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Reducing balancing cost of a wind power plant by deep learning in market data: A case study for Turkey

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HIGHLIGHTS

- A way of utilizing market data to reduce the imbalance cost is proposed for actors in a fully-fledged power market.
- Proposed method is employed six hours before the day-ahead market closure time.
- Method does not require predictions of the day-ahead and balancing market prices.
- Tests show that the method is robust to ramps in both wind power production and market prices.

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ABSTRACT

By the liberalization of energy markets, renewable energy producers are increasingly selling their electricity in the day-ahead market. However, day-ahead forecasts of wind generators are not sufficiently accurate and therefore they are exposed to an imbalance cost due to the incorrect offerings. Although extensive and detailed market data are constantly publicized by the market operator, historical market data are not utilized effectively to reduce this cost. The present study initially casts the imbalance cost reducing problem as a binary classification problem and constructs a framework that consists of a long short term memory autoencoder and a blend of advanced classifiers. Then, the method extracts information from the market data if the day-ahead or imbalance price will be higher at a given hour of the next day. Using this information, auxiliary algorithms alter existing production forecasts and prevents abrupt rises in the imbalance cost. Extensive tests throughout a year show that the strategy performs reliably well and it has provided between 6.258% and 11.195% decrease in the balancing cost for four tested wind power plants.

1. Introduction

1.1. Motivation

Global wind power is growing fast and has reached over 651 GW by an annual increase of 60.4 GW in 2019 [1]. Due to the constantly growing of the wind energy penetration, intelligent systems for scheduling and trading is vital today [2–4]. In addition to this, by the liberalization trend of the power markets, the wind energy producers are increasingly participating in the day-ahead market, which implies committing the delivery of the agreed amount of energy at the given moment. In case of a deviation in the supply, the system must be balanced by the transmission system operator and compensating the mismatch between supply and demand in real time incurs a cost, which is translated to a payment penalty to the generator, known as the imbalance cost. Wind generators with their growing intermittent and non-dispatchable production are most vulnerable to this cost compared to other renewable generators due to their deficient accuracy of the day-ahead forecasts.

While the imbalance cost is caused by the inaccuracy of the forecasts, the amount of this cost is not a sole function of the forecast accuracy. It is determined in marketplace and particularly related to volatile electricity price of the balancing market. To reduce the imbalance cost, creating an effective method applied before the day-ahead market closure time is not straightforward due to uncertainties in both balancing and day-ahead market prices. However, the present study shows that it might be possible to avoid imbalance cost spikes and reduce this cost by using historical market data. In contrast to stochastic optimization models that require accurate market price estimates or reliable price scenarios to be effective, this study argues that since the imbalance cost stems from the

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volume offered to the market by the generator rather than the price bid, implementing an effective but relatively simple strategy might be possible by correcting offerings depending on the market conditions. Nevertheless, our strategy has limits on the degree of cost reduction that will also be discussed.

In practice, many wind producers are operating under subsidy and for those that are receiving a fixed price or a premium per unit of production, an imbalance cost implies a deduction in the income. Moreover, these subsidies last for a limited period after joining. When they end, the share of the imbalance cost in the revenue can be expected to rise considerably. Therefore, developing profitable strategies for reducing the imbalance cost is gaining growing attention.

1.2. Literature review

Wind power is the most vulnerable energy source to balancing penalties and generating more accurate wind power forecasts is subject of ongoing research [5–7]. Forecasting methods can be divided into two groups as physical and statistical methods. The physical-based methods, such as the numerical weather prediction, solves the physical equations to calculate factors changing the wind speed and direction. These models are suitable for long-term forecasts [8,9]. On the other hand, the statistical-based methods rely on historical data for inference and are successfully applied for the prediction horizon from a few seconds to a few weeks [5,10]. The statistical-based methods consist of the time-series models such as the autoregressive [11] and the fractional autoregressive integrated moving average [12]; probabilistic models such as the Bayesian inference [13] and kernel estimation methods [14]; machine learning models such as the artificial neural networks [7,15], support vector regression [16], recurrent neural networks [17], extreme learning machine [18], relevance vector machine [19]; and fuzzy logic models [20,21]. In addition, there are measure-correlate-predict (or spatial correlation) methods which generate forecasts for a target site based on the measurements at another site. These methods explore the relation between two sites and then utilize the obtained correlation for forecasting [22,23]. For very short-term forecasts, the persistence (or naive) estimator is also exploited. This simple method assumes that wind behavior at time t will be same as the behavior at time t-1.

The prediction horizon of the day-ahead market participants is between 12 and 36 h. Generating accurate forecasts in this horizon is challenging. Literature has focused on hybrid methods that combine and benefit from predicting capabilities of several methods. For example, a hybrid method in [24] uses an iterative forecasting-correcting strategy and the general regression neural network with the Fibonacci search for optimizing the cross-validation error. The mean absolute percentage errors (MAPE) of two tested wind farms are found as 23.518% and 26.197% for 24 h ahead forecasts. Another hybrid method is proposed in [25] that combines an artificial neural network with the k-means clustering. This method generates day-ahead forecasts using numerical weather predictions. The method has given 10.67% normalized mean absolute error (NMAE). Another study combines the artificial bee colony algorithm with the relevance vector machine in [26]. The MAPE values are reported to be between 19.83% and 22.93%. As the horizon extends towards 36 h, the error tends to increase and a survey of wind power forecasts in [27] reports an error between 9% and 12% NMAE for 36 h ahead predictions, which implies the occurrence of even more imbalanced positions. More recently, a deep learning approach for 24 h ahead forecasts based on a convolutional neural network, whose structure and hyper-parameters are determined by the Taguchi method, is developed in [28]. It has reported as low as 13.84% MAPE in one case, while on average the error is 30.03%. Given these points, a literature review in [5] concludes that a MAPE value less than 15% might be challenging for the day-ahead predictions. As a result, although newly developed methods are showing enhancements, the accuracy of the forecasts is still posing a challenge and unable to protect a market participant from imbalance costs.

1.3. Aim and contribution

Alternatively, the present study proposes an approach to anticipate the imbalance cost spikes through mining in the market data and then it avoids them by amending existing wind power forecasts. Previous studies related to the imbalance cost have mostly focused on market design for a broader integration of renewables, assessment and mitigation of imbalance risks in the grid, uncertainty analysis of market conditions and risk management for day-ahead and intraday market bidding strategies [29–33]. A small number of studies have considered the subject from a generator's perspective [34–36] and relatively fewer methods have been proposed to reduce the imbalance cost of a wind generator directly in real market conditions. To our best knowledge, a way of effectively utilizing the market data to reduce the imbalance cost has not been developed before, although this cost is determined in marketplace and the market operators are regularly publishing extensive data.

The present study aims to reduce the annual imbalance cost of a wind producer using the information extracted from the market data without any assumption on market prices. The proposed method is designed to be employed six hours before the day-ahead market closure time.

