Influence of Increasing Renewable Power Penetration on the Future Electricity Spot Prices

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Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

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Resumo

Nos últimos anos o mundo tem testemunhado um investimento emergente em fontes de energia renovável, que estão severamente a aumentar a sua presença nos sistemas elétricos atuais. Uma das maiores preocupações é a sua influência no preço futuro dos mercados diários de eletricidade, para os quais se espera uma queda com o aumento de geração renovável. Este tópico não é apenas importante para futuros investidores, que necessitam de avaliar a viabilidade dos seus investimentos, mas também para atuais investidores que podem ver as suas receitas comprometidas. Este artigo providencia uma análise abrangente da componente de mercado diário do MIBEL, examinando o comportamento dos preços da eletricidade e a sua dependência com a geração renovável e não renovável. Esta pesquisa tem como objetivo descobrir a influência da futura composição energética do MIBEL em 2030 nos preços do mercado diário da eletricidade. Durante o processo foi desenvolvida uma análise de correlação com o intuito de avaliar a relação entre os níveis de procura elétrica, de geração das diferentes tecnologias presentes no mercado e dos preços de eletricidade. Como resultado final do estudo, dois modelos de previsão foram desenvolvidos e os futuros preços de eletricidade previstos com os mesmos. Com esta análise foi possível concluir que de facto os preços futuros de eletricidade do mercado diário vão decrescer na próxima década, promovido pelo agressivo aumento de geração renovável no mercado.

Palavras-chave: Previsão a Longo-Prazo, Energias Renováveis, Preços mercado diário de

Eletricidade, Redes Neuronais Artificiais.

Abstract

Within the last years the world has been witnessing an emerging investment in renewable energy sources, which are severely increasing its presence in today's electrical systems. One of the main concerns is their influence on future electricity market prices, which are expected to drop with the increasing in renewable generation. This topic is not only important for future investors, which need to analyze the feasibility of future investments, but also for present investors who can have their profits compromised. This paper provides a comprehensive analysis of MIBEL daily market, examining the behavior of electricity prices and its dependence with renewable and non-renewable generation. This research is motivated at finding the influence of the future 2030's energy mix on electricity prices. During the process a correlation analysis is taken trying to assess the dependences between demand levels, the different technologies present on the market and electricity prices. As final result of the study, two forecasting models were developed and electricity prices for 2030 predicted with the same. With this analysis it was possible to quantify and conclude that in fact electricity daily prices will decrease in the next decade, caused by the aggressive grown in renewable energy sources.

Keywords: Long-Term Forecast, Renewable Energy, Electricity Daily Prices, Artificial Neural

Networks.

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Glossary

AI	Artificial Intelligence
ANN	Artificial Neural Network
ARIMA	Auto Regressive Integrated Moving Average
CI	Computational Intelligence
CLR	Conventional Linear Regression
CNN	Convolutional Neural Network
EDP	“Energias de Portugal”
FFNN	Feedforward Neural Network
GRU	Gated Recurrent Unit
KNN	K Nearest Neighbor
LR	Logistic Regression
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCP	Market Clearing Price
MIBEL	“Mercado Ibérico de Eletricidade”
MLP	Multi-layer Perceptron
MLR	Multi Linear Regression
MSE	Mean Squared Error
RBF	Radial Basis Function
RE	Renewable Energy
REE	“Red Eléctrica de España”
REN	“Redes Energéticas Nacionais”
RF	Random Forest
RMSE	Root Mean Squared Error
SARIMA	Seasonal Auto-regressive Integrated Moving Average
SETAR	Self-Exciting Threshold Auto-Regressive
SPYDER	Scientific Python Development Environment
SVM	Support Vector Machine
TSO	Transmission System Operator
VEC	Vector Error Correction

Chapter 1

Introduction

1.1. Framework and Motivation

Over the last decades, electrical markets have been suffering critical changes in its composition and structural operation. First electrical markets were composed by natural generation, transmission and distribution monopolies. Around the mid-1980s a world concern around such monopolies has grown, and many electrical markets changed its structural operation basis to liberalized and competitive markets. At least in the generation component such evolution was possible, distribution and transmission still remain as natural monopolies [1].

Portugal and Spain integrate the Iberian electricity market, also known as MIBEL, which has been operating since 2007. MIBEL is one of the many liberalized markets around the world and will be subject of an intense study during the present dissertation. This market allows a free competition among the different suppliers/consumers when selling/buying electrical energy, and it is composed by different sub-markets: daily market, intraday market and future market. Daily market is by far the most important one, where almost all electrical energy is traded. Given its importance, the present dissertation will only be focused in the MIBEL daily market and, from now on, any reference to electricity prices is related with this particular market.

Daily market is based on a daily auction where energy is traded for each hour of the following day. The market operator receives and makes the aggregation of the suppliers' and consumers' offers. In each offer it is included the amount of energy that each individual supplier/consumer is willing to sell/buy and the respective price [€/MWh]. Organizing the supply offers, from lowest to highest price, and demand offers, from highest to lowest price, results in the construction of the supply and demand curves. The intersection point between the two curves, sets the market clearing price (MCP) and the total energy that will be traded in a given hour of the following day. All the suppliers that offered to sell electrical energy at a higher price than the MCP, are out of the market and cannot operate. As all the consumer that offered to buy electrical energy at price lower than the MCP, are also out of the market and cannot operate.

Nowadays, with the recent environmental concerns that have been arising, more ecological and cleaner electrical sources are required. At this point, the emerging development in renewable energies (RE) can provide a viable solution. It is expected a sharp increase of such technologies' share in the electrical market for the next decades. For example, since its creation in 2007, MIBEL has been changing its energy mix composition. In its earlier days, according to REE and REN, the share of RE in the Iberian electrical market was 20% of the total generation, today this value is around 40%. In 13 years, the share of RE has doubled and it is expected to reach values between 80%-90% of the total generation in 2030 [2].

MIBEL, like other electrical markets around the Europe, is based on marginal costs, i.e., suppliers bid their offers, in the daily market, at marginal costs. This approach was developed trying to reduce the overall costs, making the market as competitive as possible. For this reason, suppliers are encouraged to produce and to invest in more efficient technologies. Analyzing the specific case of RE such as wind and solar, which present a considerable share on the market, the associated marginal costs are zero or nearly zero. This means the respective bids of such technologies in the daily market will also be close to zero. As a consequence of the nearly null price bidding, a right shift on the supply curve occurs, creating an overall decrease in the MCP. Such effect can lead to the so called "missing money" phenomenon, i.e., the suppliers' revenues are not sufficient to cover the costs. This problem has been raising as RE policies are becoming more ambitious and two major consequences can arise from there: pre-existing powerplants can have their revenues and investment compromised and future investor are discouraged to invest in the electricity market [3]. For that purpose, an economic analysis regarding the future integration of RE in the electrical market is required.

As seen, even though RE are able to provide a decarbonized economy some problems can arise from its implementation, which requires a careful analysis and evaluation, especially in the economic perspective. The main transformations and consequences concerning the expected growing of RE in the electrical markets it is a trendy subject within the literature. One of the most important study fields is related with future electricity prices, that are expected to decrease with the increase of RE, forcing the market participants to change their strategies [4]. Such topic will also be subject of intense study in the present dissertation with special emphases in MIBEL.

As so, this research is motivated at developing models to assess the influence of increasing renewable power penetration on the future MIBEL daily prices for 2030. Results of such analysis provide future and present investors with reliable information about future electricity market prices, allowing rational and thoughtful investment decisions.

A common approach when developing forecasting models, is to use previous values of the variable under prediction as inputs of the model, in this case electricity prices, in order to improve accuracy. As it is possible to understand this is not a feasible solution when assessing electricity prices for 2030, as so, a model using explanatory variables of the underlying process was taken. The chosen explanatory variables are related with generation, demand and variable costs, which represent both the physical and economical components of the market. In the generation part the chosen variables are "hydro", "wind", "solar", "other renewables", "natural gas", "coal" and "nuclear". They represent the daily electrical energy generated from technologies using the named resources. "Variable costs" is a single variable representing the associated daily costs (fuel and CO2) of electricity generation. “Demand” is a single variable, representing the amount of daily electrical energy required to supply MIBEL’s needs. With this information is possible to model and predict electricity prices in the long run, it is just required to model those same variables (generation, demand and variable costs) for the future, in this case 2030.

The practical assessment of this dissertation is achieved by developing computational intelligence models, more precisely artificial neural networks. This work is also presented as a guideline of ideas and solutions to studies related with electricity market price forecasts.

1.2. Objectives

Attending to the previous framework, the objective of the present dissertation is to assess the influence of increasing renewable power penetration on the future MIBEL daily prices. More precisely, the main objective is to develop a model with the ability to forecast and assess future MIBEL daily prices for 2030. To achieve such goal the following methodology has been defined:

1) MIBEL data collection and analysis, assessing the main factors and variables that drive and characterize electricity daily prices.

2) Construction and training of a forecasting model using the identified factors and variables that drive electricity prices. This process consists in adapting the developed model to the previously collected information about MIBEL.

3) Model’s validation, where the model is used to forecast previous MIBEL daily prices and then results compared with real values. This way it is possible to evaluate the model’s ability to meet the proposed target.

4) Implementation of the future MIBEL’s energy mix as input of the developed model, in order to assess future electricity prices.

1.3. Structure

The present thesis dissertation is divided into seven chapters, which are:

1) Introduction

2) Literature Review – Dedicated at a careful analysis over the published studies regarding the problem under study. With the collected information it is possible to develop a model adjusted and tailored to the specific case addressed in the present dissertation.

3) Preliminary Study – Provides an overview about data's collection and analysis. A careful assessment over MIBEL's main price drives is conducted.

4) Theoretical Framework and Implementation – Presents the theoretical foundations and practical implementation of the proposed forecasting models.

5) Models' Validation – A careful analysis over the models' ability to be used as a forecasting tool is taken. This way it is possible to draw conclusion about model's reliability.

6) Results and Discussion – Provides an overview over the followed steps to assess and implement 2030's energy mix considerations into the developed model. At the same time, a careful analysis over the simulated results for future MIBEL's electricity prices is conducted.

7) Conclusions – Main conclusions and contributes of the developed study, future work proposals and improvements.

Chapter 2

Literature Review

Electricity markets are complex environments, with several variables influencing its behavior making it a sophisticated system. This complexity is related with unique characteristics of this particular market, such as the requirement of maintaining a constant balance between demand and supply, inelastic demand in a short time and oligopolist generation, making electricity prices to have particular behaviors: high frequency, non-constant mean and variance, high volatility and high percentage of unusual price movements [5].

Given the above-mentioned characteristics, electrical markets are very complex and hard to operate, requiring accurate forecasting models so investors can provide a proper economic operation in both short, medium and long term. Electricity is known to have a major volatility which can impose major challenges to forecasting methods [6,7]. Management, decision making, and strategical planning are crucial activities in every modern business, being crucial to have the right forecasting tool to perform these tasks in a proper way. Different models are available, but not all are suitable for every problem. During this section it will be explained which exist and the ones being used during this study.

2.1 Electricity Price Forecasting Models

In the literature different models have been proposed to perform electricity price forecast. Weron [8] provides an extensive and complete state of the art review on the topic, analyzing different methods and evaluating its strengths and weaknesses. According to the author these methods can be divided in 5 major categories: Multi-Agent, Fundamental, Reduced-Form, Statistical and Computational Intelligence.

2.1.1 Multi-Agent

Multi-agent models simulate the operation of a system with different agents/players interacting and competing in a regulated market, its implementation is done by equilibrium and simulation models. Equilibrium models are based on algebraic and/or differential equations trying to model the electricity market behavior. These equations are usually complex and hard to solve, and the solution is not always reachable. Simulation models provide a flexible way to model participant's behavior in the electricity market, but they also present two major barriers. On the one hand, when trying to model participant's behavior the pre-defined strategy needs to be true, valid and justifiable. On the other hand, after each iteration the strategy of each player has to be modified. This process is repeated until the final solution is achieved [9]. Multi-Agent models are extremely flexible tools to model electricity markets. However, this flexibility can be a drawback because every assumption and biding strategy needs to be verified and justified. If a strategy used does not corresponds to reality, results will not provide any useful information. Another drawback is that multi-agent models focus on the qualitative side of results and not so much on the quantitative side. This can be a major problem if quantitative conclusions need to be drawn [8].

2.1.2 Fundamental

Fundamental models try to capture both physical and economical relationships in the electricity trading market. They are so called because they use fundamental market drivers like demand, production, interconnections, etc. to explain market behavior. They are constructed on cost-based bids and offer curves to derive indicators of market prices. This type of model does not necessarily allow to make electricity price forecast, they are used to develop trading strategies as well as decision-making models for investments. In the literature they are used in hybrid approaches like regression or neural network models using fundamental factors such as loads, fuel prices, CO2 prices etc., as models' inputs. Pure fundamental models are not used to predict electricity prices in a precise way [8,10].

2.1.3 Reduced-Form

Reduced form models weren't built to provide an accurate electricity price forecast, instead they were implemented to replicate the main characteristics of electricity prices, such as marginal distributions, future points, price dynamics and correlations between commodity prices. They are widely implemented in risk management and pricing derivatives [8].

2.1.4 Statistical

Statistical methods forecast the current price based on previous prices and/or exogenous factors that are price correlated, like weather conditions, fuel prices, generation, demand, etc. This type of models is usually criticized by the limited ability to model non-linear processes. Their accuracy is dependent not only on the algorithm itself but also on the data quality used, being crucial to incorporate important electricity prices drivers. During spike times these methods tend to have a poor performance. Even though they are often target of some bad reviews in financial markets, they have proved to be a reasonable approach to forecast electricity prices in power markets [8].

2.1.5 Computational intelligence

Kok et al. [11] state that providing a concrete definition for the term “computational intelligence” is not an easy task. The precise and complex meaning of the word “intelligence” make it hard to define. However, the artificial intelligence community has been giving some guidelines and definitions to this complex term:

- systems that think like humans
- systems that act like humans
- systems that think rationally
- systems that act rationally.

Computational intelligence (CI) methods were developed to handle problems that traditional methods weren’t able to perform with the desired accuracy. These methods are flexible and can handle complex and non-linear problems, with several authors reporting their excellent performance in electricity price forecasts. However, this same flexibility can also be a drawback, not meaning a better forecast and making critical the optimization process and parameters selection [8].

2.1.5.1. Computational intelligence versus traditional methods

As stated in the beginning of this chapter having the appropriated forecasting tool providing good results is crucial in today’s electricity markets. With the liberalization of electricity markets in several countries, electricity prices were harder to forecast, and some traditional methods started to not be the best approach when performing electricity price forecast. Artificial Neural Networks (ANN) started to being used by many different authors, which have proven to be a robust and secure choice [8,12]. Statistical and Computation Intelligence are by far the most common models in literature to forecast electricity prices [13].

Neural networks are widely used to analyze and forecast time series problems. Feedforward Neural Networks (FFNN) are simple but yet capable of mapping any non-linear function [14,15], making it a powerful and robust tool [8,12].

Kohzadi et al. [16] and Zou et al. [17] compared FFNN with traditional time series models like Auto Regressive Integrated Moving Average (ARIMA) when forecasting wheat and live cattle prices, respectively. Studies show an outperforming of ANN over statistical time series models, stating one explanation for such improvement, is the non-linearity and high volatility presented in data, which cannot be captured by the linear ARIMA model.

Ghanbari et al. [18] made a comparison between linear and non-linear regression models, versus ANN to forecast electricity load in Iran. Conclusions show that ANN outperform both linear and nonlinear methods.

Kaytez et al. [19] compared Multi Linear Regression (MLR) models, ANN and Support Vector Machines (SVM) to forecast electricity consumption for Turkey. Results shown that ANN and SVM clearly outperform MLR. In some cases, SVM is better than ANN but with similar values of accuracy.

Hobbs et al. [20] states that ANN are frequently the most accurate forecast tool when compared with traditional forecasting techniques, especially when dealing with nonstationary, nonlinear, discontinuous and complicated problems. In this same paper, a survey is made in 18 electric utilities and 5 gas utilities, about forecasting accuracy on energy planning using ANN. From all the utilities using ANN on a daily basis, economic benefits were seen, such as time saving, because ANN are simple and easy to implement, and an improvements in forecasting accuracy, allowing a better and more precise management process and avoiding unnecessary money lost.

Tang et. al. [21]state that neural networks can very easily handle nonlinear, noisy or incomplete data due to its learning characteristics, making it a perfect tool to electricity market, due to prices characteristics, as mentioned before.

From all of the above-mentioned evidences it is possible to conclude that ANNs provide a simple and flexible mathematical tool, capable of mapping non-linear functions with the desired level of accuracy. This ability combined with the capacity of dealing with noisy, complex and confuse data, makes ANNs a better and more reliable forecasting tool for electricity prices when compared with traditional methods.

2.2 Electricity price forecasting horizons

Specifically talking about electricity price forecasting, there are time-range divisions concerning how long in the future forecasts are made. Literature is not clear on this topic, being highly subjective and with different interpretations among the authors. Time horizons can be divided into 3 groups: short, medium and long-term. Weron [8] defines short-term as the time ranging from a few minutes to few days, being mostly related with day-ahead market forecasts; Medium-term ranges from few days to few months and is often used for risk management and derivatives pricing; Long-term forecast ranges from a few months to several years, and is often related with strategy, planning and investment profitability. Ziel et. al. [22] provide a different definition stating that short-term is considered for time periods until one-month, medium-term ranges from one month up to a year, and long-term anytime beyond one year. Definition of the forecast horizon is critical to perform a good model. Techniques and algorithms are different in all 3-time horizons.

During the literature review it was possible to notice that the number of algorithms and techniques published for short-term largely exceeds the number of published algorithms and techniques for long-term forecasts. This is in line with the literature review performed in [22], where is stated that the proportion of long-term forecast techniques and published papers is not relevant when compared with short-term. From all the 710 papers analyzed only 8% were related to mid and long-term forecasting, being the number of studies strictly related with long-term much lower than with medium-term. In this same paper it is described all the methods, algorithms, and the differences in inputs used for short, medium and long-term forecasts. Short-term algorithms mainly use previous prices as describing variables, this is the idea of replicating time series, using historical prices as inputs. Medium and Long-term forecasts use other type of inputs. They consider physical market components such as renewable and non-renewable generation, co2 allowances, fuel prices, exports and imports, electrical load, gross domestic product, powerplants outages, time of the year, regional zones, inflation, etc. [22].

Artificial intelligence techniques like neural networks are quite popular and often used to perform electricity price forecasts. In the next paragraphs a literature review about two forecasting horizons will be presented: Short-term by its importance and enormous availability in the scientific community literature and long-term given the goal of this thesis.

2.2.1. Short-term Forecasts

The variety of techniques and algorithms used to perform short-term forecasts is enormous. In this subsection some of them will be presented ranging from simple models like FFNN until hybrid models that combine two or more techniques.

Catalão et. al. [23] proposed a FFNN to forecast short-term electricity prices. This is the most know, well-studied and simplest neural network. This specific algorithm adjusts the weights through the backpropagation algorithm, comparing the forecasted output with the real output (supervised learning), in order to minimize the error, using only historical prices of the market as input. To forecast the price at day “D” prior 42 days of historical prices are required. The model was evaluated for the Spanish and Californian markets, comparing results with ARIMA and NAÏVE models. Conclusions show that FFNN outperforms the other two models for every single case. Apart from that, FFNN are much easier to implement and less time consumer than the ARIMA model.

Some researches proved that for specific cases with high frequency and volatile prices, like the electricity prices, FFNN may not always perform the best function mapping. To solve this problem, Nima [24] proposes a different approach using a neural network with fuzzy logic to forecast electricity prices. To each node/neuron of the network is assigned a hypercube, and the output value of each unit is related with the quotient between the volume of the proposed hypercube and the value of a pre-defined hypercube. Each node performs a fuzzified classification of the input vector, outputting values ranging from zero to one. Classes with higher values, closer to 1, will have more impact on the final output and classes with lower values, closer to 0, will have less impact on the final value. Input variables correspond to historical prices of the market hours before of the forecasted day. This model was implemented in the Spanish electricity market, trying to forecast day-ahead prices on an hourly basis and then comparing it with traditional methods like ARIMA and Wavelet-ARIMA or other artificial methods like Multi-layer Perceptron (MLP) and Radial Basis function (RBF). Conclusions show an outperform of this method compared with the others. Mean Average Percentage Error (MAPE) values for the MLP and RBF are 10.97% and 10.6%, respectively, compared to 7.83% for the FFNN.

