Analysis of Near-Zero Prices in the Iberian Electricity Market and their Impact on the Profitability of Renewable Photovoltaic Plants

Jesús Eduardo Ramírez Mendoza, Iraide López Ropero,
Itxaso Aranzabal Santamaria
Department of Electrical Engineering
University of the Basque Country (UPV/EHU)
Ingeniero Torres Quevedo Plaza, 1, 48013 Bilbao, Spain
itxaso.aranzabal@ehu.eus

Amaia González-Garrido
Energy, Climate and Urban Transition Unit,
TECNALIA, Basque Research and Technology Alliance (BRTA)
Astondo Bidea, Building 700, 48160 Derio, Spain
amaia.gonzalez@tecnalia.com

***Abstract*— The increasing occurrence of near-zero market prices in the wholesale electricity markets has raised concerns about the market capture rate and impact on the viability of Photovoltaic (PV) assets. This article aims to conduct a statistical analysis of the occurrence of near-zero day-ahead prices in the Iberian electricity market along 2024 and evaluate the correlation between prices and various technologies in the energy mix. There are 838 hours of the year below 1 €/MWh. During the spring months, day-ahead prices are significantly lower, especially at daylight. Looking at spring months, the findings suggest that wind power tends to decrease them. As can be concluded, there is a strong linear correlation between the thermal gap and market prices. Finally, this article addresses the impact of such prices on the profitability of PV plants. PV is not able to influence prices (negative Pearson coefficient), resulting in a capture rate of 65%.**

***Index Terms*-- Capture Rate, Energy Storage, Iberian Market, Near-Zero Prices, Photovoltaic Profitability.**

I. INTRODUCTION

In recent years, an increased volatility has been observed among peak and off-peak daily prices in wholesale energy markets, attributed mainly to the penetration of Renewable Energy Sources (RES). While yearly average price volatility is generally driven by hydropower availability [1], daily and hourly price volatility is mostly influenced by fluctuations in solar photovoltaic (PV) and wind power (WP) availability. However, RES market correlation is complex and non-linear. For example, authors in [2] examined the impact of RES on extreme positive and negative fluctuations in wholesale electricity prices in OECD countries and they suggested that RES significantly influence market price once certain penetration thresholds are exceeded. Indeed, the increasing market penetration of zero-marginal cost variable RES led to the cannibalization and the reduction of wholesale electricity prices, due to the merit-order effect. Focused on RES cannibalization, authors in [3] identified that the negative effects of solar penetration on solar value are more pronounced than those of wind, due to the higher temporal and spatial correlation of PV. Moreover, as reported in [4], solar unit revenues and the solar value factor decreased in the CAISO market throughout the 2010s. Similarly, [5] shown that RES significantly reduced electricity prices along the same years in Germany, by reconstructing electricity prices without wind and solar plants. Most of them ([2], [3] and [4]) outlined some policy recommendation and further research to explore how the deployment of energy storage, demand management, grid infrastructure and interconnections, and new policy incentives could mitigate the cannibalization effect and impact the value of variable RES. Backup and electricity storage capacities need to be installed to ensure a reliable supply [5]. Volatility can foster investment in RES and flexibility technologies [6].

Several articles developed models for market modelling and price forecasting. For example, [6] used an ex-post econometric model for Germany applied to hourly historical to estimate the effects of dependent variables, like gas and Emission Trading System (ETS) prices. They suggested a considerably higher electricity price and higher volatility in the coming years. Similarly, [7] introduced a causal inference framework which enables the identification of non-linear treatment effects. While wind higher penetration levels are associated directly with lower electricity prices in the United Kingdom, the solar pattern is more complex and non-linear to estimate, possibly due to its currently low penetration levels.

Thus, electricity market prices depend on various factors, including energy demand, weather conditions, gas prices, RES generation, and other factors. Authors in [8] presented an hourly price forecasting method based on artificial neural networks, for two to ten days in advanced. Similarly, [9] developed a probabilistic forecasting model for day-ahead and intraday markets. Future contracts in derivatives markets and daily forecasted WP influenced hugely on the model accuracy. Finally, [10] identified the primary drivers of final wholesale electricity prices in the Iberian market, apart from the day-ahead market price, using machine learning techniques, such as network technical constraints and balancing services costs.

This work has been partially financed by a scholarship program for student internships at TECNALIA. This work was also supported by the Grant TED2021-129930A-I00 funded by MICIU/AEI/10.13039/501100011033 and by the "European Union NextGenerationEU/PRTR"; by the Grant PID2021-125881OB-I00 funded by MICIU/AEI/10.13039/501100011033 and by "ERDF A way of making Europe; and by the Basque Government under the Grant IT1647-22 (ELEKTRIKER research group).

