2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe) | 978-1-6654-3613-7/21/$31.00 ©2021 IEEE | DOI: 10.1109/EEEIC/ICPSEurope51590.2021.9584499

Impact of the Growing Penetration of Renewable Energy Production on the Iberian Long-Term Electricity Market

Sérgio F. Santos
INESC TEC and Portucalense University Infante D. Henrique
Porto, Portugal
sdfsantos@gmail.com

Matthew Gough
FEUP and INESC TEC
Porto, Portugal
mattgough23@gmail.com

João P. G. V. Pinto
FEUP
Porto, Portugal
joao20pgvp@gmail.com

Gerardo J. Osório
C-MAST/UBI and REMIT/UPT
Covilhã, Portugal
gjosilva@gmail.com

Mohammad Javadi
INESC TEC
Porto, Portugal
msjavadi@gmail.com

João P. S. Catalão
FEUP and INESC TEC
Porto, Portugal
catalao@fe.up.pt

***Abstract*— The increasing penetration of renewable energy sources in areas with wholesale energy markets may have significant impacts on the prices of electricity within these markets. These renewable energy sources typically have low or zero marginal prices and thus can bid into energy markets at prices which might be below plants using other generating technologies. This work seeks to understand the impact of these zero marginal cost plants in the Iberian Energy Market. This work makes use of an Artificial Neural Network (ANN) to evaluate the impact of growing renewable energy generation on the market-clearing price. Real data from the Iberian Energy Market is chosen and used to train the ANN. The scenarios used for renewable energy generation are taken from the newly published national energy and climate plans for both Spain and Portugal. Results show that increasing penetration of renewable energy leads to significant reductions in the forecasted energy price, showing a price decrease of about 23 €/MWh in 2030 compared to the baseline. Increasing solar PV generation has the largest effect on market prices.**

Keywords*— *Neural networks, Electricity price, Price impacts, Electricity market, Renewable energy

I. Introduction

A. Motivation, Aims and Background

The liberalization of energy markets has been taking place over the last decades. This process generally consisted of separating vertically integrated electricity monopolies into generation, transmission and distribution units and introducing competition into the generation and distribution sectors.

The generation sector traditionally relied on large and centralized power plants which burned fossil fuels. However, there is a growing awareness of the climate-related impacts of burning fossil fuels and thus power plants which used renewable sources of energy have become more widespread and popular [1].

These renewable energy (RE) plants typically have very low (or zero) marginal cost of generating electricity. Thus, their participation in energy markets changes the existing market paradigm. Typically, these energy markets have relied on a merit order curve to schedule and dispatch competing generators.

The increasing penetration of RE plants has the effect of lowering the market-clearing price as they typically bid in with zero-marginal costs thus they depress the resulting market equilibrium.

The increase in RE production, including its inherent variability, has meant that accurately forecasting energy supply and thus the market-clearing price has become more challenging. Various methods exist to carry out this forecasting including statistical approaches as well as more recent models derived from artificial intelligence. These models can help to better understand the effects on energy markets driven by widespread RE adoption.

Aforementioned changes to energy markets have been seen within the European Union, whose goals and targets for the use of renewable energy are laid out in the recast renewable energy directive which forms part of the wider Clean Energy for all Europeans Package [2].

In this context, both Spain and Portugal have developed national energy plans, Spanish National Integrated Energy and Climate Plan (PNEIC) and Portuguese National Energy and Climate Plan (PNEC) respectively, to transpose the relevant European directives. These plans seek to massively increase the amount of renewable energy production in the countries [3], [4]. Both plans aim to achieve carbon neutrality by 2050 with 42% of gross energy consumption coming from renewable sources in Spain and 47% in Portugal by 2030.

The Iberian Energy Market (MIBEL) oversees the wholesale energy markets within Spain and Portugal. There is a spot market within MIBEL which includes a day-ahead market, which is the focus of this paper, as well as an intraday market. The markets arrive at a single spot price for the entire Iberian energy system but price differentials may arise due to congestion management between the two countries [5].