Bento et. al. [25] present a FFNN with a wavelet transform. In this case original data suffers a wavelet transformation, dividing the original series into two different series on the wavelet domain. One with high frequency and other with low frequency components. Such decomposition improves primary data’s behavior, with the two different series now present less outliers and less variance, thus reducing the error. To build the input variables similar days approach was used, consisting in choosing days that have similar patterns with day “D” (forecasted day), i.e., low average absolute deviation from day D. The chosen input variables are 3 similar days and all 6 days prior to day D, without exogenous variables. Model was evaluated for the Spanish and PJM markets, comparing this algorithm with 22 others. The FFNN is within the bests algorithms for electricity forecasting being outperform only a few times. This paper reveals that hybrid approaches can be a good choice when forecasting electricity prices although they are more complicated to implement and time consuming.

Other authors propose different neural network architectures like convolutional and recurrent. Ugurlu et. al. [13] provide a great review comparing different neural network architectures and different statistical models for the Turkish electricity market. This study compares traditional methods like Markov, Naïve, Self-Exciting Threshold Auto-Regressive (SETAR) and Seasonal Auto-regressive Integrated Moving Average (SARIMA) with computational intelligence methods like Convolutional Neural Networks (CNN), Long Short-term Memory (LSTM) ang Gated Recurrent Unit (GRU) methods. Results show a clear outperform of CI techniques when compared with traditional methods. Inside the CI methods, LSTM and GRU were proven to have less error than CNN and FFNN, mainly because they are provided with a memory of previous steps, making it a great tool for time series problems like the one presented. Another interesting finding is that error is lower during autumn and winter months when compared with spring and summer showing the effect of temperature and seasonality. This specific market can be compared with the Spanish one, being similar in terms of behavior and energy mix. Conclusions shown that the generalization capability of CI methods can be a huge advantage when forecasting electricity prices.

2.2.2. Long-term Forecasts

Long term forecasting has received less attention in literature when compared with short-term, being the number of papers about this topic scarce. One explanation is the uncertainty about the price driver factors in the long run like fuel prices, regulatory policies, political intervention, technological changes, energy mix, grid operations/developments, etc. Electricity price behavior in the long-term is highly dependent on investments made into the electrical system, and also dependent on the evolution of several factors like demand, subsidies, fuel prices, carbon prices, support schemes, green taxes, energy mix and also on grid investments [26]. Even though, several authors have been proposing strategies, explanatory variables and factors that are believed to best describe electricity prices in the long run. This topic is highly subjective and dependent of each author.

Povh et. al. [27] tried to model the Nord Pool market dynamics and behavior in the long run. It is stated that the structure of short-term forecasting models is not appropriate to model the long run. The authors state that price formation in the long run can be defined by considering supply and demand curves into the future. Electrical demand can be influenced by weather, economic and demography factors while variables influencing supply are divided into 5 groups:

- Fuel Prices (oil, coal, natural gas)
- Hydro capacity and generated energy
- Co2 allowances
- Supply Capacity (Energy portfolio)
- Electricity prices in neighbor markets (imports and exports)

When forecasting future prices, it's required to have an estimate value of the mentioned variables in the same future. Longer forecasts make harder to have an accurate and reliable estimate for each explanatory variable. Conclusions show that the above-mentioned variables can be used to describe the electricity markets' dynamics in the long run. However, relationships and considerations are different within different markets.

Mohammadi [28]evaluated the relationship between the 3 most common fuel sources (coal, natural gas and oil) with long run electricity prices. This evaluation was proposed for the United States' electricity market using data from 1960 until 2007. Conclusions of this study show that electricity prices are strongly correlated with coal prices, being the major price driver from the 3 fuel sources mentioned before. Natural gas although it presents some correlation is not as significant as for coal, and finally is concluded that oil does not influence electricity prices in the long run.

Povh et. al. [29] propose a linear regression model to forecast long-term electricity prices at Nord Pool. The authors state that future prices should be modeled based on demand and supply relationships. Demand can be modeled with different factors like the daily and weekly cycle, temperature, price elasticity of electricity, daylight hours, gross domestic product, household, consumption expenditure, population, migration, etc. Supply is modeled based on two main groups: supply capacity and supply costs. Supply capacity is related to grid connections/restrictions, new capacity installed in the future, old capacity dismissed in the future, imports and exports, capacity of each individual technology etc. Supply costs are directly related with fuel costs, efficiency, type of fuel used, Co2 allowances, etc. The proposed model uses a linear combination of all these factors to construct demand and supply functions, and the final price is computed by matching those same functions, demand and supply, for a given time/period in the future.

Marcos et. al. [30] proposed a model for the Spanish electricity market using cointegration and Vector Error Correction (VEC) to forecast 1 year-ahead prices. Model variables are the electricity market spot price, future electricity price contracts in 12 and 24 months, brent crude oil spot price, electricity demand and wind generation. During this study a combination of variables was done in order to minimize the MAPE value. Four experiments were conducted consisting in forecasting the period 2011, 2012, 2011-2012 and 2013 with MAPE values of 4,63%, 6,81%, 5,67% and 22,47%, respectively. Error concerning 2013 is extremely high and is justified with the enormous amount of renewable generation in that year, which imposes some limitations to this particular model. When looking into the forecasting results even though MAPE is reduce, except for year 2013, the forecasted values do not follow the peaks exhibit by the real electricity price which suggest that the model is limited probably due to missing variables that drive electricity prices and are not accounted for.

Kotur et. al. [31] propose a FFNN for long term electricity price forecasting. During this study it is stated that ANNs using only historical prices as input to estimate future prices is not a good approach in long-term ranges, more information is needed. The author uses physical properties and inputs from the real electrical system, like the generation from convectional and non-conventional technologies, imports and exports, demand, seasonal and daily time indicators. The model is applied to the British power market, where the forecast is made for 15000 samples on an hourly basis giving almost 2 years of forecast. The associated MAPE was around 12%.

Yousefi et. al. [32] developed a model using machine learning techniques to forecast 5 years-ahead monthly prices of the Californian market. Variables that are believed to most describe electricity prices in the long run are proposed: Natural gas used, electricity generated with coal, net electricity generation, net electricity imports, gross domestic product and renewable generation. Four different models, Logistic Regression (LR), Support Vector Machine (SVM), K Nearest Neighbor (KNN), Random Forest (RF), were used and compared. Results corresponding to each algorithm are presented next. Logistic Regression: MAE = 11.68, MSE = 267.68, RMSE = 16.36; SVM: MAE = 16.58, MSE =433.33, RMSE = 20.81; KNN: MAE = 9.68, MSE = 136, RMSE = 11.66; RF: MAE = 10.86, MSE = 201.38, RMSE = 14.19. It is concluded that RF and KNN outperform LR and SVM. During this study is stated that there are several variables influencing electricity's price behavior which cannot be predicted, like political/economic factors, weather patterns, Organization of Petroleum Exporting Countries policies and international policy changes. They all drive electricity prices on a daily basis but are not predictable, this feature provides a barrier to long-term forecasts.

Azadeh et. al. [33] compared 3 ANN Algorithms, 1 Conventional Linear Regression (CLR) and 7 Fuzzy Linear Regression (FLR) models to predict electricity price for Iran in the long run. Electricity price is described using variables such as electrical demand, efficiency, inflation and fuel prices. Results show that CLR and FLR outperform ANN, with a MAPE of 11,9%,12,4% and 13,4% for the best of each algorithm. These models were used to predict the yearly average of electricity prices which don't present much volatility nor variance. It is believed that ANN are a better choice when forecasting with noisy, volatile and big variance data.

The aim of this thesis is to evaluate the influence of increasing renewable power penetration in future MIBEL daily markets, Azofra et. al. [34] present an interesting paper on the topic. The authors evaluated the influence of photovoltaic and wind generation in the Spanish electricity market. Two scenarios were proposed. Scenario A considering all the production mix except for wind generation and Scenario B considering all the production mix except for PV generation. This implicitly assumes that the energy not produced by these technologies is produced by central backup producers like coal fire and combined cycle. Authors have chosen input variables to train the model which were believed to most influence electricity prices:

Inputs (atributes):

- Total generation (GWh)
- Total generation in special regime (GWh).
- Total generation in ordinary regime (GWh).
- Total generation in thermal power plants (GWh).
- Total generation in ordinary regime with bonus (GWh).
- Generation of hydraulic power plants (GWh).
- Generation of nuclear power plants (GWh).
- Generation of coal-fired thermal power plants (GWh).
- Generation of combined cycle thermal power plants (GWh).
- Generation of small hydraulic power in special regime (GWh).
- Generation of wind power in special regime (GWh).
- Generation of photovoltaics in special regime (GWh).
- Generation of solar-thermal power in special regime (GWh).
- Generation with non-renewable term in special regime (GWh)
- Generation with renewable term in special regime (GWh).
- Electric potential available in the dams (GWh)
- Pumping (GWh)
- International balance (GWh)
- Available capacity based on nuclear thermal power plants (GW).
- Available capacity based on coal-fired thermal power plants (GW).
- Available capacity based on combined cycle thermal power plants (GW).
- Available capacity based on hydroelectric power plants (GW).
- Natural gas prices (USD/Million BTUs)

Output (class):

- Final hourly price of electricity (€/MW h)

An inverse correlation between electricity prices and wind power generation is observed, being even more pronounced when accounting for the whole technologies under the special regime. This means that the bigger the generation under special regimen, the lower the final market price, and vice versa. To model the market price, the M5P artificial intelligence algorithm [35] was used. Results show that wind power reduced the average price on the market around 9.10€/MWh and photovoltaic 2.18€/MWh for 2012.

Some companies have been proposing and developing electricity price forecasting models as a service to other investment companies. One of the best in the market is Aleasoft. This company was created in Barcelona in 1999 by Polytechnic University of Catalonia, within the context of liberalization of the European electricity markets. During this 21 years Aleasoft has become a reference in the energy sector, and also on electricity price forecasting. Nowadays, 85% of the electrical energy traded in the Spanish wholesale electricity market has Aleasoft's forecasting model as reference. The model is based on ANNs but with a SARIMA component, it's a hybrid model.

According to this company, the main variables needed to take into account when performing a good long-term forecast are:

- Demand, that uses explanatory variables such as temperatures, calendar data and socio-economic variables.
- Wind energy generation.
- Solar energy generation.
- Hydroelectric energy generation.
- Nuclear energy generation.
- International interconnections.
- CO_2 emission rights.
- Fossil fuel prices.

In the end of this literature review it is possible to observe that all the papers related with long-term forecasts are composed by physical models, based on supply and demand variables. The proposed models for this thesis will be developed using a ANNs, with physical variables related to the Iberian electricity daily market. Its implementation, construction and variable selection will be explained in chapters 4 and 5.

2.3 Forecasting Models' Validation

A good way to evaluate and compare the performance of a forecasting model is using the error. Forecasting error measures can be divided into 4 groups: Scaled-dependent measures, measures based on percentage errors, measures based on relative errors and relative measures [36].

2.3.1 Evaluation Metrics

Hyndman et. al. [36] evaluate and explain a different variety of forecasting error metrics used for different situations.

Scaled-Dependent Measures

These group of methods are useful when comparing same scale datatypes, they cannot be used to compare forecasting methods with data in different scales.

Examples of scale-dependent measures are:

- Mean Squared Error.
- Root Mean Squared Error.
- Mean Absolute Error.
- Median Absolute Error.

Measures based on percentage errors

These metrics work in relative terms, making a reference to the real value. Being scale independent enables it to compare forecasts with datatypes on different scales. Another advantage is the ability to compare the error with the real value, evaluating its relationship, allowing to state how big or small it is compared with the reference. On the other hand, it can provide unreal errors, infinite or undefined, if the real value is close to zero or is extremely large compared to the error, which in fact it is a huge disadvantage.

Some examples are:

- Mean Absolute Percentage Error.
- Symmetric Mean Absolute Percentage Error.
- Symmetric Median Absolute Percentage Error.

Measures based on relative errors

Another alternative is to compare the error with a benchmark method and evaluating how better is the model compared with the benchmark, this is called relative error. Usually, the benchmark is the Naïve method, where it’s assumed that the value in time t-1 will be the same in t.

- Mean Relative Absolute Error.
- Median Relative Absolute Error.
- Geometric Mean Relative Absolute Error.

Relative Measures

Instead of using relative errors, relative measures can be used.

For example, MAE_b represents the MAE from the benchmark method. The relative MAE is given by:

- RelMAE = MAE/MAE_b:

The present dissertation will be using classical error measures, they are simple, well known and provide a good way to evaluate the models. The Mean Absolute Error (MAE) will be used, allowing to compare the real value of the error. The Mean Absolute Percentage Error (MAPE) will be used to evaluate the relative error between forecasts. During this study data is always on the same scale, as so, MAPE and MAE, are more than enough to perform a good error evaluation.

Equations 1 and 2 correspond to MAPE and MAE respectively, where n represents the total number of samples, $\widehat{Y}_i$ corresponds to the forecasted value that ideally should be equal to the real value here represented by Y_i.

$$\boldsymbol{MAPE = \frac{1}{n}\sum_{i=1}^{n}(\frac{Y_i - \widehat{Y}_i}{Y_i})} \qquad \mathbf{(1)}$$

$$\boldsymbol{MAE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)} \qquad \mathbf{(2)}$$

2.3.2 Benchmark

The error measurements presented before, provide a way of comparison and evaluation, by quantifying the error. However, when developing a forecasting model, it is common approach to compare the errors with a given reference, only then it is possible to draw conclusions about its accuracy.

Dhakal [37] shortly describes the benchmarking approach, where several models can be used for this purpose. Benchmarking is the process of comparing some forecasting model's errors to a reference. The persistence method is widely used as benchmark, this model states that the value observed in previous time *"t-1"* will also occur at time *"t"*. Although it seems extremely unreal and not scientific at all, the Persistence method has proven to be a strong tool, and even the best approach to use in some particular situations.

2.4. Conclusions

This chapter provided an overview over forecasting techniques present in the literature with a close look into electricity prices. ANNs seemed to provide enormous advantages over other methods, with the simplicity of use, the ability of self-learning from the environment, easiness to adapt and forecast with non-linear, noisy, confuse and volatile data, unlike traditional methods. It was also provided an overview of forecasting error measurements and benchmarks, where MAPE and MAE were chosen as error metrics and the Persistence method as benchmark. This chapter was crucial for the practical work developed under this dissertation.

Chapter 3

Preliminary Study

When talking about electricity forecasting models and to be well representative of the reality, a good selection of the explanatory variables is crucial. Electricity markets are complex structures with several variables influencing its behavior. On the supply side there is a variety of technologies operating. Given their characteristic and for assessment purposes, they will be divided into two main groups: renewable and non-renewable. On the demand side different types/classifications exist such as residential, commercial and industrial but on this study, they will be described as a single variable. This chapter presents data collection and a preliminary study evaluating how the selected variables influence electricity daily prices and the differences between them.

3.1. Model Description

As stated in the last part of chapter 2, the proposed models for this thesis will be using FFNN and LSTM algorithms, comparing results from both methods.

Typically, FFNN and LSTM are used in supervised learning. This means the system is provided with training data, explanatory variables, and with the solutions also called labels, providing the system with the ability to learn, adapt and correct the error. As so, to construct the proposed models, explanatory and target variables are required. From chapter 2 it was possible to conclude that for long-term forecasts, explanatory variables are typically related with the physical and economical market components, such as the generation portfolio, fuel costs, CO2 costs, imports and exports, electrical demand, grid capacity, etc. This thesis intends to describe electricity market prices considering the generation from the different technologies present on the market, the correspondent variable costs and demand level.

3.2. Data Collection

To evaluate MIBEL's market price behavior it is necessary to collect information with reference both to Portugal and Spain. Data on electricity generation by energy source and demand were obtained from Redes Energéticas Nacionais (REN) and from Red Eléctrica de España (REE), the correspondent

Transmission System Operators (TSO) for Portugal and Spain, respectively. MIBEL market prices were obtained from OMIE, the Spanish MIBEL market operator. Coal prices were obtained from the European Association for Coal and Lignite (Euracoal) and natural gas price from Ycharts, an investment platform with information about different market stocks and prices. Information on CO2 allowances was obtained from European Energy Exchange market (EEX), a European platform related with all types of energy trade and associated factors.

MIBEL exists and is operating since 2007, giving more than 13 years to be used as learning data. Since all information was collected on a daily basis, these 13 years would correspond to more than 4 745 data samples. The importance and relevance of earlier years to the model is not the same as older years, 2007 does not describe today's MIBEL behavior as good as 2019. Having this in mind, only the last 5 years were chosen, from 2015 until 2019. As so, all the above-mentioned data was collected for the period 2015-2019. Information about generation, demand and electricity prices was collected with a daily resolution. Information about fuel and CO2 prices was collected with a monthly resolution. Table 1 summarizes the collected information concerning CO2, natural gas and coal prices for the period 2015-2019.

Table 1: Collected information concerning coal, CO2 and natural gas prices for the period 2015-2019

		2015	2016	2017	2018	2019
CO2 Prices [€/ton]	January	7	6.2	5.05	9.06	22.3
	February	7	4.86	5.09	9.58	18.35
	March	7	4.84	4.71	12.37	21.45
	April	7.22	6.61	4.7	13.35	26.92
	May	7.39	5.86	4.45	15.4	25.61
	June	7.51	5.64	4.8	14.2	24.87
	July	8.08	5.71	5.23	17.45	28.51
	August	8.4	5.78	5.75	20.9	25.93
	September	8.06	5.85	6.75	22.39	25.93
	October	8.48	5.92	7.11	18.72	24.61
	November	8.59	5.73	7.37	18.43	24.29
	December	8.36	4.82	7.07	23.4	24.7
Coal Prices [€/ton]	January	67.03	51.74	95.3	92.01	86.19
	February	60.58	47.18	91.75	85.47	81.2
	March	67.89	47.75	85.33	76.37	77.32
	April	64.23	46.4	84.41	76.13	56.69
	May	63.13	48.17	77.72	84.45	60.61
	June	59.64	52.82	80.38	94.69	52.28
	July	63.12	56.86	84.98	99.8	55.65
	August	60.37	63.49	82.83	95.5	61.56
	September	57.39	63.43	86.5	100.71	60.18
	October	57.9	80.28	91.3	103.06	63.17
	November	58.79	92.83	94.36	100.27	59.22
	December	53.32	95.24	90.61	88.2	59.22
Natural Gas Prices [€/mmBTU]	January	7.8625	3.7383	5.2224	5.627	6.1727
	February	7.0295	3.3728	5.1442	5.71115	5.1051
	March	7.0295	3.3235	4.25085	5.69245	4.40215
	April	5.7579	3.3745	4.25935	5.8888	4.1837
	May	5.6814	3.67965	4.2993	6.36395	3.68985
	June	5.6695	4.0426	4.15395	6.33165	3.0498
	July	5.6899	3.97375	4.2534	6.45915	3.077
	August	5.3941	3.4408	4.65545	6.87225	3.12545
	September	5.33715	3.6159	5.06685	8.0937	3.57425
	October	5.12295	4.53645	5.2496	7.47235	4.29845
	November	4.67585	4.83905	5.69075	7.02525	4.3775
	December	4.32905	4.6104	6.06815	6.7796	3.927

3.2.1 Portugal and Spain Generation Portfolio

Portugal and Spain have different electrical generation portfolios, not all the technologies currently available in Spain exist in Portugal.

REE provides the electrical generation for Spain discretized in the following technologies:

- Hydro (GWh/day)
- Pumping (GWh/day)
- Nuclear (GWh/day)
- Coal (GWh/day)
- Fuel + Gas (GWh/day)
- Combined Cycle (GWh/day)
- Wind (GWh/day)
- Solar Photovoltaic (GWh/day)
- Solar Thermal/Concentrated Solar Power (CSP) (GWh/day)
- Other Renewables (GWh/day)
- Cogeneration (GWh/day)
- Residues (GWh/day)

REN provides the electrical generation for Portugal discretized in the following technologies:

- Coal (GW)
- Fuel Oil (GW)
- Natural Gas (GW)
- Reservoirs (GW)
- Run of River (GW)
- Imports (GW)
- Exports (GW)
- Small-Hydro (GW)
- Cogeneration (GW)
- Wind (GW)
- Photovoltaic (GW)
- Wave (GW)
- Pumping (GW)

As it is possible to observe data about the Portuguese electrical generation is provided under the form of a load diagram. Such information needs to be converted to daily electrical energy, by calculating the integral of the power of each individual technology during the day.

On the Spanish side, residues were not considered to the model, because its relative value is small, around 1% of the total generation for Spain in 2019. On the Portuguese side, wave was not considered, due to null production. Imports and Exports were also not considered, the reason is explained later on this subsection. Those simplifications avoid a model with too many input variables.

3.2.2. Fuel Costs

According to the generation variables used to describe this model, and the literature review in Chapter 3, fuel costs will only be related with natural gas and coal. Information concerning those fuels prices is provided in a monthly basis, as shown in table 1, so it was assumed for the model that this price was constant during each month.