The main contributions and novelty of this paper are

- The study describes a way of utilizing market data in order to amend the pre-generated wind power forecasts for reducing the imbalance cost of a generator.
- It defines the imbalance cost reducing problem as a binary classification problem to mine in the market data.
- It develops a complete framework that is composed of a long short term memory recurrent neural network and a blend of classifiers along with the algorithms for autonomously amending the forecasts.
- The proposed framework can be adapted to any wind power forecasting system and it does not require predictions of the day-ahead and balancing market prices.
- The method works reliably and it is robust to sudden changes (i.e. ramps) in power production and in market prices.

1.4. Structure of the study

The paper is organized as: Section 2 describes the imbalance cost reducing problem, briefly outlines the day-ahead electricity markets and explains the evaluation of the imbalance cost in Turkey. To quickly know the proposed method and see its performance, Section 2 can be skipped. Section 3 describes the market data, wind power production data and historical power forecasts that are fed into the method. Then, it explains the feature selection process for deep learning in the market data. Section 4 reveals the proposed method. Implementation details of the long short term memory autoencoder and binary classification agents are given. In addition, this section describes the proposed algorithms that autonomously alter the forecasts. Finally, Section 5 discusses the results.

2. Imbalance cost

It is necessary to describe the factors affecting the amount of the imbalance cost in practice, since the proposed approach claims to reduce the imbalance cost of wind generators in real market conditions. This section also aims to let the proposed approach apply into another day-ahead market. It is convenient to say that the day-ahead markets operate similar to each other in Europe, and the Turkish power market's structure and the way it works are particularly similar to the Nord Pool market of Europe.

Wind power is the most vulnerable energy source to balancing penalties, which can be as much as 10% of the total income [37]. The process of determining imbalance cost and billing procedures to a wind generator[1] differ from country to country [38–40]. In most of the European countries and in Turkey, generators are responsible of their imbalances [39]. Day-ahead market door closing time is 12:00 at noon in European countries and 12:30 in Turkey for the next day delivery. This implies a prediction horizon between 12 and 36 h, and due to the limited predictability of wind for this horizon, a deviation at the time of delivery time is a frequent issue.

2.1. Turkish day-ahead market

The Turkish day-ahead market employs double-sided blind auctions with the principle of uniform pricing and the day-ahead (i.e. market clearing) price is calculated very similar to European markets with only a slight difference in handling block bids [41]. The wind power is incentivized under the renewable energy resources certification and support mechanism (RERCSM), which provides a purchase guarantee, feed-in tariff (FiT) of 73 USD/MWh. Benefiting from the FiT requires generators to participate in the day-ahead market, whereas generators only enter the amount of forecasted production into the day-ahead screens. The offers of wind generators are taken into account with zero price, but producers are always paid with 73 USD/MWh. Due to the price advantage compared with the day-ahead price (for example, it was 48.16 USD/MWh on average in 2018), all wind producers has joined in the RERCSM. Notably, the producers are responsible of their imbalances since May 1, 2016 under RERSCM. All participants in the day-ahead market are price taker and the total number of participants was 747 on average in 2018 [42].

In addition, the intraday market[2] plays a role for mitigating the imbalances closer to the delivery time. Although the proposed method aims to reduce the cost caused by the day-ahead market actions, intraday actions can be further taken after using the proposed method. It should be noted that bidding in the intraday market is risky and avoided by most of the generators in Turkey. To quantify the low liquidity, the intraday market had 2.93 TWh cleared volume in 2018 compared with the day-ahead market volume of 149.39 TWh [42].

2.2. Calculation of the imbalance cost

The imbalance cost of a generator is evaluated by a formula where the main factors are the day-ahead and balancing market prices, which are determined hourly in the day-ahead and balancing power markets, respectively. While the day-ahead market price is calculated by matching supply and demand curves for each bidding hour, the balancing market price is determined based on up- and downward regulating power offers accepted by the transmission system operator in real-time balancing. Since the evaluation method is based on the marginally accepted offers, the imbalance price is commonly known as the marginal price.

The imbalance settlement, $B_{i,j}$, for a wind power plant i at hour j is calculated through the following formula

$$B_{i,j} = (F_j - R_j \times k) \times DP_j + \begin{cases} (R_j - F_j) \times min(DP_j, MP_j) \times 0.97, & \text{if } R_j > F_j \\ (R_j - F_j) \times max(DP_j, MP_j) \times 1.03, & \text{if } F_j > R_j \end{cases} \quad (1)$$

where F_j is the day-ahead wind power production forecast for hour j of the generator, R_j is the real production, DP_j is the day-ahead price, MP_j is the marginal (i.e. imbalance) price at hour j and k is the tolerance coefficient, which is 0.97 for wind generators. By the regulator, Eq. (1) is constructed so that a negative $B_{i,j}$ implies a loss and a positive $B_{i,j}$ implies a gain for the generator. Although $B_{i,j}$ can be both positive and negative, it becomes mostly negative for wind generators due to the inaccuracy of their day-ahead forecasts. Therefore, Eq. (1) is known as imbalance cost formula. In the above formula, the intraday market actions are not included, since the imbalance cost mainly occurs due to the day-ahead actions.

The income of a wind plant i at hour j is then

$$I_{i,j} = R_j \times \text{FiT} + B_{i,j} \quad (2)$$

During the peer review of this study, the FiT price is reduced considerably to 320 TRY/MWh (~44 USD/MWh) for wind farms activated after July 1, 2021. This regulation change implies a dreadful 40% reduction in the revenue and highlights the necessity of a better control over the balancing costs.

2.3. Discussion on the imbalance cost

The balancing settlement in Eq. (1) depends on four factors: i) whether real production is higher or lower than the forecasted production, ii) the difference between real and forecasted productions, iii) which price (marginal or day-ahead price) is higher and iv) the difference between the marginal and day-ahead prices. In some countries, negative ($R_j < F_j$) and positive ($R_j > F_j$) imbalances are not penalized equally and a positive imbalance is favored by incurring less cost to the seller [43]. But formulation in Eq. (1) does not prefer a positive or negative imbalance over the other, because of the strong dependence on market prices. In addition, the cases DP > MP and DP < MP may not be equally likely in a market for some hours. If a market has a characteristic that DP > MP or DP < MP is more likely to happen, it might be suspected that a simple strategy based on constantly over- or under-promising can be leveraged. But in a competitive market with complicated dynamics, such as the one studied here, a more intricate approach is required.

The tolerance coefficient, k, in Eq. (1) is reduced from 1 to 0.97 as an incentive, creating 3% buffer in the difference between real and forecasted productions. To explain the situation, it is applied as 1 for reservoir hydroelectric, 0.995 for geothermal, 0.99 for biomass, 0.98 for channel hydroelectric and 0.98 for solar energy. A lower the k value incurs less cost for equivalent conditions. In fact, 0.97 value allows wind generators to produce an income, in other words $B_{i,j}$ can be positive at some hours provided that the forecasting accuracy is sufficiently high.

