23rd International Conference on Renewable Energies and Power Quality (ICREPQ'25)
Tenerife (Spain), 25th to 27th June 2025
ISBN-13: 978-84-09-66511-2

Statistical Regression Model for Annual Hourly Price Estimation in the Spanish Electricity Market

N. Naval, L. Tipán-Salazar and J.M Yusta

Department of Electrical Engineering
University of Zaragoza
Zaragoza, Spain
naval@unizar.es

Abstract. This article aims to obtain an annual hourly profile of Spanish electricity market prices until 2050, by estimating a statistical regression model that captures the variables that influence price formation. This model captures hourly price fluctuations, allowing identifying key dynamics that affect the planning and operation of the power system. A significant increase in wind and solar photovoltaic energy is estimated, reaching a renewable penetration of 88.36 % in 2050. As a result, the average OMIE price would be reduced by 70 %. Estimating long-term hourly electricity market prices is key to planning investments, managing costs and mitigating market risks.

Keywords. Regression model, electricity market price, forecasting

1. Introduction

The wholesale electricity market plays a crucial role in the operation of the energy system, as it determines electricity prices that affect both end consumers and industries. This market is characterized by its high volatility, influenced by factors such as energy supply and demand, weather conditions, fossil fuel prices, as well as regulatory policies.

Electricity price forecasting has undergone a significant transformation, driven by the changing dynamics of energy markets and the rise of renewables. Initial research focused primarily on point forecasts, but there has been a notable shift towards probabilistic forecasts, which provide a more comprehensive assessment of the uncertainties inherent in electricity prices. This change is motivated by the need to capture the stochastic nature of supply, demand and pricing in modern electricity markets, especially with the increasing penetration of intermittent renewable energy sources. A number of papers present an overview of electricity price forecasting methods and highlight emerging trends in the field. Work [1] provides a comprehensive review of various methods of electricity price forecasting. As a follow-up to this work, the authors of [2] focus on the various probabilistic forecasting approaches. The authors of [3] address short-term price forecasting, focusing on the comparison of univariate and multivariate model structures.

Traditional approaches to electricity price forecasting often relied on univariate techniques by modeling each hour of the day separately [4], [5], [6]. However, this method does not take into account the complex interdependencies between hourly prices. Studies have shown that multivariate models, which consider all hourly prices together, can produce more accurate forecasts, capturing the underlying market dynamics more effectively. The authors of [7] propose an ARMAHX functional model that takes into account the interrelationships between electricity price curves over time. Article [8] uses an extension of the X-model technique. This model is based on the identification of the equilibrium point between electricity supply and demand in the market in the medium and long term. Paper [9] discusses different approaches, including vector autoregressive model (VAR) and regression models with LASSO regularization. Work [10] uses a technique based on Fourier analysis for long-term forecasting of prices. In addition, it studies the possibility of coupling this data-driven model with market-based models to reduce uncertainties.

In recent years, some papers study the use of neural networks for electricity price forecasting [11], [12]. Although these present challenges in computational complexity, difficulty in reproducibility and need for large data sets.

In this context, statistical forecasting models have gained relevance as tools to establish in a complex and dynamic environment such as the electricity market. However, most of them focus on short-term periods. Therefore, there is a need for further research in the proposal of statistical models that study long-term trends with an efficient integration of critical factors in the formation of the Spanish electricity market price, such as the evolution of renewable generation capacities, fossil fuel costs, etc. A better understanding of the interaction of these factors over time can provide more robust tools for energy planning. As a consequence, this paper aims to propose a statistical regression model that allows accurate and robust prediction of hourly prices in the wholesale electricity

market in Spain up to 2050. The model will be based on a comprehensive analysis of relevant explanatory variables, including renewable and conventional generation capacity, oil and gas costs and CO_2 emissions, among others. This model will lead to improved decision making and profitability of energy projects.
The rest of the article is structured as follows: Section 1 presents the methodology for the estimation of an hourly price model for the electricity market. Section 3 analyzes the results obtained and Section 4 summarizes the main conclusions.

