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Short-Term Electricity Price Forecasting Using EEMD and GRU-NN

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Abstract **–** A vital necessity for the reliable operation of the power system as well as for the financial well-being of the consumers is an accurate forecast of the price of electricity. The price of electricity is highly volatile, nonlinear, and subject to seasonal fluctuations. The price series is also affected by electrical market uncertainty and demand, which is strongly reliant on weather and electricity usage time. This study presents a short-term electricity price forecasting method that follows the similar days approach comprising Ensemble Empirical Mode Decomposition technique. The suggested method utilizes a feature selection methodology that combines the Random Forest Regressor and the Gradient Boosting Regressor to determine which features are most important for the machine learning model. To forecast the electricity price, a Gated Recurrent Unit Neural Network (GRU-NN) is employed as the machine learning model. The GRU-NN has the capability of accurately capturing complicated temporal relationships in electricity price time series, which enables it to make correct predictions. To evaluate the validity of the proposed method, data from the PJM electricity market have been used. The simulation results demonstrate that the suggested method is superior to the existing technique, with significantly improved values achieved for both the mean absolute percentage error (MAPE) and the root mean square error (RMSE).

Keywords – Machine Learning, GRU-NN, Short-Term Electricity Price Forecasting, EEMD, Feature Selection

I. INTRODUCTION

Electricity price forecasting assures economic and reliable functioning of power system [1], as utilities and consumers need accurate electricity price prediction to optimize their utilities and maximize their benefits. Electricity price is a very important factor in the competitive energy market as it is responsible for bidding strategies and short-term generation schedule. The electricity price series [2] shows high volatility amid all commodities, as it has irregularity and variable mean which makes it non-stationary in behavior [3]. It may rise hundreds of times or sometimes it even drops to zero or negative of its regular values [4][5].

Electricity price series have high volatility, non-linearity, and seasonality. Electricity demand also affects the price series as it is highly dependent on the weather conditions and time of electricity consumption (like hour of day, day of week, time of year) [6-9]. The benefits of electricity market players can be affected due to the presence of variations in electricity price series [10]. A thorough study of the problems of electricity price forecasting is required as it serves as a valuable tool for participants in the electricity market [1]. Hence, a stable and accurate short-term electricity price prediction model is essential need of time.

In the recent past, substantial attempts have been made to develop models for short-term electricity price prediction. Although, single electricity price forecasting models failed to obtain good performance as they struggled to catch multiple features associated with electricity price series [11]. Thus, current research is focusing on developing hybrid prediction models by integrating different forecasting models to reduce prediction error. Multikernel-based extreme learning model (ELM) and water cycle optimization algorithm (WCA) are used for electricity price forecasting [12]. ELM problem of choosing a number of hidden layers of neurons, and activation functions is handled by kernel ELM having a weighted combination of individual functions that has more stability in computation. Enhanced machine learning model Extreme Gradient Boosting is used for electricity price forecasting to offload cloud computing center's data to save energy [13]. Data is offloaded node-wise to reduce storage and energy consumption. A greedy algorithm [14] is considered for a Dutch market to select best European features for forecasting model. The cross-border flows are analyzed by auto-regression models. Then greedy search algorithm is used to select the best combination of features of European countries. 24-hour locational marginal price forecasting was done [15] utilizing PJM data by integrating CNN with a genetic algorithm. A novel gene mapping strategy was encoded to search space, crossover, mutation, and selection to eliminate the unsatisfying candidates of validation fitness function. Four different distance models were used to determine the similarity among the reference forecast day and then price is forecasted through regression and artificial neural network techniques [16]. It is shown there is an improvement in accuracy using Pearson correlation coefficient model when the 45 framework days and 3 similar days are selected. Day Ahead Electricity Price forecasting was done based on Similar days approach [17]. Two methods were used a direct approach of using similar days and similar days with artificial neural network (ANN) to predict price. The Similar days technique with ANN brought better results than using direct similar days technique.

