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TECHNIUM

Romanian Journal of Applied Sciences and Technology

ISSN: 2668-778X

vol. 17 / 2023

The 7th International Conference on Science Technology

organized by
Faculty of Social Science and
Law Universitas Negeri Manado and
Consortium of International Conference
on Science and Technology

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International
Communication & PR

Technium: Romanian Journal of Applied Sciences and Technology
Vol. 17, 131-137, November, 2023
ISSN: 2668-778X
www.techniumscience.com

Short-Term Electrical Load Forecasting of 150 kV Ternate System Using Optimally Pruned Extreme Learning Machine (OPELM)

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Abstract. Short-term electrical loads forecasting is one of the most important factors in the design and operation of electrical systems. The purpose of electric load forecasting is to balance electricity demand and electricity supply. The load characteristics of Ternate City vary, so this study uses the Optimally Pruned Extreme Learning Machine (OPELM) method to predict electrical loads. The advantages of OPELM are the fast-learning speed and the selection of the right model, even though the data has a non-linear pattern. The accuracy of the OPELM method can be determined using a comparison method, namely the ELM method. Mean Absolute Percentage Error (MAPE) is used as the accuracy criterion. The results of the comparison of accuracy criteria show that the predictive performance of OPELM is better than that of ELM. The minimum error average of the OPELM forecast test results shows a MAPE of 5,2557%, for Saturday's forecast, while the ELM method gives a MAPE of 6.4278% on the same day.

Keyword: *ELM, OPELM, Short-term electrical load forecasting*

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Technium: Romanian Journal of
Applied Sciences and Technology
Vol. 17, 131-137, November, 2023
ISSN: 2668-778X
www.techniumscience.com

1 Introduction

Forecasting short-term electrical loads is one of the most important factors in the design and operation of electrical systems. Electrical load forecasting techniques usually use artificial neural networks and fuzzy theory to reduce system uncertainty and nonlinearity in electric load forecasting. Researchers have also focused on forecasting short-term loads with Artificial Neural Networks (ANN) which have two advantages, namely: having the ability to estimate any nonlinear function and being a model of determination through a learning process. Experts have also developed a support vector machine method (SVM) that can be applied to short-term load forecasting to optimally generate global values. In this paper, the Optimally Pruned Extreme Learning Machine (OPELM) method was used to predict short-term electrical loads in Ternate City. OPELM is based on the original ELM method, designed to overcome the drawbacks of feed-forward neural networks, especially in terms of learning speed.

Forecasting in the electricity sector is intended to estimate the demand for electricity load in the future. An accurate load forecasting model is very important in the planning and operation of an electric power system. Load forecasting really helps power companies in making decisions to supply electric power including decisions in managing generation, load switching, and the construction of electrical infrastructure [1]. It is hoped that with proper forecasting it can maintain the stability of the electric power system with the accuracy of allocating generators in operation. Load forecasting is categorized by looking at the time span of load data used for forecasting. Load forecasting is divided into 3 groups, namely: 1) Short-term load forecasting, hourly to weekly forecasting. 2) Medium-term, a period of per month to per year. 3) Long-term forecasting covers a period of more than one year [1], [2], [3], [4], [5]. The success of an electrical system is strongly influenced by load forecasting. To get optimal power flow, load forecasting must be done every time [6]. Routine load forecasting can improve system stability which aims to increase efficiency or reduce generation costs [7], [8].

2 Forecasting the electric load on the similar day

Forecasting the electric load for a certain period is very important when using different power plants. Short-term electric load forecasting is different from long-term load forecasting because short-term load forecasting does not require weather, temperature and economic data which affect the accuracy of the forecast itself. Consumer behavior does not change much each week during the weekdays from Monday to Friday and weekends. This pattern is repeated every week and this repetition also occurs in the load curve pattern on similar (similar) days from week to week. For example, the load curve pattern for Monday this week is similar to the load curve pattern for Monday next week. The same thing happened on other days [9], [7].

2.1 Extreme Learning Machine (ELM)

Extreme Learning Machine is a new learning method for artificial neural networks. This method was first introduced by Huang [3]. ELM is a single hidden layer feedforward neural network or often called SLFNs (Single Hidden Layer Feedforward neural network). The ELM learning method is designed to overcome the weaknesses of feedforward neural networks, especially in terms of learning speed.

