sum_{i=1}^{N} e^2[k] \tag{6.15}$$

$$g = \nabla E(w) = \left[\frac{\partial E}{\partial w_1}, \frac{\partial E}{\partial w_2}, \dots, \frac{\partial E}{\partial w_M}\right]^T \tag{6.16}$$

Several modifications of this algorithm have been proposed. One of them is to perform the update of the weights each time a pattern is presented. The reasoning behind pattern mode update is that, if is small, the departure from true gradient descent will be small and the algorithm will carry out a very close approximation to gradient descent in sum-squared error. Another modification, introduced by Rumelhart and the PDP group, is the inclusion of a portion of the last weight change, called the momentum term, in the weights update equation: [23][30].

$$w[k+1] = w[k] - \eta g[k] + \alpha(w[k] - w[k-1]) \tag{6.17}$$

Two disadvantages can be pointed out for the BP algorithm: it is not a reliable algorithm, as the training procedure can diverge, and the convergence rate is usually very slow. The limitations of the BP algorithm stimulated the development of alternative methods, such as the Levenberg-Marquardt method, explained in 6.3.3.1.

6.3.3.1 Levenberg-Marquardt method

The Levenberg-Marquardt method is a general unconstrained optimization method, which has global convergence property. The search direction for this method is:

$$(J^T[k]J[k] + v[k]I)p_{LM}[k] = -J^T[k]e[k] \tag{6.18}$$

Where the scalar $v[k]$ controls both the magnitude and the direction of $p[k]$. As v tends to infinity, $\boldsymbol{p}[k]$ tends to a vector of zeros, and a steepest descent direction. The Levenberg Marquardt method is of the “trust-region” or “restricted step” type. this type of method attempts to define a neighbourhood where the quadratic function model agrees with the actual function in some sense. If there is good agreement, then the test point is accepted and becomes a new point in the optimization; otherwise it may be rejected, and the neighbourhood is constricted. The radius of this neighbourhood is controlled by the parameter v, usually denoted the regularization factor.

To introduce the algorithm, one way of envisaging the Hessian approximation employed at every k^{th} iteration, consider a linear model for generation the data:

$$o^{(nl)}[k] = J[k]w[k] \tag{6.19}$$

Using this, the predicted error vector, after taking a step $p[k]$ is:

$$e^p[k] = e[k] - j[k]p[k] \tag{6.20}$$

So that the predicted reduction of Ω:

$$\Delta\Omega^p[k] = \Omega(w[k]) - \frac{e^p[k]^T(e^p[k])}{2} = \tag{6.21}$$

Actual reduction is given by:

$$\Delta\Omega[k] = \Omega(w[k]) - \Omega(w[k] + p[k]) \tag{6.22}$$

To measure the accuracy to which the quadratic function approximates the actual function, the ratio, $r[k]$, in equation 6.23, is used to actualize the regulation parameter v that usually uses the rule in equation 6.24:

$$r[k] = \frac{\Delta\Omega[k]}{\Delta\Omega^{p}[k]} \tag{6.23}$$

$$v[k+1] = \begin{cases} \frac{v[k]}{2}, & r[k] > \frac{3}{4} \\ 4v[k], & r[k] < \frac{1}{4} \\ v[k], & cc \end{cases} \tag{6.24}$$

For negative values of r[k] just the regularization parameter is actualized. [23][27]

6.3.4 Stopping criteria

A well performed training procedure needs also the definition of a stopping criterion, that could avoid a poor network conditioning. A good conditioning ability is referred to as generalization capacity and its defined by avoiding two specific situations, that have negative effect in the network capability to generalize: overtraining and overfitting. Overtraining is when the neural network assumes an addicted behaviour by learning too many input-output examples, ending up by memorizing the training data, losing the ability to generalize between similar input-output patterns, acting close to a look up table. Overfitting refers to exceeding the optimal ANN size which may result in a worse predictive ability of the network.

A technique used to work around the bad conditioning training and to maximize the generalization ability is the early stopping method. When training a network, the performance of the model is measured with a different, fresh and unused set (testing set). Initially the testing fit decreases and increases afterwards, representative of an overtraining in the testing set, due to the loss of generalization ability during the training. The early stopping method is therefore used in the training of the network, by evaluating the performance of the model with the testing set until it reaches the minimum in terms of fit. The figure 6.4 shows the optimal stopping criterion, this way avoiding a bad conditioning model. [23][26]

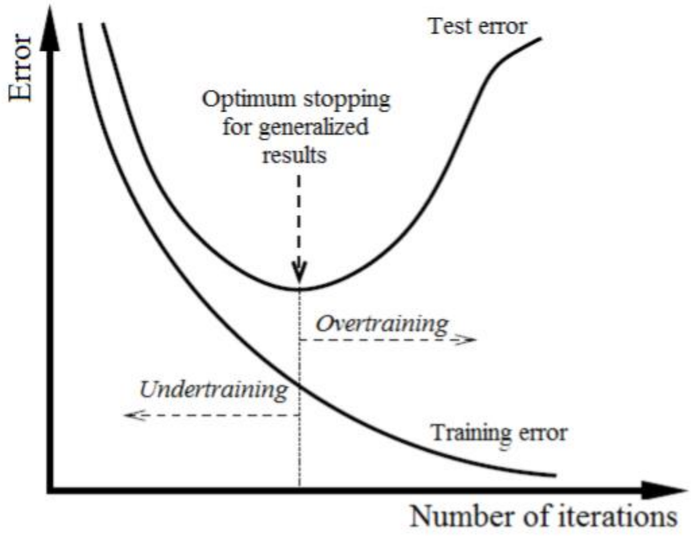

Figure 6.4 – Optimum stopping avoiding overtraining and undertraining in order to achieve a satisfied generalization. [27]

6.4 Multi Objective Genetic Algorithms

Genetic algorithms (GA) are one class of evolutionary algorithms defined by a set of procedures and operators, inspired by Darwin theory of natural selection from the survival of the fittest. In GAs, a population is composed by individuals, which evolves through several generations, the characteristics of each individual changing by mutations and, more often, with genetic information obtained by both parents (crossovers). The main idea is that, following each generation the weak unfit die and do not produce a generation. Analogous to that, in genetic algorithms, a set of solutions, represented by population of a specie, have a number of individuals that suffer operations to improve its capabilities to solve a problem. In each generation, the worst solutions are prevented to evolve.

The presence of multi objectives, sometimes presents a conflicting environment, meaning an harming to some objectives or an improvement to others. This conflicting nature, of contradicting objectives to be optimized simultaneously, originates the Pareto set of the multi objective optimization.

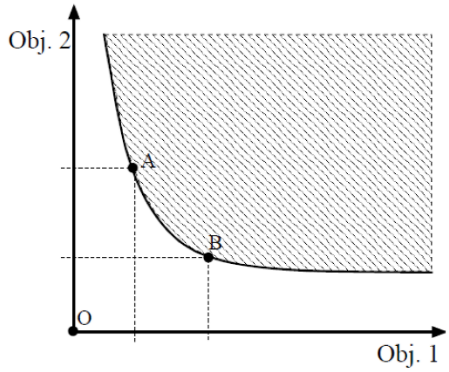

Figure 6.5 - Concept of Pareto optimality. [31]

Figure 6.5 shows an example of a two objective minimization problem. The shaded region in the space of solutions presents the dominated solutions, while the solid curve, where A and B are located, represent the non-dominated set of solutions, respective to objectives obj.1 and obj.2. In this problem, the multi objective optimization goal is to improve the surface of non-dominated solutions in such a way that the surface approaches the origin as much as possible. This way optimizing the two objectives with the minimum solution possible, as intended. The MOGA procedures initially starts with an initial population of individuals representing the solution candidates. This initial generation is the source to new other generations, sequentially through iterations. The figure 6.6 shows the procedure of the iterations flow during MOGA operation.

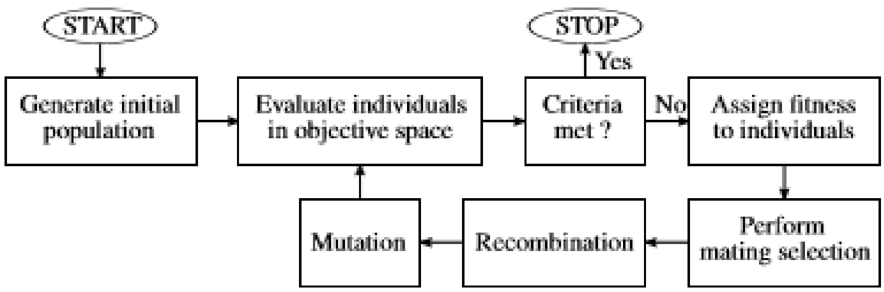

Figure 6.6 – MOGA procedure diagram. [32]

At each iteration the population is evaluated for the specified multi objectives and a verification is made to confirm if the design criteria was met. If the objectives achieve satisfactory results of the design criteria intended, the algorithm stops, and the designer obtains the individuals with the approximation to the Pareto front of the present generation.

Chromosome:

n	λ_1	λ_2	$\cdots$	λ_{d_m}	λ_{d_m+1}	$\cdots$	λ_{d_M}

Input space of q features, $\boldsymbol{F}$:

f_1	f_2		f_{a_0}	f_{a_0+1}	f_{a_0+2}		$f_{a_0+a_1}$		$f_{a_0+\cdots+a_0}$		f_q
$\downarrow$	$\downarrow$		$\downarrow$	$\downarrow$	$\downarrow$		$\downarrow$		$\downarrow$		$\downarrow$
$y(t)$	$y(t-1)$	$\cdots$	$y(t-\tau_y)$	$v_1(t)$	$v_1(t-1)$	$\cdots$	$v_1(t-\tau_{v_1})$	$\cdots$	$v_0(t)$	$\cdots$	$v_0(t-\tau_{v_0})$

Figure 6.7 – Chromosome composition and representation of the input equation of a neural network. [32]

A fitness value is assigned to each individual. This way, the individuals are ranked and pairs of parents are chosen accordingly. Each mated pair will generate two offspring by the application of the recombination operator, thus forming the next generation. Lastly, the mutation operator is applied to each individual generated in the new generation before repeating the whole process. [32]

Each individual in the MOGA population is represented by a string of integers, denominated as the chromosome, as shown in figure 6.7. In a MOGA chromosome, the first component, n, highlighted in a dark grey background, corresponds to the number of neurons, those highlighted by a light grey background represent the minimum number of inputs, dm, and remaining are a variable number of inputs up to a given total d_M. [32][31]

As we shall be dealing with dynamic mappings, we use the set of input features, non-linear autoregressive (NAR) with exogenous inputs (NARX) formulation, represented by:

$$y(t+1) = g(y(t), y(t-1), \dots, y(t-\tau_y),$$

$$v_1(t), v_1(t-1), \dots, v_1(t-\tau_{v_1}), \dots,$$

$$v_0(t), v_0(t-1), \dots, v_0(t-\tau_{v_0}))$$

Where y is the output, g is a RBFNN, v_1 to v_o are the exogenous inputs and τ_y, τ_{v_i} and τ_{v_0} the maximum lags of each respective input.

Chapter 7

Methodology Applied

In this chapter a detailed explanation of the practical procedures applied in the creation of several forecasting models, using radial basis function neural networks optimized by a multi objective genetic algorithm is done. Several aspects are going to be covered such as a brief overview of the early experimental work undertaken, the data collection specifications, different data approaches supported by the specific patterns of consumption of the data case study, as well as, the methodology applied in the models design. The objective is to achieve the best prediction models possible between different prediction horizons, yearly and seasonal models, as well as, multiple input variables, that could recreate the seasonal, temperature and daily characteristics influences in the energy consumption.

7.1 Early work development overview

The work developed and presented in this report, followed several stages of improvement, preparation or exploratory nature, until the achievement of satisfactory results. This served to deepen the knowledge of the themes covered in this work and to perfect the final results. In figure 7.1, a general overview, of the various stages of progress over the course of this project is presented.

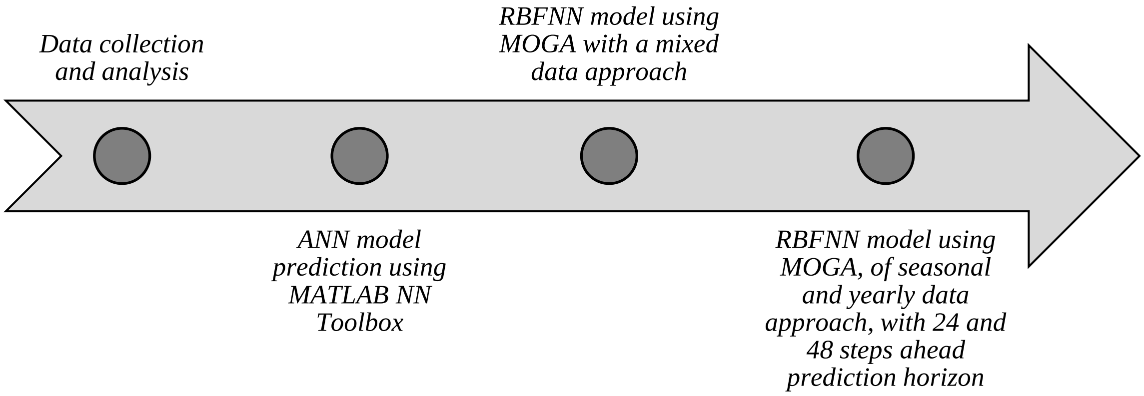

Figure 7.1 – Early work development during this project.