Information on natural gas prices was converted from euros per million British Thermal Units into euros per Megawatt hour to be easily implemented into the model. Information provided by EuraCoal concerning coal prices in Europe is presented in euros per ton, being also converted to euros per Megawatt hour. Having this information about prices is then required to compute the amount of each fuel used on a daily basis. Technologies' efficiency provided by Energy Plan on Pereira's study [2] will be used to perform this task. According to that study, natural gas technologies, which include different technologies such as cogeneration, combined cycle and normal gas turbines, are considered to have an average efficiency of 55%. Coal power plants are considered into the model with a normal efficiency for this technology, around 35%. With the efficiencies values and having the electrical daily generation it is possible to compute the daily primary energy used, and consequently compute the daily fuel costs, using the prices presented in table 1.

3.2.3. CO2 Costs

Portugal and Spain both integrate the European Emission Trade System (EU ETS). Carbon prices are defined based on a cap-and-trade system, having a certain cost/value measured in euros per ton of equivalent Co2 [€/ton eq. Co2] [38]. EEX provides information about CO2 the defined CO2 costs on a monthly basis, so it was also assumed for the model that this price was constant during each month. To compute the daily CO2 costs of MIBEL, information about generation emissions was needed. REE provides this same information for Spain on a daily basis under a value called "emission factor" [Eq.CO2/MWh], which is the quotient between total emissions and total generation (renewable and non-renewable). This same information is not publicly available for Portugal, and to overcome this problem it was assumed that both countries have a relatively equal generation mix and the emission factor would be the same for them. This means that 1 MWh of energy produced in Portugal would have in average the same CO2 emissions as one produced in Spain in each day. Using this emission factor, the electrical generation for both countries and the Co2 allowances, it is possible to compute the daily emissions and respective costs.

3.2.4. Imports and Exports

International power interconnections were not considered in the developed models, for two main reasons. Firstly, the system under study is MIBEL, with interconnections between France, Morocco and Andorra. According to REE, the total energy traded, import and exports, in 2019 corresponded to 3% of the Iberian market demand, making a relatively small number. Secondly the difficulty to model imports and exports on a daily basis for the year 2030 was also taken into account. To avoid this situation and having in mind that is a relatively small value, international exchanges were not considered.

3.2.4. Demand

Electrical demand was considered as a single variable for the Iberian Market aggregating Portugal's and Spain's demand. Information was collected from REE and REN for Portugal and Spain respectively. Again, Portuguese's demand data is provided in the form of a load diagram, requiring a transformation to obtain final value of daily demand.

3.2.5. MIBEL Price

MIBEL price was collected on a daily basis, this information will be the target data used in the supervised learning to adapt and correct the parameters of the neural network algorithms. Electricity price in MIBEL is usually the same for Portugal and Spain. This equilibrium can be disturbed when available power capacity between countries is saturated, leading to a phenomenon called as market splitting. When such phenomenon occurs the two countries have different electricity prices. This market splitting effect was important in the early MIBEL years. In 2008 it occurred more than 62% of the time, representing an expressive portion of the time. With the improvement of power interconnections, it has been mitigated and from 2014 forward, it occurred less then 10% of the time. In the year 2015 market splitting only occurred 2% of the time [39]. According to this fact and with the relative dimension of the Spanish electrical system in MIBEL, no market splitting was considered into the models, and prices always correspond to the Spanish side.

3.3. Data Treatment

To construct a single model, it is required a pre-defined group of variables used to describe MIBEL's price behavior. As so, an adaptation and articulation between variables of the two countries was conducted. Spain has an electrical system around 5 times bigger than Portugal, making its importance to MIBEL also 5 times bigger. Attending to this fact Portuguese variables were adjusted and converted into Spanish variables and not the other way around.

3.3.1 Portugal and Spain Generation Portfolio

A careful choice when adapting variables had to be done so the model was not compromised, even though some simplifications and assumptions were taken. Reservoirs and Run of River from the Portuguese side were converted into a single variable called Hydro. Fuel was assigned into Fuel + Gas and Natural Gas (NG) assigned into Combined Cycle. According to EDP (Energias de Portugal), Small Hydro represent small producers until 10MVA, corresponding to a low energy produced which cannot be integrated into the big Hydro group. Following this rational it was more coherent to assign it into Other Renewables. Pumping, coal, wind, cogeneration and Photovoltaic had direct connection with Spanish Variables. Table 2 shows the articulation performed from the Portuguese variables into the Spanish variables.

Table 2: Articulation between Portuguese and Spanish generation technologies

PORTUGAL	SPAIN
Reservoirs + Run of River	Hydro
Pumping	Pumping
----------------------------------	Nuclear
Coal	Coal
Fuel Oil	Fuel + Gas
Natural Gas	Combined Cycle
Wind	Wind
Solar Photovoltaic	Solar Photovoltaic
----------------------------------	Solar Thermal/CSP
Small Hydro	Other Renewables
Cogeneration	Cogeneration

Later on, there was the need to model the electrical energy portfolio for the year 2030 and respective productions. Assumptions used to model it are authored by Pereira [2] which developed his study with the help of Energy Plan Software.

Final variables presented in [2] to model the generation portfolio in the year 2030:

- Wind (GWh)
- Solar Photovoltaic + Solar Thermal (GWh)
- Hydro (GWh)
- Geothermal (GWh)
- Nuclear (GWh)
- Natural Gas (GWh)
- Coal (GWh)
- Demand (GWh)

Again, an articulation and adjustment between variables was required. Nuclear and Coal have direct correspondence. Solar is now considering the Photovoltaic and Thermal technologies. Geothermal corresponds to Other Renewables and was created a single called Natural Gas where all technologies using this resource to produce electricity were integrated making the correspondence with the Natural Gas variable used in [2]. Finally, Hydro variable aggregates all technologies producing electricity using water resources. There are some simplifications in this process, since not all the electrical energy produced by combined cycle and cogeneration technologies use only natural gas as fuel. At the same time, there was the combination of all hydro variables together dispatchable and non-dispatchable technologies in the same group, which is not entirely representative of the reality. However, due to lack of options this was the most logical approach. Final variables used to describe electricity prices will be the predictors/inputs used in the forecasting models.

Final variables/predictors used in the model:

- Wind (GWh/day)
- Solar (GWh/day)
- Hydro (GWh/day)
- Other Renewables (GWh/day)
- Nuclear (GWh/day)
- Natural Gas (GWh/day)
- Coal (GWh/day)
- Demand (GWh/day)
- Variable costs (€/day)

3.4. Data Analysis

After data collection it is important to make a preliminary analysis. Gelabert, et. al. [40] present a study where it is proposed a correlation analysis to assess the relationship between the different variables and electricity prices, also for MIBEL. Correlation values range from -1 to +1, indicating perfect negative and positive correlation, respectively, and the zero-value indicating no correlation at all. In this sub-chapter a similar procedure was taken but to the variables used in the model.

According to King, et. al. [41], there are typically two methods used to calculate correlations between variables. If variables are normally distributed then Pearson's correlation should be used, if not then Spearman's Correlation is the one to be chosen. In this case, data is not normally distributed, so Spearman's correlation (r_s) will be used.

$$r_s = 1 - \frac{6\sum_{i=1}^{n} {D_i}^2}{n^3-n}, \text{ where } \quad D_i = X_i - Y_i$$

From “n" samples, this correlation ranks X_i and Y_i variables independently, on an ascending or descending order, and posteriorly calculating its differences (D_i). Table 3 presents the obtained Spearman’s daily correlation using the models’ inputs.

Table 3: Daily correlation between generation technologies, demand and electricity market prices

	Hydro	*Nuclear*	*Coal*	*Natural Gas*	*Wind*	*Solar*	*Demand*	*Electricity Prices*
Hydro	1							
Nuclear	-0.113	1						
Coal	-0.264	-0.001	1					
Natural Gas	-0.346	-0.003	0.111	1				
Wind	0.152	-0.023	-0.409	-0.415	1			
Solar	-0.164	0.051	-0.164	0.171	-0.368	1		
Demand	0.072	0.152	0.297	0.281	0.104	-0.111	1	
Electricity Prices	-0.392	-0.017	0.621	0.489	-0.441	-0.081	0.276	1

Results presented in table 3 are coherent and similar with the ones presented by Gelabert et. al. [40]. In table 3 it is possible to observe a positive daily correlation between fossil fuel technologies (coal and natural gas) and demand with electricity prices. This means that days with higher electricity from fossil fuel technologies and/or higher demand values are associated to higher daily market prices. On the other hand, it is observable the negative correlation between renewable technologies (hydro, wind and solar) and electricity prices. This means that days with higher electricity from renewable technologies are associated to lower market prices. Solar technology is a less developed technology on the market, with a smaller share, so its influence will also be smaller, as represented by the low correlation factor. Nuclear technologies also have a small influence on the electricity market as it is shown by the almost null correlation with electricity prices.

The difference between the two analysis is related with hydro technologies, that in Gelabert’s results presents a positive daily correlation with electricity prices. The author justifies this positive value stating that this particular technology can store and shift energy to periods with higher demands and higher electricity prices. The positive correlation reflects the positive opportunity cost of hydro. However, this also means that days with higher hydro generation are associated with higher electricity prices.

Other authors provide different results and conclusions on the same topic. Pereira, et. al. [42] evaluated the effect of large hydro generation and Azofra, et. al. [43]the effect of small hydro generation in the Spanish electricity price. Both studies report a decrease in electricity prices with the increase of generation from these sources. Pereira, et. al. [42] states that large hydro plants with reservoirs can help to maintain price stability and decrease the occurrence of high prices and variances caused by intermittent production, decreasing the average price of electricity. On another study conducted by Lopéz, et. al. [44] it is assessed the effect of stopping hydro production in Nord Pool market. Conclusions show that the non-production from hydro technologies can increase the average price of electricity, because this production is replaced by higher marginal cost technologies, mainly fossil fuel technologies.

The information presented in table 3 was constructed on a daily basis, giving an overview of the correlation between days but not an intra-day relationship between variables. As so, and for a better understanding of the problem, a second correlation was performed, but with all the information discretized and presented on an hourly basis. However, hourly information is only publicly available for Portugal, and therefore this correlation was built only with Portuguese information. Even though this lack of information exists, results can be a good approximation of the reality given the fact that Portugal and Spain are side by side, so when renewable resources like water, wind and sun are present in Portugal, they are most likely to also be in Spain. It is important to notice that nuclear technologies are not present on the Portuguese electrical system, so they are not considered for this correlation analysis. Table 4 presents the results of Spearman's correlation using Portugal's hourly information.

Table 4: Hourly correlation between generation technologies, demand and electricity market prices.

	Hydro	*Coal*	*Natural Gas*	*Wind*	*Solar*	*Demand*	*Electricity Prices*
Hydro	1						
Coal	0.175	1					
Natural Gas	0.192	0.233	1				
Wind	-0.132	-0.338	-0.346	1			
Solar	0.097	0.056	0.314	-0.209	1		
Demand	0.562	0.319	0.474	0.009	0.383	1	
Electricity Prices	0.282	0.740	0.343	-0.337	0.075	0.473	1

This new correlation analysis provides a different overview of the interaction between market prices, generation technologies and demand, allowing an assessment of the relationships within each day.

Wind continues to present a negative correlation with electricity, mainly because it is a mature technology with a considerable share on the market biding at prices close to 0€/MWh, which induces a drop in electricity prices. Reservoirs are dispatchable technologies, meaning they have the ability to allocate the stored energy during any period of the day. As it is clear to understand periods of higher prices will be chosen to increase the profit, this strategy is reflected in the obtained positive correlation between reservoirs and electricity prices. As stated before, solar is a less developed technology, with a smaller share on the energy market, its energy output is not significant making a smaller influence on energy markets, reflected on a null or almost null correlation. Fossil fuel technologies continue to present a positive correlation with electricity prices, as expected.

From both analyzes, it is possible to state that an increase in renewable generation tends to decrease the average daily market price and an increase in fossil fuel generation and demand levels tends to increase market prices. It is also possible to state that hydro technologies have a positive opportunity cost, represented by the positive hourly correlation with electricity prices, but does not necessarily mean that such technologies increase market prices. In fact, an increase in hydro generation tends to decrease the average daily electricity prices, which is shown by the negative daily correlation.

3.6. Conclusion

In this chapter, collection, treatment and a preliminary data analysis was conducted. Making an articulation between variables it was possible to develop a single model to describe MIBEL's prices behavior. The performed analysis consisted in two correlation matrixes, allowing to evaluate how variables influence daily prices. It is concluded that an increase in renewable generation tends to decrease electricity prices and an increase in fossil fuel generation and/or demand levels tends to increase market prices. Such analysis is crucial to evaluate the forecasting results that will be performed.

Chapter 4

Theoretical Framework and Implementation

From the literature review in chapter 2, FFNN and LSTM were chosen between a variety of CI algorithms to develop the practical component of this thesis. This chapter explains the mathematical theory and implementation of such algorithms.

4.1 History and Foundations

Géron, et. al. [45] present the history, foundations and evolution of ANN throughout time. First created by the neurophysiologist Warren McCulloch and the mathematician Walter Pitts, back in 1943, ANNs were based and inspired on biological neurons, similar to the ones present in the human brain. The brain is a complex and organized system, still under study by scientific community, but with some interesting findings at the date. Some parts of this biological architecture could be already mapped by scientists, and apparently, biological neurons are organized in layers, composed of several neurons processing and transmitting electrical signals/stimulus, containing a certain information, within that network. Following this same idea, the first neural network was created.

4.2. Neural Networks' Theory

This section will briefly introduce the theory behind neural networks algorithms, from its construction to training. The validation procedure will be addressed in chapter 5.

4.2.1. Artificial Neurons

Artificial neurons are the base units of a neural network, trying to reproduce the biological units of the brain. Figure 1 presents one of the simplest artificial neurons, usually implemented in FFNN. Those artificial units are mathematical functions, commonly built with different connections (w_i), inputs (x_i) and only one output (y) that propagates to other units in subsequent layers.

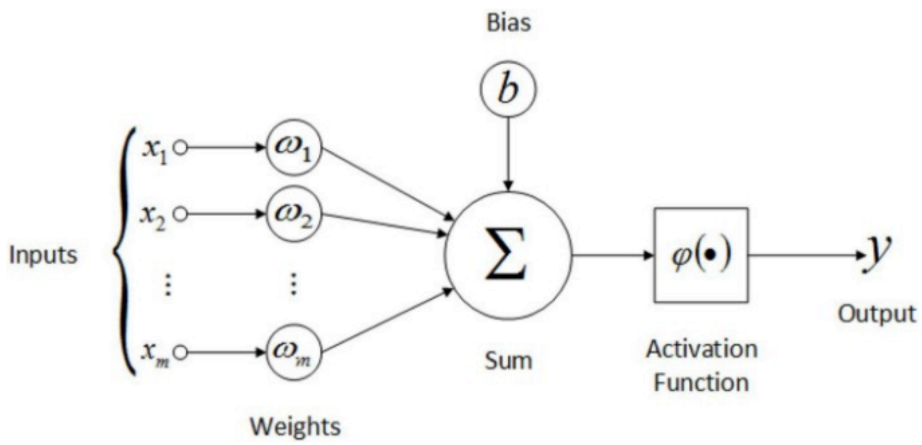


Figure 1: Mathematical Representation of an Artificial Neuron

A given neuron composing a neural network receives, processes and propagates information within the network. The inputs (x_i) received by the neuron are passed through a propagation/integration function, usually the weighted summation, equation 3, and transformed into a total input (net_j). The magnitude of the total input is determined by the strength in connections between neurons, reflected in the weights (w_{ij}), and the magnitude of the different inputs. Neural Networks can also be provided with a bias term (b), which is also adjustable, providing an extra freedom degree during the training procedure.

$$net_j = \sum_{i=1}^{n} x_i w_{ij} + b \qquad (3)$$

After computing the total input (net_j), this value is transformed by an activation function, $\varphi(net_j)$, and the result corresponds to the neuron's output (y). This value can either be used as input for other neurons in the subsequent layers, or as the output value of the network if the neuron is located in the last layer.

4.2.2. Activation Function

Different activation functions can be used within a neural network, from the simplest ones to the most complex, depending on the goal. According to Géron, et. al. [45], to solve complex and non-linear problems, activation functions are also required to be non-linear. If a neural network is only composed by linear activation functions, the final relationship between inputs and outputs is also linear. This is a critical aspect of deep learning, and if this non-linearity is not present, then, even the deeper networks won’t be able to solve non-linear and complex problems. Activation functions provide the model with desired non-linearity behavior, crucial in practical applications.

Theoretically, any non-linear and differentiable function is suitable to be used, however, in practical cases, bounded, monotonically increasing, and differentiable functions are preferred over others, being its implementation into the model easier [46]. In a general way, and for the majority of applications, ANN are implemented having the same activation function in all neurons, but is also possible to have different activation functions in different neurons within an ANN.

The integration of continuous and derivable functions in these algorithms, was a revolutionary step, they are crucial in the optimization process as it will be explained later on this chapter.

4.2.3. Topology and Architecture

After understanding the concept of an artificial neuron, it is important to understand how they can be organized in such a way to form a network. Figure 2, presents a visual interpretation of a neural network, composed by one input layer, "n" hidden layers and one output layer. By definition, the resulting network, formed by the neurons and their connections, is also a mathematical function, created by the chain of all the individual activation functions and weights.

Within the network, neurons are organized in layers with connections between each other. The input layer receives exogenous information and propagates it to the subsequent layers, called as hidden layers. Hidden layers are responsible for processing and propagating data coming from the input until the output layer. The output layer is responsible for receiving information coming from the hidden layers, and transferer it to the exterior of the network.

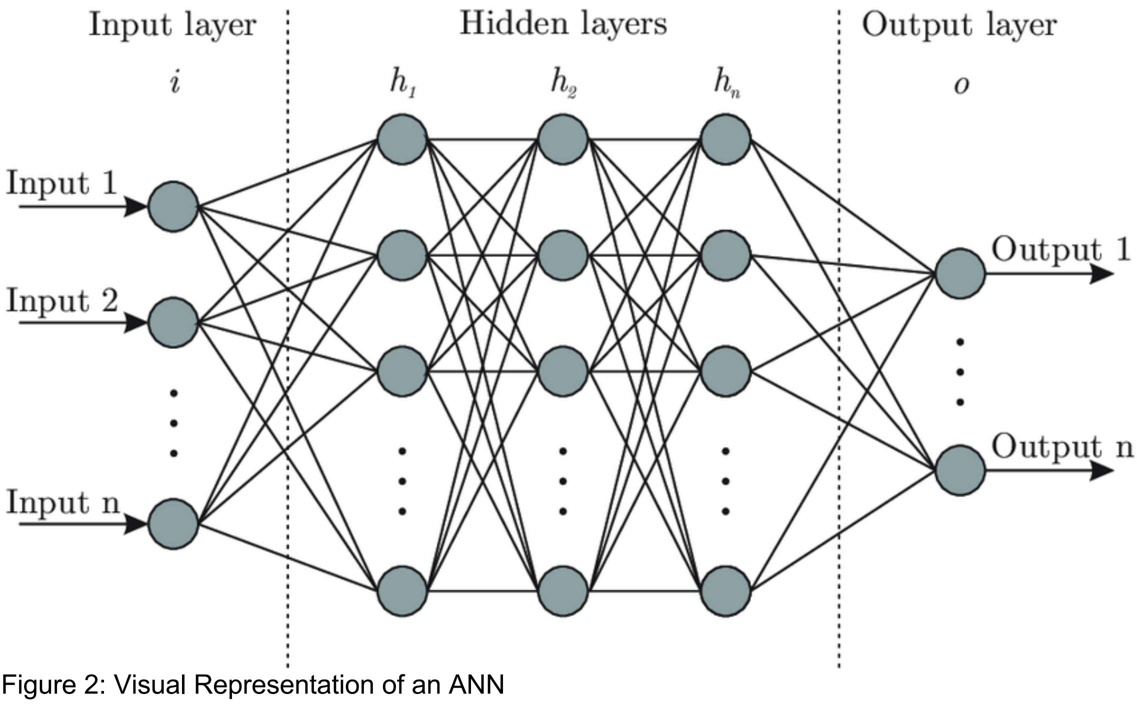


Figure 2: Visual Representation of an ANN

Number of input neurons

This value is defined based on the length of the input vector used to describe the process. Ideally this number should be as small as possible, but assuring that all the relevant data is present, i.e., crucial information describing the process is not discarded [46].

