energies

MDPI

Article

Predictive Trading Strategy for Physical Electricity Futures

Claudio Monteiro [1], L. Alfredo Fernandez-Jimenez [2,*] and Ignacio J. Ramirez-Rosado [3]

[1] Department of Electrical and Computer Engineering, Faculty of Engineering, University of Porto, 4200-465 Porto, Portugal; cdm@fe.up.pt
[2] Electrical Engineering Department, University of La Rioja, 26004 Logroño, Spain
[3] Electrical Engineering Department, University of Zaragoza, 50018 Zaragoza, Spain; ijramire@unizar.es
* Correspondence: luisafredo.fernandez@unirioja.es; Tel.: +34-941-299-473

Received: 5 May 2020; Accepted: 8 July 2020; Published: 10 July 2020

Abstract: This article presents an original predictive strategy, based on a new mid-term forecasting model, to be used for trading physical electricity futures. The forecasting model is used to predict the average spot price, which is used to estimate the Risk Premium corresponding to electricity futures trade operations with a physical delivery. A feed-forward neural network trained with the extreme learning machine algorithm is used as the initial implementation of the forecasting model. The predictive strategy and the forecasting model only need information available from electricity derivatives and spot markets at the time of negotiation. In this paper, the predictive trading strategy has been applied successfully to the Iberian Electricity Market (MIBEL). The forecasting model was applied for the six types of maturities available for monthly futures in the MIBEL, from 1 to 6 months ahead. The forecasting model was trained with MIBEL price data corresponding to 44 months and the performances of the forecasting model and of the predictive strategy were tested with data corresponding to a further 12 months. Furthermore, a simpler forecasting model and three benchmark trading strategies are also presented and evaluated using the Risk Premium in the testing period, for comparative purposes. The results prove the advantages of the predictive strategy, even using the simpler forecasting model, which showed improvements over the conventional benchmark trading strategy, evincing an interesting hedging potential for electricity futures trading.

Keywords: electricity markets; mid-term forecasting; energy trading; electricity price forecasting

1. Introduction

1.1. Context of This Research

New trading scenarios for electricity markets have arisen over the last three decades. Electricity can be traded as any other commodity: it can be bought or sold in deregulated electricity markets. The main difference with respect to other commodities is the limited storage capability that electricity has nowadays. Wholesale electricity markets are organized in a set of different niche markets, in which agents exchange energy and reserves from mid-term to very short-term periods. Mid-term periods, from days to some years ahead, are covered by forward markets, while short and very short-term periods are covered by day-ahead, intraday and real-time markets. In these markets, i.e., day-ahead, intraday and real-time markets, only agents who sell or buy electricity can trade, unlike forward markets where financial agents can also operate. In order to distinguish the electricity markets, the day-ahead market, organized with trade auctions, is called the spot market [1]. The spot market presents higher price fluctuations than the forward markets.

Forward electricity markets provide hedging opportunities against the price uncertainty of the spot market, and therefore, they contribute to reducing the operational risks. In Europe, the highest volume of electricity is traded in forwards markets. The products traded in European forward markets include electricity forwards, electricity futures, electricity swaps, contract for differences (CfDs), electricity price area differentials (EPADs) and spreads and electricity options [2]. The most traded product, by volume of energy, is the electricity forward, which corresponds to the bilateral contract, by which the buyer and seller agree on a price for a volume of electricity and for a specified delivery period in the future. Bilateral contracts are traded in a nonstandardized market, the "over the counter" (OTC) market, and can be arranged directly between buyer and seller or by means of a broker. Most of the contracts are usually offset in a clearing house and settled in cash.

Electricity futures contracts share the main feature of bilateral contracts as an agreement between buyer and seller, but these contracts guarantee transparency and anonymity to the agents involved. Electricity futures are contracts with standardized exchange terms and conditions, carried out on exchange platforms and with lower fees than other traded electricity products. Electricity futures can be physical contracts, i.e., exchange contracts for the delivery of a quantity of electricity over a specified period or financial (cash-settled) contracts, which correspond to back-up transactions or speculation transactions.

1.2. Literature Review

The price at which agents sell electricity, through futures, is called the bid. The price at which agents buy electricity, through futures, is known as the ask. The difference between the maximum ask and the minimum bid is called the bid/ask spread. The agents participating in the electricity futures market indicate, by submitting asks or bids, their willingness to buy or sell electricity and their prices. They are, therefore, indirectly reflecting their perception about the average value of the prices that will be cleared in the spot market during the delivery period. In most commodity markets, it has been observed that when the end of the delivery period for a futures contract is approached, the futures price converges to the spot price of the underlying commodity [3]. An initial study [4] using electricity forward contracts price in the two US markets showed that the forward contracts price was a downwardly biased predictor of the future spot price under a low power demand and a moderate risk demand. On the other hand, several studies on European markets have shown the inefficiency of such markets, revealing that the futures prices are not unbiased predictors of the future spot prices [5–7]. Nevertheless, other studies, such as [8], have successfully used the futures price to predict the electricity price on the spot market. The differences in the predictive capacity of futures prices among diverse markets may be due to the different types of electricity supply in each market. For example, [9] shows that the storability of the fuels used to produce most of the energy in an electricity market leads the futures price to contain not only information about expected changes in the spot price but also risk premiums.

The risk premium (RP) can be obtained as the price of a futures contract minus the price of the underlying commodity [10]. The ex ante RP is calculated by using the expected price (price estimate) of the underlying commodity at the time of delivery, while the ex post RP is calculated by using its real price at this time. Electricity futures are slightly different from commodity futures, i.e., electricity is delivered over a period (day, weekend, week, etc.); it is not delivered at a specific moment. Since the calculation of the ex ante RP for electricity forward contracts requires a significant effort in modelling the dynamics of the electricity market in order to estimate (by forecasting) the average spot price during the delivery period, in economic studies, it is more common to analyse the ex post RP. Thus, the ex post RP corresponds to the sum of the ex ante RP and the average spot price forecasting error (i.e., the difference between the forecasted average spot price and the average real price during the delivery period) [11]. Several studies have analysed factors affecting the RP in different electricity markets: [12] found significant RPs in the electricity forward prices in an American market; [13] reported a term structure of the RP in the German electricity market due to the combination of two factors related to the agents; [14] reported a positive impact of the water reservoir level on the RP in the Nord Pool market; [15] found that the RP decreased over time as the delivery period approached in the Nordic and German/Austrian electricity markets; and [16] described that the RP for peak and off-peak hours in the UK spot market are clearly different, as they are the RP for the different seasons in the forward markets. Furthermore, [11] showed that the sign of the ex post forward RPs in Germany, France and Spain had a positive correlation.

The Iberian Electricity Market (MIBEL) was created in 2004 through the integration of the previous Portuguese and Spanish electricity markets. Any consumer in the Iberian Peninsula can buy electricity produced by any power producer or sold by any retailer in the same area. The spot market (day-ahead, intraday and real-time) is managed by the Iberian Energy Market Operator–Spanish Division (OMIE), while the forward market is managed by the Iberian Energy Market Operator–Portuguese Division (OMIP). In the territory covered by the MIBEL, there are two areas, the Spanish and Portuguese areas, with different locational marginal prices. The electricity prices in MIBEL are identified as SPEL (Spanish area) and PTEL (Portuguese area).

The power derivatives portfolio for the MIBEL includes physical and financial futures contracts. The physical futures contracts can be base-load or peak-load [17]. A base-load contract involves the reception or supply of electricity at a constant power of 1 MW throughout all hours of the delivery period, while a peak-load contract involves the reception or supply of this constant power every day in the delivery period but between 8:00 a.m. and 8:00 p.m. The traded contracts correspond to delivery periods of 1 week, month, quarter or 1 year; therefore, they are called weekly, monthly, quarterly and yearly physical electricity futures. In practice, futures contracts are classified according to their maturities. The maturity of a futures contract corresponds to the time that must pass until the delivery period. For example, a monthly base-load futures contract with a maturity of i months means that the delivery month is the i-th month after the month of the current day, i.e., if the current day (negotiation day, n) belongs to June and the maturity of the futures contract is 3 months, then the delivery month corresponds to September.

The relationship between futures and spot prices in MIBEL was studied by [18], concluding that there is a unidirectional Granger causality from monthly and quarterly futures price with maturity of 1 month to spot prices. A similar conclusion is reported in [19], which shows that futures prices, close to the delivery period, are predictive of spot prices, and in [20], which checks the positive correlation between spot and futures markets across all maturities. Therefore, on the basis of these research studies, such relationships could be used to establish trading strategies to maximize the profits of the agents who buy/sell in the MIBEL. Such strategies should rely on mid-term forecasts of the prices settled on the spot market.

In general, very little research has been conducted on mid-term electricity price forecasting [21]. Forecasting of electricity prices in the mid-term is more complex than in the short term, i.e., an important characteristic as the trend from the immediate past cannot be used for the mid-term forecast [22]. Despite everything, several studies in recent years have dealt with the mid-term forecasting of the price that will be settled in the spot market. The techniques used are similar to those used for the short-term prediction, although models with good short-term predictive performance tend to degrade with longer forecasting horizons [23]. The techniques include support vector machines [22,24], linear regression [25,26], factor models [27,28], grey models [29], neural network with extreme learning machine algorithm and evolutionary optimization [30] and deep neural networks [31]. The forecasting horizon ranges from 1 week [26,30] to 6 months [22,24], although in the studies with forecasting horizon over 2 months, the authors assume that the future values of the explanatory variables are perfectly known (they use real future values, rather than forecasts for some explanatory variables that evolve over time). A complete overview of the state-of-the-art in mid- and long-term electricity forecasting models can be found in [32].

There are very few applications of machine learning techniques for trading in electricity markets described in the international literature [33]. An application for the Colombian electricity market is described in [34], in which a combination of a fuzzy inference system and learning algorithm provides information about the amount of electricity to buy through bilateral contracts, according to the agent's profile, in order to maximize the profit, but less than a month in advance. For the MIBEL market Pinto et al. [35] present a decision support scheme, based on a spot price forecasting model, to optimize agents' profits. In this sense, several electricity market simulators have been developed in order to gain insight about the optimal trading strategy [36,37]. A recent work [38] has dealt with the direct forecast of the RP for year-ahead products in the German electricity market, although it leaves the user to choose the trading strategy to follow. Other approaches, designed for imbalance or intraday markets and based on statistical forecasting models, have explored risk-constrained strategies to increase profits and reduce risk by hedging against penalizing imbalance prices [39] or apply a density forecast provided by a stochastic latent moment model to predict imbalance volumes in order to optimize the positions on the intraday market [40].

In the different works published in the international literature, we can find diverse definitions for the term RP. The terms risk premium, forward risk premium, forward premium or market price of risk have been used interchangeably [14]. In this article, we used an ex post definition for the RP corresponding to the difference between the log of the average realized price in the delivery period and the log of the settlement futures price at the time of negotiation. This definition has been used in [19]. A similar definition, although without the log function, is used in [6,11,15,16]. The MIBEL Board of Regulators also defines the term risk premium on the basis of such difference [41]. On the other hand, some authors use the ex ante risk premium, which is defined as the difference between the futures price and the expected spot price in the delivery period [9,10,12,13]. With the definition used in this article, operations on the spot market correspond to a null value of RP. Additionally, in Section 2.2 of this article, we have established two different formulas for RP (with difference in sign) for buyers and sellers. Thus, with our convention for the RP signal used by the original predictive trading strategy presented in this article, a positive value of the signal represents always profits or savings for the agent, and a negative value represents losses, always with respect to the operations (purchases/sales) traded on the spot market.