2.1.1 ELM model

The speed of the feed-forward neural network method is enhanced by ELM [3], [10] with an architectural design as shown in the figure below.

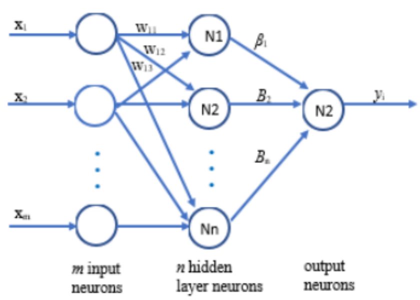

Fig. 1. Extreme learning machine model design

2.1.2 ELM Mathematical models for ELM training

The mathematical model for ELM [5], [11], [12] training can be seen as follows.

1. Initialize W_{jk} weight randomly.
2. Calculate the hidden layer output with the following formulation

$$H = \frac{1}{(1+\exp(-H_{init}))} \quad (1)$$

$$H_{init} = X_{train}\ x\ (W_{jk})^T \quad (2)$$

3. Weight is calculated by:

$$\beta = H^+\ x\ Y_{train} \quad (3)$$

$$H^+ = (H^t\ x\ H)^{-1}\ x\ H^t \quad (4)$$

2.1.3 Mathematical models for ELM testing

The mathematical model for ELM testing is as follows [5], [3], .

1. It is known the weight (W_{jk}) and final weight ($\hat{\beta}$) from the training results.
2. Calculate the hidden layer output using the following formula.

$$H = \frac{1}{(1+\exp(-H_{init}))} \quad (5)$$

$$H_{init} = X_{train}\ x\ (W_{jk})^T \quad (6)$$

Technium: Romanian Journal of Applied Sciences and Technology
Vol. 17, 131-137, November, 2023
ISSN: 2668-778X
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3. Calculate the forecast using the following formula.

$$\hat{Y} = H \; x \; \hat{\beta} \tag{7}$$

2.2 Calculating forecasting accuracy

Forecasting accuracy is calculated using MAPE with the following formula [13], .

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{Y_{prediction} - Y_{target}}{Y_{target}} \right| x \; 100\% \tag{8}$$

2.3 MAPE interpretation

MAPE values interpretation (Lewis, 1982 p. 40) [1], [14] is shown in Table 1 below.

Table 1. MAPE Value Interpretation

MAPE Value	Result of Interpretation
< 10	Forecasting of highly accurate
10 – 20	Forecasting of good
20 – 50	Forecasting of reasonable
>50	Forecasting of inaccurate

2.4 OPELM model

The OPELM method is based on the ELM algorithm using SLFN [5], [15], [16]. The translation steps of the OPELM algorithm are shown in the figure below.

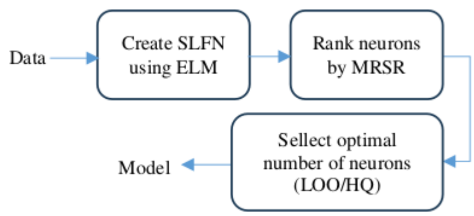

Fig. 2. OPELM algorithm stages

3 Materials and methods

3.1 Materials

The data used in this study is the load data for the 150 kV electrical system of Ternate City, Kastela substation, Line Ternate 1, on September 15, 2022.