Number of hidden layers and neurons

Hidden layers are crucial when defining a neural network's architecture. These layers are responsible for capturing the pattern present in data and providing the ability of mapping non-linear and complex functions. Without these layers a neural network would be equivalent to a linear transformation between the input and output vectors. For the majority of practical cases, evidence shows that on hidden layer provides good solutions, two hidden layers can have advantages in terms of accuracy, but more than two is only indicated for specific cases [46]. In terms of hidden nodes evidence shows that in most cases a small number of units is preferred over a large number [46]. Some rules have been proposed to define this number:

- $2n + 1$
- $2n$
- n
- $n/2$
- $(n + m)/2$

In this case "n" represents the number of input nodes and "m" for the number of output nodes. This parameter is not a fixed and strict, the same network can have different number of hidden neurons and provide the same error/accuracy.

Number of output nodes

This number is easy and simple to specify, being only dependent on the output vector's length. For example, in a time series it is dependent on the time horizon, with one-step-ahead forecast requiring only one output node, multi-step-ahead forecasting requiring multi output nodes [46].

Interconnection between neurons

Interconnections between neurons are characterized by the weight value assigned to each connection. Those weights are responsible for adjusting the algorithm, being its definition and tweaking crucial to obtain good results. A network can be fully connected if a neuron in layer "$n - 1$" connects to all the neurons in layer "n", and partially connected if the same neuron only connects with some units on the subsequent layer. For practical applications, fully connected networks are more commonly used over the others [46].

4.2.4. Feedforward and Long-Short Term Memory.

Two of the most common algorithms present in the literature were used during the practical component of this thesis, FFNN and LSTM. It is important to notice that LSTM is a specific case of a bigger group called Recurrent Neural Networks (RNN). The two topologies are represented in figure 3, presenting some differences especially in the information flux.

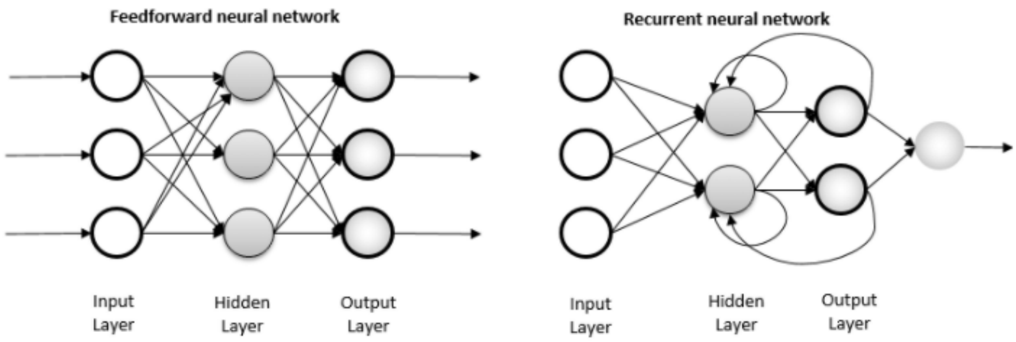


Figure 3: Visual representation of a FFNN and an RNN.

Feedforward Neural Network

Feedforward Neural Networks are the basics of deep learning, this specific architecture is efficient and simple to use, being widely applied in supervised learning. The “Feedforward” designation comes from the information flux, that is processed in only one direction, from the input through the hidden layers until the output, called as forward direction.

Long Short-Term Memory

As previously stated, LSTM is a specific case of RNN and is considered as a generalization of the FFNN, with the upgrade of having an internal memory. LSTM provides the neurons with information feedback, which can be from "n" time steps before. This means that after computing the output of a given neuron, that same information flows back into the network so the algorithm can analyze it, process it and use it to compute the next output. According to Hochreiter,et. al. [47] the general idea behind LSTM is the introduction of the cell state, where information can be added or removed and passed to other cells. Unlike FFNN, in this case information is propagated using unit gates (forget, input and output gate) which are responsible for updating the cell state and computing neurons’ outputs. LSTM neurons are much more complex than basic artificial neurons presented in the beginning of this chapter. Figure 4 presents a visual representation of a LSTM neuron with all its gates.

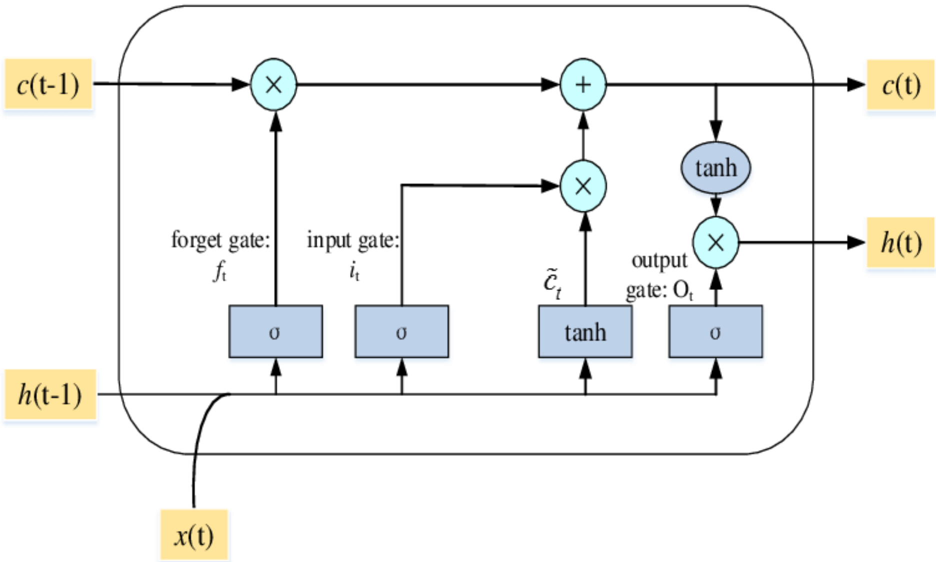


Figure 4: Visual representation of a LSTM neuron.

Forget Gate

This gate receives information from the previous hidden state ($h(t-1)$) and the current input ($x(t)$) in a form of a concatenated vector ($h(t-1)+x(t)$). It is responsible for deciding which information coming from the previous cell state ($c(t-1)$) should be kept or forgotten. The concatenated vector is transformed by the sigmoid function, being the output on the interval [0,1]. Information with values close to zero is to be forgotten and close to one is to be kept. The sigmoid output vector will then be multiplied by the previous cell state ($c(t-1)$) removing or maintaining information from the previous cell state.

Input Gate

The input gate has the purpose of choosing the updating information for the cell state. The concatenated vector ($h(t-1)+x(t)$) is transformed simultaneously by a hyperbolic tangent (tanh) and sigmoid functions. The resulting vector obtained in the tanh transformation is the candidate information to update the cell state, and again, the resulting vector obtained in the sigmoid transformation states which information should be kept and forgotten. The sigmoid and tanh outputs are multiplied, and the resulting vector containing the relevant information, is then added to the cell state updating its value and creating the new cell state ($c(t)$).

Cell State

Cell State is constantly being updated with relevant information which is then propagated into the subsequent unit. This information is used to create the new hidden state ($h(t)$), combining its information with the one coming from the output gate.

Output Gate

The output gate decides which information should be passed for the next hidden state ($h(t)$). The concatenated vector ($h(t-1)+x(t)$) is transformed by a sigmoid function, deciding which information is relevant. The cell state, that has already been updated, is transformed by the tanh function creating the candidate information. When both outputs are multiplied the next hidden state is created.

4.2.5. Training

Training is the process of determining the value of the parameters/hyperparameters that minimize the error. For that purpose, it is required to feed the model with specific data, called training data, containing predictors and solutions, ensuring the model is able to learn, adapt and minimize the error. There are several algorithms, called optimizers, used to find the value of each hyperparameter that minimizes the global error, being the majority based on gradient descent techniques.

Backpropagation Algorithm and Gradient Descent

When constructing a neural network, initial parameters' values will certainly not conduct to the optimal solution, it exists an error between the output/forecasted value and the target/real value. The cost function evaluates the magnitude of this error and provides information about models' accuracy. Two of the most common cost functions used in regression models are:

- Mean Squared Error $C = \frac{1}{n}\sum_{i=1}^{n}(o_i - t_i)^2$ (4)
- Mean Absolute Error. $C = \frac{1}{n}\sum_{i=1}^{n}|o_i - t_i|$ (5)

Where C represents the total cost, o_i and t_i the output and target values of node i, respectively. Gradient based algorithms use information from the cost function but also from its gradient (∇C) (equation 6), which is a vector in the weight space (w_i) presenting the direction of the steepest increase of the cost function's value. The idea in the optimization process is to move in the opposite direction of that vector, in order to minimize the error.

$$\nabla C = (\frac{\partial C}{\partial w_1} + \frac{\partial C}{\partial w_2} + \cdots + \frac{\partial C}{\partial w_i}) \qquad (6)$$

Figure 5 shows a visual interpretation of the gradient descent principle, where the weight value (θ) is being tuned in order to minimize the cost function [45].

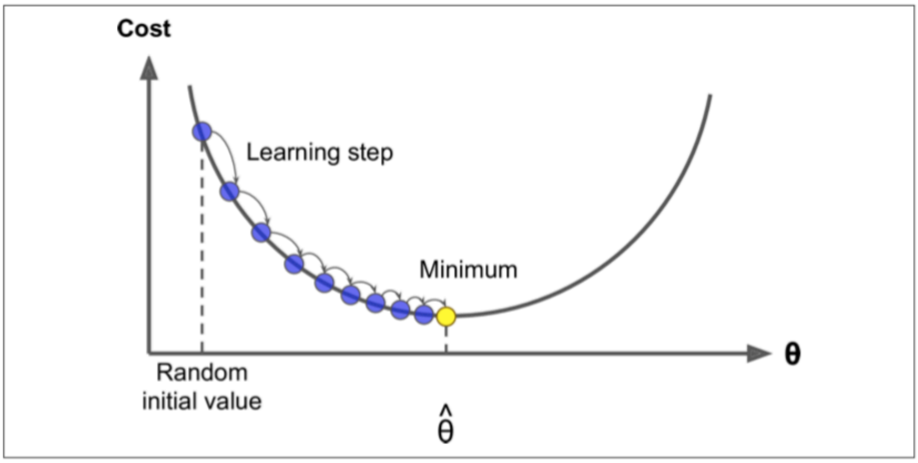


Figure 5: Visual Representation of a Cost Function and the Gradient Descent Optimization Process.

As it was possible to observe in figure 5, the random initial value (θ) did not conduct to the optimal solution, a tweaking process of this parameter is required. On the left side the cost function's gradient is negative, and the parameter is being tuned in the positive direction, i.e., in the opposite direction of the gradient.

The objective of the Backpropagation algorithm is to calculate, in an effectively way, the gradient of the cost function, i.e., the sensitivity/derivative of the error with respect to each weight composing the neural network. That same gradient will then be used by the optimizer in order to tune the weights [45,48,49]. Backpropagation algorithm can be divided into 3 steps: Feedforward computation, backpropagation and weights update. During the Feedforward computation the network is presented with an input vector and computes the respectively output vector, the values are then compared with the target vector, being the error magnitude evaluated through the cost function. Backpropagation is exactly the opposite; it consists in taking the error and backpropagate it into the network. This way is possible to evaluate the contribution of each individual parameter to the final cost value and the best tweaking process to minimize the global error. Given the fact that neural networks are equivalent to a chain composition of functions, it is expected that the chain rule of differential calculus provides a major help finding the gradient [45,49]. For a proper application, backpropagation algorithm requires continuous and differentiable functions, that is why such functions are crucial and were considered a big step in deep learning techniques.

Training Diagram

Figure 6 presents a diagram with the standard training process using Backpropagation and Gradient Descent optimizers. The number of times the training data is provided to the algorithm, called as epochs, is represented by "n" , the error magnitude evaluated through the cost function is represented by "C".

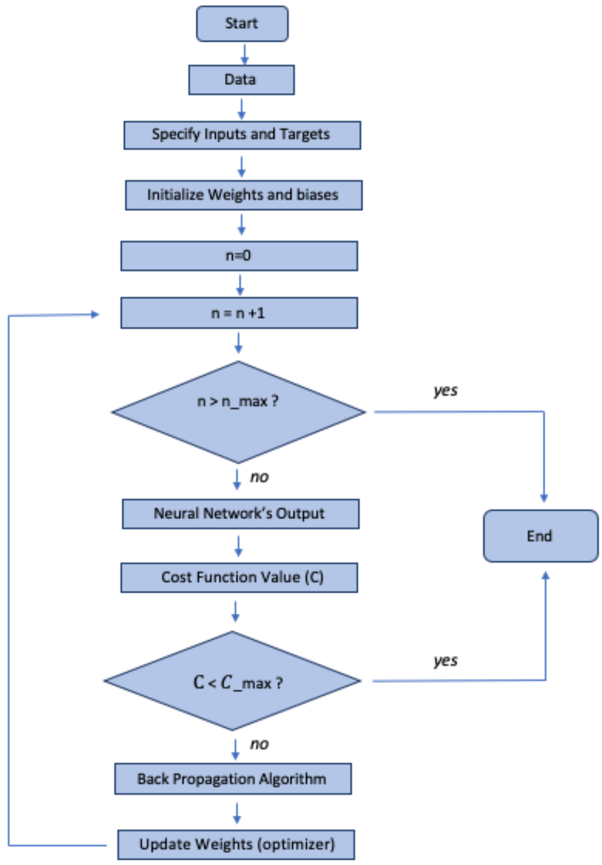


Figure 6: ANN Training Diagram

In short, is possible to simplify the training process in the following steps:

I. Create the neural network.

II. In the learning data specify the inputs/predictors and the respective targets/solutions.

III. Initialize neural network's parameters

IV. Update the epochs counter.

V. Provide the algorithm with the training data and calculate the output.

VI. Evaluate the error through the cost function

VII. Use backpropagation algorithm to calculate the gradient.

VIII. Update the weights using the optimizer.

IX. Go back to step IV.

During this process if the maximum number of epochs defined or the minimum value for the cost function is achieved, training is stopped.

Training is a fundamental piece regarding forecasting algorithms, otherwise it would not be possible to make reliable predictions. During this process two major problems can arise, underfitting and overfitting, which can lead to biased and unreal results. Such situations are common, undesirable and need to be avoided at maximum cost.

Overfitting

Overfitting is a recurrent and critical problem in CI algorithms. It happens when the algorithm is too complex relatively to the data sample, i.e., it performs too well regarding the learning data, but it is not able to generalize for other cases. It can occur for different reasons like a small and noisy data sample, which induces the model to detect patterns on the noise, something that is not supposed to happen; excess of training epochs which makes the algorithm to improve its performance in an excessive way regarding the training sample, making it biased; too many inputs describing the process making the algorithm strict and rigid instead of flexible and adaptable; etc. To overcome this problem, one can reduce the number of training epochs, reduce model's complexity, reduce the number of predictors describing the process, improve the quality of the training data, etc. [45].

Underfitting

Underfitting is exactly the opposite of the previous case. In this situation the model is too simple for the data, i.e., the algorithm is not able to describe and capture the pattern present in data in a reasonable way, making it inaccurate. This can be solved by constructing a more complex model with more parameters, feeding the algorithm with better features and reducing the model constrains [45].

4.2.6. Validation model

After the training process, and to evaluate how well or not a model can generalize, it is crucial to evaluate its performance regarding new data samples. This process is called validation and to perform it a validating data is required. Validating data is also provided with the targets/solutions but is only used after the model's training. By comparing the forecasted value with the real value, it is possible to draw conclusions about the model's accuracy. If one compares the obtained accuracy for the training data and the validating data, and if the former is relatively higher, it means the model is overfitted and is not able to generalize. In order to have a forecasting tool both errors must be similar, meaning the model is adapted to the learning data but is also able to generalize. Model's validation will be addressed with more detail in chapter 5.

4.3. Practical implementation

Several compilers and code editors are available to construct and implement neural networks. During the practical component of this thesis, SPYDER (Scientific Python Development Environment) was the one used. Different libraries can be found with specific use in Machine Learning applications such as Keras, Sklearn and TensorFlow. Those libraries provide the basics for constructing ML algorithms, like the activation functions, optimizers, backpropagation algorithm, weights initializers, etc. However, all the compilation process and code writing were processed during the practical development of this thesis.

4.3.1. Topology and Architecture

Number of input Nodes

According to chapter 3, there are 9 predictors used to forecast the Iberian electricity market prices. Each variable/dimension of the input vector corresponds to an input neuron, making a total of 9 input. This particular set of neurons only propagates the signal into the first hidden layer, not performing any data transformation.

Number of output nodes

The number of output nodes is related with the dimension of the output vector, that in this case, is the daily average price of MIBEL's electricity. For each set of the input vector, it is expected to be obtained one value of the average daily price of electricity, which corresponds to one output node.

Number of hidden layers and neurons

The number of hidden layers and neurons can be subjective and hard to define, not following a strict rule. It is possible to use formulas to compute this number, or by trial-and-error until the best value is found. Given the literature review and evidence found during the practical implementation, two hidden layers were assigned for both neural networks, each one composed of nine hidden neurons. Figure 7 shows a visual representation of the neural networks' architecture used, the difference between the FFNN and LSTM is that the latter has a feed-back of information that is not represented in figure 7.

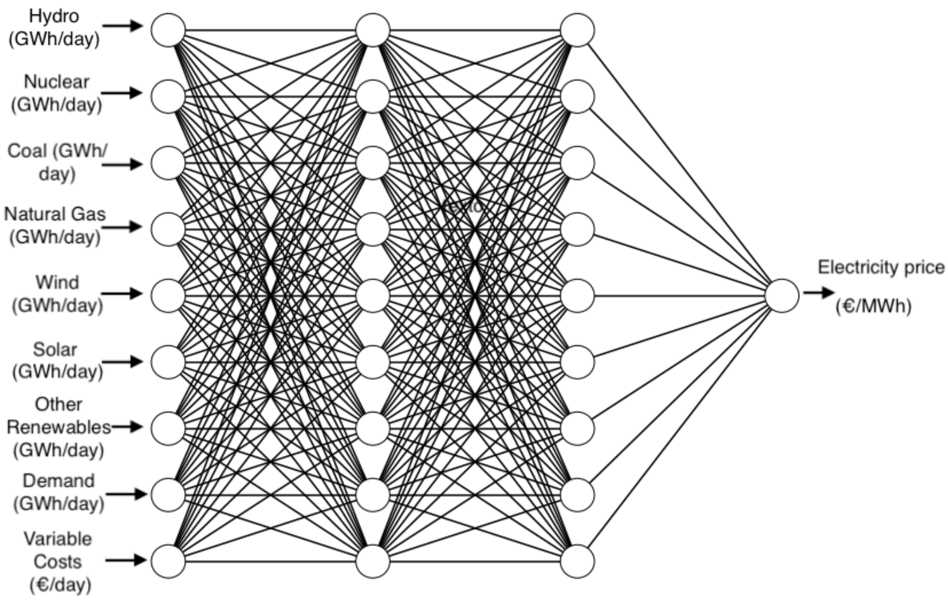


Figure 7: Schematic representation of the developed ANNs

4.3.2. Training

As explained before, training is the process of tuning the parameters (hyperparameters) in order to reach the optimal solution. The flexibility of neural networks is a huge advantage over other models; however, it can also be its main drawback. Not only is possible to have different architectures, such as Feedforward, Recurrent, Convolutional etc., but within each of those types it is possible to tune and adjust an enormous number of hyperparameters in such different ways [45,46]. One option to perform the tunning process is to try different combinations of the parameters values and evaluate which one provides the best accuracy. Another way, must more efficient, is to use a function from Sklearn library called GridSearchCV. This particular function explores the hyperparameters space optimizing the cost function within a cross validation model, presenting the value of each hyperparameter that minimizes the global error. During the practical component of this dissertation, all the parameters presented bellow were optimized using GridSearchCV.

Batch Size

Training data, in a general way, is composed by an enormous number of points that are used in the training process. Purely gradient descent methods use each individual data point to calculate the cost function's value, its respective gradient and the necessary tunning for the hyperparameters. As it is possible to understand this is hardly time-consuming and computationally demanding, as so, a good option to solve this problem is to use what is called as mini batch gradient descent. This method divides the training data in several subsets (mini batches), each one composed by "n" data points. In this case, instead of using individual points as before, the algorithm uses batches of data points to calculate the cost function’s value, its gradient and the necessary tunning for the hyperparameters. This procedure is much less time consuming and less computationally demanding.

The dimension of the batch size is also important for the algorithm’s solution. Big batch sizes can lead to underfitting and poor convergence and small batch sizes can lead to overfitting and biased algorithms. For this thesis the optimal number of data points composing each batch was found to be 30, meaning the neural network only calculates the cost function, gradients and weights updates, after processing 30 points of the learning data.

