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A hybrid extreme learning machine and sine cosine algorithm model for accurate electricity price forecasting

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ABSTRACT

Electricity demand is continually rising due to the advancement of new technology, the switch to greener energy, and the popularity of electric vehicles over conventional ones. The proliferation of businesses in the generation and distribution sectors has increased competition in the electricity market. Forecasting electricity prices enables consumers to control their monthly electricity bills and consumer-owned distributed generation by knowing the forecasted hourly price. For demand management, generation scheduling, and bidding price quotations, electricity price forecasting is crucial for buyers, generation businesses, and bidders alike. Electricity price data is highly nonlinear and affected by numerous factors because of which EPF models are more complex, highly volatile and slow in convergence. A range of neural network models, training algorithms, and hybrid systems comprising two or more models have been suggested for precise and efficient electricity price forecasting by researchers over the decade. This study involves the development of a hybrid neural network model with two intelligent algorithms sine cosine algorithm (SCA) and extreme learning machine (ELM) to predict electricity price for a particular duration. The newly developed network model is trained and tested with real-time Indian electricity price data from the year 2022. The selected annual price data set is divided into three different sets to explore seasonal variations and all the sets are given as the input to the model for training and testing to obtain the effective price forecasting.

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1. INTRODUCTION

The price of power that is fixed for various consumers is different from the price of other supplies because it has certain characteristics, such as the need to balance supply and demand, demand fluctuation, accurate and unexpected generation, particularly from renewable energy sources, and non-storability. Both producers and customers must forecast electricity prices in the current competitive electricity market. They can also use it to plan facility management, negotiate bilateral contracts, allocate assets, and mitigate hazards. Participants in the market can also use the same value to forecast different power market indices and thus comprehend the behaviors of both operators and loads. The idea of dynamic energy pricing necessitates the real-time calculation of the cost of the power to be sold to various users [1]–[3].

Since its inception, Electricity boards established by state governments will control all aspects of the entire power system. It integrates the production, transmission, and distribution of power within their purview. The regulatory commission, which the board appointed, determined tariffs and frequently took into account issues other than economics. The power industry's deregulation separated transmission from generation, ensuring the power system's dependable and effective functioning. As a result, power trading has gradually grown to be an essential aspect of the power sector.

The availability of hydroelectric power and other renewable energy outputs, fuel prices, power exchange between local and regional markets through long-term contracts, and system load demand are parameters to be considered for forecasting electricity prices. The aforementioned variables can be utilized as input variables to the market clearing price (MCP) to obtain accurate forecasts. Regression, linear curve fitting, and state-space methods are the traditional techniques for predicting the price of electricity [4]–[6]. Accurate pricing prediction with many more limitations is made possible by the development of contemporary approaches.

2. RELATED WORKS

Among the tools now available for prediction assignments, artificial neural networks (ANN) are a well-known technique that has drawn increasing interest. The reason is that it performs well, is simple to implement, and has a clear modeling technique [7]–[9]. This method uses past data to identify the characteristics that would suit a predetermined mathematical formula and then uses the generated models to project future energy prices. The actual inputs fed to the model are going to determine the forecast. Although this approach is relatively simple to use, it is unable to account for temporal differences such as congestion and contingency [10], [11].

In the pursuit of accurate electricity price forecasting for a minimal time, a novel adaptive hybrid model has been proposed by combining variational mode decomposition (VMD), self-adaptive PSO, seasonal autoregressive integrated moving average (SARIMA), and deep belief network (DBN) algorithms and forecasted results were analyzed in Zhang *et al.* [12]. Empirical evaluations demonstrate that this integrated approach significantly enhances forecasting accuracy and stability. Concurrently, Wang *et al.* [13] has developed an innovative outlier-robust neural network model for electricity price forecasting (EPF), which synergizes a robust forecasting engine based on an outlier-resistant extreme learning machine (ELM) model with three novel algorithms. A key component of this model is a newly formulated sine cosine algorithm (SCA) to optimize the selected variables for phase space reconstruction. Additionally, the authors discussed the new feature selection technique that facilitates to creation of the most relevant feature set for modeling electricity prices accurately.

