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Analysis of the Suitability of the EOLO Wind-Predictor Model for the Spanish Electricity Markets

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Abstract: Wind energy forecasting is a critical aspect for wind energy producers, given that the chaotic nature and the intermittence of meteorological wind cause difficulties for both the integration and the commercialization of wind-produced electricity. For most European producers, the quality of the forecast also affects their financial outcomes since it is necessary to include the impact of imbalance penalties due to the regularization in balancing markets. To help wind farm owners in the elaboration of offers for electricity markets, the EOLO predictor model can be used. This tool combines different sources of data, such as meteorological forecasts, electric market information, and historic production of the wind farm, to generate an estimation of the energy to be produced, which maximizes its financial performance by minimizing the imbalance penalties. This research study aimed to evaluate the performance of the EOLO predictor model when it is applied to the different Spanish electricity markets, focusing on the statistical analysis of its results. Results show how the wind energy forecast generated by EOLO anticipates real electricity generation with high accuracy and stability, providing a reduced forecast error when it is used to participate in successive sessions of the Spanish electricity market. The obtained error, in terms of RMAE, ranges from 8%, when it is applied to the Day-ahead market, to 6%, when it is applied to the last intraday market. In financial terms, the prediction achieves a financial performance near 99% once imbalance penalties have been discounted.

Keywords: EOLO; Wind prediction; statistical analysis; Spanish electricity markets

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1. Introduction

Europe is immersed in a deep and complex energy crisis. Energy prices have risen sharply in 2022, as a consequence of the Russia–Ukraine war and its supplies of gas as a weapon of war, impacting the economy adversely. This crisis makes it necessary for Europe to reconsider its renewable energy policy and minimize fossil sources. Furthermore, the environmental pursuits of the European Union (EU), which call for member states to be decarbonized by 2050 [1] in order to mitigate the effects of global warming, have increased the generation of electricity from technologies based on renewable sources, especially wind energy [2,3]. As an example, more than 20% of the energy consumed in the EU is currently generated from renewable sources, which is more than double the amount in 2004 [4]. Another example is involves Spain's energy consumption, where wind energy provided 23.3% of the energy demand during 2021, according to [5]. At the end of 2022, there were 21,574 wind turbines in operation, confirming wind energy providing the most electricity in the country.

In this context of energy transition towards a system supplied by renewable energies, natural resources such as wind energy are limited by the variability and intermittence (non-cyclical) inherent in their complex natures [6]. This disadvantage is crucial to consider since there must be a balance between the amount of electricity consumed and its generation in order to meet the operating demands of the electrical network [7,8].

Knowing how much energy is needed by customers beforehand is difficult to predict. However, agents involved with transport and distribution have applications with which they can predict demand during different periods. In addition, commercialization agents buy electric power transactions for the next day based on the purchase offers presented through market agents. These predictions should have a forecast horizon, such that it helps to calculate power output and improve the fit of real demand curves [9,10].

Furthermore, with the implementation of the 54/1997 Electricity Law [11], the electricity market in the EU transformed the landscape of the sector [12–14], and most European and Western countries had a liberated electricity market, in which the energy produced is agreed upon in previous auctions. This economically penalizes those agents whose production then deviates from their predictions [15,16]. In Europe, this change means the opening of the networks to third parties, the establishment of an organized energy trading market, and the reduction in public intervention in the management of the system [17]. The objectives are to develop an integrated electricity market that acts as an efficient instrument for secure, affordable, and sustainable energy acquisition [18].

However, it is more difficult to predict the energy produced by renewable energies, particularly in the case of wind energy because of its variability. Therefore, agents who come to the electricity market to sell wind-farm energy need to develop methods that the wind farm to adjust its production hourly (horizon). In recent years, a great effort has been devoted to the development of forecasting systems for wind energy production forecasts, because these forecasts have important economic and technical implications for the overall electricity economy.

To meet these challenges, wholesale electricity markets are structured based on the "horizon" [19], which is defined as the period that determines the future moment for which we make the predictions [20]. For this research, the horizon was classified as: (i) a short-term horizon prediction (up to 8 h in advance), which was used to improve dynamic network security and secondary regulation management as well as to plan the electricity system; (ii) a medium-term horizon prediction (from a few hours to 72 h in advance) allows the electricity market operators to take the necessary measures to ensure the future stability of the system and manage market activities (e.g., when the energy producers need to perform maintenance, they use that horizon); and (iii) a long-term horizon prediction (several days in advance) is interested in the future organization of power stations (e.g., reducing economic losses for individual wind farm maintenance or planning for the creation of a new farm).

Bidding auctions are performed hours before production with different horizons. This is problematic for renewable power plants since their production uncertainty increases with the prediction horizon, resulting in the accrual of significant penalties if they are unable to meet their energy commitments [15,16]. The horizon of much interest in the literature is the medium-term, as it is the most useful. We chose this as the target prediction horizon for the EOLO wind-predictor model.

For the medium-term horizon, there are different families of prediction models based on conventional sources to facilitate energy management on wind farms in order to balance demand and generation, or even to halt generation if there is no demand. According to [9], predicting energy production on wind farms should be performed using quantitative models based on physical and statistical methods. The first approach is based on the prediction of the conditions of the lower layer of the atmosphere via numerical weather forecasting systems (numerical weather predictions, NWP), which use forecast data of temperature, pressure, coefficients of ground friction, and orographic conditions. These models involve significant computational resources and require solving and modeling processes at different scales, which are highly complex both theoretically and numerically. On the other hand, statistical models are based on variables of interest in the historical data, such as wind speed, air temperature, and previously generated data. The goal is to detect relationships or patterns between the variables using time series, statistical models, and artificial intelligence in order to extrapolate relevant associations for predictions.

