Circuit: Jurnal Ilmiah Pendidikan Teknik Elektro
Volume 9 No. 2 March 2025 -August 2025
ISSN: 2549-3698; E-ISSN: 2549-3701
DOI: 10.22373/crc.v9i2.25549

Short-Term Electricity Load Forecasting Using Bayesian Regularization-Based Neural Network: A Case Study in Langsa City

Ahmad Fauzi[a], Tarmizi[a], Ramzi Adriman[a]

[a]Universitas Syiah Kuala, Indonesia

E-mail: bachtiar@mhs.unsyiah.ac.id

Submitted: 10-08-2024 Accepted: 29-08-2025 Published: 02-09-2025

Abstract

This study focuses on enhancing the accuracy of artificial neural network (ANN) methods in electricity load prediction for intelligent energy systems. Various optimization techniques, such as Bayesian regularization, have been introduced to improve model performance and generalization capability. A major challenge in ANN-based prediction models is overfitting, which occurs when the network topology fails to generalize input–output relationships, leading to poor prediction accuracy on unseen data. The research aims to develop an improved electricity load prediction model for Langsa City by applying a Bayesian regularization algorithm to minimize overfitting in the neural network topology. A quantitative experimental approach was used, which multiple ANN architectures with historical electricity load datasets. The Bayesian regularization algorithm optimized weight adjustments and minimized mean squared error during training. Results indicate that the proposed model effectively reduces overfitting and enhances predictive accuracy, achieving a Mean Absolute Percentage Error (MAPE) of 2.45%. These findings demonstrate that Bayesian regularization significantly enhances ANN reliability, stability, and forecasting capability for future intelligent energy management applications.

***Keywords**: Jaringan syaraf tiruan, regularisasi Bayessian, MAPE*

Abstrak

Penelitian ini berfokus pada peningkatan akurasi metode jaringan saraf tiruan (ANN) dalam prediksi beban listrik untuk sistem energi cerdas. Berbagai teknik optimasi, seperti regularisasi Bayesian, telah diperkenalkan untuk meningkatkan kinerja model dan kemampuan generalisasi. Tantangan utama dalam model prediksi berbasis ANN adalah overfitting, yang terjadi ketika topologi jaringan gagal menggeneralisasi hubungan input-output, yang menyebabkan akurasi prediksi yang buruk pada data yang tidak terlihat. Penelitian ini bertujuan untuk mengembangkan model prediksi beban listrik yang lebih baik untuk kota Langsa dengan menerapkan algoritma regularisasi Bayesian untuk meminimalkan overfitting pada topologi jaringan saraf tiruan. Pendekatan eksperimental kuantitatif digunakan, dengan Algoritma regularisasi Bayesian mengoptimalkan penyesuaian bobot dan meminimalkan kesalahan kuadrat rata-rata selama pelatihan. Hasil menunjukkan bahwa model yang diusulkan secara efektif mengurangi overfitting dan meningkatkan akurasi prediktif, mencapai Mean Absolute Percentage Error (MAPE) sebesar 2,45%. Hasil menunjukkan bahwa regularisasi Bayesian secara signifikan meningkatkan keandalan, stabilitas, dan kemampuan peramalan JST untuk aplikasi manajemen energi cerdas di masa mendatang.

Kata kunci: Jaringan syaraf tiruan, Bayessian regularization, MAPE

Introduction

In order for an electric power system to function, electrical load forecast is essential. This position's responsibility is to make sure that the capacity for projected electrical energy production matches consumer demand. Accurate electrical load forecasting is critical due to the high demand for precision in predicting power consumption. While the concept of load forecasting has been utilized in power grid systems for several decades, significant advancements in prediction methodologies have been achieved over time [1]. Despite these improvements, accurately anticipating electrical loads remains a complex and challenging task. This is due to the fact that complex and nonlinear factors have a significant impact on electrical energy usage.