From the literature, it is found that ANNs are popularly adopted for price prediction of electricity since they work effectively for nonlinear relationship problems. However, conventional methods such as the back-propagation (BP) algorithm used for training ANNs suffer from the problem of slow convergence rates and the potential to become trapped in local optima. Addressing these limitations, Chen *et al.* [14] has introduced a quick price prediction method for the electricity market using ELM, a recently emerged learning algorithm for single-layer feedforward neural network (SLFN), which overcomes the inherent drawbacks of the BP algorithm.

Mirjalili [15] proposed a SCA which works efficiently on complicated optimization problems. It initializes numerous random variables and attains the solution toward the global optimum through the functions based on sine and cosine equations. Empirical results and performance metrics demonstrate the SCA's ability to explore diverse regions of the search space effectively, avoid premature convergence to local optima, and efficiently exploit promising regions, making it a widely adopted optimization technique in various research domains in Rizk-Allah and Hassanien [16]. An SCA algorithm with a multi-mechanism variant that can solve the multidimensional problem is developed to address the premature convergence while deriving a solution for six constrained nonlinear problems. The results are compared with results from the experimental setup to check the quality of the proposed method in Yang *et al.* [17]. A hybrid model is designed by combining the SCA and hill climbing optimizer to find load dispatch patterns. The proposed hybrid model improves its exploitation ability for SCA to effectively solve the load dispatch problem, this model is tested with various real-time problems and results were compared in Al-Betar *et al.* [18]. A hybrid network by combining the SCA and marine predator algorithms is built to choose the best-suited value of the parameters for hybrid active power filters. The performance evaluation of the developed network is analyzed with results of already proven network models in Ali *et al.* [19].

Similarly, during the past years, researchers have merged and applied a variety of neural network and optimization algorithms for forecasting and prediction applications in Udaiyakumar and Victorie [20]. A hybrid model with multilayer perceptron which is trained by ELM and optimized by PSO is recommended for predicting the cost of electricity, its results were compared with various other forecasting methods in Udaiyakumar *et al.* [21]. For the prediction of Iran's daily electricity price, a new algorithm by combining the convolutional neural network and long short-term memory network is proposed and found to produce accurate prediction in Heidarpanah [22]. In this paper, we are going to discuss the modeling of a novel algorithm that is developed by combining the ELM and SCA for electricity price forecasting, both are selected due to their simplicity, high problem-solving ability and number of various models availability.

3. THEORETICAL BACKGROUND

The network model which is feed-forward [23] consists of six input layers of neurons, three hidden layers each with fifteen neurons, and one neuron as an output layer is modeled to solve the considered problem statement of electricity forecasting. Figure 1 depicts the proposed neural network's topology. A new model is developed by combining an ELM and SCA to train the network. This section describes in detail the working of ELM and SCA.

ELM is selected because of its simple yet powerful generalization capability also the training speed is very high when compared with most of the neural network training algorithms. ELM gives flexibility in choosing the weights and bias of expecting the final hidden layer; to effectively optimize these weights and the bias optimization algorithm comes into play. In this paper Sine Cosine Algorithm is used as an optimization algorithm because of its higher variable handling capacity, faster convergence and simple methodology.

