Electric Load Forecasting Using Artificial Neural Network Method with Limited Data

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ABSTRACT — As time changes, electric load demand forecasting is one of the vital things in generation and distribution planning. Various ways can be implemented in forecasting electrical energy demands, one of which is by using the artificial neural network method, which is a method that mimics the ability of the human brain to receive an input and then carry out processing between the neurons within to produce information based on the processes that occur within the neurons. This research uses a neural network method to forecast the electric load in Jayawijaya Regency. This research builds a neural network architecture suitable to the data obtained from National Electricity Company (Perusahaan Listrik Negara, PT PLN Indonesia) UP 3 Wamena to find an architecture model suitable with high accuracy. Due to the limited data owned to forecast electric load, an interpolation method based on the owned original data was carried out to increase the amount of the existing data. In this way, more data can be used as input, allowing the model to forecast load requirements more accurately. These propagated data were used as input data in the artificial neural network model. After conducting iterative testing using a neural network, it is found that the model that fitted the data was feed-forward long short-term memory (LSTM) network, this model can obtain errors in accordance with the standards of a model to perform forecasts of 0.04% with nine epochs.

KEYWORDS — Load Forecasting, Artificial Neural Network, Limited Data, Interpolation.

I. INTRODUCTION

Alongside technological advancements, one of the most common problems in the world of electricity is unmet electrical energy demands. The demand for electrical energy increasing along with the addition of consumers, business growth, industry, the economy, regional development, population growth, regional conditions, living standards, as well as current and future development plans requires electrical energy forecasts [1].

In order to meet the needs of electrical energy, electric load forecasting is required in planning electricity demand and supply. Data in the form of time series are required within a certain period of time to forecast the electric load. The used data are historical data aiming to determine the characteristics of the electric load in the previous time span to forecast the future electric load. In addition, the data used are data on electricity user characteristics, including household, business, industrial, and public user characteristics. In which each user characteristic has different peak load characteristics [2].

Due to the unpredictability (dynamism) of the demand for electrical energy, it is necessary to forecast the growth of electric loads and the distribution of electrical power in accordance with electric load requirements. In the electricity system, electric energy demand forecasting is required to forecast the exact electrical power required to serve the load and electrical energy needs in the distribution of electrical energy. A too-small forecast will result in insufficient power capacity being supplied to meet load requirements, while a too-large forecast will result in excess power capacity leading to losses [3].

Despite its limitations, Jayawijaya Regency is a fast-growing area compared to other districts in the Central Highlands of Papua Province. According to the data from the Population and Civil Registry Office of Jayawijaya Regency, the average growth of the population of Jayawijaya Regency from 2013 to 2018 was 0.7% per year, gross regional domestic revenue (GRDP) from 2013 to 2018 was an average of 13.33% per year, peak load data from 2013 to 2018 was an average of 12.48%. It demonstrates that Jayawijaya Regency experiences growth in the household, commercial, public, and industrial sectors. These sectors are consumers of electrical energy in Jayawijaya Regency [4].

A neural network is an artificial intelligence system capable of learning and accumulating knowledge of learning results in its network of cells (neurons) to enable the network as a whole to respond more intelligently to the given input. This ability to learn and accumulate knowledge allows the neural network system to adapt to the environment that provides input.

This research aims to forecast the electric load in Jayawijaya Regency using a neural network and build a neural network architecture in accordance with the data obtained from National Electricity Company (Perusahaan Listrik Negara, PT PLN) Indonesia UP 3 Wamena in order to discover a suitable architecture model with a high level of accuracy. Due to the limited data available for electric load forecasting, it is necessary to increase the amount of existing data using the data interpolation method based on the available data.

II. METHODOLOGY

This research was conducted based on several studies that have been done before. Some of which carried out study on electric load forecasting using the long short-term memory (LSTM) method [5]. Research [6] has conducted a load forecast using a convolutional neural network method.