The artificial neural network approach is one that is frequently created to create electrical load prediction models and has shown itself to be accurate [2]. In addition to load prediction, artificial neural networks are also employed to evaluate and allocate the optimal channel based on multiple parameters and sensor queue levels, demonstrating their versatility in handling complex decision-making and optimization problems in dynamic systems [2]. With its learning mechanism, the artificial neural network approach has the benefit of being able to find intricate correlations between variables [3]. Furthermore, approaches based on the linearity assumption are unable to handle data sets with non-linear features [4], which the artificial neural network approach excels at handling [5]. The artificial neural network approach has issues even if it has been shown to provide accurate prediction models. The condition of overfitting in the ensuing prediction model is one of the issues that emerges. When the prediction model is unable to comprehend the intended outcomes, it is said to be overfitting.

An instance of overfitting occurs when the artificial neural network method's network structure is not adaptable. The neural network structure in this scenario is defined by its ease of identifying patterns in training data, but its poor performance in identifying data that is not part of the training data [6]. Moreover, overfitting also happens when the prediction model's neural network topology is very intricate. This kind of performance is undoubtedly detrimental. The neural network structure generates output values with low precision when overfitting occurs, as neural networks are parameterized non-linear mathematical models that, while well suited for pattern classification and non-linear function approximation, can lose generalization ability under such conditions [7]. To mitigate the risk of overfitting in artificial neural network-based prediction models, specific tactics are required.

By employing an artificial neural network topology, the Bayessian regularization technique can lessen the likelihood of overfitting in a prediction model, according to his research [8]. In a technical sense, the neural network topology incorporates the Bayesian principle prior distribution in the Bayesian regularization process. As a result, during the model testing phase, the prediction model becomes more responsive to testing data and more adaptive to training data. The recurrent neural network (RNN) topology is linked to the Bayesian regularization technique in research [9], where the sequences representing time stamps or samplings of a continuous process collectively form a time series dataset that is utilized to train RNN architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) for pattern prediction [10].

It has been demonstrated that for predictive models with a recurrent neural network (RNN) topology, the Bayessian regularization approach offers the highest accuracy. The MAPE (Mean Absolute Percentage Error) figure of 1.4792% illustrates this precision. These findings demonstrate that the Bayessian regularization technique may prevent overfitting and generate extremely accurate predictive models. A short-term electrical load forecast model was developed in the city of Serang using the Bayessian regularization algorithm in research [11]. The Bayessian regularization algorithm has been demonstrated to generate extremely accurate predictive models while avoiding overfitting, according to simulation findings. This is demonstrated by the model's MAPE value being less than 10%. Basicly, the mean absolute percentage error (MAPE) was usually used as indices of error and accuracy, in general the smaller these values, the lower the error [12].

A short-term electrical load prediction model for Langsa City is developed in this study using a Bayesian regularization approach. This combines a multilayer feedforward network topology with the Bayesian regularization process. The Langsa City 24-hour power load, air temperature, humidity, and hourly variables make up the data model that was used to construct the model. At two distinct stages, the model's accuracy is assessed using the Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) tools, where the Mean Squared Error (MSE) represents the average squared difference between the observed values in a statistical study and the values predicted by the model [13].

During the model training simulation stage, the prediction model is evaluated using the MSE instrument, while during the testing simulation, the model's accuracy level is measured using the MAPE instrument. The Mean Absolute Percentage Error (MAPE) is a statistical measure used to determine how closely the predicted values correspond to the actual values, providing a clear indication of the model's predictive accuracy [14]. A short-term electricity load prediction model in Langsa City with a highly accurate interpretation is the first contribution that this research can offer. The second is demonstrating that the Bayesian regularization algorithm can effectively mitigate the risk of overfitting in the prediction model on the artificial neural network topology. This approach has become increasingly in computational power have enabled the practical implementation of Bayesian estimation techniques [15].