It can be hypothesized that if it was possible to estimate the day-ahead and marginal prices along with the difference between them in advance, an efficient strategy could have been directly adapted for the day-ahead offerings. But, predicting the day-ahead price for a given hour of the next day is equally difficult task compared with the wind power forecasting. Mean absolute error of the day-ahead price prediction has been reported to be lower than the error of the wind power predictions for an equivalent horizon in some studies [44–47]. However, day-ahead price predictions could be valuable only together with accurate marginal price predictions. In this regard, our experience on the Turkish balancing market has shown that the marginal price is more volatile and its prediction gives a larger error than the error of the day-ahead price predictions. A combination of two inaccurate price predictions eventually leads to inefficient and unreliable results. Alternatively, the present study tries to anticipate whether the day-ahead or marginal price will be higher at given hour and exploit this information to reduce the

[1] If a wind generator join in a balance responsible party (BRP), the imbalance penalty is billed to the BRP. Then BRP shares out the cost proportional to individual imbalances of its members.

[2] A plant under the RERCSM is, in fact, allowed to trade in the day-ahead, intraday, balancing markets and/or by bilateral agreements. Bilateral agreement was not viable in 2018 for most of the plants, since feed-in-tariff price was significantly higher than the spot price. And wind generators are not qualified currently to place offers to the balancing market.

imbalance cost.

3. Data and feature selection

3.1. Data description

The market data used in this study covers a period between September 16, 2017 and December 31, 2018, having hourly resolution. Market data are publicly available and downloaded from the transparency platform of the Turkish market operator, EXIST. The proposed strategy is tested with the hourly production data from four different onshore wind power plants (WPPs) having capacities of 86.2 MW (WPP1), 60 MW (WPP2), 40 MW (WPP3) and 40 MW (WPP4). WPP1, WPP2 are located in Bandirma and Tekirdag regions, respectively, WPP3 and WPP4 are located in Canakkale region. The data used contain hourly power production and their historical power forecasts. Both of these data are covering 2018.

3.2. Feature selection

Although significant amount of market data showing diverse hourly measures are publicized, which of these parameters carry relevant information about the market prices has to be investigated. A correlation analysis has been initially conducted. The Pearson correlation coefficients, ρ, between two variables are calculated by

$$\rho(X,Y) = \frac{cov(X,Y)}{\sigma_x \sigma_y} \tag{3}$$

where cov is the covariance, σ_x and σ_y are the standard deviations of two variables.

The degrees of correlation between market variables are obtained in Fig. 1. MP is the marginal (balancing market) price, IP is the weighted average intraday price based on transaction volume at the contract hour, DP is the day-ahead price, LP is the hourly demand that the EXIST forecasts, WP is the wind production plan entered by the producers, GP is the daily gas reference price, NGP is the gas price for negative imbalances, GQ is the matched quantity (sm^3) of gas, TV is the trade volume in the day-ahead market, which is hourly value of the marching bids, WC is the active wind power capacity, PI is the positive imbalance quantity (MWh) and NI is the negative imbalance quantity (MWh). All these parameters in Fig. 1 belong to the same hour. Gas variables have been included in the exploration, since natural gas power stations have relatively short activation time to place offers to the balancing market and they had the highest portion in overall generation by 33% in terms of energy source in 2018.

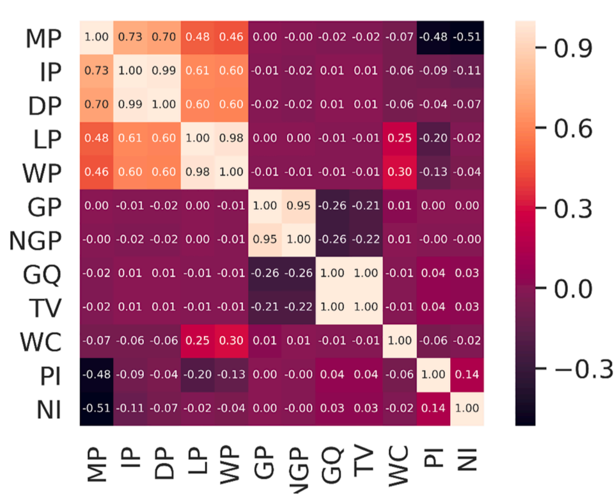

Fig. 1. Values of correlation coefficient between market variables.

In the correlation matrix of Fig. 1, a correlation value closer to 1 or −1 implies a higher correlation. The sign depicts the positive or the negative correlation between variables. A correlation with the marginal price (MP) and/or with the day-ahead price (DP) is sought. Negative imbalance (NI) data are labeled with a minus sign by the market operator, meaning that its volume increases, as its value becomes smaller. Therefore, its correlation coefficient is calculated negative. The results show that MP, IP, DP, LP, NI and PI are relatively correlated with each other. It is important to note that at the time of the day-ahead offering, all of these variables are not simultaneously available, since some of them are determined next day close to the delivery. Therefore, the intraday price, marginal price, positive imbalance and negative imbalance volumes are fed to the method with 48 h lag to meet realistic conditions. On the other hand, load forecasts (i.e. LP values) for the next day are already provided in the platform. Thus, LP values for the same hour are used with the MP, where the correlation between LP and MP is found as 0.48.

Fig. 2 investigates further the degrees of correlation between possible features to be used in the classifier. {number}back means that the value belongs to the same hour but {number} days earlier. Based on the correlation degrees in Fig. 2, for the MP at hour i in day j, thirteen features are selected as the input, $IP_{i,j-2}$, $IP_{i,j-7}$ $IP_{i,j-14}$, $DP_{i,j-1}$, $DP_{i,j-7}$, $DP_{i,j-14}$, $WP_{i,j-1}$, $WP_{i,j-7}$ $WP_{i,j-14}$, $LP_{i,j}$, $LP_{i,j-7}$, $LP_{i,j-14}$ and day number (Monday = 1 to Sunday = 7). Day number is included to take into account weekends and to recognize possible day patterns.

4. Proposed method

An efficient imbalance cost reducing strategy could be adopted if the electricity prices were predicted accurately. However, predicting the day-ahead and the marginal electricity prices simultaneously for hourly base in an acceptable level of accuracy is not an easy task. As described earlier, the present study attempts to predict if day-ahead (DP) or marginal (i.e. imbalance) price (MP) will be higher. Then it corrects the pre-generated forecasts to avoid abrupt rises in the imbalance cost. Fig. 3 illustrates the framework of the proposed method. The proposed method is adaptable into any forecasting system. All predictions are generated six hours before the day-ahead market gate closure time to meet practical operating conditions. In other words, the method is implemented with a prediction horizon between 18 and 42 h. The problem has initially been constructed as a binary classification problem: if MP is greater than DP, classifier is asked to return −1; if MP is less than or equal to DP, it is asked to return 1.

The features have a low inter-correlation as shown in Fig. 2. To highlight a possible pattern in the market data, before applying the classifiers, a long short term memory (LSTM) autoencoder has been employed to represent the data, as detailed in the following section. An LSTM autoencoder is a type of recurrent gated artificial neural network, which is applicable to time-series data and capable of learning secular variations in data [48]. It is used here for accentuating the underlying trends, if exists, among variables. Employing an LSTM autoencoder for pre-processing the market data has in fact improved the performances of the classifiers. The results with and without the autoencoder are provided in Section 5.