A forecast on short-term electric load demand has been done by combining several neural network models based on load characteristics, and external factors affecting them [7]. The result is that the proposed model could perform load forecasting well. Earlier forecast research conducted using the convolutional neural network method combined with the recurrent neural network has shown that this method could perform load forecasting with better results than other neural network models that have been used on the same research object [8].

Another research on short-term electric load forecasting has been carried out by combining the methods of improved environmental adaptation with real parameters (IEAM-R) and controlled gaussian mutation (CGM) [9]. The result of this research showed that by combining the two methods, the neural network could perform forecasts more accurately because the neural network of this type was modeled to be able to adapt to the environment.

A. ELECTRIC LOAD FORECASTING

Electric load forecasting is essential in planning electrical power system operations. The forecasting results can be used to plan generation and formulate an economical generation schedule [10], [11]. The objectives of load forecasting are to improve power system stability, improve power system security, reduce generation costs, and improve overall utility efficiency, as well as achieve optimal performance through demand-side management [12].

According to the forecast period and supply strategy, power system load forecast consists of three kinds of load forecast: long-term, medium-term, and short-term load forecasts [13]. In general, electric load forecasting uses time series data.

Short-term load forecasts have several characteristics, including the followings.

- Load is almost always the same within a 24-hour period, trend similarity within different weeks on the same day of the week, trend similarity of weekdays or holidays, and trend similarity of the same major holidays in different years.
- It is affected by various environmental (external) factors, such as seasonal changes, sudden changes in weather factors, equipment breakdowns or repairs, large-scale cultural or sports activities, and others. Those factors can cause the system load to experience random and temporary variations.

Forecast methods using time series data have two main characteristics: the model structure is simple, and amount of data required for load forecasting is small. Since time series forecasting methods emphasize data for a specific time span, without regard to external factors, they can produce significant errors [14].

B. INTERPOLATION

The interpolation method is a method to search for a value associated with an interpolation function. The interpolation function is formed by several points with a certain range. The search for the value of the function associated with the point located in the range is called the interpolant [15].

The simplest form of interpolation is interpolation involving two points (x_1, y_1 and x_2, y_2), the characteristics of the connection of these two points are represented by a linear function $y(x)$ connecting the two points, which is called the interpolation function. The value of the interpolation function at a point whose abscissa is x_3 (located between x_1 and x_2), is $y(x_3)$, referred to as the interpolant of x_3.

In practice, the interpolation function involves a number of points, the commonly used is interpolation which involves three points. Therefore, the interpolation function form is quadratic. The quadratic approach better reflects the characteristics of the distribution of points [16], because in practice, these points are distributed through a random pattern. The interpolant is expected to follow this function which better reflects practical everyday quantities. The search for a quadratic function can be done through the process of curve fitting, the parameter values of the quadratic function are determined on the basis of the least squares error principle.

C. ARTIFICIAL NEURAL NETWORK

A neural network is an artificial intelligence capable of learning and processing the learned knowledge within its network (neurons) so as to enable the entire network to be more responsive to the given input. The ability of this artificial intelligence to learn and process knowledge makes the neural network adaptable to the set of variables that provide input into it. This intelligence mimics the working principle of the human brain in responding to different conditions, the role of a neural network in the field of science is essential in the future which demands automation aspects between humans and tools [17]. The work of a neural network is assessed from three points: network architecture, training method, and activation function.

In this system, a collection of neurons will form a layer called a neuron layer. Each layer will be connected between one and the other. Information will be propagated from one layer to the next layer, starting from the input layer, the hidden layer, then the output layer.

Neurons are information processing units that are the basis of neural networks. A neural network itself consists of three elements [18]. The first element is a set of units connected by connecting lines, these lines have different weights, weights with positive values strengthen the signal and those with negative values will weaken the signal. The second element is a summation unit sums the input signals that have been multiplied by their weights. The last element is an activation function that determines the output of the neuron. The frequently used neural network architectures are the single-layer, multilayer, and recurrent network models.