1.3. Contributions and Structure of This Article

This article proposes an original trading strategy for both buyers and sellers in futures electricity markets (predictive strategy). The strategy is based on the use of a decision signal obtained with a new mid-term forecast of the average spot price for the delivery period. Depending on the forecast and on the value of the last settlement price for the futures, the decision signal indicates whether the agent should buy/sell the electricity through futures or to wait to buy/sell on the spot market.

In traditional trading strategy approaches, the "best guess" of the agents is the last known futures settlement price, reflecting the aggregated guess of all agents about an estimated average spot price in the corresponding delivery period. The predictive trading strategy proposed in this article achieves an advantage in relation to the traditional trading strategy, anticipating the good/wrong decision of buying/selling electricity through futures instead of waiting for the spot market. The predictive strategy succeeds when it is possible to forecast a mid-term average spot price with better accuracy than the traditional "best guess" of the agents, used as a benchmark in this article.

We also present a new mid-term average spot price forecasting model, implemented by a single hidden layer feed-forward neural network, trained with the extreme learning machine (ELM) algorithm, which exclusively uses available information from electricity derivatives and spot markets. The selection of the explanatory variables of the mid-term monthly average spot price forecasting model of this article is based on the experiences of market agents, and the set of explanatory variables is not exhaustive. The article is not focused on the exploration of improving forecasting performance; there is still room to improve the forecasts, in terms of both techniques and features. This kind of spot price forecast (several months ahead) is not as common as a short-term spot price forecast (1–7 days), but it is an issue of increasing interest for trading agents. For comparison purposes, a linear regression mid-term forecasting model is also tested. This alternative forecasting model is based on the ordinary least square (OLS) technique. Both the predictive trading strategy and the spot forecasting models have been successfully tested with historical data of the MIBEL, although they could be applied to other electricity markets.

Additionally, an original evaluation of the proposed predictive strategy is presented in this article. This evaluation is based on the comparison of the trading results achieved with the proposed predictive strategy with those obtained with two other reference strategies, defined as the “best” and the “worst” ones. These reference strategies assume knowing beforehand the actual values of the average spot price in the delivery period. They provide the inner limits of the scale where the RP of the predictive strategy performs.

The article is structured as follows: Section 2 presents the mid-term average spot price forecasting model and the trading strategy for agents in the futures market; Section 3 presents the results obtained for both buyers and sellers acting on the MIBEL and finally, Section 4 presents the conclusions.

2. Conditional Predictive Trading of Electricity Physical Futures

In this article, we present a novel approach for predictive trading and hedging of physical futures on electricity markets. It is applied to physical delivery futures, where the buyer or the seller will keep the product until the electricity delivery period (constant power, delivered in a predefined month). This commitment until the delivery is similar to that established in forward contracts, with the difference that for futures contracts, trading is carried out in a clearing house for derivatives exchange, without direct contact between buyer and seller. Instead, the forward contract also has a commitment to keep the product until delivery, but it is a direct contract between buyer and seller stipulated on the OTC market.

The objective is to decide, on each negotiation day (from a set of days before the delivery period), if the agent (buyer or seller) should buy/sell the electricity in advance through a futures contract, for a certain period ahead (days, weeks, months or years), or if he/she should wait for the spot market, on the eve of each day of the delivery period. At the time of negotiation, the price in the spot market is unknown; therefore, the decision about buying/selling the physical electricity through futures is based on an average of the futures prices at the time of negotiation and on the speculation about whether it will be higher or lower than the average spot price in the delivery period. The approach presented in this article uses a prediction that only utilizes electricity market price information at the time of negotiation in order to forecast the average spot price in the delivery period. Assuming that the forecast is a better indicator of the average spot price than the indicative price of the futures, we estimate a decision signal (buying/selling electricity through futures instead of waiting for spot market) based on the difference between the futures price and an average spot price forecast on the day of the decision, i.e., some time before the delivery. This section presents the proposed mid-term forecasting model and the predictive trading strategy illustrated with monthly futures (called “Futures” in the rest of the article), although it can be adapted to futures with different time frames (weekly, quarterly or yearly). Subsequently, the results obtained with the predictive strategy applied to a real electricity market (the Iberian Electricity Market, MIBEL) are presented in Section 3.

2.1. Proposed Mid-Term Forecasting Model of Average Spot Prices

The main component needed to set up a decision signal on a negotiation day n is provided by a mid-term forecasting model of the average spot price over the delivery period. Such forecasting model should only use electricity market price information at the time of negotiation, i.e., variables related to electricity prices on the days prior to the negotiation day. As mentioned above, we will describe the forecasting model for the trading of physical electricity monthly futures (Futures).

The forecasting model predicts the monthly average spot price for the delivery month. The model uses six input variables and is implemented with a single hidden layer feed-forward neural network trained with the ELM algorithm (referred to as the ELM neural network in this article), which randomly chooses the input weights and biases, thereby avoiding the tuning of other hidden layer parameters. We selected that model because it provided the best forecasting results with the cross-validation procedure within a set of models that included different types of feed forward neural networks with one hidden layer. The ELM algorithm was proposed by Huang et al. [42,43] as an alternative to gradient-based training strategies such as back-propagation and Levenberg–Marquardt algorithms. The ELM algorithm offers a very fast training process with minimal tuning requirements (number of neurons in the hidden layer). In recent years, the ELM algorithm has been successfully applied for forecasting purposes in the electricity field, with approaches for short-term load forecasting [44–46], generation forecasting in power plants based on renewable sources [47–50] and price forecasting in electricity spot markets [30,51,52].

The six input variables used by the forecasting model are the following:

1. DM: delivery month, with values 1 to 12. It represents the number of the month when the traded electricity will be delivered.
2. $LagD$: period, in days, between the negotiation day (any day, i.e., n) and the last negotiation day before the start of the delivery period corresponding to DM.
3. $\overline{MF}_{n,DM}$: Average monthly futures settlement price for delivery month DM in the last 7 days before negotiation day n. So, this input variable is calculated by (1):

$$\overline{MF}_{n,DM} = \frac{1}{ND_7} \sum_{p=n-6}^{p=n} MF_{p,DM} \tag{1}$$

where $MF_{p,DM}$ represents the monthly futures settlement price for delivery month DM on the trading phase of day p, i.e., that established at the end of that phase on the previous negotiation day, and ND_7 corresponds to the number of futures negotiation days in the last 7 days. Observe that the $MF_{p,DM}$ values for nonmarket days (day p with no futures market) are not included in the summation.
4. $\overline{QF}_{n,DM}$: Average quarterly futures settlement price for the quarter including the DM in the last 90 days before negotiation day n. This is calculated by (2), where the delivery quarter DQ must include the delivery month DM:

$$\overline{QF}_{n,DM} = \frac{1}{ND_{90}} \sum_{p=n-89}^{p=n} QF_{p,DM} \tag{2}$$

where $QF_{p,DM}$ represents the quarterly futures settlement price for the quarter (including the DM) established at the end of the previous negotiation day and ND_{90} corresponds to the number of futures negotiation days in the last 90 days. Observe that $QF_{p,DM}$ values for nonmarket days (day p with no futures market) are not included in the summation.
5. $\overline{S}_n$: Average spot price in the last 7 days before day n; this is calculated by (3):

$$\overline{S}_n = \frac{1}{7 \times 24} \sum_{p=n-6}^{p=n} \sum_{h=1}^{h=24} S_{p,h} \tag{3}$$

where $S_{p,h}$ represents the spot price for day p hour h. Observe that the spot prices for day n were established on the previous day.
6. $\dot{\overline{MF}}_{n,DM}$: variation of the average monthly futures settlement price for delivery month DM in the last 7 days before negotiation day n; this is calculated by (4):

$$\dot{\overline{MF}}_{n,DM} = \overline{MF}_{n,DM} - \overline{MF}_{n-7,DM} \tag{4}$$

where $\overline{MF}_{n,DM}$ represents the average monthly settlement futures price for delivery month DM in the last 7 days before negotiation day n and $\overline{MF}_{n-7,DM}$ corresponds to its value 7 days before.

The output variable, $\hat{S}_{n,DM}$, corresponds to the forecast of the monthly average spot price for the delivery month *DM* forecasted on day *n*.

As indicated above, the mid-term forecasting model is implemented with a single hidden layer feed-forward neural network trained with the ELM algorithm. In our work, the neural network has 6 nodes (neurons) in the input layer and only one node in the output layer (one output). The training dataset is composed by N samples, $\left(\boldsymbol{x}_j, o_j\right)$; $\boldsymbol{x}_j = \left[x_{j1}, x_{j2}, \ldots, x_{j6}\right]^T \epsilon\, \boldsymbol{R}^6$ is the input vector for the sample j; and o_j is the desired output value for such sample (target value). The output of a neural network with L nodes in the hidden layer and linear activation function in the output node can be represented by (5):

$$o_j = \sum_{i=1}^{L} \beta_i g\left(\boldsymbol{a}_i \cdot \boldsymbol{x}_j + b_i\right), \quad j = (1, 2, \ldots, N) \tag{5}$$

where $\boldsymbol{a}_i = \left[a_{i1}, a_{i2}, \ldots, a_{i6}\,\right]^T$ is weight vector that stores the weights between the input layer nodes and hidden layer node i; b_i is the bias of hidden layer node i; β_i is the weight between the hidden layer node i and the output layer; g is the activation function of the nodes in the hidden layer and $\boldsymbol{a}_i \cdot \boldsymbol{x}_j$ represents the inner product of $\boldsymbol{a}_i$ and $\boldsymbol{x}_j$.

The Equation (5) can be represented, in compacted form, by (6):

$$\boldsymbol{H\beta} = \boldsymbol{O} \tag{6}$$

where $\boldsymbol{H}$ is the hidden layer output matrix, $\boldsymbol{\beta}$ is the output weights vector and $\boldsymbol{O}$ is the target vector. So, the matrix $\boldsymbol{H}$ and the vectors $\boldsymbol{\beta}$ and $\boldsymbol{O}$ can be represented by (7):

$$\boldsymbol{H} = \begin{bmatrix} g(\boldsymbol{a}_1 \cdot \boldsymbol{x}_1 + b_1) & \cdots & g(\boldsymbol{a}_L \cdot \boldsymbol{x}_1 + b_L) \\ \vdots & \ddots & \vdots \\ g(\boldsymbol{a}_1 \cdot \boldsymbol{x}_N + b_1) & \cdots & g(\boldsymbol{a}_L \cdot \boldsymbol{x}_N + b_L) \end{bmatrix}, \ \boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_L \end{bmatrix}, \ \boldsymbol{O} = \begin{bmatrix} o_1 \\ \vdots \\ o_N \end{bmatrix} \tag{7}$$

In the training process of the single hidden layer feedforward neural network with the ELM algorithm, the bias of each neuron (node) in the hidden layer and the weights connecting input and hidden layers are randomly chosen (i.e., the $\boldsymbol{a}_i$ and b_i values). From these random values, the matrix $\boldsymbol{H}$ is determined according the input samples, and the training process is converted into solving, by least squares, the linear equations $\boldsymbol{H\beta} = \boldsymbol{O}$, to obtain $\boldsymbol{\beta}$, what can be represented by (8):

$$\|\boldsymbol{H}\hat{\boldsymbol{\beta}} - \boldsymbol{O}\| = \min_{\boldsymbol{\beta}} \|\boldsymbol{H\beta} - \boldsymbol{O}\| \tag{8}$$

The least squares solution of (8) is estimated by (9):

$$\hat{\boldsymbol{\beta}} = \boldsymbol{H}^{+}\boldsymbol{O} \tag{9}$$

where $\boldsymbol{H}^{+} = \left(\boldsymbol{H}^T\boldsymbol{H}\right)^{-1}\boldsymbol{H}^T$ is the Moore–Penrose generalized inverse [53] of the hidden layer output matrix.