2. Estimation model of Spanish electricity market price

Figure 1 defines the methodology followed for the estimation of hourly prices of the Spanish electricity market.
First, historical data, trends in the coming years of renewable and conventional generation sources, gas, oil and CO_2 emissions prices, cross-border interconnections, etc., are compiled.
Afterwards, the variables that influence the price of the Spanish electricity market are identified, and a correlation analysis is carried out to select the most significant variables.
Subsequently, a multivariate regression model is developed to obtain an annual hourly profile of the Spanish electricity market prices until 2050. The balance between the fit and the complexity of the model is measured by means of the Mallows Cp value.
From this statistical model, hourly price profiles are generated for the period 2023-2050. Finally, the results obtained are analyzed and the actual price in 2024 and the estimated price are compared.

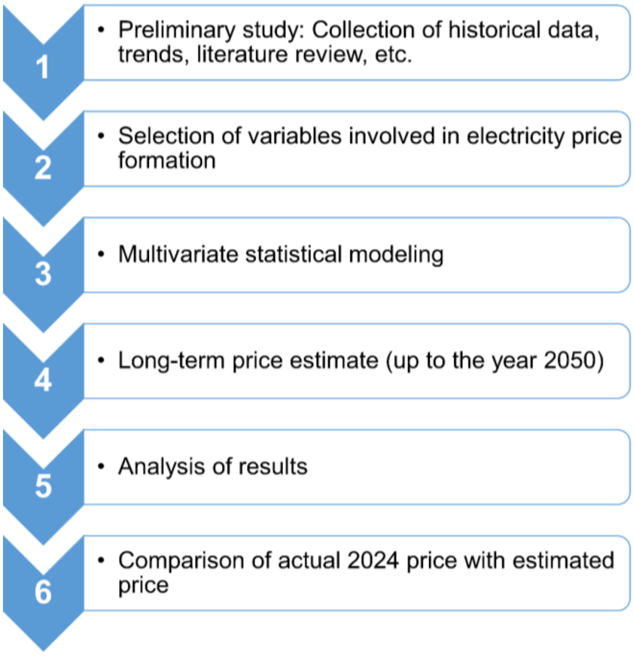

Fig. 1. Methodology for electricity market price estimation

The correlation study makes it possible to evaluate the relationship between the response variable and the predictor variables, and to analyze the best subsets to determine the set of 17 variables in the study, measuring the balance between the fit and the complexity of the model by means of the Mallows Cp value. In the estimation of the regression model, it has been found that the Solar Thermal variable is not statistically significant, and therefore it has been removed from the regression study, finally having 16 predictor variables (see Table I).

Table I. Predictive variables

Variable	Description
Brent price	cost of a barrel of Brent crude oil, in $/barrel
Gas price	cost of natural gas, in €/MWh
CO_2 price	cost of CO_2 tax, in €/ton CO_2
Wind	hourly operating schedule for wind power production, in MWh
PV	hourly operating schedule for photovoltaic power production, in MWh
Hydro	hourly operating schedule of hydro production, in MWh
Turbination-Pumping	hourly operating schedule of pumped-turbine production, in MWh
Other renewables	hourly operating schedule of production of other minor renewables, in MWh.
Nuclear	hourly operating schedule of nuclear production, in MWh
Combined Heat and Power	hourly operating schedule of combined heat and power production, in MWh
Cogeneration	hourly operating schedule of cogeneration production, in MWh
Coal	hourly operating schedule for coal-fired production, in MWh
Waste	hourly operating schedule for production from waste burning, in MWh
Available power	available generation power, in MWh
Import France	import France, in MWh
Export France	export France, in MWh

The model uses data from various sources to estimate the evolution of prices and installed capacity:

- Crude oil, gas and CO_2 prices:
  - The International Energy Agency (IEA) World Energy Outlook 2023 report is used [13].
  - The intermediate scenario "Announced Pledges Scenario" (APS) is selected as the most viable frame.

- Prices are interpolated for the intermediate years between 2030 and 2050.

- Installed power generation capacity:
  - Integrated National Energy and Climate Plan (PNIEC) through 2030 are used [14].
  - For the period 2030-2050, the report by Mark Z. Jacobson of Stanford University, which projects a 100 % renewable scenario, is used [15].
  - The Spanish government's Energy Storage Strategy, which projects 30 GW of storage by 2050, is considered [16].
  - The objectives set by the PNIEC are expected to be met by 2035, based on the trend of recent years. This assumption is used for the regression model.