Although these three previous research articles focus on the Iberian electricity market, the market dataset horizon is quite limited and outdated: 2015 to 2017 [9], 2017 to 2018 [8], and 2017 to 2021 [10]. They do not cover the latest years, especially when there is a growing trend of prices approaching zero and even becoming negative. Throughout 2024, this trend is being considered a structural upward trend in the Iberian electricity market rather than a sporadic occurrence. Thus, this price trend is an increasing concern for the RES sector, mostly PV.

To the best of the authors' knowledge, there is no recent analysis of market prices with a significant occurrence of near-zero prices, even though this situation seems more likely in the coming years, along with increased intraday price volatility.

Therefore, this article aims to first conduct a statistical analysis of the occurrence of near-zero and negative prices in the day-ahead market, focusing on the Iberian market as a case study. Secondly, this article evaluates the correlation between day-ahead market prices and the technologies within the hourly energy mix and other market conditions. The study aims to identify the key factors that influence day-ahead prices. Finally, this article addresses the impact of such prices on the profitability of renewable plants, especially focused on a typical solar plant and its capture rates in the Iberian market in 2024.

II. CASE STUDY AND STATISTICAL METRICS

Section II provides a description of the case study, detailing the sources of market data analyzed and the specific time horizon covered. The study focuses on day-ahead market prices in the Iberian market (Spain and Portugal) throughout 2024, a year characterized by high occurrence of near-zero prices.

Hourly data on the electricity generation mix and day-ahead prices have been obtained through the ESIOS website [11] and API service, provided by REE (Red Eléctrica de España), which is the Spanish Transmission System Operator (TSO).

As indicated, the year 2024 has been selected as the study period due to its relative stability, characterized by a year with a high occurrence of near-zero prices, but without exceptional exogenous non-market-related events that could distort the analysis. Given the huge volume of data and the need for efficient automation in the analysis, a Python script has been developed to read, process, filter and analyze the download data, in order to extract relevant patterns and trends. Special attention has been given to those generation types that not only contribute significantly to the energy supply, but also play a key role in price formation, as price-maker technologies.

To analyze the behavior and volatility of day-ahead market prices, some statistical metrics have been calculated. First, the Interquartile Range (IQR) is calculated as the difference between the first and the third quartile (Q1-Q3) as expressed in eq. (1), which measures the spread of the middle 50 % of data. IQR assesses price dispersion, a robust against outliers.

$$IQR = Q_3 - Q_1 \tag{1}$$

Secondly, the Coefficient of Variation (CV) is a standardized measure of dispersion of the probability distribution, defined as the ratio of the standard deviation (σ) to the mean (μ), as indicated in eq. (2). The CV is employed to evaluate relative variability of prices across months.

$$CV = \sigma / \mu \tag{2}$$

Thirdly, the Pearson coefficient (r) is used to extract the linear correlation among the day-ahead prices and each technology of the energy mix. This coefficient can take values ranging from +1 (direct) to -1 (inverse relationship). That is, positive values means that when one variable increases, the other increases proportionally. The $r_{g,T}$ coefficient is calculated for each generation technology (x_g) during a given period of time (T), i.e., a month or a year, being expressed as in eq. (3):

$$r_{g,T} = \frac{\sum_h \left(x_{g,h} - \mu_{x_g}\right) \cdot \left(y_h - \mu_y\right)}{\sigma_{x_g} \cdot \sigma_y} \quad \forall h \in T \tag{3}$$

where $x_{g,h}$ is the energy value of a given generation technology (g) at hour h ; y_h is the price at hour h ; μ_{x_g} is the mean value of each x_g ; μ_y is the mean price; σ_{x_g} is the standard deviation of the energy value of x_g ; and σ_y is the price standard deviation.

III. NEAR-ZERO PRICES ANALYSIS

Section III presents the day-ahead price analysis along 2024. Fig. 1 illustrates the distribution of monthly prices, including the mean, median, quartiles and outliers. It can be observed that spring months (March, April, and May), the day-ahead prices were significantly lower compared to the rest of the year. The mean price in April was 13.7 €/MWh in contrast to December, where it reaches 110.5 €/MWh. This pattern may suggest seasonal behavior, characterized by lower demand rates and higher availability of renewable resources. Along 2024, there were 247 hours with negative prices, 537 hours with zero prices, and 838 hours (9.6 %) below 1€/MWh.

To compare monthly price dispersion in greater detail, two statistical metrics were calculated, as described in Section II. Fig. 2 depicts the monthly statistical metrics for IQR and CV. As can be observed, the IQR is higher outside spring, especially in June and September. This indicates greater dispersion in usual prices during these months, reflecting higher volatility. In contrast, the lowest IQR values were recorded in March and April, suggesting lower price dispersion and variability. In conclusion, these Spring months not only have the lowest absolute values, but also exhibit relatively price stability compared to those recorded throughout the rest of the year.