In machine learning, neural networks have been employed to solve problems, and recurrent neural networks have been utilized for problems regarding time dependent series. Particularly the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are designed to deal with time series prediction. A new multi layered GRU technique was proposed for electricity price prediction [18]. Turkish market data of 3 years were used to test the technique and proposed technique significantly performed better than other recurrent neural networks (RNNs). Smart grid enables electricity consumers to alter the electricity consumption pattern in according to the incentives and electricity prices. Electricity price and load forecasting done using big data implementing LSTM optimized by Jaya Algorithm [19]. The data is optimized by Jaya algorithm and forecasted by the LSTM up to 3 months. The accuracy of proposed model evaluated with other models. Wavelet transform has been used extensively in electricity price forecasting models but empirically determining its orders and layers affects price forecasting accuracy, so a new hybrid model is presented [10] based on wavelet transform, stacked autoencoder and LSTM. This model used optimally determined layers and orders of wavelet transform along with fine tuning using stacked autoencoder along with LSTM for prediction to improve accuracy. Four Modules based deep learning framework [20] is implemented on seasonal dataset to predict electricity price forecasting. Raw data is preprocessed using isolation forest (IF) and Lasso based features selection technique, then deep learning prediction modules deep belief network (DBN), convolutional neural network (CNN), and LSTM are applied. Probabilistic module then estimates the uncertainty issue under different confidence levels. Benchmarks are compared with other techniques to show effectiveness of the model.

This study proposes a short-term electricity price prediction method making use of similar days-based approach followed by ensemble empirical mode decomposition (EEMD) technique. Features selection model is applied on the decomposed price data to select optimal input features for the machine learning forecasting model Gated Recurrent Unit Neural Network (GRU-NN).

II. Materials and Method

The proposed prediction method is represented in Fig. 1. Seasonally collected hourly price, load and weather data is firstly made as lagged data of last 24 hours for each day to be used as features. Then, a new time series is formed by appending together the data of same days [21]. The motivation of appending the historical data of similar days is that to forecast electricity price of a given day, past observation of similar days are used as training dataset. After the creation of similar days time series, EEMD is applied on it which decomposes the electricity price into 7 to 10 components. To maintain number of IMFs same for each dataset, the model was trained and tested starting with two IMFs and a residue. There was a small improvement observed in terms of performance when number of IMFs went above four [21]. As we are forecasting each IMF one by one, training and forecasting time of each IMF is high, so we selected four as appropriate number of IMFs. Then, the obtained four IMFs and residue for each time series are passed to the feature selection algorithms. Both feature selection algorithms Gradient Boosting (GB) and Random Forest (RF) run individually and choose the best input features and after that we use intersection of best input features selected individually by them. Afterwards, a dataset with best selected features is given as input to GRU-NN model to train and predict electricity price of the test week.

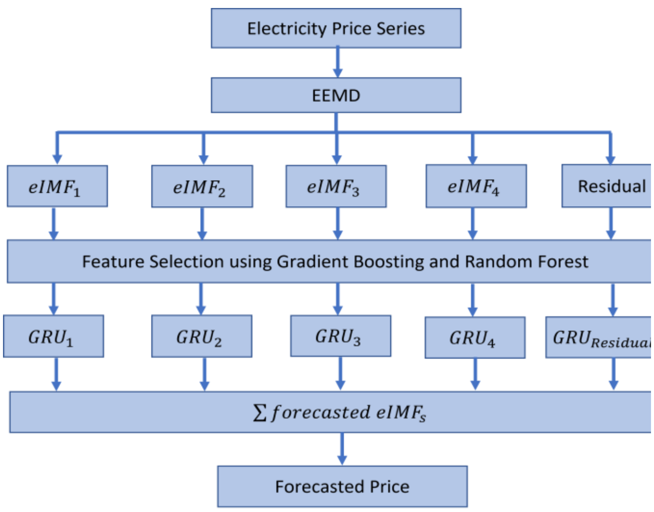

Fig. 1 The proposed method

In the following sub-section, the most important parts of the method that has been suggested will be discussed.

