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Research Article

Short-Term Load Forecasting using Artificial Neural Network in Indonesia

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Abstract

Short-term Load Forecast (STLF) is a load forecasting that is very important to study because it determines the operating pattern of the electrical system. Forecasting errors, both positive and negative, result in considerable losses because operating costs increase and ultimately lead to waste. STLF research in Indonesia, especially the State Electricity Company (PLN Sulselrabar), has yet to be widely used. Methods mainly used are manual and conventional methods because they are considered adequate. In addition, Indonesia's geographical conditions are extensive and diverse, and the electricity system is complex. As a result, the factors affecting each country's electricity demand are different, so unique forecasting methods are needed. Artificial Neural Network (ANN) is one of the Artificial Intelligent (AI) methods widely used for STLF because it can model complex and non-linear relationships from networks. This paper aims to build an STLF forecasting model that is suitable for Indonesia's geographical conditions using several ANN models tested. Based on several ANN forecasting models, the test results obtained the best model is Model-6 with ANN architecture (9-20-1). This model has one hidden layer, 20 neurons in the hidden layer, a sigmoid logistic activation function (binary sigmoid), and a linear function. Forecasting performance values obtained mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) of 430.48 MW2, 15.07 MW, and 2.81%, respectively.

Keywords: Short-Term Load Forecast; Artificial Neural Network; Forecasting Performance; State Electricity Company.

Introduction

In the management and operation of electrical systems, electrical load forecasting becomes a compelling and essential process. Electrical load forecasting helps make operating decisions, including generating capacity, reliability analysis, and maintenance plans [1]. Forecasting positive or negative inaccuracies can result in significant losses due to increased operating costs [2]. Adding an average of 1% forecasting error daily can result in wasted costs [3]. Accurate electrical load forecasting can increase energy utilization rates, secure power system operation, and save costs [4]. Therefore, the accuracy of electrical load forecasting becomes essential to improve.

Three electrical load forecasting categories: are short-term, medium-term, and long-term [5]. Based on these three categories, short-term load forecasting excels in optimizing unit commitments, turning backup controls, turning thermal units on and off, and playing a role in interconnected systems such as buying and selling electricity [6]. Short-term load forecasting (STLF) is imperative to study because it can determine the operating pattern of the electrical system [7]. Based on the literature study, STLF is done by making modeling. In recent years researchers have developed STLF models such as time series models [8], artificial intelligence models [9], and hybrid models [10], [11]. Time series models are effective in dealing with predictions of linear functions but not for non-linear functions. Handling non-linear predictions can be overcome by using artificial intelligence models [4].

Artificial neural network (ANN) [12], [13], support vector machine (SVM) [14], bagged regression tree [15], and random forest [16] are artificial intelligence models that are usually used. In practice, forecasting systems with ANN have attracted attention and are well received. ANN is widely applied because it has excellent forecasting ability. Also, it can model complex and non-linear relationships of the network using training daily load history data [17].

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With this capability, this paper uses the ANN model.

Researchers have conducted several STLF forecasting studies using the ANN model [18–30]. Applying the model used in these studies may not necessarily apply in Indonesia. It is caused by different geographical conditions, seasons, and especially the completeness of weather data. Therefore, it is necessary to find a model that can represent the area of the electrical system. One of the causes of disruption of electricity supply services to customers is forecasting errors. These errors are generally caused by factors that have not been predicted previously, such as the use of electrical equipment, the influence of weather on a location [31], seasonal data, and differences in electricity consumption between weekdays, holidays, and commemorations of religious holidays (Christmas, Eid, Vesak, Nyepi, and Chinese New Year).

STLF studies using the ANN model have been conducted in China [4], Iran [5], Nigeria [12], Macedonia [32], and the USA [33]. However, STLF studies have yet to be widely carried out in Indonesia. Indonesia's geographical conditions are wide and varied, and the electricity system is complex. Specific STLF studies can be carried out according to the conditions in each region. In Indonesia, the company that handles electricity is the State Electricity Company. The State Electricity Company still uses manual and conventional methods because they are considered adequate. The developments currently forecasting the electrical load in Indonesia are growing at a dynamic and high growth rate. Therefore, a suitable ANN model is needed for STLF in the operation of the electrical system.