J.P.S. Catalão acknowledges the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under POCI-01-0145-FEDER-029803 (02/SAICT/2017). G.J. Osório acknowledges the support by UIDB/00151/2020 research unit (C-MAST) funded by FCT.

The effect of increased RE generation in Portugal has been studied by [6] where the authors have used a combination of a Seasonal Autoregressive Moving Average with exogenous regressors and a Generalized Autoregressive Conditional Heteroskedasticity model to examine the effects on the electricity price.

The authors found that the increase in the use of solar PV is especially significant in reducing both the electricity price and the volatility of the wholesale market.

However in the same paper, [6], the authors have only considered the generation in Portugal which leaves out the much larger Spanish electricity sector which is tightly coupled through the MIBEL market.

A work that took both sides of the MIBEL market into account was developed by [7]. The authors have investigated the balance between the decrease in the clearing price of electricity due to the low marginal costs of RE generation and the increase in the cost of energy due to the so-called regulated premium that RE generators were paid, which is more than the market price.

In the consequent years, the price of RE generation has continued to decrease so the effect of this regulated premium is reduced and thus an up-to-date investigation into the effects of RE generation is needed.

Within Europe, the authors of [8] have investigated the impact of RE generation on the electricity price in Germany for the years 2014-2018. The authors found that increased RE generation led to a reduction in the costs for consumers and the authors estimate that this reduction in costs saved the German consumers €40 billion during the period 2014-2018. Also, the RE generation had other benefits such as increased security of supply for the German electricity system.

Still, within Europe, the authors of [9] used a neural network to forecast the day-ahead electricity prices in six price zones in Italy. The authors create three different neural networks and investigate their validity in several case studies. The authors do not consider the future impact of RE penetration on electricity prices.

Another combination of neural networks was used for electricity price forecasting in [10] using data from the Pennsylvania-New Jersey-Maryland electricity markets. The combined approach is compared to existing forecasting methods using evaluation criteria such as the Mean Absolute Percentage Error (MAPE), root mean square error and the mean absolute error. The combined approach performed significantly better than existing methods.

B. *Contributions and Paper Organization*

In this paper, the impacts of the growing penetration of electricity generation from renewable energy plants are studied on the Iberian long-term electricity market. This paper has the following main contributions:

- Develop and investigate operational situations that represent future energy mixes of the Portuguese and Spanish energy systems, with different levels of RES growth based on values for 2030 extrapolated from the respective national energy plans.

- Create an Artificial Neural Network (ANN) to carry out extensive simulations and perform an extensive analysis of the influence that the greater integration of renewables will have on the price of electricity within MIBEL.

The rest of the paper is organized as follows: Section II contains the methodological approach. Section III then contains the results obtained from the model as well as a discussion of these results. Conclusions drawn from these results are presented in Section IV.

II. METHODOLOGY

To examine the potential impacts of continued RE penetration on the MIBEL market, simulations using an ANN were carried out. The model was developed and trained using historic data from MIBEL before being validated. Once it was validated, various simulations were carried out to investigate the effects of increased participation of RE plants. This section details methodology followed for the data collection, model development and training, validation, and final simulations.

A. *Collection and processing of data*

The data used in this work were obtained from MIBEL for 2018 and 2019 [11]. The data collected included the electricity price, the energy produced by each type of technology as well as the energy consumed by the market.

In the simulations, data from wind, solar, hydro, nuclear, coal, cogeneration, fuel, natural gas, and combined cycle generation were used. Additionally, the thermal generation production from the special regulatory regime, the import balance, the energy consumption, and the electricity price were also used. The wind and temperature data were obtained from [12] and the precipitation data were obtained from [13].

B. *Time periods considered*

The data collected for the two years resulted in 17520 hourly data points. Similarly, to the existing literature as referred in [14] 80% of the database was used for training the ANN model and the remaining 20% was used for testing purposes. This corresponds to four months of data for testing and the rest for training.