In neural networks, the single-layer network is the simplest, where neurons in the input layer are directly processed to the output layer without any feedback [19]. In a single layer, if a hidden layer is added in addition to the input and output layers, it may disrupt the performance of the network. Therefore, there is another type of network called a multilayer network, which consists of input, hidden, and output layers. The way it works is by transmitting a signal from the input layer, which will then be automatically computed in the hidden layer before being transmitted to the output layer. This type of network has a longer training time as it is more complex than a single-layer network. Meanwhile, the recurrent network model is formed because the two networks above require feedback in each loop of the network while this type of feedback is obtained from inputs that are being used in the network [20].

The activation function serves to determine the output value of a neuron. Frequently used activation functions include the sigmoid, hyperbolic tangent, and the leakyReLU functions. The sigmoid function is the most commonly used function because the function value maps the value between 0 and 1. The hyperbolic tangent function or sigmoid bipolar has a similar character to the usual sigmoid, but the mapped input value is the value of -1 to 1. The leakyReLU function is a development of ReLU, the difference is that if ReLU can map the input values of 0 to x, then leakyReLU can map unlimited input values ($y = x$*0.01) [21].

The working principle of a neural network is more or less the same as how the human brain processes information. Each neuron in the human brain is connected to each other and then spreads the information the brain has received to each unit. Neuron then receives input and processes it with a weight, then sums it (weighted sum) and adds an additional bias or input. The result of this operation is the parameters of the neuron's activation function. When performing learning using a neural network, two processes are performed, namely training and evaluation. There is one optional process, i.e., testing. Each neuron's weight and bias are updated repetitively when training until the resulting output value is as desired. Each loop is evaluated to determine whether the network still needs training or can stop the training process [22].

D. VALIDATION TEST

The forecast model validation is done by evaluating the forecast results. The frequently conducted method in the evaluation process is the mean squared error (MSE) method [23]. MSE is the mean square error, the error in question is the difference between the actual and forecast values. If the MSE value is low or close to zero, it indicates that the model obtained is good, the forecast results are very close to the actual values and finally this model can be used as a reference for forecasting in the future period. The MSE is formulated as follows:

$$MSE = \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n} \qquad (1)$$

where,

A_t = actual value
F_t = forecast result value
n = number of data.

III. CASE STUDY

This research discusses electric load forecasting using a neural network modeled in MATLAB. There are several stages in its process, namely modeling the neural network in accordance with the data characteristics, conducting training, then testing the performance of the model, conducting analysis, and finalizing with a conclusion.

Figure 1 displays the research flowchart. As per the flowchart shown in Figure 1, the first step is obtaining the original data through data collection methods from relevant agencies. The next is to select data suitable for the purpose of making this forecast. After obtaining the required data, then data interpolation is carried out. These limited data are reproduced through quadratic interpolation. The interpolated results of this quadratic interpolation function are added with noise as a reflection of the real situation in the field, where changes always occur. The initially limited data can be multiplied by generating sufficient interpolants, and a large amount of data produces a more accurate model. When this multiplying data stage is successful, the next step is to design the structure or architecture of the neural network.

This neural network architecture is to perform load forecasting in Jayawijaya District. The modeling used in this research is a neural network with the type of feed-forward backpropagation LSTM because the data are in the form of annual and monthly time series. The training and testing of this neural network were done with several trials and structure modifications: the number of hidden layers, neurons, and epochs to get the best modeling form with low error.