Since the training process of the neural network does not need to adjust the values of the weights between the input layer and the hidden layer and the biases of the hidden layer nodes, the ELM algorithm generates an optimal solution in a fast training process while maintaining a great capacity of generalization [54]. Only the number of nodes or neurons in the hidden layer needs to be optimized in order to achieve the best forecasting performance.

2.2. *Predictive Trading Strategy of Physical Futures*

In the case of trading physical Futures, the general objective is to hedge against the volatility of spot market prices. Thus, the objective, at the time of negotiation, is to choose between buying/selling electricity through Futures several days, weeks or months in advance or waiting and accepting the spot market price settled for every hour of every day in the delivery period. Buyers and sellers have opposite strategies for this physical product (e.g., if the seller succeeds in selling electricity through Futures, then the buyer succeeds in waiting for the spot market).

Assuming that, at the negotiation moment, the monthly average spot price forecast is closer to the actual value (the ex post monthly average spot price) than the Futures price for the delivery period, we can define a signal indicating whether it is more favourable to trade in the futures market. This is the basis for deciding whether to buy/sell electricity through Futures or wait for the spot market. As will be presented in the analysis of the forecasting results, this assumption is not always true. However, if the error of the monthly average spot price forecast is lower than the error obtained by using the Futures price as this forecast then the assumption is more true than false, and there is a chance of success.

Based on this assumption, the predictive trading strategy for buyers and for sellers is defined by (10) and (11), respectively.

$$\text{for buyers} \begin{cases} \text{if} \quad \hat{S}_{n,\ DM} < MF_{n,DM} & \text{then buy on spot market} \\ \text{if} \quad \hat{S}_{n,DM} \geq MF_{n,DM} & \text{then buy on futures market} \end{cases} \tag{10}$$

$$\text{for sellers} \begin{cases} \text{if} \quad \hat{S}_{n,\ DM} \leq MF_{n,DM} & \text{then sell on futures market} \\ \text{if} \quad \hat{S}_{n,DM} > MF_{n,DM} & \text{then sell on spot market} \end{cases} \tag{11}$$

Obviously, in order to participate in the futures market, the seller should submit a bid at a price equal to the Futures settlement price established at the end of the previous trading day. On the other hand, the buyer should submit an ask with the same price value if he/she wants to participate in the futures market following the proposed strategy. The submission of a bid or an ask does not guarantee the realization of the transaction, because an opponent with an ask or bid is needed to close the contract. From a seller's perspective, if a Futures contract is closed, the final price will be at least equal to that submitted in the bid; from a buyer's perspective, if the Futures contract is closed, the final price will be at most equal to that submitted in the ask.

The success of the trading approach could be evaluated by calculating the ex post Risk Premium (RP) under the worst-case scenario, i.e., when the Futures contract is closed with the price submitted in the bid (for a seller) or in the ask (for a buyer). Therefore, the RP assessment test used in this article is the most pessimistic assessment, considering the changes in market uncertainty that may occur on the trading day. In any case, the RP evaluates the premium associated with the option of buying/selling electricity through Futures instead of waiting for the spot market.

Therefore, at each negotiation moment, the RP resulting from the proposed predictive trading strategy can be formulated as a conditional buying/selling only on some negotiation days n, and only for some delivery months, for which a favourable signal is obtained. Thus, RPs for buyers and sellers using the predictive trading strategy ($\text{RP}_{n,DM}^{\text{buyers,predictive}}$ and $\text{RP}_{n,DM}^{\text{sellers,predictive}}$) are calculated by (12) and (13), respectively:

$$\text{for buyers} \begin{cases} \text{if } \hat{S}_{n,DM} < MF_{n,DM} \Rightarrow \text{RP}_{n,DM}^{\text{buyers,predictive}} = 0 \\ \text{if } \hat{S}_{n,DM} \geq MF_{n,DM} \Rightarrow \text{RP}_{n,DM}^{\text{buyers,predictive}} = ln\left(\overline{S}_{DM}\right) - ln(MF_{n,DM}) \end{cases} \tag{12}$$

$$\text{for sellers} \begin{cases} \text{if } \hat{S}_{n,DM} \leq MF_{n,DM} \Rightarrow \text{RP}_{n,DM}^{\text{sellers,predictive}} = ln(MF_{n,DM}) - ln\left(\overline{S}_{DM}\right) \\ \text{if } \hat{S}_{n,DM} > MF_{n,DM} \Rightarrow \text{RP}_{n,DM}^{\text{sellers,predictive}} = 0 \end{cases} \tag{13}$$

where $\overline{S}_{DM}$ represents the average actual (ex post) value of the spot price in the month DM. Note that in this article, we calculate the RP as a logarithmic difference, as in [14,55]. Additionally, as we mentioned in Section 1.2, we have defined the RP for buyers with the opposite sign to the RP for sellers. With such sign convention for the RP formulation, a positive value represents always profits or savings for the agent and a negative value represents losses. If the agent does not buy/sell through futures and does it on the spot market, then the associated RP is null.

The computer results will be evaluated by comparing the RP values resulting from the predictive strategy, with the conventional ex post RP values obtained from Equations (14) and (15), i.e., simply buying/selling electricity through Futures on any negotiation day. The main difference between the predictive and the conventional strategies is that the predictive strategy uses a conditional decision, about whether or not to buy/sell, instead the conventional strategy assumes always buying/selling electricity through Futures instead of trading in the spot market. Another possible trading strategy for the agents is to trade exclusively on the spot market, which corresponds to a null RP.

$$\text{for buyers } \mathrm{RP}_{n,DM}^{\text{buyers,conventional}} = ln\left(\overline{S}_{DM}\right) - ln(MF_{n,DM}) \tag{14}$$

$$\text{for sellers } \mathrm{RP}_{n,DM}^{\text{sellers,conventional}} = ln(MF_{n,DM}) - ln\left(\overline{S}_{DM}\right) \tag{15}$$

Thus, the benchmark measure of ex post RP that will be labelled in the charts (shown later in Section 3.2) as RP Futures, consists in always buying/selling electricity through Futures, on every negotiation day (n), for all holding periods or maturities ($LagM$ from 1 to 6) and at the last settlement price, i.e., $MF_{n,DM}$.

In order to evaluate the scale for the ex post RP using the predictive trading strategy, we analysed the values achieved with the best and the worst possible trading strategies, defined as those resulting from knowing beforehand the actual values of the monthly average spot price in the delivery month. Thus, the ex post RP for the best possible strategy (for buyers and sellers) is calculated using (16) and (17), respectively, which always leads to a nonnegative RP value, i.e., profits for the agents.

$$\text{for buyers} \begin{cases} \text{if } \overline{S}_{DM} < MF_{n,DM} \Rightarrow \mathrm{RP}_{n,DM}^{\text{buyers,best}} = 0 \\ \text{if } \overline{S}_{DM} \geq MF_{n,DM} \Rightarrow \mathrm{RP}_{n,DM}^{\text{buyers,best}} = ln\left(\overline{S}_{DM}\right) - ln(MF_{n,DM}) \end{cases} \tag{16}$$

$$\text{for sellers} \begin{cases} \text{if } \overline{S}_{DM} \leq MF_{n,DM} \Rightarrow \mathrm{RP}_{n,DM}^{\text{sellers,best}} = ln(MF_{n,DM}) - ln\left(\overline{S}_{DM}\right) \\ \text{if } \overline{S}_{DM} > MF_{n,DM} \Rightarrow \mathrm{RP}_{n,DM}^{\text{sellers,best}} = 0 \end{cases} \tag{17}$$

We can also evaluate the worst possible strategy, which always leads to a negative RP value (losses for the agents), that is symmetrical to the one obtained with the best possible strategy. The worst strategy and the associated ex post RP (for buyers and sellers) are calculated using (18) and (19), respectively.

$$\text{for buyers} \begin{cases} \text{if } \overline{S}_{DM} < MF_{n,DM} \Rightarrow \mathrm{RP}_{n,DM}^{\text{buyers,worst}} = ln\left(\overline{S}_{DM}\right) - ln(MF_{n,DM}) \\ \text{if } \overline{S}_{DM} \geq MF_{n,DM} \Rightarrow \mathrm{RP}_{n,DM}^{\text{buyers,worst}} = 0 \end{cases} \tag{18}$$

$$\text{for sellers} \begin{cases} \text{if } \overline{S}_{DM} \leq MF_{n,DM} \Rightarrow \mathrm{RP}_{n,DM}^{\text{sellers,worst}} = 0 \\ \text{if } \overline{S}_{DM} > MF_{n,DM} \Rightarrow \mathrm{RP}_{n,DM}^{\text{sellers,worst}} = ln(MF_{n,DM}) - ln\left(\overline{S}_{DM}\right) \end{cases} \tag{19}$$

In the "testing" period, the RP is computed for each negotiation day and each $LagM$ ($LagM$ represents the maturity or holding period in months with values from 1 to 6). In order to summarize the results for the entire testing period, an average value of the RP indicator, $\overline{\mathrm{RP}}$, is used. The average ex post RP for both perspectives (buyers and sellers) is calculated for an overall evaluation of the performance of the above-defined strategies using (20) for a maturity and using (21) for all maturities. These RP Indexes are applied for the four possible strategies (predictive, conventional, best and worst strategies) and for both types of agents, i.e. buyers and sellers.

$$\overline{\mathrm{RP}}_{LagM}^{\text{agents,strategy}} = \frac{\sum_{DM=DM_i}^{DM=DM_f} \sum_{n=ni_{LagM,DM}}^{n=nf_{LagM,DM}} \mathrm{RP}_{n,DM}^{\text{agents,strategy}}}{\sum_{DM=DM_i}^{DM=DM_f} ND_{LagM,DM}} \tag{20}$$

$$\overline{\mathrm{RP}}_{All}^{\text{agents,strategy}} = \frac{\sum_{LagM=1}^{LagM=6} \sum_{DM=DM_i}^{DM=DM_f} \sum_{n=ni_{LagM,DM}}^{n=nf_{LagM,DM}} \mathrm{RP}_{n,DM}^{\text{agents,strategy}}}{\sum_{LagM=1}^{LagM=6} \sum_{DM=DM_i}^{DM=DM_f} ND_{LagM,DM}} \tag{21}$$

where $\mathrm{RP}_{n,DM}^{\text{agents,strategy}}$ represents the RP for negotiation day n corresponding to the delivery month DM following the trading strategy (predictive, conventional, best and worst) and for the agents (buyers and sellers); DM_i is the first delivery month and DM_f the last delivery month in the testing period; $ni_{LagM,DM}$ is the first negotiation day and $nf_{LagM,DM}$ is the last negotiation day for the delivery month DM with a maturity $LagM$; and $ND_{LagM,DM}$ is the total number of negotiation days for delivery month DM with a maturity $LagM$. Observe that only the $\mathrm{RP}_{n,DM}^{\text{agents, strategy}}$ values corresponding to negotiation days are included in the summation.