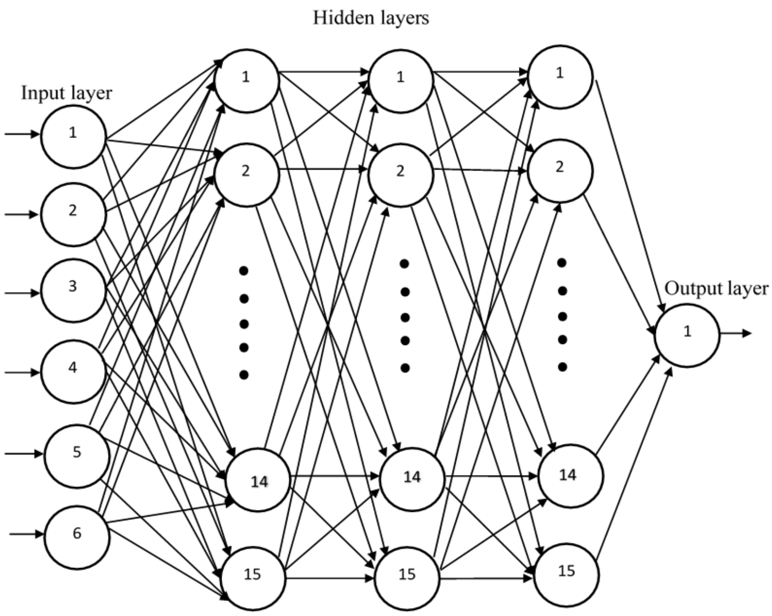

Figure 1. Neural network model for EPF

3.1. Extreme learning machine

The following is the equation of the output layer function with the input variable be x_i, y be the network's final output for h number of hidden neurons,

$$y = u\left(b + \sum_{j=1}^{h} w_j v_j\right) \tag{1}$$

the variable w_{ij}, b_j, $g_j(.)$ denotes the weight assigned between the input layer and hidden layer, hidden layer bias and activation function respectively for n number of input variables. In addition, new variable w_j is assigned for the weight of the connections between the hidden layer and output layer [24]. The equation of the hidden layer neurons output is given as (2),

$$v_j = g_j\left(b_j + \sum_{i=1}^{n} w_{ij} x_i\right) \tag{2}$$

The activation function of the output neuron is given by the (3) and the vector form of the (3) is given by the (4).

$$y = \sum_{j=1}^{h} w_j v_j \tag{3}$$

$$Y = (W_o^T V)^T \tag{4}$$

The network output vector is $Y = [y(1), y(2), \cdots, y(N)]^T$ and the weight vector is $W_o = [w_1, w_2, \cdots, w_h]^T$, The matrix of the hidden layer output is given by (5) and the Input weight and bias matrix are framed as shown in (6).

$$V = \begin{bmatrix} v_1(1) & v_1(2) & \cdots & v_1(N) \\ \vdots & \vdots & \ddots & \vdots \\ v_h(1) & v_h(2) & \cdots & v_h(N) \end{bmatrix} \tag{5}$$

$$W = \begin{bmatrix} b_1 & b_2 & \cdots & b_h \\ w_{11} & w_{12} & \cdots & w_{1h} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nh} \end{bmatrix} \tag{6}$$

Output weight is estimated as shown in (7), where $V^{\dagger}$ the generalized inverse of the output matrix is developed by the Moore-Penrose and $y_d = [y_d(1), y_d(2), \cdots, y_d(N)]^T$ is the desired output and it is given by (8).

$$w_0 = V^{\dagger} y_d \tag{7}$$

$$V^{\dagger} = (V^T V)^{-1} V^T \tag{8}$$

By substituting (7) in (6) w_0 is estimated by least-squares solution.

$$w_0 = (V^T V)^{-1} V^T y_d \tag{9}$$

3.2. Sine cosine algorithm

A new population-based algorithm called as sine cosine algorithm (SCA) is developed by incorporating the concept of basic waveforms of sine and cos functions. This algorithm is widely used by researchers due it its simplicity and its powerful optimization [25]–[27]. SCA is carefully designed to adjust the weights of the connection established between input and hidden layers to improve the forecasting capability of the proposed hybrid model. In this technique, the randomly selected particles travel towards the best possible solution. The following equation is used to randomly initialize the appropriate population size.

$$R_{kl} = LL_l + (UL_l - LL_l) \times r \tag{10}$$

Where R_{kl} is variable, *LL* is the lower limit and *UL* upper limit. r is assigned as the random number whose value lies between 0 and 1. Each variable is initialized and the same is used to calculate the output from which the best variable is selected. Then each variable is updated using the sine cosine function which is shown in (11) and (12).

$$R_{i+1} = R_i + r_1 \times sin(r_2) \times |r_3 R_b - R_i| \tag{11}$$

$$R_{i+1} = R_i + r_1 \times cos(r_2) \times |r_3 R_b - R_i| \tag{12}$$

In (11) and (12), R_i is the current iteration variable, R_b is the overall best variable, and r_1, r_2, and r_3 are random variables chosen between 0 and 1. For the implementation of a random selection of sin or cosine function, equations (11) and (12) are combined as (13).

$$R_{i+1} = \begin{cases} R_i + r_1 \times sin(r_2) \times |r_3 R_b - R_i|, r_4 < 0.5 \\ R_i + r_1 \times cos(r_2) \times |r_3 R_b - R_i|, r_4 \geq 0.5 \end{cases} \tag{13}$$

The value of r_4 is chosen between 0 and 1. The updated variable is used in the next iteration and all the steps are carried out until a specified number of iterations are carried out.