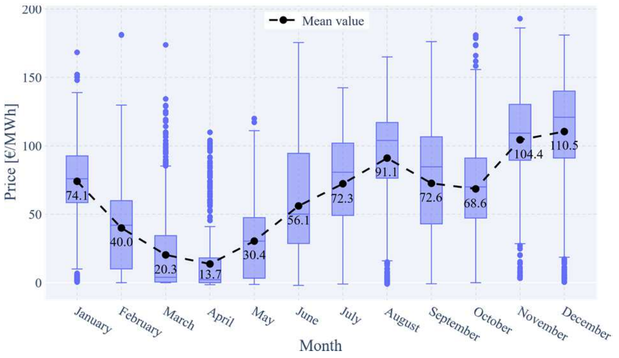

Figure 1. Average market prices during 2024.

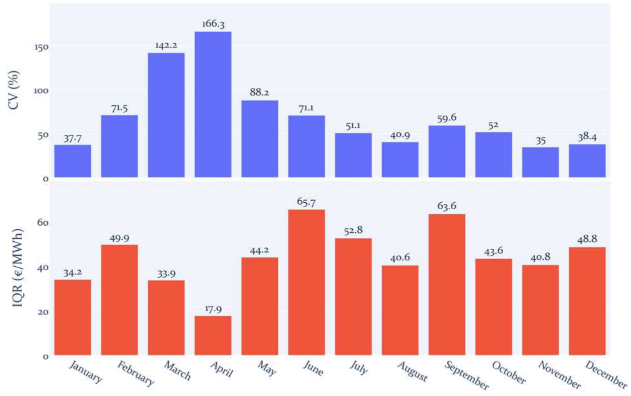

Figure 2. (a) Cofficient of variation and (b) Interquartile range during 2024.

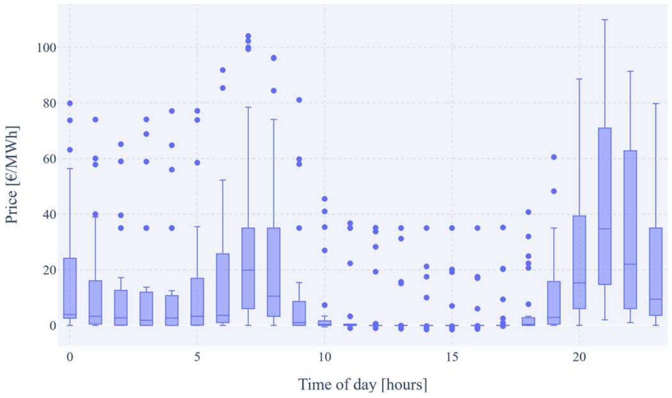

Figure 3. Hourly price distribution by hour during April, 2024.

In contrast, the CV reaches its highest values in spring months (especially March and April), which measures price variability compared to the mean. On the one hand, the mean prices along these months are closer to zero. On the other hand, high CV values indicate that there is higher variability of prices, that is, a higher relative dispersion of data points around the mean, considering the influence of outliers. Thus, it might be more challenging to estimate the hourly prices in these months.

To illustrate the hourly distribution of months with high CV and low IQR, Fig. 3 presents the hourly prices distribution for the month of April, highlighting the intraday behavior. As can be observed, there are numerous outliers, which contribute to the high CV value; and low hourly IQR boxes at daylight hours. As can be concluded, there are a significant number of hours with near-zero prices in April, especially during the daylight hours (from 10h to 17h). Although PV might be partially responsible for this price formation, PV seems to be the most affected technology, as will be discussed in Section IV.

IV. PRICE-TECHNOLOGY CORRELATION ANALYSIS

Section IV discusses the correlation between the price and technologies in the generation mix to identify the key factors responsible for near-zero prices, especially in April and March.

Fig. 4 presents the monthly generation share of each technology in the energy mix during 2024. It can be observed that Nuclear (NU), Onshore Wind (OWP), Solar Photovoltaic (PV), and Reservoir-Based Hydroelectric Generation (RBH) technologies account for 81.7%, 81.9%, and 78.9% of electricity production during the spring months. Especially during March and April, there is a higher share of RBH (as a controllable RES technology, which reaches its peak reservoir levels along spring season), and a lower share of fossil fuels technologies, like Combined Cycle Gas Turbine (CCGT), and Natural Gas Combined Heat and Power (CHP). There are residual technologies in the energy mix, such as Concentrated Solar Thermal Power (CSP) and Run-of-River Hydroelectric Generation (ROR) with minimal contribution but relevant for their adaptability when needed. It is important to note out that demand in spring is lower than in the rest of the year, leading to the lowest market prices, as the demand can be easily satisfied with RES technologies. In contrast, the winter season, with high demand and a high share of fossil fuel technologies, leads to higher market prices.