The overall balance of the ex post RP can be computed by summing the profits/losses for the buyers/sellers. Thus, the following overall RPs are defined using (22)–(25).

$$\overline{\mathrm{RP}}_{All}^{\text{both,conventional}} = \overline{\mathrm{RP}}_{All}^{\text{buyers,conventional}} + \overline{\mathrm{RP}}_{All}^{\text{sellers,conventional}} \tag{22}$$

$$\overline{\mathrm{RP}}_{All}^{\text{both,best}} = \overline{RP}_{All}^{\text{buyers,best}} + \overline{\mathrm{RP}}_{All}^{\text{sellers,best}} \tag{23}$$

$$\overline{\mathrm{RP}}_{All}^{\text{both,worst}} = \overline{\mathrm{RP}}_{All}^{\text{buyers,worst}} + \overline{\mathrm{RP}}_{All}^{\text{sellers,worst}} \tag{24}$$

$$\overline{\mathrm{RP}}_{All}^{\text{both,predictive}} = \overline{\mathrm{RP}}_{All}^{\text{buyers,predictive}} + \overline{\mathrm{RP}}_{All}^{\text{sellers,predictive}} \tag{25}$$

The $\overline{\mathrm{RP}}_{All}^{\text{both,conventional}}$ indicator is always 0 by mathematical definition. The $\overline{\mathrm{RP}}_{All}^{\text{both,best}}$ indicator is always positive and the $\overline{\mathrm{RP}}_{All}^{\text{both,worst}}$ indicator is always negative. The $\overline{\mathrm{RP}}_{All}^{\text{both, predictive}}$ indicator leads to a RP value between the RP values obtained from the worst and the best strategies. When the $\overline{\mathrm{RP}}_{All}^{\text{both, predictive}}$ indicator reaches positive values, then it is better than the $\overline{\mathrm{RP}}_{All}^{\text{both, conventional}}$ indicator from the conventional trading approach, whereas the $\overline{\mathrm{RP}}_{All}^{\text{both, predictive}}$ indicator is worse (than the $\overline{\mathrm{RP}}_{All}^{\text{both, conventional}}$ indicator) if it leads to negative values.

3. Results of Conditional Predictive Trading of Physical Futures

The new conditional predictive trading strategy of electricity physical futures presented in this article has been successfully tested with historical data of an electricity market, the Iberian Electricity Market (MIBEL). The available data from the MIBEL corresponded to 56 months, from January 2015 to August 2019. These data include the prices of monthly futures for base-load in the Spanish zone (called SPEL base monthly futures) and the prices established in the daily spot market in the same period. The data were divided into two sets: The training dataset with data corresponding to the period from January 2015 to August 2018, with a total of 5060 records, and the testing dataset with data from September 2018 to August 2019, with a total of 1004 records.

Section 3.1 gives the results corresponding to the proposed forecasting model in the prediction of the monthly average spot prices (described in Section 2.1). Afterwards, Section 3.2 provides the results corresponding to the predictive trading strategy of physical Futures in the MIBEL (described in Section 2.2).

3.1. Results of the Forecasting Model in the Prediction of the Monthly Average Spot Price

The ELM neural network, applied as the implementation of the mid-term forecasting model of the monthly average spot price, used the six input variables described in Section 2.1 and the sigmoidal activation function. Initially, the number of nodes (neurons) in the hidden layer was selected by a fivefold cross-validation procedure with the data from the training dataset. An extensive set of ELM neural networks with number of neurons in the hidden layer ranging from 6 to 100 was analysed.

The ELM neural network with the lowest average mean square error with the 5 folds had 25 neurons in the hidden layer, and afterwards, it was trained with the complete training dataset.

After the training, the proposed forecasting model was applied for the forecast of the monthly average spot price in the testing period, from September 2018 to August 2019. This was a particularly difficult period with spot and Futures prices exceptionally high in September 2018 compared with the values belonging to the training dataset.

Figure 1 plots the monthly average Futures price (for different holding lapses, i.e., *LagM* values) and the daily average spot prices for the training and testing periods (the first months of the training period are not represented in the figure). We can see that shorter *LagM* values correspond to faster reaction to the variation of the spot price. Thus, the shorter maturities are more reactive and more difficult to forecast. The influence of the average spot price input variable is more important for these shorter maturities.

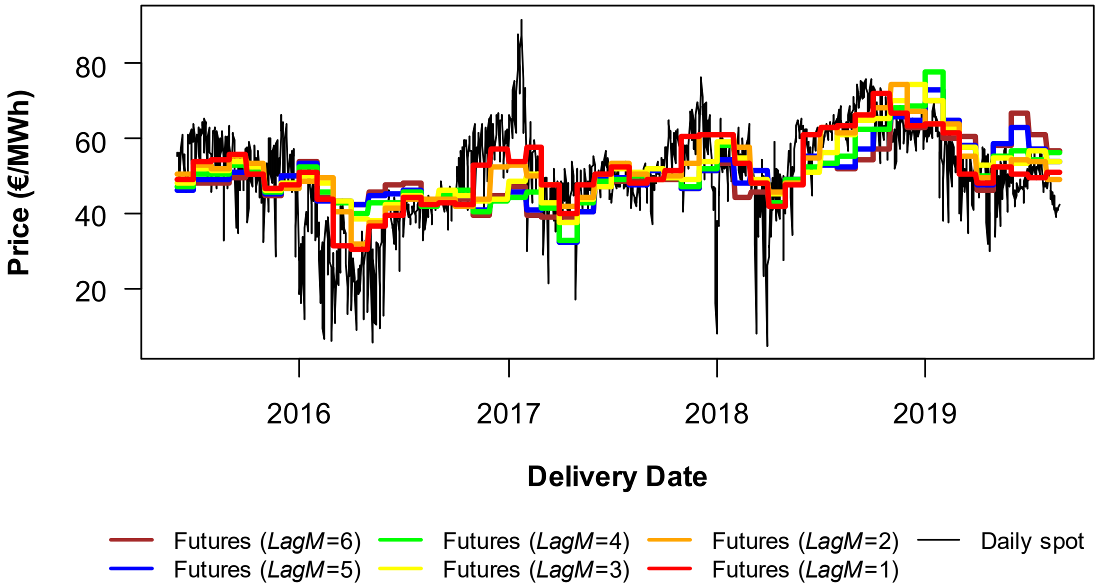


Figure 1. Futures and daily average spot prices for Iberian Electricity Market (MIBEL) in the period studied.

The statistics for the training and testing periods are shown in Tables 1 and 2. The testing period shows higher maximum, minimum and mean values for the Futures price. The standard deviation (SD) is slightly higher for the testing period. The decrease in the SD for longer maturities (large *LagM*) indicates high volatility for shorter maturities.

Table 1. Training period prices (€/MWh).

Statistic	Spot (Daily)	Futures (All)	Futures (*LagM*=1)	Futures (*LagM*=2)	Futures (*LagM*=3)	Futures (*LagM*=4)	Futures (*LagM*=5)	Futures (*LagM*=6)
Maximum	91.88	67.40	65.40	67.40	65.21	60.02	56.30	55.44
Minimum	4.50	27.48	27.48	29.10	33.82	31.50	32.05	30.57
Mean	48.51	47.52	49.02	48.37	47.34	46.82	46.88	46.50
SD	12.43	6.09	8.10	6.75	5.72	5.26	4.62	4.59
Skewness	−0.594	0.05	−0.16	0.14	0.12	−0.37	−0.52	−0.69
Kurtosis	0.969	0.61	−0.28	0.12	0.12	0.39	0.62	1.02

The forecast was carried out for each day of the testing period, providing six forecasts each day for the corresponding six types of holding periods, *LagM*, with a forecasting horizon from 1 to 6 months. Figures 2 and 3 plot the ex post monthly average spot price, $\overline{S}_{DM}$ (average actual spot price in the delivery month *DM*), labelled as "Ex post monthly average spot"; the forecast of the monthly average spot price, $\hat{S}_{n,DM}$, labelled as "Spot forecast"; and the monthly futures settlement price for negotiation day *n*, labelled as "Futures," for each *LagM* (1 to 6). For delivery months in the second half of 2018, the forecast generally leads to a negative error. In the following first half of 2019, the Futures and spot prices were more regular in relation to their historical behaviours and, consequently, both were relatively close. The forecast error is lower for smaller holding periods or maturities (*LagM*) but it increases significantly with larger values. Note that for the negotiation days in the first half of each month for the maturity $LagM = 6$ (Figure 3c), there is no forecast. This is because the values of the input variable $\overline{\dot{MF}}_{n,DM}$ are not available for those days, i.e., the negotiation of Futures with a 6-month maturity ($LagM = 6$) begins on the first trading day of each month and 14 days have to elapse to obtain the value of such input variable because Futures trading for the corresponding delivery month has not taken place before.

Table 2. Testing period prices (€/MWh).

Statistic	Spot (Daily)	Futures (All)	Futures (*LagM*=1)	Futures (*LagM*=2)	Futures (*LagM*=3)	Futures (*LagM*=4)	Futures (*LagM*=5)	Futures (*LagM*=6)
Maximum	75.93	81.00	75.50	77.75	78.81	81.00	78.87	71.42
Minimum	26.69	44.78	46.60	48.00	50.40	47.35	46.85	44.78
Mean	55.75	60.18	58.04	59.88	61.58	61.12	60.59	59.87
SD	9.35	7.48	8.17	8.19	7.54	7.39	6.66	6.31
Skewness	0.010	0.20	0.25	0.20	0.37	0.68	−0.02	−0.37
Kurtosis	−0.559	−0.60	−1.38	−1.16	−1.02	0.11	0.03	0.02

The root mean square error (RMSE), in relation to the ex post (actual) monthly average spot price ($\overline{S}_{DM}$) was computed for the forecast of the monthly average spot price ($\hat{S}_{n,DM}$) according to the expression (26). Furthermore, for comparative purposes, the RMSE was computed by (27) using the Futures settlement price ($MF_{p,DM}$) as "forecast":

$$\mathrm{RMSE}_{LagM}^{\text{Spot price forecast}} = \left(\frac{\sum_{DM=DM_i}^{DM=DM_f} \sum_{n=ni_{LagM,DM}}^{n=nf_{LagM,DM}} \left(\hat{S}_{n,DM} - \overline{S}_{DM} \right)^2}{\sum_{DM=DM_i}^{DM=DM_f} ND_{LagM,DM}} \right)^{\frac{1}{2}} \tag{26}$$

$$\mathrm{RMSE}_{LagM}^{\text{Futures price}} = \left(\frac{\sum_{DM=DM_i}^{DM=DM_f} \sum_{n=ni_{LagM,DM}}^{n=nf_{LagM,DM}} \left(MF_{p,DM} - \overline{S}_{DM} \right)^2}{\sum_{DM=DM_i}^{DM=DM_f} ND_{LagM,DM}} \right)^{\frac{1}{2}} \tag{27}$$

where $\mathrm{RMSE}_{LagM}^{\text{Spot price forecast}}$ represents the root mean square error of the spot forecast for each maturity $LagM$; $\mathrm{RMSE}_{LagM}^{\text{Futures price}}$ represents the root mean square error of the average Futures settlement price for each maturity $LagM$; $\overline{S}_{DM}$ is the average actual spot price in the delivery month DM; DM_i is the first delivery month and DM_f the last delivery month in the testing period; $ni_{LagM,DM}$ is the first negotiation day and $nf_{LagM,DM}$ is the last negotiation day for the delivery month DM with a maturity $LagM$ and $ND_{LagM,DM}$ is the total number of negotiation days for delivery month DM with a maturity $LagM$. Note that only negotiation days n are included in the summations.