For the validation, there were different periods selected to account for the different metrological conditions in the Iberian Peninsula. Three periods, each of four months duration, were created. These periods covered the four warmest months, four months with the most precipitation, and the four months with the highest average wind speeds. These are as follows:

- Period 1 (4 warmest months): August 2018, September 2018, July 2019, and August 2019,
- Period 2 (4 months with the highest precipitation): March 2018, November 2018, November 2019 and December 2019,
- Period 3 (4 months with highest wind speeds): March 2018, December 2018, November 2019 and December 2019.

C. *Performance evaluation*

Several scenarios were used to examine the potential impacts of increased RE penetration. These scenarios used the price forecast by the model while holding constant the electricity generation by the various technologies.

This allows the forecasted price to be compared to the actual price for the chosen period. This comparison was done using the Mean Absolute Percentage Error (MAPE) as is used in other studies [15]. The value of MAPE is calculated using (1) and (2) where (2) calculates the arithmetic mean of the actual values.

$$MAPE = \frac{100}{N} \sum_{n=1}^{N} \frac{|\hat{p}_n - p_n|}{\bar{p}} \quad (1)$$

$$\bar{p} = \frac{1}{N} \sum_{n=1}^{N} p_n \quad (2)$$

In (1) $\hat{p}_n$ represents the forecast values while p_n represents the actual values recorded. The mean value is represented by $\bar{p}$ [16]. Furthermore, the average values were used to avoid unstable situations which may occur when values are close to zero. The MAPE was only used in the test scenarios since in the final scenarios the production values are different. It should be noted that it is normal that the output values of the price are different from the actual values. For the test scenarios, MAPE compares the real values of the price with the outputs resulting from the ANN simulations in MATLAB, for the 3 chosen periods.

D. *Artificial Neural Network*

ANNs were designed to replicate the neural pathways in a human brain and mimic the way that they store and evaluate patterns within information based on experience and learning. These systems can account for changes in the environment through learning and adapting to the new environment.

Also, ANNs are well suited to solving complex and non-linear problems. It is important to state that ANNs do not solve the underlying mathematical relationships between a set of inputs and outputs but arrives at a solution through learning from experience.

Training of the ANN is the first step which involves introducing the input parameters which influence the targeted output variables, as can be seen in Fig.1. The ANN then determines relationships between the inputs and the desired outputs and alters the inputs to arrive at forecasted values which are as close to possible to the actual outputs.

Once this training phase is concluded the model is tested or validated using a new set of input parameters and the relationships identified in the training phase to arrive at a new set of forecast outputs. In Fig. 2, a general flowchart for model creation is shown for an ANN.

The simulations using the ANN were carried out using the *nftool* (neural fitting tool) in MATLAB. This work made use of multi-layer ANNs where there is a hidden layer composed of a certain number of neurons.

A back-propagation feed-forward network with $2n + 1$ hidden neurons was used, where n represents the number of inputs in the ANN [17].

E. *Changing Operational Situations by Technology Production Output*

The changes made to the penetration of RES were made in accordance with the Portuguese National Energy and Climate Plan (PNEC) 2021-2030 as well the Spanish National Integrated Energy and Climate Plan (PNIEC) 2021-2030. A comparison was made between the current installed capacity and the planned capacity in 2030 where there was a major increase in RES, especially PV technology and a decrease in the amount of installed coal fired technology. Using these installed capacities, an average energy mix for each hour was made for the entire database. Table I shows the percentage change in the energy mix between current installed capacity and the planned capacity in 2030 in the Iberian Peninsula.

