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

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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 spot 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.

Keywords: long-term forecast, renewable energy, electricity spot prices, Artificial Neural Networks.

1. Introduction and Literature Review

Over the last decades, electrical markets have been suffering critical changes in its composition and structural operation, going from monopolist to more liberalized structures [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 intense study during the present paper. Within the different markets composing MIBEL, spot market is by far the most important one, where almost all electrical energy is traded. Given its importance, the present paper will only be focused in the MIBEL spot market and, from now on, any reference to electricity prices is related with this particular market.

With the recent emerging development in renewable energies (RE) and its expected increase and integration into the global electrical markets, some concerns have been arising. One of the most important study fields is related with future electricity prices, that are expected to decrease with the increase in RE, creating a phenomenon called "missing money". This problem occurs when the suppliers' revenues are not sufficient to cover the costs, forcing the market participants and future investors to change their strategies in the electrical markets [2,3]. Management, decision making, and strategical planning are crucial activities in every modern business, and even more important in environments with such uncertainty as is it the electricity market [4,5]. As so, it is crucial to have the right forecasting tool to perform these tasks in a proper way.

Attending to the expected change in the energy mix from today until 2030, with an increase in the renewable share from 40% to 80-90% of the total electricity generation [6], this paper presents an enormous importance and relevance. The developed study was motivated at finding how electricity prices will be affected with this drastic modification in the energy mix until 2030.

During this research it is proposed a methodology concerning the development of forecasting models, the objective is to assess the influence of the increasing renewable power penetration on the 2030's MIBEL spot prices. 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, especially for short periods, is to use previous values of the variable under prediction, in this case electricity prices, as inputs of the model to improve accuracy. As it is possible to understand, this is not a feasible solution when assessing electricity prices for 2030, as so, a different approach was taken, with models using only explanatory variables of the underlying process.

Within the literature different models have been proposed to perform electricity prices forecast. Weron [7] provides an extensive and complete state of the art review on the topic, evaluating the strengths and weaknesses between a variety of models and methods used for that specific purpose. Statistical and computation intelligence (CI) are by far the most commonly used models for electricity price forecasting [7,8]. With the liberalization of electricity markets in several countries, future electricity prices were harder to assess, and some traditional/statistical methods were considered incomplete and insufficient. Literature shows that CI algorithms such as Feedforward Neural Networks (FFNN) are simple but yet capable of mapping any non- linear function [9,10], making it a powerful and robust tool [7,11]. Artificial Neural Networks (ANN) are frequently the most accurate forecasting tool when compared with traditional forecasting techniques, especially for nonstationary, nonlinear, discontinuous and complicated problems [12]. Such algorithms can very easily handle nonlinear, noisy or incomplete data due to their learning characteristics, making it a perfect tool for electrical markets, considering the electricity prices characteristics [13]. For these reasons, CI algorithms, more precisely ANNs, were used during this study.

Electricity prices forecasts can be divided in short, medium and long-term, with extremely different methodologies when addressing each of the above-mentioned time ranges. Attending to the proposed problem and the definition provided in [7], this paper will be focused on long-term electricity price forecasts. Literature is not extensive for this particular time range, presenting a scarce number of papers and studies addressing the problem. One explanation is the uncertainty about price driver factors in the long run such as fuel prices, regulatory policies, political intervention, technological changes, energy mix, grid developments, etc. Electricity's price behavior in the long-term is highly dependent on investments made into the electrical system and also on political interventions [14]. Even so, different authors have been presenting different methodologies and considerations when modeling and forecasting long-term electricity prices. For such time range, more important than the model itself, is the selection of the right variables, which allow to describe the process in the long run. Several studies have been proposing sets of variables and considerations that are believed to best describe electricity prices in the long-term.

Some authors focus more on physical properties of the electrical market, considering variables such as the generation from conventional and non-conventional technologies, imports and exports, demand, etc. and with few considerations on the economic and social components of the market [15,16,17]. Other authors, apart from that information, can also consider price elasticity of electricity, gross domestic product, household, consumption expenditure, population, grid connections/restrictions, new capacity installed in the future, old capacity dismissed in the future, fuel costs, CO2 allowances, technologies efficiency, inflation, etc. [18,19,20].