Method

All of the steps used in this research are shown in these below explanation.

a. Input data

The variables of time, temperature, air humidity, today's electrical load, and tomorrow's load make up the input data needed for this study. The neural network structure uses the variables of time, temperature, air humidity, and electrical load as input variables, and uses the variable of electrical load for tomorrow as the target variable. The period of collection for these data variables was January 1–31, 2024. While the variables of today's and tomorrow's loads were taken from the daily dispatcher reports of UP2D PLN Aceh, the temperature and air humidity variables were taken from the https://power.larc.nasa.gov/ page.

b. Normalisasi data

Data normalization is the next step after data collection. By altering the data attribute values in accordance with the requirements of the neural network topology algorithm, data normalization seeks to speed up the neural network topology learning process. The following equation 1 is a method for normalizing data [16].

$$X_{norm} = \frac{x_{data-}x_{min}}{x_{max-}x_{min}} \qquad \text{……….(1)}$$

Where X_norm is the normalized data value, x_data is the original data value, x_min is the minimum data value of the original data model and x_max is the maximum data value of the original data model. The data normalization stage is carried out using MATLAB R 2015a software.

c. Separation of testing and training data

The data must then be separated into two categories: test data and training data. Eighty percent of the data is used for training, while twenty percent is used for testing. The neural network topology training simulation procedure uses both types of data.

d. Neural Network Topology

A multilayer feedforward network is the neural network topology employed in this investigation. There are three layers in this network topology: input, hidden, and output. The input variables and target training data are used to create the input and output layers. Five, ten, fifteen, twenty, and twenty-five units make up the secret layer, which is chosen at random. This study developed a short-term electrical load prediction model using five different neural network topologies. One of the neural network topologies utilized to create the prediction model is depicted in Figure 1 below.

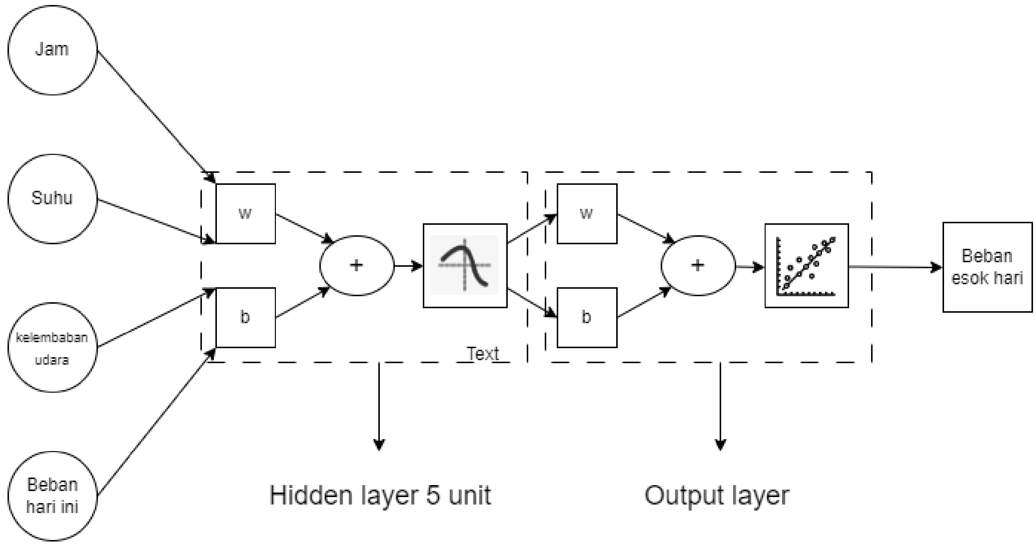

Figure 1. Neural Network Topology with 5 Hidden Layer Units

e. Set up and initialize the algorithm for Bayesian regularization.

Setting the neural network topology's training settings comes next once the neural network topology has been created. The neural network architecture training simulation's training parameters are detailed in Table 1 below.