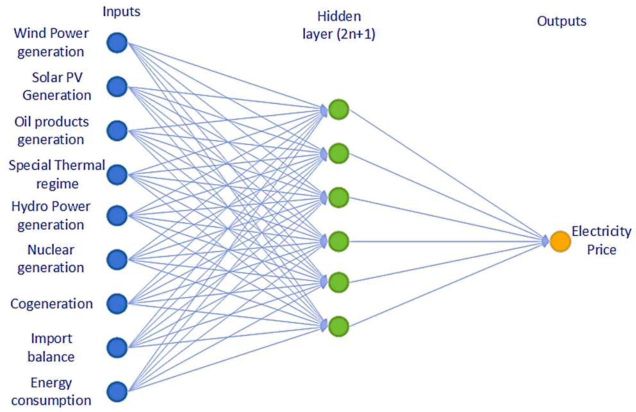

Figure 1- Input and output layers of the artificial neural network.

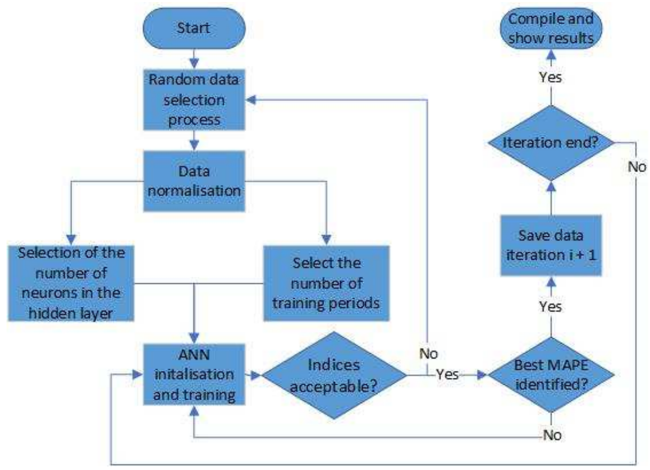

Figure 2- Flowchart for the ANN and strategy used in this work.

TABLE I- PERCENTAGE CHANGE IN RENEWABLE ENERGY PENETRATION IN 2030 RELATIVE TO THE CURRENT ENERGY MIX.

Technology	Percentage Change
Wind	+60
Solar PV	+130
Coal	-78
Hydroelectric	+8
Cogeneration	-52

A set of variables was used to create the various operational situations. In this work, all the technology production variables from Portugal and Spain were grouped and used, together with the Iberian Peninsula's import balance, the difference between import and export between the countries, the Iberian Peninsula's consumption, and the marginal energy price (€/MWh).

The marginal price is used for the network's target, since it is the variable under analysis in ANN, and the network's output is a vector of prices, which will later be compared with the actual price. The weather variables were treated only to study the chosen periods, and no chronological variables were used.

This is because this work does not deal with electricity price forecasts, but rather with the impact that increased renewable output has on the price of electricity in MIBEL. The use of time variables would affect the grid and the price, which would follow these values, this could lead to a better forecast for real production values but would undermine the influence of renewable production on the price, i.e., the change in production values in the test set would not be as significant if time variables were included in the model.

This work also included a correlation analysis of the variables collected with the electricity price. When the degree of relationship between variables is evaluated, it is possible to observe the interference that a given variable has in the result of another, in this case, in the price result. For this purpose, Pearson's correlation is used, as is consistent with the literature on neural networks [18].

In this case, the coefficient identifies the connection between two groups of neurons in the network. The Pearson's coefficient shows the linear relationship between data sets and their value ranges from -1 to +1. Thus, Pearson's coefficient is defined as the ratio of the covariance of two variables to the output of their standard deviations [18]. Table II shows the Pearson coefficient calculation values of all variables collected and treated relative to price.

III. Analysis and Results Discussion

This section presents the results for both the test and the final scenarios. To evaluate the results several statistical indexes are calculated and used to evaluate the results are the regression value, which is provided when training the network in the MATLAB software, MAPE values, absolute error, relative error, percentage error and percentage absolute error.

A. *Test scenarios*

Test scenarios for three chosen periods were performed to ensure the credibility of the model. These scenarios serve only to forecast the market price without changing the amount of electricity produced from various technologies. Thus, it is possible to determine if the values of the outputs follow the real price values for the periods under analysis through the simulations performed. These tests also allow the evaluation of the MATLAB training model to enhance the model's predictive ability.