4. PROPOSED HYBRID ALGORITHM

ELM and SCA algorithms are combined in such a way to form a hybrid forecasting model with high accuracy. Both algorithms have specific roles to play with their highlights. The weights between the hidden layer and output layer are calculated using the ELM technique while the weights of the link between the input and hidden layers are randomly generated, which are optimized by SCA, and by this both ELM and SCA are combined to form the powerful hybrid forecasting model. This evaluation of the best value of weight between the hidden layer and the output layer is a minimization problem [28]. The Euclidean norm used to find the minimum norm is given by the equation.

$$min(\|y - y_d\|_2) \tag{14}$$

The equation (14) can be modified by adding the output weight matrix with the regularization parameter α which will be always greater than zero, it is given in (15) and its solution is given in (16).

$$min(\|y - y_d\|_2 + \alpha\|w_0\|_2) \tag{15}$$

$$w_0 = (V^T V + \alpha I)^{-1} V^T y_d \tag{16}$$

Where I is the identity matrix. The optimization problem of the proposed SLFN is the minimization function whose objective function is as given in (17).

$$\psi = E_{rmse}(y, y_d) \tag{17}$$

By estimating the error function for actual output (y_d) and predicted output (y) the accuracy of the proposed algorithm for price forecasting. Root mean square error (RMSE) is calculated by (18).

$$E_{rmse}(y, y_d) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - y_d(k)]^2} \tag{18}$$

During the execution of optimization, individual parameters will be constituted by (19) in which s_j is an integer variable that defines the activation function. Output layer activation function f_j is given as (19).

$$P_k = [w_{11}, \cdots, w_{1h}, b_1, \cdots, b_h, s_1, \cdots, s_h, \alpha]^T \tag{19}$$

$$f_j(v) = \begin{cases} 0 & if\ s_j = 0 \\ 1/(1+e(-v)) & if\ s_j = 1 \\ (e(v) - e(-v))/(e(v) + e(-v)) & if\ s_j = 2 \\ (1 - e(-2v))/(1 + e(2v)) & if\ s_j = 3 \\ v & if\ s_j = 4 \end{cases} \tag{20}$$

The hidden layer can be adjusted based on the value assigned to the parameter s_j, the following activation function is selected for various values of s when s_j=0 that particular neuron is not considered, sigmoid function, tangent function, hyperbolic function, and linear is selected as activation function with s_j as 1, 2, 3, 4 respectively. Implementation of the adjustable hidden layer by five different activation functions and a combination of SCA and ELM are the novelty of this work. The flowchart of the proposed hybrid extreme learning machine–sine cosine algorithm (ELM–SCA) algorithm is shown in the Figure 2.

4.1. Selection of training data

In this paper hybridization of SCA and ELM algorithms is used for training the proposed neural network model. The annual electricity price pattern data set for the year 2022 has been chosen to validate the proposed network model and algorithm. The price data for 12 months are divided into three sets of data involving seasonal variations, for the inclusion of the regional variation Indian electricity market price is selected. The first set of data is electricity prices for January, February, and March Indian electricity marked for the year 2022 and it is shown in Figure 3. Similarly, the second data include the price data set of May, June, and July and is shown in Figure 4, and the price of September, October, and November comprises the third data set which is shown in Figure 4. The training data will be the data for three months and price forecasting is done for next month for one week for each set. In this research three sets of data are trained and shown in Figures 3, 4, 5 respectively. The graph obtained shows the pattern, the variation of electricity price with to time in hours for a three-month duration of 2,160 hours (24*(31+28+31).

