RESEARCH PAPER

MULTISTEP ELECTRICITY PRICE FORECASTING USING FEEDFORWARD NETWORK TRAINED BY HYBRID SINE COSINE ALGORITHM AND EXTREME LEARNING MACHINE

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ABSTRACT

Electricity price forecasting is one of the complicated processes due to its varying nature and non-linearity. In the current scenario, forecasted price is very much needed for the bidding process in the deregulated electricity markets all over the globe. In this paper, multistep ahead electricity price forecasting is done using multiple hidden layer feedforward neural network trained by novel hybrid Sine Cosine Algorithm and Extreme Learning Machine (SCA-ELM). The proposed network is trained using Finland and Indian hourly electricity price data from their respective electricity markets. The trained neural network is used to forecast one-step, three-step, and five-step ahead price data for two weeks. The forecasted electricity price data is compared with various other algorithms using graphical representation and tabulation of different error metrics.

Key words: Electricity price, Time series, Sine cosine algorithm, Multi-step.

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INTRODUCTION

Electricity price forecasting (EPF) has been attracting resarchers for past few decades due to its importance and complexity. Multistep ahead and accurate electricity price forecasting is needed for major electricity market participants for managing their selling and buying prices of electricity in the deregulated electricity market. In the past two decades, electricity markets across the globe have gone through several modifications to deregulate the market. The introduction of various renewable energy like solar and wind energy for electric power production and its integration with the central grid system makes the electricity power market more complex and competitive.

Hybrid EPF model consisting of grey correlation analysis, stacked denoising auto-encoder, dimension reduction process, and ANN is proposed and Grey correlation analysis is used as parameter segregation, to denoise the data denoising auto-encodersis used, dimension reduction process is implemented to detect main features of input data and though ANN electricity price forecasting is done for Ontario and Canada electricity markets[1]. hybrid forecasting model based on the heterogeneous structure of a long short-term memory neural network model and its hyperparameters are optimized by Sequence Model-Based Optimization (SMBO). Decomposed and reconstructed electricity price data is used to construct the LSTM[2]. Hybrid model for electricity price forecasting in which Coyote optimization is used to tune parameters of EMD which is used for decomposing time series price data and three machine learning models such as ELM, gradient boosting and SVR are appropriately used forecast the decomposed waveforms[3] Performance evaluation of various forecasting algorithm for day-ahead electricity price forecasting. Estimation of the relation between the electricity spot price and the explanatory variable is done by econometric, data mining, and machine learning algorithms[4]. short-term EPF based on Variational Mode Decomposition (VMD), Convolutional Neural Network (CNN), and Gated Recurrent Unit (GRU). VDM is used for time series data decomposition, CNN is employed for extracting time-domain features of decomposed data, and GRU is employed for final forecasting of electricity price using features extracted by CNN[5]. A novel hybrid model for long term electricity price forecasting is proposed by hybriding wavelet decomposion, artificial bee colony optimization and Extreme learning machine. The proposed hybrid model is used to forcast the various real time electricity price data and the results are compared with different methods for performance analysis[6]. Combination of various neural networks and optimization algorithms are used for electricity price forecasting and various other forcasting [7-12]

This paper is organized as follows, section 2 explains the proposed neural network model used in this paper, section 3 explains the implementation of the proposed model for electricity price forecasting, section 4 contains results and discussion of electricity price forecasting using the proposed model and section 5 concludes this paper.

1 HYBRID NETWORK MODEL FOR EPF

In this paper feedforward neural network[13] with an input layer having six neurons, three hidden layers each having fifteen neurons, and an output layer having one neuron is adopted as a neural network model for EPF. The structure of the proposed neural network is shown in Figure 1 and it is trained using a hybrid Sine Cosine Algorithm and Extreme Learning Machine (SCA-ELM). The training algorithm used to train the proposed neural network model is explained in this section.

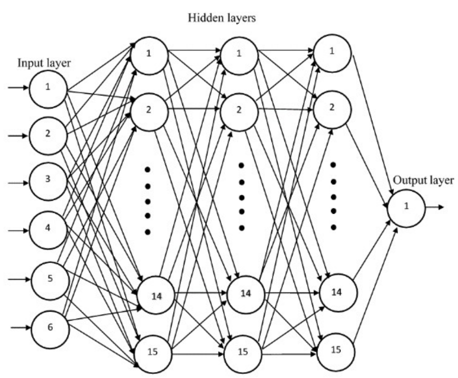

Figure 1 Network model for EPF

The neural network used in this paper is single hidden layer feed forward neural network (SLFN) which is shown in the fig 1 and it is represented as follows.