3. Results

Table 2 shows the evolution of prices and installed capacity of the different predictor variables established in this study up to 2050, based on the above-mentioned sources. In the scenario foreseen for 2050, wind and photovoltaic energy will be dominant with respect to the rest of the energy generation technologies. Also noteworthy is the progressive increase in storage, which will play a decisive role in integrating the high penetration of renewable energy while guaranteeing security of supply.

In addition, installed capacity in cogeneration and combined heat and power plants is maintained to ensure security of supply, especially in island systems.

Table II. Evolution of commodity prices and installed capacity of different technologies until 2050.

	Brent price	Gas price	CO_2 price	Wind	PV	Hydro	Turbination and pumping	Other renewables	Nuclear	Combined Heat and Power	Cogeneration	Coal	Waste	Available power
	$/barril	€/MWh	€/tCO_2	MW	MW	MW	MW	MW	MW	MW	MW	MW	MW	MW
2023	83.55	46.11	84.46	29746	22681	17096	3331	1087	7117	24562	5589	3223	387	117124
2024	82.19	42.51	88.54	35945	39709	15678	6413	1087	7117	25587	4829	1612	362	140641
2025	80.82	38.91	92.62	42144	56737	14261	8828	1087	7117	26612	4068	0	338	163492
2026	79.46	35.30	96.70	44134	58702	14311	9800	1087	7117	26612	4011	0	315	168890
2027	78.09	31.70	100.78	46124	60667	14361	10771	1087	6068	26612	3954	0	295	173240
2028	76.73	28.10	104.86	48114	62632	14411	11743	1087	5024	26612	3898	0	275	177596
2029	75.36	24.49	108.94	50104	64597	14461	12714	1087	5024	26612	3841	0	257	182997
2030	74.00	20.89	113.02	52094	66562	14511	13686	1087	3181	26612	3784	0	240	186557
2031	73.30	20.71	113.86	54084	68527	14511	14657	1087	3181	26612	3784	0	224	191468
2032	72.60	20.53	114.71	56074	70492	14511	15629	1087	2154	26612	3784	0	209	195352
2033	71.90	20.36	115.56	58064	72457	14511	16600	1087	2154	26612	3784	0	196	200265
2034	71.20	20.18	116.41	60054	74422	14511	17572	1087	2154	26612	3784	0	183	205179
2035	70.50	20.00	117.25	62044	76387	14511	18543	1087	0	26612	3784	0	171	207939
2036	69.80	19.83	118.10	65197	77939	14511	19307	1087	0	26612	3784	0	159	213397
2037	69.10	19.65	118.95	68350	79491	14511	20071	1087	0	26612	3784	0	149	218855
2038	68.40	19.47	119.80	71503	81044	14511	20834	1087	0	26612	3784	0	139	224315
2039	67.70	19.30	120.64	74656	82596	14511	21598	1087	0	26612	3784	0	130	229774
2040	67.00	19.12	121.49	77809	84148	14511	22362	1087	0	26612	3784	0	121	235235
2041	66.30	18.94	122.06	80962	85700	14511	23126	1087	0	26612	3784	0	113	240696
2042	65.60	18.77	122.62	84115	87252	14511	23890	1087	0	26612	3784	0	106	246158
2043	64.90	18.59	123.19	87269	88805	14511	24653	1087	0	26612	3784	0	99	251620
2044	64.20	18.41	123.75	90422	90357	14511	25417	1087	0	26612	3784	0	92	257082
2045	63.50	18.24	124.32	93575	91909	14511	26181	1087	0	26612	3784	0	86	262545
2046	62.80	18.06	124.88	96728	93461	14511	26945	1087	0	26612	3784	0	81	268009
2047	62.10	17.88	125.45	99881	95013	14511	27709	1087	0	26612	3784	0	75	273472
2048	61.40	17.71	126.01	103034	96566	14511	28472	1087	0	26612	3784	0	70	278936
2049	60.70	17.53	126.58	106187	98118	14511	29236	1087	0	26612	3784	0	66	284401
2050	60.00	17.35	127.14	109340	99670	14511	30000	1087	0	26612	3784	0	61	289866

Figure 2 represents the estimated average OMIE price until 2050. It can be observed a decrease in prices year by year as a consequence of the integration of renewable energy. It should be taken into account that there may be variations due to changes in energy policies, fluctuations in demand, variations in the availability of energy sources, among others.