The development of this project could be separated into three major phases: An initial phase, an experimental phase and a final definition phase. In an initial phase, the development of the project was dedicated exclusively to the collection of data. A process of data analysis and identifying patterns of consumption.

The first experience exploring the ANN forecast, served as an experimental phase, by using the Neural Network Time Series Toolbox provided by MATLAB. This method served the purpose of introducing the subject of neural networks forecast, with the use of various combinations of NAR and NARX networks time series trained using Levenberg-Marquardt algorithm. Also, in this period, the RBF neural networks using MOGA framework were introduced. A mixed seasonal data approach experimented, with data ranging from 1st August till 31st of December, with different input variables, allowing the exploring of MOGA properties and to adjust the parameters. This phase was plentiful in experiments of different variations of data and ANN model design exploring, which set the standards for the final definition of this project.

In the final phase, the final methods were idealized, with an yearly data approach and a seasonal data approach, training with various input variables and considering different prediction horizons. These yearly and seasonal methods represent the main case studies of this project, and their methodology are going to be explained, in full detail, in the following sections.

7.2 Data set

The Rolear Group headquarters building based in Areal Gordo, Faro, was the DPC energy consumption data used for this work.

Figure 7.2 – Google maps screenshot of the Rolear group headquarters. coordinates: 37°02'26.5"N 7°53'49.0"W.

Being this DPC, a medium voltage client of Rolear Viva, this data was obtained by the available D+1 stream of data received and collected by the supplier for the purpose of this work. In chapter 4 is fully explained the availability of data. This data set has hourly energy values in MWh unit, with no missing data, from 20th March 2017 to 20th March 2018.

For the atmospheric contributions, temperature data was considered as an exogenous input, and obtained by manually collecting minimum temperature *Tmin* and maximum temperature *Tmáx*, in ºC unit, for every day of data of energy considered, with no missing days, taken by the site www.ipma.pt in Faro location, as well as, in site www.accuweather.pt in Faro location. Unlike the energy values, this data has a daily basis, defined by the mean temperature *Tméd* given by the formula:

$$Tméd = \frac{Tmáx + Tmin}{2} \tag{7.1}$$

As it can be analysed in more detail in the section 7.3.1, the Rolear Group headquarters presents a regular behaviour of working labour schedule, having its energy consumption mostly from Monday to Friday, and minimal energy consumption on weekends, holidays or “bridge” days. For that reason, another exogenous input variable was created, by assigning a specific code to every characteristic day matching in the energy data set. This data has also no missing days, and like temperature, has a daily periodicity. Table 7.1 shows the code assigned to each day. This method was used in the paper [33].

Day of week	Regular day	Holiday	Bridge day
Monday	0.05	0.40	0.70
Tuesday	0.10	0.80	
Wednesday	0.15	0.50	
Thursday	0.20	1.00	
Friday	0.25	0.60	0.90
Saturday	0.30	0.30	
Sunday	0.35	0.35	

Table 7.1 – Code assigned to each day. [33]

Summing up, the complete dataset covers from 20th March 2017 to 20th March 2018 and is composed by 3 input variables: energy (MWh), temperature (ºC) and characteristic day code, with hourly, daily and daily periodicity, respectively, with no missing values.

Variable	Type	Unit	Periodicity	Range of data
Energy	Modelled	MWh	Hourly	[0.0111, 0.0948]
Day	Exogenous	Code	Daily	[0.05, 1.00]
Temperature	Exogenous	ºC	Daily	[8.5, 31.5]

Table 7.2 – Overview of the complete data set.

7.3 Patterns of consumption

The load diagram translates the variation of the energy consumption during hours of a day and days of a year. This allows to define a client profile by analysing the characteristics of the energy consumption in a temporal basis, enabling to understand the meteorological and seasonal contributions. The next sections support the forecast approach methodology and exogenous variables chosen, by demonstrating the temporal and meteorological influence in energy consumption.

7.3.1 Characteristic days patterns

The type of day of the week reveals an influential temporal factor in energy consumption mainly in 5 different cases: Working days (Monday to Friday), Saturdays, Sundays, holidays, and bridge days (working days between holidays, more properly Mondays or Fridays). In the sequence of working days, the behaviour pattern can be explained by the daily routine of a work schedule, from 09h to 18h, on a regular company, such as the case of Rolear Group headquarters. On weekends, there is another type of behaviour characteristic of offices and companies, in which the energy consumption decreases to is minimal possible, since its out of regular work schedule. The holidays are another specific case in which the consumption decreases, similar to what happens in weekends. Another specific characteristic are the “bridge” days, Mondays or Fridays in between holidays, in which some employers take the day off, that represents a less use of electrical equipments, resulting in a small decrease in energy consumption. The following figure demonstrates the different characteristics days present in the complete data set and which supports the coding scheme for day type idealized in section 7.2.

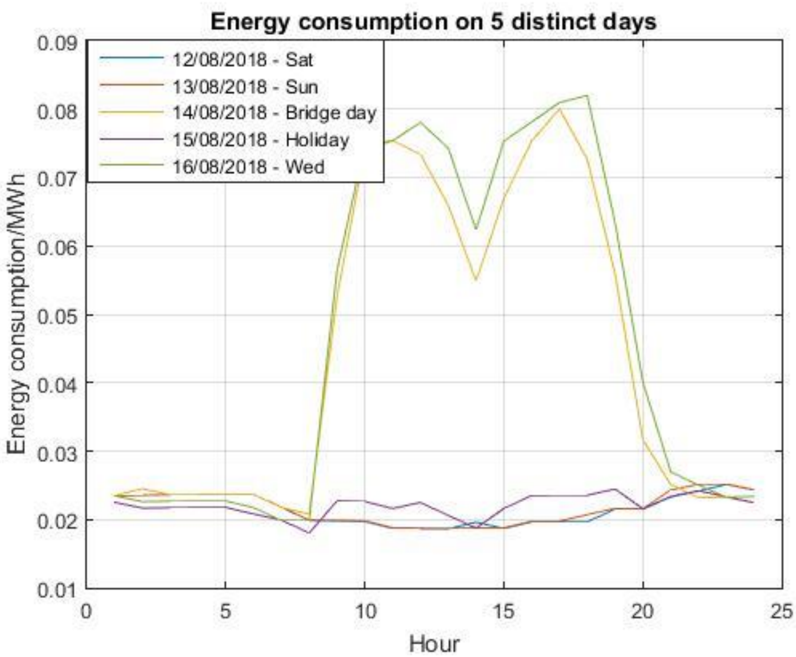

Figure 7.3 – Comparison of the energy consumption between 5 days distinct days.

7.3.2 Temperature influences

Besides the temporal factors, the meteorological factors, in this case temperature, are the ones that most affect the patterns of energetic consumption. The use of heating systems in the Winter and cooling/air conditioner in the Summer translate in an increase of electric energy consumption. This way, an input variable temperature can perform an import role in the case of a good forecast, since it contains information relative to seasonality and explains the behaviour of consumption along the different months. As can be seen in figure 7.4, the energy consumption, in the complete data set, varies according to the temperature changes. The habits of consumption are higher, when lower or higher temperatures are noted. The usage of heating systems in the winter and cooling systems in the summer translates in an increase of the energy consumption.

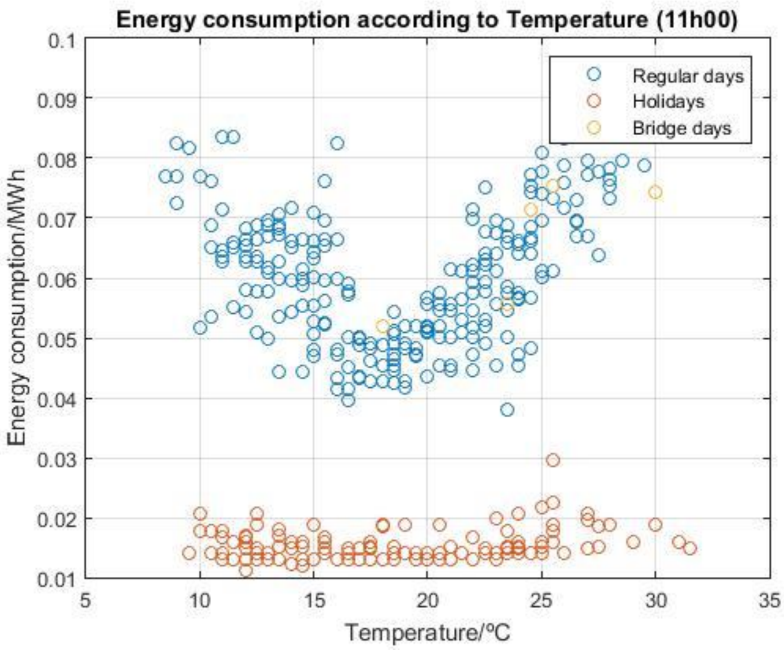

Figure 7.4 – Comparison of the energy consumption at every 11h00 of the data set.

7.4 Data approaches

The methodology applied was idealized to train the RBF neural networks, by covering different situations needs with the best possible accuracy, to obtain optimized prediction models enabling to forecast in between a few hours till a maximum of 48 hours. These optimized tools serve the purpose of being able to guarantee flexibility in forecasting, several steps ahead, the energy consumption of a certain individual. This way, is possible to plan the participations in the different electricity markets, referred in chapter 4, namely in the OMIE day after and intraday markets. This being said, for every approach, two horizon prediction were experimented in training, 24 hours and 48 hours ahead.

In order to model the forecasting systems several network structures were put in place, taking into account the individual profile consumption, previously analysed in more detail in section 7.3. The forecasting models were built according to two major approaches of data sets: a seasonal approach defined by a spring period, a summer period, an autumn period and a winter period, and an yearly approach. These data collections are explained in more detail in the next sections. As inputs, the respective approach datasets were built with energy (MWh) as the modelled variable, local air temperature (ºC) and a specific characteristic day coding as the exogenous variables, like previously referred in more detail in section 7.2. Based on this, the models will present delayed values of those inputs, with a forecast time step of 1 hour, for a total of 24 or 48 hours time steps.

In figure 7.5, the different design approaches according to data set inputs used and prediction horizons are presented.

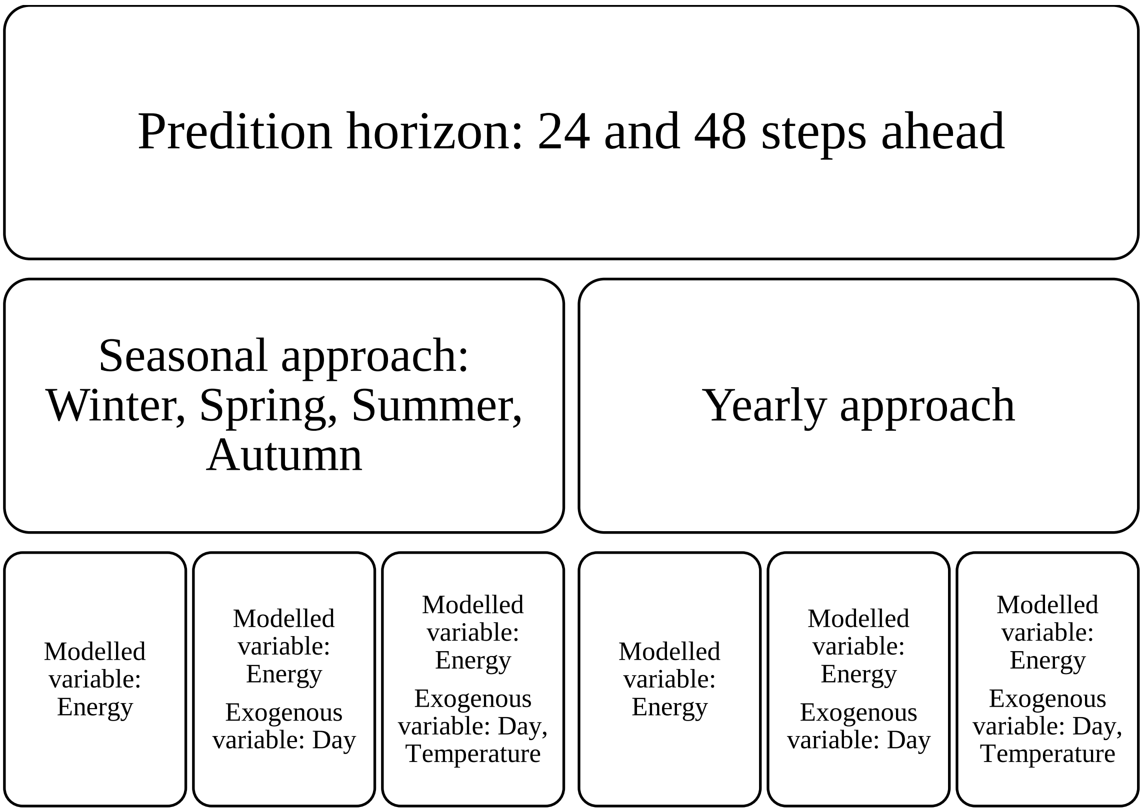

Figure 7.5 – Developed models according to each data approach.