Not all the electricity markets around the globe operate in the same way, different variables and considerations should be taken into account for different markets and different problems. According to Aleasoft, a highly specialized company in the Spanish energy sector, the main variables needed to take into account when performing a good long-term electricity price forecast are demand, wind electricity generation, solar electricity generation, hydroelectric electricity generation, nuclear electricity generation, international interconnections, CO2 allowances and fossil fuel prices. Aleasoft's model is based on Artificial Neural Networks but with a Seasonal Autoregressive Integrated Moving Average (SARIMA), it's a hybrid model.

In this paper two ANNs, Feedforward and a Long Short-Term Memory, will be used to assess and forecast the influence of the increasing renewable power penetration on MIBEL spot market, more precisely for 2030. Having different models allows to compare the forecasting results and draw conclusions about the same. If both models present similar results for the simulated 2030's electricity prices, this provides an extra confidence degree over the obtained results. The chosen explanatory variables take into account the generation, demand and variable costs, representing the physical and economic components of the market. As so, the final explanatory variables used consider the daily electricity generation from solar, hydro, wind, other renewables, coal, natural gas and nuclear technologies, the associated fuel and CO2 daily costs of generating such electrical energy, and the daily demand level.

The present study provides a different approach to the forecasting procedures, trying to reproduce the electrical market with a detailed combination of both physical and economical components. The idea is to make a complete analysis regarding the influence of each individual variable on MIBEL and evaluate future results.

This paper is organized in 3 further sections. In section 2 it is described the data sources and the applied methodology during the study. Section 3 is dedicated to all the obtained results during the developed research. Finally, in section 4, conclusions about the obtained results are drawn.

Data and methods

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 market operator on the Spanish side. Coal prices were obtained from the European Association for Coal and Lingnite (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. 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 fuel, CO2 and natural gas prices for the period 2015-2019

	2015	2016	2017	2018	2019
CO2 Prices [€/ton]	7.76	5.65	5.67	16.27	24.46
Coal Prices [€/ton]	61.12	62.18	87.12	91.39	64.44
Natural Gas Prices [€/mmBTU]	5.8	3.88	3.86	6.52	4.08

The proposed methodology to evaluate the influence of the future renewable generation in MIBEL prices is comprised in 5 steps: A – Data treatment and analysis, assessing the influence of the different components of the energy mix (demand and generation) on electricity prices; B – Construction of the two CI models that will be used to predict electricity prices; C – Models' training and tunning; D – Models' validation; E – Modelling of the 2030's energy mix, that will be used as model inputs to obtain the simulated electricity price for 2030.

A. Data treatment and analysis

With the collected information about the daily demand and electricity generation by source, it is then required to compute the associated daily CO2 and fuel costs, which in this case are only related with natural gas and coal technologies.

To calculate the fuel costs, it is required to compute the daily primary energy used by natural gas and coal technologies to generate electricity. Such information can be obtained using the correspondent efficiencies. In the first case, natural gas, different technologies are being considered, from combined cycle and cogeneration to normal gas turbines, for that reason it was assumed an average efficiency of 55%. For coal technologies it was assumed the regular efficiency presented by this technology, around 35%. With these values and the unitary fuel costs in table 1, it is possible to compute the daily fuel costs.

The daily CO2 costs were computed using information about the daily emissions and the unitary price of CO2.

Posteriorly, a correlation analysis was then taken trying to assess the relationship/influence of the selected/collected variables, for previous years (2015-2019), on electricity prices. When talking about forecasting models it is not only important to select the right variables, but also to assess their influence on the final output. This way it is possible to evaluate the coherence of future results.

According to King, et. al. [21] there are two methods typically used to calculate correlations between variables. If variables are normally distributed Pearson's correlation should be used, if not then Spearman's Correlation is the one to be chosen. For this specific case, data is not normally distributed, so Spearman's correlation ($\mathrm{r_s}$) will be used. From "n" samples, this correlation ranks $\mathrm{X_i}$ and $\mathrm{Y_i}$ variables independently, on an ascending or descending order, and posteriorly calculating its differences ($\mathrm{D_i}$). Using that information is possible to compute the Spearman's correlation between them using equation 1.