Table 1. Neural Network Topology Training Parameters

No	Simulation Parameters	Description
1	Algoritma training	*Bayessia regularization* (trainrb)
2	Maximum epoch	500
3	Minimum goal error	1e-03
4	Learning rate	0,1
5	Accuracy	MSE

f. Training Topologi Jaringan Syaraf

Training the developed neural network architecture is the following step. At this point, the MSE value must achieve the designated goal error value, 1e-03, in order to be considered stopped. Equation 2 below represents MSE [17] .

$$\boldsymbol{MSE} = \sum_{i=1}^{n} \sqrt{\left(\frac{\boldsymbol{target\ score - output}}{\boldsymbol{total\ target}}\right)} \qquad \text{.......(2)}$$

The optimal network topology will be chosen and tested based on the trained network topology's least MSE value. MATLAB R2015a software is used for the training phase of neural network topology.

g. Testing of Prediction Models

Model testing comes next after the optimal network topology has been chosen as the prediction model. Finding out how adaptable the trained network architecture is to data outside of the training dataset is the goal of prediction model testing. In order to predict the electrical load value for February 2–8, 2024, this stage uses data from February 1, 2024, including the hour, temperature, humidity, and electrical load variables. The electrical load value for that time period is calculated using Equation 3. Data denormalization is the term for this phase [18].

$$X_{data} = X_{norm} \cdot (x_{max-} x_{min}) \qquad \text{.......(3)}$$

Where X_norm is the prediction model's output value, X_data is the electrical load's expected value, X_min is the input data's lowest value, and X_max is the input data's highest value. Based on the testing phases, the accuracy level of the electrical load prediction model is assessed using the MAPE (Mean Absolute Percentage Error) tool. The MAPE value produced by the electrical load forecast model is described in Equation 4 below [19], [20], and [17].

$$MAPE = \sum_{i=1}^{n} abs\left(\frac{nilai\ aktual - output\ model}{nilai\ aktual}\right) x\ 100\% \qquad \text{........ (4)}$$

The values that the MAPE instrument generates are described. The following is a description of the MAPE values [19]:

1. The prediction model is highly accurate if the MAPE value is less than 10%.
2. The prediction model is accurate if the MAPE value falls within the 10% to 20% range.
3. The prediction model is reasonable if the MAPE value falls between 20% and 50%.
4. The prediction model's accuracy is extremely low if the MAPE value is more than 50%.

Result and Discussion

The outcomes of the neural network topology training simulation, which creates the electrical load prediction model, are displayed in Table 2 below.

Table 2. Results of Neural Network Topology Training

Network Topology	Epoch	MSE	R Training	R testing
4-5-1	5	0,000998	0,939	0,948
4-10-1	6	0,000933	0,947	0,945
4-15-1	9	0,000986	0,941	0,950
4-20-1	12	0,000995	0,941	0,952
4-25-1	6	0.000950	0,947	0,930

Table 2 shows that all network topologies' MSE values were within the designated target error range. A network design consisting of four inputs, ten hidden layer units, and one output produced the low MSE value, which was 0.000933. Additionally, both the training and testing R coefficient values were excellent. The R coefficient values that were obtained were nearly one. The data variables that comprise the prediction model exhibit a strong association, according to the R coefficient values for both training and testing. This indicates that output values around the goal value can be produced by the trained network structure.

The neural network structure with four inputs, ten hidden layers, and one output yields the lowest MSE value, as shown in Table 2. The MSE curve generated by the neural network topology with four inputs, ten hidden layers, and one output is displayed in Figure 2 below.