Table 2. Load Data of Kastela Substation, Ternate 1 Line

Days	Hour(s)	Loads (MW)				Day
10	1	8.8	6.4	9.8	7.9	Mon.
10	2	8.7	6.1	9.2	7.4	Mon.
10	3	7.2	5.9	8.5	7.2	Mon.
10	4	7.1	5.8	7.9	7.2	Mon.
10	5	7.2	5.7	7.8	7.1	Mon.
10	6	7.1	5.5	7.8	7.0	Mon.
10	7	7.3	6.2	7.7	6.9	Mon.
10	8	7.8	7.7	8.8	6.7	Mon.
10	9	8.2	10.1	8.7	7.6	Mon.
10	10	8.3	10.8	10.6	8.6	Mon.
10	11	9.5	11.0	10.8	9.2	Mon.
10	12	9.8	10.9	10.9	9.1	Mon.
10	13	10.3	10.9	11.1	9.2	Mon.
10	14	10.4	11.4	10.9	9.9	Mon.
10	15	10.5	11.7	11.0	10.2	Mon.
10	16	11.4	11.1	10.5	10.6	Mon.
10	17	9.7	10.7	8.2	10.5	Mon.
10	18	9.7	10.5	9.6	10.8	Mon.
10	19	12.3	12.6	9.5	13.0	Mon.
10	20	12.2	12.6	8.6	12.5	Mon.
10	21	11.9	12.5	8.3	11.6	Mon.
10	22	11.0	11.2	10.8	11.8	Mon.
10	23	9.3	10.3	10.1	11.5	Mon.
10	24	8.6	10.3	9.1	10.6	Mon.
20	1	8.9	9.2	6.9	8.0	Tue.
20	2	8.1	8.2	6.6	5.7	Tue.
20	3	8.0	8.3	6.7	5.9	Tue.
20	4	7.4	7.2	6.0	5.7	Tue.
20	5	7.1	7.1	6.1	5.7	Tue.
20	6	7.2	7.3	5.9	5.5	Tue.
20	7	6.7	7.2	5.5	6.1	Tue.
20	8	7.9	8.3	11.1	6.8	Tue.
20	9	8.5	8.9	11.7	6.9	Tue.
20	10	8.8	9.1	10.6	7.7	Tue.
20	11	9.1	9.1	11.0	7.8	Tue.
20	12	9.1	9.4	11.0	8.8	Tue.
20	13	9.9	10.9	11.6	8.7	Tue.
20	14	10.6	10.9	11.8	8.9	Tue.
20	15	10.4	10.7	11.1	8.0	Tue.
20	16	10.2	10.9	11.0	9.1	Tue.
20	17	9.5	9.8	10.4	11.4	Tue.
20	18	10.2	9.6	9.9	9.7	Tue.
20	19	13.2	12.6	13.3	9.9	Tue.
20	20	12.2	12.9	12.7	10.9	Tue.
20	21	11.7	11.8	12.7	10.6	Tue.
20	22	11.3	11.3	11.7	10.4	Tue.
20	23	10.7	10.9	11.0	10.1	Tue.
20	24	9.0	10.0	10.4	9.6	Tue.
30	1	8.6	9.5	10.2	7.2	Wed.
30	2	7.9	8.3	8.0	7.5	Wed.
30	3	7.5	7.8	8.6	6.8	Wed.
30	4	6.8	7.3	7.7	6.7	Wed.
30	5	6.5	7.2	7.5	6.3	Wed.
30	6	6.8	7.5	7.4	6.6	Wed.
30	7	6.4	6.8	7.9	6.5	Wed.
30	8	7.3	7.8	8.2	6.6	Wed.
30	9	8.0	7.3	9.5	6.9	Wed.
30	10	9.2	7.2	10.2	7.6	Wed.
30	11	9.6	7.5	11.1	7.9	Wed.
30	12	9.9	10.2	10.7	8.5	Wed.
30	13	9.9	10.9	11.4	9.1	Wed.
30	14	9.9	10.6	11.6	9.5	Wed.
30	15	8.9	11.0	11.7	9.5	Wed.
30	16	8.3	10.6	11.5	9.9	Wed.
30	17	8.5	9.6	10.7	9.8	Wed.

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Technium: Romanian Journal of Applied Sciences and Technology
Vol. 17, 131-137, November, 2023
ISSN: 2668-778X
www.techniumscience.com