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

B. Construction of CI models

Attending to all the evidences found during the literature review, CI models like ANNs show an enormous potential dealing with noisy, volatile and non-linear environments as it is the electrical market. During the practical component of this paper, two ANNs algorithms will be used to evaluate MIBEL's 2030 electricity prices. The first is called Feedforward Neural Network (FFNN), one of the most simple and basic algorithms, the second is called Long Short-Term Memory (LSTM), a more complex and sophisticated algorithm that integrates the group of the Recurrent Neural Networks (RNN).

FFNN 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.

LSTM is a specific case of RNN and is considered as a generalization of FFNN, with the upgrade of having an internal memory. LSTM provides the neurons with information feedback 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. [22] the general idea behind LSTM algorithms is the introduction of the cell state, where information can be added or removed and passed to other cells. Unlike FFNN, 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 used in FFNN.During this study both developed neural networks present one input layer, two hidden layers and one output layer. The number of input neurons is determined by the number of variables used to describe the process, in this case nine. Figure 1 makes a schematic representation of the neural network, its inputs and outputs. The difference between the two algorithms is only in the information flow, in the LSTM case there is the previously mentioned feedback that is not represented in figure 1.

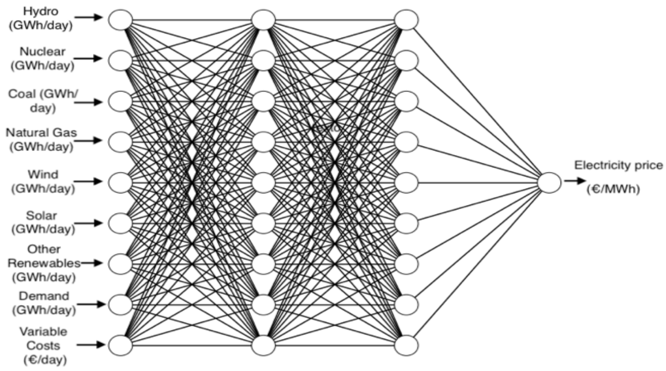


Figure 1- Schematic representation of the developed ANNs

C. Models' training

For the training procedure it is required to feed the model with specific data, training data, containing predictors/inputs and the correspondent solutions/targets, ensuring the model is able to learn, adapt and minimize the error. The majority of the neural networks, including the ones presented in this study, are trained based on gradient descent techniques using the backpropagation algorithm as explained in [23,24].

In this paper models' training is performed using previous information concerning MIBEL's generation, demand, marginal costs and real electricity prices in the spot market for the period 2015-2019, i.e., using the variables presented in previous figure 1. This way the model is able to adapt to previous information and hopefully generalize for new cases and problems.

D. Models' 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 also required a data set composed of predictors/inputs and targets/solutions, so it is possible to predict and quantify the error. For this paper, the idea for the validation process consisted in predicting previous MIBEL prices, from 2015 until 2019 and compare it with the real values. 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. It is common approach to compare models' accuracy with a benchmark, in this case it was used the Persistence method. This model states that the value observed in previous time *"t-1"* will also occur at time *"t"*.

Error is quantified with using 2 basic indicators: Mean Absolute Percentual Error (MAPE) and Mean Absolute Error (MAE), as shown in equations 2 and 3, respectively.

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{Y_i - \widehat{Y}_i}{Y_i}\right) \qquad (2)$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i) \qquad (3)$$

In this case "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". Apart from these two indicators, a statistical analysis is also done for a better understanding of the error, calculating the associated statistical indicators as the mean (μ) standard deviation (σ) and median (M).

E. Modelling of the 2030's energy mix.

In order to forecast electricity prices for 2030 and attending to the construction of the models previously explained, it is required to have information about the 2030's MIBEL energy mix. Pereira et. al. [6] present an interesting study on the topic, where it is simulated the Iberian power system, following the provided guidelines by the European Commission until 2040. Such paper provides information about future generation technologies and demand, allowing an assessment of the future power system. Table 2 summarizes the obtained energy mix for 2030, during Pereira's study with a comparison with the real 2019's energy mix.