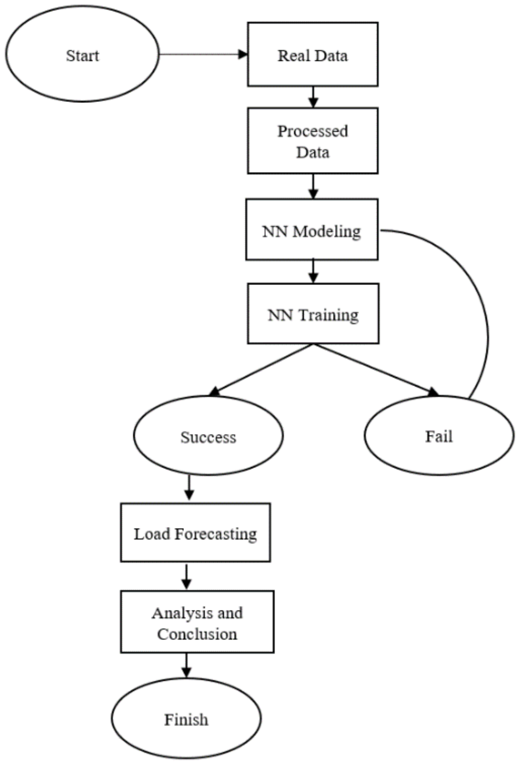

Figure 1. Research flowchart.

IV. RESULT AND DISCUSSION

A. DATA PREPARATION

The data used as input were peak load historical data of PT PLN Indonesia UP 3 Wamena Jayawijaya Regency, population, and GRDP from 2013 to 2018. After obtaining the required input data, data sorting was performed to sort out the data to be used as input data. Initially, the data were in the form of data per year for a period of six years, which is listed in Table I.

Neural networks work like the human brain, learning from an example, then the network formed tries to solve a particular problem such as pattern recognition or classification due to the learning process. Therefore, the more examples received and processed by the brain, the better the results of brain analysis will be.

Based on this, it can be stated that the neural network requires a large amount of data to perform modeling and forecasting training. The more data it has, the more likely the network can produce more accurate output. Because the data were very limited, interpolation was carried out aiming at increasing the amount of data but still in accordance with the range of real data available, and also in accordance with the variable and nonlinear data values. Therefore, the interpolation performed was a quadratic interpolation, performed piecewise with three data (three years) each.

Quadratic interpolation was done per three years to get an interpolant, a quadratic model with the following formula:

$$q(x) = ax^2 + bx + c. \qquad (2)$$

After successfully interpolating, the interpolated data (interpolant) were added with noise which reflected the variation of the data, in order to describe the development of the data in the field. The following is an example of the data generation process through quadratic interpolation, using the 2013 and 2014 data. The quadratic functions for peak load, population, and GRDP data (y) are expressed as follows.

TABLE I
INPUT DATA

Year	Peak Load	Population Data	GDRP
2013	5,436	204,954	415,665
2014	5,560	206,568	419,194
2015	6,070	212,533	421,928
2016	6,280	214,740	424,294
2017	6,648	216,861	427,595
2018	6,645	216,360	430,543

TABLE II
INPUT DATA AFTER INTERPOLATION

Year	X Value	Year	Peak Load	Population Data
2013	1.08	5.436	185.431	412.716
	1.16	5,436	188,255	413,065
	1.24	5,435	189,913	413,411
	1.32	5,437	193,009	413,815
	1.40	5,436	195,497	413,798
	1.48	5,438	197,108	414,354
	1.56	5,445	199,967	414,387
	1.64	5,446	201,481	414,719
	1.72	5,447	200,036	414,897
	1.80	5,452	203,085	415,186
	1.88	5,459	203,096	415,739
	1.96	5,462	203,098	415,537
2014	2.08	5,475	205,902	416,034
	2.16	5,484	206,523	416,675
	2.24	5,480	206,949	416,678
	2.32	5,501	207,338	417,047
	2.40	5,498	207,626	417,249
	2.48	5,513	207,691	417,456
	2.56	5,520	207,675	417,827
	2.64	5,529	207,484	418,055
	2.72	5,540	207,080	418,425
	2.80	5,547	206,672	418,892
	2.88	5,554	206,095	418,978
	2.96	5,576	205,342	419,403

Peak load:

$$y = 40.5x^2 - 90.5x + 5485. \quad (3)$$

Population:

$$y = -10763x^2 + 53642x + 140820. \quad (4)$$

GRDP:

$$y = 81.5x^2 + 3093.5x + 409411 \quad (5)$$

where x is the year. For interpolation purposes, the x values were multiplied in months, so that in one year there are twelve data points. The interpolant values of $y(x)$ for each month can finally be calculated for values of x = 1.08; 1.16; ......; 1.88; and 1.96 in one year. For the next year, it can be done in the same way with the initial value of x = 2.08 increment 0.8.