7.4.1 Seasonal data approach

In this approach, the complete dataset was distributed in to four seasonal periods used for training: Winter, Spring, Summer and Autumn, differentiated by calendar date and not by the characteristics of the seasons. In table 7.3, the calendar limits and input variables information of the seasonal data sets, are represented.

		Max	Min	Mean	Start date	End date
Spring	Energy (MWh)	0.0889	0.0112	0.0279	20/03/2017	21/06/2017
	Temperature (ºC)	31	10	19.829		
Summer	Energy (MWh)	0.0948	0.0131	0.0343	21/06/2017	22/09/2017
	Temperature (ºC)	31.5	18	24.596		
Autumn	Energy (MWh)	0.0806	0.0121	0.0298	22/09/2017	21/12/2017
	Temperature (ºC)	25	11	18.291		
Winter	Energy (MWh)	0.0855	0.0111	0.0333	21/12/2017	20/03/2018
	Temperature (ºC)	16.5	8.5	12.978		

Table 7.3 – Overall information of the seasonal data sets.

In figure 7.6, the energy consumption during each seasonal data set is presented.

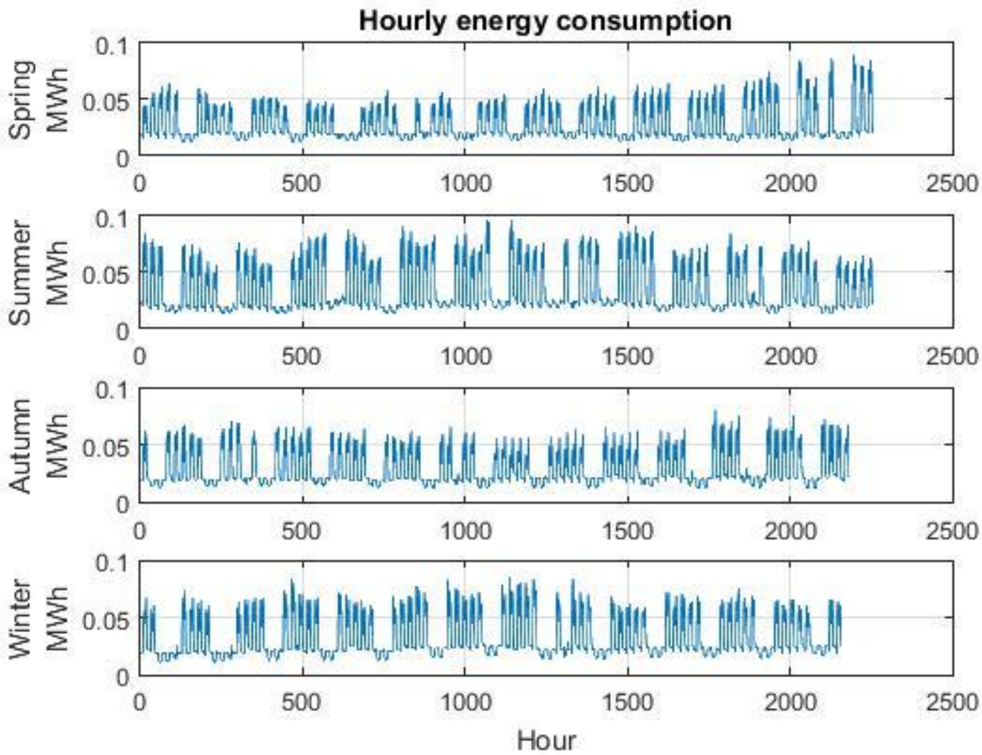

Figure 7.6 – Energy consumption in each seasonal data set.

7.4.2 Yearly data approach

In the yearly approach, the complete dataset was used for training. In table 7.4, the calendar limits and input variables information of this complete data set are presented.

	Max	Min	Mean	Start date	End date
Energy (MWh)	0.0948	0.0111	0.0313	20/03/2017	20/03/2018
Temperature (ºC)	31.5	8.5	18.9945		

Table 7.4 - Overall information of the yearly data sets.

In the figure 7.7, the energy consumption during a complete year can be seen.

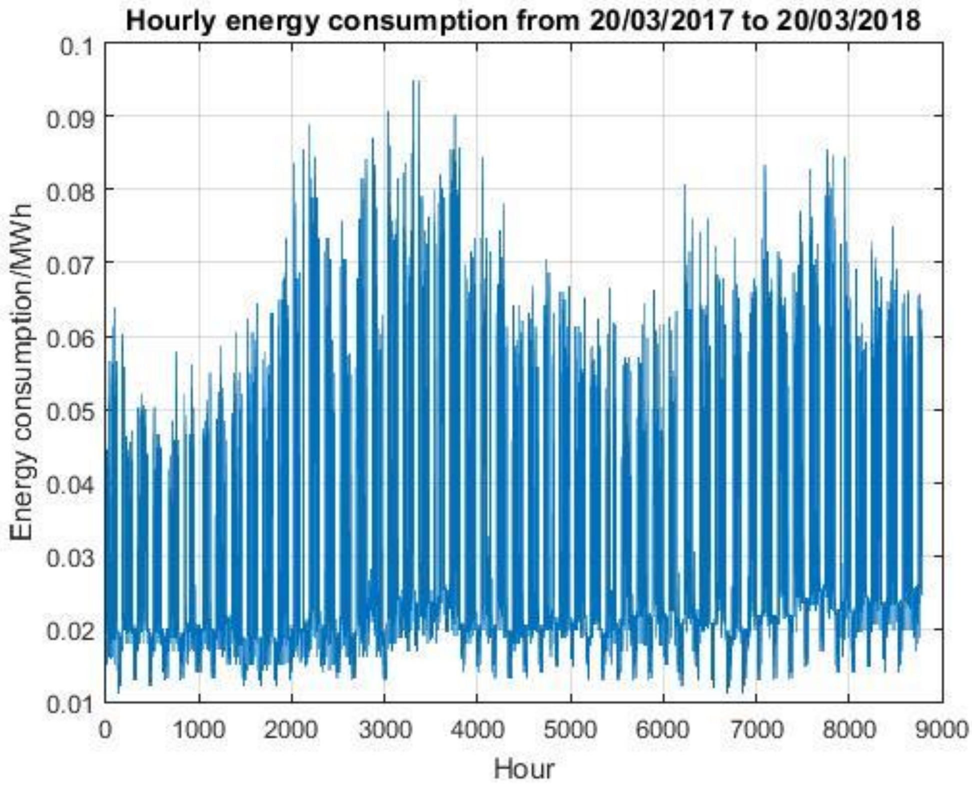

Figure 7.7 - Energy consumption in the entire data set corresponding to a year.

7.5 RBFNN model design using MOGA

The RBF neural network model design uses an existing multi objective genetic algorithm framework implemented in a computer cluster, due to its computational demand and computation time, in the University of Algarve, Electronics and Informatics Engineering Department (DEEI), using MATLAB, Python, and C programming languages.

The multi objective genetic algorithm, MOGA, is an evolutionary approach, inspired by the theory of natural selection and the notion of survival of the fittest, which performs a population-based search by employing operators, such as selection, mating and mutation. [35] The purpose use of MOGA in this work, is to achieve the design of RBF neural networks models with ensure efficiency and satisfactory performance, by the determination of optimized structure and parameters of RBFNN based models. This optimization process is accomplished by selecting combinations of input variables (and their lags), as well as the number of neurons, that optimize pre-specified model performance criteria. The neural network model design strategy employed, can be divided into a two stage procedure that contemplates: the ANN parameters and the ANN structure. The ANN parameters are obtained by a suitable training algorithm. In this case, neural network models are trained by the Levenberg-Marquardt algorithm using a modified training criterion. The ANN model structure is evolved using MOGA, by the selection of suitable input terms and number of neurons. These processes are going to be explained in the next sections. [34]

7.5.1 RBFNN Training

For a specified number of neurons, n, and for a determined set of inputs, X, training a RBFNN, formulated by the equation 6.6 in section 6.2, corresponds to determining suitable values of w, C, and σ. These network parameters will be denoted as the parameter vector p:

$$p = [w_i, C_i, \sigma_i] \qquad i = 1, 2, \dots, n \tag{7.2}$$

When each individual in the population is evaluated in MOGA, the training process for each model is made using a Levenberg-Marquardt algorithm minimizing an error criterion, that exploits the linear-nonlinear relationship of the RBF NN model parameters p. The training procedure stops using an early stopping technique, that evaluates over a second data set used for generalization, the testing data set, ceases to decrease within a maximum number of iterations, pre-specified in MOGA framework. The initial values of the nonlinear parameters

(C and σ) are obtained using an adaptive k-means clustering algorithm, w is determined as a linear least-squares solution. [36]

7.5.2 MOGA model optimization

The training procedure only obtains the optimal values of the parameters in equation 7.2, the MOGA model optimization covers the remaining main procedure stated in section 7.5, the ANN structure.

In the full implementation of the model design, it is necessary to define the preferred specifications measures of the model design criteria, that could set the objectives for the determination of the network structure and parameters. Assume the data set composed of N input-output pairs as $D = (X, y)$, divided into a training set D^t, a testing set D^g and a validation set D^v, also, a set F of the complete input features possible (lags of modelled and exogenous variables) and the vector parameter p. Using these assumptions, the execution of model design by MOGA can be expressed as the following: The model design preferences are given to the MOGA, by setting, the input features in the range of $d \in [d_m; d_M]$, from F, and the number of neurons in the range of $n \in [n_m; n_M]$. Other specifications are used in the MOGA but are relative to the genetic algorithm functioning and not to the multi objective oriented optimization and model typology. After the execution, the MOGA generates a non-dominated set of RBF models according to the restriction or minimization of the multi objective set $[\mu_p, \mu_s]$, where μp refers to the neural network parameters objectives p**,** and μs refers to the neural network structure objectives. The corresponding objectives $[\mu_p, \mu_s]$, can be represented as:

$$\mu_p = [\varepsilon(D^t), \varepsilon(D^g), \varepsilon(D^s, PH)] \qquad (7.3)$$

$$\mu_s = [O(\mu)] \qquad (7.4)$$

In μ_p, the $\varepsilon(D^t)$ and $\varepsilon(D^g)$ represent the root mean squared error (RMSE) of the training and testing dataset, respectively. PH refers to the prediction horizon, in this work case it assumes values of 24 and 48 steps ahead, and D^s is an additional data set, that has m data points and for each data point the model is used to make predictions up to PH steps ahead. The error forecast matrix can be expressed as:

$$E(D^s, PH) = \begin{bmatrix} e[1,1] & e[1,2] & \cdots & e[1, PH] \\ e[2,1] & e[2,2] & \cdots & e[2, PH] \\ \vdots & \vdots & \ddots & \vdots \\ e[m-PH, 1] & e[m-PH, 2] & \cdots & e[m-PH, PH] \end{bmatrix} \tag{7.5}$$

Being $e[i, j]$ the model prediction error taken from the instant i of D^s, at step j within the PH value. Denoting the RMSE function operating over the i^{th} column of the argument matrix by $q(.\,, i)$ then the $\varepsilon(D^s$, PH) can be defined as:

$$\varepsilon(D^s, PH) = \sum_{i=1}^{PH} q(E(D^s, PH), i) \tag{7.6}$$

In μs, $O(\mu)$ refers to the model complexity, that reflects the RBF input-output topology, and is calculated by:

$$O(\mu) = (d + 1) \times n \tag{7.7}$$

Through a specified generated population, in each generation the individuals are trained, evaluated on the specified objectives [μ_p, μ_s] and ranked. In the case of unsatisfactory results, by means of operators such as recombination and mutation, the next generation chromosomes are determined, and the algorithm performs another iteration. Hopefully after a sufficient number of generations, a preferable set of models has been evolved, which meet the specified design criteria. [33][35][38]

7.5.3 Model design cycle

The model design optimization using MOGA problem can be synthesized as a sequence of actions, which should be repeated until prespecified design goals are achieved. These actions can be partitioned as three phase cycle: problem definition, solution(s) generation and analysis of results.

Initially, the problem definition is characterized by the datasets preprocessing, by choosing the number of relevant variables and corresponding lagged terms, number of neurons, as well as, the set of objectives and goals to be attained. This is a crucial phase since, a poor problem definition could affect the size of the search space, as well as, the quantity and quality of the resulting solutions. Then, in the solution(s) generation phase, MOGA does a full guided search to obtain models that satisfy the predefined objectives and goals. In the third and final stage, the set of the resulting models obtained that lie in the Pareto front are analysed. In this resulting set, the performance of the models in the validation set, assume major importance, since its not involved in the design and is capable of measuring the models generalization capability.