To evaluate the relationship between the market prices and technologies in the energy mix, the Pearson's correlation is depicted in Fig. 5 for 2024, and in Fig. 6 for April and March.

Figure 4. Monthly generation mix by source (2024)

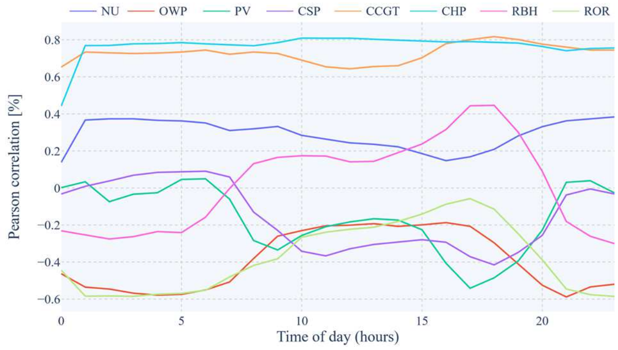

Figure 5. Hourly price-generation Pearson correlation during 2024.

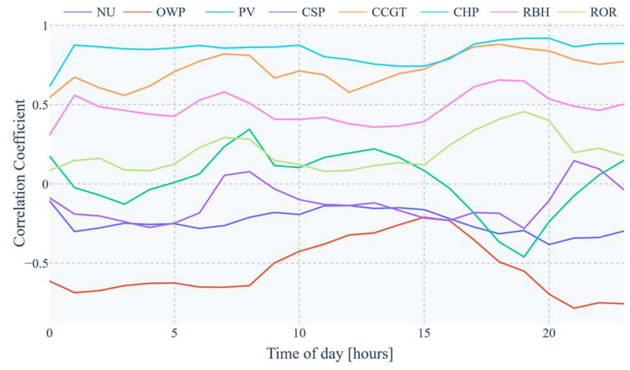

Figure 6. Hourly price-generation Pearson correlation (March and April)

As can be expected, the CCGT and CHP have the highest positive Pearson coefficient, both annually and during the spring season (March and April), as they are typically price-maker technologies with high offered day-ahead prices. NU has a flat shape, which may indicate that NU is not able to influence the price, due to its inflexible control and stable capacity load. On an annual basis, its Pearson coefficient is around +0.3, while in the spring months, it is negative by a similar proportion. Within the hydro technologies, it can be observed a similar monthly shape for RBH and ROR, due to similar monthly load factor (linked to the water availability). Obviously, RBH has real and significant influence on market prices (pink curve above the light green), as it is a controllable RES. During March and April, the RBH curve has a shape like fossil fuels, with a positive coefficient (around +0.5), indicating that RBH is operating under a price marker strategy. Notably, the Pearson coefficient is higher during evening hours (at peak demand).

Regarding solar and wind technologies, OWP has a more predominant hourly negative coefficient during nighttime, while PV and CSP have higher negative coefficient during daylight hours, as illustrated in Fig. 5. In contrast, during the spring months in Fig. 6, OWP shows a predominant negative Pearson coefficient (-0.5), which may indicate its influence on low price formation. For CSP and PV, the correlation is not as strong, suggesting that these technologies have a lower impact on prices. Therefore, it can be concluded that RBH tends to increase prices, while OWP tends to decrease them in spring.

As observed, Pearson correlation reveals important patterns in price behavior and linear relationship between generation and price. However, a causal relationship cannot be established solely based on this bi-variate correlation. That is, even with high positive or negative correlation, the relationship cannot be considered fully deterministic in price formation, as price is influenced by multiple variables in a pay-as-clear market.

Furthermore, the relationship between annual price and RES-based technologies (PV, CSP, OWP, and RBH) and fossil fuel-based technologies (CCGT and CHP) can be discussed for March and April, as depicted in Fig. 7 to 11. Scatter plots are used to illustrate the relationship between market price, hourly generation per technology, and the hour of the day, using a color scale. Yearly scatter plot data are included in Appendix A.

It can be concluded that PV technology is not able to influence prices (no clear tendency), neither on a yearly horizon nor in the spring, as can be observed in Fig. 7 (March-April) and Fig. A.1 (year). The vast majority of high PV generation in March and April occurred during periods of near-zero prices. In contrast, CSP is able to capture higher prices thanks to thermal storage, as observed with the dark blue and brown dots in Fig. 8. Of course, it is not able to influence prices as its share in the energy mix is low, as observed in Fig, A.2 for yearly results, but it can shift a part of production to peak prices.