Values of the first two years of data that have been interpolated are presented in Table II. Similar steps in accordance with the provisions in Table II were carried out for other data types. The results obtained 84 data that would be used as neural network inputs.

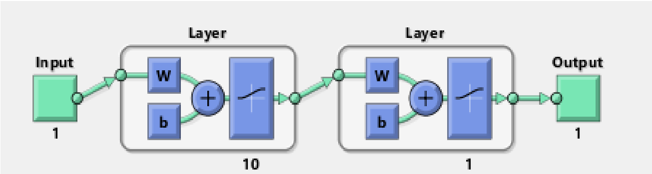

Figure 2. Neural network architecture.

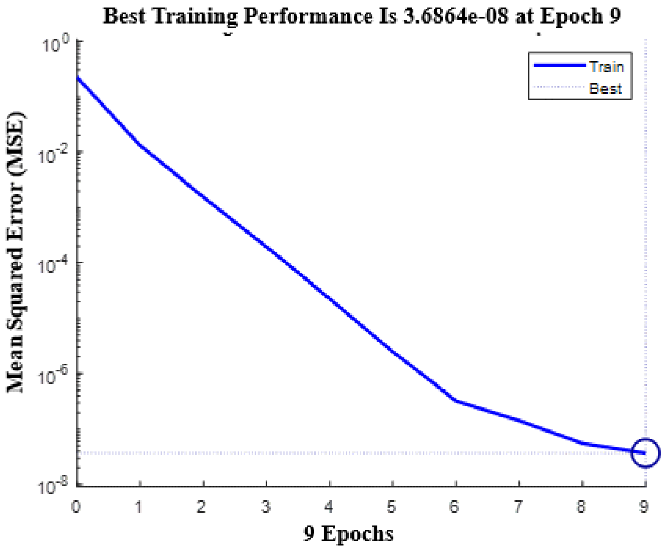

Figure 3. Training performance.

B. NEURAL NETWORK MODELING

After completing the data preparation, the neural network architecture modeling was carried out using the parameters described in the previous subsection. The first was to determine the type of network to be used, the network to be used in this forecasting was a multilayer network with the method of backpropagation neural network LSTM. This type of network was used since the data were in the form of time series. After obtaining the type of network to be used, the next step was to design the network architecture. It is because a good network model for load demand forecasting is a network with a high level of accuracy. This level of accuracy was obtained by doing a lot of variations in the number of hidden layers and the number of neurons in each hidden layer, the level of accuracy can be judged by the size of the resulting error. After that, repeated training was carried out by adjusting the number of layers, the number of neurons, and the number of epochs until obtaining the best results. After conducting repeated experiments, it was found that a good network model for forecasting is a network model consisting of:

- one neuron in the input layer
- ten neurons in the first hidden layer
- one neuron in the second hidden layer
- one neuron in the output layer

The final result of this modeling can be seen in Figure 2.

C. LOAD FORECASTING

With the model architecture as shown in Figure 2, the model's performances are two hidden layers, ten neurons in the 1st hidden layer, and one neuron in the 2nd hidden layer. Figure 3 shows the training performance with the model structure.