4.1. Long short term memory (LSTM) autoencoder

An LSTM autoencoder is composed of two symmetric artificial recurrent neural networks and a bridge layer between these two networks. The encoder (first half of the network) maps data onto the latent space, while the decoder (the second half) reconstructs the data from the latent space by highlighting the underlying pattern during the reconstructing process. Fig. 4 demonstrates the structure of the autoencoder. The data are initially reshaped to 11303x24x13 (samples × time step × features). For every prediction, last 90 days are used in the re-training of the autoencoder. An encoder architecture with two hidden layers have

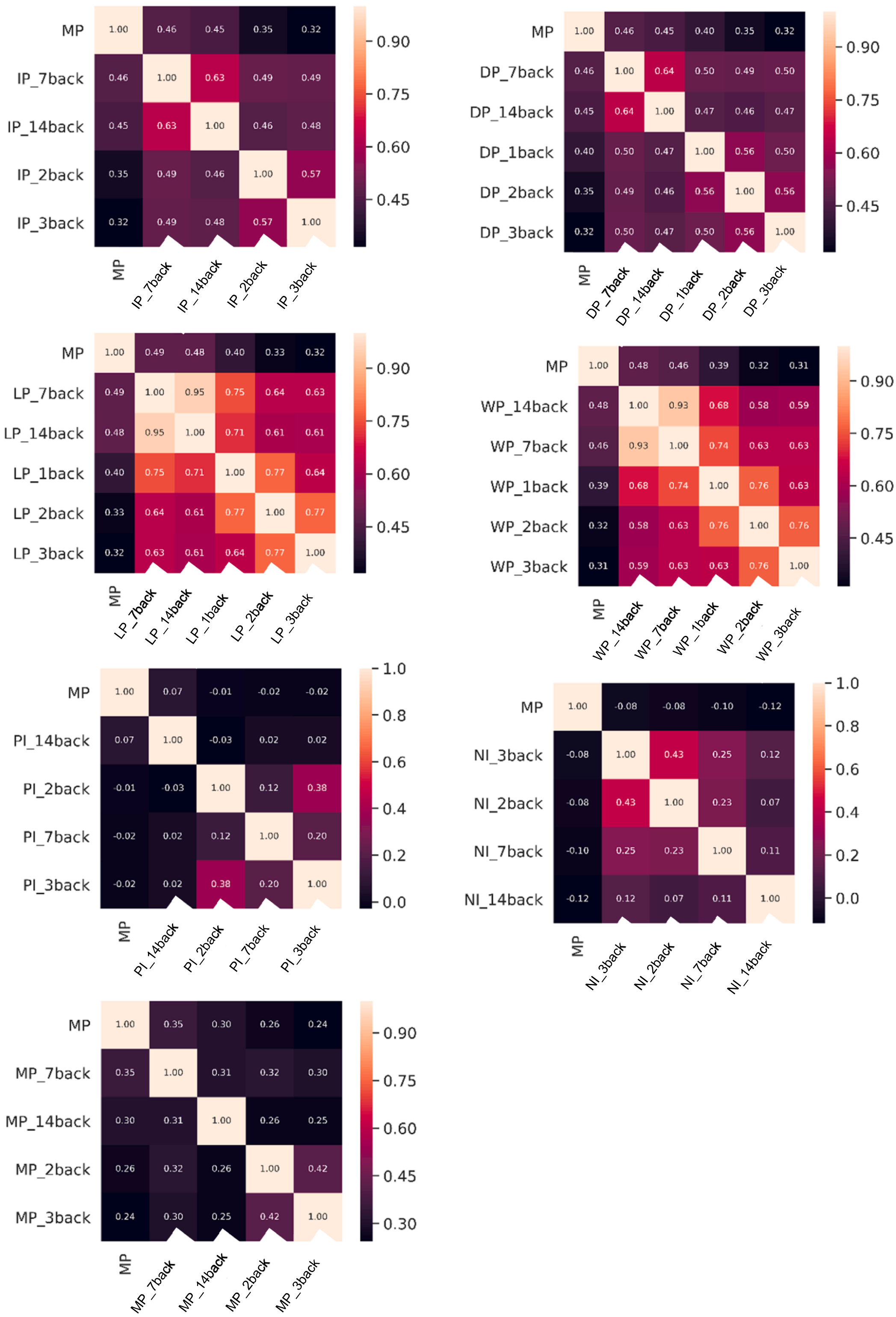

Fig. 2. Values of correlation coefficient between possible features to be used in the classifier. {number}back means that the value belongs to the same hour {number} days earlier.

been utilized with 128 and 64 memory units, respectively.

The memory unit or cell consists of input, forget and output gates. The LSTM cell incorporates secular variations in the data by having a hidden state. The hidden state h_t at time t of the cell is calculated from the previous time step h_{t-1} and the input x_t at time t using the input, forget and output gates. Details of these gates can be found in [49]. In our architecture, the input gate i is implemented as

$$i = \sigma(W_i h_{t-1} + U_i x_t) \tag{4}$$

where σ is the hard sigmoid function. W and U are the weight matrices that keep the parameters of the gates, which are learned during training. Subscripts i, f and o of W and U denote the input, forget and output gates,