With this in mind, this study employed the EOLO prediction model as a decision-making tool for the characterization of energy sale offers among the different electrical markets in Spain. The objective was to perform an analysis of the capabilities of the EOLO predictor model and to adjust it according to the requirements of each market.

This paper is organized according to the following structure. Section 2 is divided into four subsections: Section 2.1 contains an introduction to electricity markets and their processes; Section 2.2 describes the EOLO tool, which was developed by several of the authors; Section 2.3 describes 30 Spanish wind farms used in the present study; and finally, the methodology is described in Section 2.4. Section 3 presents the analysis of the results based on day-ahead and intraday markets in the dataset. Finally, this paper ends with a discussion about the results, the limitations of the analysis, and our recommendations for future studies in Section 4.

2. Materials and Methods

This section describes all materials used to carry out this research, which includes three essential elements:

- European electricity markets, which for this study, were located in Spain.
- The wind-predictor model, EOLO.
- The datasets for the study.

Next, the methodology to obtain and evaluate the results is described in detail.

2.1. European Electricity Markets

In 1996, the European electricity market began when the European Parliament and the European Council approved the first electricity directive (96/92/EC) [18]. This continued the development and integration of the European electricity market to harmonize and liberate the energy market of the EU.Measures enacted since 1996 have established the following, as indicated in [21]:

- The state, with its resources, only intervenes in energy transport planning.
- All activities of the electricity industry were divided into regulated activities (transport and distribution) and non-regulated activities (generation, commercialization), so that energy is available for all users.
- Any independent company can access the network for both generation and demand purposes.
- Regulated activities in network businesses are considered regulated natural monopolies, with tariffs paid by all network users.
- The regulatory commission's responsibilities include promoting and achieving competition and supervising the transparency and independence of the system's operation.
- The creation of calendar that establishes when and who participates in different electricity markets, as well as the amount of energy each participant can produce
- All energy producers can participate under equal conditions and with diverse bidding strategies for different electricity markets.

These measures are intended to build a more competitive, customer-focused, flexible, and non-discriminatory EU electricity market with market-based supply prices [22]. This process is slow but provides a great degree of integration among the EU electricity markets, where electricity is bought and sold using supply and demand curves to determine the price.

Data concerning the interchange of energy and pricing in the different electrical markets are available in each country from the corresponding nominated electricity market operator (NEMO). Table 1 lists the main NEMOs and a reference link for each country. In the cases of Spain and Portugal, it is the Iberian Energy Market Operator (OEMI) that manages the different electricity markets (day-ahead, intraday, and continuous) [19,20]. In this study, we focused on the Spanish markets (Section 2.1.1).

Table 1. European electricity market operators [23].

Electricity Market	Countries	Reference
EXAA	Austria	https://www.exaa.at (accessed on 9 January 2023)
EPEX	Belgium, France, Germany, Netherlands, and Switzerland	https://www.epexspot.com (accessed on 9 January 2023)
IBEX	Bulgaria	https://ibex.bg (accessed on 9 January 2023)
CROPEX	Croatia	https://www.cropex.hr (accessed on 9 January 2023)
OTE	Czech Republic	https://www.ote-cr.cz (accessed on 9 January 2023)
GME	Italy	https://www.mercatoelettrico.org (accessed on 9 January 2023)
HENEX	Greece	https://www.enexgroup.gr (accessed on 9 January 2023)
HUPX	Hungary	https://hupx.hu (accessed on 9 January 2023)
Nord Pool Spot	Scandinavian and Baltic countries	https://www.nordpoolgroup.com (accessed on 9 January 2023)
POLPX	Poland	https://www.tge.pl (accessed on 9 January 2023)
OPCOM	Romania	https://www.opcom.ro (accessed on 9 January 2023)
SEEPEX	Serbia	https://www.seepex-spot.com (accessed on 9 January 2023)
OMIE	Spain and Portugal	https://www.omie.es (accessed on 9 January 2023)
OKTE	Slovakia	https://www.okte.sk (accessed on 9 January 2023)
SOUTHPOOL	Slovenia	https://www.bsp-southpool.com (accessed on 9 January 2023)

The preliminary measures and the increased interconnection capacity ensure an integrated, efficient, and secure European electricity market [18,21].

2.1.1. The Spanish Case

With the implementation of the 54/1997 Electricity Law [11], the Spanish electricity system began its transition towards a liberated market: The supply of electricity was no longer considered a public service, and new private companies took charge of many competencies previously held by the State. No profound change occurred in the agents of the electricity market as a result of the law, but it introduced a differentiation between the following [24]:

- Generation activity is made up of natural or legal persons who have the capacity to generate electricity. That electricity can be for their own consumption or for third parties. Furthermore, other activities include the set-up, operation, and maintenance of their production centers.
- Iberian Energy Market Operator (OMIE) is the distribution agent in charge of carrying out the activities of economic and technical management of the electrical system; that is, OMIE generates the supply and demand curves for the electricity market.
- *Red Eléctrica de España* (REE) is the transportation company that is responsible for transporting electric energy, as well as building, maintaining, and maneuvering the transportation facilities used for this activity. Furthermore, it is responsible for the operation of the electrical system, which involves balancing electricity production and consumption to guarantee the proper functioning of the electrical system so that consumers receive the electricity they need safely and securely, without the system becoming overloaded or collapsing.

The OMIE is responsible for organizing the electricity market in Spain. Therefore, this operator creates a day-ahead market (DAM), where they establish the production and consumption schedules for each hour of the following day. Only the energy producers with the best prices participate in that market, and those with the highest bids are removed.