In case of satisfactory results in the analysis of solutions provided by MOGA, the procedure stops. Otherwise the problem definition steps should be revised, either by variables, reducing the input space by removing reducing the number of input terms by choosing the more favourable ones from the resulting set of solutions, or by, restricting the trade-off surface coverage by changing objectives or redefining goals, this way guiding the MOGA operation to converge to a set of results closer to satisfactory results. This cycle actions could be repeated until satisfactory solutions are obtained.

The procedure described can be visualized in the figure 7.8. [35][38]

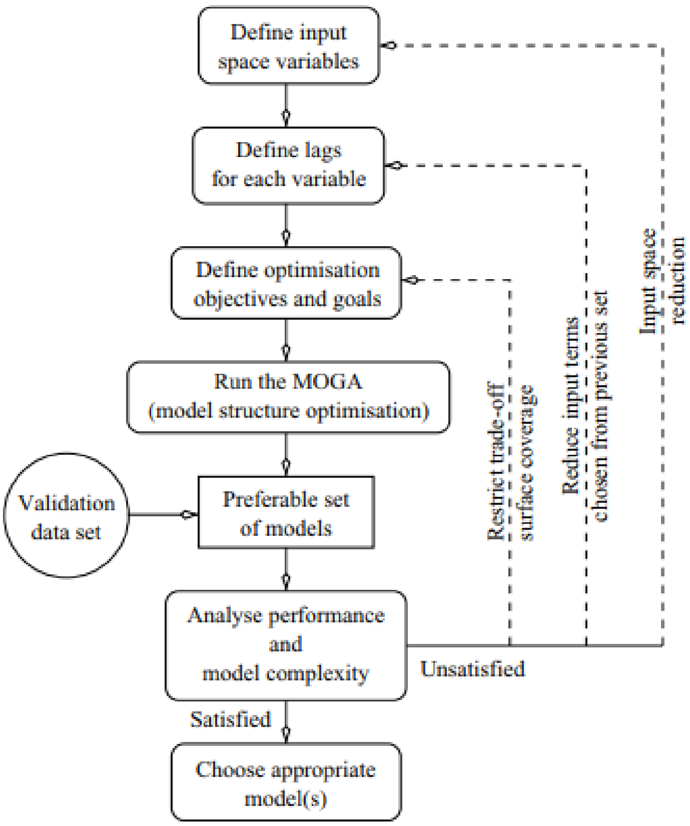

Figure 7.8 – MOGA design cycle. [35]

7.5.4 Dataset preparation

As previously summarized in figure 7.5, for each data approach, 3 models were built according to the input variables used and for each model proposed, a corresponding input lag combination was required. In table 7.5, the models idealized are assigned with the respective range of lags of each variable for the design experiments.

Variable	Notation	Model I	Model II	Model III
Energy	X1	20 lags	20 lags	20 lags
Day	X2	-	1 lag	1 lag
Temperature	X3	-	-	1 lag

Table 7.5 - Models input lags combinations.

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As can be seen, Model *I* correspond to a NAR model where no exogenous variable is considered. Model *II* corresponds to a NARX model which uses as exogenous variable, day type with 1 lag, and Model *III* also corresponds to a NARX model using as exogenous variables temperature and day type, with 1 lag. In energy variable (*X1*), the 20 lags used are [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 22, 23, 24, 25, 26, 46, 47, 48, 49, 50], while in day code (*X2*) and temperature (*X3*), the 1 lag used is [1]. The reasons behind these decisions are due to the periodicity nature of each variable, described in section 7.2.

Data for each approach was prepared using the ApproxHull algorithm [37] as a method for determining the datasets. The ApproxHull algorithm application was computed using the computer cluster in the University of Algarve, Electronics and Informatics Engineering Department (DEEI). The lagged dataset of each model proposed, was computed in the Approxhull application to incorporate convex points reflecting the whole input range in which the model is supposed to be used in the training set, and allowing a normalization, important to a proper learning of relevant patterns, as relationships became clear when data is compressed. This compression of data defines the lower and upper values of the data ranging from [-1, 1].

Finally, the Approxhull application generates the training (D^t), testing (D^g) and validation (D^v) sets with proportions of 60%, 20% and 20%, respectively. Additionally, an additional data set (not included in the original data set used for ApproxHull application), was used to create an additional set (D^s) with the purpose to be used in the MOGA forecast modelling.

7.5.5 Models design

Based on the model design cycle described in 7.5.3, several cycles of design can be conducted leading to a definition of new designs, by redefining variables and their corresponding lag terms, as well as, imposing restrictions on objectives. This guides MOGA in the search of solutions closer to satisfactory results.

In the execution of this work, two cycles of actions were conducted. In the first cycle, all the idealized data approach models had their structure, parameters and objectives similar, only differing in the prediction horizon of 24, for the 24 step ahead models and 48, for the 48 steps ahead models. The MOGA parameters, structures and objectives used in the first cycle of design are shown in the table 7.6.

Model type	
Nº of neurons	1 to 10
Centers selection	k-means algorithm
Nº input features	1 to 20
Training stopping	Early stopping (with maximum 50 iterations)
Objectives	
RMSE training	Minimize $\varepsilon(D^t)$
RMSE testing	Minimize $\varepsilon(D^g)$
Complexity	Minimize $O(\mu)$
Forecasting error	Minimize $\varepsilon(D^s, PH)$ (PH = 24 and 48, with additional set)
MOGA configuration	
Population size	100
Nº of generations	50

Table 7.6 – MOGA parameters used in the first cycle.

After analysing the results, a second and final design cycle was performed in order to achieve optimized results, but this time, given the specific results of the previous iteration, a set of restrictions were attributed to strictly minimize the results according to specific structure, parameters and objectives. The MOGA parameters, structures and objectives used, specific for each model, in the second cycle of model design are shown in the table 7.7 for the models related to the prediction horizon of 24 steps ahead and table 7.8 for the models related to the prediction horizon of 48 steps ahead.

	PH 24	**Restrictions/Objectives values**			
	Model	**RMSE Training** ***$\varepsilon(D^t)$***	**Complexity** ***$O(\mu)$***	**Nº input features**	**Nº of neurons**
Spring	*I*	0.1	130	1 to 15	1 to 8
	II	0.08	120	1 to 19	1 to 7
	III	0.1	130	1 to 16	1 to 8
Summer	*I*	0.13	140	1 to 17	1 to 9
	II	0.13	130	-	1 to 8
	III	0.13	130	1 to 16	1 to 9
Autumn	*I*	0.1	130	1 to 18	-
	II	0.1	130	1 to 18	-
	III	0.11	120	1 to 16	1 to 9
Winter	*I*	0.16	130	1 to 15	1 to 6
	II	0.13	150	1 to 18	1 to 5
	III	0.12	130	1 to 18	1 to 8
Yearly	*I*	0.12	130	1 to 14	1 to 8
	II	0.13	130	1 to 13	1 to 5
	III	0.13	130	1 to 12	1 to 6

Table 7.7 – Restriction/objectives applied in the second cycle of MOGA design for the models of 24 steps ahead prediction horizon.

	PH 48	**Restrictions/Objectives values**			
	Model	**RMSE Training** $\varepsilon(D^t)$	**Complexity** $O(\mu)$	**Nº input features**	**Nº of neurons**
Spring	*I*	0.1	130	1 to 16	1 to 8
	II	0.09	120	1 to 16	1 to 9
	III	0.1	110	1 to 16	1 to 8
Summer	*I*	0.12	130	-	1 to 6
	II	0.1	110	1 to 18	1 to 8
	III	0.12	140	1 to 14	1 to 8
Autumn	*I*	0.09	120	1 to 19	1 to 9
	II	0.11	130	1 to 18	1 to 8
	III	0.11	120	1 to 17	1 to 7
Winter	*I*	0.12	120	1 to 19	1 to 6
	II	0.12	130	1 to 19	1 to 5
	III	0.09	150	-	-
Yearly	*I*	0.09	110	1 to 19	1 to 8
	II	0.12	130	1 to 15	1 to 5
	III	0.13	130	1 to 10	1 to 3

Table 7.8 – Restriction/objectives applied in the second cycle of MOGA design for the models of 48 steps ahead prediction horizon.

The cases in which the restriction values present "-", denotes no changes from the first cycle to the next ones. Having done this extensive work of optimized model designs, in the next chapter the respective results will be presented, enabling comparisons between experiments and leading to the final conclusions.

Chapter 8

Results

This chapter purpose comes in the sequence of the detailed explanation of the procedures taken in this project in chapter 7. In here, are going to be presented the results and performance comparisons involving all different models. The models were generated using radial basis function neural networks optimization using MOGA framework and their performance is going to be evaluated according to their capability of generalization and forecasting up to several steps ahead. After a brief description of the early works developed, this chapter is separated in the two prediction horizons idealized, 24 and 48 hours ahead, and in each of those horizons, different periods of data were compared using multiple input variables.

8.1 Early experimental work

As stated in chapter 7, section 7.1, at an initial stage of this work, an exploratory phase was conducted, by experimenting the Neural Network Time Series Toolbox application provided by MATLAB. Using this method several ANN models were designed and trained. In order to get a perception of these experimental models, the network performance evaluations of a NAR model for each approach is presented in table 8.1. For all models the parameters and structure used in their design were the same:

- Network topology: 1 hidden layer with 5 neurons;
- Activation function: Sigmoid function;
- Number of input features: 20 lags, from 1 to 20, of variable *X1*, following the notation in table 7.5;

- Training algorithm: Levenberg-Marquardt algorithm;
- Training stopping: Early stopping (with the validation set).

Approach	RMSE Training ($\times 10^{-3}$)	RMSE Testing ($\times 10^{-3}$)	RMSE Validation ($\times 10^{-3}$)
Spring	3.10	3.45	3.27
Summer	5.68	5.42	5.27
Autumn	4.51	4.81	4.41
Winter	3.82	3.98	4.44
Yearly	4.59	4.37	4.81

Table 8.1 – Network evaluations of the models generated using MATLAB NN Time Series Toolbox.

This experimental models evaluations are going to be compared with the final results further ahead in this chapter, in order to understand the improvement with the final optimization technique using MOGA.

8.2 RBFNN model design using MOGA optimization

The model design with MOGA with prediction horizon comes in the sequence of what was previously reported. In order to improve the results obtained in an initial phase, the application of RBF neural networks using the MOGA framework was implemented as an optimization method. In the following sections are going to be analyzed and compared the results of the models idealized.

8.2.1 Prediction horizon 24 steps ahead

The proper evaluation of the models network capability to generalize and forecasting performance was made through the minimum root mean square error, RMSE, of the validation set and the model evolution for several prediction steps. This allows the performance of forecasting models to be assessed across different steps. In this section, only the 24 steps ahead will be presented and compared. In the scope of this thesis the performance evaluation will be done for each season, and for the whole year.

8.2.1.1 Seasonal approach

This section contains the approaches of the four weather stations: Spring, Summer, Autumn and Winter. Each will present the corresponding input model equations, RBFNN structures, RBFNN parameters and performance evaluations of the models selected. For each model design, in each approach, only one RBF neural network was selected according to the best possible compromise between performance, complexity and forecasting ability. Using the notation in table 7.5, section 7.5.4, the formal description of models are given by the following input model equations:

Spring Approach	
Model I	*y(k)=f(X1(k-1), X1(k-2), X1(k-3), X1(k-5), X1(k-6), X1(k-7), X1(k-8), X1(k-10), X1(k-24), X1(k-25), X1(k-49))*
Model II	*y(k)=f(X1(k-1), X1(k-2), X1(k-6), X1(k-8), X1(k-9), X1(k-10), X1(k-22), X1(k-24), X1(k-25), X1(k-26), X1(k-47), X1(k-48), X1(k-49), X2(k-1))*
Model III	*y(k)=f(X1(k-1), X1(k-2), X1(k-4), X1(k-5), X1(k-9), X1(k-24), X1(k-25), X2(k-1))*
Summer Approach	
Model I	*y(k)=f(X1(k-1), X1(k-2), X1(k-3), X1(k-5), X1(k-6), X1(k-7), X1(k-8), X1(k-10), X1(k-24), X1(k-25), X1(k-49))*
Model II	*y(k)=f(X1(k-1), X1(k-2), X1(k-6), X1(k-8), X1(k-9), X1(k-10), X1(k-22), X1(k-24), X1(k-25), X1(k-26), X1(k-47), X1(k-48), X1(k-49), X2(k-1))*
Model III	*y(k)=f(X1(k-1), X1(k-2), X1(k-4), X1(k-5), X1(k-9), X1(k-24), X1(k-25), X2(k-1))*
Autumn Approach	
Model I	*y(k)=f(X1(k-1), X1(k-2), X1(k-3), X1(k-5), X1(k-6), X1(k-7), X1(k-8), X1(k-10), X1(k-24), X1(k-25), X1(k-49))*
Model II	*y(k)=f(X1(k-1), X1(k-2), X1(k-6), X1(k-8), X1(k-9), X1(k-10), X1(k-22), X1(k-24), X1(k-25), X1(k-26), X1(k-47), X1(k-48), X1(k-49), X2(k-1))*
Model III	*y(k)=f(X1(k-1), X1(k-2), X1(k-4), X1(k-5), X1(k-9), X1(k-24), X1(k-25), X2(k-1))*
Winter Approach	
Model I	*y(k)=f(X1(k-1), X1(k-2), X1(k-3), X1(k-5), X1(k-6), X1(k-7), X1(k-8), X1(k-10), X1(k-24), X1(k-25), X1(k-49))*

Model II	*y(k)=f(X1(k-1), X1(k-2), X1(k-6), X1(k-8), X1(k-9), X1(k-10), X1(k-22), X1(k-24), X1(k-25), X1(k-26), X1(k-47), X1(k-48), X1(k-49), X2(k-1))*
Model III	*y(k)=f(X1(k-1), X1(k-2), X1(k-4), X1(k-5), X1(k-9), X1(k-24), X1(k-25), X2(k-1))*

Table 8.2 – NAR and NARX models of the selected network models of each seasonal approach, for a 24 step ahead prediction horizon.