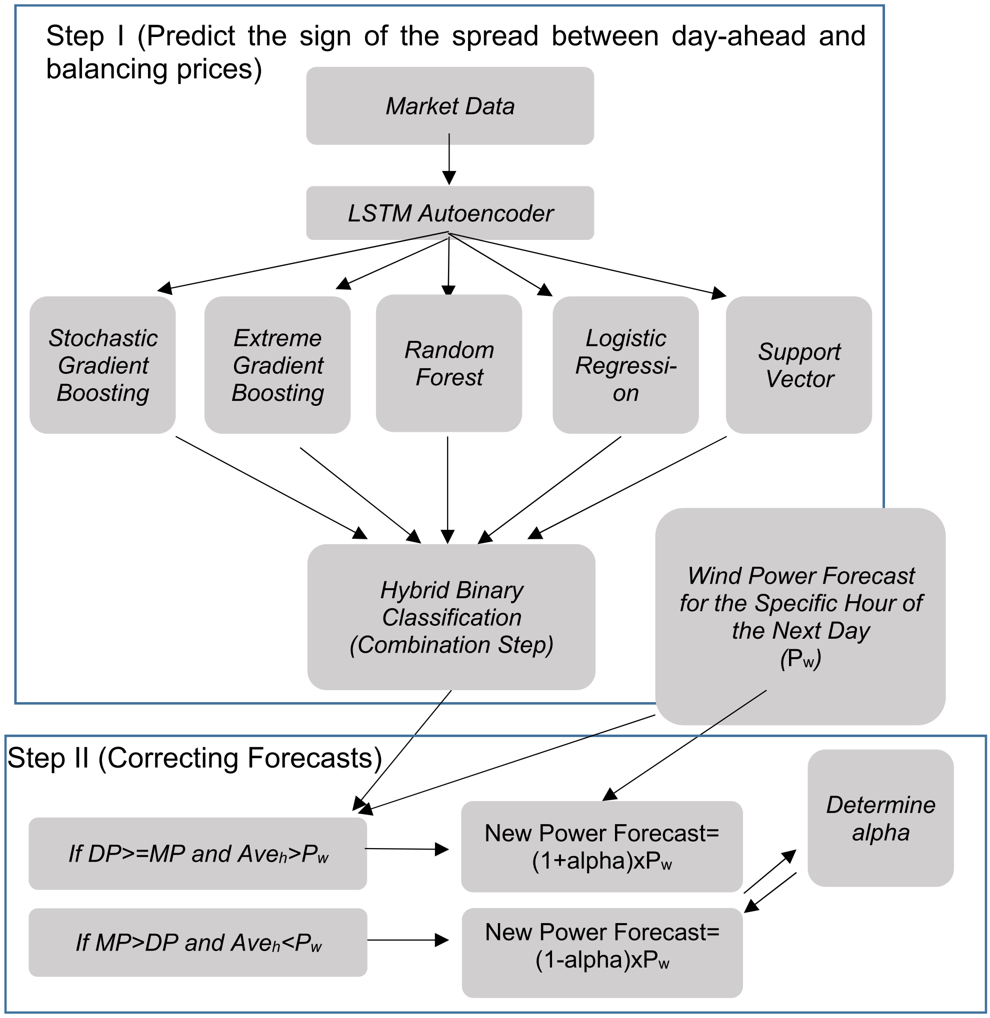

Fig. 3. Framework of the proposed method.

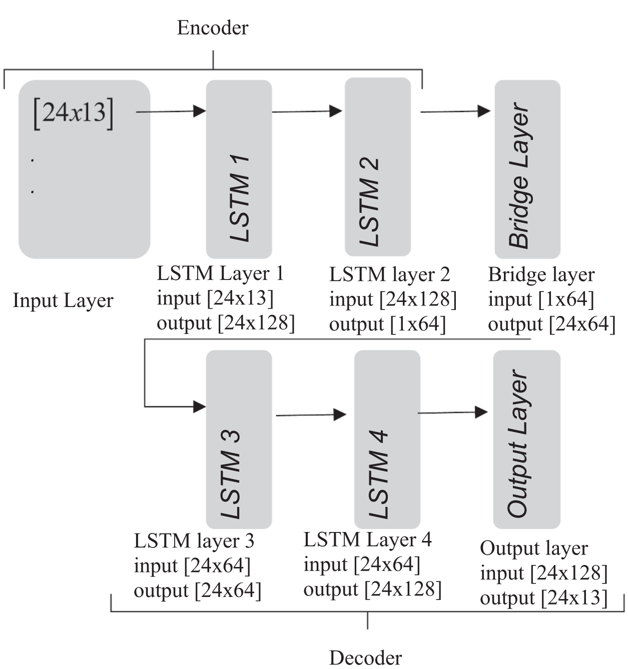

Fig. 4. Architecture of the LSTM autoencoder.

respectively. A bias vector is not used.

The forget is implemented as

$$f = \sigma(W_f h_{t-1} + U_f x_t) \tag{5}$$

How much information of the current cell state pass through the next layer is defined by the output gate, which is formulated as

$$o = \sigma(W_o h_{t-1} + U_o x_t) \tag{6}$$

The cell state vector c_t at time t is calculated by

$$c_t = (c_{t-1} \otimes f) \oplus (i \otimes \mathrm{relu}(W_c h_{t-1} + U_c x_t)) \tag{7}$$

where $\otimes$ is the Hadamard product and similarly $\oplus$ denotes the element-wise addition. W_c and $U_c$are weight matrices and again learned during training. The rectified linear unit function $\mathrm{relu}(x) = max(0, x)$ is used as the activation function instead of hyperbolic tangent function. At the beginning of the computation, initial vectors of h_0 and c_0 are specified as zero vectors. The current hidden state is obtained by

$$h_t = \mathrm{relu}(c_t) \otimes o \tag{8}$$

Training has been carried out to minimize reconstruction error in terms of mean squared error using the adam stochastic optimizer algorithm, which is designed specifically for training deep neural networks. First layer of the encoder emits a sequence of signals since return_sequence is set to true. The bridge layer is a formed as repeat_vector that replicates the feature vector 24 times. LSTM layers 3 and 4 are the mirror images of layers 1 and 2. At the final step, time_distributed layer transforms the output into the size of the input. The LSTM network is implemented in python3 language using the keras library.

4.2. Hybrid binary classification

After the LSTM autoencoder, five state-of-the-art classifiers are run, namely, the stochastic gradient boosting, random forest, extreme gradient boosting (xgboost), logistic regression and support vector classifier. In the combination step, the majority rule is used. Each classifier returns 1 or −1 and then the results of five classifiers are summed. The hybrid classifier returns −1 if this sum is negative and 1 if the sum is positive. All classifiers are coded in python3 using sklearn library and xgboost package. A trial-and-error approach is used for hyper-parameter selection.

The stochastic gradient boosting classifier has been implemented with 10^4 boosting stages. The exponential loss function is employed to be optimized. The learning rate is set to 0.1. The maximum depth of the individual regression estimators is 10^3, max_features option is 'sqrt', the fraction of samples to be used for fitting the individual base learners is specified as 0.8 to lower the variance. The Friedman mean square error function is used for measuring the quality of a split.

The extreme gradient boosting classifier has been used with the binary logistic objective function. The subsample ratio of columns is 0.3, the subsample ratio of the training instance is 0.1, the learning rate is 0.05 and the maximum tree depth for base learners is set to 10^3. The number of trees to fit is 10^5, the minimum loss reduction required to make a further partition on a leaf node of the tree is 0.01 and maximum threads available on the system is used.

The random forest classifier has been implemented by $5\text{x}10^3$ trees together with out-of-bag samples to estimate the generalization accuracy. The Gini criterion is employed to measure the quality of a split. The bootstrap samples are utilized when building trees. The minimum number of samples required to split an internal node is set to 2.

The logistic regression classifier has been coded with l_2 penalty. The weak regularization together with the limited memory Broyden-Fletcher-Goldfarb-Shanno (LBFGS) solver is used. Finally, for the support vector classifier, the radial basis kernel $K(x,x^{'}) = exp(-\gamma\|x - x^{'}\|^2)$ is used. Here, x and $x^{'}$ are two inputs, the norm is the Euclidian distance and γ is the spread. γ is selected as the inverse of the number of features. In the implementation, the one-vs-rest decision function shape is employed.

4.3. Altering the day-ahead power forecasts

This section gives the algorithm for altering the power forecasts using the classification results. This algorithm is devised to reduce the imbalance cost by avoiding outrageous imbalance events which occur in the instances when the difference between MP and DP is high and prediction accuracy is low. After the price prediction is obtained via the hybrid classifier, which returns either 1 or −1, the proposed method amends the hourly power forecasts by the following algorithm:

Algorithm 1:.

1. ***If*** *the classifier predicts the sign of the spread between DP and MP as positive*
2. ***If*** *average of the real wind power of past M days at hour j > power forecast for hour j* (P_j):
3. $_j = P_j \times (1 + alpha)$
4. ***End***
5. ***Elseif*** *the classifier predicts the sign of the spread between DP and MP as negative*
6. ***If*** *average of the real wind power of past M days at hour j < power forecast for hour j* (P_j):
7. $P_j = P_j \times (1\text{-}alpha)$
8. ***End***
9. ***End***

Varying values of M in the algorithm 1 is benchmarked in the next section. Results show that M value is not a key factor in the performance and specifying M as 30 days might be a good choice. On the other hand, the alpha parameter in steps 3 and 6 has a critical role. It is the correction coefficient, which is determined for each N days adaptively by algorithm 2. It should be noted that a low value of alpha alters the forecasts conservatively, while a high value alters them aggressively. All tests have been run with N = 7 and validation for the choice of N is given in Section 5. The alpha determining algorithm is

Algorithm 2:.