Based on Figure 3, there is a very significant decrease in MSE from the 1st to 6th iteration. Then, in the 6th to 8th iteration, there is still a decrease in MSE, even though it is less

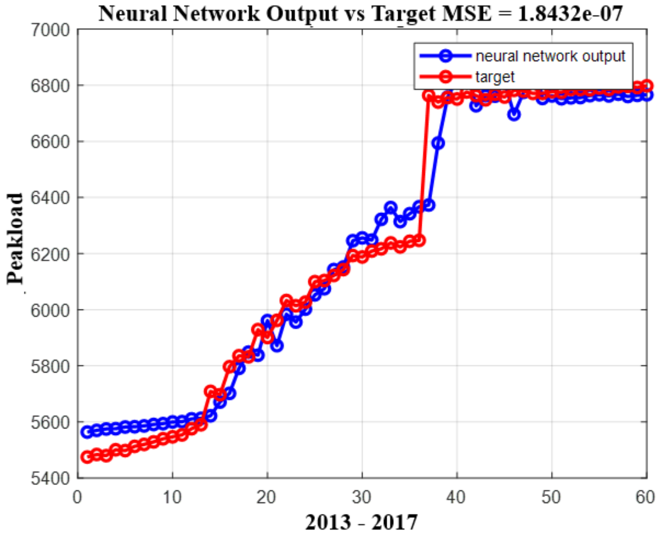

Figure 4. Output values of neural network vs output target.

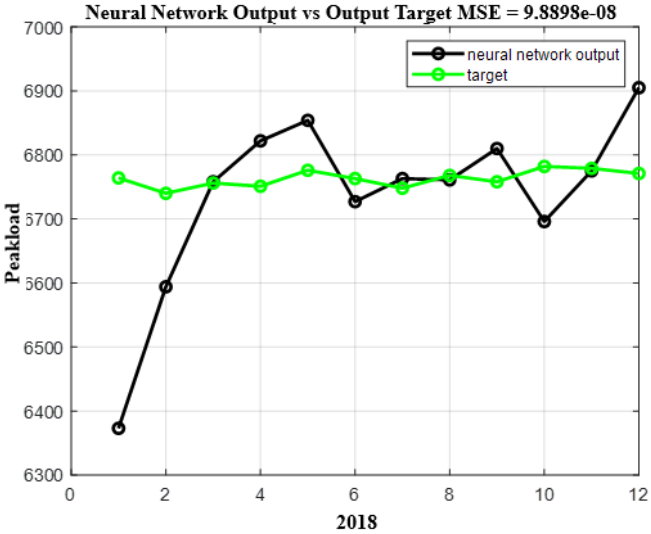

Figure 5. Output values of neural network vs output target.

significant. The best result was achieved at the 9th (epoch) iteration when the network successfully performed the calculation with the smallest error. At that time, the neural network automatically stopped the training process. The small MSE is depicted by the blue line which is decreasing towards 0 (zero), it can be said that the modeling has met the expectations marked by the MSE value of 3.6864 × 10^{8}.

An illustration of the success of the training process can be seen in Figure 4, for 48 data inputs and 48 data results of a neural network specifically the peak load. The figure shows the results of network training conducted using neural network feed-forward backpropagation with three types of data input where there are two lines, the red line is the training target and the blue is the output of the neural network. If noticed carefully, the training of this network can be considered successful training because the difference between the target and output neural network is not significant, which indicates that the architecture can process the data input well.

The comparison between the test results and the target can be seen in the graph shown in Figure 5. This figure shows the test results of the network after prior training. The data entered were new data that had never been used during training. This network test aims to see if the network that has been built can quickly and adaptively recognize and learn new data without significantly reducing the network's performance. Figure 5 shows a not-so-significant difference between the test target and the test results. However, when compared to the training results, the error of the test results is more significant. It should be noted that the data used to conduct the test were new data that had not been recognized by the network, and the test results were still in accordance with the MSE standard. It indicates that the network has met the requirements for forecasting electricity demand and indicates that the network is ready to be given input data that has not been used before.