In the DAM, purchase-for-sale transactions of electricity must be made between 14 and 38 h of the horizon, and the gate closure time is $10D$ (where one day is D and $D+1$ is the next day). In this market, the affected hours are $1-24\ D+1$.

The DAM price is accounts for the last bid matched in each hour. All energy producers are remunerated at the hourly marginal price, regardless of the hourly marginal price or the bids submitted. In addition, settlements are also calculated with this price. However, the OMIE only takes economic factors into consideration.

Therefore, after the DAM, the system operator carries out an analysis with the support of simulation applications, into which the database from the daily schedule is input in order to determine whether the power system is safe or if there is a risk of blackouts. If the schedule is not technically feasible, the system operator modifies it, for example, by reducing the output of the generators causing the overloads on the grid and increasing the load of others by the same proportion. This process is called "constraint management", and it is aimed at making the free-contracting approach in the markets feasible from the aspect of system security.

Otherwise, unexpected breakdowns or unforeseen changes in demand, both upward and downward, may require the OMIE to adjust their strategies. When this occurs, the OMIE creates two news markets: the intraday market (IM), which has six sessions and is described in Table 2; and the continuous market (CM), where the adjustments are made one hour in advance. The aim of these markets is to anticipate all possible incidents that occur in the daily market and suggest solutions to ensure a stable day-ahead market. These markets are used by generators who may need to withdraw their energy offerings or sell more energy. Marketing agents also use these markets to buy more power or to get rid of excess energy due to errors in their consumption forecast. The IM and CM both operate similarly to the DAM.

Table 2. Spanish intraday market structure [25,26].

Session Number	**1**	**2**	**3**	**4**	**5**	**6**
Session Opening	14:00 D	17:00 D	21:00 D	1:00 $D+1$	4:00 $D+1$	9:00 $D+1$
Hourly periods	1–24 $D+1$	21–24 D y 1–24 $D+1$	1–24 $D+1$	5–24 $D+1$	8–24 $D+1$	13–24 $D+1$
Schedule horizon	10–34	3–31	3–27	3–23	3–20	3–15
Number of hours	24 h	28 h	24 h	20 h	17 h	12 h

As shown in Table 2, there are three kinds of markets that allow energy producers to adjust their energy commitments hourly. However, this study only considered day-ahead and intraday markets because they are challenging to predict due to the stark differences between the two (see in Figure 1).

Electrical energy is easily generated, transported, and transformed. However, until now, it has not been possible to store it in a practical, easy, and economical way in large quantities, so it must be produced at the same time it is consumed [27]. Regardless of the time of day, the REE's Electricity Control Center (Cecoel) adjusts the balance between electricity generation and consumption, as well as energy transport to the distribution networks, according to the highest quality and safety conditions required and at the lowest possible price. All energy traffic in Spain and neighboring countries is coordinated by Cecoel and is available 24 h a day, 365 days a year.

Because of Cecoel and the significant demand for renewable energy that has increased in recent years, the Control Center of Renewable Energies (Cecre) was created [28], with the objective to integrate the maximum amount of renewable energy possible into the electric market. according to Cecre, the primary form is wind energy, due to the significant increase in wind power generation in Spain.

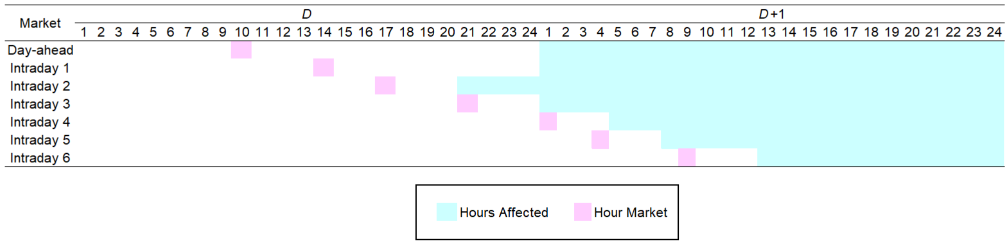

Figure 1. Spanish electricity markets.

However, this form of energy has its own limitations, some of which are caused by the irregularity and variability of wind, while others are related to wind turbines being disconnected due to voltage dips. Cecre's mission is to anticipate these incidents and propose solutions when they occur. To accomplish this, it diagnoses and evaluates real-time outages to develop practical operating measures in order to prevent energy disruptions in the future.

Each market, except the day-ahead, is expected to remedy any imbalance between generation and demand created in a previous market as forecasts exist for one or more consecutive hourly periods. Energy producers take advantage of this to reduce their established schedules or to increase their production. Furthermore, technical restrictions enforced by OMIE ensure the security of the market economy.

2.2. Wind-Predictor Model: EOLO

The tool used to obtain the forecasts of the energy produced in wind farms and analyze the data is EOLO [29]. EOLO was created by several authors of this paper and presented in detail in [29]. The main concept is that in fringe electricity markets, the forecast with the smallest margin of error is not necessarily the best forecast for economic performance.

The main characteristics of EOLO include its use of public information and its ability to account for the financial aspect of the fringe electricity markets. Based on this data, it provides an estimate that minimizes prediction errors while maximizing its economic value, resulting in a useful tool for wind energy producers. They are able to maximize their income while avoiding economic penalties due to inaccurate energy offers across the different Spanish electricity markets.