Epochs

This parameter states how many times the entire training data is passed through the algorithm during the training process. In this particular case the entire data set is passed through the algorithm 60 and 50 times for FFNN and RNN-LSTM, respectively.

Optimizer

Optimizers are algorithms used to tune the hyperparameters following certain rules, making different optimizers to correspond to different procedures in the optimization process. For this specific case, Adam optimizer was found to be the best approach for both neural networks, this algorithm computes adaptive learning rates and momentums for each parameter, i.e., parameters that highly influence the cost function are assigned with lower momentums and learning rates and vice-versa. This provides a levelized approach between the parameters, providing a smoother algorithm’s convergence [50,51].

Momentum is a feature of Adam’s optimizer, and can be explained as the inertia regarding the evolution of the parameter in the weight spade. It keeps track of previous steps done during the optimization process and avoids sudden changes in the optimization direction. It is helpful for complex cost functions, where the gradient is constantly changing. Without momentum if the gradient is constantly changing the path of optimization is also constantly changing, i.e., the parameter would be tuned in one direction and in the next step on another direction, not converging to a specific point. With the help of this feature, it is possible to keep track of previous steps and directions of optimization, so that the next step is calculated based on the new but also on previous gradients, providing a smoother convergence to the minimum.

Learning rate is described as the importance/magnitude of each step in the optimization process, they are usually higher in the early steps, providing a faster convergence rate, but its value starts to decrease when getting closer to the solution point, providing a smoother convergence to the minimum.

Weight Initializer

Weight initializer is responsible for assigning an initial value to each branch/weight of the neural network. There are several ways to initialize the weights, one that is widely used is known as “random uniform”, meaning the weights are initialized in a total random way. This procedure has some advantages over constant initialization, where the value for each branch is pre-defined. For the latter case, where the value for each branch is constant, is hard to know if the algorithm is trapped in a local minimum, since the convergence path is similar each time the network is trained. On the other hand, if the values are initialized in a random way, it means the path followed by the algorithm, towards the solution, in the weight space is different each time the neural network is initialized. If in the last case results are always similar each time the neural network is trained, it probably means that the algorithm is not trapped in a local minimum and it reaches the global minimum.

Activation Function

Both neural networks are assigned with linear activation functions in the first layer. This is a feature of this type of algorithms, since these neurons are only used to propagate the information to the hidden layers not performing data transformation.

For the FFNN case, all the remaining neurons were assigned with a Selu (Scaled Exponential Linear Unit) function. For the LSTM case, activation functions for each neuron are already predefined as shown in the previous figure 4.

Cost Function

As explained before cost function measures the magnitude of the error between the neural network’s output and the real/target value. The optimization process is highly dependent on this parameter, meaning that different functions represent different optimization procedures. In this case, the function that best fits the model was the root mean squared error. Table 5 summarizes all the information about hyperparameter optimization and its values.

Table 5: Hyperparameters Optimization values

Hyperparameter	Neural Network	
	FFNN	RNN-LSTM
batch_size	30	30
epochs	60	50
optimizer	Adam	Adam
cost function	root_mean_squared_error	root_mean_squared_error
weight_initializer	random_uniform	random_uniform
activation function	Selu	Sigmoid and Tanh

4.4. Conclusions

Chapter 4 provided a close look into the theory and practical implementation of neural networks algorithms. Initialization and training procedures were addressed, and a final model was constructed. The following step, model validation, will be addressed in chapter 5, evaluating model’s performance and the ability of generalize for new cases.

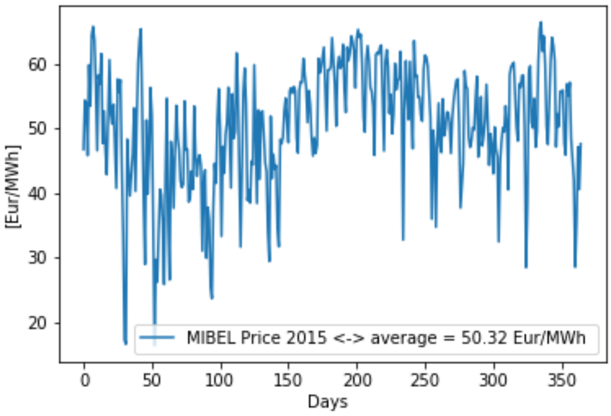
Chapter 5

Model Validation

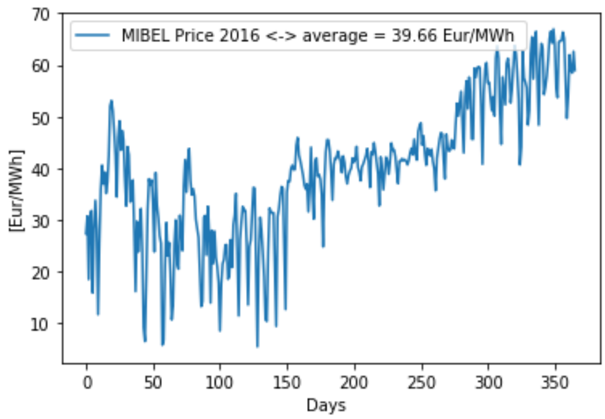
After model's construction and training, it is crucial to evaluate its accuracy when generalizing for new cases, this assessment is called model validation. To perform this task, it is required a data set composed of predictors and targets, so it is possible to quantify the error. For this thesis, the idea for the validation process consisted in predicting previous MIBEL prices and compare it with the real values. This chapter is divided in 3 sections. First section presents a visual comparison of the models' forecasts and real values; second section presents a detailed and numerical evaluation of their accuracy; third section presents a comparison between the models' and literature studies' accuracy.

5.1. MIBEL daily prices 2015-2019

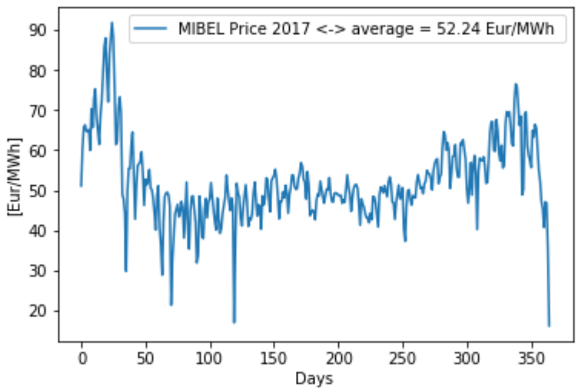
The validation procedure was conducted forecasting previous MIBEL's daily daily prices during an entire year, for the interval 2015-2019, and then compare the results with the real values. Figure 8 presents the real average daily electricity price distribution with respect to each individual year of the above-mentioned interval.



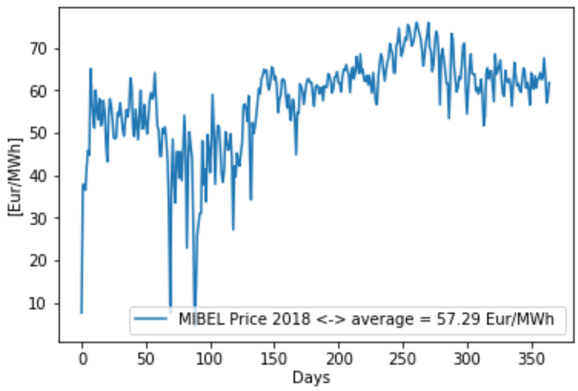
a) MIBEL’s average daily price 2015



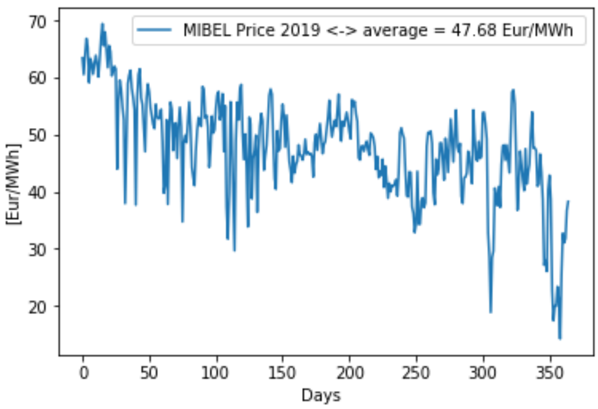
b) MIBEL’s average daily price 2016



c) MIBEL’s average daily price 2017



d) MIBEL’s average daily price 2018



e) MIBEL’s average daily price 2019

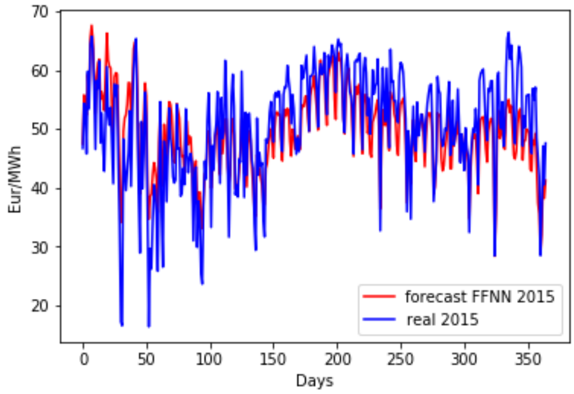
Figure 8: MIBEL's Average Daily Prices for the period 2015-2019

5.2. Forecasting Results and Error analysis

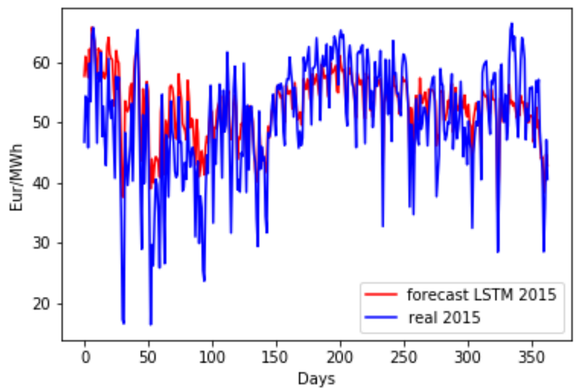
5.2.1. Real price vs Models' forecasts

With information about MIBEL's generation, demand and variable costs for the interval 2015-2019, it was possible to run the models, make yearly predictions and compare results with real electricity prices for the respective years. A critical point to perform a good model validation is when forecasting a specific year, the model cannot have access to data regarding that year in the training part. For example, if one wants to forecast the year 2015 then, for the learning data it is only possible to use the years from 2016 until 2019, the same reasoning happens for the other years.

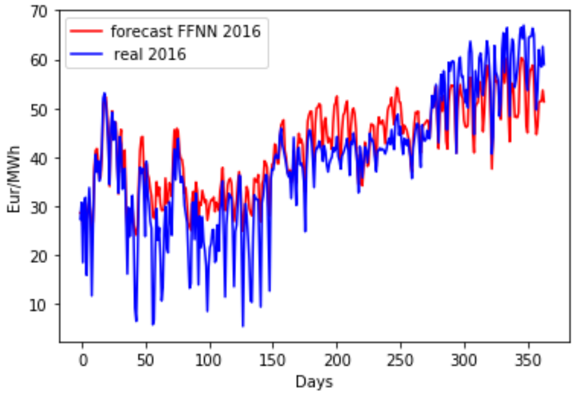
Figure 9 presents a visual comparison between the real and forecasted daily electricity price for the above-mentioned interval using both algorithms, FFNN and LSTM.



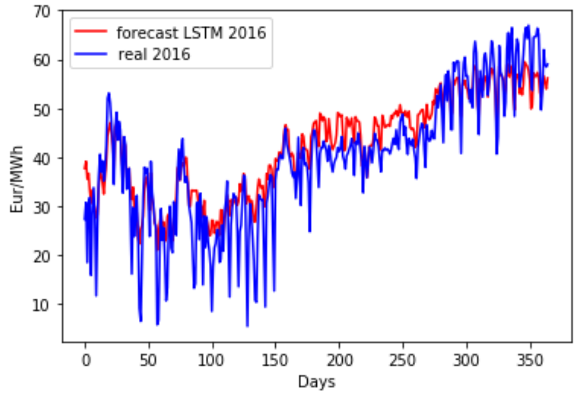
a) Real and FFNN forecasted MIBEL prices for 2015



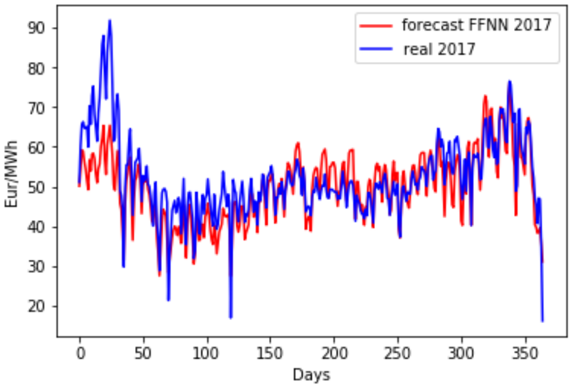
b) Real and LSTM forecasted MIBEL price for 2015



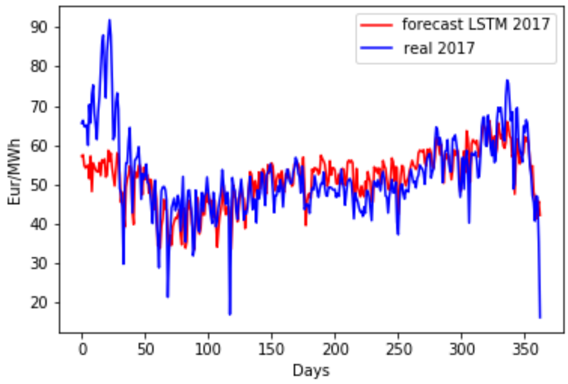
c) Real and FFNN forecasted MIBEL price for 2016



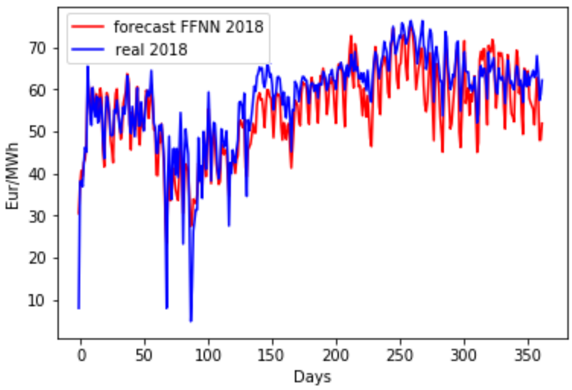
d) Real and LSTM forecasted MIBEL price for 2016



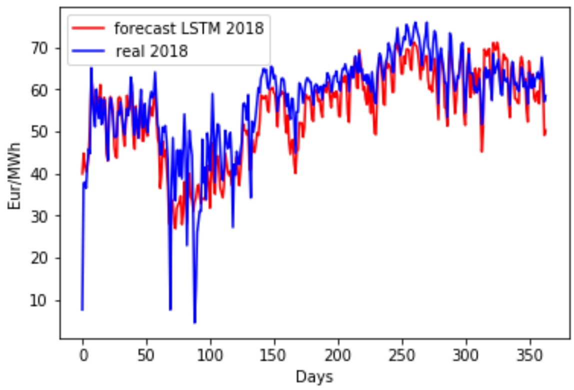
e) Real and FFNN forecasted MIBEL price for 2017



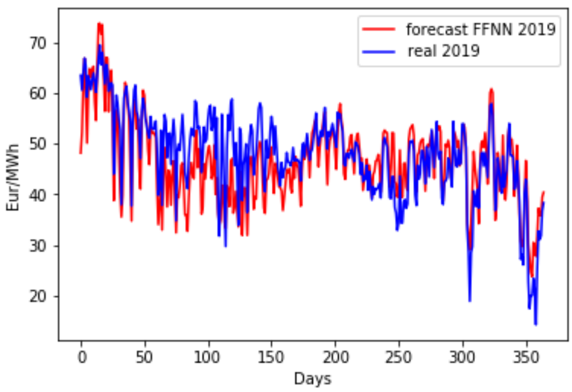
f) Real and LSTM forecasted MIBEL price for 2017



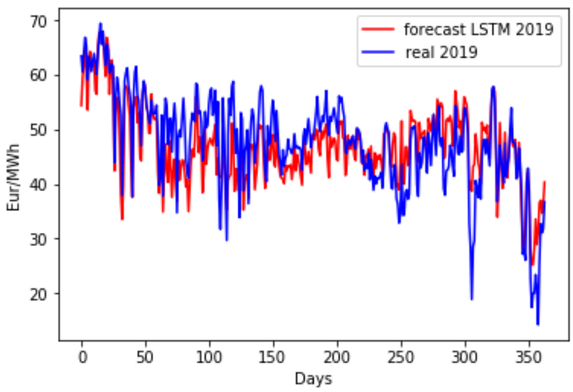
g) Real and FFNN forecasted MIBEL price for 2018



h) Real and LSTM forecasted MIBEL price for 2018



i) Real and FFNN forecasted MIBEL price for 2019



j) Real and LSTM forecasted MIBEL price for 2019

Figure 9: Real and Forecasted Daily Electricity Prices using both algorithms, for the period 2015-2019

As it is possible to observe, both algorithms provide similar results and are able to predict the main pattern of electricity prices. At the same time, it is clear that they both present some limitations forecasting days with singularities, such as price spikes or drops. The reason for such limitation will be explained in detail on the next sub-chapter about the numerical results.

5.2.2. Numerical Results

After the previous visual analysis, which can provide an overview over the models' ability to forecast, it is crucial to make a numerical evaluation. Besides that, it is also important to compare the models with a benchmark, in this case the Persistence method. Results of such analysis, using MAPE and MAE indicators, are presented in table 6.

Table 6: Yearly forecasting error using FFNN, LSTM and the Persistence methods.

Year	FFNN		LSTM		Persistance	
	MAPE(%)	MAE(Eur/MWh)	MAPE(%)	MAE(Eur/MWh)	MAPE(%)	MAE(Eur/MWh)
2015	10.63	4.93	10.49	4.53	13.6	6.14
2016	21.32	5.11	18.83	4.43	17.8	4.87
2017	8.95	4.72	8.01	4.33	8.7	4
2018	11.52	4.63	11.03	4.55	10.5	4.14
2019	10.68	5.03	10.52	4.32	11	4.49

Results of the ANN's simulations show MAPE values between 8% and 11,5 % corresponding to MAE values between 4,32€/MWh and 5,11€/MWh, except for 2016 which presents higher MAPE values. The error per se is not indicative of the models' accuracy, it is important to compare it with the benchmark. When making such comparison, an interesting point arises because they present similar results. The second interesting point is the high MAPE value presented by both methods in 2016. Apparently, this particular year is providing a bigger forecasting error with a relatively higher MAPE value, 21,32% and 18,83% for FFNN and LSTM algorithms, respectively. The two points will be analyzed in detailed in the next two sub-sections.

5.2.2.1. Benchmark Comparison

Intuitively, one could say that ANNs should outperform the benchmark (persistence method), since they are more complex models using explanatory variables to describe the process. However, such similarity can be justified by the ANNs' construction, which tries to simulate electricity prices using variables on a daily basis while the real market operates on an hourly basis. For sure this is a big limitation in terms of accuracy, and it is not possible to overcome it due to the lack of hourly data for Spain. The second reason is the variables used by the ANNs. In [2] it is provided a set of 8 variables describing the energy mix for 2030, demanding ANNs to be previously trained using those same variables/inputs. This means the models are required to fully describe electricity prices' behavior using nothing but the 8 given explanatory variables. As it was possible to observe in the previous visual analysis, this imposes some limitations specially in times of high variability and price singularities.

To prove the previous statement, and instead of only having generations and demand as models' inputs, the market price of the last "n" days was also introduced as explanatory variable. Having conducted several experiences, it was concluded that the optimum number of previous days, that conducts to the minimum error, is equal to 5. This means the new models are now using demand, generation and variable costs from day "n" but also electricity prices from day "n-1, n-2, …, n-5" to predict electricity prices at day "n". To distinguish from the previous cases these new models will be called "FFNN 5 days" and "LSTM 5 days". The forecasting procedure and interval was the same as used in the FFNN and LSTM algorithms. Results of such analysis are also compared with the benchmark and results presented in table 7.

Table 7: Yearly forecasting error using FFNN 5 days, LSTM 5 days and the Persistence methods.