In the equations of table 8.2, *y(k)* is the output of the corresponding RBF neural network, represented in equation 6.6. The following table 8.3 show the selected networks performances evaluations, number of terms selected (already shown in previous table 8.2), respective number of neurons and complexity. The best RMSE of training, testing and validation for each approach is highlighted.

	Model	RMSE Training ($\times 10^{-3}$)	RMSE Testing ($\times 10^{-3}$)	RMSE Validation ($\times 10^{-3}$)	Complexity	Nº input features selected	Nº of neurons
Spring	I	2.59	2.58	2.50	84	11	7
	II	2.38	3.06	2.64	90	14	6
	III	2.38	3.08	2.84	72	11	6
Summer	I	4.25	3.85	4.19	91	12	7
	II	4.03	4.22	3.60	90	14	6
	III	3.19	4.03	4.37	90	9	9
Autumn	I	2.86	3.12	3.04	84	11	7
	II	2.25	2.73	3.22	112	13	8
	III	2.63	2.82	2.71	84	13	6
Winter	I	4.31	3.52	3.54	80	15	5
	II	3.16	3.45	3.57	60	11	5
	III	3.15	3.36	3.32	96	11	8

Table 8.3 – Network evaluation of the best models generated using MOGA optimization for each seasonal approach.

The forecasting ability of the models selected are shown in the following figure 8.1 and in table 8.4, with the respective RMSE evolution of the forecast models for 24 steps ahead, each step separated by a time interval of 1 hour. This RMSE of the forecast error is originated from the last 500 samples, present in the original data set of the respective data approach.

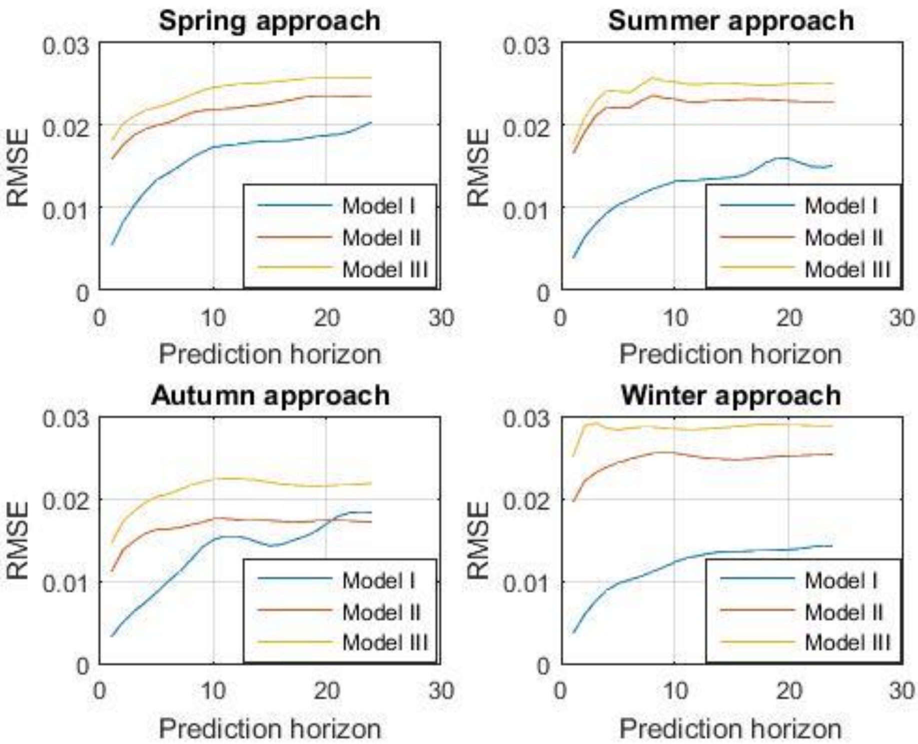

Figure 8.1 – Performance of the models chosen for each seasonal approach, for the forecasting error of 24 steps ahead.

	Model	RMSE 1 step ahead ($\times 10^{-3}$)	RMSE 24 steps ahead ($\times 10^{-3}$)	Sum RMSE forecast ($\times 10^{-3}$)
Spring	I	5.4	20.4	388
	II	15.9	23.6	520
	III	18.1	25.7	578
Summer	I	3.9	15.1	302
	II	16.6	22.9	538
	III	17.7	25.2	586

Autumn	I	3.3	18.4	320
	II	11.2	17.3	400
	III	14.6	22	506
Winter	I	3.7	14.3	284
	II	19.7	25.4	592
	III	25.3	28.9	688

Table 8.4 – 1 step ahead, 24 steps ahead and sum of the forecasting error for the models of each seasonal approach.

8.2.1.2 Yearly Approach

This subsection is defined by the yearly approach. It will present the corresponding input model equations, RBFNN structures, RBFNN parameters and performance evaluations. Using the notation in table 7.5, section 7.5.4, the formal description of models are given by following input model equations:

Yearly Approach	
Model I	*y(k)=f(X1(k-1), X1(k-2), X1(k-3), X1(k-5), X1(k-6), X1(k-8), X1(k-10), X1(k-23), X1(k-24), X1(k-25), X1(k-26), X1(k-49))*
Model II	*y(k)=f(X1(k-1), X1(k-3), X1(k-6), X1(k-7), X1(k-10), X1(k-24), X1(k-25), X1(k-48), X1(k-49), X2(k-1))*
Model III	*y(k)=f(X1(k-1), X1(k-2), X1(k-4), X1(k-6), X1(k-7), X1(k-8), X1(k-9), X1 (k-24), X1(k-25), X1(k-47), X1(k-49), X2(k-1))*

Table 8.5 - NAR and NARX models of the selected network models of the yearly approach, for a 24 step ahead prediction horizon.

y(k) in the equations of table 8.5, is the output of the corresponding RBF neural network, representing in equation 6.6. The following table 8.6 show the selected networks performances evaluations, number of terms selected (already shown in previous table 8.5), respective number of neurons and respective complexity. The best RMSE of training, testing and validation for this approach is highlighted.

	Model	RMSE Training ($\times 10^{-3}$)	RMSE Testing ($\times 10^{-3}$)	RMSE Validation ($\times 10^{-3}$)	Complexity	Nº input features selected	Nº of neurons
Yearly	I	3.45	3.47	3.45	78	12	6
	II	3.69	3.44	3.76	44	10	4
	III	3.29	3.03	3.57	78	12	6

Table 8.6 - Network evaluation of the best models generated using MOGA optimization for the yearly approach.

The forecasting ability of the models selected are shown in the following figure 8.2 and in table 8.7, with respective RMSE evolution of the forecast models for 24 steps ahead, each step separated by a time interval of 1 hour. This RMSE of the forecast error is originated from the last 500 samples, present in the original data set of the respective data approach.

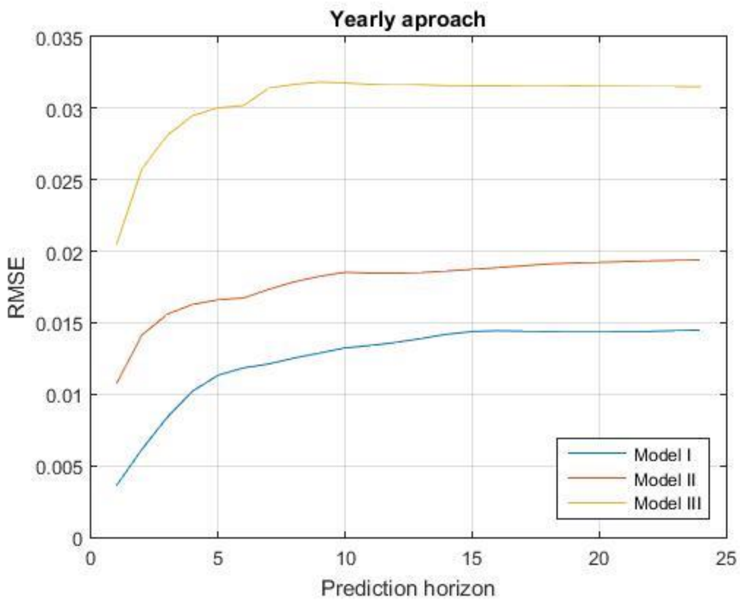

Figure 8.2 - Performance of the models chosen for the yearly approach, for the forecasting error of 24 steps ahead.

	Model	RMSE 1 step ahead ($\times 10^{-3}$)	RMSE 24 steps ahead ($\times 10^{-3}$)	Sum RMSE forecast ($\times 10^{-3}$)
Yearly	I	3.6	14.5	302
	II	10.8	19.4	428
	III	20.5	31.5	733

Table 8.7 – 1 step ahead, 24 steps ahead and sum of the forecasting error for the models of the yearly approach.

8.2.1.3 Models comparison

Analyzing the table 8.3, from the seasonal approach, the models complexity range from 72 to 112, while the nº features and the nº of neurons selected range from 9 to 15 and 5 to 9, respectively. The RMSE of training, testing and validation present slightly higher values in the summer and winter approach, contributing to the fact that in these periods the data presents patterns with greater discrepancies in terms of energy consumption, while in autumn and spring, the data patterns behave more stable and constant. In the yearly approach, as shown in table 8.6, the models complexity ranges from 44 to 78, while the nº features selected and the nº of neuron range from 10 to 12 and 4 to 6, respectively. The RMSE of training, testing and validation present intermediate values within the range of values in the seasonal approach. It is worth notice the fact that, the proposed exogenous variable, *X3*, representing the mean daily temperature, wasn't selected in any model 3 approach as shown in the input equations of tables 8.2 and 8.5. This suggest that this variable had little influence in the construction of the models and the information that it offered to the network did not contribute to a better performance.

As for the RMSE forecast comparison, all models used the last 500 samples of the respective data approach, to evaluate their forecast ability. In figures 8.1, 8.2 and tables 8.4, 8.7, can be seen that in those specific samples, the approaches of model *I* in a general way present a smaller forecast error, and in summer and winter approach comparing model *II* and *III* with model *I* present the higher difference. Although in these cases the RMSE of the forecast error may give preference to the models *I*, the generalization capability of the models measured by the RMSE of the validation set, shows that some of the best models in every approach have a favorable response with the use of an exogenous variable, in this case, *X2*, representing the type of day.

The best model of each data approach, in sections 8.2.1.1 and 8.2.1.2, are going to be selected for comparison purposes, mainly in terms of generalization capacity present in the RMSE of validation set, but also giving importance to model complexity and forecasting capacity in 24 steps ahead with RMSE forecasting evaluation. The RBFNN models chosen from each data approach can be seen in the table 8.8.

Approach	**Spring**	**Summer**	**Autumn**	**Winter**	**Year**
Model	**I**	**II**	**III**	**III**	**I**
RMSE Training ($\times 10^{-3}$)	2.59	4.03	2.63	3.15	3.45
RMSE Testing ($\times 10^{-3}$)	2.58	4.22	2.82	3.36	3.47
RMSE Validation ($\times 10^{-3}$)	2.50	3.60	2.71	3.32	3.50
Complexity	84	90	84	96	78
Nº input features	11	14	13	11	12
Nº of neurons	7	6	6	8	6

Table 8.8 - Best models of each approach.

To evaluate the models generalization capacity, is going to be presented to each model an equal set of data chosen randomly from the original dataset. The models are compared according to the evolution of the respective forecasting error 24 steps ahead, separated by a time interval of 1 hour. The data chosen is defined by 1500 data points ranging from 20th March 2017 to 21st May 2017. This way the different models can be evaluated by the way they perform when presented to the same input data. The performance results can be compared in the figure 8.3 and table 8.8.