To provide an accurate forecast for a wind farm, EOLO combined two sources of public information:

- Meteorological predictions published by the Spanish State Meteorological Agency (AEMET) through the API AEMET Opendata (https://opendata.aemet.es accessed on 15 October 2022). It is important to note that the EOLO wind predictor model must replace this source of information with a corresponding one when it is used for another country. Some options to replace the meteorological information are available in Table 3.
- Data concerning the state of the electric system and the evolution of the different markets were obtained from REE'sSystem Operator Information System (e-sios) (https://www.esios.ree.es accessed on 15 October 2022) through its API. When the EOLO wind-predictor model is outsourced to another country, this information source must be replaced with a corresponding one. Some options to replace this information are available in Table 1.

Pairing this information with the historic production of wind farms, EOLO created different predictors and new indicators (described in [29]), which were used to feed several automatic learning models. Figure 2 roughly summarizes the inputs and outputs of the EOLO model.

Table 3. European information about meteorology agencies.

Country	Meteorology Agency	Reference
Austria	Central Institute for Meteorology and Geodynamics	https://www.zamg.ac.at (accessed on 9 January 2023)
Belgium	Institut Royal Météorologique	https://www.meteo.be (accessed on 9 January 2023)
France	Meteo France	https://meteofrance.com (accessed on 9 January 2023)
Germany	Deutscher Wetterdienst	https://www.dwd.de (accessed on 9 January 2023)
Netherlands	Royal Netherlands Meteorological Institute	https://www.knmi.nl (accessed on 9 January 2023)
Switzerland	MeteoSwiss	https://www.meteoswiss.admin.ch (accessed on 9 January 2023)
Bulgaria	National Institute of Meteorology and Hydrology	http://www.meteo.bg (accessed on 9 January 2023)
Croatia	Meteorological and Hydrological Service	http://meteo.hr (accessed on 9 January 2023)
Czech Republic	Czech Hydrometeorological Institute	https://www.chmi.cz (accessed on 9 January 2023)
Italy	Servizio Meteorologico	http://www.meteoam.it (accessed on 9 January 2023)
Greece	Hellenic National Meteorological Service	http://www.emy.gr (accessed on 9 January 2023)
Hungary	Meteorological Service of the Republic of Hungary	https://www.met.hu (accessed on 9 January 2023)
Scandinavian	Danish Meteorological Institute; Swedish Meteorological and Hydrological Institute; Norwegian Meteorological Institute	https://www.dmi.dk https://www.smhi.se https://www.met.no (accessed on 9 January 2023)
Baltic countries	Estonian Weather Service; Latvian Environment, Geology and Meteorology Agency; Lithuanian Hydrometeorological Service; Finnish Meteorological Institute	https://www.ilmateenistus.ee https://videscentrs.lvgmc.lv http://www.meteo.lt https://www.ilmatieteenlaitos.fi (accessed on 9 January 2023)
Poland	Institute of Meteorology and Water Management	https://www.imgw.pl (accessed on 9 January 2023)
Romania	National Meteorological Administration	https://www.meteoromania.ro (accessed on 9 January 2023)
Serbia	Republic Hydrometeorological Service of Serbia	https://www.hidmet.gov.rs (accessed on 9 January 2023)
Spain	Agencia Estatal de Meteorología	https://www.aemet.es (accessed on 9 January 2023)
Portugal	Institute Português do Mar e da Atmosfera	https://www.ipma.pt (accessed on 9 January 2023)
Slovakia	Solvak Hydrometeorological Institute	https://www.shmu.sk (accessed on 9 January 2023)
Slovenia	Meteorological Office	http://www.arso.gov.si (accessed on 9 January 2023)

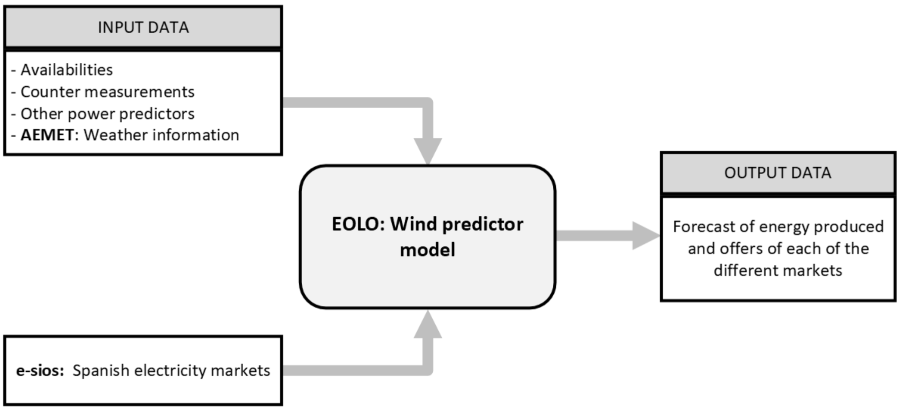

Figure 2. EOLO input and output scheme.

Using these data and indicators, EOLO employed a two-stage approach: in the first stage, it attempts to estimate accurate wind energy production; and in the second, the best forecast from an economic point of view. This second stage involves the analysis of the economic impact of energy policies on the market, and then the predictions of the first stage are evaluated based on the economic trends in prices and imbalance penalties.

EOLO only used a few variables to feed the automatic learning models. The variables were selected based on their correlation with the objective data, the historic production (first stage), and the ideal economic performance (regardless of penalties). This is one of the main benefits of the EOLO model. The correlation analysis of all available variables in the input dataset identifies those that have the most influence on energy production. This allows a reduced set of variables to be used when training the model and ensures a rapid response in time to facilitate a timely offer of sale in the markets. It also provides estimates that represent the real-time production, independent of weather conditions or time of year. Furthermore, this characteristic allows specific parameters be adjusted for the individual characterization of each wind farm.