A. *Ensemble Empirical Mode Decomposition (EEMD)*

Ensemble Empirical Mode Decomposition was developed by Huang and Wu [22] which is an enhanced version of Empirical Mode decomposition (EMD). EMD had mode mixing problem which was solved by EEMD. Normally, data is composed of signal and noise. Consider x as data recorded at time t, signal as s and noise as n [21]. This can be written as (1):

$$x(t)= s(t)+n(t) \tag{1}$$

Practically, noise is considered to be most unwanted part of data as it intervenes the data analysis process. EMD removes the noise from data by decomposing data into number of fluctuating and variable functions with respect to amplitude and frequency called IMFs and a residual. A time series is decomposed into number of IMFs by firstly identifying local minimum and maximum and then connecting it by a cubic spline as the lower and upper envelope. Second thing to do is to determine the mean of lower and upper envelopes. Then, subtraction of obtained mean from actual time series is done to extract first IMF. A shifting process is followed by this procedure identified through local minimum and maximum. This procedure is repeated till the last part residue behaves as monotonic function from which we cannot extract more IMF. This procedure can be presented mathematically as (2):

$$x(t)= \sum_{i=1}^{n} c_j + r_n \tag{2}$$

Where n is extracted number of IMF and r is the residue.

Mode mixing arise because of signal intermittency suggesting that different physical processes may be involved within IMF. This result in affecting the signal's decomposition process. This problem of mode mixing was solved by Wu and Huang by suggesting that effect of actual noise can be cancelled by adding the white noise data. This result in preserving the dyadic characteristic of each IMF. A well-recognized statistical rule can be used to control the effect of white noise added which can be stated as (3):

$$\epsilon = \frac{\epsilon}{N} \tag{3}$$

Where ϵ is amplitude of added noise and N shows the ensemble members.

B. *Random Forest and Gradient Boosting*

Random forest [23] is an ensemble learning algorithm which is employed for classification as well as for regression. A decision forest ensemble is formed by regression and classification tress which are formed differently from each other [24]. Estimation process is executed on the collected results while forming the decision forest. A hierarchical arrangement of number of constraints or conditions is done and executed successively from root to leaf of regression tree. Trees are constructed with selected bootstrap samples and m estimators which are selected randomly in every node separation. During the regression process, trees are divided continuously till leaf node is left with smaller number of units.

Boosting is among the most effective tree-based ensemble method approaches [25] as it save the weights and labels of leaf nodes which ease the handling of prediction interpretations. Gradient Boosting [26][27] technique which states that a strong learner can be obtained in gradient boosting process by combination of weak learners. Classification in this technique rely on the prior iteration's residual and a sequential method is used to evaluate the impact of every feature up till aimed accuracy is achieved.

C. *Gated Recurrent Unit-RNN (GRU-NN)*

For sequential time series that has temporary or short-term dependency, RNN [28] has been implemented because of its ability of using the previous data to process current data. RNN had problems while training data having long-term dependencies. These problems were resolved by advanced versions of RNNs, LSTM [29], and GRU [30] as these models used the hidden layer unit termed as memory cells.

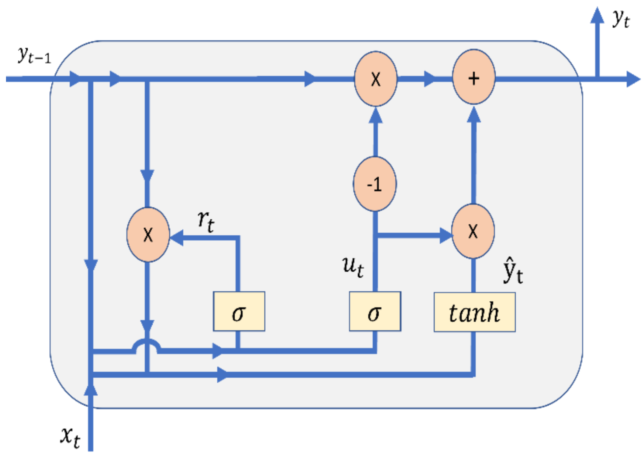

Fig. 2 The GRU model

In 2014, GRU model was developed [30] [31] that was pretty much alike LSTM but easier to evaluate and execute. GRU has two gates [32], one termed as reset gate and other as an update gate which are shown in Fig. 2. These gates in GRU can keep the useful information while filtering out any irrelevant information. The update gate assists the model to decide how much past information of previous steps needs to pass along in the future. The mathematical equation of this operation can be presented as (4):