Regarding OWP technology, Fig. 9 shows that OWP captures zero prices throughout all hours of the day and across all production levels. Even at nighttime, the capture price is zero, indicating a tendency to decrease prices, which aligns with the deductions made previously in Fig. 6. Looking at the yearly pattern in Fig. A.3, it is noted that the capture price of OWP is higher at nighttime with low generation. In contrast, it is observed lower prices with higher generation, indicating the negative Pearson correlation. OWP seems to be able to depress prices, as other zero-marginal-cost generation technologies.

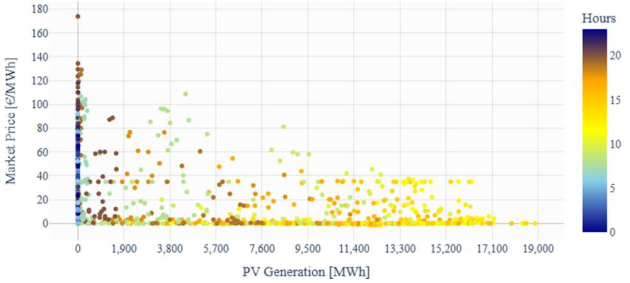

Figure 7. Hourly PV generation vs day-ahead price in March and April.

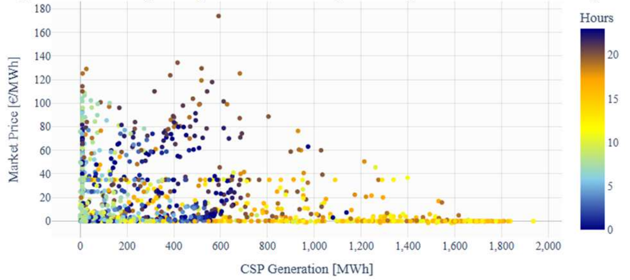

Figure 8. Hourly CSP generation vs day-ahead price in March and April.

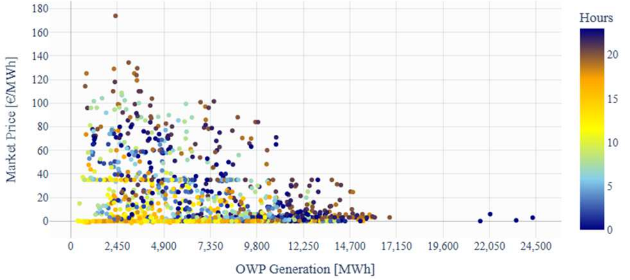

Figure 9. Hourly OWP generation vs day-ahead price in March and April.

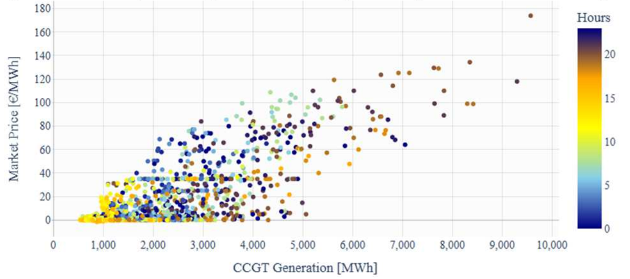

Figure 10. Hourly CCGT generation vs day-ahead price in March and April.

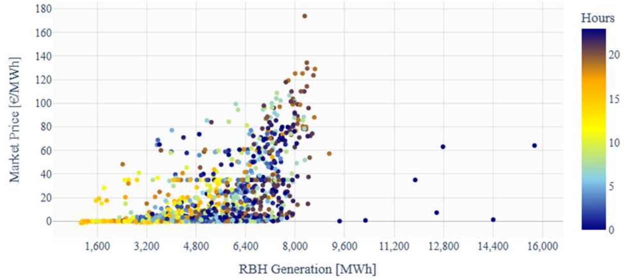

Figure 11. Hourly RBH generation vs day-ahead price in March and April.

Regarding fossil-fuel technologies, the CCGT is analyzed, as having more installed capacity compared to CHP. As can be observed, the scatter plot of CCGT on Fig. 10 reveals significant patterns in electricity market price formation. It is observed a positive correlation between CCGT generation and market prices. CCGTs aim to produce at sunrise, sunset, and nighttime hours (green, blue, orange and brown dots), when market prices tend to be higher. However, due to their ramp-up operation and start-up times, CCGTs need conditional market bids, which result in them entering the market even when prices are low at midday (as shown by the dots in the lower left corner). This performance is more clearly illustrated in Fig. A.5. The CCGT exhibits a positive logarithmic trend, indicating that it operates most of the time at high prices (operating as a price-maker), while it operates at low level during daylight hours. This strategy allows CCGTs to maximize their profitability.