The output of EOLO is an optimized forecast with minimal deviations and excellent economic performance. In this study, we analyzed its results for the day-ahead and intraday electricity markets. The details of EOLO exceeded the scope of this article; therefore, interested readers can find detailed explanations in [29].

2.3. Dataset

To analyze the suitability of the EOLO, we focused on the different markets in Spain, and we included a set of 30 Spanish wind farms that were part of the same electric company. The 30 wind farms were distributed throughout Spain, including in the insular territories. Table 4 summarizes the nominal power (KW) and the period studied, along with the proposed predictor of each wind farm. The available period allowed us to analyze the different horizons in the electricity markets.

Table 4. Wind farms analyzed using the EOLO wind predictor, including the nominal power (KW) of each wind farm and the study period (from–to) [29].

Wind Farm	Power (KW)	From	To
Farm_1	5500	31 May 2020 UTC	28 Jan 202 UTC
Farm_2	28,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_3	29,900	31 May 2020 UTC	28 Jan 202 UTC
Farm_4	17,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_5	14,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_6	11,900	31 May 2020 UTC	28 Jan 202 UTC
Farm_7	21,710	31 May 2020 UTC	28 Jan 202 UTC
Farm_8	5000	31 May 2020 UTC	28 Jan 202 UTC
Farm_9	5000	31 May 2020 UTC	28 Jan 202 UTC
Farm_10	12,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_11	50,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_12	49,900	31 May 2020 UTC	28 Jan 202 UTC
Farm_13	36,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_14	50,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_15	30,800	31 May 2020 UTC	28 Jan 202 UTC
Farm_16	16,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_17	36,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_18	30,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_19	16,900	31 May 2020 UTC	28 Jan 202 UTC
Farm_20	18,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_21	30,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_22	21,250	31 May 2020 UTC	28 Jan 202 UTC
Farm_23	24,000	31 May 2020 UTC	28 Jan 202 UTC
Farm_24	39,600	31 May 2020 UTC	28 Jan 202 UTC
Farm_25	13,600	31 May 2020 UTC	28 Jan 202 UTC
Farm_26	6600	31 May 2020 UTC	28 Jan 202 UTC
Farm_27	9610	31 May 2020 UTC	28 Jan 202 UTC
Farm_28	7000	31 May 2020 UTC	28 Jan 202 UTC
Farm_29	10,800	31 May 2020 UTC	28 Jan 202 UTC
Farm_30	49,500	31 May 2020 UTC	28 Jan 202 UTC

2.4. Methodology

The methodology consisted of the use of the EOLO wind-predictor model, described in [29], including some considerations to improve its performance in the time horizons affected by the different Spanish electrical markets and to reduce the computational costs required to compute the results. In this section, we summarize the steps, and we explain, in detail, the adjustments introduced into the EOLO predictor:

1. The application of the EOLO predictor: the wind farms used in this period. These aspects are described in Section 2.3. The only criteria for the selection of these wind farms and the study period were the availability of evaluation data from a collaborative wind farm company. Detailed information about these wind farms, including their nominal power, is shown in Table 4.
   In [29], the EOLO predictor computed the output for all time horizons considered in different markets, including results from the second hour (the closest horizon considered in the different electricity markets, either the continuous market) up to 38th hour (the furthest horizon for the daily or day-ahead market). In this study, we have allowed the EOLO to choose the target market, either the day-ahead, 1st-6th hour intraday, or continuous market; in order to reduce its computational demands as we only computed the specific outputs for the different markets. The options are summarized in Table 2. This resulted in the EOLO providing a reduced output for the different markets (e.g., for the day-ahead market, EOLO generated the output for the horizons from the 14th to the 38th hours; or for the sixth intraday market, EOLO only generated the output for the horizons from the 3rd to the 15th hours).
2. In [29], several basic predictors based on historical data are used to generate new data to feed the automatic learning models. In practical applications, the following models have been used for that purpose: (i) persistence models, which are based on the assumption that the energy produced in the future will be the same as it is now; (ii) moving average models, which are based on the assumption that the energy produced in the future is rational according to past events, which is also known as the mean value of the past productions; and (iii) meteorological models, which estimate the energy to be produced as a function of the meteorological forecast. Based on [29], these authors concluded that the proposed models were not enough to predict a long-term horizon.
   Therefore, we used the same models but included more variants of the moving average models to estimate the behavior of a wind farm based on the previous days. Based on all the data presented to the automatic learning models, EOLO chose variables that had the strongest association to the target in the training data. Thus, the computational cost derived from the increased input data was minimal. Furthermore, the training of the automatic learning models was only conducted when the relative correlation order between the different variables had changed.
3. After the incorporation of the these improvements, the simulations were performed for the selected wind farms. In total, 210 simulations were executed, with 7 simulations for each of the 30 wind farms, one for each of the different markets (the day-ahead market and the 6 intraday markets).
   These simulations were performed in the Calendula cluster, a property of Castilla y León Supercomputing Center (SCAYLE (http://www.scayle.es accessed on 15 October 2022)), where we used the Cascade Lake cluster, which was made up of 37 servers with the following technical specifications: 2 Intel Xeon Gold 6240 processors, with 18 cores each and working at a frequency of 2.6 GHz; 192 GB of RAM; and an Infiniband HDR 100 Gbps connection. In addition, this cluster had 7 NVidia Tesla V100 GPU units.
   For each simulation, we used 4 servers and 1 processor. With these resources, it required approximately 60 h to perform 210 simulations.