Thus, Table III presents the values of the MAPE error for the test simulations across the three time periods and with several different training periods. In the three periods, there are training sets that do not have MAPE values, due to the regression value provided by MATLAB software being below 0.94 and thus the model was not finalized, and its outputs were not obtained.

However, for the three periods, the outputs obtained were always close to the actual values of the energy price in MIBEL. These results show that the model was stable and reliable. Thus, the final simulations performed with the modified national energy mixes resulted in credible changes in the electricity price.

These values are credible for the new production values, although one can never predict entirely what will happen in 2030. For the analysis and discussion of the results, both for the test scenarios and the final scenarios, only the values of Time Period 1 were chosen, since it was the period that had the most complete results in both scenarios.

Time period 1 includes the four hottest months, August 2018, September 2018, July 2019 and August 2019, and these months constituted the test set for this period. These four months correspond to about 20% of the training data. To ensure that the predictions made with the model were as accurate as possible, additional tests were carried out regarding the number of training periods to be performed in the simulations of this model and for this period.

The results were evaluated according to the analysis of the MAPE error result. Time period 1 had the most complete set of forecast values as well the greater price stability during the four months in comparison to the other time periods. The model with the best result for the MAPE error used just one training period and had an error value of 9.23%.

In Fig. 3, a comparison between the actual and forecasted values resulting from the ANN in time period 1 of the test scenario are shown. Fig. 4 presents an hourly average of both the actual and forecasted values for each hour of the day during the four selected months. The forecast values follow the actual values very closely.

Table IV presents the average price per hour across the four months for both forecast and actual values and the difference between the two. The forecast values were approximately 7% below the actual recorded values for the four months.

B. *Final Scenarios*

In this section, the results of the final scenarios are shown. These scenarios investigated the impact of increased renewable energy penetration on the market price for electricity. The increased penetration of renewable energy sources was made per the respective national energy plans for Spain and Portugal as discussed previously. Time period 1 consisting of the four hottest months is used again to display the results in this paper.

The best results for these scenarios were again obtained from the ANN with only one training period as it has the lowest MAPE error. Fig. 5 presents a comparison between the actual and forecasted values across the four selected months, and Table V shows the average hourly forecast price as well the average actual price during the same period.

In Fig. 5, forecasted prices (with increased RE penetration) are below the actual prices. The larger difference between the forecast and actual values in the first half of the data set is due to the higher actual prices.

TABLE II. - PEARSON COEFFICIENT OF VARIABLES RELATIVE TO PRICE.

Pearson Coefficient relative to Price			
Variable	Value	Variable	Value
Consumption	0.430	Coal	0.768
Imported balance	0.163	PRO-Thermal	0.305
Wind	-0.449-	Hydro	0.223
PV	0.064	Nuclear	0.114
Fuel, GN and CC	0.236	Cogeneration	0.510

TABLE III - MAPE ERROR RESULTS FOR TEST SCENARIOS.

Number of training periods	1	2	3	5	6	9
Period 1	9.23	9.39	9.43	9.4	-	9.96
Period 2	20.06	17.78	-	18.69	-	15.98
Period 3	19.07	-	16.99	16.91	15.22	18.54

TABLE IV - AVERAGE PRICE PER HOUR FOR THE FOUR MONTHS IN THE TEST SCENARIO.

	Average price per hour (€/MWh)
Actual value	57.895
Forecast value	53.463
Difference	4.432

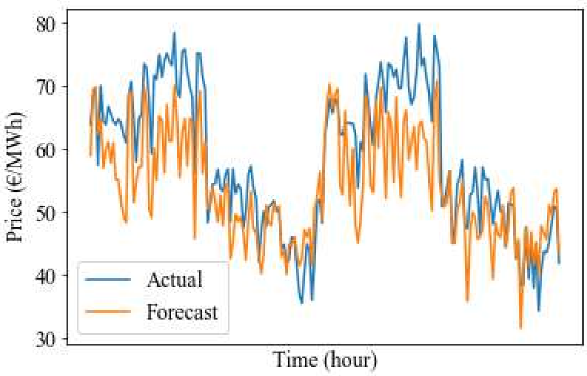

Figure 3- Comparison between forecast and actual values for time period 1 in the test scenario