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

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

Where n is number of input variable, h is number of hidden neuron, x_i is the input variable for i=1, 2, … , n, w_{ij} is weight of the connections between input layer and hidden layer for j=1, 2, … , h, b_j is the bias of the hidden layer, $f_j(.)$ is the activation function of the hidden layer neurons, v_j is the output of the hidden layer neurons, w_j is the weight of the connections between hidden layer and output layer, g(.) is the activation function of the output layer neuron and y is the final output of the network.

In [14] Extreme Learning Machine (ELM) for SLFN, the weights between input and hidden layer are randomly chosen and the weights between hidden and output layer is computed by Moore-Penrose generalized inverse method.

Considering number samples as N, output bias as zero and the output neuron has linear activation function equation (1) can be written as

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

Equation 3 can be vectorized as

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

Where $Y = [y(1), y(2), \cdots, y(N)]^T$ is the vector of the outputs of the network, $W_o = [w_1, w_2, \cdots, w_h]^T$ is the vector of the weight of the connections of hidden layer and output layer and V is matrix of the hidden layer output

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

W is input weight and bias matrix and it is given by

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

W_0 – Output weight is estimated as

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

Where $V^{\dagger}$ is the Moore-Penrose is generalized inverse of the output matrix and $y_d = [y_d(1), y_d(2), \cdots, y_d(N)]^T$ is the desired output and is given by

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

By substituting equation (7) in (6) w_0 can be obtained as follows by least-squares solution

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

2.1 Extreme Learning Machine - Sine Cosine Algorithm (ELM- SCA)

The best weight for the connections between the hidden layer and output layer are obtained by solving the following problem [15]

$$\min\left(\|y - y_d\|_2\right) \tag{10}$$

Where $\|\bullet\|_2$ is the Euclidean norm and it the minimum norm solution to the problem which is defined in the equation (9). Equation 10 is modified with inclusion of output weight matrix

$$\min\left(\|y - y_d\|_2 + \alpha\|w_0\|_2\right) \tag{11}$$

Where α is the regularization parameter and $\alpha > 0$ The solution to the problem in equation (11) is explained in [30] and it is given by

$$w_0 = (V^T V + \alpha I)^{-1} V^T y_d \tag{12}$$

Where I is identity matrix.

The objective function for optimization of SLFN is minimization of the function given below

$$\psi = E_{rmse}(y, y_d) \tag{13}$$

Where ψ is the objective function

$$E_{rmse}(y, y_d) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left[y(k) - y_d(k)\right]^2} \tag{14}$$

Where $E_{rmse}(y,y_d)$ is the Root Mean Square Error (RMSE) of the real output (y_d) and the predicted output (y). In the process of optimization each individual will be constituted by the following equation

$$P_k = \left[w_{11}, \cdots, w_{1h}, b_1, \cdots, b_h, s_1, \cdots, s_h, \alpha\right]^T \tag{15}$$

Where k=1,…,m., m is the number of population size, s_j is an integer variable that defines the activation function f_j of the each neuron separately in the hidden layer and $s_j \in \{0,1,2,3,4\}, j = 1, \cdots, h$ .the activation function f_j is given as follows

$$f_j(v) = \begin{cases} 0 & if\ s_j = 0 \\ 1/(1+\exp(-v)) & if\ s_j = 1 \\ (\exp(v) - \exp(-v))/(\exp(v) + \exp(-v)) & if\ s_j = 2 \\ (1 - \exp(-2v))/(1 + \exp(2v)) & if\ s_j = 3 \\ v & if\ s_j = 4 \end{cases} \tag{16}$$

Adjustable hidden layer is possible by using the parameter s_j, when s_j=0 that particular neuron is not considered, when s_j=1 sigmoid function is used, when s_j=2 tangent function used, when s_j=3 hyperbolic function is used and when s_j=4 linear function is used.

2.2 Sine cosine algorithm

Sine Cosine Algorithm (SCA) is a population-based optimization algorithm based on the mathematical model of sine and cosine functions[16].