The RMSE results, plotted in Figure 4, show a general better proximity (lower RMSE) of the monthly average spot price forecast than of the Futures settlement price. By comparing the RMSE values ("All" in Figure 4), we conclude that the monthly average spot price forecast improves the prediction achieved using the Futures settlement price from 7.95 to 6.12 €/MWh (RMSE values). As expected, the error of the Futures settlement price is lower for shorter *LagM* (holding period or forecasting horizon). The monthly average spot price forecast improves the RMSE for almost all the six types of maturities, with the exception of $LagM = 1$, where the Futures settlement prices are very close to the ex post monthly average spot prices. These RMSE values summarize the observations shown in Figures 2 and 3 of the three price features (ex post monthly average spot price, forecast of the monthly average spot price and Futures settlement price) throughout the testing period.

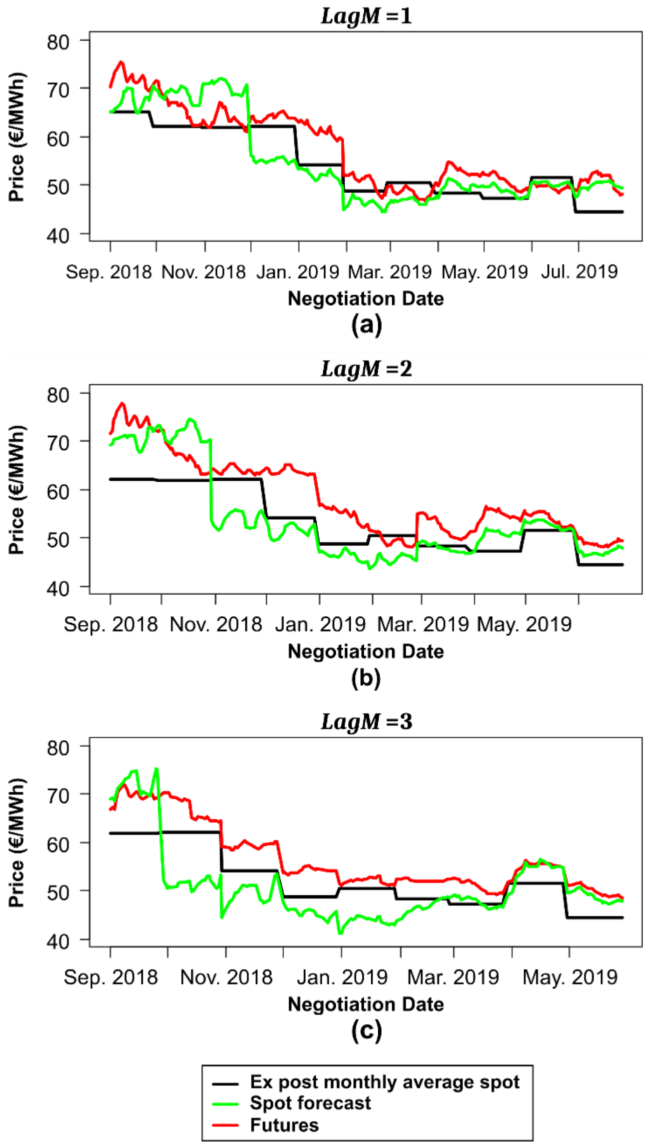


Figure 2. Futures, spot forecast and ex post monthly average prices for the delivery months in the testing period for different maturity (*LagM*) values: (**a**) for *LagM* = 1, (**b**) for *LagM* = 2 and (**c**) for *LagM* = 3.

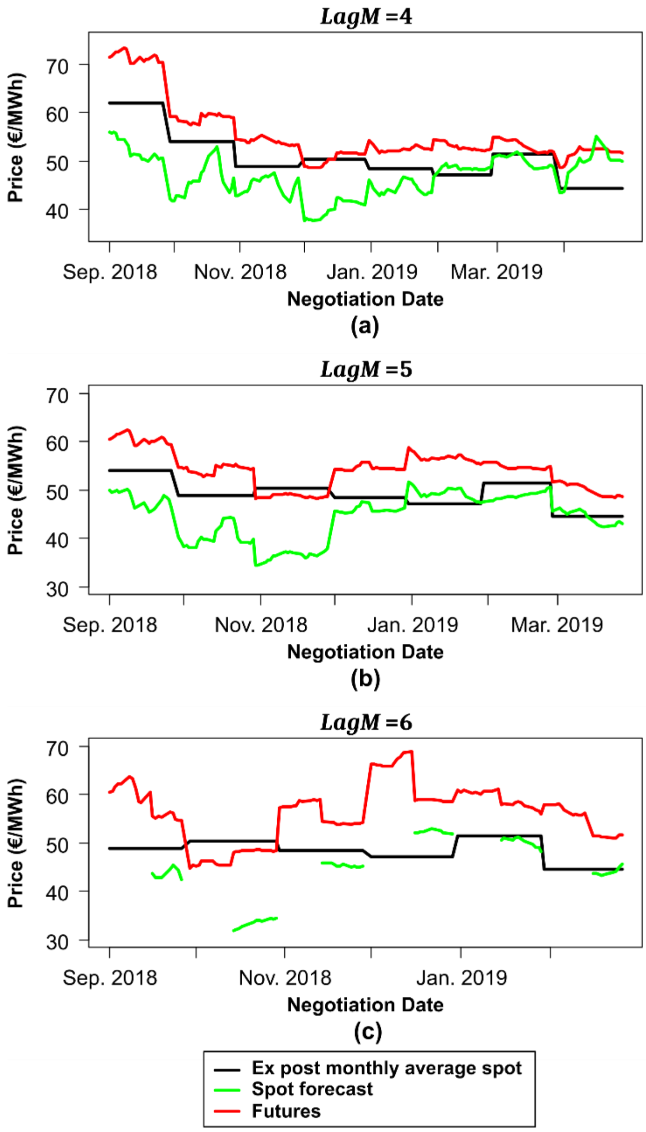
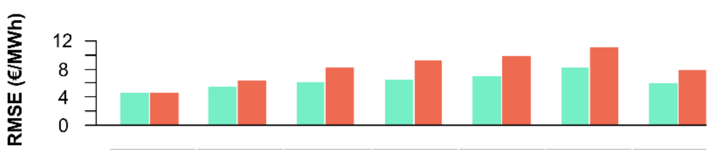


Figure 3. Futures, spot forecast and ex post monthly average prices for the delivery months in the testing period for different maturity (*LagM*) values: (**a**) for *LagM* = 4, (**b**) for *LagM* = 5 and (**c**) for *LagM* = 6.



	LagM=1	LagM=2	LagM=3	LagM=4	LagM=5	LagM=6	All
Spot forecast	4.71	5.60	6.19	6.61	7.03	8.24	6.12
Futures	4.66	6.47	8.30	9.35	9.94	11.20	7.95

Figure 4. Root mean square error, RMSE, of the monthly average spot forecast price (Spot forecast) and the Futures prices (Futures) in relation to the ex post monthly average spot price.

3.2. Results of the Predictive Trading Strategy of Physical Futures with the ELM Neural Network Model

In the testing period (last 4 months of 2018 and first 8 months of 2019), the Futures settlement price was generally higher than the ex post monthly average spot price. For this reason, the sellers obtained large economic profits (positive ex post RP) and the buyers suffered economic losses (negative ex post RP). Obviously, the amount of profits was equal to the amount of losses.

The profits or losses for buyers and sellers are perfectly symmetrical for the benchmark measure of ex post RP (labelled as RP Futures in the charts and the dotted lines presented later in Figures 5 and 6). This observation is not valid for the proposed predictive strategy based on forecast information (labelled as RP Forecast in the charts and the thin lines presented later in both figures). The RP equal to zero means a decision of waiting for the spot market, when the expectation is to lose (economic losses); otherwise, if the expectation is to earn (economic profits), then the RP can take positive or negative values for buying electricity through Futures (this defined behaviour can be observed in the charts of RP evolution throughout the testing period).

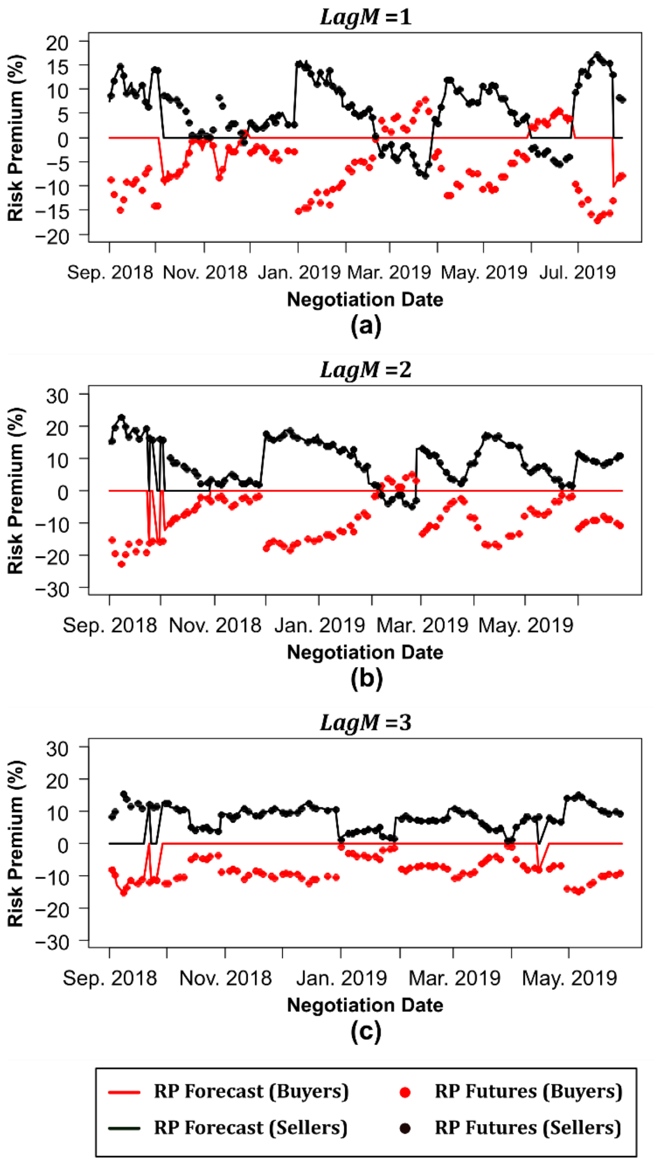


Figure 5. Risk Premium values for buyers and sellers following the predictive (RP Forecast) and the conventional (RP Futures) strategies: (**a**) for *LagM* = 1, (**b**) for *LagM* = 2 and (**c**) for *LagM* = 3.