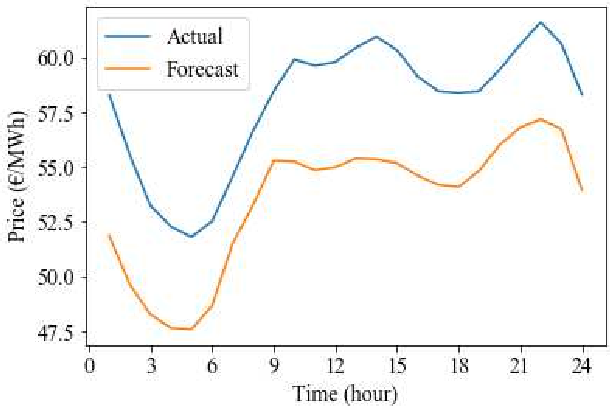

Figure 4- Hourly energy prices for forecast and actual values in time period 1 in the test scenario

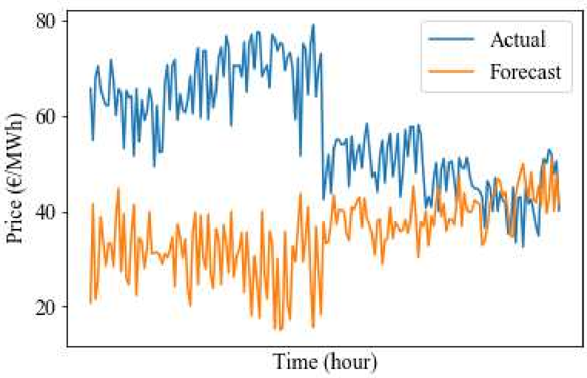

Figure 5- Comparison between forecast and actual values for time period 1 in the final scenario.

The average price per hour (€/MWh) for the entire time period 1 presented in Fig 5 can be seen in Table VI. This table shows both the actual price values and the values obtained through the ANN and the difference between the two averages. Thus, there is a decrease in the average values of 22.711 €/MWh for the whole set under analysis. This means, that there was a 39.3% decrease in price when using the energy mix as laid out in the national energy plans for 2030 in the Iberian Peninsula.

Figure 5 and Table VI highlight the differences between the forecast price and the actual price. The difference between the two values increases significantly after 09:00 and decreases again at approximately 19:00. This fluctuation is due to the impact of a large amount of solar PV generation which generates electricity during these hours.

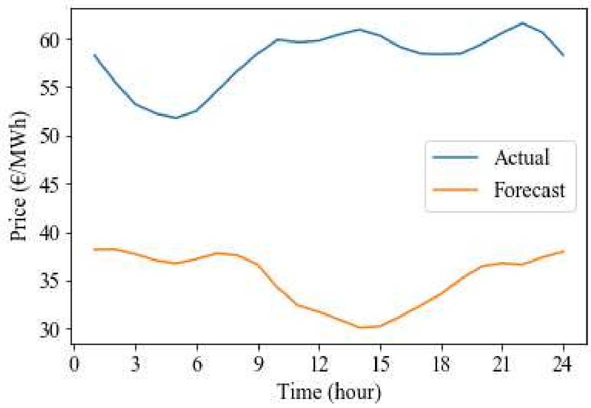

Figure 6- Hourly energy prices for forecast and actual values in time period 1 in the final scenario.

TABLE V-AVERAGE PRICE PER HOUR FOR THE 4 MONTHS IN THE FINAL SCENARIO.

	Average price per hour (€/MWh)
Actual value	57.895
Forecast value	35.184
Difference	22.712

TABLE VI- AVERAGE HOURLY PRICE PER HOUR FOR THE 24 HOURS IN THE FINAL SCENARIO.