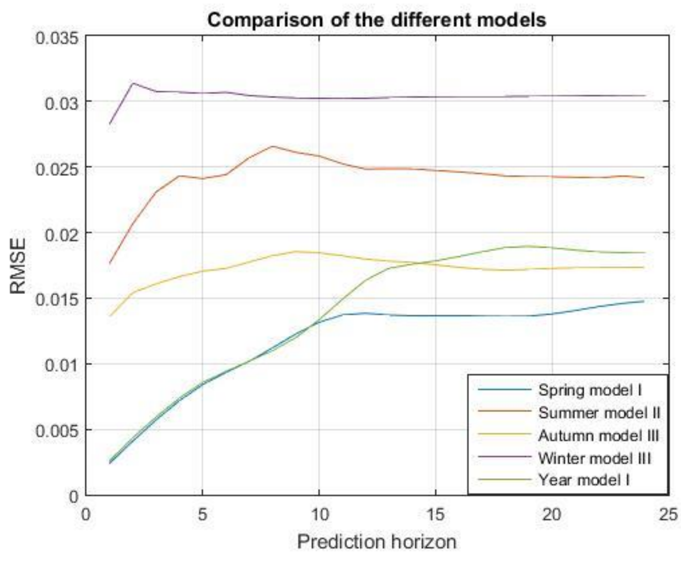

Figure 8.3 - Performance of the best models for 24 steps ahead prediction horizon.

Approach	**Spring**	**Summer**	**Autumn**	**Winter**	**Year**
Model	**I**	**II**	**III**	**III**	**I**
RMSE 1 step ahead ($\times 10^{-3}$)	2.4	17.7	13.6	28.3	2.6
RMSE 24 step ahead ($\times 10^{-3}$)	14.8	24.2	17.4	30.5	18.4
Sum RMSE forecast ($\times 10^{-3}$)	279	582	414	729	336

Table 8.9 – 1 step ahead, 24 steps ahead and sum of the forecasting error for the best models of each approach, for 24 steps ahead prediction horizon.

By analyzing figure 8.3 and table 8.9, as expected, the spring and yearly approach present the best results, since the samples chosen for this evaluation were inside the spring seasonal data and consequently in the yearly data. Both models present a similar behavior until 10 steps ahead, where the yearly model increases its RMSE, even ending with slightly worse result than the autumn model. The autumn model is the best model that shows best generalization capability, outside of those who were trained with this type of data. The summer and winter models present a not so good performance when presented to this input samples, also partly expected, since they are models trained with different specific patterns in their datasets.

8.2.2 Prediction horizon 48 steps ahead

The proper evaluation of the models network capability to generalize and forecasting performance was made through the minimum root mean square error, RMSE, of the validation set and the model evolution for several prediction steps. This allows the performance of forecasting models to be assessed across different steps. In this section, only the 48 steps ahead will be presented and compared. In the scope of this thesis the performance evaluation will be done for each season, and for the whole year.

8.2.2.1 Seasonal approach

This section contains the approaches of the four weather stations: Spring, Summer, Autumn and Winter. Each will present the corresponding input model equations, RBFNN structures, RBFNN parameters and performance evaluations of the models selected. For each model design, in each approach, only one RBF neural network was selected according to the best possible compromise between performance, complexity and forecasting ability. Using the notation in table 7.5, section 7.5.4, the formal description of models are given by the following input model equations:

Spring Approach	
Model I	*y(k)=f(X1(k-1), X1(k-2), X1(k-3), X1(k-5), X1(k-6), X1(k-8), X1(k-10), X1(k-22), X1(k-24), X1(k-25), X1(k-26), X1(k-47), X1(k-48), X1(k-49))*
Model II	*y(k)=f(X1(k-1), X1(k-5), X1(k-6), X1(k-7), X1(k-10), X1(k-24), X1(k-26), X1(k-46), X1(k-48), X1(k-49), X2(k-1))*
Model III	*y(k)=f(X1(k-1), X1(k-3), X1(k-4), X1(k-6), X1(k-8), X1(k-10), X1(k-24), X1(k-25), X1(k-46), X1(k-48), X1(k-50), X2(k-1))*
Summer Approach	
Model I	*y(k)=f(X1(k-1), X1(k-2), X1(k-3), X1(k-4), X1(k-5), X1(k-6), X1(k-7), X1(k-8), X1(k-9), X1(k-10), X1(k-22), X1(k-23), X1(k-24), X1(k-25), X1(k-26), X1(k-47), X1(k-48), X1(k-49), X1(k-50))*
Model II	*y(k)=f(X1(k-1), X1(k-2), X1(k-4), X1(k-5), X1(k-6), X1(k-7), X1(k-10), X1(k-24), X1(k-25), X1(k-26), X1(k-49), X1(k-50), X2(k-1))*
Model III	*y(k)=f(X1(k-1), X1(k-2), X1(k-5), X1(k-6), X1(k-9), X1(k-10), X1(k-22), X1(k-24), X1(k-26), X2(k-1))*
Autumn Approach	
Model I	*y(k)=f(X1(k-1), X1(k-2), X1(k-5), X1(k-6), X1(k-7), X1(k-8), X1(k-9), X1(k-10), X1(k-24), X1(k-25), X1(k-26), X1(k-47), X1(k-49), X1(k-50,)*
Model II	*y(k)=f(X1 (k-1), X1(k-5), X1(k-8), X1(k-9), X1(k-10), X1(k-22), X1(k-23), X1(k-24), X1(k-25), X1(k-26), X1(k-49), X2(k-1))*
Model III	*y(k)=f(X1(k-1), X1(k-2), X1(k-4), X1(k-6), X1(k-7), X1(k-8), X1(k-9), X1(k-24), X1(k-25), X1(k-26), X2(k-1))*
Winter Approach	
Model I	*y(k)=f(X1(k-1), X1(k-2), X1(k-3), X1(k-4), X1(k-6), X1(k-8), X1(k-9), X1(k-10), X1(k-23), X1(k-24), X1(k-25), X1(k-26), X1(k-46), X1(k-49))*
Model II	*y(k)=f(X1(k-1), X1(k-2), X1(k-3), X1(k-4), X1(k-6), X1(k-7), X1(k-10), X1(k-22), X1(k-24), X1(k-25), X1(k-26), X1(k-46), X1(k-48), X1(k-49), X1(k-50), X2(k-1))*

Model III	*y(k)=f(X1(k-1), X1(k-3), X1(k-6), X1(k-10), X1(k-25), X1(k-46), X1(k-47), X1(k-48), X1(k-49), X1(k-50), X2(k-1))*

Table 8.10 - NAR and NARX models of the selected network models of each seasonal approach, for a 48 step ahead prediction horizon.

In the equations of table 8.10, *y(k)* is the output of the corresponding RBF neural network, representing in equation 6.6. The following table 8.11 show the selected networks performances evaluations, number of terms selected (already shown in previous table 8.10), respective number of neurons and complexity. The best RMSE of training, testing and validation for each approach is highlighted.

	Model	**RMSE Training ($\times 10^{-3}$)**	**RMSE Testing ($\times 10^{-3}$)**	**RMSE Validation ($\times 10^{-3}$)**	**Complexity**	**Nº input features selected**	**Nº of neurons**
Spring	I	2.45	2.62	2.43	105	14	7
	II	2.17	2.79	2.46	96	11	8
	III	2.38	2.73	2.82	78	12	6
Summer	I	4.15	3.81	4.14	100	19	5
	II	4.72	5.19	4.37	98	13	7
	III	4.03	3.88	4.67	77	10	7
Autumn	I	2.67	3.10	3.15	90	14	6
	II	2.42	2.88	3.56	97	12	7
	III	2.66	2.91	2.70	72	11	6
Winter	I	4.38	3.70	3.51	60	14	4
	II	3.18	3.09	3.48	85	16	5
	III	2.51	3.30	3.37	120	11	10

Table 8.11 – Network evaluation of the best models generated using MOGA optimization for each seasonal approach.

The forecasting ability of the models selected are shown in the following figure 8.4 and in table 8.12, with respective RMSE evolution of the forecast models for 48 steps ahead, each step separated by a time interval of 1 hour. This RMSE of the forecast error is originated from the last 500 samples, present in the original data set, respective to each data approach.

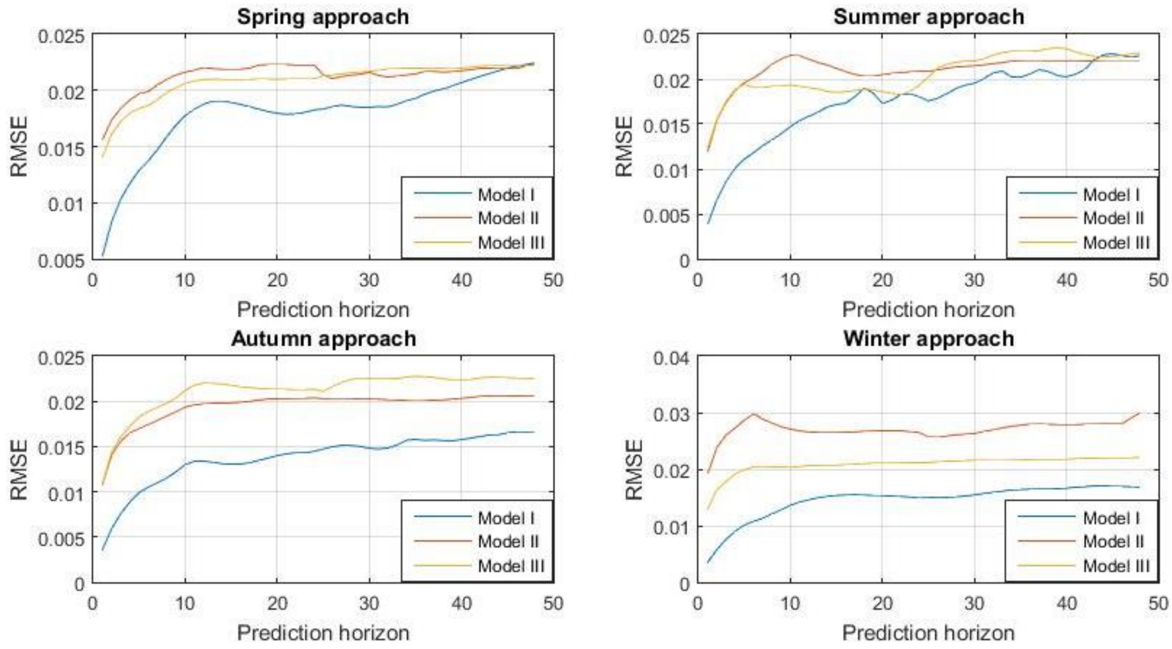

Figure 8.4 - Performance of the models chosen for each seasonal approach, for the forecasting error of 48 steps ahead.

	Model	RMSE 1 step ahead ($\times 10^{-3}$)	RMSE 48 steps ahead ($\times 10^{-3}$)	Sum RMSE forecast ($\times 10^{-3}$)
Spring	I	5.3	22.5	866
	II	15.6	22.4	1023
	III	14.1	22.2	1002
Summer	I	3.9	22.6	845
	II	11.9	22	1009
	III	12.3	22.9	984
Autumn	I	3.6	16.7	661
	II	10.8	20.6	935
	III	10.9	22.5	1017

Winter	I	3.5	16.8	698
	II	19.2	30	1298
	III	12.9	22.1	1002

Table 8.12 –1 step ahead, 48 steps ahead and sum of the forecasting error for the models of each seasonal approach.

8.2.2.2 Yearly approach

This subsection is defined by the yearly approach. It will present the corresponding input model equations, RBFNN structures, RBFNN parameters and performance evaluations. Using the notation in table 7.5, section 7.5.4, the formal description of models are given by following input model equations:

Yearly Approach	
Model I	*y(k)=f(X1(k-1), X1(k-2), X1(k-4), X1(k-6), X1(k-7), X1(k-8), X1(k-10), X1(k-23), X1(k-24), X1(k-25), X1(k-26), X1(k-47), X1(k-48), X1(k-49))*
Model II	*y(k)=f(X1(k-1), X1(k-2), X1(k-6), X1(k-8), X1(k-10), X1(k-24), X1(k-25), X1(k-49), X2(k-1))*
Model III	*y(k)=f(X1(k-1), X1(k-2), X1(k-3), X1(k-4), X1(k-9), X1(k-24), X1(k-25), X1(k-26), X1(k-46), X2(k-1))*

Table 8.13 - NAR and NARX models of the selected network models of the yearly approach for a 48 step ahead prediction horizon.

In the equations of table 8.13, *y(k)* is the output of the corresponding RBF neural network, representing in equation 6.6. The following table 8.14 show the selected networks performances evaluations, number of terms selected (already shown in previous table 8.13), respective number of neurons and respective complexity. The best RMSE of training, testing and validation for this approach is highlighted.

	Model	RMSE Training ($\times 10^{-3}$)	RMSE Testing ($\times 10^{-3}$)	RMSE Validation ($\times 10^{-3}$)	Complexity	Nº input features selected	Nº of neurons
Yearly	I	3.58	3.58	3.55	75	14	5
	II	3.54	3.29	3.58	50	9	5
	III	4.02	3.80	4.29	33	10	3

Table 8.14 - Network evaluation of the best models generated using MOGA optimization for the yearly approach.

The forecasting ability of the models selected are shown in the following figure 8.5 and in table 8.15, with respective RMSE evolution of the forecast models for 48 steps ahead, each step separated by a time interval of 1 hour. This RMSE of the forecast error is originated from the last 500 samples, present in the original data set of the respective data approach.