1. $alpha = 0.2$
2. ***For*** *each N days*
3. $alpha\_previous = alpha$
4. *Find the alpha value minimizing the imbalance cost of previous N days and name it as alpha0*
5. $alpha = alpha\_previous + (alpha0\text{-}alpha\_previous)/2$
6. ***End***

The alpha determining algorithm above starts with assigning an initial alpha value, which is set to 0.2 for all sites for comparison reasons. If the N value increases to 30 (a month), then initial value could affect the results. However, for N = 7, influence of the initial value is found to be negligible. The optimum value of alpha for past N days is found in step 4 by checking over the alpha values between 0 and 1 with an increment of 0.1 and then by comparing imbalance costs for each alpha value.

5. Results and discussion

Individual performances of the classifiers along with the results of the hybrid classifier are given in Tables 1-2. These binary classifiers return 1 for $DP \geqslant MP$ and −1 for $MP > DP$, where MP is the marginal (balancing market) price and DP is the day-ahead market price. Table 1 gives the results without the LSTM autoencoder. Table 2 shows that the LSTM autoencoder improves the accuracy all classifiers. The hybrid classifier gives the best accuracy with 61.08%. Accuracy of the hybrid classifier is found to be the highest in May with 73.889% and it is lowest in September with 50.694%. Monthly accuracies of the hybrid classifier are listed in Tables 5 and 8. Classifiers are having particular difficulty in identifying the true negatives, where the MP is higher than the DP. The logistic regression and support vector classifiers are less sensitive to rises of the MP. Whereas relatively more advanced classifiers are able to capture these hours, such as the extreme gradient boosting classifier that has given 1450 true negatives. The random forest, stochastic and extreme gradient boosting classifiers are found to be vital for obtaining a reliable performance in imbalance cost reduction.

Table 3 shows the imbalance cost reduction performances of the proposed method for WPP1-4. Reduction in the balancing cost has been calculated by

$$\text{Reduction in the imbalance cost } (\%) = \frac{(\text{Cost}_{normal} - \text{Cost}_{Method})}{\text{Cost}_{normal}} \times 100 \tag{9}$$

where Cost_{normal} is the real imbalance cost and Cost_{Method} is the cost with the proposed method.

Tests in Table 3 reveal that the N value in the algorithm 2, which is the frequency that the alpha is changed, is an important factor in the performance, and when the alpha is adapted weekly (i.e. N = 7), the method gives the best performance. An autocorrelation analysis for the optimum alpha values depicts a very low correlation between past and current alpha values. This implies that formulating the change of alpha in algorithm 1 instead of using algorithm 2 is not straightforward. The autocorrelation analysis is given in the Supplementary Information. In addition, the role of M value in algorithm 1 is rather small compared with the N value, as shown in Table 3, and M is set to 30 in the tests.

Table 4 demonstrates the benchmark tests for the hybrid classifier against individual classifiers in terms of cost reduction. The proposed

Table 1
Binary classification results without the LSTM autoencoder. Classifier decides whether marginal (MP) or day-ahead price (DP) will be higher at a specific hour of the next day.

	Random Forest	Logistic Regression	Stochastic Gradient Boosting	Extreme Gradient Boosting	Support Vector
Accuracy	57.77%	59.21%	56.75%	56.06%	60.02%
Number of True Positives	3651	4324	3650	3436	4837
Number of True Negatives	1340	792	1254	1408	349
Number of False Positives	2056	2604	2142	1988	3047
Number of False Negatives	1593	920	1594	1808	407

Table 2
Binary classification results using the LSTM autoencoder. Classifier decides whether MP or DP will be higher at a specific hour of the next day.

	Random Forest	Logistic Regression	Stochastic Gradient Boosting	Extreme Gradient Boosting	Support Vector	Hybrid Classifier
Accuracy	60.41%	60.52%	59.57%	59.35%	60.61%	61.08%
Number of True Positives	3875	4243	3737	3678	4788	4065
Number of True Negatives	1344	986	1410	1450	449	1212
Number of False Positives	2052	2410	1986	1946	2947	2184
Number of False Negatives	1369	1001	1507	1566	456	1179

Table 3
Reduction in the balancing cost (%) is calculated by formula (9) for the values of M and N in the algorithms 1 and 2. M is the number of days averaged for the imposed condition in the second and sixth steps of the algorithm 1. N is the frequency that alpha has been changed adaptively in the second step of the algorithm 2. The best score is written in bold.

	Frequency that alpha has been changed adaptively (N value)				Number of days averaged in the algorithm 1 (M value)
	30 days	15 days	7 days	1 day	
WPP1	3.2115	3.8435	**6.2581**	2.1067	15 days
	2.7375	3.1191	6.1483	2.1140	30 days
	2.6518	3.2266	6.2458	2.1023	45 days
	2.5207	3.1058	6.0058	2.0705	60 days
WPP2	1.1322	2.6376	8.1452	4.5268	15 days
	1.0460	2.7175	**8.2402**	4.1522	30 days
	1.0359	2.5827	8.1441	4.1280	45 days
	1.0387	2.4449	7.9602	4.1804	60 days
WPP3	5.1249	6.5526	11.053	7.9418	15 days
	5.3269	6.4590	10.634	7.8527	30 days
	5.6317	6.7057	10.744	7.8022	45 days
	5.9462	6.9854	**11.195**	8.0696	60 days
WPP4	5.1554	4.9942	9.3836	6.4518	15 days
	5.7914	5.8168	**9.9037**	6.3530	30 days
	5.3547	5.4221	9.5284	6.1523	45 days
	5.2913	5.4396	9.3586	6.1054	60 days

method with the hybrid classifier outperforms the cases when a single classifier is used. Although classification accuracy of the support vector method is close to that of the hybrid classifier, as given in Table 2, the results show that the majority rule improves the cost reduction substantially. As expected, the results also show that accuracy of the classifiers plays a pivotal rule, and the support vector and logistic regression classifiers give better reductions in the balancing cost than the other individual classifiers.

The majority rule in the combination step benefits from the odd number of learners. To be more general, a weighted averaging could be used. When it is implemented to compare, even for an in-sample (i.e. training set) test, the result has shown 59.93% accuracy, which is unable to outperform three of the individual classifiers, given in Table 2. It can be said that extra attention might be necessary for an alternative combination procedure.

In addition, the proposed method has an advantage of evading the difficulty of generating accurate price predictions. It can be suspected that this imposes a limit for the method from an optimal offering perspective. To discuss this, by assuming a perfectly accurate classification (i.e. knowing in advance whether the day-ahead or balancing market pricing will be higher), the method has been tested. The results show 19.338%, 18.820%, 26.802% and 26.059% decreases in the imbalance costs for WPP1-4, respectively, for a year. These reductions can be defined as the upper limits of the proposed approach for tested WPPs.