In this algorithm, the randomly initialized partials move towards the optimal best solution using the sine and cosine functions. For random initialization of the desired number of population, equation 1 is used.

$$P_{kl} = LB_l + (UB_l - LB_l) \times r \tag{17}$$

Where P_{kl} is the variable, LB and UB are lower bound and upper bound of the variable and, r is the random number between 0 and 1. Each variable in the initialized population is used to calculate the value of the objective function and the best variable is selected. Then each variable is updated using the sine and cosine function which is shown in Equations 2 and 3.

$$P_{i+1} = P_i + r_1 \times \sin(r_2) \times |r_3 P_b - P_i| \tag{18}$$

$$P_{i+1} = P_i + r_1 \times \cos(r_2) \times |r_3 P_b - P_i| \tag{19}$$

Where P_i is the current iteration variable, P_b is the overall best variable, and r_1, r_2, r_3 are random variables between 0 and 1. For the implementation of a random selection of sin or cosine function, equations 2 and 3 are combined as follows

$$P_{i+1} = \begin{cases} P_i + r_1 \times \sin(r_2) \times |r_3 P_b - P_i|, r_4 < 0.5 \\ P_i + r_1 \times \cos(r_2) \times |r_3 P_b - P_i|, r_4 \geq 0.5 \end{cases} \tag{20}$$

Where r_4 is the random variable in the range 0 to 1. The updated variable is used in the next iteration and the above-mentioned steps are carried out until stopping criteria are met or until a specified number of iterations.

2 IMPLEMENTATION OF PROPOSED HYBRID NETWORK MODEL

The neural network model which is adopted in this paper is trained using hybrid Sine Cosine Algorithm and Extreme Learning Machine (SCA-ELM), SCA and ELM is explained in the previous sections. In this paper hybridization of SCA and ELM algorithms used for training the proposed neural network model is explained in this paper.

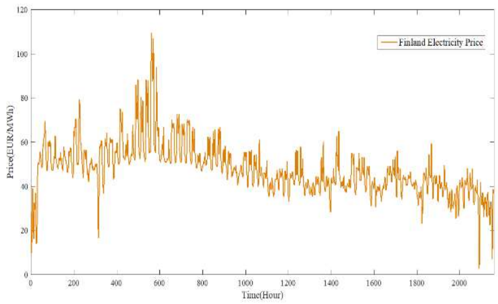

Figure 2 Finland electricity price data for training used as test case 1

3.1 Selection of training data for the proposed neural network model

For training of the proposed neural network model, two separate price data are used from Finland and Indian electricity markets during the year 2019. A total of 2160 electricity price data from January to March of Finland electricity price in the year 2019 is taken as test case 1 and it is shown in Figure 2. Similarly, a total of 2208 electricity price data from the Indian electricity market from ugust to October 2019 is taken as test case 2 and it is shown in Figure 3.

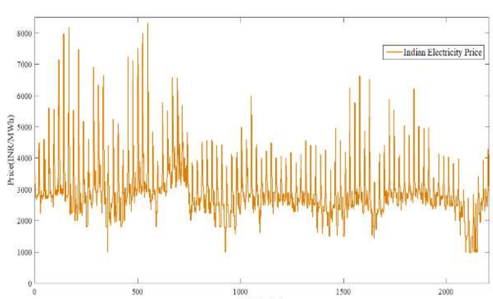

Figure 3 Indian electricity price data for training used as test case 2

3.2 Training of the proposed neural network model

The proposed neural network model is trained using hybrid SCA-ELM algorithm, SCA is used to optimize the bias and weights of all the hidden layers except the weights between the final hidden layer and output layer, which is calculated using ELM. While ELM is used to calculate the weights between the final hidden layer and the output layer, SCA optimizes all other weights and biases in the proposed neural network. SCA also selects the best activation function suitable for each hidden layer neurons of all three hidden layers from five different activation functions.

Optimal selection of bias, weights except for weights between the final hidden layer and output layer, selection of best activation function for each hidden neuron separately among the five activation functions makes the training of the proposed multilayer feedforward neural network the most efficient one. The overall training process which is the training of three hidden layer feedforward neural networks by hybrid SCA-ELM algorithm makes it a power forecasting model, the use of three hidden layers in the proposed model, rigorous training method, and training using a large number of data makes proposed neural network model a deep neural network. The number of hidden neuron for all the three hidden layers are selected as fifteen hidden neurons by trial and error method. In the previous chapters, twenty hidden neurons are used whereas in this paper the proposed neural network model produces the best forecasting results when the number of hidden neurons is selected as fifteen.