According to Fig. 11, RBH shows high levels of generation especially during evening and nighttime when prices tend to be higher. However, there is notable price dispersion, which indicates that the RBH needs to generate with the reservoirs nearly full (spring season has higher share of RBH). Despite having excessive water availability, the Pearson's correlation indicates positive trend to produce more at higher price periods.

Lastly, the thermal gap is calculated as the difference between the total energy demand and the combined generation from NU, PV, CSP, OWP, and ROR. Indeed, it represents the portion of energy demand that needs to be met by other sources, typically fossil fuels or controllable RBH generation, which are price-maker technologies. As can be clearly deduced from this thermal gap relationship depicted in Fig. 12, there is a strong linear correlation between the thermal gap and market prices. That is, higher market prices correspond to a higher thermal gap. Moreover, the thermal gap is usually lower during daylight hours and higher at sunrise, sunset, and nighttime.

Finally, this article evaluates the impact of such market prices on the profitability of PV during 2024, especially focused on typical solar plants and its capture rate in the Iberian market. The PV capture rate represents the mean price captured by solar PV technology relative to the weighted average price settled in the market, as presented in [12]. In 2024, the solar capture rate has drastically reduced due to the occurrence of zero prices during daytime. To provide a national PV capture rate, the hourly PV generation profile at the national level is considered for the analysis. As shown in Fig. 13, the annual PV capture rate is 41.27 €/MWh compared to 63.04 €/MWh, the mean day-ahead price during 2024, resulting in a PV capture ratio of 0.65.

As can be concluded, the monthly PV capture rates vary extremely throughout the year 2024, being extremely low during spring season and higher during autumn and winter. Despite having a significant PV penetration in the energy mix (18.8% in 2024), it can be stated that PV does not strongly influence the formation of near-zero market prices. However, it has the lowest capture rate among RES technologies, which significantly affects investor decision-making due to the uncertain economic viability of current and future PV assets.

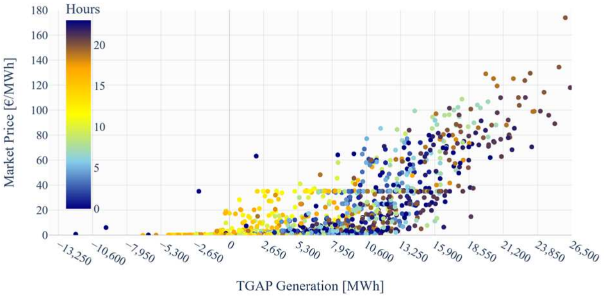

Figure 12. Thermal gap 2024.

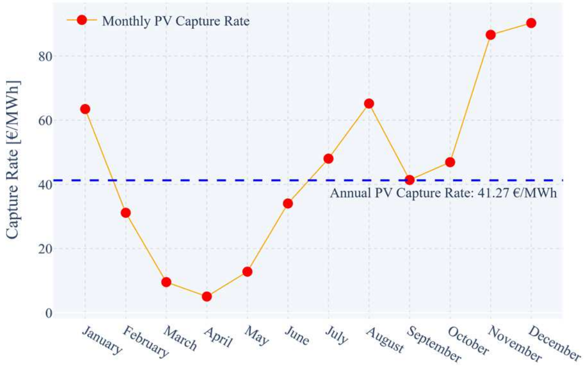

Figure 13. Monthy and annual mean PV capture rate during 2024.

V. CONCLUSIONS

This article aims to conduct a statistical analysis of the occurrence of near-zero and negative prices in the day-ahead market and evaluate the correlation between prices and various technologies in the energy mix. The analysis reveals that during the spring months (March, April, and May) in 2024, day-ahead prices are significantly lower, with the lowest IQR values recorded in March and April, indicating lower price dispersion and higher predictability around near-zero prices. Conversely, the CV reaches its highest values in these months, highlighting increased price variability compared to the mean. As can be expected, the near-zero prices are located at daylight hours. Looking at spring months, the findings suggest that RBH and CCGT tends to increase prices, while OWP tends to decrease them. Despite significant PV penetration in the energy mix, PV technology does not exhibit a clear tendency to influence prices, but it has the lowest capture rate among RES technologies, with a PV capture ratio of 0.65. As can be concluded, there is a strong linear correlation between the thermal gap and market prices, where higher market prices correspond to a higher thermal gap.

This market data analysis suggests that the future viability of renewable projects will depend on implementing both technical and policy recommendation, like the deployment and strategic operation of energy storage systems, diversification of revenue streams through bilateral contracts, other markets or balancing services, or the evolution of wholesale market design to better reflect the value of RES generation in a future decarbonized energy mix, in which the thermal gap seems to decrease, and curtailed energy tends to increase. Future work will be oriented to design a Power Purchase Agreement (PPA) with complex price-indexed rules to assess the impact of market price, and the usage of storage to maximize the revenues.