$$u_t=\sigma(W^{(u)}x_t+W^{(u)}y_{t-1}) \tag{4}$$

Reset gate is utilized to determine what amount of the past information to forget. The mathematical equation of this operation can be shown as (5):

$$r_t=\sigma(W^{(r)}x_t+W^{(r)}y_{t-1}) \tag{5}$$

The "•" denotes the element-wise multiplication. The candidate state $\hat{y}_t$ (6) and output y_t (7) are given as:

$$\hat{y}_t=\tanh((W^{(y)}x_t+W^{(y)}\left(r_t \bullet y_{t-1}\right))) \tag{6}$$

$$y_t=(1-u_t)y_{t-1}+y_t \bullet \hat{y}_t \tag{7}$$

III. SIMULATIONS

A. *Data Description*

The performance of proposed method is evaluated using the data of real-world electricity price market of PJM 2018[33]. PJM is amongst the world's largest electricity markets which is located in United States. The hourly data of price, load and weather for year 2018 is divided into four seasons as winter, spring, summer and fall. Complete dataset is divided into training, and testing dataset. Test week for winter season is from February 15 to 21, for spring season is from May 15 to 21, for summer season is from August 15 to 21 and lastly for fall season is from November 15 to 21 [33].

B. *Experimental Setup and Evaluation Metrics*

Google COLAB [34] is used to implement and validate the proposed model. Seasonally collected data is further divided on basis of similar days [21]. We considered the data of 12 weeks of each season as complete data set. To predict electricity price of a given day (e.g for Sunday), we used the historical data of same last 11 days (11 Sundays) as training data. Primary reason to use observations of similar days for training of model is that different pattern noticed for the electricity price/consumption/generation on each day like electricity price/consumption/generation pattern for

Mondays is quite different from pattern observed on Sundays.

The performance of proposed model is evaluated using two of the most widely used evaluation metrics [33], the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) as shown in (8) and (9) respectively:

$$\mathrm{MAPE}=\frac{1}{N}\sum_{i=1}^{N}\frac{|S_i^{ACT}-S_i^{FOR}|}{S_i^{ACT}}x100\% \quad (8)$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i^{ACT}-S_i^{FOR})^2} \quad (9)$$

Where N is the total number of data instances, S_i^{ACT} is actual electricity price value, and S_i^{FOR} is forecasted electricity price value

IV. RESULTS AND DISCUSSION

The data from the real-world PJM electricity market for the year 2018 is considered to validate the performance of the proposed method. Good results have been shown by the proposed method for all seasons, but we are discussing here the results of summer season as it has worst average results than other seasons. Hourly historical data of 12 weeks is considered as complete dataset for summer, the same case goes for other seasons. After creating the similar days time series, the decomposed electricity price values using the EEMD for each day of week results in 4 IMFs and a residual for each day. Original price curves along with its 4 IMFs and residual for Thursdays of the summer season are shown in Fig. 3. It can be seen that frequency ranges from high to low as we shift from IMF1 to IMF4 and it also has varying amplitude.

Afterward, a combination of two feature selection algorithms RF and GB is applied to select the most important features to feed as input to the machine learning model. Table 1 shows that the average values of MAPE of 4.59% and 1.65 RMSE are achieved for the summer season by implementing the proposed method.

The results obtained for the summer season are shown in Fig. 4, as it can be seen that the proposed method is capable of predicting the electricity price values with improved accuracy Comparison of results obtained from this study and the LSTM-NN method proposed in [33] are shown in Table 2. Hence, it can be concluded that improved average results of MAPE and RMSE are achieved by the method proposed in this study.