Hour	Actual Price (€/MWh)	Forecast Price (€/MWh)	Difference (€/MWh)
1	58.288	38.191	20.097
2	55.543	38.212	17.331
3	53.245	37.723	15.522
4	52.274	37.065	15.208
5	51.804	36.754	15.050
6	52.520	37.199	15.321
7	54.564	37.893	16.771
8	56.649	37.609	19.041
9	58.460	36.642	21.818
10	59.907	34.215	25.692
11	59.641	32.408	27.233
12	59.791	31.754	28.037
13	60.442	30.934	29.509
14	60.948	30.093	30.855
15	60.336	30.227	30.109
16	59.142	31.242	27.900
17	58.471	32.404	26.068
18	58.391	33.573	24.817
19	58.468	35.151	23.317
20	59.448	36.445	23.003
21	60.593	36.773	23.820
22	61.615	36.635	24.980
23	60.637	37.402	23.235
24	58.313	37.967	20.346

In this case, the installed capacity of solar PV increases by 130% compared to the currently installed capacity. The impact of solar PV on the price is the most pronounced in this time period as this period contains the most amount of sunlight hours. During hours when there is no generation from solar PV, the forecast price is still below the actual price due to the impact of wind and hydro generation. Besides, generation from coal and cogeneration is significantly reduced according to the national energy plans.

IV. CONCLUSIONS

The main objective of this work was to analyze the impact that the increasing penetration of electricity production from renewable energy sources has on the Iberian electricity market in the long term. This was done through the development and investigation of operational situations that represent future energy mixes of the Portuguese and Spanish energy systems based on the targets for RE capacity proposed for 2030. Using this framework, simulations were carried out using an ANN that was created and implemented using the MATLAB software. The results showed that an increase in renewable production and the decrease in non-renewable leads to a significant decrease in the market price of electricity of 18.279 €/MWh.

This is calculated as the difference between the actual and forecast market price after the forecasting error has been removed. Also, a significant impact of solar PV generation on the market price was clearly seen, and this is relevant as this technology will have the largest deployment in the Iberian Peninsula according to the two national energy plans. Results from this work showed that significant changes will occur in the MIBEL market and other wholesale energy markets. These changes require novel regulatory regimes to harness the full potential of the shift towards a zero-carbon energy system. This work has shown that the forward-thinking energy plans set out by the governments of Spain and Portugal can positively affect the price of energy within the Iberian energy market while reducing emissions caused by combustion of fossil fuels.

This work has only considered the impact of increased generating capacity, there are numerous other factors which may influence market price such as regulations, energy storage systems, new business models and the growth of electric mobility. These factors will be incorporated into future work to better understand the impacts on electricity market prices.

REFERENCES

[1] M. R. M. Cruz, D. Z. Fitiwi, S. F. Santos, and J. P. S. Catalão, "A comprehensive survey of flexibility options for supporting the low-carbon energy future," *Renewable and Sustainable Energy Reviews*, vol. 97, pp. 338–353, Dec. 2018, doi: 10.1016/j.rser.2018.08.028.

[2] Directorate-General for Energy, "Clean energy for all Europeans.," European Commision, Brussels, Belgium, Jul. 2019. Accessed: Nov. 09, 2020. [Online]. Available: http://op.europa.eu/en/publication-detail/-/publication/ b4e46873-7528-11e9-9f05-01aa75ed71a1/language-en.

[3] Government of Spain, "INTEGRATED NATIONAL ENERGY AND CLIMATE PLAN 2021-2030," Madrid, Spain,Jan. 2020.[Online].Available:https://ec.europa. eu / en ergy/sites/ener/files/documents/es_final_necp_main_en.pdf.

[4] Ministry of environment and climate change, "National Energy and Climate Plan 2030." [Online]. Available: https://www.portugal.gov.pt/pt/gc22/comunicacao/comunicado?i=plano-nacional-energia-e-clima-2030-aprovado-em-conselho-de-ministros.