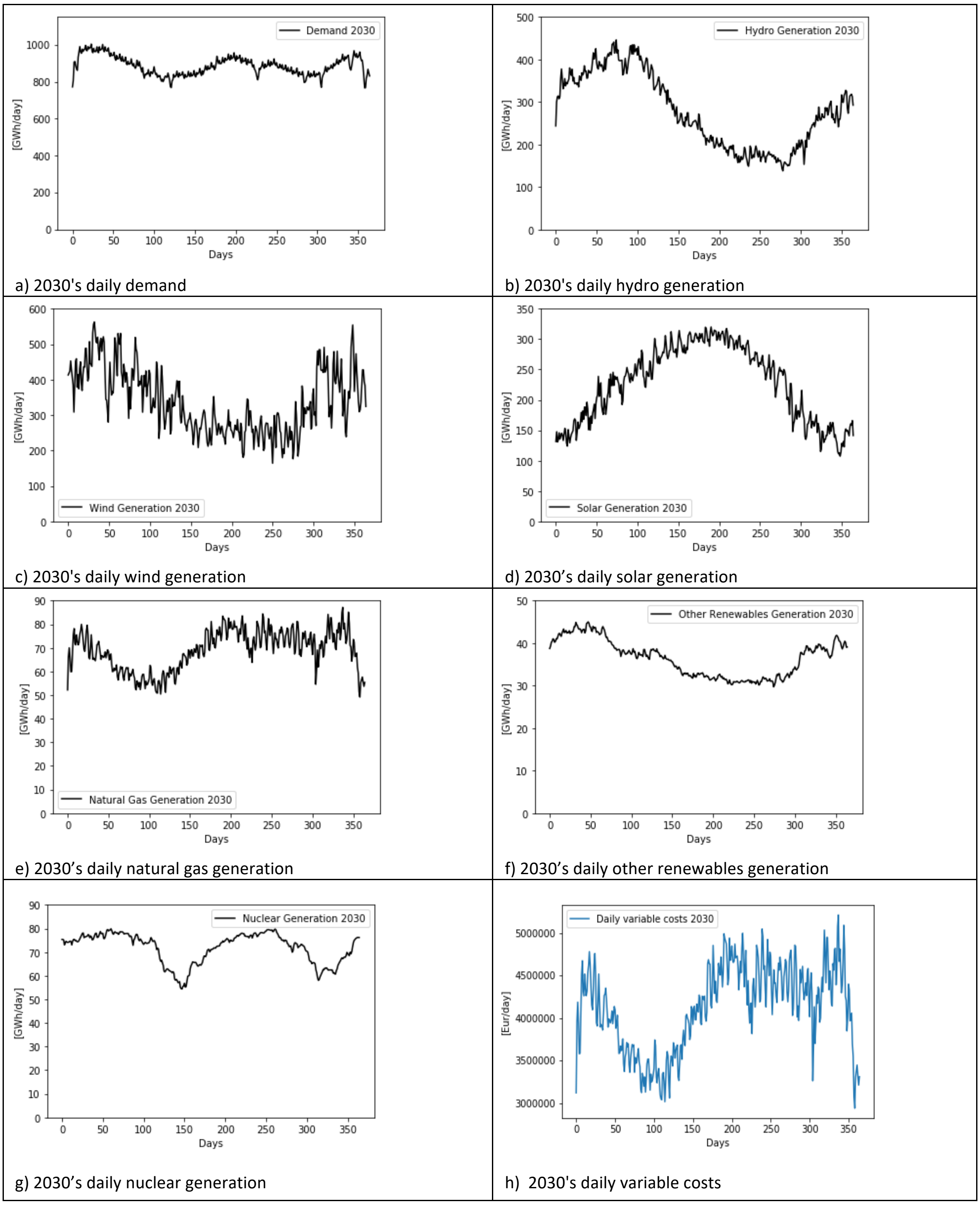
Table 2 - 2030's MIBEL energy mix simulation, Pereira et. al. [6], with a comparison with 2019

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 provided information in [6] is presented on a yearly basis and needs to be converted into models' predictors/inputs, i.e., it needs to be converted into a daily basis. To solve this problem, the best solution was to capture past patterns of generation and demand 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 distribution. To obtain these 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, and an "average year" was created, because any unusual event that may appear in one year is disguised in the average of the interval.