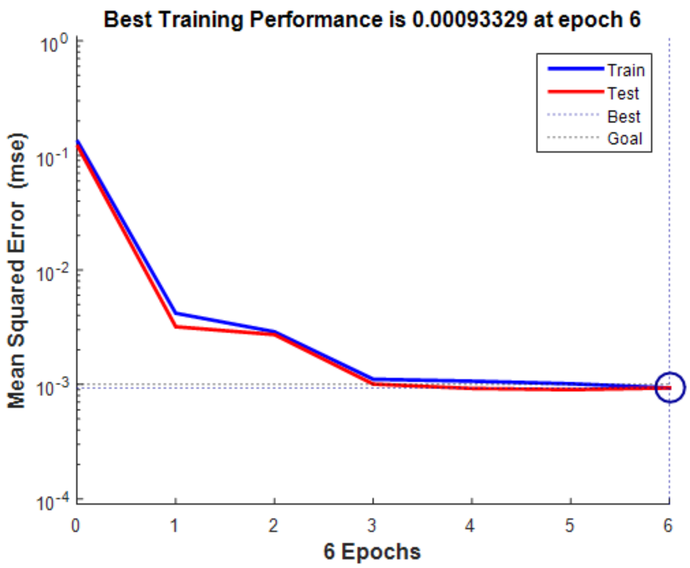

Figure 2. Neural Network Structure MSE Curve with Four Inputs, Ten Hidden Layers, and One Output

Figure 2 shows that both the red testing curve and the blue training curve decrease toward the designated goal error value. This suggests that both were able to avoid the risk of overfitting, which could have an impact on the network structure. When the testing curve travels up or away from the goal error value while the training curve falls down, becoming closer to the target error value, this is known as overfitting. The network topology needed a relatively short computation time to generate the optimal MSE value.

This suggests that the neural network topology's calculation time during training simulations was accelerated by the data normalization technique.

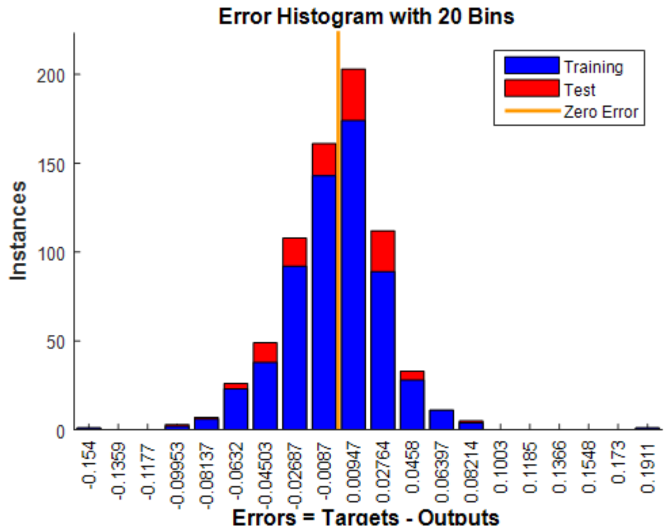

Figure 3. Neural Network Error Histogram

A histogram of error values produced by a network topology consisting of four inputs, ten hidden layers, and one output is displayed in Figure 3 above. The calculated error values in Figure 4 fall between -0.154 to 0.1911. The model's output value is bigger than the target value when the error value is negative, and it is smaller than the target value when the error value is positive. Additionally, a normal distribution may be seen in the resulting histogram. This is distinguished by a bell-shaped graph that is symmetrical, sloping at the edges and peaking in the middle. The network topology produces a normal distribution, which shows that the output numbers are extremely accurate. Testing the network topology with four inputs, ten hidden layers, and one output is the next step.

Table 3. MAPE Values From Network Topology Testing Results

Testing Date	MAPE(%)	High Error (%)	Small Error (%)
2 Feb	8,46	12,68	3,95
3 Feb	7,76	12,60	0,83
4 Feb	8,16	13,74	0,07
5 Feb	5,28	13,89	0,54
6 Feb	2,45	9,13	0,46
7 Feb	8,02	23,49	2,70
8 Feb	6,11	10,08	0,14

According to Table 3, the prediction model produced the lowest MAPE value for February 6, 2024, at 2.45%. The network structure of four inputs, ten hidden layers, and one output that made up the prediction model yielded extremely accurate results, based on the interpretation of the MAPE value. With a score of 23.49%, the prediction model for February 7 produced the largest inaccuracy in terms of the final error value. On the other hand, the forecast model for February 4 produced the least error value, 0.07%.