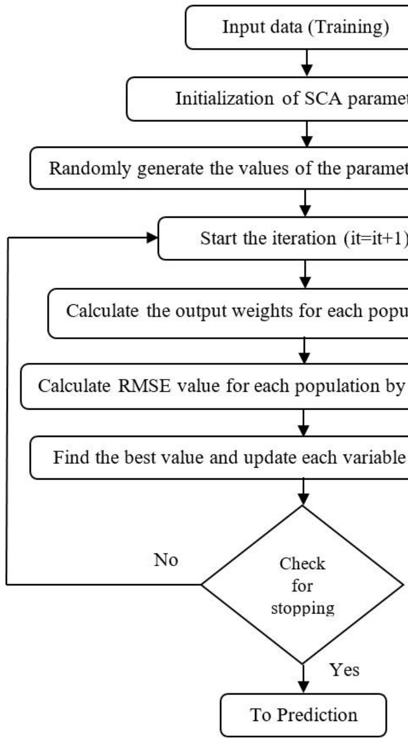

Figure 2. Flowchart of the proposed hybrid algorithm

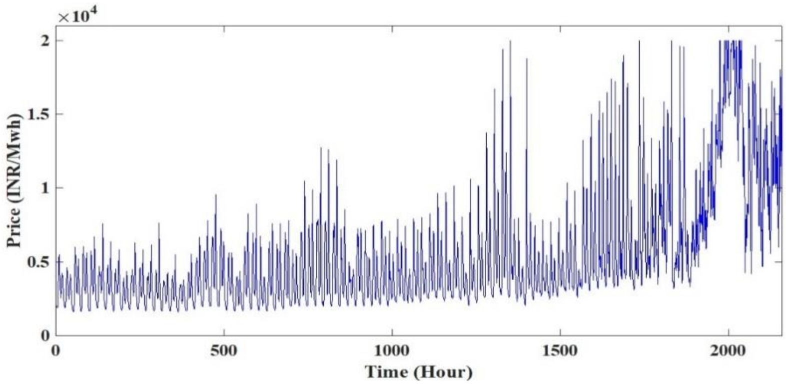

Figure 3. Electricity price data for training (data set 1)

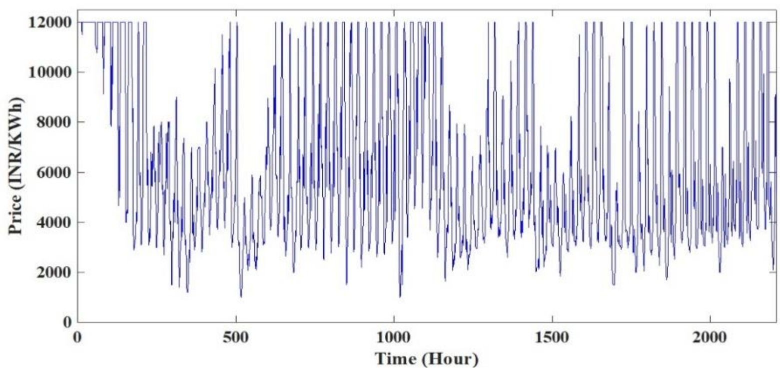

Figure 4. Electricity price data for training (data set 2)

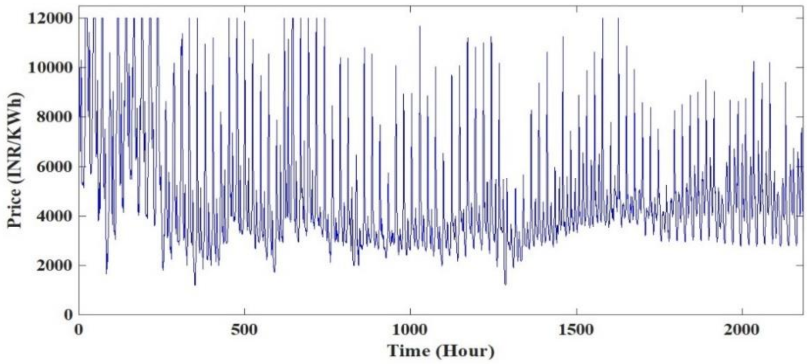

Figure 5. Electricity price data for training (data set 3)