Year	FFNN 5 days		LSTM 5 days		Persistance	
	MAPE(%)	MAE(Eur/MWh)	MAPE(%)	MAE(Eur/MWh)	MAPE(%)	MAE(Eur/MWh)
2015	8.82	3.82	8.51	3.67	13.6	6.14
2016	14.3	3.51	13.6	3.43	17.8	4.87
2017	7.14	3.66	6.84	3.54	8.7	4
2018	8.72	3.34	8.56	3.21	10.5	4.14
2019	8.54	3.89	8.45	3.53	11	4.49

Results for the new models' simulations show MAPE values between 7% and 9% corresponding to MAE values between 3,34€/MWh and 3,89€/MWh, except for 2016 which presents a MAPE value around 14%. It is also possible to observe an overall error decrease using "FFNN 5 days" and "LSTM 5 days" when comparing with FFNN and LSTM. At the same time, an outperform of the new models when comparing with the benchmark is observed, which did not happen before. This means that having previous daily electricity prices as an explanatory variable is important to the model, but at the same time, it is not a feasible solution to predict 2030's electricity prices, because it is not possible to have access to such information for 2030.

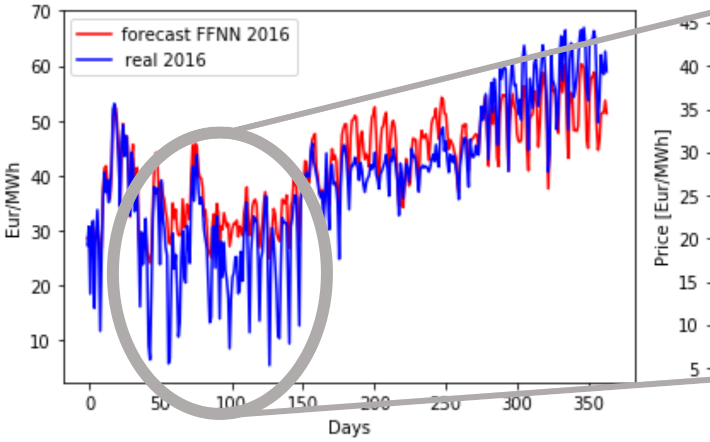
In short, this analysis shows that previous models, FFNN and LSTM, could be improved using other explanatory variables, but at the same time, its main purpose of forecasting the 2030's electricity prices would be compromised. On the other hand, it is not possible to just use the Persistence method to assess electricity prices for 2030. Mainly because in this model it is not possible to reflect the new energy mix regarding 2030, which will definitely affect the market prices. FFNN and LSTM models' accuracy is not perfect and is not even better than the benchmark. But based in results from table 6, they are able to describe the market prices relatively well and represent the only viable solution to be used in the electricity prices assessment for 2030.

5.2.2.2. Relative Error 2016

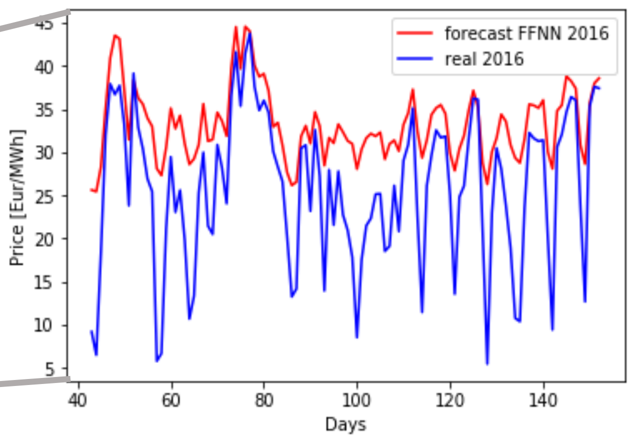
The second interesting point is the high MAPE value presented by both methods in 2016. Apparently, this particular year is providing a bigger error with a relatively higher MAPE value, 21,32% and 18,83% for FFNN and LSTM algorithms, respectively. In fact, this is not true, because when looking at the absolute error (MAE), present in table 6, results are very similar to the rest of the years. To understand such high MAPE value, it is important to remember that this indicator is calculated with the quotient of the error by the target/real value. And this particular year was somehow atypical, with several days registering electricity prices close to zero and an enormous price variability, causing unusual price singularities, which leads to extremely high MAPE values.

The following paragraphs will introduce a detailed MAPE analysis, in order to assess the reasons that lead to such high values for 2016 when compared with the rest of the years. The analysis will be comparing the year with the highest and the lowest MAPE values, 2016 and 2017, respectively, so it is possible to find the differences between them. In fact, observations and conclusions drawn for 2017 are extensible to the rest of the years, except 2016, given the similarity of MAPE values between them. This analysis is only performed for the FFNN algorithm, but it is also extensible for the LSTM algorithm, given the similarity of results between them, as demonstrated before

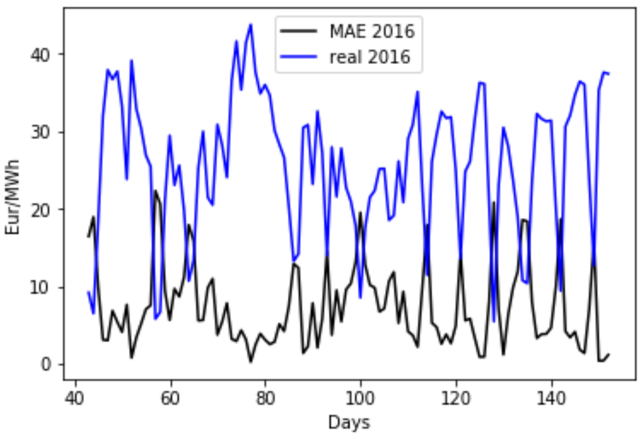
Figure 10 provides a useful understanding and justification of the high MAPE value registered for 2016. Figure 10 a) presents the forecasted values versus the real price for 2016. Figure 10 b) presents a zoom-in of the forecasted values versus the real price during the period of extreme MAPE values. Figures 10 c) and 10 d) provide information about MAPE and MAE values for that same period, respectively.



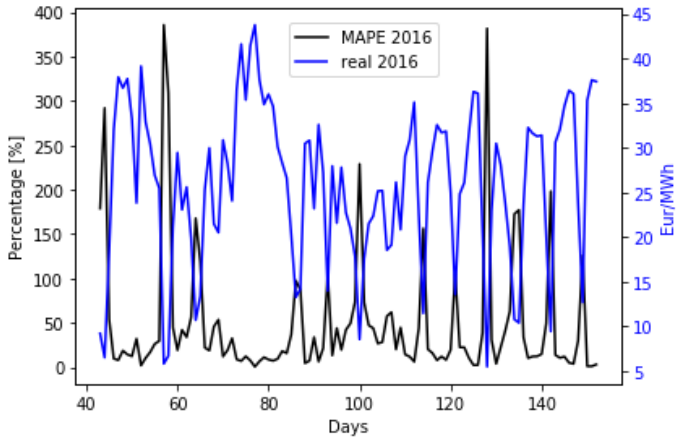
a) Real and FFNN forecasted MIBEL price for 2016



b) Sub-period of 2016 under evaluation



c) MAE values for the sub-period under evaluation



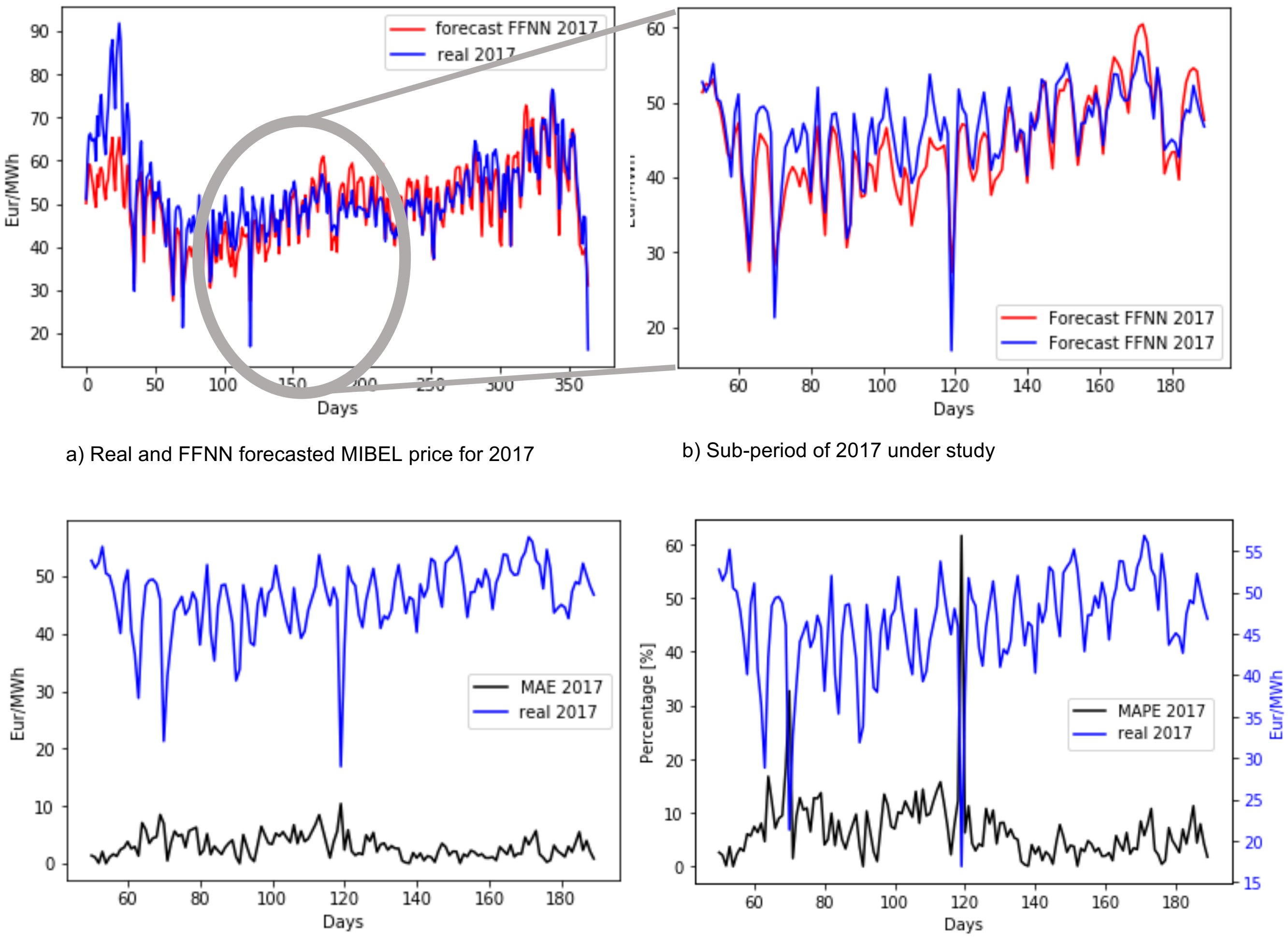
d) MAPE values for the sub-period under evaluation

Figure 10: MAPE Analysis for 2016

Analyzing the previous figures, it is clear to understand the reasons why 2016 has such a high

MAPE. Firstly, because for the period illustrated in figure 10 b), an unusual variability and price singularities is presented, which imposes limitations to the models' accuracy, as explained before. Secondly and most important, that same period registers several real electricity prices close to zero, which leads to a sharp increase in the MAPE values, as proven in figure 10 d). As a consequence, the extremely high MAPE values registered during that period, will increase the overall MAPE value for that particular year. The observed evidence reinforces, once again, the idea that the model is provided with sufficient information to describe the main pattern in electricity prices but not as detailed and as refined information, so it is able to describe the singularities present in the data.

On the other hand, 2017 has the lowest MAPE of the validation set, for both algorithms, FFNN and LSTM. This can be explained with the price stability for that year and the low number of price singularities. Figure 11 provides a useful understanding and justification of the low MAPE value registered for 2017. Figure 11 a) presents the forecasted values versus the real price for 2017. Figure 11 b) presents a zoom-in of the forecasted values versus the real price, providing a more detailed evaluation. Figures 11 c) and 11 d) provide information about MAPE and MAE values for that same period, respectively.



a) Real and FFNN forecasted MIBEL price for 2017

b) Sub-period of 2017 under study

c) MAE values of the sub-period under study

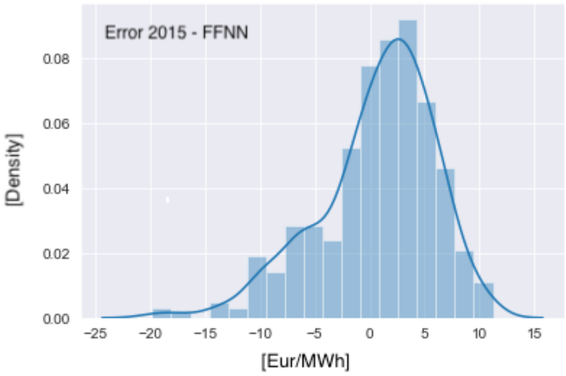
d) MAPE values of the sub-period under study

Figure 11: MAPE Analysis for 2017

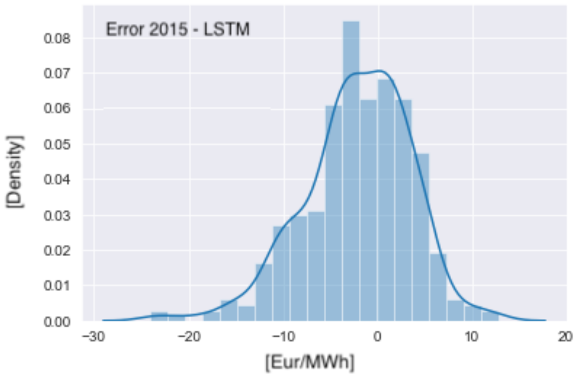
Analyzing the previous figures, it is clear to understand why 2017 has the lowest MAPE. Price stability with almost no price singularities, enables the model to fully describe the process under study and provide quality results. At the same time, real electricity prices are not close to zero as in 2016, which provides a small and stable MAPE value for the almost entire year. Conclusions drawn for 2017 are extensible to the rest of the years apart from 2016.

5.2.3. Statistical analysis of the error

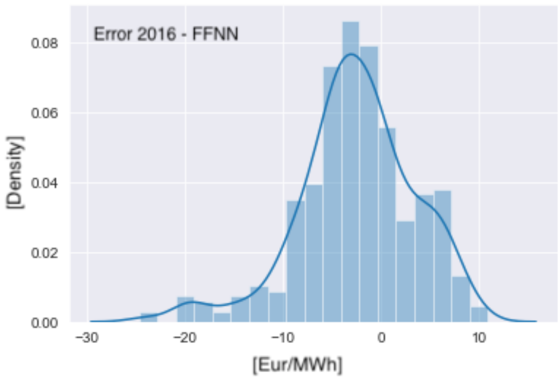
In this part a statistical analysis regarding the error was conducted. Results are presented in figure 12, and statistical indicators such as the mean (μ) standard deviation (σ) and median (M) in table 8.



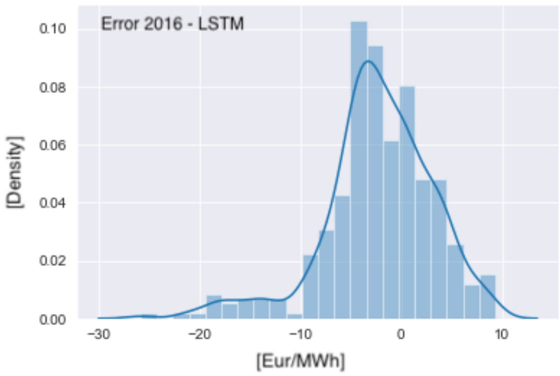
a) Statistical error distribution of FFNN's forecast for 2015



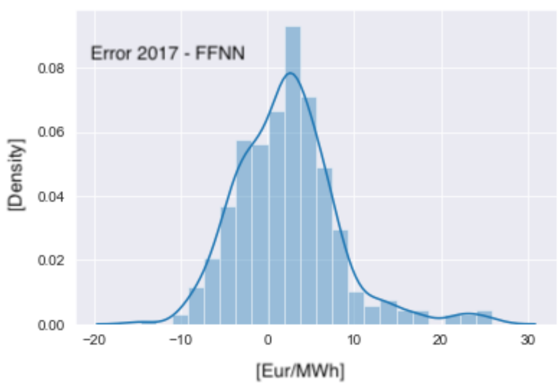
b) Statistical error distribution of LSTM's forecast for 2015



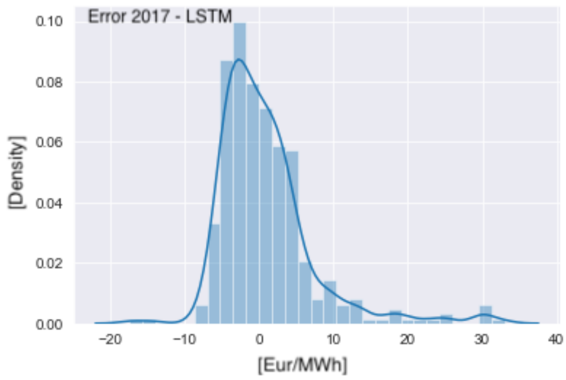
c) Statistical error distribution of FFNN's forecast for 2016



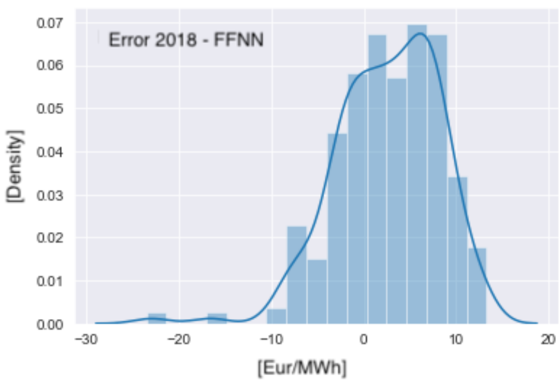
d) Statistical error distribution of LSTM's forecast for 2016



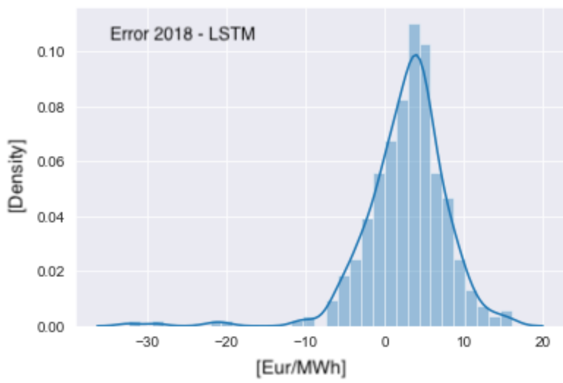
e) Statistical error distribution of FFNN's forecast for 2017



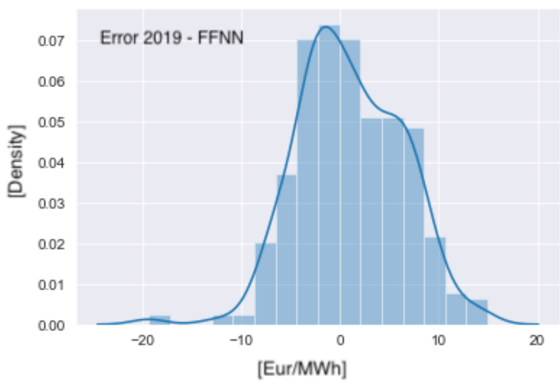
f) Statistical error distribution of LSTM's forecast for 2017



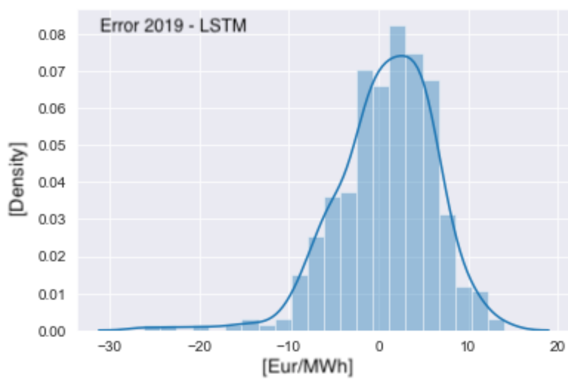
g) Statistical error distribution of FFNN's forecast for 2018



h) Statistical error distribution of LSTM's forecast for 2018



i) Statistical error distribution of FFNN's forecast for 2019



j) Statistical error distribution of LSTM's forecast for 2019

Figure 12: Statistical Error Analysis for FFNN and LSTM forecasts

Table 8: Values of the statistical error indicators, μ, σ and M, for both algorithms.

Year	FFNN			LSTM		
	μ (Eur/MWh)	σ (Eur/MWh)	M(Eur/MWh)	μ (Eur/MWh)	σ (Eur/MWh)	M (Eur/MWh)
2015	0.67	5.29	1.68	-0.69	5.48	-1.45
2016	-2.53	6	-2.52	-2.51	5.47	-2.49
2017	2.25	5.83	2.07	0.94	6.24	-0.26
2018	2.6	5.67	3.22	2.46	5.16	3.03
2019	0.99	5.26	0.7	0.49	5.15	0.88

As it is possible to observe, statistical error distributions are lookalike for both neural networks, as expected given all the previous evidence. In a general way, it is possible to say errors are somehow normally distributed, with mean values close to zero. This information provides some confidence and security about the model. If instead errors were all positive or all negative, it would mean the neural network was probably biased or overfitted regarding some parameter(s).