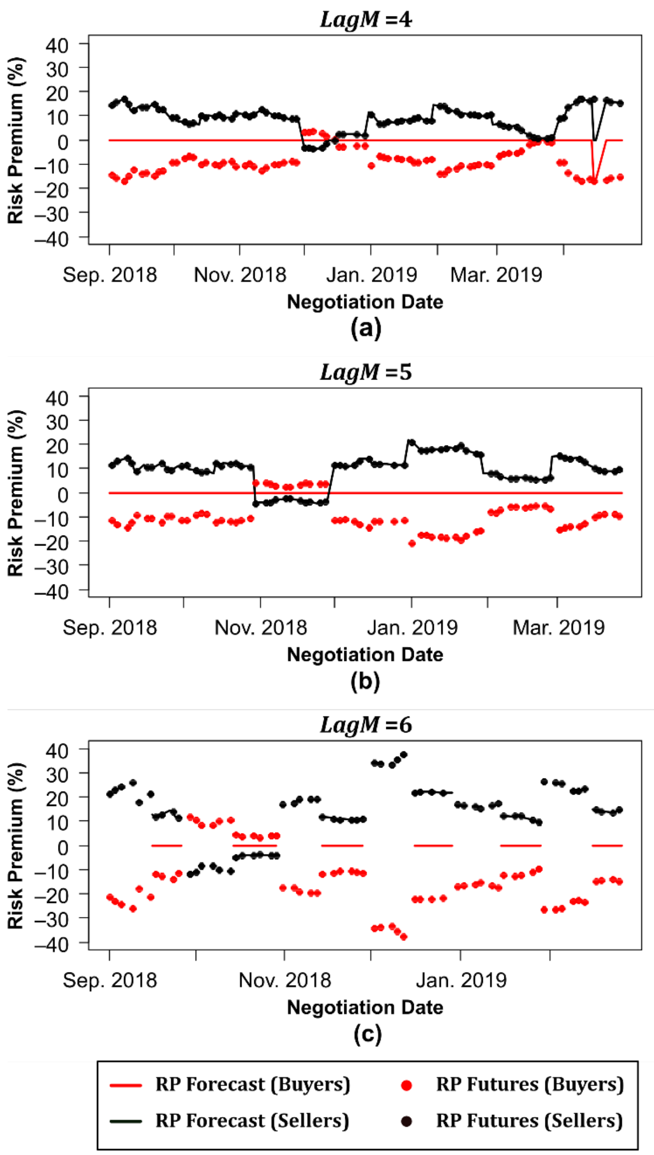


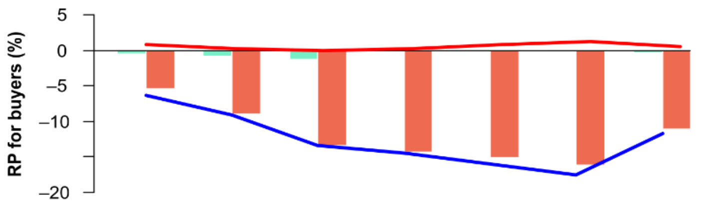
Figure 6. Risk Premium values for buyers and sellers following the predictive (RP Forecast) and the conventional (RP Futures) strategies: (**a**) for *LagM* = 4, (**b**) for *LagM* = 5 and (**c**) for *LagM* = 6.

Figures 5 and 6 present the four RP indicators throughout the testing period, in six separated subfigures, one for each *LagM* maturity. The dotted lines represent the RP of the benchmark or "conventional" strategy, red is the RP for buyers (labelled "RP Futures (Buyers)") and black is the RP for sellers (labelled "RP Futures (Sellers)"). The thin lines represent the RP achieved following the conditional predictive strategy, red is the RP for buyers (labelled "RP Forecast (Buyers)") and black is the RP for sellers (labelled "RP Forecast (Sellers)"). When the thin line follows the dotted line, it means that the predictive strategy is aimed at buying/selling electricity through Futures, whereas when the thin line is zero, it means that the predictive strategy is aimed at buying/selling on the spot market. The agent, by following the predictive strategy, succeeds if the RP thin line value is positive and loses if the RP thin line value is negative. The black and red thin lines never overlap, i.e., if one of the them presents a zero value, then the other shows a positive or negative value.

In Figure 5a, for *LagM* = 1, we can see that most of the time the sellers have a positive RP value and the buyers have a negative RP value for both trading strategies, predictive and conventional ones. The predictive strategy for sellers (represented by the black thin line) succeeded most of the time (RP $\geq$ 0). However, on some negotiation days in October and November 2018, the predictive strategy failed because it wrongly suggested selling in the spot market instead of selling electricity through Futures. In February and March 2019, the predictive strategy for sellers did not predict that selling electricity through Futures would become a wrong option for some weeks. However, in June 2019, the predictive strategy succeeded when it suggested selling on the spot market instead of selling electricity through Futures. For buyers, the predictive strategy (represented by the red thin line) failed in October and November 2018 because it indicated to buy electricity through Futures, and failed again in February and March 2019 suggesting to wait for the spot market. In the other 8 months, the predictive strategy for buyers rightly pointed to buy electricity on the spot market.

Situations of successes or failures of the predictive strategy can be observed in the charts for other maturities (*LagM* = 2 to 6 in Figure 5 and *LagM* = 4 to 6 in Figure 6). For instance, for *LagM* = 2, the predictive strategy failed in September and October 2018 and in February 2019; for *LagM* = 3, it failed in September 2018, and one day in April 2019 and for *LagM* = 4, it failed in the first half of December 2018 and one day in April 2019. For larger maturities (*LagM* = 5 and 6 in Figure 6), the predictive strategy pointed to waiting for the spot market for buyers and to selling through Futures for sellers, for most of the period.

The average ex post RP from the perspectives of buyers (Figure 7) or sellers (Figure 8), and for each maturity *LagM*, was calculated in order to evaluate the overall performance of the trading strategies. In Figure 7, the average ex post RP was always negative from the perspective of buyers following the conventional strategy (labelled as "RP Futures (Buyers)"), and it remained negative even with the conditional predictive strategy (labelled as "RP Forecast (Buyers)"). However, with such predictive strategy, the losses decreased very significantly (RP value from −11.2% to −0.3% for all maturities, "*All*" in Figure 7), with a very significant improvement in each maturity. Observe that red and blue lines in the chart (Figure 7) represent the best and worst possible RP values (best and worst strategies). Then, for the maturities, Figure 7 clearly allows to observe the significant improvements of the losses, provided by the predictive strategy, in the inner scale limits delimited by the best and worst possible strategies, (−11.7% and 0.5%). Furthermore, for buyers, the predictive strategy led to results very close to the ones of the best strategy.

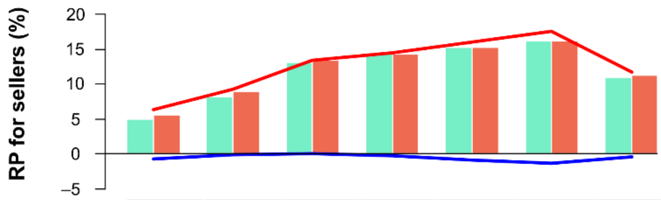


	LagM=1	*LagM*=2	*LagM*=3	*LagM*=4	*LagM*=5	*LagM*=6	*All*
RP Forecast (Buyers)	−0.5%	−0.8%	−1.3%	−0.3%	0.0%	0.0%	−0.3%
RP Futures (Buyers)	−5.5%	−9.0%	−13.4%	−14.3%	−15.2%	−16.2%	−11.2%
RP Best (Buyers)	0.8%	0.2%	0.0%	0.3%	0.9%	1.4%	0.5%
RP Worst (Buyers)	−6.3%	−9.2%	−13.4%	−14.5%	−16.0%	−17.6%	−11.7%

Figure 7. Risk Premium for buyers.

From the perspective of sellers (Figure 8), the predictive strategy ("RP Forecast (Sellers)") was extremely favourable with positive RP value in each maturity (*LagM*), very slightly lower than the ones of the conventional strategy ("RP Futures (Sellers)") and of the best strategy ("RP Best (Sellers)"). Observe that the RP of sellers for all maturities was 10.9% ("*All*" in Figure 8), which indicates significant overall profit for sellers under the predictive strategy. Thus, for sellers, the predictive strategy led to profits (in the maturities) very close to the ones of the best strategy. Lastly, observe that the decreases of sellers' profits are much less significant than the improvement in the decreases of buyers' losses.

In general, the proposed predictive trading strategy, using the monthly average spot price forecast, achieved gains or losses depending on several volatility conditions. We concluded that the predictive strategy has interesting potential as a hedging strategy. In the testing period (a representative year with special volatility perturbations in spot and Futures prices), the conditional predictive strategy provides excellent hedging against losses for buyers and it slightly reduces the profits for sellers. In Figures 7 and 8, in an overall balance (RP for all maturities), the conditional predictive strategy provides a positive balance of 10.6% (overall benchmark strategy of buying Futures is 0% by definition), which is quite good compared with the best possible ex post strategy that could obtain a maximum of 12.2%. These percentage values can be calculated by (28) and (29) using the results from Figures 7 and 8.



	LagM=1	*LagM*=2	*LagM*=3	*LagM*=4	*LagM*=5	*LagM*=6	*All*
RP Forecast (Sellers)	5.0%	8.2%	13.1%	14.3%	15.2%	16.2%	10.9%
RP Futures (Sellers)	5.5%	9.0%	13.4%	14.3%	15.2%	16.2%	11.2%
RP Best (Sellers)	6.3%	9.2%	13.4%	14.5%	16.0%	17.6%	11.7%
RP Worst (Sellers)	−0.8%	−0.2%	0.0%	−0.3%	−0.9%	−1.4%	−0.5%

Figure 8. Risk Premium for sellers.

$$\overline{\mathrm{RP}}_{All}^{\text{both, predictive}} = \overline{\mathrm{RP}}_{All}^{\text{buyers,predictive}} + \overline{\mathrm{RP}}_{All}^{\text{sellers,predictive}} = -0.3\% + 10.9\% = 10.6\% \quad (28)$$

$$\overline{\mathrm{RP}}_{All}^{\text{both, best}} = \overline{\mathrm{RP}}_{All}^{\text{buyers, best}} + \overline{\mathrm{RP}}_{All}^{\text{sellers, best}} = 0.5\% + 11.7\% = 12.2\% \quad (29)$$

Furthermore, notice that $\overline{\mathrm{RP}}_{All}^{\text{both, worst}}$ can be calculated by (30).

$$\overline{\mathrm{RP}}_{All}^{\text{both, worst}} = \overline{\mathrm{RP}}_{All}^{\text{buyers, worst}} + \overline{\mathrm{RP}}_{All}^{\text{sellers, worst}} = -11.7\% - 0.5\% = -12.2\% \quad (30)$$

The overall RP of the predictive strategy for all maturities was 10.6% (the limits were −12.2% and 12.2%) which showed that this RP was quite a good (positive) indicator. Thus, the set of reference trading strategies ("best," "worst" and "conventional," formulated in Section 2.2) were efficient for the evaluation of the performance of the proposed predictive trading strategy.

3.3. Results of the Predictive Trading Strategy of Physical Futures with a Simpler Forecasting Model

As a benchmark, a simpler forecasting model than the ELM neural network model was selected to be used with the predictive trading strategy. This benchmark model was an ordinary least square forecasting model (OLS model), whose coefficients were adjusted with the data corresponding to the training dataset (using the six input variables described in Section 2.1). This model obtained worse forecasting results than the ELM neural network model in the initial selection phase with the cross-validation procedure, i.e., the average RMSE with the five folds used as testing sets was 7.41 €/MWh for the ELM model and 8.10 €/MWh for the OLS model. However, because of its simplicity, the OLS model was used for comparative purposes in the trading of physical Futures in the MIBEL market.

The forecasting results obtained by the OLS model with the data from the testing dataset gave an RMSE value of 6.15 €/MWh, slightly worse than the 6.12 €/MWh value achieved by the ELM neural network model. Table 3 shows the RMSE values for the different maturities (*LagM* values).

Table 3. Root mean square error (RMSE) values for the testing period for the extreme learning machine (ELM) neural network model and the ordinary least square (OLS) model.

LagM (Months)	RMSE ELM (€/MWh)	RMSE OLS (€/MWh)
1	4.71	7.20
2	5.60	6.86
3	6.19	5.94
4	6.61	5.30
5	7.03	4.84
6	8.24	4.75
All	6.12	6.15

In addition to the forecasting accuracy measurements provided by the RMSE values, the Diebold-Mariano (D-M) test [56] was used to test the statistical significance of the forecasts provided by both models. The D-M test aims to test the null hypothesis of equal accuracy of the forecasts provided by both models against an alternative hypothesis of different accuracy. In order to ensure a better evaluation, we used the modified D-M [57], i.e., an improved version that corrects some shortcomings of the original D-M test. The mean square error was selected as the loss function. A complete information about the D-M test and the modified D-M (mD-M) test can be found in [56,57]. These tests have been used in numerous applications to compare the forecasts provided by two competing models. In the literature related to price forecasting in electricity markets, good application examples can be found in [58–60].