After computing the average year, data normalization is required, dividing each individual predictor's daily value by its yearly total, and then converted into 2030's predictors, multiplying the normalized value by the correspondent annual information provided in table 2. Figures 2 represents the obtained demand and generation distributions for each individual predictor in 2030.



a) 2030's daily demand

b) 2030's daily hydro generation

c) 2030's daily wind generation

d) 2030's daily solar generation

e) 2030's daily natural gas generation

f) 2030's daily other renewables generation

g) 2030's daily nuclear generation

h) 2030's daily variable costs

Figure 2: Daily Demand, Generation and Variable Costs for 2030

With the 2030's daily generation distribution throughout the year it is possible to calculate the associated variable costs. Daily fuel costs, concerning the 2030's electricity generation, follow the same methodology as explained for previous years (2015-2019).

For the daily CO2 costs a different approach was taken, since it is not possible to have access to information about the 2030's daily emissions as it happened for previous years. To solve this problem a "natural gas emission factor" was created dividing the total emissions by the total electricity generated, only concerning natural gas technologies, for the period 2015-2019. With the obtained resulting factor, with the value of 0.448 ton.eq.CO2/MWh_{NG}, it is possible to compute the daily emissions and respective costs.

Table 4 presents the collected CO2 and Natural Gas prices, obtained from Portugal's integrated national energy and climate plan 2021-2030 and Statista, respectively.

Table 4 - Natural Gas and CO2 prices previsions for 2030

Commodity	2030
CO2 Prices [€/ton]	35
Natural Gas Prices [€/mmBTU]	6

In previous figure 2 h) is presented the obtained variable costs distribution for 2030, that are directly correlated with the natural gas distribution.

2. Results

2.1. Correlation analysis

In this section results concerning the performed correlation analysis will be taken. Table 5 presents the obtained daily correlation for the period 2015-2019.

Table 5 – 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 5 are coherent and similar with a study performed by Gelabert et. al. [25] where this same daily correlation is also assessed for MIBEL. 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 and wind) 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 small share, so its influence will also be small, as represented by the low correlation factor. Nuclear technologies also have a small influence on the electricity market, proven by the almost null correlation with electricity prices.

The difference between the two analysis is related with hydro technologies, that in Gelabert's results it is presented a positive daily correlation with electricity prices. The author justifies the positive correlation stating that this particular technology can store and shift energy to periods with higher demands and higher electricity prices. This positive correlation reflects the positive opportunity cost of hydro.

For a better understanding of the problem, a second correlation was performed, but with all the information discretized and presented on an hourly basis. Unfortunately, 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 6 presents the results of Spearman's correlation using Portugal's hourly information.

Table 6 – 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 analysis provides a different overview of the interaction between market prices and the generation technologies in the market, 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 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 during peak times 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 tend 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 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 [26,27,28].

2.2. Model Validation

In this paper, the validation process consisted in predicting previous years of MIBEL, from 2015 until 2019, and compare it with the real values. Results were also compared with a benchmark, in this case the persistence method. Results using MAPE and MAE indicators are presented in table 7.

Table 7 - Yearly forecasting error using FFNN, LSTM and 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 point will be analyzed in detailed in the next two sub-sections.

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 a more detailed data. The second reason is the variables used by the ANNs. As stated in the beginning of this paper, it is common approach, in forecasting models, to use previous information about the variable under forecast as inputs of the model, allowing a better accuracy. To prove this 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. With several experiences conducted, 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 8.

Table 8 – Yearly forecasting error using FFNN 5 days, LSTM 5 days and 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 possible to observe an overall error decrease using "FFNN 5 days" and "LSTM 5 days" when comparing with FFNN and LSTM. And at the same time, an outperform of the new models when comparing with the benchmark, which did not happen before. This means that having previous daily 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. On the other hand, it is not possible to use the Persistence method to assess electricity prices for 2030. Mainly because in this model it is not possible to reflect the forecasted energy mix for 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 7, they are able to describe the market prices relatively well and represent the only viable solution to use in the electricity prices assessment for 2030.

2.2.2. Relative Error 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), table 7, results are very similar to the rest of the years.

The high MAPE is happening firstly because for this particular year, an unusual variability and price singularities are present, which imposes some limitations to the models' ability to follow those singularities. Secondly and most important, it registers several real electricity prices close to zero, which leads to a sharp increase in the MAPE values. As a consequence, the extremely high MAPE values registered in some days, will increase the overall MAPE value for that particular year. Such effect is not verified for the rest of the years in the interval 2015-2019.