The errors have mean values close to zero, a standard deviation between 5 and 6 [Eur/MWh] and Median values similar to μ, for both algorithms. If the error was a perfect normal distribution, which is not, then around 95 % of the error values would be in the interval [$\mu - 2\sigma$, $\mu + 2\sigma$], which for a standard deviation between 5 and 6 [Eur/MWh] represents a relatively high dispersion around the mean. Such dispersion is not ideal but according to the optimization process conducted before, those are the best obtained results.

5.3. Error Comparison

After comparing the 2 models and the benchmark with each other, and with a posteriorly detailed analysis on the error, it is important to compare results with other studies on the same topic. As explained in chapter 2, literature about this topic is extremely scarce, and studies with similar conditions as the model developed in this dissertation, are even scarcer. Three different studies were found for comparison purposes. All of them follow the same methodology, which is equal to the one implemented during this dissertation. First step is to identify variables that can describe electricity prices; second step is to train the model using those same variables; third step is to validate the model by comparing forecasting results with real values.

Azadeh, et. al. [33] compared 3 ANN Algorithms with 1 Conventional Linear Regression (CLR) and with 7 Fuzzy Linear Regression (FLR) models to predict electricity price for Iran in the long run. Electricity price is described using variables such as electrical demand, generation technologies' efficiency, inflation and fuel prices. Available data, provided in a yearly basis, ranges from 1972 up to 2007 and was divided in training and validating years. The interval used for the training part was [1972, 2007$-n$] and the interval used for the validation part was]2007$-n$, 2007], where n represents the number of forecasted years. Several experiments were performed forecasting from 7 years up to 18 years of the data set, i.e., $n \in$ [7,18]. Best results were obtained for shorter forecasting periods, 7 or 8 years, and models' accuracy was evaluated with the MAPE indicator, calculating the quotient of the error by the real electricity price. The best MAPE values are 11,9%,12,4% and 13,4 % for the CLR, FLR and ANN algorithms, respectively.

Yousefi, et.al. [32] developed a model using machine learning techniques to forecast up to 5 years-ahead of monthly average electricity prices in the California's market. The used predictors to model the electricity prices were: Natural gas used in power sector, electricity generated by coal, net electricity generation, net electricity imports, natural gas consumed by industrial sector, gross domestic product and renewable generation. Four different models, Logistic Regression (LR), Support Vector Machine (SVM), K Nearest Neighbor (KNN) and Random Forest (RF), were evaluated and compared with each other's. Models were trained with the variables above-mentioned for the period between 2001 and 2014. Models' validation consisted in predicting the monthly average electricity prices for California's market between 2014 and 2017 using MAE indicator, i.e., calculating the difference between the real and forecasted electricity prices. Results for the best 4 models are: LR with MAE values of 11,68 €/MWh; SVM with MAE values of 16,58 €/MWh; KNN with MAE values of 9,68 €/MWh; RF with MAE values of 10,86 €/MWh.

Kotur, et. al. [31], used ANN to forecast electricity prices in the British market. The author used physical properties and inputs from the real electrical system, like the generation from convectional and non-conventional technologies, imports and exports, demand and also seasonal and daily time indicators, to describe electricity price's behavior. The article does not specify the years used for the learning and validation data set; it is only known that the validation period has an hourly resolution composed of 15000 samples, which corresponds approximately to 2 years. Model's accuracy is evaluated with the MAPE indicator, calculating the quotient of the error by the real electricity price. Such model produces a MAPE value of 12% and forecasting results are presented in figure 13. It is possible to state that results are somehow similar to the ones obtained in this thesis. The model is totally capable of describing the main behavior of electricity prices but has some difficulty dealing with singularities such as price spikes or drops. This is again justified by difficulty in finding variables that can describe electricity prices in the long run and at the same time provide the maximum detail and price resolution.

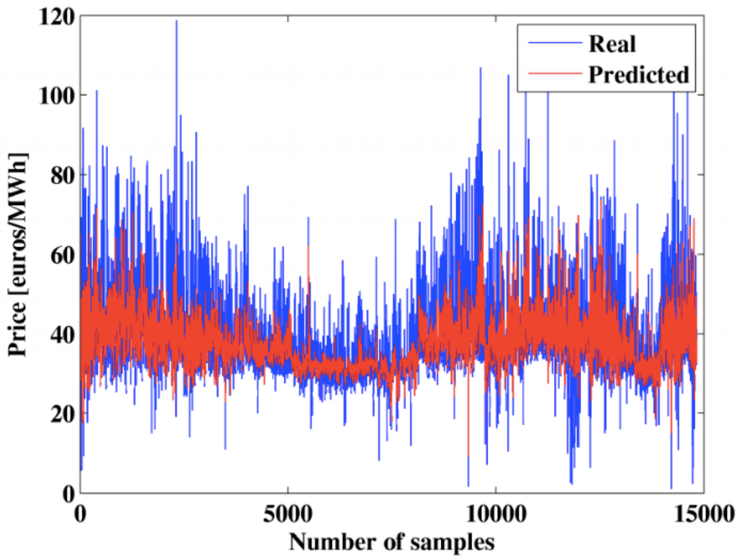


Figure 13: Real versus Forecasted Hourly Electricity Prices. Kotur, et. al. [31]

Table 9 synthetizes the above information presenting the MAPE and MAE valuess corresponding to each study and to this thesis.

Table 9: Error comparison between dissertation's and literature's results

	Thesis	Kotour. et. al. [31]	Yosefi. et. al. [32]	Azadeh. et. al. [33]
MAPE	8% - 11.5%	12%	-----------------------	11.9 % - 13.4 %
MAE	4.32 €/MWh - 5.11 €/MWh	-----------------	9.68 €/MWh - 16.58€/MWh	------------------

Even though the number of studies for comparison is reduced, by analyzing the results it is possible to state that the developed models in the present dissertation show reasonable values of accuracy, that are in line with the presented results in the literature. Again, long term forecasts correspond in general to higher error values, because the time scale is bigger and is harder to choose variables that can describe electricity price's behavior for such long periods with maximum accuracy. Apart from that, electrical markets are based in other factors that are not being considered in the models, such as bidding strategies, regulatory policies, inter-country decisions and other variables that impose difficulties in the forecasting process.

5.4. Conclusions

During this chapter a detailed error analysis was conducted, concluding that the developed models, FFNN and LSTM, are able to forecast and generalize for new data samples. Even though their accuracy is not better than the benchmark method, it is the only viable way to assess electricity price's behavior for 2030. It was also proved that the error is random, meaning the models are not biased or overfitted. Finally, a comparison with other studies was conducted and the model's accuracy verified with similar values of error.

After model's validation next step is to use it for real forecasting purposes, having the security that it will produce reliable results. This topic will be addressed in the next chapter.

Chapter 6

Results and Discussion

Posteriorly to construction, training and validation, the models are in proper conditions to be used for forecasting purposes, assuring a good confidence level and reliability in the obtained results. This chapter is divided in two sections: first section explains the construction of the models' predictors/inputs regarding 2030; second section presents the simulated results for 2030 with a detailed discussion of the same.

6.1. Predictors

As explained in previous chapters, predictors are the variables/inputs used to run the models (FFNN and LSTM), and in that way obtaining forecasting results. Data provided in [2], regarding 2030's MIBEL energy mix is presented on an annual basis, Table 10, not having a daily resolution as the previous data used for the models' training. It is required a predictors' conversion from an annual basis to a daily basis, so the model can be properly applied. Besides that, information about 2030's variable costs (fuel + CO_2 costs) is not presented in [2] and as a required model predictor, an estimation of its future value is also needed. All these subjects will be addressed in this section.

Table 10: 2030's energy mix simulation, Pereira [2]

Variable	2030 [TWh]
Demand	323.12
Hydro	101.76
Wind	123.81
Solar	82.93
Other Renewables	13.29
Natural Gas	25.14
Nuclear	26.21
Coal	0

6.1.1 Generation and Demand Patterns for 2030

Given the previous explanation, generation and demand information for 2030 needs to be converted from an annual basis [GWh/year] to a daily basis [GWh/day]. This means it is required to be created a future yearly distribution concerning demand and generation predictors. The best solution was to capture past patterns of such variables and reproduce them for 2030, i.e., assuming that today's predictors' distribution will be similar in 2030. This assumption is fairly true, because the biggest changes for the future will be in the overall values of production and demand but not in their pattern. For example, it is expected that in 2030 hydro generation is also maximum during the winter period and that solar generation is also maximum during the summer period, as it happens today. The difference, as stated before, will be in the overall values of production and demand, and those are totally different. To obtain previous patterns one could use a single year of the interval 2015-2019 or make an average concerning all the years composing that same interval. The latter approach is preferred over the other, because any unusual event that may appear in one year is disguised in the average of the interval.

For that purpose, an "average year" was created regarding the interval from 2015 until 2019, i.e., day "n" of the "average year" was calculated through a mean of the corresponding days "n" of the years in the above-mentioned interval, with respect to each individual predictor/input. After computing the average year, data normalization is required, dividing each individual predictor's daily value by its yearly total. For example, hydro normalization was conducted dividing each day of the "average year", concerning hydro production, by its total annual production. The same procedure was applied for the remaining predictors and the final result is a "normalized average year" [$\frac{GWh}{GWh \cdot day}$]. To obtain the daily distribution for 2030, it is only required to multiply the normalized predictors by the correspondent yearly value for 2030, provided in Table 10. The final result corresponds to the pattern of each individual predictor/input thorough 2030. Figures 14 to 20 show the yearly distribution of demand and generation variables/predictors with respect to 2030.

Electrical Demand, figure 14, follows a typical pattern with consumption spikes during periods of extreme temperatures, winter and Summer, due to an additional energy requirement for heating and cooling. And also, valley periods during mild temperatures seasons, Autumn and Spring.

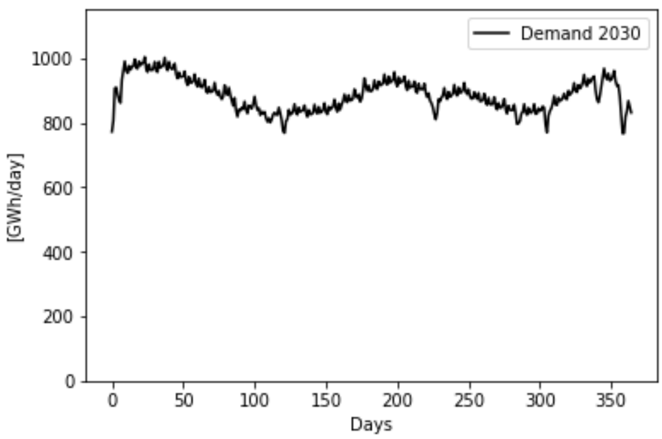


Figure 14: 2030's Daily Demand

Hydro generation, figure 15, presents its maximum production during wintertime, for obvious reasons, and also in the early Spring days, since reservoirs have stored water during the rainy season and rivers still have considerable water flows. During the summer period hydro generation goes to minimum levels, mainly due to the lack of river's water flow and also the rationing of reservoirs' hydro resources. In the end of October/beginning of November with the initial period of the rainy season, hydro production starts to increase.

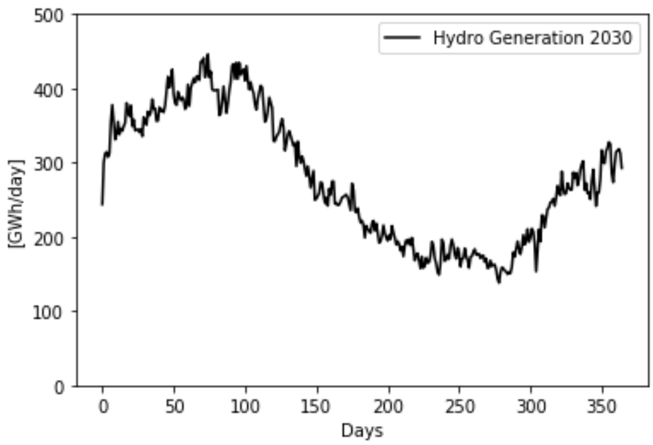


Figure 15: 2030's Daily Hydro Generation

Wind generation, figure 16, presents a more random pattern when compared with the other cases, consecutive days can present extremely different values of production. At the same time, it is also possible to observe a higher production during winter and autumn seasons when, in a general way, higher wind speeds are recorded and for longer periods.

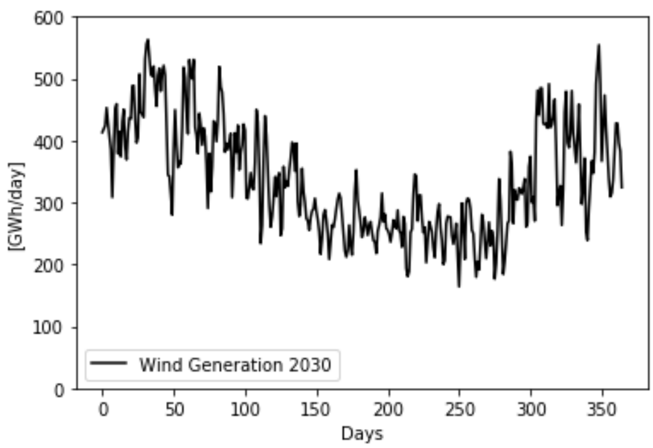


Figure 16: 2030's Daily Wind Generation

Solar generation, figure 17, follows the typical pattern associated to such technology. Constant increasing production from the end of the winter until the summer, when the maximum generation is achieved. And constantly decreasing production from the end of summer until the winter, when the minimum generation is verified. This happens for obvious reasons, during Summertime the sky is clearer, irradiation is bigger, and is verified the maximum number of sun light hours. During wintertime the opposite happens with cloudier sky, lower irradiation and is verified the minimum number of sun light hours.

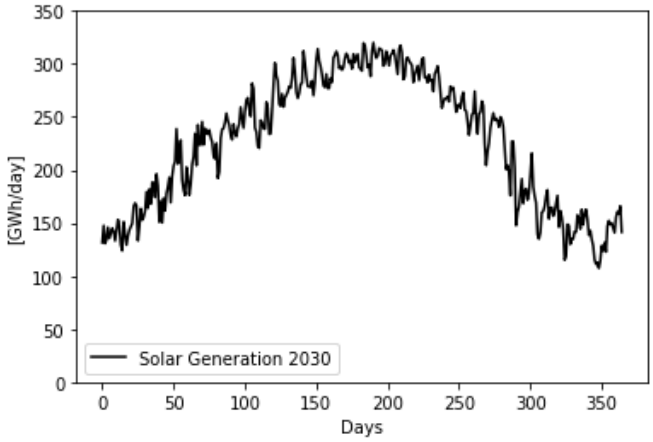


Figure 17: 2030's Daily Solar Generation

Natural gas' distribution, figure 18, is not uniform throughout the year and being the only fossil fuel source in the market, it is highly dependent on renewables' electricity production. During periods of high renewable production Natural Gas' production is low and vice-versa. The yearly distribution of such technology will be addressed in more detail later on this chapter, so as its relationship with renewable generation and electricity prices.

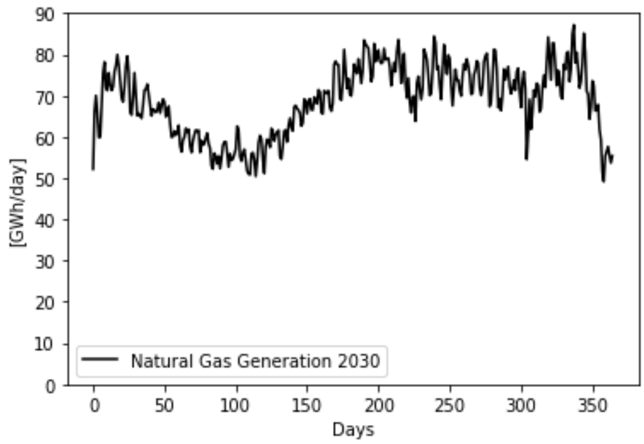


Figure 18: 2030's Daily Natural Gas Generation

Other renewable generation was previously assigned into the variable “other renewables”, as explained in chapter 3, so the pattern of this technology, figure 19, is equal to the previous pattern of “other renewables” in the electrical market.

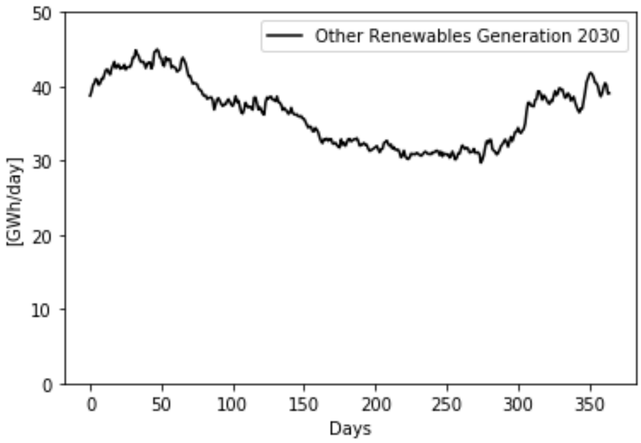


Figure 19: 2030's Daily Other Renewables Generation

In a general way, nuclear generation pattern is quite stable during several days, and not as unstable as the one presented in figure 20 for 2030. But since the obtained results were computed with the average of 5 years (2015-2019), it is not possible to have a constant pattern during several days as it would be for a single year. This irregular pattern is not critical to the model because, as seen before, the influence of nuclear technology in electricity price is small.

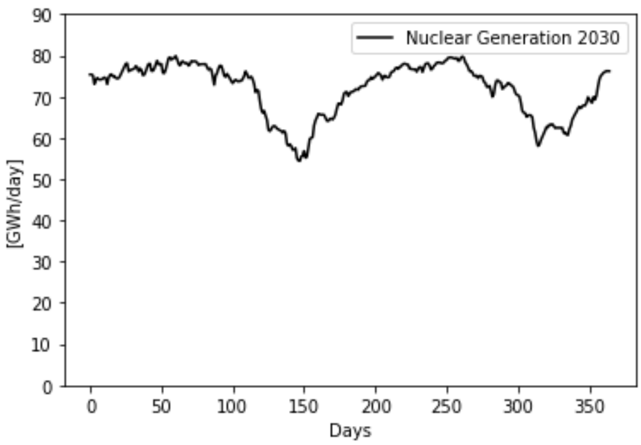


Figure 20: 2030's Daily Nuclear Generation.

6.1.2 Fuel Costs 2030

Observing table 10, that shows the 2030's energy mix, it is possible to observe that coal technologies have a null production, meaning that fuel costs will only be assigned to natural gas technologies. Those costs will be computed the same way as done for previous years (2015-2019), using the values of technologies' efficiencies, daily productions and also the unitary prices of natural gas. The values of the technology's efficiency is assumed constant and equal to the one used for previous years. The daily generation of natural gas technologies was already explained and computed in section 6.1.1. As so, it is only required information about natural gas' prices for 2030, which can be found in Statista. According to the provided information, this study uses values of 6€/mmBTU for 2030's natural gas prices. Having all the above-mentioned information it is possible to compute the daily fuel costs with respect to 2030.

6.1.3. CO2 Costs

For previous years (2015-2019), and as explained in chapter 3, the total daily emissions were computed using the daily "emission factor" provided by REE. The daily emissions cost was then computed multiplying the total daily emissions by the unitary emissions cost. For 2030 this emission factor is not available, it is required to make a forward-looking trying to estimate its value. The idea was to separate and quantify, for previous years, the amount of emissions from coal and from natural gas technologies. Posteriorly, it was created a "natural gas emission factor", dividing the total emissions by the total electricity generated, only concerning natural gas technologies, for the period 2015-2019. The resulting factor, with the value of 0.448 ton.eq.CO2/MWh_{NG}, shows the amount of emissions created per MWh of electricity generated using natural gas. With the "natural gas emission factor" and the daily fossil fuel electricity generation for 2030, it is possible to compute the total daily emissions. Posteriorly, the daily cost was calculated multiplying the total daily emissions by the unitary emission cost of 35 €/ton.eq.CO2 for 2030, provided in [52]. During this process it is assumed that natural gas technologies' efficiency is the same in the period of 2015-2019 as it is in 2030. Figure 21 presents the daily variable costs (fuel + CO2) for 2030.