4. Once all the simulations were completed, we evaluated the performance of the EOLO forecasts for the different markets. For this purpose, we used the normalized mean absolute error ($RMAE$) as a measure of the quality of the forecasts:

$$RMAE = \frac{\sum_{i=1}^{n} |\hat{P}_i - P_i|}{n * P_{i(max)}} \cdot 100 \tag{1}$$

where P_i refers to the i^{th} measure of the production, $\hat{P}_i$ corresponds to the predicted value, $P_{i(max)}$ refers to the nominal power of the wind farm, and n is the total sample number of the validation set. $RMAE$ provided an idea of the magnitude of the error concerning the magnitude of the prediction to be performed (i.e., a certain absolute error may be excellent if the magnitude of the data evaluated is greater than the error, but it can also be poor if the magnitude of the data evaluated is in the same order of magnitude). This type of error was used to compare all the wind farms without the influence of their power.
5. Finally, we grouped both the forecasts obtained by EOLO and the error indices, utilizing different criteria, and we designed several graphical representations to assist in interpreting the results. Results are provided with details in Section 3.

3. Results

This section gathers and analyses the results obtained by the EOLO predictor for 30 wind farms located in different regions in Spain. We also generated the forecasts for different Spanish electrical markets, namely the day-ahead market and six intraday markets.

3.1. The Day-Ahead Market

Several graphics were used to evaluate the EOLO predictions for the day-ahead market. The first one was a bubble map, which is plot that identifies each of the 30 wind farms together with each $RMAE$ error with a point located at the corresponding geographical coordinates of the corresponding wind farm. The color of the point depends on the magnitude of the $RMAE$ error for the predicted day-ahead market. This visualization allowed us to evaluate error dependencies according to the location of the wind farms but also based on the uniformity of errors.

This graph is shown in Figure 3. The $RMAE$ error was generally less than 8, with only one case having a higher $RMAE$ error, near 12. These results indicated that the EOLO predictor provided very reliable results with good accuracy. The wind farm with the highest $RMAE$ is located in complex terrain, to which we attributed the higher error.

Down-scaling methodologies, as described in [30], would allow for an individual analysis of this outlier, and we will use a more detailed analysis in future works. Another option was to use the portfolio effect since the 30 wind farms belonged to the same company, allowing them to represent a grouped offer to the electrical markets. In [29], the authors analyzed the advantages of this option.

Figure 4 to compares the probability distributions of the real and predicted data. Therefore, the data from the 30 wind farms were classified by month to analyze if different seasonal parameters were correctly identified. The comparison of these density distributions showed that the energy forecast by EOLO accurately reproduced the density profiles from the real data.

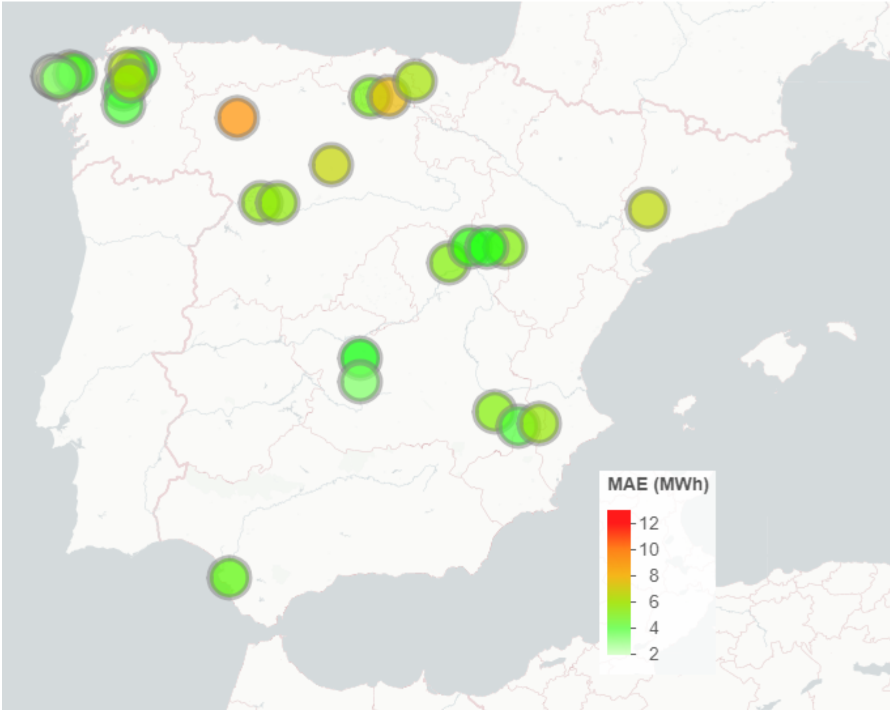

Figure 3. *RMAE* error in the day-ahead forecast according to the location of the wind farms under study.