Apart from the MAPE and MAE evaluations, a statistical analysis over the errors was also conducted. Statistical indicators such as the mean (μ), standard deviation (σ) and median (M) are presented in table 9.

Table 9- Error statistical indicators, mean (μ), standard deviation (σ) and median (M), concerning FFNN and LSTM errors.

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

Statistical errors 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 models. If instead errors were all positive or all negative, it would mean the neural networks were 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.

2.3. Simulation results of the 2030's electricity market prices

As explained in previous sections, predictors are the variables/inputs used to run the models (FFNN and LSTM), and that way obtain the desired forecasting results. During section 2, it was explained how the models' predictors, that will be used in this section, were constructed. The following analysis is divided in two parts. In the first one, it is assessed the annual average of the simulated electricity prices for 2030. In the second, it is assessed the pattern of the simulated electricity prices for 2030.

2.3.1. 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 10 presents the average of the forecasted electricity prices for 2030 with respect to both models, FFNN and LSTM.

Table 10 – Forecasted annual average electricity price for 2019 in MIBEL

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 table 11.

Table 11 – Annual average MIBEL's electricity prices with respect to the period 2015-2019

Year	Annual average electricity price in MIBEL [€/MWh]
2015	50.32
2016	39.66
2017	52.24
2018	57.29
2019	47.68

The observed reduction effect can be justified by the expected highly increase in electricity renewable production and the decrease in fossil fuel electricity generation for 2030. This is coherent with previous findings, 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.

2.3.2. Annual electricity price distribution for 2030

It is important to assess the behavior of the forecasted values 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 forecasted prices for 2030, and also its relationship with renewable and non-renewable generation. Figures 10 and 11 provide an overview of the yearly price distribution for 2030 with respect to both algorithms, FFNN and LSTM respectively.

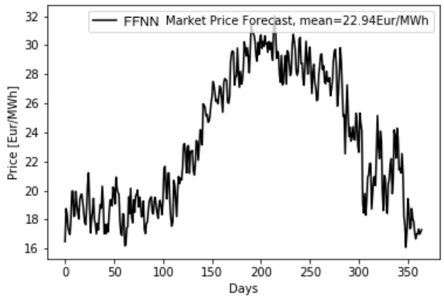


Figure 3 – Forecasted electricity price for 2030 in MIBEL using FFNN

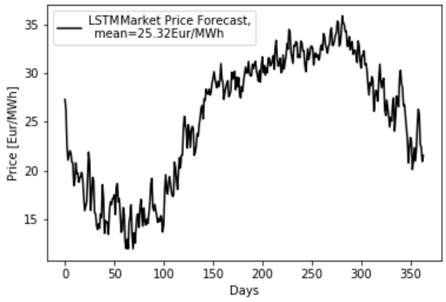


Figure 4 - Forecasted electricity price for 2030 in MIBEL using LSTM

Looking at the results for both methods, figures 10 and 11, 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, daily average 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 12. For 2030 the behavior is different, with several months of electricity prices below and above the mean, as shown in figure 13.

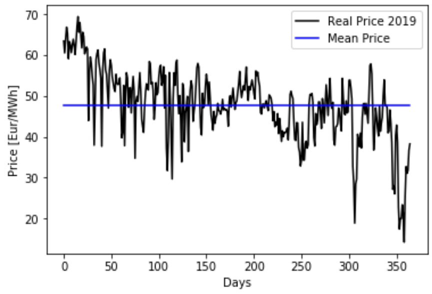


Figure 5 – 2019 real electricity prices in MIBEL and yearly average price

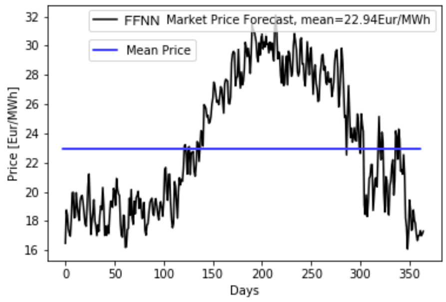


Figure 6 – 2030 forecasted prices and yearly distribution average price

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. Figures 14 and 15 show the relationship between electricity prices and renewable generation for both algorithms. Figures 16 and 17 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 14, is only performed for the FFNN algorithm, but drawn conclusions are also extensible to the LSTM algorithm, given the similarity of results.

