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ELECTRICITY PRICE FORECASTING USING LSTM

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Abstract
Electricity Price Forecasting(EPF) is a branch of forecasting at the interface of electrical engineering, statistics ,computer science, and finance that focuses on predicting prices in wholesale electricity markets for a whole spectrum of horizons. These range from a few minutes (real-time/intraday auctions and continuous trading); throughdays(day-ahead [DA] auctions); to weeks, months, or even years(exchange and over the counter traded futures and forward contracts).DA markets are the workhorse of power trading, particularly in Europe, and a commonly used proxy for “the electricity price”. The vast majority-up to 90%-of the EPF literature has focused on predicting DA prices. These are typically determined around noon during 24 uniform-price auctions,one for each hour of the next day. This has direct implications for the way EPF models are built.
Keywords: Electricity Price Forecasting, Spectrum, Machine Learning, Auctions, Intraday.

Introduction

Wholesale energy market price, also known as settlement point prices or dynamic tariff, was discussed in the early 1980s [1]. When the electricity market is compared with othercommodities, the power trade exhibits multiple attributes: constant balance between production and consumption [2]; dependence of the load with seasonality at, weekly, and annual levels; and load and generation that are influenced by external weather conditions [3], neighboring markets [4], and other factors like fuel price [3]. In a deregulated power market such as the locational marginal pricing (LMP) based market, the prices are significantly influenced by the above-mentioned attributes. Electricity price forecasting has become a fundamental input to market participants’ decision-making mechanisms. Generally, wholesale electricity prices are likely tobe high during peak demandperiods and low during off- peak demand periods [5,6]. Thedynamic tariff or price is an inherent load management method for properly allocating resources, thus ensuring overall economic reliability [7]..The proposed ILRCN model consists of hybrid neural network architecture, i.e.,LRCN,with In the case study section, theElectric Reliability Council of Texas (ERCOT)wholesale market price and its contributing factors such as load and weatherconditions for the Houston region of Texas are considered to demonstrate theproposed ILRCN model. In summary, the maincontributions of this paper are: A hybrid neuralnetwork architecture, i.e., LRCN, with an additionalconditional error correction layer, is used Anelectricity price forecasting performance analysiswith both hour and day ahead comparison ismade. The practicality and feasibility of the proposed electricity price forecasting algorithm are comparedto existing algorithms.

Related Work

1.Preliminaries:

1.1 Electricity market Price: There are two main types of electricity market prices: day-ahead market (DAM) price and real- time market (RTM) price [25]. In the day-ahead market, bids are submitted for intervalhours of the operating day one day in advance, while real-time market bids are submitted onlya couple of hours in advance. These bids are highly dependent on several factors, including the demand for the particular interval, demand response operating for the area, while real-time market bids are submitted onlya couple of hours in advance. These bids are highly dependent on several factors, including thedemand for the particular interval, demand response operating for the area, weather conditions, and bidding strategies for the participating players. These bids are defined per interval, i.e., every market player can submit bids or use default bids. Market operators use the

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collected bids to compute the market settlement point price for each interval, as well as the generation schedule. Locational marginal pricing is used to price energy on the market in response to changes in supply and demand and the system's physical consthat (i) simply takes the electricity prices of day d − 1 as the forecasted electricity prices of day d when conducting real-time price prediction one day ahead, or (ii) simply takes the electricity prices of hour t − 1 as the forecasted electricity prices of hour twhen conducting real-time price prediction one hour ahead. This naive method works best for short-term price forecasting (predictions over a short look-ahead period such as 15 min), where the electricity pricehas relatively less volatility and is unlikely to change substantially during consecutive short time intervals.