3 RESULTS AND DISCUSSION

The proposed neural network model is trained by SCA-ELM using two different electricity price data obtained from two different electricity markets, the trained neural network is used to forecast the consecutive 336 electricity price data after the electricity price data used for training. Three different steps ahead electricity price forecasting namely one-step, three-step, and five-step is done using the proposed neural network model, the forecasted results are compared with other forecasting models like backpropagation, ELM, and ABC-ELM, the comparison of the different models is done by the graphical representation using plots of actual and the forecasted electricity price by different models and by tabulating the nine different error metrics which are mentioned in the previous chapter as set 1 and set 2 error metrics

4.1 Results of test case 1

In this subsection one-step, three-step, and five-step ahead forecasting results of the proposed neural network trained by the SCA-ELM algorithm for the training data mentioned as test case 1 are discussed

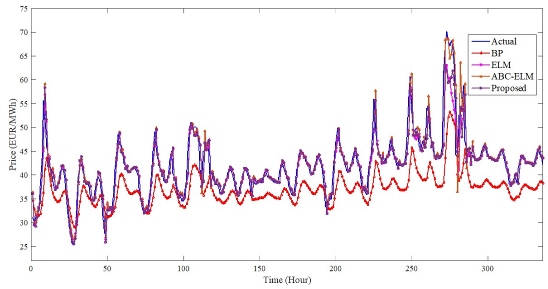

Figure 4 One-step ahead forecasted electricity price data.

Table 1 Error metrics of one-step ahead forecasted electricity price data.

Error Metrics / Methods	BP	ELM	ABC-ELM	Proposed
MAE	0.026406958	0.007960025	0.007618129	0.007567459
MSE	0.001039659	0.000179354	0.000166357	0.000158166
RMSE	0.032243749	0.013392326	0.012897933	0.012576387
MARE	0.118807	0.036013494	0.035767488	0.034572983
MAPE	11.88069997	3.601349355	3.576748825	3.457298258
MSRE	0.018187196	0.003082356	0.00328919	0.002888533
RMSRE	0.134859912	0.055518967	0.057351462	0.05374507
MSPE	1.818719576	0.308235568	0.328919019	0.288853259
RMSPE	1.348599116	0.555189669	0.573514619	0.537450704

Figure 4 shows the plots of actual electricity price and one-step ahead forecasted electricity price using the proposed model and other models for test case 1. From the plots in the graph, it is inferred that the proposed model has better forecasting results than the other models. Likewise, Table 1 shows the comparison of nine different error metrics for the forecasted results of different models, from the comparison of different error metrics in one-step ahead forecasting, it is observed that the proposed method performs better than the other methods used for comparison.

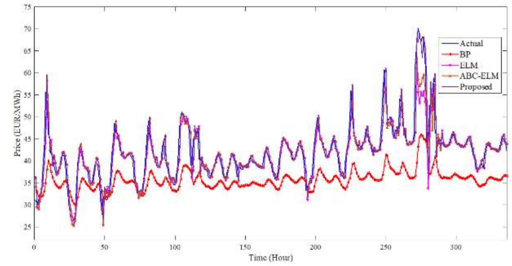

Figure 5 Three-step ahead forecasted electricity price data

Figure 5 shows the plots of actual electricity price and three-step ahead forecasted electricity price using the proposed model and other models for test case 1. The comparison plots show that the proposed method performs better than other methods and also only the proposed method addressed the sudden change in values whereas other models simply form the smooth curve.

Table 2 Error metrics of three-step ahead forecasted electricity price data.

Error Metrics / Methods	BP	ELM	ABC-ELM	Proposed
MAE	0.033200109	0.008431281	0.007832705	0.007580538
MSE	0.001591755	0.000222548	0.000172924	0.000162825
RMSE	0.039896804	0.014918058	0.013150047	0.01276029
MARE	0.148896355	0.037717479	0.035485222	0.035621621
MAPE	14.88963549	3.771747921	3.548522164	3.562162098
MSRE	0.027520121	0.003581679	0.003003358	0.003234881
RMSRE	0.165891896	0.05984713	0.054802905	0.056876011
MSPE	2.752012111	0.358167899	0.300335845	0.323488061
RMSPE	1.658918959	0.598471302	0.548029055	0.568760109

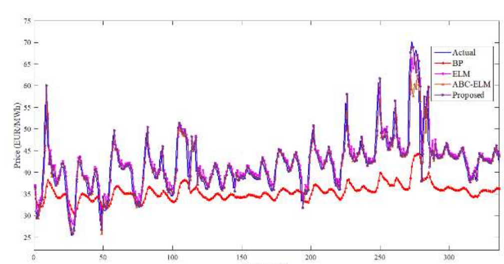

Figure 6 Five-step ahead forecasted electricity price data

Similarly, Table 1 shows the comparison of nine different error metrics for the forecasted results of different models for three-step ahead forecasting and the comparison results show that the proposed model has less error when compared with other forecasting methods. Figure 6 shows the plots of actual electricity price and five-step ahead forecasted electricity price using the proposed model and other models for test case 1, the comparison of the forecasted plot reveals that the proposed method performs better than the other method. Similarly, Table 3 shows the comparison of nine different error metrics for the forecasted results using different models for three-step ahead forecasting and the comparison results show that the proposed model forecasts the electricity price better than other models.