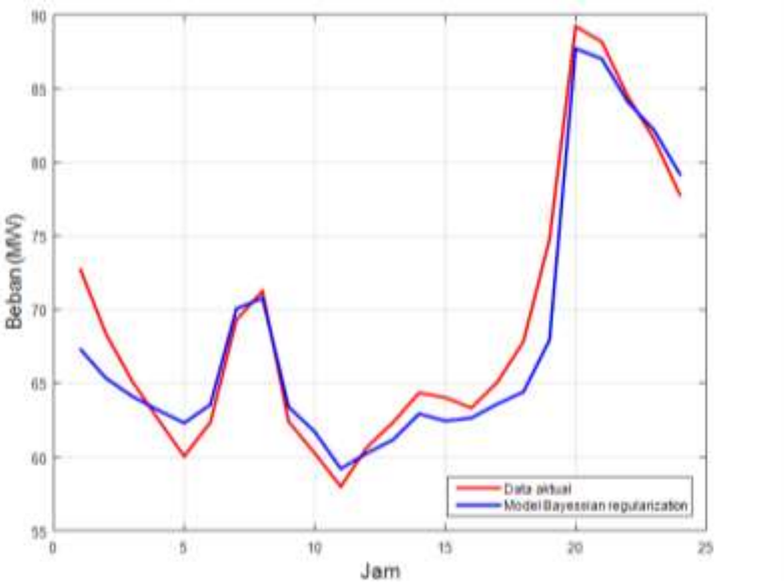

Figure 4. Predicted versus Actual Output on February 6

For the test data on February 6, 2024, Figure 4 compares the output value of the prediction model with the actual data. At 6:00 PM WIB, Figure 5 demonstrates a notable disparity between the two. At that moment, the actual data value was 67.95 MW, whereas the forecast model's output value was 74.78 MW. For both, the error rate is 9.13%. According to these findings, the amount of electricity used at 6:00 PM WIB is rather variable and not very predictable. Furthermore, there is no discernible difference between the two around 9:00 PM WIB. The actual data load value at that moment was 84.09 MW, whereas the prediction model's output value was 84.48 MW. For both, the error percentage is 0.46%. This suggests that the amount of electricity used during that period is highly consistent and reasonably predictable.

Conclusion

The accuracy of prediction models constructed with artificial neural networks may be impacted by the possibility of overfitting. When a model is overfit, it is unable to interpret the intended output value. The Bayesian regularization technique integrated into the network topology may provide extremely accurate prediction models, according to simulation findings for both training the network topology and evaluating the prediction models. Additionally, the Bayesian approach effectively guards against possible overfitting of the network architecture. As a result, the Bayessian regularization process is ideal for creating models that estimate electrical load.

References

[1] A. Zabin, Rifat. Haque, Khandaker Foysal. Abdelgawad, "PredXGBR: A Machine Learning Framework for Short-Term Electrical Load Prediction," *MDPI*, vol. 13, no. 27, 2024.

[2] V. R. Swarna, Sreechandra. Kolluru, "Active Channel Selection by Sensors using Artificial Neural Networks," *Forex Press*, vol. 12, no. 4, pp. 1466–1473, 2024.

[3] J. S, "Short Term Load Forecasting using Artificial Neural Network in Indonesia"," *Ilk. J. Ilm.*, vol. 15, no. 1, 2017.