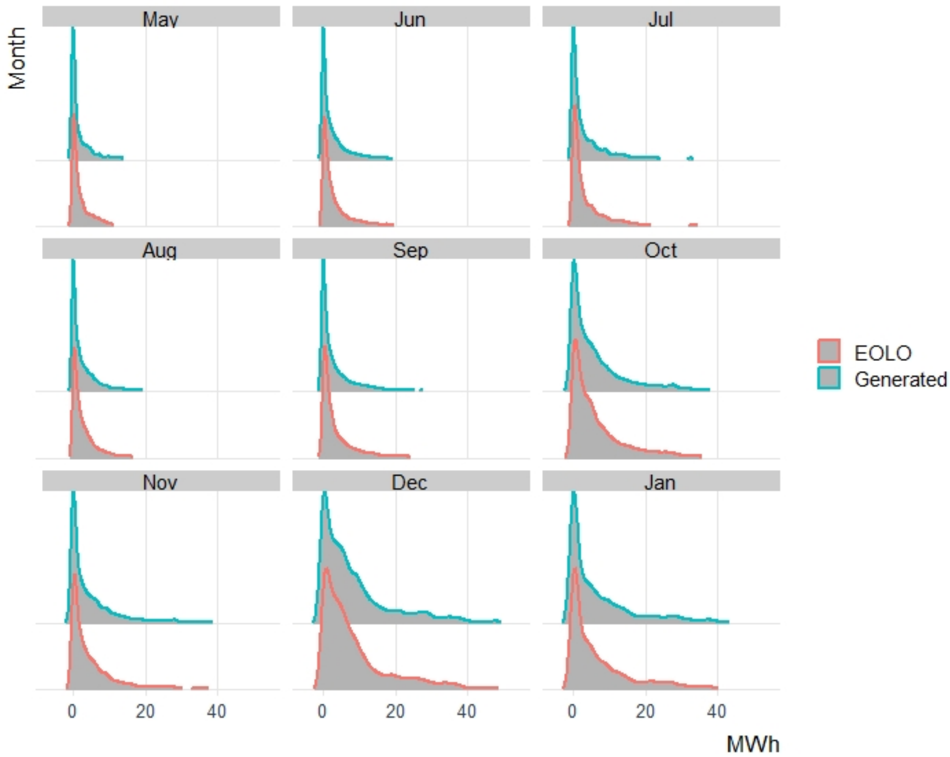

Figure 4. Hourly densities of power generated and predicted by EOLO (day-ahead market).

3.2. Intraday Markets

Regarding the intraday markets, we should distinguish between the 6 markets (see Table 2): Intraday 1 (I1), Intraday 2 (I2), Intraday 3 (I3), Intraday 4 (I4), Intraday 5 (I5), and Intraday 6 (I6).

Figure 5 represents the $RMAE$ observed by Intraday 6 along different horizons. The $RMAE$ was less than 6.25 for all horizons, and the error level increased with the horizon. Moreover, the last horizon presented the most significant variability.

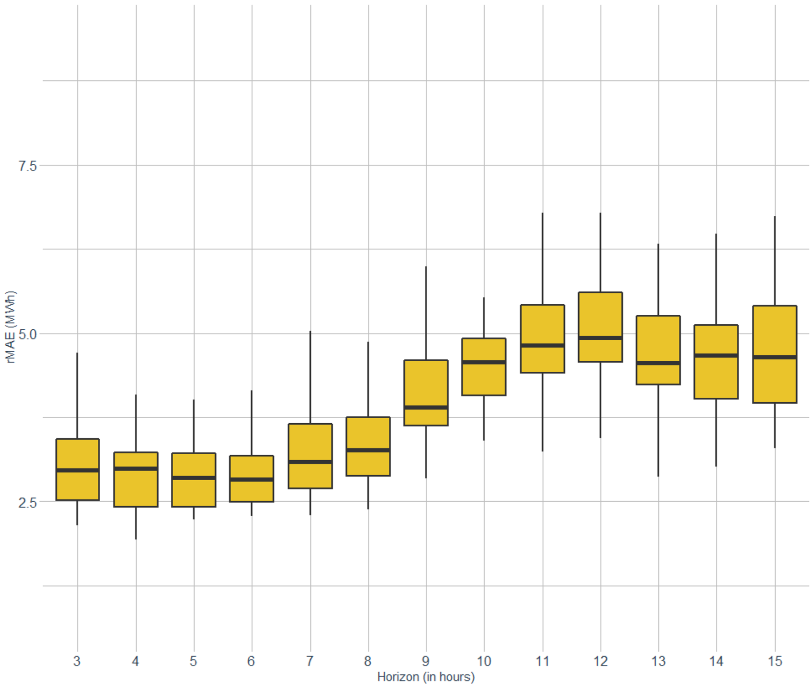

Figure 5. $RMAE$ distribution by horizon for Intraday 6.

The box-plot in Figure 6 compares the errors generated by the six intraday markets. The $RMAE$ decreased as the sessions advanced and the interquartile range was also smaller in the final session, which indicated a similar error level for all wind farms.

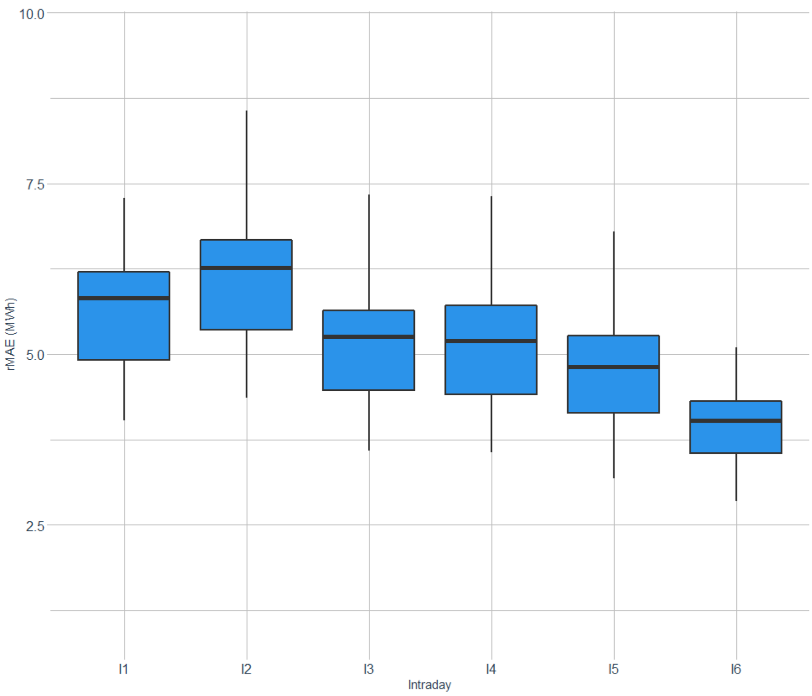

Figure 6. $RMAE$ distribution by intraday session.