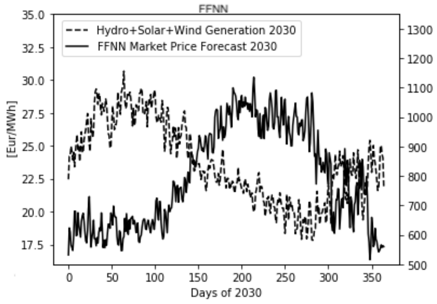


Figure 7 – Forecasted FFNN electricity prices versus hydro, solar and wind generation for 2030

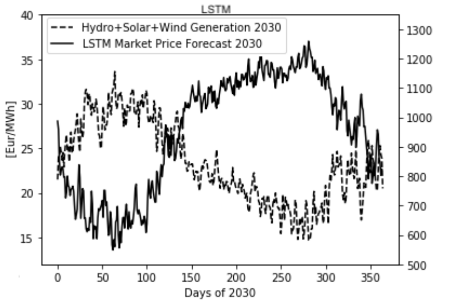


Figure 8 – Forecasted LSTM electricity prices versus hydro, solar and wind generation for 2030

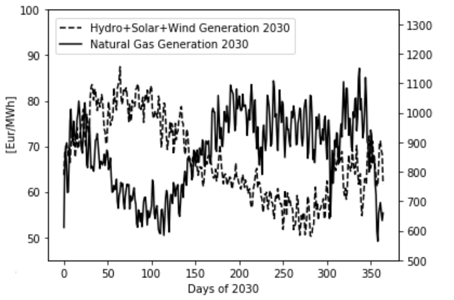


Figure 9 – Hydro, Solar and Wind versus Natural Gas generation for 2030

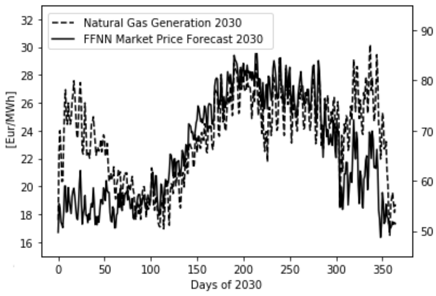


Figure 10 – Natural Gas generation versus electricity prices for 2030

From figures 14 and 15 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 16 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 17, 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.

3. Conclusions

The main goal of this research was to evaluate the influence of increasing renewable power penetration on the future MIBEL spot prices, with special focus into 2030. The developed models were constructed using explanatory variables of the underlying process. The chosen explanatory variables are related with generation, demand and variable costs, which represent the physical and economic components of the market.

During this process a daily and hourly correlation between generation, demand and electricity prices was taken, trying to assess its influence on electricity prices. From the obtained results, 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 tend 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. However, an increase in hydro generation tends to decrease electricity prices, which is shown by the negative daily correlation.

During models' validation, both FFNN and LSTM algorithms were used to forecast previous years (2015-2019) of MIBEL prices and errors compared with a benchmark. 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. 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, and is also explained with the fact that only explanatory variables about the process are being used. To justify this statement two other models were constructed, that apart from previous inputs they also use information about the last "n" days of electricity prices, more precisely from the last 5 days. Results show that these models, with the extra inputs, can improve their accuracy and outperform the benchmark model with MAPE and MAE values between 6.84-8.81% and 3.21-3.89€/MWh, respectively. 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 paper, 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 and the only viable option for the problem under study.

Using the developed models that have been previously trained, it was possible to assess the 2030's electricity prices. From the simulated results 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, which corresponds 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 found, it is coherent the verified drop in the average of the forecasted electricity prices for 2030. At the same time, such increase in renewable installed capacity will lead to periods of uneven renewable electricity distribution throughout the year effects. This means that during some periods of the year the share of renewable electricity in the market will be much larger than in other periods, leading to an uneven distribution throughout the year. 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, while for 2030 the behavior is different, with several consecutive months of electricity prices below and above the mean.

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