[4] C. Nataraja, M. B. Gorawar, G. N. Shilpa, and S. Harsha.J, "Short Term Load Forecasting using Time Series Analysis: A Case Study for Karnataka, India," *Int.*

J. Eng. Sci. Innov. Technol. (IJESIT, vol. 1, no. 2, pp. 45–53, 2023.
[5] M. O. Okelola, S. O. Ayanlade, and E. I. Ogunwole, “AN ARTIFICIAL NEURAL NETWORK APPROACH TO SHORT-TERM LOAD FORECASTING FOR NIGERIAN ELECTRICAL POWER NETWORK,” *Int. J. Innov. Eng. Res. Technol.*, vol. 8, no. 08, pp. 168–177, 2021, doi: 10.17605/OSF.IO/539DV.
[6] L. Hernández, “Artificial neural network for short-term load forecasting in distribution systems,” *Energies (Basel*, vol. 7, no. 3, pp. 1576–1598, 2014, doi: 10.3390/en7031576.
[7] B. K. Ø. Gundersen, A. O. Kluken, O. R. Myhr, J. E. Jones, V. Rhoades, J. Day, J. C. Jones, *The Use of an Integrated Multiple Neural Network Structure for Simultaneous Prediction of Weld Shape, Mechanical Properties, and Distortion in 6063-T6 and 6082-T6 Aluminium Assemblies*. Taylor & Francis Group Logo, 2002.
[8] M. A. Yahya, S. P. Hadi, and L. M. Putranto, “Short-Term Electric Load Forecasting Using Recurrent Neural Network (Study Case of Load Forecasting in Central Java and Special Region of Yogyakarta,” in *2018 4th International Conference on Science and Technology (ICST*, Yogyakarta, Indonesia, 2018, pp. 1–6,. doi: 10.1109/ICSTC.2018.8528651.
[9] B. A, M. M, S. S, and V. A, *Probabilistic electric load forecasting through Bayesian Mixture Density Networks”*. Italy: Institute of Inteligent Industrial Technologies and Systems for Advanced Manufacturing, 2021.
[10] Ü. Yatkin, Muhammed Adil. Kõrgesaar, Mihkel. Işlak, “A Topological Approach to Enhancing Consistency in Machine Learning via Recurrent Neural Networks,” *Appl. Sci.*, vol. 15, no. 2, 2025.
[11] H. Singh.S and BazaazMA, “Short Term Load Forecasting Using Artificial Neural Network,” in *2017 Fourth International Conference on Image Information Processing (ICIIP*, 2017.
[12] Y. Liu, Jingtao. Zhai, Zhihong, Zhang and Y. Wang, Yixian, Ding, “Comparison of Energy Consumption Prediction Models for Air Conditioning at Different Time Scales for Large Public Buildings,” *J. Build. Eng.*, vol. 96, no. 1, 2024.
[13] K. Stewart, “mean squared error,” *Britannica*, 2025.
[14] Coralogix Team, “A Comprehensive Guide to Mean Absolute Percentage Error (MAPE),” *Coralogix*, 2023.
[15] G. Sariev, Eduard. Guido, “Bayesian Regularized Artificial Neural Networks for the Estimation of the Probability of Default,” *Quant. Financ.*, vol. 20, 2020.
[16] I. Samuel, T. Ojewola, A. Awelewa, and P. Amaize, “Short-Term Load Forecasting Using The Time Series And Artificial Neural Network Methods,” *IOSR J. Electr. Electron. Eng. Ver*, vol. 11, no. 1, pp. 2278–1676, 2014, doi: 10.9790/1676-11137281.
[17] A. A. M. Hartono and S. M, “Comparison methods of short term electrical load forecasting”,” in *The 1st International Conference on Industrial, Electrical and Electronics (ICIEE 2018*, 2018.
[18] H. Patel, “Application of Artificial Neural Network for Short Term Load Forecasting,” *Int. J. Adv. Eng. Res. Dev.*, vol. 2, no. 04, 2015, doi: 10.21090/ijaerd.020439.
[19] R. G.T, S. J.G, F. N, C. Mariani.V, and S. Coelho.L, “Bayesian Optimized Echo State Network Applied to Short Term Load Forecasting”,” *Energies*, 2020, doi: doi:
[20] K. Chapagain.K, “Short term Electricity Load Forecasting Model and Bayesian Estimation for Thailand Data”,” *ACPEE*, 2016, doi: 10.1051/matecconf/201.