5. RESULTS AND DISCUSSION

The electricity price forecasting is done using the proposed hybrid model using MATLAB R2021a in Windows 10 with Intel core i5 7th generation and 16 GB RAM. Since the proposed hybrid network model is simple and powerful, moderate computational devices are enough to run the proposed model and the device used smoothly runs the proposed model. One week of data is forecasted and various error metrics are calculated by using the forecasted electricity price value and original electricity price value. These metrics are the parameters generally used for the evaluation of the accuracy of forecasted prices. The price forecasting is obtained and the above-mentioned error metrics were calculated based on the training set data of 2160 hours with three methods namely the back-propagation (BP) algorithm, the Extreme learning method (ELM), and also proposed hybrid model. The comparison plot is shown in the Figure 6 for April month 168 hours. From Table 1 the error metrics MSE and RMSE were found to be reduced thus promising good accuracy in prediction.

The price forecasting and error metrics are evaluated based on the training set data of the next three months (May, June, and July) with the same model as the previous data set. The comparison plot is shown in Figure 7 for the first week of August month. From Table 2 it is found that for this particular set, error metrics are less than the BP algorithm but slightly greater than ELM. The RMSE of the proposed method was reduced by more than 10 percent when compared with other models.

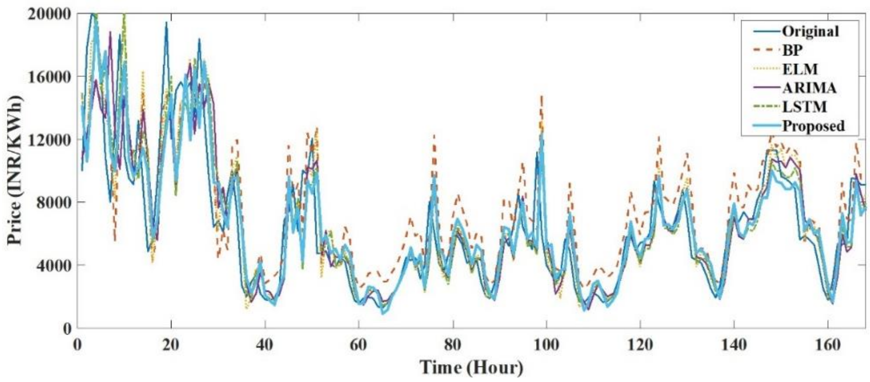

Figure 6. Comparison plots for data set 1

Table 1. Error metrics comparison of data set 1

Error metrics/methods	BP	ELM	ARIMA	LSTM	Proposed
MAE	0.104205	0.076939	0.080535	0.083711	0.080929
MSE	0.017644	0.013174	0.013015	0.013148	0.012979
RMSE	0.132829	0.114779	0.114786	0.119328	0.113924
MARE	0.418316	0.250781	0.255594	0.268021	0.270234
MSRE	0.298908	0.124744	0.124178	0.121431	0.12468
RMSRE	0.546725	0.353191	0.355062	0.35055	0.3531