3.3. Comparison of All Markets

The last analysis evaluated the participation in successive intraday session and its impact on the error level. The resultant heat-map is shown in in Figure 7. The horizontal axis corresponds to the hours of the day while the vertical axis refers to each market session. This plot demonstrated the evolution of the error level as a new intraday market corrected the previous predictions. The sixth intraday contained the lowest error level (green and yellow colors), and in general, all hours were corrected by the end of the process (black boxes in Figure 7).

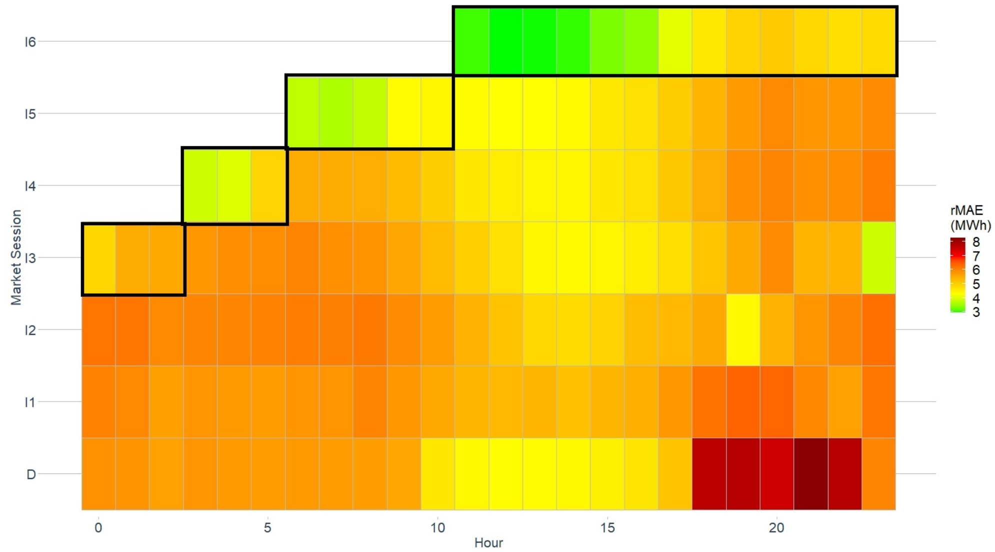

Figure 7. Error evolution by market session.

4. Discussion

Climate change and the reduction in CO_2 have caused a significant shift in electrical energy production. Currently, the world is focused on renewable energies, mainly wind energy. In Spain, wind energy was the primary source of electricity generation in 2021, exceeding 23% of the demand [5].

However, the principal interest of renewable energy producers is the prediction of production, as they need to know the amount of energy to offer in the different markets, which, for this study, involved the Spanish energy markets.

The present study evaluated the predictive tool EOLO for the improved demand predictions of wind energy according to different Spanish markets. As our results demonstrated, the set of algorithms used to program EOLO were well-adapted for the selected markets, which was indicated by the low $RMAE$ of the results.

Multiple studies, as noted throughout this paper, found the best participation for wind energy producers at different hours. The analyzed evidence suggested this differed between markets, especially when comparing the initial hours of each market. If the first hour of the market was the first hour affected, the prediction was better.

Another important consideration affecting wind energy producers was the Intraday 6 market data. This intraday market was probably the best opportunity for wind energy producers in the market due to the low $RMAE$. However, other considerations may have impacted these results, such as that bidding is free at this time.

EOLO has proved to be valuable tool for processing of this type of data, and it provides an adaptable framework for more specific and advanced modeling of real wind farms. Furthermore, while the EOLO predictor model was developed with the Spanish markets in mind, it is able to be adapted for other markets by substituting different sources of information that are available in each country and by considering the differences in the timetables of each electrical market.

Limitations of the Study and Avenues of Future Research

Due to the specific analysis of this article, some limitations should be noted. First, the historic production sample used only included Spanish wind farms, limiting the generalizability of the results and requires additional validation in other national contexts [13]. Second, this study was limited to information regarding the local characteristics of the terrain of each wind farm, which was provided by AEMET at the closest municipalities.

Future studies should also include methods that have been successfully tested in other scenarios by the authors of [30], and they should include the use of NWP models, specifically microscale models [31], to adapt the predictive AEMET information. Other ways to improve the estimation of energy production in wind farms include the application of vertical wind profiles to transfer the forecasts to the height of the nacelle, or the use of advanced air density models under different meteorological conditions. Furthermore, improving EOLO with information regarding superficial temperature studies in group TIDOP would be worth exploring in future studies.

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Abbreviations

The following abbreviations are used in this manuscript:

AEMET	Spanish State Meteorological Agency
Cecoel	Electrical Control Center
Cecre	Special Regime Control Center
CM	Continuous Market
CO_2	Carbon Dioxide
D	On day
$D+1$	The next day
DAM	Day-ahead Market
EU	European Union
IM	Intraday Market
$RMAE$	Normalized Mean Absolute Error
NWP	Numerical Weather Predictions
OMIE	Iberian Energy Market Operator
REE	*Red Eléctrica de España*
SCAYLE	Castilla y León Supercomputing Center

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