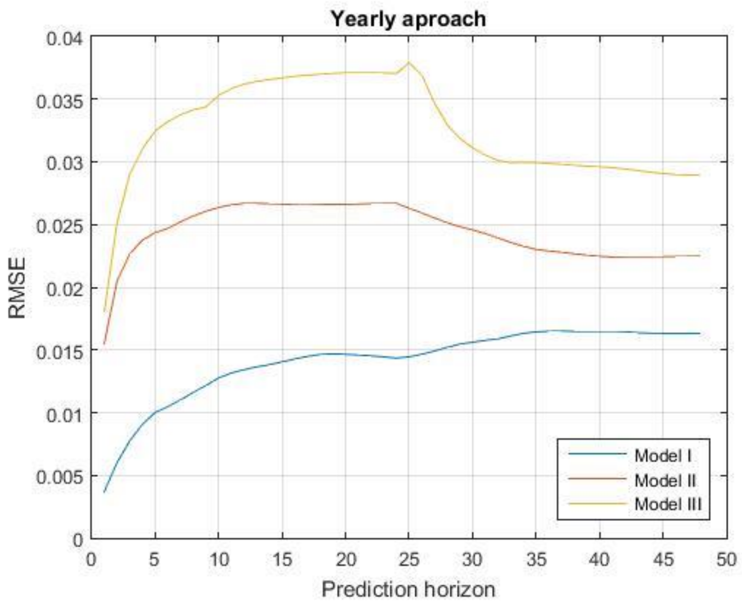

Figure 8.5 - Performance of the models chosen for the yearly approach, for the forecasting error of 48 steps ahead.

	Model	RMSE 1 step ahead ($\times 10^{-3}$)	RMSE 48 steps ahead ($\times 10^{-3}$)	Sum RMSE forecast ($\times 10^{-3}$)
Yearly	I	3.7	16.3	678
	II	15.5	22.5	1171
	III	18.1	28.9	1559

Table 8.15 – 1 step ahead, 48 steps ahead and sum of the forecasting error for the models of the yearly approach.

8.2.2.3 Models comparison

Analyzing table 8.11, from the seasonal approach, the models complexity ranges from 72 to 120, while the nº features and the nº of neurons selected range from 10 to 19 and 4 to 10, respectively. The RMSE of training, testing and validation present slightly higher values in the summer and winter approach, contributing to the fact that in these periods the data presents patterns with greater discrepancies in terms of energy consumption, while in autumn and spring, the data patterns behave more stable and constant. In the yearly approach, as shown in table 8.14, the models complexity ranges from 33 to 75, while the nº features selected and the nº of neuron range from 9 to 14 and 3 to 5, respectively. The RMSE of training, testing and validation present intermediate values within the range of values in the seasonal approach. It is worth notice the fact that, the proposed exogenous variable, *X3*, representing the mean daily temperature, wasn't selected in any model 3 approach as shown in the input equations of tables 8.10 and 8.13. This suggest that this variable had little influence in the construction of the models and the information that it offered to the network did not contribute to a better performance. This networks information resembles what was analyzed in the models for the 24 steps ahead forecast.

As for the RMSE forecast comparison, all models used the last 500 samples of the respective data approach, to evaluate their forecast ability. In figures 8.4, 8.5 and tables 8.12, 8.15, can be seen that in those specific samples, the approaches of model *I* in a general way present an initial smaller forecast error, but in spring and summer approach the ending forecast error is similar to all models, and slightly different to the remaining autumn, winter and yearly models. Although in some cases the RMSE of the forecast error may give preference to the models *I*, the generalization capability of the models measured by the RMSE of the validation set, shows that some of the best models in every approach have a favorable response with the use of an exogenous variable, in this case, *X2*, representing the type of day.

The best model of each data approach, in sections 8.2.2.1 and 8.2.2.2, are going to be selected for comparison purposes, mainly in terms of generalization capacity present in the RMSE of validation set, but also giving importance to model complexity and forecasting capacity in 48 steps ahead with RMSE forecasting evaluation. The RBFNN models chosen from each data approach can be seen in the table 8.16.

Approach	**Spring**	**Summer**	**Autumn**	**Winter**	**Year**
Model	**I**	**I**	**III**	**III**	**II**
RMSE Training ($\times 10^{-3}$)	2.45	4.15	2.66	2.51	3.54
RMSE Testing ($\times 10^{-3}$)	2.62	3.81	2.91	3.30	3.29
RMSE Validation ($\times 10^{-3}$)	2.43	4.14	2.70	3.37	3.58
Complexity	105	100	72	120	50
Nº input features	14	19	11	11	9
Nº of neurons	7	5	6	10	5

Table 8.16 - Best models of each approach.

To evaluate the models generalization capacity, is going to be presented to each model an equal set of data chosen randomly from the original dataset. The models are compared according to the evolution of the respective forecasting error 48 steps ahead, separated by a time interval of 1 hour. The data chosen is defined by 1500 data points ranging from 20th March 2017 to 21st May 2017. This way the different models can be evaluated by the way they perform when presented to the same input data. The performance results can be compared in the figure 8.6 and table 8.17.

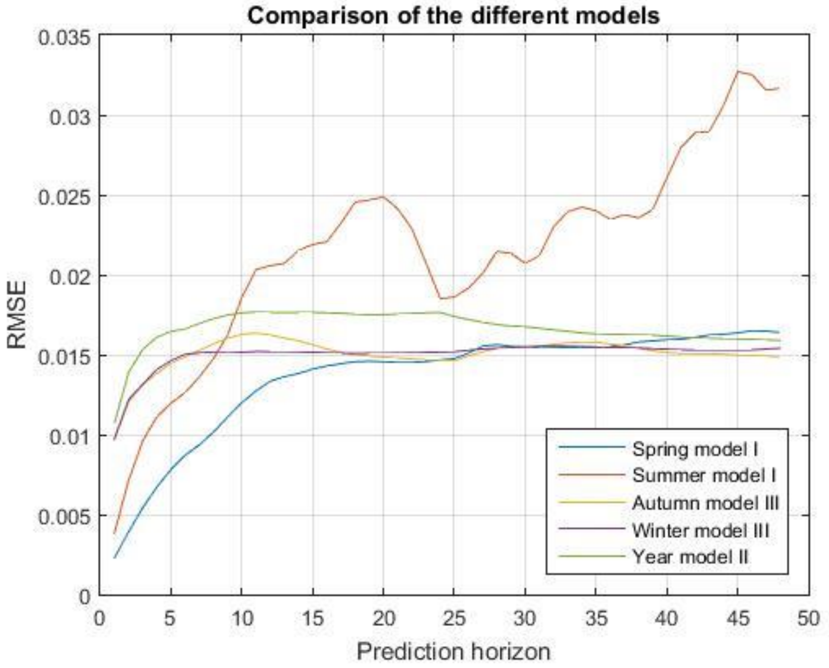

Figure 8.6 - Performance of the best models for 48 steps ahead prediction horizon.

Approach	Spring	Summer	Autumn	Winter	Year
Model	**I**	**I**	**III**	**III**	**II**
RMSE 1 step ahead ($\times 10^{-3}$)	2.3	3.8	9.7	9.8	10.7
RMSE 48 step ahead ($\times 10^{-3}$)	16.4	31.7	14.9	15.4	15.9
Sum RMSE forecast ($\times 10^{-3}$)	655	1034	722	721	799

Table 8.17 – 1 step ahead, 48 steps ahead and sum of the forecasting error for the best models of each approach, for 48 steps ahead prediction horizon.

By analyzing figure 8.6 and table 8.17, it was expected that the spring model and yearly model would present the best results, since the samples chosen for this evaluation were inside the spring seasonal data and consequently in the yearly data. Although the spring model presents the best forecast ability, the winter and autumn models present a slightly better performance than the yearly model, meaning a good generalization capability for these models who were not trained with this type of data. The summer model presents a very particular behavior, having an initial good performance until near the 9 steps ahead forecast but becoming worse until the end.

8.3 Models final comparison

To analyse how the use of the MOGA framework has improved the model design, the models generated by the MATLAB toolbox in table 8.1, and the RBFNN models using MOGA in table 8.8 and 8.16, will be compared for each idealized approach. Additionally, it is possible to compare the network performance of the models designed through MOGA optimization of the different forecast horizons. Table 8.18 presents the results, where the best RMSE of training, testing and validation for each approach is highlighted.

	Model design method	**RMSE Training ($\times 10^{-3}$)**	**RMSE Testing ($\times 10^{-3}$)**	**RMSE Validation ($\times 10^{-3}$)**	**Complexity**	**Nº input features**	**Nº of neurons**
Spring approach	MATLAB NN Toolbox	3.10	3.45	3.27	105	20	5
	RBFNN using MOGA for PH 24	2.59	2.58	2.50	84	11	7
	RBFNN using MOGA for PH 48	2.45	2.62	2.43	105	14	7
Summer approach	MATLAB NN Toolbox	5.68	5.42	5.27	105	20	5
	RBFNN using MOGA for PH 24	4.03	4.22	3.60	90	14	6
	RBFNN using MOGA for PH 48	4.15	3.81	4.14	100	19	5
Autumn approach	MATLAB NN Toolbox	4.51	4.81	4.41	105	20	5
	RBFNN using MOGA for PH 24	2.63	2.82	2.71	84	13	6
	RBFNN using MOGA for PH 48	2.66	2.91	2.70	72	11	6

Winter approach	MATLAB NN Toolbox	3.82	3.98	4.44	105	20	5
	RBFNN using MOGA for PH 24	3.15	3.36	3.32	96	11	8
	RBFNN using MOGA for PH 48	2.51	3.30	3.37	120	11	10
Year approach	MATLAB NN Toolbox	4.59	4.37	4.81	105	20	5
	RBFNN using MOGA for PH 24	3.45	3.47	3.50	78	12	6
	RBFNN using MOGA for PH 48	3.54	3.29	3.58	50	9	5

Table 8.18 – Comparison of the NAR and NARX models performances of the different model design methods used in this work, from an early experimental phase to an optimization phase.

As can be observed, in every approach, the RBFNN using MOGA optimization presents overall better RMSE performance results, in comparison with the MATLAB NN Toolbox application. In terms of model complexity, the models designed for a 48 step prediction horizon with RBFNN using MOGA in the spring and winter approach, the complexity is equal and worse, respectively, compared to the models generated with MATLAB toolbox. Comparing the model performances for every approach, of the 24 and 48 prediction horizons RBFNN using MOGA, the RMSE results present a good balance between them, with the models generated for a prediction horizon of 48 steps ahead presenting better performance in the winter and spring, while the models generated for a prediction horizon of 24 steps ahead performed better in the summer, autumn and year approach.

In order to make a comparison of the 24 and 48 prediction horizons RBFNN using MOGA models generalization capacity, is going to be presented to each model an equal set of data chosen randomly from the original dataset. Although some models were designed with the objective to forecast until 48 steps ahead prediction horizon, all the models are compared according to the evolution of the respective forecasting error for 24 steps ahead, separated by a time interval of 1 hour. The data chosen is defined by 1500 data points ranging from 16th August

2017 to 17th October 2017. This way the different models can be evaluated by the way they perform when presented to the same input data. The performance results can be compared in the figure 8.7 and table 8.19.

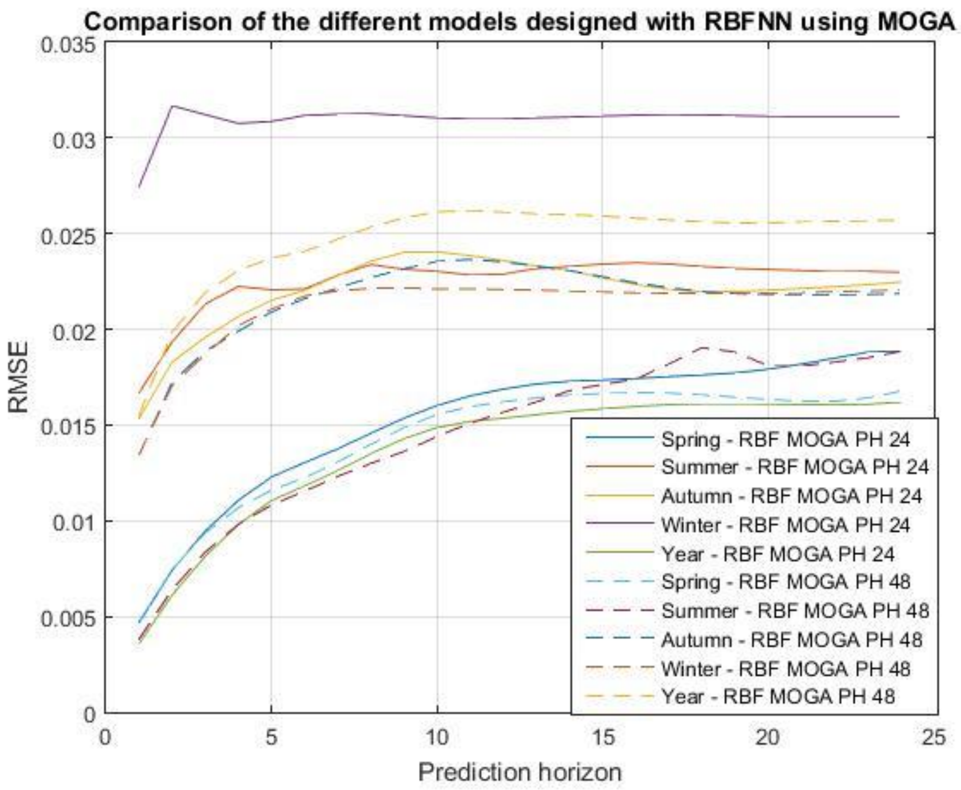

Figure 8.7 - Comparison of the performance of the models designed with RBFNN using MOGA optimization.