The one-sided version of the mD-M test was applied to determine whether the difference in accuracy of both models was statistically significant. In this test, the null hypothesis was the equality of accuracy, whereas the alternative hypothesis corresponded to a better accuracy of the forecasts provided by the ELM neural network model. Table 4 shows the results obtained with the mD-M test, the statistic values and the p-values for a significance level of 5%. Table 4 shows that the forecasts provided by the ELM neural network model were significantly better for maturities of 1 and 2 months (p-values under the significance level imply the rejection of the null hypothesis). Note that the results of this test also suggested a significant difference in accuracy for the maturities of 4 and 5 months, but in this case, favourable to the OLS model.

Table 4. Modified Diebold-Mariano test results.

LagM (Months)	mD-M Statistic	p-Value
1	−7.88	0.0000
2	−2.13	0.0172
3	0.45	0.6741
4	1.83	0.9658
5	2.26	0.9874
6	1.47	0.9270

On the other hand, the results obtained with the predictive trading strategy using the forecasts of the OLS model corresponded to a RP value of 0.0% for buyers and a value of 11.2% for sellers. Note that the RP results obtained using the forecasts of the OLS model were slightly better that the achieved using the forecasts of the ELM neural network model. It should be noted that the forecasted values provided by the OLS model were lower than the last settlement Futures prices throughout the entire testing period. Since the decision signal of buying/selling through Futures is based on the comparison of the output of the forecasting model and the last settlement Futures price, this signal was not activated for buyers on any negotiation day of the testing period (obviously, for sellers it was activated every day). Therefore, the trading results for sellers obtained using the forecasts of the OLS forecasting model were similar to those obtained by the conventional strategy.

Furthermore, the trading results obtained using the OLS forecasting model should be equal to those obtained with any other forecasting model, independently of its forecasting accuracy, under the condition that its forecasts were always lower than the last Futures settlement prices. Consequently, it can be inferred that the success of the predictive trading strategy presented in this article does not only depend on the accuracy of the mid-term monthly average spot price forecasting model but also on the fact that there is an ex ante decision for either buying/selling on the futures market or on the spot market.

4. Conclusions

This article presents a novel trading strategy for physical monthly futures (Futures) to help electricity agents (buyers and sellers) decide between buying/selling on spot markets or respectively buying/selling on the derivatives markets, several months in advance. The predictive strategy is essentially based on the forecast provided by a mid-term forecasting model of the monthly average spot price, which is also presented in this article. The strategy takes advantage of the forecasting model predictions to define a decision signal (buy/sell electricity through Futures instead of waiting for the spot market). The signal is generated at the decision time, when the forecast of the monthly average spot price is carried out and the last Futures settlement prices are available, several months before the clearing of the spot prices.

The trading strategy only requires access to the electricity derivatives market. This access could be done with online platforms for trading electricity through futures or with any other technological mode of trading that could be established in the different countries or regions that have this type of market. The trading strategy can also be applied to forward electricity contracts on the OTC market. The proposed predictive trading strategy is applicable to any possible negotiation day, open for the trading of physical Futures several months in advance. The trading strategy was studied from the perspectives of electricity buyers and sellers.

The predictive strategy and the mid-term forecasting model of the spot price were successfully applied to the Iberian Electricity Market (MIBEL). They could also be adapted and used in other forward contracts and other electricity derivatives markets. Despite the difficulty in obtaining good performance for the results (forecast) of the monthly average spot price forecasting model, the computer results achieved were promising, proving that it is possible to predict monthly average spot prices with lower errors (deviations) than the ones corresponding to using the Futures settlement prices as the forecast.

The evaluation of the new predictive trading strategy uses the measures of ex post Risk Premium (RP) applied to the following strategies: The new conditional predictive trading strategy ("predictive"), the conventional trading strategy ("conventional"), the ex post best conditional trading strategy ("best"), and the ex post worst conditional trading strategy ("worst"). All RP measures are ex post because profits/losses are measured against the ex post monthly average spot price. The "best" and "worst" strategies lead to RP reference indicators, representing the inner limits of the scale where the RP of the "predictive" strategy performs. The "conventional" strategy is a realistic reference for evaluating the relative performance obtained for the "predictive" strategy. The "predictive," "best" and "worst" strategies are conditional strategies, where at each negotiation moment, the agent decides between trading in futures or on the spot markets. Conversely, for the "conventional" strategy, there is no conditional decision: buying/selling electricity on the futures market instead of on the spot market is always assumed. All the trading strategies ("predictive," "best," "worst" and "conventional") were tested for buyers and sellers. The sum of the RP of buyers and sellers for each trading strategy was used for the purposes of comparing the overall performance of the set of strategies for both perspectives jointly (of buyers and sellers). The average of these types of RP indicators was computed for the testing period (all delivery months) and for each futures maturity. The comprehensive use of these overall RP indicators for comparisons in this article constitutes a structured innovative evaluation approach.

The strategies were evaluated for 1 complete year, a period with exceptionally high price values for futures trading, what tended to economic losses for buyers and profits for sellers under the "conventional" strategy. The results obtained shown that the proposed predictive trading strategy achieved an overall benefit using any of the two mid-term monthly average spot price forecasting models tested in this article, although under a practical perspective, the OLS forecasting model could be preferred due to its easy use and implementation.

As a final conclusion of the article, it can be stated that there are advantages when using the new predictive trading strategy for negotiation in electricity futures markets. It can be effectively used for hedging operations in electricity markets.

Further research is underway in order to improve the benefits of the proposed trading strategy by addressing an ex ante approach and enhancing the forecasting model using more powerful forecasting techniques, a more exhaustive feature selection and using other influence variables external to electricity markets.

Author Contributions: Conceptualization, C.M.; formal analysis, L.A.F.-J.; investigation, C.M., L.A.F.-J. and I.J.R.-R.; methodology, C.M., L.A.F.-J. and I.J.R.-R.; validation, L.A.F.-J. and I.J.R.-R.; writing—original draft, C.M. and I.J.R.-R. and writing—review and editing, L.A.F.-J. and I.J.R.-R. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the "Ministerio de Ciencia, Innovación y Universidades," Spanish Government, under the research project ENE-2016-78509-C3-3-P, and the European Regional Development Fund, EU.

Acknowledgments: The authors would like to thank the "Ministerio de Ciencia, Innovación y Universidades" of the Spanish Government for supporting this research under the project ENE2016-78509-C3-3-P and the ERDF funds of the European Union.

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

$\boldsymbol{a}_i$	Vector of weights between the input layer and the hidden layer node i
b_i	Bias of the hidden layer node i
$\boldsymbol{\beta}$	Output weights vector
$\hat{\boldsymbol{\beta}}$	Least square estimation of the output weights vector
β_i	Weight from the hidden layer node i to the output node
DM	Delivery month
DM_f	Last delivery month in the testing period
DM_i	First delivery month in the testing period
D-M	Diebold-Mariano
g	Activation function
h	Hour Index
$\boldsymbol{H}$	Hidden layer output matrix
$\boldsymbol{H}^+$	Moore–Penrose generalized inverse of the hidden layer output matrix
L	Number of nodes in the hidden layer
$LagD$	Number of days between the negotiation day n and the last negotiation day for the delivery month
$LagM$	Maturity or holding period in months ($LagM$ = 1,2, ... , 6)
$MF_{p,DM}$	Monthly futures settlement price for delivery month DM on the trading phase of day p, i.e., the established at the end of previous trading day to day p
$\overline{MF}_{n,DM}$	Average monthly futures settlement price for delivery month DM in the last 7 days before negotiation day n
$\dot{\overline{MF}}_{n,DM}$	Variation of the average monthly futures settlement price for delivery month DM in the last 7 days before negotiation day n
n	Negotiation day

N	Number of samples in the training data set
ND_i	Number of futures negotiation days in the last i days
$ND_{LagM,DM}$	Total number of negotiation days for delivery month DM with a maturity $LagM$
$nf_{LagM,DM}$	Last negotiation day for delivery month DM with maturity $LagM$
$ni_{LagM,DM}$	First negotiation day for delivery month DM with maturity $LagM$
$\boldsymbol{O}$	Target vector
o_j	Target value for the sample j
p	Day Index
$\overline{QF}_{n,DM}$	Average quarterly futures settlement price for the quarter including the DM established on the last 90 days before negotiation day n
$QF_{p,DM}$	Quarterly futures settlement price for the quarter including the DM established in the last negotiation day before day p
RMSE	Root mean square error
$\mathrm{RMSE}_{LagM}^{\mathrm{variable}}$	Root mean square error of the variable with respect to the ex post monthly average spot price for a holding period $LagM$ (variable = spot price forecast, Futures price)
RP	Risk Premium
$\overline{\mathrm{RP}}_{All}^{\mathrm{agents,strategy}}$	Average value of $\mathrm{RP}_{n,DM}^{\mathrm{agents,strategy}}$ for the all maturities, agents = (buyers, sellers, both) and strategy = (predictive, conventional, best, worst)
$\overline{\mathrm{RP}}_{LagM}^{\mathrm{agents,strategy}}$	Average value of $\mathrm{RP}_{n,DM}^{\mathrm{agents,strategy}}$ for maturity $LagM$, agents = (buyers, sellers, both) and strategy = (predictive, conventional, best, worst)
$\mathrm{RP}_{n,DM}^{\mathrm{agents,strategy}}$	Risk Premium for agents for negotiation day n corresponding to the delivery month DM following the trading strategy, agents = (buyers, sellers, both) and strategy = (predictive, conventional, best, worst)
$\overline{S}_{DM}$	Average actual spot price in the delivery month DM
$\overline{S}_n$	Average spot price in last 7 days before negotiation day n
$\hat{S}_{n,DM}$	Forecast of monthly average spot price evaluated in day n for delivery month DM
$S_{p,h}$	Spot price for day p hour h
$\boldsymbol{x}_j$	Input vector for the sample j

References

1. Edwards, D.W. *Energy Trading and Investing: Trading, Risk Management and Structuring Deals in the Energy Market*; McGraw-Hill: New York, NY, USA, 2009.
2. Economic Consulting Associates Limited. European Electricity: Forward Markets and Hedging Products—State of Play and Elements for Monitoring 2015. Available online: www.acer.europa.eu (accessed on 28 April 2020).
3. Hull, J. *Options, Futures, and Other Derivatives*, 9th ed.; Prentice Hall: Upper Saddle River, NJ, USA, 2015.
4. Bessembinder, H.; Lemmon, M.L. Equilibrium pricing and optimal hedging in electricity forward markets. *J. Financ.* **2002**, *57*, 1347–1382. [CrossRef]
5. Wilkens, S.; Wimschulte, J. The pricing of electricity futures: Evidence from the European energy exchange. *J. Futures Mark.* **2007**, *27*, 387–410. [CrossRef]
6. Furio, D.; Meneu, V. Expectations and forward risk premium in the Spanish deregulated power market. *Energy Policy* **2010**, *38*, 784–793. [CrossRef]
7. Umutlu, G.; Dorsman, A.; Telatar, E. The Electricity Market, Day-Ahead Market and Futures Market. In *Financial Aspects in Energy*; Dorsman, A., Westerman, W., Karan, M.B., Arslan, Ö., Eds.; Springer: Berlin, Germany, 2011; pp. 109–128. [CrossRef]
8. Steinert, R.; Ziel, F. Short- to mid-term day-ahead electricity price forecasting using futures. *Energy J.* **2019**, *40*, 105–127. [CrossRef]
9. Huisman, R.; Kilic, M. Electricity Futures Prices: Indirect Storability, Expectations, and Risk Premiums. *Energy Econ.* **2012**, *34*, 892–898. [CrossRef]
10. Fama, E.F.; French, K.R. Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage. *J. Bus.* **1987**, *60*, 55–73. [CrossRef]