REFERENCES

[1] E. Kabir, V. Srikrishnan, M. V. Liu, S. Steinschneider, and C. L. Anderson, “Quantifying the impact of multi-scale climate variability on electricity prices in a renewable-dominated power grid,” *Renew Energy*, vol. 223, Mar. 2024, doi: 10.1016/j.renene.2024.120013.

[2] G. Wang, E. Sbai, L. Wen, and M. Selena Sheng, “The impact of renewable energy on extreme volatility in wholesale electricity prices: Evidence from organisation for economic co-operation and development countries,” *J Clean Prod*, vol. 484, Dec. 2024, doi: 10.1016/j.jclepro.2024.144343.

[3] C. Stiewe, A. L. Xu, A. Eicke, and L. Hirth, “Cross-border cannibalization: Spillover effects of wind and solar energy on interconnected European electricity markets,” 2024. doi: 10.48550/arXiv.2405.17166.

[4] J. López Prol, K. W. Steininger, and D. Zilberman, “The cannibalization effect of wind and solar in the California wholesale electricity market,” *Energy Econ*, vol. 85, Jan. 2020, doi: 10.1016/j.eneco.2019.104552.

[5] 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, Dec. 2020, doi: 10.1016/j.rser.2020.110307.

[6] M. Liebensteiner, F. Ocker, and A. Abuzayed, “High electricity price despite expansion in renewables: How market trends shape Germany’s power market in the coming years,” *Energy Policy*, vol. 198, p. 114448, Mar. 2025, doi: 10.1016/j.enpol.2024.114448.

[7] D. Cacciarelli, P. Pinson, F. Panagiotopoulos, D. Dixon, and L. Blaxland, “Do we actually understand the impact of renewables on electricity prices? A causal inference approach,” 2025.

[8] E. Belenguer, J. Segarra-Tamarit, E. Pérez, and R. Vidal-Albalate, “Short-term electricity price forecasting through demand and renewable generation prediction,” *Math Comput Simul*, vol. 229, pp. 350–361, Mar. 2025, doi: 10.1016/j.matcom.2024.10.004.

[9] J. R. Andrade, J. Filipe, M. Reis, and R. J. Bessa, “Probabilistic price forecasting for day-ahead and intraday markets: Beyond the statistical model,” *Sustainability*, vol. 9, no. 11, Oct. 2017, doi: 10.3390/su9111990.

[10] C. Ballester and D. Furió, “Analysing the impact of renewables on Iberian wholesale electricity market prices using machine learning techniques,” *Green Finance*, vol. 6, no. 2, pp. 363–382, 2024, doi: 10.3934/GF.2024014.

[11] “ESIOS website.” Accessed: Feb. 09, 2025. [Online]. Available: https://www.esios.ree.es/en

[12] C. Stiewe, A. L. Xu, A. Eicke, and L. Hirth, “Cross-border cannibalization: Spillover effects of wind and solar energy on interconnected European electricity markets,” *Energy Econ*, vol. 143, p. 108251, Mar. 2025, doi: 10.1016/j.eneco.2025.108251.

APPENDIX A: YEARLY DATA PER TECHNOLOGY

In Appendix A, yearly scatter plot data for several technologies are presented to be compared against the data for near-zero months in Section IV. Fig. A.1 to Fig. A.6 illustrate the relationship between annual price and PV, CSP, OWP, RBH, CCGT, and CHP technologies, respectively. Fig. A.7 and Fig. A.8 depicts the NU and ROR scatter plots, which have been dismissed to be discussed in Section IV. NU has been dismissed due to its more stable capacity load (no flexible), and ROR due to its uncontrollability and low share in the energy mix. Finally, the thermal gap for all the year 2024 is depicted in Fig A.9.

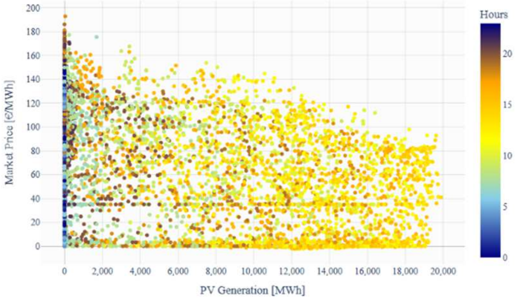

Figure A.1. Hourly PV generation vs day-ahead price in 2024.

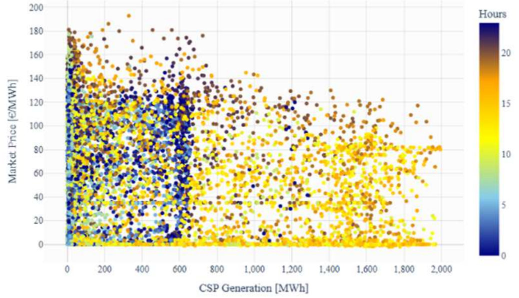

Figure A.2. Hourly CSP generation vs day-ahead price in 2024.