30	18	9.1	10.0	10.7	9.9	Wed.
30	19	10.5	12.1	13.3	12.6	Wed.
30	20	10.3	12.0	13.2	12.1	Wed.
30	21	9.8	11.7	12.9	12.4	Wed.
30	22	9.3	11.6	12.3	12.1	Wed.
30	23	9.0	10.2	11.7	11.9	Wed.
30	24	7.9	9.2	13.4	11.0	Wed.
40	1	6.5	8.5	13.3	10.5	Thu.
40	2	6.4	8.0	12.1	9.6	Thu.
40	3	5.8	7.7	12.0	9.7	Thu.
40	4	5.9	7.3	11.0	9.8	Thu.
40	5	5.8	7.1	11.2	9.2	Thu.
40	6	6.0	6.7	10.6	8.5	Thu.
40	7	6.0	6.6	10.1	7.7	Thu.
40	8	6.2	6.6	12.3	8.1	Thu.
40	9	6.9	7.7	12.4	6.3	Thu.
40	10	7.8	7.9	12.8	9.3	Thu.
40	11	8.1	8.2	14.0	10.1	Thu.
40	12	9.2	8.4	14.5	10.5	Thu.
40	13	9.1	8.2	14.3	10.4	Thu.
40	14	9.3	10.8	14.1	10.6	Thu.
40	15	9.0	10.7	13.8	10.0	Thu.
40	16	9.5	10.8	13.5	10.1	Thu.
40	17	9.3	9.5	13.4	10.0	Thu.
40	18	9.5	9.2	13.3	10.3	Thu.
40	19	12.6	12.5	16.4	12.0	Thu.
40	20	12.5	12.3	15.7	11.6	Thu.
40	21	11.4	11.5	15.6	12.1	Thu.
40	22	10.4	11.2	14.4	11.4	Thu.
40	23	9.0	10.6	14.0	11.7	Thu.
40	24	8.0	10.0	13.1	10.6	Thu.
50	1	7.3	9.1	12.6	10.0	Fri.
50	2	7.3	8.3	12.5	9.0	Fri.
50	3	6.5	8.4	11.2	8.8	Fri.
50	4	6.5	7.6	11.1	9.1	Fri.
50	5	6.1	7.5	10.8	8.8	Fri.
50	6	6.2	7.5	10.4	8.0	Fri.
50	7	5.9	6.4	9.8	7.5	Fri.
50	8	6.0	6.9	10.2	7.1	Fri.
50	9	7.3	7.3	11.2	7.8	Fri.
50	10	7.3	8.1	11.8	8.3	Fri.
50	11	7.2	8.4	11.0	9.2	Fri.
50	12	7.5	8.9	11.0	9.4	Fri.
50	13	8.9	9.0	13.4	9.5	Fri.
50	14	8.9	7.3	12.6	9.8	Fri.
50	15	8.8	8.5	12.3	10.1	Fri.
50	16	9.0	10.0	12.3	9.9	Fri.
50	17	8.8	9.5	12.4	10.0	Fri.
50	18	8.6	9.5	12.8	9.9	Fri.
50	19	11.0	12.6	13.1	11.1	Fri.
50	20	11.3	12.5	14.7	11.0	Fri.
50	21	11.0	12.1	14.6	11.4	Fri.
50	22	10.4	11.0	14.0	11.2	Fri.
50	23	9.8	10.3	13.1	10.9	Fri.
50	24	9.1	9.9	12.8	9.6	Fri.
60	1	8.2	9.3	12.5	9.0	Sat.
60	2	7.6	9.2	12.6	8.9	Sat.
60	3	6.8	8.6	10.8	8.0	Sat.
60	4	6.5	8.2	10.7	7.9	Sat.
60	5	6.4	8.0	10.6	8.1	Sat.
60	6	6.3	7.1	10.6	8.2	Sat.
60	7	6.4	6.9	9.3	7.4	Sat.
60	8	5.9	7.3	10.2	5.8	Sat.
60	9	6.2	7.6	10.4	6.7	Sat.
60	10	6.4	8.3	11.3	7.2	Sat.
60	11	6.6	8.4	11.5	7.6	Sat.
60	12	6.1	8.9	12.1	7.7	Sat.
60	13	6.6	8.3	12.5	8.2	Sat.
60	14	6.9	9.7	12.4	8.4	Sat.
60	15	7.2	9.4	12.2	8.0	Sat.
60	16	8.2	9.3	12.4	8.4	Sat.
60	17	7.5	9.0	12.0	8.6	Sat.
60	18	8.2	8.9	12.2	11.5	Sat.
60	19	10.1	11.8	15.3	10.9	Sat.
60	20	9.9	12.8	15.6	10.8	Sat.
60	21	8.9	12.1	15.0	10.5	Sat.
60	22	8.9	11.3	14.1	10.3	Sat.
60	23	7.6	10.5	13.6	9.9	Sat.
60	24	7.3	9.9	13.1	8.9	Sat.
70	1	7.7	9.2	12.3	8.1	Sun.
70	2	7.2	8.2	11.8	7.5	Sun.
70	3	5.7	7.7	11.3	7.7	Sun.
70	4	5.4	7.7	11.1	7.8	Sun.
70	5	6.2	7.6	10.9	7.3	Sun.
70	6	7.5	7.3	11.2	7.0	Sun.
70	7	7.2	6.9	10.6	6.9	Sun.
70	8	7.2	7.9	11.8	6.8	Sun.
70	9	7.8	9.2	12.1	7.6	Sun.
70	10	7.9	9.4	12.4	8.9	Sun.
70	11	8.6	10.0	12.8	9.7	Sun.
70	12	6.2	10.4	13.2	9.8	Sun.
70	13	9.1	11.0	14.0	10.0	Sun.
70	14	9.1	11.0	14.3	9.7	Sun.
70	15	9.1	10.9	14.2	9.9	Sun.
70	16	9.5	10.6	15.0	9.5	Sun.
70	17	8.9	10.3	14.5	9.3	Sun.
70	18	8.9	9.9	12.2	9.4	Sun.
70	19	11.5	13.3	13.4	11.8	Sun.
70	20	11.7	13.0	14.4	14.3	Sun.
70	21	10.8	12.5	13.3	10.9	Sun.
70	22	9.7	11.7	12.3	10.7	Sun.
70	23	9.1	9.7	11.6	9.8	Sun.
70	24	8.8	12.2	10.7	10.8	Sun.