2. Long - Short term memory neural network :

Recurrent neural network (RNN) is another framework of DL, which uses the internalstate to process a sequence of inputs [32]. Long short-term memory is an extended frameworkof RNN which can exhibit the temporal behavior of time series input data. LSTM is capable oflearning long-term dependencies from time sequential data such as electricity prices. The fundamental equations of an LSTM network can be represented as follows: ht = (1 − zt) ∗ ht−1+ zt ∗ ht (5) zt = σ Wf [ht−1, xt] + bf where, xt is the network input; ht is the output stateof the neuron from the LSTM network; ht−1 is the previous state of the neuron; zt computes the necessary information and removes the irrelevant data; σ is the sigmoid function; Wf is theweight function; and bf is the bias value.The price forecasting is classified into short-term, medium-term, and long-term forecasting A short term ranges from one hour ahead to several hours ahead; a few hours to 1 week ahead forecasting is medium-term forecasting; and beyond that it is long- term forecasting. We focus on hour-ahead and day- ahead forecasting in this work. The proposed forecasting model can be formulated as: MPt = Ft + E∗ t−1(7) where t is the current time interval; MPt is the forecasted market price by the proposed ILRCN model; Ft is the price forecasted by the hybridneural network model, LRCN, that is explained in Section 4.2; and E ∗ t−1 is the electricity price forecasting error correction component from the previous time interval and is also referred to as the calibrated value that is defined in Section 4.3. The E ∗ t−1 aims to reduce forecasting errors that are partially due toinsufficient details/features contributing to energy price in the dataset under consideration. It can consider the prediction errors of a few previous time intervals. Figure 6 illustrates the flowchart of short- term electricity price forecasting usingthe proposed ILRCN model based on several prior hours of input data. The historical data is the input forming theinitial stage for the establishment of the proposedILRCN model. The linear and nonlinear behavior andcharacteristics of the input data are analyzed using the proposed ILRCN model. Input feature pre-processing is used to normalize, scale, and definethe features from the input data to improve the accuracy of price forecasting. In order to tune the parameters of the model, optimization and hyper-parameter tuning method with cross-validation are utilized along with the LRCN model. Finally, the forecasted price coming fromthe proposed LRCN model is adjusted to incorporate the conditional error correction component; the desired output is then obtained in this study. The detailed explanation of the various components of the proposed ILRCN model is introduced in detail in the following subsections. Electricity prices are mainly affected by electricaldemand, which varies over time depending on theseason, weather, and generation cost. model. The performance of the proposed ILRCN electricity price forecasting model is verified using performance/evaluation metrics like mean absoluteerror and accuracy. Case studies reveal that the proposed ILRCN model shows the highest accuracy and efficiency in electricity price forecasting as compared to the support vector machine (SVM) model, fully connected neural network model, LSTMmodel, and the traditional LRCN model without the conditional error correction stage.In order to find the optimal network architecture, several combinations were evaluated. These combinations included networks with different number of hidden layers, different number of units in each layer and different types of transfer functions. We converged to a configuration consisting of a one hidden layer that usesa hyperbolic tangent sigmoid transfer function, defined as: f (s) = 1 − e−s 1 + e−s (1) where s is the weighted input of the hidden layer, and f(s) is the output of the hidden layer. The output layer has only one unit with a pure linear transfer function. This configuration has beenproven to be a universal

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mapper, provided that the hidden layer has enough units [33]. On the one hand, if there are too few units, the network will not be flexible enough to model the data well and, on the other hand, ifthere are too many units, the network may overfit the data. Typically, the number of units in the hidden layer is chosen by trial and error, selecting a few alternatives and then running simulations to find out the one with thebest results. Forecasting with neural networks involves two steps: training and learning. Training of feedforward networks is normally performed in a supervised manner. One assumes that a training set is available, given by thehistorical data, containing both inputs and the corresponding desired outputs, which is presented to the network.

3.System model: In the learning process a neural network constructs an input– output mapping, adjusting the weights and biases at each iteration based on the minimization of some errormeasure between the output produced and the desired output. Thus, learning entails an optimization process. The error minimization process is repeated until an acceptable criterion for convergence is reached. The knowledge acquired by the neural network through the learning process is tested by applying new data that it has never seen before, called the testing set. The networkshould be able to generalize and have an accurate output for this unseen data It is undesirableto overtrain theneural network, meaning that the network would only work well on the training set, and would not generalize well to new data outside the training set [20]. Overtraining the neural network can seriously deterioratethe forecasting results. Also, providing the neuralnetwork with too much or wrong information can confuse the network and it can settle on weights that are unable to handle variations of larger magnitude in the input data

The performance of the proposed ILRCN electricity price forecasting model is verified using performance/evaluation metrics like mean absolute error and accuracy.