Table 3 Error metrics of five-step ahead forecasted electricity price data.

Error Metrics / Methods	BP	ELM	ABC-ELM	Proposed
MAE	0.034351299	0.009035057	0.007879129	0.007592252
MSE	0.001718951	0.000186623	0.000174732	0.000163988
RMSE	0.041460229	0.01366102	0.013218609	0.012805763
MARE	0.153856754	0.043349909	0.035875147	0.035717004
MAPE	15.38567539	4.334990861	3.587514738	3.571700359
MSRE	0.029555655	0.003968394	0.00312383	0.003289578
RMSRE	0.171917583	0.062995191	0.055891232	0.057354847
MSPE	2.955565548	0.396839413	0.312382981	0.328957844
RMSPE	1.719175834	0.629951913	0.55891232	0.573548467

Figure 7 shows the comparison graph of three different error metrics for one-step, three-step, and five-step forecasting using the proposed model of Finland electricity price data. The graph shows that there is a slight increase in the errors when the step ahead forecasting is increasing, whereas in the other model large increase in the error is noted which signifies the performance of the proposed neural network model.

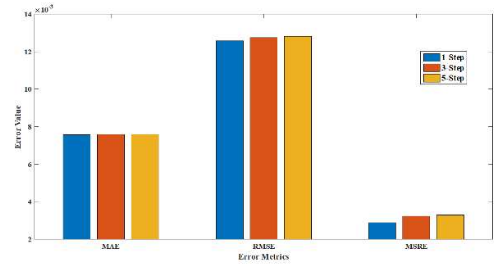

Figure 7 Comparison of different error metrics for one-step, three-step, and five-step ahead forecasting using the proposed model and test case 1

4.2 Results of test case 2

In this subsection one-step, three-step, and five-step ahead forecasting results of the proposed neural network trained by the SCA-ELM algorithm for the training data mentioned as test case 2 are discussed.

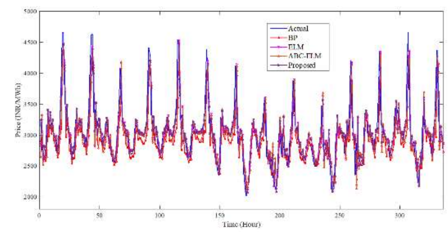

Figure 8 One-step ahead forecasted electricity price data.

Figure 8 shows the plots of actual electricity price and one-step ahead forecasted electricity price using the proposed model and other models for test case 2. The comparison of the plots shows that the proposed model performs better than the other models in test case 2 as of in test case 1. Likewise, Table 4 shows the comparison of nine different error metrics for the forecasted results using the proposed model and other models for one-step ahead electricity price forecasting, and the comparison results show that the proposed model has better error values.

Table 4 Error metrics of one-step ahead forecasted electricity price data.

Error Metrics / Methods	BP	ELM	ABC-ELM	Proposed
MAE	0.023862609	0.02143429	0.021380516	0.015935503
MSE	0.001135156	0.000943897	0.000923553	0.000502073
RMSE	0.03369208	0.030722912	0.030390012	0.022406992
MARE	0.095641972	0.089121153	0.089238435	0.06751211

MAPE	9.56419723	8.912115347	8.923843494	6.751210957
MSRE	0.015743668	0.015139168	0.015186884	0.008709746
RMSRE	0.125473774	0.123041327	0.123235075	0.09332602
MSPE	1.574366803	1.51391681	1.518688371	0.870974595
RMSPE	1.254737743	1.230413268	1.23235075	0.933260197

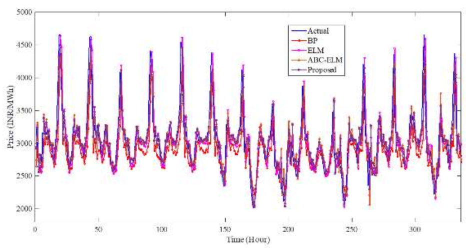

Figure 9 Three-step ahead forecasted electricity price data.