[5] J. Sousa and I. Soares, "Demand response, market design and risk: A literature review," *Utilities Policy*, vol. 66, p. 101083, Oct. 2020, doi: 10.1016/j.jup.2020.101083.

[6] D. P. Macedo, A. C. Marques, and O. Damette, "The impact of the integration of renewable energy sources in the electricity price formation: is the Merit-Order Effect occurring in Portugal?," *Utilities Policy*, vol. 66, p. 101080, Oct. 2020, doi: 10.1016/j.jup.2020.101080.

[7] J. Roldán-Fernández, M. Burgos-Payán, Á. Trigo-García, J. Díaz-García, and J. Riquelme-Santos, "Impact of renewable generation in the Spanish Electricity Market," in *11th International Conference on the European Energy Market (EEM14)*, May 2014, pp. 1–5, doi: 10.1109/EEM.2014.6861239.

[8] S. Kolb, M. Dillig, T. Plankenbühler, and J. Karl, "The impact of renewables on electricity prices in Germany - An update for the years 2014–2018," *Renewable and Sustainable Energy Reviews*, vol. 134, p. 110307, Dec. 2020, doi: 10.1016/j.rser.2020.110307.

[9] A. Rosato, R. Altilio, R. Araneo, and M. Panella, "Neural Network Approaches to Electricity Price Forecastingly in Day-Ahead Markets," in *2018 IEEE International Conference on Environment and Electrical Engineering and 2018 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I CPS Europe)*, Jun. 2018, pp. 1–5, doi: 10.1109/EEEIC.2018.8493837.

[10] R. Zhang, G. Li, and Z. Ma, "A Deep Learning Based Hybrid Framework for Day-Ahead Electricity Price Forecasting," *IEEE Access*, vol. 8, pp. 143423–143436, 2020, doi: 10.1109/ACCESS.2020.3014241.

[11] REN, "SIMEE - Daily and Intraday - Prices," *Sistema de Informação de Mercados de Energia*. https://www.mercado.ren.pt/EN/Electr/MarketInfo/MarketResults/OMIE/Pages/Prices.aspx (accessed Nov. 10, 2020).

[12] "Weather History & Data Archive | Weather Underground." https://www.wunderground.com/history (accessed Nov. 09, 2020).

[13] "SNIRH - Mapas Resumo da Precipitação." https://snirh.apambiente.pt/snirh/_dadossintese/precipitacao/mapas_resumo/entrada.php?periodo=2000%2F2019&mes=12&ano=2019&tp_mapa=mensal (accessed Nov. 09, 2020).

[14] G. J. Osório, J. N. D. L. Gonçalves, J. M. Lujano-Rojas, and J. P. S. Catalão, "Enhanced Forecasting Approach for Electricity Market Prices and Wind Power Data Series in the Short-Term," *Energies*, vol. 9, no. 9, Art. no. 9, Sep. 2016, doi: 10.3390/en9090693.

[15] S. Kim and H. Kim, "A new metric of absolute percentage error for intermittent demand forecasts," *International Journal of Forecasting*, vol. 32, no. 3, pp. 669–679, Jul. 2016, doi: 10.1016/j.ijforecast.2015.12.003.

[16] J. Estevão and C. Raposo, "The impact of the 2030 Climate and Energy Framework Agreement on electricity prices in MIBEL: A mixed-methods approach," *Journal of Business Research*, vol. 89, pp. 411–417, Aug. 2018, doi: 10.1016/j.jbusres.2017.12.037.

[17] S. Karsoliya, "IJEET - Approximating Number of Hidden layer neurons in Multiple Hidden Layer BPNN Architecture," *International Journal of Engineering Trends and Technology - IJETT*, vol. 3, no. 6, pp. 714–717, 2012.

[18] E. Reggiani, E. D'Arnese, A. Purgato, and M. D. Santambrogio, "Pearson Correlation Coefficient Acceleration for Modeling and Mapping of Neural Interconnections," in *2017 IPDPSW*, May 2017, pp. 223–228, doi: 10.1109/IPDPSW.2017.63.