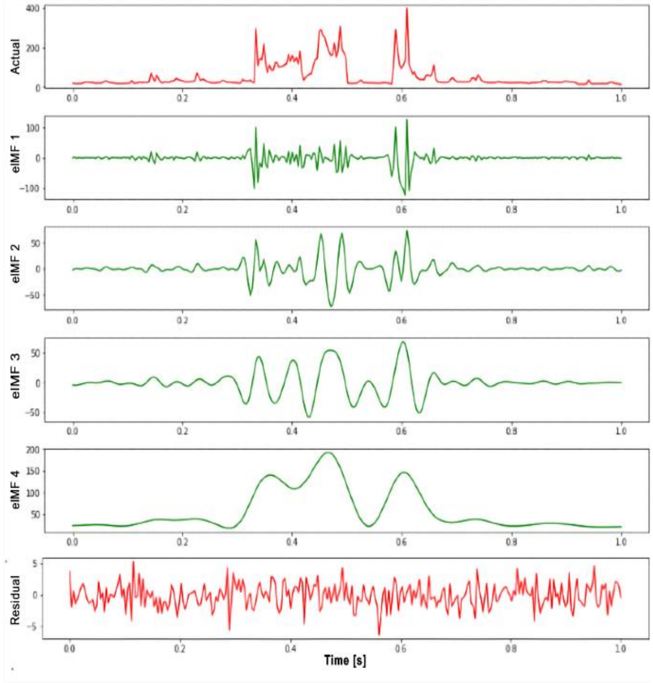

Fig. 3 The Actual price curve, IMFs and residual of Thursdays of summer

V. CONCLUSION

The electricity price suffers from a number of factors which makes it difficult to predict. In this study, a short-term electricity price forecasting method has been proposed which uses a widely tested machine learning model GRU-NN combined with EEMD, Gradient Boosting, and Random Forest Regressor. Using the similar days approach along with well-known models resulted in improved prediction accuracy. The average value of MAPE obtained was 3.88% while the RMSE is 1.43 which are improvements when compared to LSTM-NN.

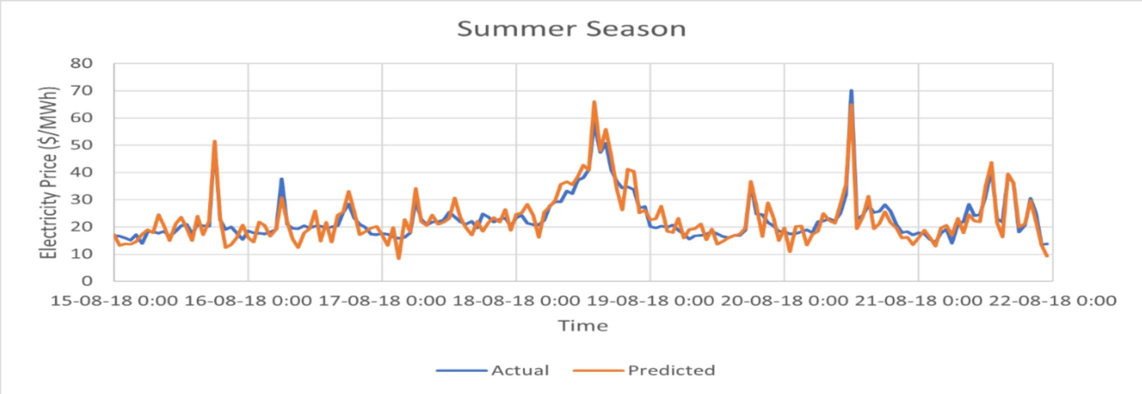

Fig. 4 The Actual and predicted electricity price of summer season

Table 1 Summer Season Results

Evaluation Metrics	Weekdays							Average
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**	
MAPE	5.56	3.583	4.13	6.34	4.87	3.41	4.23	4.59
RMSE	1.43	1.06	2.38	2.88	1.57	1.05	1.20	1.65

Table 2 Comparison of Results

Methods	Evaluation Metrics	Seasons				Average
		Winter	**Spring**	**Summer**	**Fall**	
LSTM-NN[33]	MAPE	4.05	4.93	5.88	2.64	4.38
	RMSE	1.88	2.24	2.23	0.84	1.80
Proposed Method	MAPE	3.37	4.39	4.59	3.18	3.88
	RMSE	1.12	1.08	1.65	1.88	1.43

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