V. CONCLUSION

Neural network can work with limited data by using the assistance of data interpolation to increase the amount of available data, through a process that is in accordance with the applicable provisions. After conducting iterative testing, it is found that the model that matched the obtained data was the LSTM network. This model yielded a very small error at 0.04% with nine epochs.

CONFLICT OF INTEREST

The author declares that there is no conflict of interest in preparing this research with the title "Electric Load Forecasting Using Artificial Neural Network Method with Limited Data," either in personal interests that might be interpreted to affect the representation or interpretation of the research results.

AUTHOR CONTRIBUTION

Research theme, Elang Bayu Trikora and Sasongko Pramonohadi; software, Elang Bayu Trikora; validation, Elang Bayu Trikora, Sasongko Pramonohadi, and M. Isnaeni Bambang Setyonegoro; formal analysis, Elang Bayu Trikora and Sasongko Pramonohadi; parameter data preparation, Elang Bayu Trikora; writing—organizing the original draft, Elang Bayu Trikora and Sasongko Pramonohadi; writing—reviewing and editing, Elang Bayu Trikora and Sasongko Pramonohadi; programming, Elang Bayu Trikora, Sasongko Pramonohadi, M. Isnaeni Bambang Setyonegoro.

REFERENCES

[1] Q. Feng and S. Qian, "Research on Power Load Forecasting Model of Economic Development Zone Based on Neural Network," *Energy Rep.*, Vol. 7, pp. 1447–1452, Nov. 2021, doi: 10.1016/j.egyr.2021.09.098.

[2] W. Kong *et al.*, "Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network," *IEEE Trans. Smart Grid*, Vol. 10, No. 1, pp. 841–851, Jan. 2019, doi: 10.1109/TSG.2017.2753802.

[3] S.N. Fallah, M. Ganjkhani, S. Shamshirband, and K.-W. Chau, "Computational Intelligence on Short-Term Load Forecasting: A Methodological Overview," *Energies*, Vol. 12, No. 3, pp. 1–21, Jan. 2019, doi: 10.3390/en12030393.

[4] "Kabupaten Jayawijaya dalam Angka 2017," Badan Pusat Statistik Kabupaten Jayawijaya, 2017.

[5] Y. Liang, D. Niu, and W.-C. Hong, "Short Term Load Forecasting Based on Feature Extraction and Improved General Regression Neural Network Model," *Energy*, Vol. 166, pp. 653–663, Jan. 2019, doi: 10.1016/j.energy.2018.10.119.

[6] J. Kim, J. Moon, E. Hwang, and P. Kang, "Recurrent Inception Convolution Neural Network for Multi Short-Term Load Forecasting," *Energy, Build.*, Vol. 194, pp. 328–341, Jul. 2019, doi: 10.1016/j.enbuild.2019.04.034.

[7] X. Liu, Z. Zhang, and Z. Song, "A Comparative Study of the Data-Driven Day-Ahead Hourly Provincial Load Forecasting Methods: From Classical Data Mining to Deep Learning," *Renew. Sustain. Energy Rev.*, Vol. 119, pp. 1–17, Mar. 2020, doi: 10.1016/j.rser.2019.109632.

[8] L. Yin, Z. Sun, F. Gao, and H. Liu, "Deep Forest Regression for Short-Term Load Forecasting of Power Systems," *IEEE Access*, Vol. 8, pp. 49090–49099, Mar. 2020, doi: 10.1109/ACCESS.2020.2979686.

[9] P. Singh, P. Dwivedi, and V. Kant, "A Hybrid Method Based on Neural Network and Improved Environmental Adaptation Method Using Controlled Gaussian Mutation with Real Parameter for Short-Term Load Forecasting," *Energy*, Vol. 174, pp. 460–477, May. 2019, doi: 10.1016/j.energy.2019.02.141.

[10] L. Wu, C. Kong, X. Hao, and W. Chen, "A Short-Term Load Forecasting Method Based on GRU-CNN Hybrid Neural Network Model," *Math. Probl. Eng.*, Vol. 2020, pp. 1–10, Mar. 2020, doi: 10.1155/2020/1428104.