3.2 Methods

The forecasting method used in this study is OPELM. The ELM method is used for comparison or validation. The research flow chart can be seen in the following figure.

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Technium: Romanian Journal of Applied Sciences and Technology
Vol. 17, 131-137, November, 2023
ISSN: 2668-778X
www.techniumscience.com

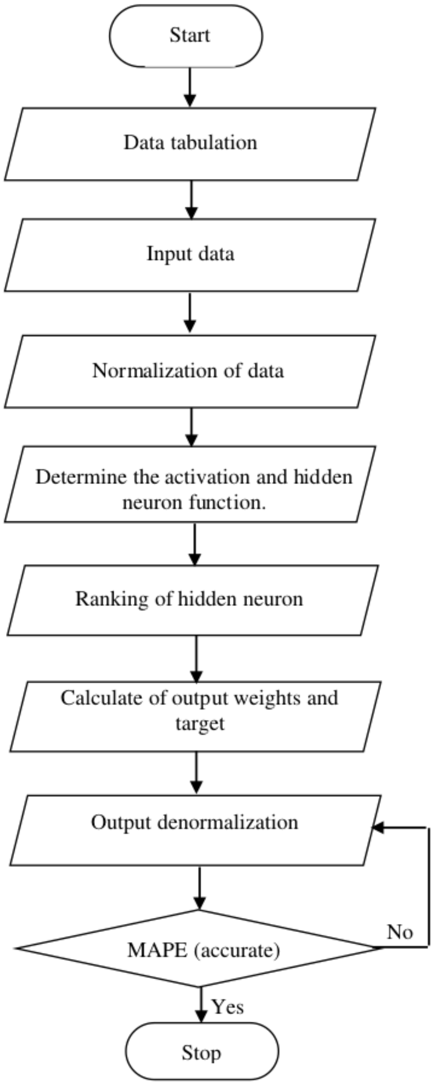

Fig. 3. Research flowchart

4 Results and discussion

Load prediction starts with the training process using the OPELM method to identify load patterns and is expected to produce accurate results similar to the target training data. The resulting model is then used in the testing process to predict future electrical loads. The following is the forecast for next week using OPELM and ELM. Table 3 shows the accuracy of the following week's training data using the OPELM and ELM methods. Considering that the OPELM method is not carried out by trial and error like the ELM method, it is not necessary to try many times to get good practicum results. In OPELM, ELM parameters were optimized using MRSR and LOO validation for classification and pruning of neurons. The activation function used is a combination of linear, sigmoid and Gaussian, with a total of 25 hidden neurons. The optimization results produce a smaller number of hidden neurons, namely 5 hidden neurons. Linear functions are used in ELM because the predicted data is static with the same number of hidden neurons as in OPELM.