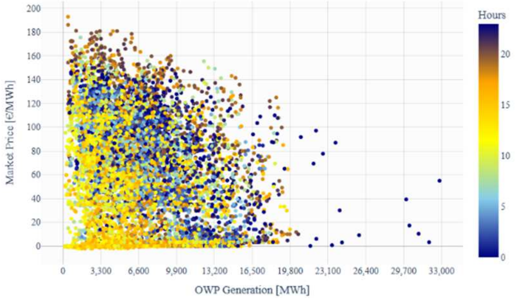

Figure A.3. Hourly OWP generation vs day-ahead price in 2024.

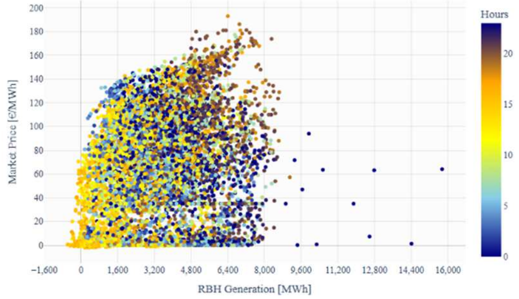

Figure A.4. Hourly RBH generation vs day-ahead price in 2024.

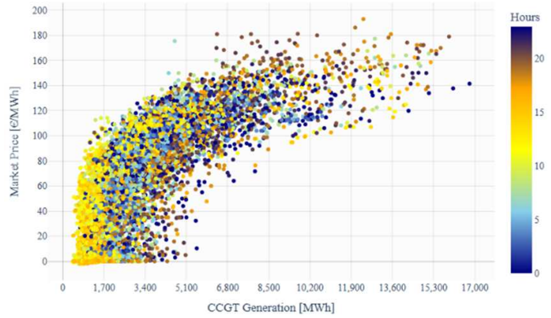

Figure A.5. Hourly CCGT generation vs day-ahead price in 2024.

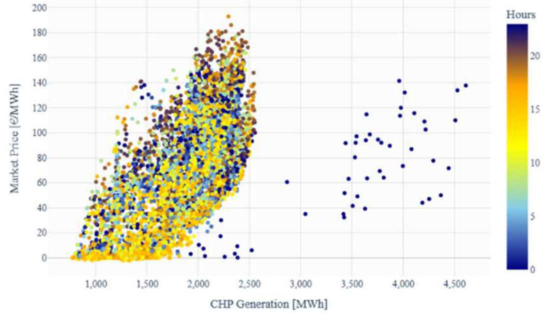

Figure A.6. Hourly CHP generation vs day-ahead price in 2024.

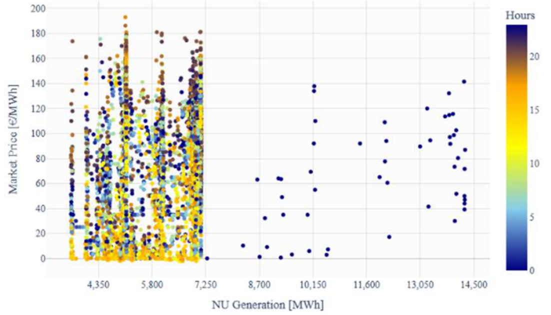

Figure A.7. Hourly NU generation vs day-ahead price in 2024.

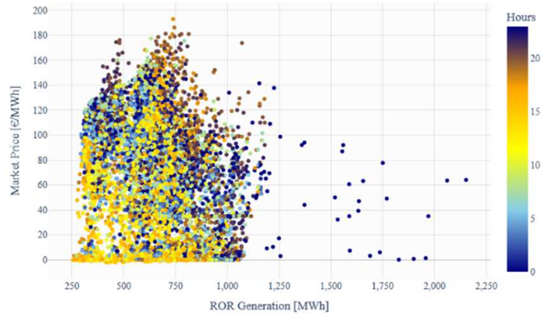

Figure A.8. Hourly ROR generation vs day-ahead price in 2024.

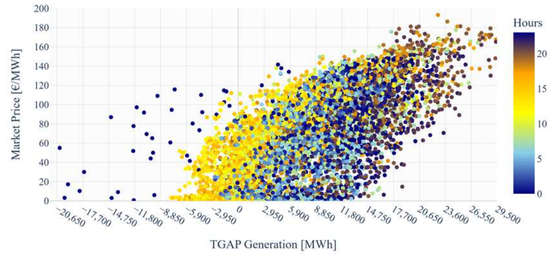

Figure A.9. Hourly thermal gap vs day-ahead price in 2024.