Reduction in the imbalance cost by the proposed method is analyzed in monthly manner, which is the billing period, in Tables 5–8. Each month is considered as 30 days for inter-comparison reasons. Accuracy of the hybrid classifier varies from month to month between 50.694% and 73.8890% as listed in the second column of Tables 5–8. The third column gives the amount of imbalance cost that the generator would pay normally. The balancing cost obtained by the proposed method has been given in the fourth column.

Tables 5–8 show 6.2581%, 8.2402%, 11.195% and 9.9037% overall reduction during 2018 for WPP1-4, respectively. The results indicate that with the accuracy of the classifier, the balancing cost tends to decrease, as expected. The proposed method shows a reasonably consistent performance for different seasons. In 46 out of 48 months, a reduction in the balancing cost is obtained. It should be noted that the feed-in-tariff (FiT) subsidy lasts for ten years after joining in Turkey, which is close to end for some generators. In addition, the FiT price will be lowered from 73 USD/MWh to 320 TRY/MWh (~44 USD/MWh) for

Table 4
Performance of the proposed method using a single classifier against the case using the hybrid classifier. Performance is measured by the reduction in the balancing cost (%).

		Individual Classifier Performances					Hybrid Classifier Performance
		Random Forest	Logistic Regression	Stochastic Gradient Boosting	Extreme Gradient Boosting	Support Vector	
Reduction in the balancing cost (%)	WPP1	3.9263	3.9222	3.5327	2.7845	5.4855	**6.2581**
	WPP2	5.1171	6.5429	5.3799	4.6519	6.5164	**8.2402**
	WPP3	8.4662	7.3155	6.7572	9.3164	10.053	**11.195**
	WPP4	5.8882	6.6110	5.3726	5.8111	8.2070	**9.9037**

Table 5
Results for WPP1.

	Accuracy of the hybrid classifier (%)	Imbalance cost (USD)	Imbalance cost with LSTM (USD)	Number of power up-ramps	Number of power down-ramps	Number of imbalance price up-ramps w.r.t. the day-ahead price	Number of imbalance price down-ramps w.r.t. the day-ahead price	Reduction in the balancing cost (%) by the proposed method
January	56.389	−24,950	−23,196	131	140	0	0	7.0322
February	57.778	−17,014	−15,528	136	132	2	6	8.7337
March	56.111	−13,819	−13,070	159	151	9	2	5.4190
April	70.278	−13,697	−12,425	178	174	0	0	9.2847
May	73.889	−14,140	−12,701	199	192	4	9	10.1797
June	67.083	−12,590	−11,983	223	211	1	6	4.8198
July	59.583	−5,709	−5,038	210	209	0	0	11.7494
August	58.889	−23,725	−23,307	197	208	0	0	1.7609
September	50.694	−31,285	−29,539	218	214	0	1	5.5808
October	65.972	−39,679	−39,507	209	219	1	10	0.4336
November	55.139	−20,005	−19,693	199	196	0	0	1.5585
December	61.111	−20,187	−15,994	193	185	9	10	20.7734
Overall	61.076	−236,800	−221,979	2252	2231	26	44	**6.2581**

Table 6
Results for WPP2.

	Accuracy of the hybrid classifier (%)	Imbalance cost (USD)	Imbalance cost with LSTM (USD)	Number of power up-ramps	Number of power down-ramps	Number of imbalance price up-ramps w.r.t. the day-ahead price	Number of imbalance price down-ramps w.r.t. the day-ahead price	Reduction in the balancing cost (%) by the proposed method
January	56.389	−17,323	−15,653	205	212	0	0	9.6391
February	57.778	−14,701	−14,302	224	218	2	6	2.7147
March	56.111	−14,179	−13,964	252	241	9	2	1.5137
April	70.278	−19,157	−17,869	226	215	0	0	6.7219
May	73.889	−15,646	−12,117	173	174	4	9	22.5546
June	67.083	−12,336	−8,703	164	157	1	6	29.4507
July	59.583	−7,429	−6,728	166	164	0	0	9.4472
August	58.889	−24,445	−22,927	198	201	0	0	6.2114
September	50.694	−36,558	−36,739	215	214	0	1	−0.4954
October	65.972	−38,512	−36,201	229	231	1	10	6.0000
November	55.139	−18,947	−17,624	224	218	0	0	6.9790
December	61.111	−20,056	−16,743	211	214	9	10	16.516
Overall	61.076	−239,287	−219,560	2487	2459	26	44	**8.2402**

Table 7
Results for WPP3.

	Accuracy of the hybrid classifier (%)	Imbalance cost (USD)	Imbalance cost with LSTM (USD)	Number of power up-ramps	Number of power down-ramps	Number of imbalance price up-ramps w.r.t. the day-ahead price	Number of imbalance price down-ramps w.r.t. the day-ahead price	Reduction in the balancing cost (%) by the proposed method
January	56.389	−21,536	−20,631	158	154	0	0	4.2051
February	57.778	−11,845	−9,680	160	160	2	6	18.2801
March	56.111	−9,910	−8,943	171	177	9	2	9.7647
April	70.278	−7,321	−5,841	148	152	0	0	20.2172
May	73.889	−5,306	−3,190	153	143	4	9	39.8765
June	67.083	−6,533	−5,332	188	181	1	6	18.3959
July	59.583	−3,593	−3,098	186	189	0	0	13.8066
August	58.889	−12,524	−11,269	206	187	0	0	10.0204
September	50.694	−14,132	−13,117	223	209	0	1	7.1809
October	65.972	−17,322	−16,652	216	220	1	10	3.8707
November	55.139	−9,369	−9,275	207	214	0	0	1.0077
December	61.111	−11,565	−9,273	207	208	9	10	19.8248
Overall	61.076	−130,960	−116,299	2223	2194	26	44	**11.1946**

wind farms activated after July 1, 2021 in Turkey. When the FiT subsidy ends or a low FiT applies or alternatively if the k coefficient is increased towards 1 in the formula (1), in any of these cases, revenues decrease and the share of the imbalance cost in the revenue increases, meaning that the obtained reductions can lead to significant savings proportional to the income.

Effects of the occurrence of sudden changes (ramps) in the power production and ramps in the marginal price have also been examined. A ramp in the power production is defined as an increase up to three times of the previous hour's power production or a decrease into a value lower than one third of the previous hour's production. In other words, an upward ramp occurs when $P_{t+1}/P_t > 3$ and a downward ramp occurs when $P_{t+1}/P_t < 0.33$. On the other hand, a ramp in marginal price is defined as the occurrence of a marginal price either larger than twice of the day-ahead price (i.e. $MP/DP > 2$) or less than half of it (i.e. $DP/MP < 0.5$) at that hour. The results show that the performance of the proposed method and the number of ramps do not indicate an apparent correlation. It is concluded that the method is robust to abrupt variations in the marginal price with respect to the day-ahead price. The method has resulted in reduction in the balancing cost in December by 20.7734%, 16.516%, 19.8248% and 12.2597% for WPP1-4, respectively, although most of the ramps in marginal price have been observed in this month.