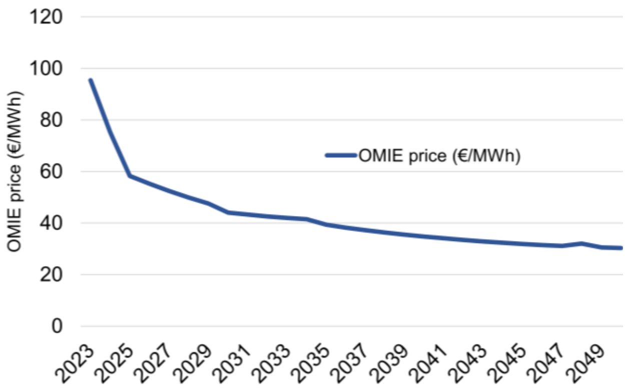

Fig. 2. Estimated average OMIE price to 2050

Figures 3 and 4 represent a comparison of the estimated hourly OMIE price in 2024 using the regression model of this article and the actual OMIE price in 2024 for one day in the month of April and September. The penetration of wind and photovoltaic generation plants will produce two large price drops: one at night when demand is low and there is wind generation and another in the afternoon when, in addition to wind production, there is a large amount of solar photovoltaic generation, resulting in a large drop in prices. These large drops in hourly prices between 7 a.m. and 8 p.m. result in what is called a "duck curve" because of its duck shape. The large deployment of photovoltaic energy means that during solar hours there are large drops in prices, reaching at times close to 0 €/MWh. This large price collapse creates a great opportunity to develop energy storage. It can be seen how in these hours the estimated price and the actual price practically coincide. Therefore, the model offers reasonable price estimates.

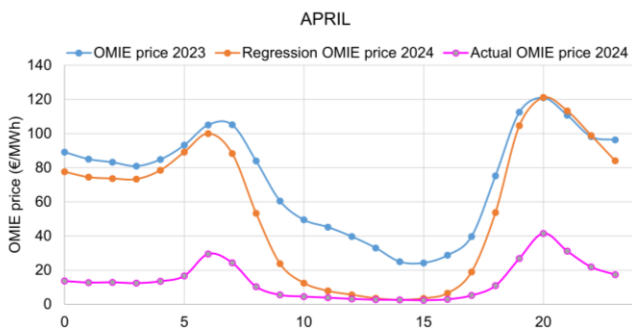

Fig. 3. Comparison of the estimated hourly OMIE price and the actual OMIE price for one day in April of 2024

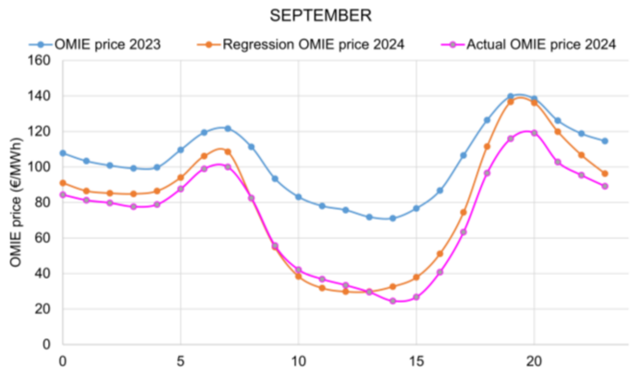

Fig. 4. Comparison of the estimated hourly OMIE price and the actual OMIE price for one day in September of 2024

4. Conclusion

The objective of this paper is to estimate a statistical regression model that captures the variables that influence the formation of the electricity market price. An annual hourly profile of the Spanish electricity market prices until 2050 is obtained. The model foresees a significant change in the Spanish energy mix towards a model dominated by renewable energy. In the scenario foreseen for 2050, wind and photovoltaic energy will be dominant with respect to other energy generation technologies. Also noteworthy is the gradual increase in energy storage. It highlights the importance of energy storage to integrate the high penetration of renewable energy and ensure system reliability. The model also recognizes the need to maintain certain non-renewable technologies to cover demand in specific situations.