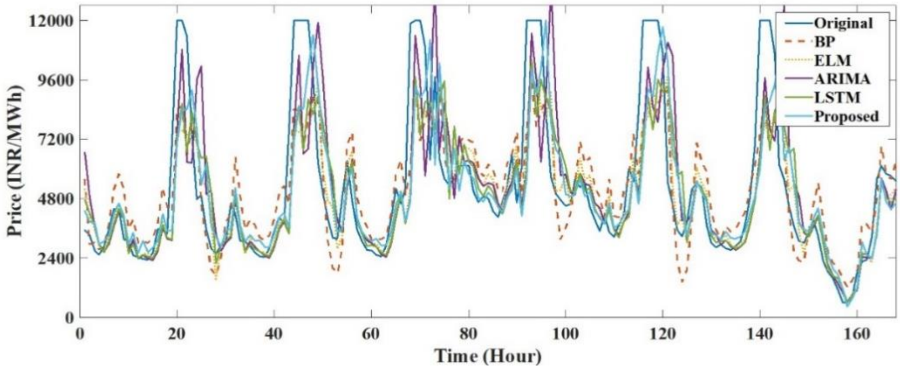

Figure 7. Comparison plots for data set 2

Table 2. Error metrics comparison of data set 2

Error Metrics/Methods	BP	ELM	ARIMA	LSTM	Proposed
MAE	0.121548	0.10584	0.110785	0.109867	0.109545
MSE	0.025704	0.024524	0.021028	0.021068	0.026002
RMSE	0.160324	0.1566	0.180625	0.184724	0.161252
MARE	0.292567	0.212196	0.234988	0.240441	0.232219
MSRE	0.12883	0.068164	0.086554	0.086849	0.086949
RMSRE	0.358929	0.261083	0.290173	0.293669	0.294872

The prediction of electricity price and error metrics are assessed based on the last set of training data (September, October, and November month data) with all models as previous data sets. The comparison plot is shown in Figure 8 for the first week of December. Table 3 with error metrics and different algorithm results illustrates the reduction in error metrics that assures the improved accuracy of prediction.

In this research, electricity forecasting was done for one year (2022) of data with the formation of the three sections of data sets. The predicted value of electricity prices is assessed for its accuracy of prediction with the different error metrics. The process is carried on backpropagation, ELM, and hybrid model and output is compared with the original value of the price that existed in the planning horizon. From the graph obtained and error metric comparison table, it is found the proposed has enhanced prediction capability which serves the purpose.

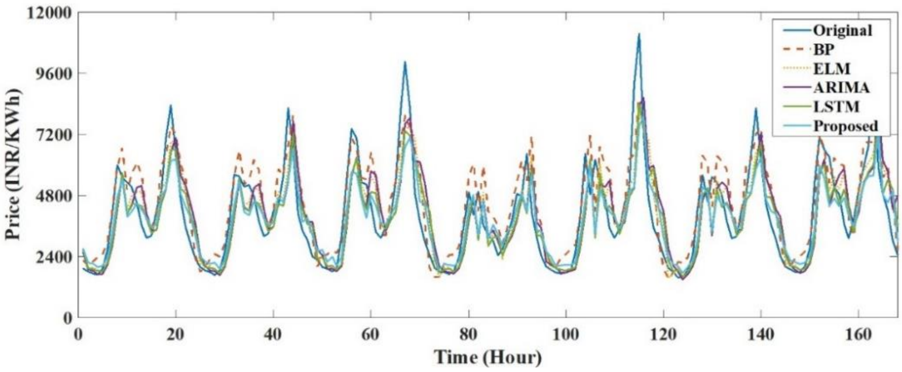

Figure 8. Comparison plots for data set 3

Table 3. Error metrics comparison of data set 3

Error Metrics/Methods	BP	ELM	ARIMA	LSTM	Proposed
MAE	0.07002	0.06913913	0.081404078	0.06964571	0.065547532
MSE	0.008115	0.008625	0.011236296	0.00890971	0.008205
RMSE	0.090081	0.092869	0.1060013	0.0943912	0.09058
MARE	0.225383	0.198619	0.1955071	0.1977209	0.189367
MSRE	0.077395	0.061581	0.057298	0.051202	0.049927
RMSRE	0.278199	0.248154	0.225462	0.22739	0.223443

6. CONCLUSION

The forecasting models such as the back-propagation algorithm, extreme learning machine, autoregressive integrated moving average, and proposed ELM-SCA model are simulated and results were compared. It is evident from the comparison graph and error metrics comparison that the hybrid versions of the suggested neural network model produce more accurate forecasts. The main benefit of this technique is their speedy calculation times, which allow them to efficiently extract more precise results from extremely volatile pricing data sets by creating the variable hidden layer neurons and independently selecting the various activation functions for each neuron for all the hidden layers. The outcomes demonstrate the efficacy of this suggested method for accurate online price forecasting in spot market analysis. It is found that the variables influencing price prediction are time and the pattern of electricity demand. This sort of real-world accurate electricity price forecasting will help the electricity market participants in a better bidding and selling process and for the consumer as a reduced electricity bill.

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