	Model design method	RMSE 1 step ahead $(\times 10^{-3})$	RMSE 24 steps ahead $(\times 10^{-3})$	Sum RMSE forecast $(\times 10^{-3})$
Spring approach	RBFNN using MOGA for PH 24	4.7	18.9	366
	RBFNN using MOGA for PH 48	4.8	16.8	344
Summer approach	RBFNN using MOGA for PH 24	16.7	13	540
	RBFNN using MOGA for PH 48	3.8	18.9	350

Autumn approach	RBFNN using MOGA for PH 24	15.3	22.5	528
	RBFNN using MOGA for PH 48	13.4	21.9	518
Winter approach	RBFNN using MOGA for PH 24	27.5	31.1	744
	RBFNN using MOGA for PH 48	13.5	22.1	508
Year approach	RBFNN using MOGA for PH 24	3.6	16.2	328
	RBFNN using MOGA for PH 48	15.5	25.7	591

Table 8.19 - 1 step ahead, 24 steps ahead and sum of the forecasting error for the models designed with RBFNN using MOGA.

By analyzing figure 8.7 and table 8.19, it was expected that the summer, autumn and yearly models would present the best results, since the samples chosen for this evaluation were in its majority inside the summer seasonal data and partly in the autumn seasonal data, while consequently in the yearly data. Although the “Summer – RBF using MOGA for PH 48” and the “Year – RBF using MOGA for PH 24” presented a good forecast ability, both spring models presented a good performance, meaning a good generalization capability. On the contrary, autumn and winter models didn’t perform so well, as well as, the “Year – RBF using MOGA for PH 48” and “Summer – RBF using MOGA for PH 24” which didn’t perform as expected.

Chapter 9

Conclusions and Future work

9.1 Conclusions

This work comes after a period of internship in the Rolear group company, where I passed through two departments, but given the circumstances ended up establishing myself in the commercialization department of electricity and natural gas in the free energy market, more properly in the department Rolear Viva. In both departments the experience was rewarding, characterized by a constant learning and acquired knowledge. It was motivating and inspiring to work alongside excellent professionals, who were always available to teach, answer my doubts, and who have always tried to make me feel comfortable during my internship period.

The execution of the processes of purchasing electricity and participation in the electricity markets is of great importance, since large amounts of energy are traded involving a significant monetary commitment. For this reason, a study was made of the various Iberian electricity markets, their function, the composition and hierarchy of the national electricity system and the way the data is processed and made available among the different agents of the electricity sector. Based on this, and in a perspective of implementation in the present but adapting itself to the future technological innovations in the sector, RBF neural networks using multi objective genetic algorithms optimizations, MOGA, were designed for prediction intervals of 24 and 48 hours ahead, several data approaches and different combinations of inputs were tested.

The experimented models presented satisfactory results with good performance and generalization capability for a multi-step prediction. The use of the exogenous day type variable contributed most of the time to good conditioning in some models. On the contrary, the daily temperature variable did not offer guarantees, being not selected by the MOGA optimization in any model. The models in a summer approach were those that always presented worse results. This was due to the characteristic of electricity consumption in the summer, in which larger quantities are consumed, presenting higher unexpected peaks which increases the degree of difficulty in the forecast. Except for the summer models, the remaining seasonal models showed a slightly better performance than the annual models, although the annual models were characterized by viable and well-balanced performance models. Comparing the models designed for 24 and 48 hours prediction horizon, in general, both performances of the models and forecasting capacity, presented fairly balanced behaviours.

9.2 Future Work

The atmospheric conditions show a direct impact in the energy consumption. The most obvious one is temperature, which was experimented in this work, but only a daily periodicity was used due to the limitations of the data availability. A future work would be the application of the hourly temperature as an exogenous variable, this way reflecting the real impact of climatic conditions on the energy consumption. Another atmospheric condition that could be experimented is cloudiness, since the presence of clouds motivate the turning on of lights in a building, causing an increase of energy consumption.

Another future work to be implemented is a web platform where it would be possible to the Rolear Viva energy supplier to perform, when necessary, the prediction for the next day or intraday electricity markets, as well as, making possible to train RBF neural network model for a given client newly entered in the portfolio. This way simplifying the process for the agent and making possible to analyse the consumption of clients, as well as, the entire client portfolio.

One major factor in electricity markets is the volatility of electricity prices. A possible future work is to apply a forecasting model to the prediction of electricity price in the same range of energy consumption forecast. Consequently, creating an optimization algorithm, it would guarantee a proper efficient method in the participation on the electricity markets.

References

[1] Rolear Group. Rolear Portfolio. [online]. Available: <http://www.rolear.pt/uploads/files/Portfolio_Grupo_.pdf> [Accessed in: 04/08/2018];

[2] P. Silva, "Análise numérica dos resultados do Mercado de Electricidade em Portugal inserido no Mercado Ibérico de Eletricidade MIBEL do ano de 2008", Master's Dissertation in Electrical and Computer Engineering, FEUP, Porto, 2009;

[3] J. P. Tomé Saraiva, J. L. P. Pereira da Silva, e M. T. Ponce de Leão. "Mercados de Electricidade - Regulação e Tarifação de Uso das Redes". 1st edition, 2002;

[4] R. A. Soares, "Abordagem à Previsão do Preço de Energia Eléctrica Via Métodos de Suavização Exponencial", Master's Dissertation in Electrical Engineering, ISEL, Lisbon, 2013;

[5] J. L. Gonçalves, "Modelos para a Comercialização de Energia Elétrica em Ambiente de Merdaco", Master's in Automation and Communications in Energy Systems, ISEC, Coimbra, 2013;

[6] ERSE, Produção de electricidade, 2017. [online]. Available: <http://www.erse.pt/pt/electricidade/actividadesdosector/producao/Paginas/default.aspx> [Accessed in: 20/05/2018];

[7] ERSE, Tarifas e Preços de electricidade, 2017. [online]. Available: <http://www.erse.pt/pt/electricidade/tarifaseprecos/Paginas/default.aspx> [Accessed in: 22/05/2018];

[8] ERSE, Construção e desenvolvimento, 2017. [online]. Available: <http://www.erse.pt/pt/mibel/construcaoedesenvolvimento/Paginas/2001.aspx> [Accessed in: 21/05/2018];

[9] ERSE, Protocolo de colaboração do MIBEL, 2017. [online]. Available: < http://www.erse.pt/pt/mibel/construcaoedesenvolvimento/Documents/ProtocolodeCoopera%C3%A7%C3%A3o.pdf> [Accessed in: 21/05/2018];

[10] ERSE, "Consumer Guide of Electricity in the Liberalized Market", 2010. [online]. Available: <http://www.erse.pt/pt/electricidade/liberalizacaodosector/escolhadofornecedor/Documents/Guia%20do%20consumidor%20de%20electricidade%20ML.pdf> [Accessed in 18/05/2018];

[11] MIBEL, "Mercado Ibérico da Energia Elétrica – MIBEL". [online]. Available: <http://mibel.com/>[Accessed in: 15/05/2018];

[12] L. Braga da Cruz. "A liberalização do sector da energia, o MIBEL e o OMIP", 2008;

[13] F. P. Fragoso. “Contratos Bilaterais em Mercados de Energia Elétrica Multiagente: Protocolo de Rede de Contratos”. Master’s in electrical and Computer Engineering, UNL, Lisbon, 2015;

[14] CNE, ERSE, “Modelo de Organização do Mercado Ibérico de Electricidade”, 2002. [online]. Available: < http://www.erse.pt/pt/mibel/construcaoedesenvolvimento/Documents/Modelo%20MIBEL.pdf> [Accessed in: 04/04/2018];

[15] OMIE, “Mercado Diário”. [online]. Available: <http://www.omie.es/pt/principal/mercados-e-produtos/mercado-da-electricidade/os-nossos-mercados-de-eletricidade/mercado-di> [Accessed in 05/04/2018];

[16] ERSE, “Mercado Diário”. [online]. Available: <http://www.erse.pt/pt/supervisaodemercados/mercadodeelectricidade/mercadodiario/Paginas/default.aspx> [Accessed in 05/04/2018];

[17] OMIE, “A operação nos mercados diário e intradiário”. [online]. Available: <http://www.omie.es/pt/principal/mercados-e-produtos/mercado-da-electricidade/os-nossos-mercados-de-eletricidade/diario-e-i> [Accessed in 05/04/2018];

[18] ERSE, “Mercado a Prazo”. [online]. Available: <http://www.erse.pt/pt/supervisaodemercados/mercadodeelectricidade/mercadoaprazo/Paginas/default.aspx> [Accessed in 06/04/2018];

[19] OMIE, “Mercado intradiário”. [online]. Available: <http://www.omie.es/pt/principal/mercados-e-produtos/mercado-da-electricidade/os-nossos-mercados-de-eletricidade/mercado-in> [Accessed in 05/04/2018];

[20] M. J. L. da Silva, “Smart Grids em Portugal, Plano de Negócio para Serviço de Planeamento e Gestão Remota de Consumos Elétricos”, Master’s in electrical and Computer Engineering, IST, Lisbon, 2011;

[21] EDP Distribuição, Energy suppliers meeting Powerpoint, 22/02/2018. [not online];

[22] EDP Distribuição, Energy suppliers meeting Powerpoint 31/10/2017. [not online];

[23] A. E. Ruano, “Artificial neural networks,” 2003;

[24] Digitaljunky, “What is an Artificial Neural Network (ANN)?”, 2014. [online]. Available: <https://www.digitaljunky.io/playing-around-with-neural-networks-and-r/>. [Acessed in: 27/08/2018];

[25] J. P. Paulos, “Previsão de Consumo de Energia Elétrica e do Preço da Electricidade através de Redes Neuronais de Regressão Generalizada”, Master’s in electrical and Computer Engineering, FEUP, Porto, 2017;

[26] S. Haykin. “Neural Networks and Learning Machines”. 3rd edition, 2009;

[27] I. A. Martins, “Neural models design for solar radiation and atmospheric temperature forecast”, Masters in Electronics and Telecommunications Enginering, Ualg, Faro, 2010;

[28] J. Moody and C. J. Darken, “Fast learning in networks of locally-tuned processing units,” Neural Computation 1, MIT Press, 1989;

[29] C. Chinrungrueng and C. H. Séquin, “Optimal adaptive k-means algorithm with dynamic adjustment of learning rate,” Neural Networks 6, IEEE Transactions, 1995;

[30] D. Broomhead and D. Lowe, “Multi-variable functional interpolation and adaptive net works,” Complex Systems, vol. 2, pp. 321–355;

[31] H. R. Khosravani, M. D. M. Castilla, M. Berenguel, A. E. Ruano, P. M. Ferreira, “A Comparison of Energy Consumption Prediction Models Based on Neural Networks of a Bioclimatic Building”. Energies 2016, 9, 57;

[32] P. M. Ferreira, A. E. Ruano, “Evolutionary Multiobjective Neural Network Models Identification: Evolving Task-Optimised Models”, In New Advances in Intelligent Signal Processing, 21-53, ISBN: 978-3-642-11738-1. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011;

[33] P. M. Ferreira, A. E. Ruano, R. Pestana. “Improving the identification of RBF predictive models to forecast the Portuguese electricity consumption”, in Control Methodologies and Technology for Energy Efficiency, In IFAC Conference on Control Methodologies and Technology for Energy Efficiency (2010), Vilamoura, 2010;

[34] G. Mestre, A. E. Ruano, H. Duarte, S. Silva, H. Khosravani, S. Pesteh, P. Ferreira, R. Horta. 2015. An Intelligent Weather Station. Sensors. 15. 31005-31022;

[35] A. E. Ruano, Intelligent control systems using computational intelligence techniques. IEE Press, London (UK), 2005;

[36] A. E. Ruano, P. M. Ferreira, H. Mendes. “MOGA design of temperature and relative humidity models for predictive thermal comfort”, Control Methodologies and Technology for Energy Efficiency, In Proceedings of the IFAC Conference on Control Methodologies and Technology for Energy Efficiency (2010), Vilamoura, 2010;

[37] A. E. Ruano, P. M. Ferreira, H. Khosravani, “A Randomized Approximation Convex Hull Algorithm for High Dimensions”, in 2nd IFAC Conference on Embedded Systems, Computer Intelligence and Telematics in Control (CESCIT) 2015;

[38] H.R. Khosravani, M.D.M. Castilla, M. Berenguel, A.E. Ruano, P.M. Ferreira. “A Comparison of Energy Consumption Prediction Models Based on Neural Networks of a Bioclimatic Building”. Energies 2016, 9, 57.