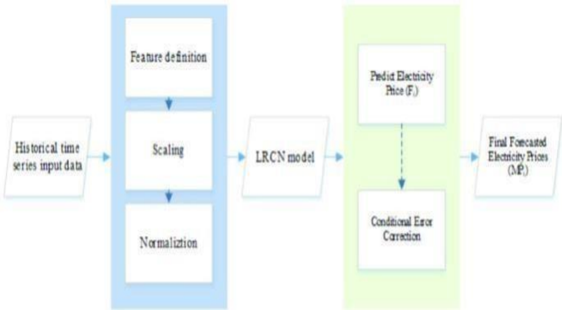

Fig 1:Short term electric price forecasting with ILRCN

Based on (4) to (6), the neural network model is employed to capture the relationship and the linear and nonlinear behavior within the input data. After the input processing stage, the processed data and the best subset of parameters containing the information obtained frominput features are used in the proposed ILRCN model to forecast electricity prices. Figure 7shows the structure of the proposed LRCN model, a hybrid neural network, which correspondsto the thirdblock in Figure 6. The proposed

3.1 Conditional error correction term:

It is unlikely that the LRCN model can predict the outlier prices with high accuracy. The forecasting error can be substantial when there are great differences among the input data sets due to nonlinearities and spikes in the input data and when there is not sufficientinformation available for accurate prediction. To address this issue, wepropose a novel conditional error correction term that is added to the price forecasted by the LRCN model to establish the price prediction. The predicted value of the electricity price from the model is compared with the actual value of the settlement point price obtained from ERCOT. Then, thecalibrated value $E * t-1$ from (7) accounting for insufficient input features contributing to electricity price is formulated as follows:

$E * t-1 = Pt-1 - Ft-1$

where $Pt-1$ denotes the actual price of time intervalt $- 1$; $Ft-1$ is the forecasted price of the same time interval $t - 1$ by the proposed ILRCN model. Since the LRCN model can handle regular

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electricity prices well, the proposed conditional errorcorrection term will only be applied in scenarios wherein the electricity price is very high and the error of price forecastingin the previous time periodis beyond the pre-specified threshold.

4.Results

The proposed forecast model is tested against the Texas electricity market, ERCOT, to validate its effectiveness and efficiency. The electricity price per hour is calculated by averaging the prices over four consecutive 15-min dispatches in the same hour. The prediction accuracies for the proposed ILRCN model and other benchmarking models are constructed for different error thresholds.Table1 shows the accuracy percentages for hour-ahead and
day- ahead forecasting using the naive method LSTM and LRCM Model explained in Section 3 forthe test dataset.

Forecasting threshold($/MWh)	**Actual price**				
	SVR	**FCN**	**LSTM**	**LRCN**	**ILRCN**
MAE	**0.35**	**0.13**	**0.32**	**0.02**	
MSE	**0.31**	**0.05**	**0.02**	**0.01**	
TIME	**231**	**14.890**		**2246**	

TABLE: Accuracy percentage

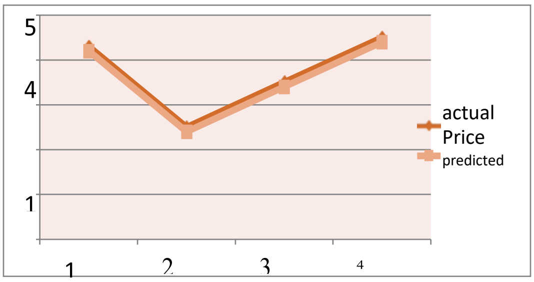

Fig: Actual Vs predicted price

5.Conclusion

The proposed ILRCN model predicts the electricity price with high accuracy and low error both hour- ahead and day-ahead as compared to the naive method, SVR, FCNN, LSTM, and LRCN models. The proposed conditional error correction term can further improve the prediction performance of the ILRCN model., the proposed ILRCN model outperforms both the traditional models and other neural network models, and it is proven to be an accurate and efficient model in settlement point price forecasting. Accurate price prediction also benefits utility companies when formulating their longterm strategies. paper may also be applied in other fields such as load forecasting and variable renewable generation forecasting.

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