[11] C. Tian, J. Ma, C. Zhang, and P. Zhan, "A Deep Neural Network Model for Short-Term Load Forecast Based on Long Short-Term Memory Network and Convolutional Neural Network," *Energies*, Vol. 11, No. 12, pp. 1–13, Dec. 2018, doi: 10.3390/en11123493.

[12] A. Sherstinsky, "Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) Network," *Phys. D Nonlinear Phenom.*, Vol. 404, pp. 1–28, Mar. 2020, doi: 10.1016/j.physd.2019.132306.

[13] M.S. Hossain and H. Mahmood, "Short-Term Load Forecasting Using an LSTM Neural Network," *2020 IEEE Power Energy Conf. Illinois (PECI)*, 2020, pp. 1–6, doi: 10.1109/PECI48348.2020.9064654.

[14] L. Sehovac and K. Grolinger, "Deep Learning for Load Forecasting: Sequence to Sequence Recurrent Neural Networks with Attention," *IEEE Access*, Vol. 8, pp. 36411–36426, Feb. 2020, doi: 10.1109/ACCESS.2020.2975738.

[15] J. Ma *et al.*, "A Temporal-Spatial Interpolation and Extrapolation Method Based on Geographic Long Short-Term Memory Neural Network for PM2.5," *J. Clean. Prod.*, Vol. 237, pp. 1–11, Nov. 2019, doi: 10.1016/j.jclepro.2019.117729.

[16] Y. Sun, T. Yang, and Z. Liu, "A Whale Optimization Algorithm Based on Quadratic Interpolation for High-Dimensional Global Optimization Problems," *Appl. Soft Comput.*, Vol. 85, Dec. 2019, doi: 10.1016/j.asoc.2019.105744.

[17] Z. Deng *et al.*, "Multi-Scale Convolutional Neural Network with Time-Cognition for Multi-Step Short-Term Load Forecasting," *IEEE Access*, Vol. 7, pp. 88058–88071, Jul. 2019, doi: 10.1109/ACCESS.2019.2926137.

[18] S. Muzaffar and A. Afshari, "Short-Term Load Forecasts Using LSTM Networks," *Energy Procedia*, Vol. 158, pp. 2922–2927, Feb. 2019, doi: 10.1016/j.egypro.2019.01.952.

[19] O.I. Abiodun *et al.*, "State-of-the-Art in Artificial Neural Network Applications: A Survey," *Heliyon*, Vol. 4, No. 11, pp. 1–41, Nov. 2018, doi: 10.1016/j.heliyon.2018.e00938.

[20] A. Tealab, "Time Series Forecasting Using Artificial Neural Networks Methodologies: A Systematic Review," *Future Comput., Inform. J.*, Vol. 3, No. 2, pp. 334–340, Dec. 2018, doi: 10.1016/j.fcij.2018.10.003.

[21] S.M.J. Jalali *et al.*, "A Novel Evolutionary-Based Deep Convolutional Neural Network Model for Intelligent Load Forecasting," *IEEE Trans. Ind. Inform.*, Vol. 17, No. 12, pp. 8243-8253, Dec. 2021, doi: 10.1109/TII.2021.3065718.

[22] B.-S. Kwon, R.-J. Park, and K.-B. Song, "Short-Term Load Forecasting Based on Deep Neural Networks Using LSTM Layer," *J. Elect. Eng., Technol.*, Vol. 15, pp. 1501–1509, Jul. 2020, doi: 10.1007/s42835-020-00424-7.

[23] M.A. Al Amin and M.A. Hoque, "Comparison of ARIMA and SVM for Short-Term Load Forecasting," *2019 9th Annu. Inf. Technol. Electromech. Eng., Microelectron. Conf. (IEMECON)*, 2019, pp. 205–210, doi: 10.1109/IEMECONX.2019.8877077.