11. Cartea, A.; Villaplana, P. An analysis of the main determinants of electricity forward prices and forward risk Premia. In *Quantitative Energy Finance*; Benth, F., Kholodnyi, V., Laurence, P., Eds.; Springer: New York, NY, USA, 2014; pp. 215–236. [CrossRef]
12. Longstaff, F.A.; Wang, A.W. Electricity forward prices: A high-frequency empirical analysis. *J. Financ.* **2004**, *59*, 1877–1900. [CrossRef]
13. Benth, F.E.; Cartea, A.; Kiesel, R. Pricing forward contracts in power markets by the certainty equivalence principle: Explaining the sign of the market risk premium. *J. Bank Financ.* **2008**, *32*, 2006–2021. [CrossRef]
14. Weron, R.; Zator, M. Revisiting the relationship between spot and futures prices in the Nord Pool electricity market. *Energy Econ.* **2014**, *44*, 178–190. [CrossRef]
15. Fleten, S.-E.; Hagen, L.A.; Nygård, M.T.; Smith-Sivertsen, R.; Sollie, J.M. The overnight risk premium in electricity forward contracts. *Energy Econ.* **2015**, *49*, 293–300. [CrossRef]
16. Bunn, D.W.; Chen, D. The forward premium in electricity futures. *J. Empir. Financ.* **2013**, *23*, 173–186. [CrossRef]
17. The Iberian Energy Derivatives Exchange, OMIP. Available online: http://www.omip.pt (accessed on 29 April 2020).
18. Ballester, J.M.; Climent, F.; Furió, D. Market efficiency and price discovery relationships between spot, futures and forward prices: The case of the Iberian Electricity Market (MIBEL). *Span. J. Financ. Accoun.* **2016**, *45*, 135–153. [CrossRef]
19. Ferreira, M.; Sebastião, H. The iberian electricity market: Analysis of the risk premium in an illiquid market. *J. Energy Markets* **2018**, *11*, 61–82. [CrossRef]
20. Da Silva, R.R.; Dias, M.F.; Madaleno, M. Iberian electricity market spot and futures prices: Comovement and lead-lag relationship analysis. *J. Sustain. Energy Plan. Manag.* **2019**, *19*, 59–68. [CrossRef]
21. Hong, T.; Pinson, P.; Fan, S.; Zareipour, H.; Troccoli, A.; Hyndman, R.J. Probabilistic energy forecasting: Global energy forecasting competition 2014 and beyond. *Int. J. Forecast.* **2016**, *32*, 896–913. [CrossRef]
22. Yan, X.; Chowdhury, N.A. Mid-term electricity market clearing price forecasting: A hybrid LSSVM and ARMAX approach. *Int. J. Electr. Power* **2013**, *53*, 20–26. [CrossRef]
23. García-Martos, C.; Rodríguez, J.; Sánchez, M.J. Forecasting electricity prices and their volatilities using unobserved components. *Energy Econ.* **2011**, *33*, 1227–1239. [CrossRef]
24. Yan, X.; Chowdhury, N.A. Mid-term electricity market clearing price forecasting: A multiple SVM approach. *Int. J. Electr. Power* **2014**, *58*, 206–214. [CrossRef]
25. Kristiansen, T. A time series spot price forecast model for the Nord Pool market. *Int. J. Electr. Power* **2014**, *61*, 20–26. [CrossRef]
26. Torbaghan, S.S.; Motamedi, A.; Zareipour, H.; Tuan, L.A. Medium-term electricity price forecasting. In Proceedings of the 2012 North American Power Symposium (NAPS), Champaign, IL, USA, 9–11 September 2012; pp. 1–8. [CrossRef]
27. Cheng, C.; Luo, B.; Miao, S.; Wu, X. Mid-term electricity market clearing price forecasting with sparse data: A case in newly-reformed Yunnan electricity market. *Energies* **2016**, *9*, 804. [CrossRef]
28. Vehviläinen, I.; Pyykkönen, T. Stochastic factor model for electricity spot price—the case of the Nordic market. *Energy Econ.* **2005**, *27*, 351–367. [CrossRef]
29. Maciejowska, K.; Weron, R. Short-and mid-term forecasting of baseload electricity prices in the UK: The impact of intra-day price relationships and market fundamentals. *IEEE Trans. Power Syst.* **2016**, *31*, 994–1005. [CrossRef]
30. Chakravarty, S.; Mohapatra, P.; Dash, P.K. Evolutionary extreme learning machine for energy price forecasting. *Int. J. Knowl.-Based Intell. Eng. Syst.* **2016**, *20*, 75–96. [CrossRef]
31. Windler, T.; Busse, J.; Rieck, J. One month-ahead electricity price forecasting in the context of production planning. *J. Clean Prod.* **2019**, *238*, 117910. [CrossRef]
32. Ziel, F.; Steinert, R. Probabilistic mid- and long-term electricity price forecasting. *Renew. Sustain. Energ. Rev.* **2018**, *94*, 251–266. [CrossRef]
33. Ghoddusi, H.; Creamer, G.G.; Rafizadeh, N. Machine learning in energy economics and finance: A review. *Energy Econ.* **2019**, *81*, 709–727. [CrossRef]
34. Moreno, J. Trading strategies modeling in Colombian power market using artificial intelligence techniques. *Energy Policy* **2009**, *37*, 836–843. [CrossRef]

35. Pinto, T.; Sousa, T.M.; Praça, I.; Vale, Z.; Morais, H. Support Vector Machines for decision support in electricity markets' strategic bidding. *Neurocomputing* **2016**, *172*, 438–445. [CrossRef]
36. Santos, G.; Pinto, T.; Praça, I.; Vale, Z. MASCEM: Optimizing the performance of a multi-agent system. *Energy* **2016**, *111*, 513–524. [CrossRef]
37. Lopes, F. MATREM: An Agent-based Simulation Tool for Electricity Markets. In *Electricity Markets with Increasing Levels of Renewable Generation: Structure, Operation, Agent-Based Simulation and Emerging Designs*; Springer: Cham, Switzerland, 2018; pp. 189–225. [CrossRef]
38. Krečar, N.; Benth, F.E.; Gubina, A.F. Towards Definition of the Risk Premium Function. *IEEE Trans. Power Syst.* **2020**, *35*, 1085–1098. [CrossRef]
39. Browell, J. Risk Constrained Trading Strategies for Stochastic Generation with a Single-Price Balancing Market. *Energies* **2018**, *11*, 1345. [CrossRef]
40. Bunn, D.W.; Gianfreda, A.; Kermer, S. A Trading-Based Evaluation of Density Forecasts in a Real-Time Electricity Market. *Energies* **2018**, *11*, 2658. [CrossRef]
41. MIBEL Board of Regulators. Estudio Sobre Comparativa de los Precios MIBEL (Contado y Plazo) con otros Mercados Europeos y su Relación con el Mercado único. Internal Report. July 2019. Available online: https://www.mibel.com/wp-content/uploads/2020/03/20190705SE_ESb.pdf (accessed on 12 June 2020).
42. Huang, G.-B.; Zhu, Q.-Y.; Siew, C.-K. Extreme learning machine: Theory and applications. *Neurocomputing* **2006**, *70*, 489–501. [CrossRef]
43. Huang, G.-B.; Wang, D.H.; Lan, Y. Extreme learning machines: A survey. *Int. J. Mach. Learn. Cybern.* **2011**, *2*, 107–122. [CrossRef]
44. Li, S.; Wang, P.; Goel, L. Short-term load forecasting by wavelet transform and evolutionary extreme learning machine. *Electr. Power Syst. Res.* **2015**, *122*, 96–103. [CrossRef]
45. Chen, Y.; Kloft, M.; Yang, Y.; Li, C.; Li, L. Mixed kernel based extreme learning machine for electric load forecasting. *Neurocomputing* **2018**, *312*, 90–106. [CrossRef]
46. Rafiei, M.; Niknam, T.; Aghaei, J.; Shafie-Khah, M.; Catalao, J.P.S. Probabilistic load forecasting using an improved wavelet neural network trained by generalized extreme learning machine. *IEEE Trans. Smart Grid* **2018**, *9*, 6961–6971. [CrossRef]
47. Hossain, M.; Mekhilef, S.; Danesh, M.; Olatomiwa, L.; Shamshirband, S. Application of extreme learning machine for short term output power forecasting of three grid-connected PV systems. *J. Clean Prod.* **2017**, *167*, 395–405. [CrossRef]
48. Wan, C.; Xu, Z.; Pinson, P.; Dong, Z.Y.; Wong, K.P. Probabilistic forecasting of wind power generation using extreme learning machine. *IEEE Trans. Power Syst.* **2014**, *29*, 1033–1044. [CrossRef]
49. Behera, M.K.; Nayak, N. A comparative study on short-term PV power forecasting using decomposition based optimized extreme learning machine algorithm. *Eng. Sci. Technol. Inter. J.* **2020**, *23*, 156–167. [CrossRef]
50. Wu, C.; Wang, J.; Chen, X.; Du, P.; Yang, W. A novel hybrid system based on multi-objective optimization for wind speed forecasting. *Renew. Energy* **2020**, *146*, 149–165. [CrossRef]
51. Chen, X.; Dong, Z.Y.; Meng, K.; Xu, Y.; Wong, K.P.; Ngan, H. Electricity price forecasting with extreme learning machine and bootstrapping. *IEEE Trans. Power Syst.* **2012**, *27*, 2055–2062. [CrossRef]
52. Shrivastava, N.A.; Panigrahi, B.K. A hybrid wavelet-ELM based short term price forecasting for electricity markets. *Int. J. Electr. Power* **2014**, *55*, 41–50. [CrossRef]
53. Wang, G.; Wei, Y.; Qiao, S. *Generalized Inverses: Theory and Computations*; Springer: Singapore, 2018.
54. Ding, S.; Zhao, H.; Zhang, Y.; Xu, X.; Nie, R. Extreme learning machine: Algorithm, theory and applications. *Artif. Intell. Rev.* **2015**, *44*, 103–115. [CrossRef]
55. Botterud, A.; Kristiansen, T.; Ilic, M.D. The relationship between spot and futures prices in the Nord Pool electricity market. *Energy Econ.* **2010**, *32*, 967–978. [CrossRef]
56. Diebold, F.X.; Mariano, R.S. Comparing predictive accuracy. *J. Bus. Econ. Stat.* **1995**, *13*, 253–263. [CrossRef]
57. Harvey, D.; Leybourne, S.; Newbold, P. Testing the equality of prediction mean squared errors. *Int. J. Forecast.* **1997**, *13*, 281–291. [CrossRef]
58. Nowotarski, J.; Raviv, E.; Trück, S.; Weron, R. An empirical comparison of alternative schemes for combining electricity spot price forecasts. *Energy Econ.* **2014**, *46*, 395–412. [CrossRef]

59. Kath, C.; Ziel, F. The value of forecasts: Quantifying the economic gains of accurate quarter-hourly electricity price forecasts. *Energy Econ.* **2018**, *76*, 411–423. [CrossRef]
60. Lago, J.; De Ridder, F.; De Schutter, B. Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms. *Appl. Energy* **2018**, *221*, 386–405. [CrossRef]