Fig. 5 demonstrates two spikes in the imbalance cost and the

Table 8
Results for WPP4.

	Accuracy of the hybrid classifier (%)	Imbalance cost (USD)	Imbalance cost with LSTM (USD)	Number of power up-ramps	number of power down-ramps	Number of imbalance price up-ramps w.r.t. the day-ahead price	Number of imbalance price down-ramps w.r.t. the day-ahead price	Reduction in the balancing cost (%) by the proposed method
January	56.389	−16,769	−15,648	164	150	0	0	6.6876
February	57.778	−12,184	−10,784	153	151	2	6	11.4847
March	56.111	−10,534	−9,572	146	166	9	2	9.1297
April	70.278	−7,024	−5,264	162	150	0	0	25.0699
May	73.889	−6,780	−6,065	178	170	4	9	10.5625
June	67.083	−8,678	−7,628	213	205	1	6	12.1047
July	59.583	−4,470	−4,232	199	206	0	0	5.3252
August	58.889	−12,017	−10,131	196	208	0	0	15.6896
September	50.694	−12,643	−11,704	212	222	0	1	7.4297
October	65.972	−12,183	−12,225	221	202	1	10	−0.3455
November	55.139	−9,202	−8,301	203	195	0	0	9.7959
December	61.111	−8,829	−7,747	202	192	9	10	12.2597
Overall	61.076	−121,320	−109,301	2249	2217	26	44	**9.9037**

corresponding conditions at the same hours (wind power prediction, classification result and spread between the day-ahead and balancing market prices). These spikes cost 9,188 USD and 11,180 USD, respectively. It can be seen in Fig. 5 that they occur when the difference between day-ahead and marginal prices is relatively large combined with the low accuracy of the forecasts. At the hour of spike 1, the hybrid classifier has signaled a false negative, but the algorithm appropriately decides not to alter the forecast. Interestingly, for 8640 h of tests for each

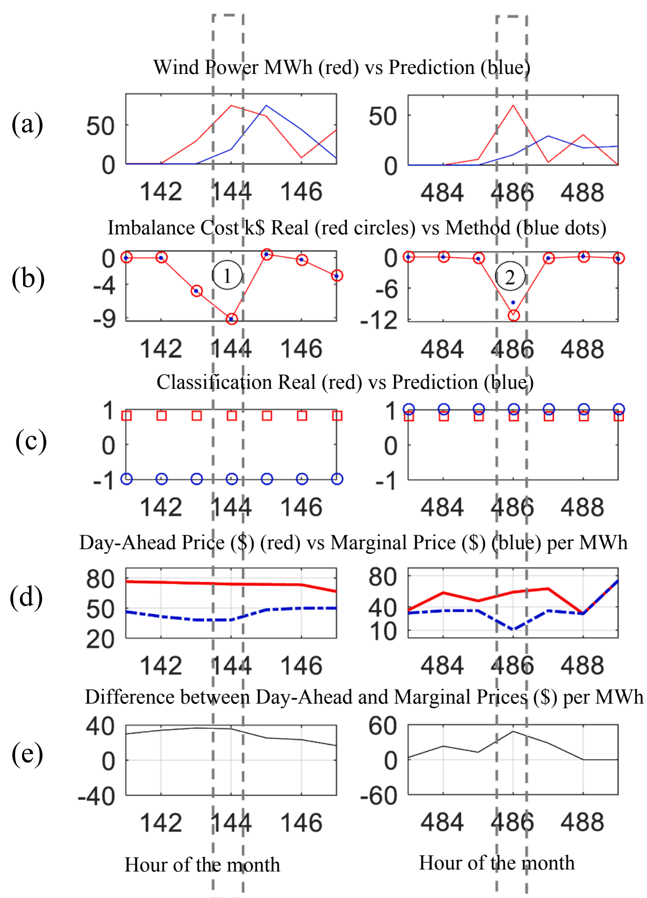

Fig. 5. Two balancing cost rise events (downward spikes) in (b), numbered in circle. They are highlighted along with the market conditions and classifier results at the same hours in (a) and (c)-(e). Left column is from WPP1 in September, as an example case that the classifier is wrong, whereas the right column is from WPP2 in October, as an example case that the classifier is right. Time series of the whole months are placed into the SI.

WPP, at the spike hours costing more than 2000 USD, a noticable additional increase in the cost due to the method has not been observed. For the spike 2, the hybrid classifier has given a true positive. It then successfully decides to alter the offer and reduces the imbalance cost to 8,770 USD, saving 2,410 USD at this hour.

The results for WPPs are also scrutinized in terms of their forecasting errors and capacity factors. The data show that the capacity factors of WPP1-4 are 25.23%, 32.67%, 31.72% and 29.03%. Accompanied day-ahead forecasts have mean absolute percentage errors (MAPE) of 26.06%, 29.79%, 24.29% and 30.54%, respectively. The amount of cost is determined by the market conditions, therefore the overall imbalance costs are not entirely in parallel with the error magnitudes. Likewise, the imbalance costs are evaluated from Tables 5–8 as 2,747 USD, 3,988 USD, 3,274 USD and 3,033 USD per MW capacity, respectively. This shows that an improvement in power forecasts may not necessarily reduce the cost and an imbalance cost reduction strategy is demanded. Regarding the reductions in the imbalance costs, which are 6.2581%, 8.2402%, 11.195% and 9.9037%, they are also not correlated with the forecasting errors.

6. Conclusion

By the liberation of electricity markets, energy producers are exposed to an imbalance cost. Imbalance cost of a wind power producer is mostly incurred by the inaccuracy of the day-ahead predictions. Although, market operators are commonly publicizing significant amount of data, these data are not effectively utilized to reduce the balancing cost. This study proposes a balancing cost reducing method using advanced mining techniques in market data. The method particularly avoids outrageous imbalances which occur in the instances when the difference between marginal and day-ahead prices is high and the prediction accuracy is low. An algorithm is developed to alter the wind power forecasts and an auxiliary algorithm is proposed to adaptively adjust the alpha parameter in it.

The proposed method initially preprocess the data using a long short term memory (LSTM) autoencoder and then it combines five binary classifiers to construct a hybrid classifier. The results show that the LSTM autoencoder improves the accuracy all classifiers and the hybrid classifier gives the best accuracy of 61.08%. The method therefore extracts information whether the day-ahead or balancing market price will be higher at a given hour of the next day. Then, using this information, auxiliary algorithms alter existing production forecasts and prevents abrupt rises in the imbalance cost. The tests show that the proposed method consistently reduces the imbalance cost. The method is robust to varying number of sudden changes (i.e. ramps) in both wind power production and the marginal price. As the accuracy of the hybrid classifier increases, reduction in the balancing cost tends to increase.

The proposed method has resulted in 6.2581%, 8.2402%, 11.195%

and 9.9037% reduction in the annual imbalance costs of wind power plants (WPPs) 1–4, respectively. The proposed method works reliably well and in 96% of the tested months, the method has reduced the cost. The proposed method is adaptable to any forecasting system and it is concluded that the method has capability of reducing the balancing cost of a wind generator more than 10%.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.116728.

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