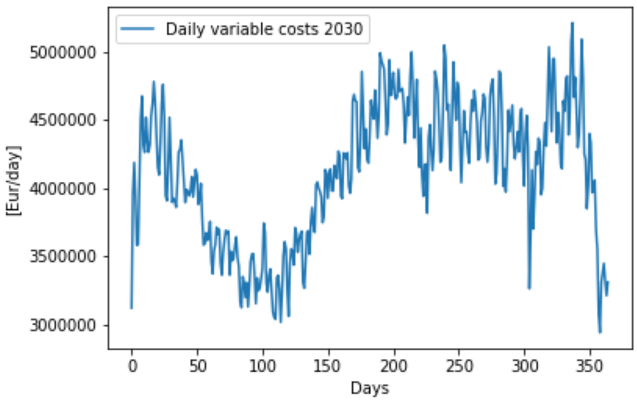


Figure 21: 2030's Daily Variable Costs

6.2. Simulation Results

Having described, on a daily basis, all the required models' predictors for 2030, it is possible to feed the models and obtain forecasting results.

This analysis is divided in two parts. In the first part, it is assessed the annual average of the simulated electricity prices for 2030. And in the second, it is assessed the pattern of the simulated electricity prices for 2030.

6.2.1. Annual average electricity price for 2030

With this analysis it is possible to assess the general behavior of electricity prices for 2030, i.e., how the new energy mix affects its overall values. Table 11 presents the average of the forecasted electricity prices for 2030 with respect to both models, FFNN and LSTM.

Table 11: Average of the forecasted prices for 2030

Neural Network	Average Price 2030 (€/MWh)
FFNN	22.94
LSTM	25.32

Looking at the simulated results it is possible to observe a slightly difference, of approximately 2,38€/MWh, in the annual average price between the two algorithms. Such difference is not relevant because both values are of the same order of magnitude, and they both provide the same information.

Results show a general drop in the average price for 2030 when compared with any year of the period 2015-2019, as shown in figure 8. For example, the last year of that interval, 2019, has a mean price of 47,68€/MWh, which is almost the double when compared with 2030's average price. The observed reduction effect can be justified by the highly increase in electricity renewable production and the decrease in fossil fuel electricity generation for 2030. Table 12 presents the relative variation, with reference to 2019, of each technology's yearly production.

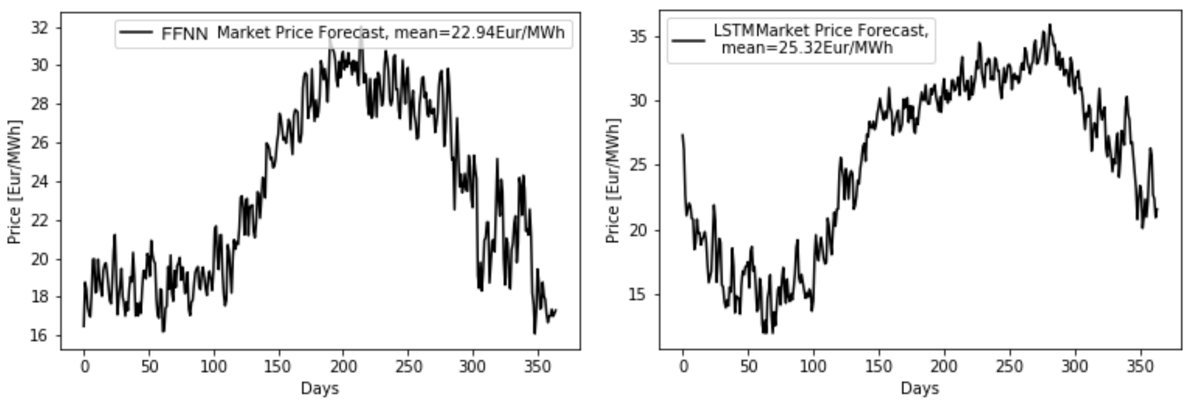
Table 12: Relative Variation of technologies' yearly generations from 2019 to 2030

Technology	2019 [TWh]	2030 [TWh]	Relative variation
Hydro	37.162	101.76	174%
Wind	67.64	123.81	83%
Solar	10.273	82.93	707%
Other Renewables	4.673	13.29	184%
Coal	17.845	0	-100%
Natural Gas	109.718	25.14	-77%
Nuclear	55.824	26.21	-53%

It is clear that renewable generation will highly increase its share on the electrical market, and fossil fuel generation will be drastically reduced, with coal technologies presenting null production. For 2019 the amount of electricity originated in renewable sources was around 39% of the total generation, for 2030 that number rises up to 86%. The biggest investment goes to solar technologies that should increase its production by 707% when compared with 2019. The effect of such drastic change in the energy mix is reflected in the overall decrease of electricity prices. This is coherent with findings in chapter 3, where is stated that an increase in renewable electricity production, with null variable costs, tends to decrease market prices since it is replacing fossil fuel technologies with high marginal costs.

6.2.2. Annual electricity price distribution for 2030

After the annual average electricity price analysis, it is important to assess its behavior throughout the year and understand if the general pattern differs or not from todays', and if it does, why it happens. For that purpose, it is presented in the following figures the simulated prices for 2030, and also its relationship with renewable and non-renewable generation. Figure 22 provides an overview of the forecasted yearly price distribution for 2030 with respect to both algorithms, FFNN and LSTM respectively.

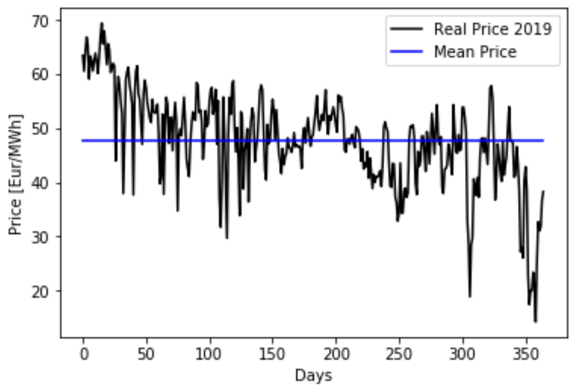


a) FFNN simulated yearly price distribution for 2030 b) LSTM simulated yearly price distribution for 2030

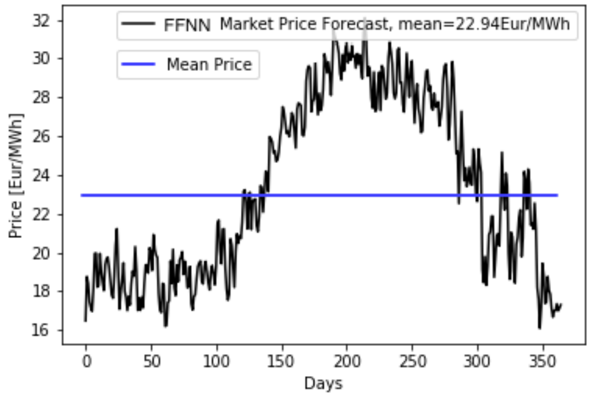
Figure 22: Forecasted Daily Electricity Prices for 2030 with FFNN and LSTM algortihms

Looking at the results for both methods, figure 22, it is possible to observe consistency and a similarity in the price distribution throughout the year, with valley prices corresponding to winter and spring periods, and spike prices corresponding to summer and autumn periods.

It is found a new pattern for electricity prices when compared with today. For previous years of MIBEL like 2019, prices tend to oscillate around the mean, i.e., one day the value is below the mean the next day is above the mean, always oscillating around a certain value, as shown in figure 23 a). For 2030 the behavior is different, with several months of electricity prices below and above the mean, as shown in figure 23 b).



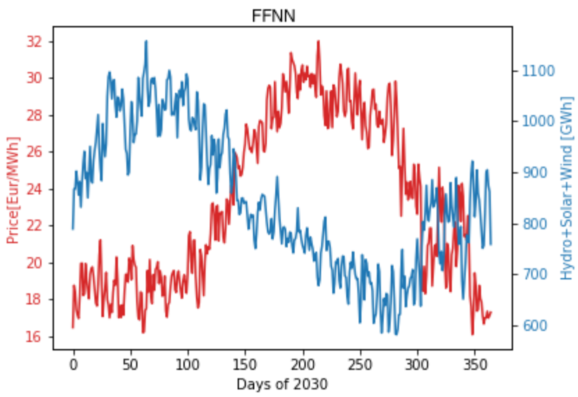
a) 2019 real prices' distribution around the mean



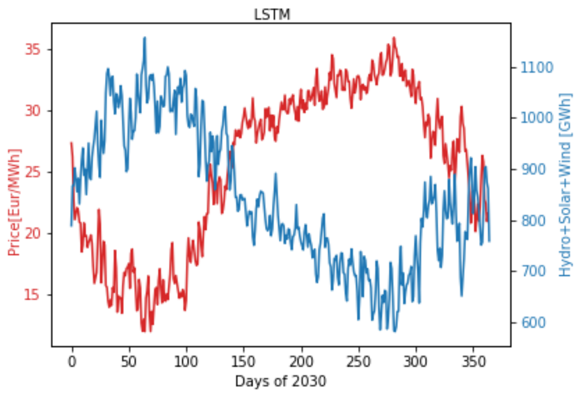
b) 2030 simulated prices' distribution around the mean

Figure 23: Electricity Prices Pattern around the mean, 2019 versus 2030.

More important than the simulations, it is fundamental to understand the reasons that led to such results. For that purpose and knowing that electricity market prices are dependent on marginal cost, the relationship between renewable/non-renewable generation and the simulated electricity prices will be assessed. Figure 24 shows the relationship between electricity prices and renewable generation for both algorithms. Figure 25 a) and 25 b) provide information about the correlation between renewable and fossil fuel production and between fossil fuel production and electricity prices, respectively. The assessment between fossil fuel production and the simulated electricity prices, figure 25 b), is only performed for the FFNN algorithm, but drawn conclusions are also extensible to the LSTM algorithm, given the similarity of results.

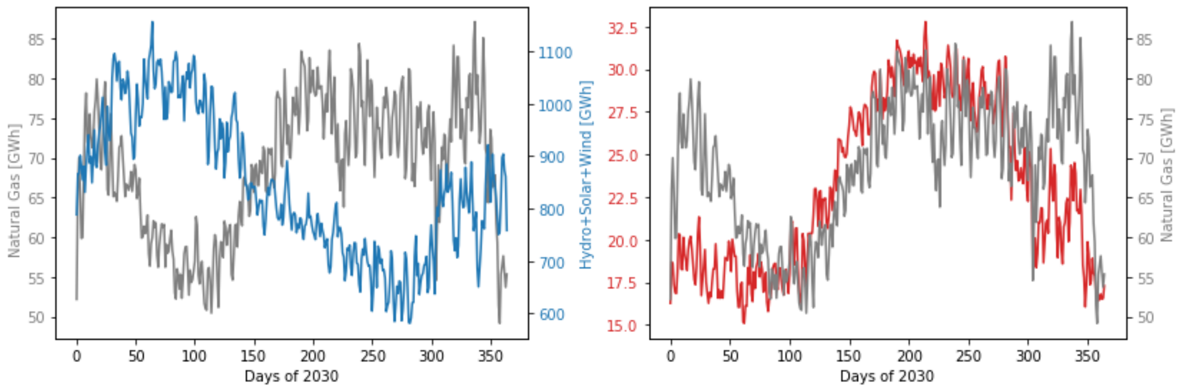


a) Simulated FFNN electricity prices versus renewable generation for 2030



b) Simulated LSTM electricity prices versus renewable generation for 2030

Figure 24: Forecasted Electricity Prices versus Renewable Generation for 2030.



a) Renewable versus fossil fuel generation for 2030

b) Fossil fuel generation versus electricity prices

Figure 25: Natural Gas Generation versus Renewable Generation and Electricity Prices for 2030.

From figure 24 it is perceptible the inverse relationship between electricity prices and renewable generation, with periods of higher renewable production presenting lower prices and periods of lower renewable production presenting higher prices. Figure 25 a) presents the negative correlation between renewable and fossil fuel generation, i.e., in periods of higher renewable generation, fossil fuel technologies reduce their energy output and vice-versa. And at the same time, it is shown in figure 25 b), that periods with higher market prices are directly connected with periods of higher fossil fuel generation, in this case natural gas, due to higher marginal costs.

From this analysis it is clear to understand the reasons why 2030 has a different electricity price pattern. It is mainly caused by the enormous renewable installed capacity for 2030 that leads to an uneven distribution of renewable electricity throughout the year, as seen in figures 11 and 12. Since electricity prices are highly related with the energy mix, the uneven renewable distribution will also induce an uneven price distribution throughout the year, periods with high renewable production correspond to low prices and vice-versa.

6.3. Conclusions

Form this chapter is possible to conclude that an overall decrease of electricity prices will be present in 2030. Such effect is caused by the enormous amount of renewable electricity generation, that increases from 39% in 2019 to 86% in 2030. At the same time, a new electricity price pattern is found caused by periods the uneven renewable generation throughout the year. This efect will induce an uneven price distribution, since the two are directly correlated.

Chapter 7

Conclusions

During the present dissertation, and to achieve the main goal, several topics were covered. This chapter is dedicated at highlighting the major findings and conclusions of this research and is divided in 2 sections. First section reports the most relevant conclusions and findings of all study process. Second section presents topics concerning future works and improvements.

7.1. Findings and Conclusions

The main goal of this dissertation was to assess the influence of increasing renewable power penetration on the future MIBEL daily prices and, at the same time, forecast and quantify electricity prices in 2030. A common approach when developing forecasting models, is to use previous values of the variable under prediction as inputs of the model. This was not a feasible solution to assess the 2030's electricity prices, as so, a model using explanatory variables of the underlying process was taken. The chosen explanatory variables are related with generation, demand and variable costs, which represent the physical and economic components of the market. In the generation part the chosen variables are hydro, wind, solar, other renewables, natural gas, coal and nuclear. They represent the daily electrical energy generated from technologies using the named resources. "Variable costs" is a single variable representing the associated daily costs (fuel and CO2) when generating electricity. "Demand" is a single variable, representing the amount of daily electrical energy required to supply MIBEL's needs. With this information it was possible to train the models and predict electricity prices in the long run, it was just required to model those same variables (generation, demand and variable costs) for the future, in this case 2030.

By the end of this dissertation, and looking at all the developed work, it is possible to highlight some important findings and conclusions achieved during all process.

Selection of the best explanatory variables is crucial to the model and is also important to have a pre-knowledge of their influence on the underlying problem. For that purpose, a data collection, treatment and analysis concerning MIBEL components was taken.

Data analysis was taken trying to assess how the selected variables influence MIBEL's daily market prices. The idea was to reproduce part of a study conducted addressing the same topic, where a daily correlation between demand, generation and market prices was done. Such analysis provided an inter-day correlation between variables and electricity prices. For a better understanding and modulation of the problem, a similar correlation analysis was taken where all the information was presented on an hourly basis. However, this hourly information is only available for Portugal. This analysis provided an intraday correlation between variables and electricity prices.

From the obtained results, it is possible to state that an increase in renewable generation tends to decrease the average daily electricity market price and an increase in fossil fuel generation and/or demand levels tend to increase the average daily electricity market prices. It is also possible to state that hydro technologies have a positive opportunity cost, represented by the positive hourly correlation with electricity prices, meaning this technology will try to allocate its production during periods of higher market prices to increase profits. However, this does not necessarily mean that such technologies increase market prices, in fact, an increase in hydro generation tends to decrease electricity prices, which is shown by the negative daily correlation. Such conclusions are coherent with other studies presented in the literature addressing the same topic. The two above-mentioned analyses, daily and hourly correlations, are crucial when developing a forecasting model, with the draw conclusions allowing to address the consistency and coherence of future results.

Having identified which and how variables influence electricity market prices, it was possible to use them as explanatory variables/inputs to train the forecasting model. The developed models were two ANNs, FFNN and LSTM, which according to the literature, are two widely used algorithms when forecasting long term electricity prices.

It is common practice, and extremely important, to ally models' training with models' validation. With this process it is possible to evaluate how well or not a certain previously trained model can generalize for new cases. During the present dissertation the idea was to use the developed models to predict each individual year of the interval 2015-2019, and then compare it with the real results. During this process the developed models' accuracy is compared with each other and with a benchmark, the Persistence method. Results show a similarity of results between the two models and the benchmark, with MAPE and MAE values around 8-11.5% and 4.32-5.11€/MWh, respectively. At the same time, a higher value of MAPE is found for a particular year, 2016, with values around 18%-21%, for both algorithms.

The higher MAPE value in 2016 is explained with the unusual price volatility and singularities presented for that particular year. Such findings suggest the idea that the developed models are able to forecast the main pattern present in data but are not provided with sufficient information that allows them to forecast periods with high price volatility and singularities. Also, the fact that 2016 has electricity prices with values close to zero, sharply increases MAPE values for that particular year, since this indicator is a relative measure of the error, diving the forecasted error by the real electricity price value.

The similarity of accuracy between both algorithms and the benchmark is justified by the models' construction, which uses daily information to forecast an hourly market. Certainly, this is not the best approach, but due to the lack of more detailed information it was the only available option. Such similarity is also explained with the fact that only explanatory variables about the process are being used. To explain and justify the last statement, both models (FFNN and LSTM) were compared with other two developed models called "FFNN 5 days" and "LSTM 5 days". The new models are exactly equal to the others except in the number of inputs used to describe and forecast electricity prices. Apart from the previous inputs (demand, generation and variable costs) the new models also use information about the last "n" days of electricity prices, more precisely from the last 5 days. Results show that the models, with the extra inputs, can improve their accuracy and outperform the benchmark model with MAPE and MAE values of 6.84-8.81% and 3.21-3.89€/MWh, respectively.

At first sight one could say that the new models (FFNN 5 days and LSTM 5 days) are more suitable for the problem since they provide less errors. In fact, such statement is not true, because for the year 2030 it is not possible to have access to the information concerning the last 5 days of the market price, so it is not possible to apply such methodology. This comparison is only used to prove that FFNN and LSTM algorithms could be further improved adding more variables. But, at the same time, their ability to meet the main goal of the dissertation, which is to assess electricity prices' behavior for 2030 would be compromised. And even though results for the FFNN and LSTM are not better than the benchmark, it is shown that they provide reasonable values of accuracy that are in line with other published studies on the literature.

With the models trained and validated it was possible to use them for real forecasting purposes, assuring a good level of confidence and reliability in the obtained results. With that in mind, it was only required to feed the model with explanatory variables concerning the 2030's energy mix. From the simulated results, using both algorithms, two interesting findings arise. The first is the annual average drop in electricity prices for 2030, with values of 22.94€/MWh and 25.32€/MWh for the FFNN and LSTM algorithms, respectively. In comparison with 2019, with an average electricity price of 47.68 €/MWh, the forecasted values represent a reduction of 24.74€/MWh and 22.36€/MWh in the annual average price, corresponding to a relative reduction of around 52% and 47%, respectively. The second is that the simulated electricity prices present a different pattern around the year when compared with today.

According to the collected information, from 2019 until 2030 the share of renewable electricity in the electrical market shall increase from 39% up to 86 % of the total electrical generation, promoted by the continuous increase in the installed renewable capacity. The effect of such drastic change in the energy mix composition is reflected in the two above-mentioned points.

With the referred increase in renewable production from 39% to 86%, and given all the evidence so far, it is coherent the verified drop in the average of the simulated electricity for 2030. At the same time, such increase in renewable installed capacity will lead to an uneven renewable distribution during the year. Meaning that during some periods of the year the share of renewable electricity in the market will be much larger than in other periods. Since electricity prices are directly correlated with the energy mix composition, the uneven renewable distribution will also lead to an uneven electricity price distribution during the year. For previous years of MIBEL like 2019, prices tend to oscillate around the mean, i.e., one day the value is below the mean the next day is above the mean, always oscillating around a certain value. For 2030 the behavior is different, with several consecutive months of electricity prices below and above the mean price for the year.

7.2. Future Work

With all the evidence and information presented during this dissertation, it is clear that the developed models could be further improved to a more depth understanding of the problem. With this in mind suggestions for future work can be summarized in the following points:

- **Detailed information** - It is crucial to train the models on the same time basis as the real market operates, allowing a better modulation of the underlying process. During the present dissertation information was provided on a daily basis, while the real electricity market operates on an hourly basis.

- **Different forecasting models** - Other models beside ANNs should be used and tested for long term electricity forecast, assessing its strengths and weaknesses.

- **Different explanatory Variables** - Generation, demand and variable costs, were the chosen explanatory variables to model electricity prices in the long run. Other variables can be found more suitable for the proposed problem.

- **Models' factors, variables and constrains** - Introduce other factors, variables and constrains that were not considered during this study such as: electrical interconnections between MIBEL (Portugal and Spain) with France, Morocco and Andorra; storage technologies that will certainly be present in the future electrical system.

- **Future Energy Mix** – Test different 2030's energy mixes, different considerations about future generation and demand can influence the obtained results.

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