References

[1] R. Weron. Electricity price forecasting: A review of the state-of-the-art with a look into the future. International Journal of Forecasting. 2014. vol. 30, no. 4. pp. 1030–1081. doi: 10.1016/j.ijforecast.2014.08.008.

[2] J. Nowotarski and R. Weron. Recent advances in electricity price forecasting: A review of probabilistic forecasting. Renewable and Sustainable Energy Reviews. 2018. vol. 81, no. May 2017. pp. 1548–1568. doi: 10.1016/j.rser.2017.05.234.

[3] J. Lago, G. Marcjasz, B. De Schutter, and R. Weron. Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark. Applied Energy. 2021. vol. 293, no. December 2020. p. 116983. doi: 10.1016/j.apenergy.2021.116983.

[4] C. González, J. Mira-McWilliams, and I. Juárez. Important variable assessment and electricity price forecasting based on regression tree models: Classification and regression trees, Bagging and Random Forests. IET Generation, Transmission and Distribution. 2015. vol. 9, no. 11. pp. 1120–1128. doi: 10.1049/iet-gtd.2014.0655.

[5] E. Raviv, K. E. Bouwman, and D. van Dijk. Forecasting day-ahead electricity prices: Utilizing hourly prices. Energy Economics. 2015. vol. 50. pp. 227–239. doi: 10.1016/j.eneco.2015.05.014.

[6] F. Ziel and R. Steinert. Electricity price forecasting using sale and purchase curves: The X-Model. Energy Economics. 2016. vol. 59. pp. 435–454. doi: 10.1016/j.eneco.2016.08.008.

[7] J. P. González, A. M. S. Roque, and E. A. Pérez. Forecasting functional time series with a new hilbertian ARMAX model: Application to electricity price forecasting. IEEE Transactions on Power Systems. 2018. vol. 33, no. 1. pp. 545–556. doi: 10.1109/TPWRS.2017.2700287.
[8] F. Ziel and R. Steinert. Probabilistic mid- and long-term electricity price forecasting. Renewable and Sustainable Energy Reviews. 2018. vol. 94, no. May. pp. 251–266. doi: 10.1016/j.rser.2018.05.038.
[9] F. Ziel and R. Weron. Day-ahead electricity price forecasting with high-dimensional structures: Univariate vs. multivariate modeling frameworks. Energy Economics. 2018. vol. 70. pp. 396–420. doi: 10.1016/j.eneco.2017.12.016.
[10] P. Gabrielli, M. Wüthrich, S. Blume, and G. Sansavini. Data-driven modeling for long-term electricity price forecasting. Energy. 2022. vol. 244. p. 123107. doi: 10.1016/j.energy.2022.123107.
[11] F. Wang et al. Daily pattern prediction based classification modeling approach for day-ahead electricity price forecasting. International Journal of Electrical Power and Energy Systems. 2019. vol. 105, no. July 2018. pp. 529–540. doi: 10.1016/j.ijepes.2018.08.039.
[12] A. Poggi, L. Di Persio, and M. Ehrhardt. Electricity Price Forecasting via Statistical and Deep Learning Approaches: The German Case. AppliedMath. 2023. vol. 3, no. 2. pp. 316–342. doi: 10.3390/appliedmath3020018.
[13] International Energy Agency. World Energy Outlook., 2023.
[14] Ministerio para la Transición Ecológica. Plan Nacional Integrado de Energía y Clima 2021-2030, 2020. [Online]. Available: https://www.miteco.gob.es/es/prensa/pniec.aspx.
[15] M. Z. Jacobson. The cost of grid stability with 100 % clean, renewable energy for all purposes when countries are isolated versus interconnected. Renewable Energy. 2021. vol. 179. pp. 1065–1075. doi: 10.1016/j.renene.2021.07.115.
[16] El Gobierno aprueba la Estrategia de Almacenamiento Energético, clave para garantizar la seguridad del suministro y precios más bajos de la energía. https://www.miteco.gob.es/es/prensa/ultimas-noticias/2021/02/el_gobierno_apruebalaestrategiadealmacenamientoenergeticoclavepa.html (accessed Dec. 10, 2023).