Table 5 Error metrics of three-step ahead forecasted electricity price data.

Error Metrics / Methods	BP	ELM	ABC-ELM	Proposed
MAE	0.025374784	0.021552984	0.021447225	0.016577833
MSE	0.001240962	0.001022545	0.000913492	0.000573893
RMSE	0.03522729	0.031977252	0.030224034	0.023956066
MARE	0.100936095	0.088355816	0.089825805	0.070216198
MAPE	10.0936095 1	8.835581641	8.982580469	7.021619816
MSRE	0.016489613	0.015468722	0.015263291	0.009905981
RMSRE	0.128411887	0.124373318	0.123544691	0.099528794
MSPE	1.648961262	1.54687223	1.526329063	0.99059808
RMSPE	1.284118866	1.243733183	1.235446908	0.995287938

Figure 9 shows the plots of actual electricity price and three-step ahead forecasted electricity price using the proposed model and other models for test case 2, comparison of the plots reveals the electricity price forecasting capacity of the proposed model better than other models. Table 5 shows the comparison of nine different error metrics for the forecasted results of different models for three-step ahead electricity price forecasting and the comparison results show that the proposed neural network model has solid forecasting capacity.

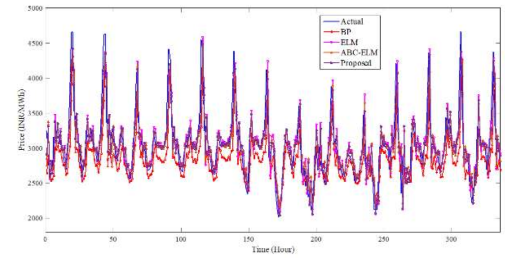

Figure 10 Five-step ahead forecasted electricity price data.

Figure 10 shows the plots of actual electricity price and five-step ahead forecasted electricity price using the proposed model and other models for test case 2 and the comparison of the plots shows that the proposed model gives the best results for electricity price forecasting. Likewise, Table 6 shows the comparison of nine different error metrics for the forecasted results of different models of five-step ahead electricity price forecasting, and the comparison results show that the proposed hybrid model has the lowest error values and it shows the effectiveness of the proposed model.

Figure 11 shows the comparison graph of three different error metrics for one-step, three-step, and five-step forecasting using the proposed model of Indian electricity price data. The comparison plot shows that the error increases slightly while forecasting steps increase, also the proposed model gives the best results for the different step forecasting.

Table 6 Error metrics of five-step ahead forecasted electricity price data.

Error Metrics / Methods	BP	ELM	ABC-ELM	Proposed
MAE	0.027700045	0.021883599	0.021775193	0.018359076
MSE	0.00140153	0.00092684	0.000935335	0.000665593
RMSE	0.037437019	0.030444042	0.030583244	0.025799098
MARE	0.109856309	0.092457543	0.091378755	0.077255752
MAPE	10.9856309	9.245754339	9.137875471	7.725575183
MSRE	0.018397519	0.015804233	0.01553187	0.011203981
RMSRE	0.135637456	0.125714887	0.124626922	0.105848857
MSPE	1.839751938	1.58042327	1.553186956	1.120398059
RMSPE	1.356374557	1.257148865	1.246269215	1.058488573

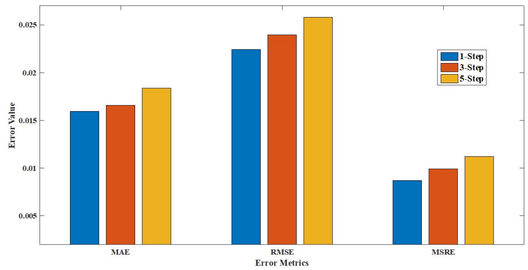

Figure 11 Comparison of different error metrics for one-step, three-step, and five-step ahead forecasting using the proposed model and test case 2

4 CONCLUSION

In this paper, a forecasting model for multistep electricity price forecasting trained by hybrid SCA-ELM algorithm is proposed and it is used to forecast 336 electricity price data of Finland and the Indian electricity market. One-step, three-step, and five-step electricity price forecasting are done for both the electricity markets using the proposed hybrid model. The forecasted results are compared with various other methods by graphical representation of the forecasted data and by tabulation of nine different error metrics values of the forecasted data. The overall comparison shows the performance and effectiveness of the proposed model for multistep electricity price forecasting. The simplicity of the SCA and ELM algorithm and their combination makes the training of the three hidden layers feedforward neural network an easy and effective one.

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