Table 3. Accuracy of the Training Data Prediction Model Using the OPELM and ELM Methods for the Next Week

Methods	Activation Function	Number of Hidden Neuron	MAPE Training (%)
OPELM	lsg	5	5,7421
ELM	linear		6,1002

Description: lsg = linear, sigmoid, gaussian

Based on the table, it is known that the OPELM method's MAPE value is 5.7421%, while the ELM method is 6.1002. The OPELM MAPE value is lower than the ELM method. A comparison graph of OPELM and ELM training results is shown in the following figure. Then the input weights, the bias of the hidden neurons and the output weights obtained in the training process are used as input in the testing process to predict the electrical load. The prediction results of OPELM are then compared with ELM which both use 5 hidden neurons.

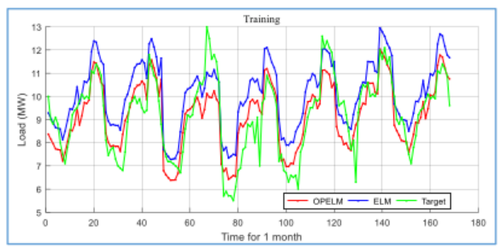

Figure 4. Plot Comparison of the Results of the Electrical Load Forecasting Training for the Next Week

To see how well the model is formed, model validation is carried out with testing data. The following table compares the accuracy of forecast results from the OPELM and ELM methods.

Table 4. Comparison of the Accuracy of Testing Results Using the OPELM and ELM Methods for the Next Week

Methods	MAPE Training (%)	MAPE Testing (%)
OPELM	5,7421	6,2110
ELM	6,1002	6,7029

Description: lsg = linear, sigmoid, gaussian

Based on Table 4, it is known that the OPELM method has a MAPE testing value of 6.2110% and an ELM of 6,7029%. OPELM's MAPE value is smaller than that of ELM. This shows that the OPELM method has better accuracy than ELM. The results of testing using

Technium: Romanian Journal of Applied Sciences and Technology
Vol. 17, 131-137, November, 2023
ISSN: 2668-778X
www.techniumscience.com

the OPELM and ELM methods are shown in the following figure.

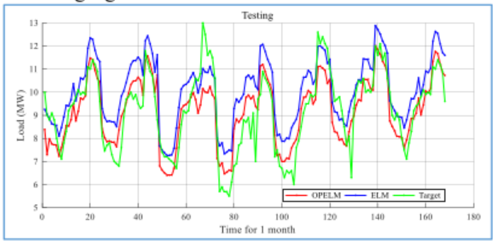

Figure 5. Plot of Testing Results Using the OPELM and ELM Methods for the Next Week

The picture above shows that the forecasting results with the OPELM method have the same load pattern as the actual data load pattern but have a smaller error than the forecasting results with the ELM method.

The forecasting test results represented in the amount of load (MW) per day based on MAPE errors can be seen in the following table.

Table 5. Overall results of Forecasting Tests on All Days Using the OPELM and ELM Methods.

	MAPE Testing (%)						
	Mon.	Tue.	Wed.	Thu	Fri.	Sat.	Sun.
OPELM	6,6121	6,5736	6,5748	5,5665	7,2769	5,2557	5,6177
ELM	7,5638	6,6928	6,5427	6,6747	6,5837	6,4278	6,4349

In Table 3, the MAPE values are obtained from the OPELM and ELM method testing processes. The smallest MAPE test using the OPELM method occurred on Saturday at 5,2557%. Meanwhile, the largest MAPE test occurred with the OPELM method which showed the most inaccurate forecast results, with a forecast of 7,2769% for Friday. Based on the results of the MAPE error obtained, forecasting with the OPELM method generally has a better accuracy value than the ELM method. The test results are strongly influenced by the selection of data and load patterns which vary widely and generally have an increasing trend and cannot be certain. The results of these forecasts are estimates intended to reduce this uncertainty.

5 Conclusion

The following conclusions can be drawn from this study:

1. Forecasting short-term electrical loads using the OPELM method provides forecasting results that are more accurate than the ELM method.
2. The best OPELM results are seen in the load forecast on Saturday with the MAPE test of 6,2557%, while the MAPE ELM test is 6.4278%.

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