In Indonesia, STLF studies have been carried out on the electricity systems in Kalimantan [34], Java-Bali [35], [36], South Sulawesi, Southeast Sulawesi, and West Sulawesi [37], and Papua-Maluku [38]. In particular, STLF studies on the electricity system in South Sulawesi, Southeast Sulawesi, and West Sulawesi [37] have investigated the method of obtaining forecast input data, including weather data from weather observation locations representing load centers in the coverage area of the electricity system. In this paper, we present the continuation of this study. Thus, this paper aims to use forecasting input data to build an STLF forecasting model suitable for Indonesia's geographical conditions based on trials of several ANN models. It is hoped that this STLF model can provide a reference for the best ANN model according to the condition of the location of the electrical system and contribute to STLF planning in Indonesia.

Method

A. Research Data

The data used are: (a) Data logger, which is the business data in the form of load realization data on the PLN Region of South Sulawesi, Southeast Sulawesi, and West Sulawesi, Indonesia electricity system. (b) Data on the load plan for the PLN Region of South Sulawesi, Southeast Sulawesi, and West Sulawesi, Indonesia, electricity system. (c) Weather data at the Weather Observation Station at Sultan Hasanuddin International Airport, Makassar. (d) PLN Region of South Sulawesi, Southeast Sulawesi, and West Sulawesi, Indonesia customer data. (e) Base map of Indonesia, provincial boundaries in Indonesia, local government boundaries in South Sulawesi Province, and (f) a List of Indonesian national holidays.

The data are grouped into 4 (four) groups, including business, weather, customer, and holiday trip data. Business and customer data are taken at PLN (Persero) Region of South Sulawesi, Southeast Sulawesi, and West Sulawesi, Indonesia. Customer data is obtained from the Information Technology (IT) Division related to customer identification and geospatial data. The critical concession data, including the planning data and the realization of the load, are obtained from the Area of Arrangement and Distribution of Loads (AP2B). The weather data was obtained from the Meteorology, Climatology, and Geophysics Agency (BMKG) of Makassar Great Hall and the Weather spark website. Data on holidays is obtained from the list of official holidays in Indonesia from government institutions (Ministry of Religion, Ministry of Social Affairs, and other government agencies).

B. Variable

Calculate forecasting errors, including MSE (Mean Square Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error), to determine forecasting performance. The variables needed are input variables, target variables, and output variables. Forecasting input variables are a predictor matrix containing weather data for forecasting targets and seasonal data. The target variable is the load data used in the ANN training process to build a forecasting model. The output variable is the load data from the proposed model's forecasting results. In addition, for forecasting, other variables are also used for the clustering process and weighting of customer data.

C. Model Prototype Design and Architecture

Forecasting models, in principle, use weather variables representing weather conditions in the electrical system area as forecasting input. The proposal begins by dividing the electrical system area into several clusters, which is especially effective for sizeable electrical system areas. Due to the large area, there will likely be non-uniform weather conditions in all areas of the electrical system. It affects the tendency of customer behavior in consuming different electrical energy. This model is suitable to be implemented in Indonesia, where the electrical system generally has a wide coverage area. The specifics of the model are the application of the approach method to obtain a set of training data or forecasting data for the forecasting model in each cluster and the method for finding the cluster's center by weighting customer data [37].

The input to the model at the training stage is seasonal data consisting of an hour of the day, day of the week, and holiday. Hour-of-day data shows the order of time series data in one day (range of values 1-48). Day-of-week data shows the order of days of time series data in one week (range of values 1-7). The holiday data indicates whether the time data is a holiday (range of values 0 and 1). The historical load data input is the historical load time series data in each cluster with 8 clusters. The three historical load data are the average load in the last 24 hours (LH1) in megawatts (MW), the load in the previous 24 hours (LH2) (MW), and the load in the previous week or 168 hours (LH3) (MW). The last input for the training phase is weather data, which is historical weather data for each cluster. Three weather parameters, including temperature (T) with unit value (ºC), dew point (DP) (ºC), and humidity (H) (range value 0-1).

D. Artificial Neural Network (ANN) Training

Cluster formation has been carried out in a previous study [37]. Training using the ANN method on the model is carried out after all clusters are formed. The training is carried out individually for each cluster, meaning each has its forecasting model. The ANN architecture for the proposed STLF model is shown in Figure 1. Tests on several ANN parameters were carried out to get the best model. There is no theoretical approach to calculating the exact number of neurons in the hidden layer [1]. Hence, the selection of the ANN model was carried out based on trials [1]. In addition, the number of nodes in the hidden layer, starting from the minimum number of layers (1 layer) and then increasing the number gradually (2 layers) and (3 layers). Likewise, the activation function used in the hidden layer is a binary or logistic sigmoid and hyperbolic tangent function. Initialization of the initial weight is a random number, and the performance function used is MSE. In contrast, the activation function used in the outer layer is linear [2]. Some of the tested ANN parameters are shown in **Table 1**.

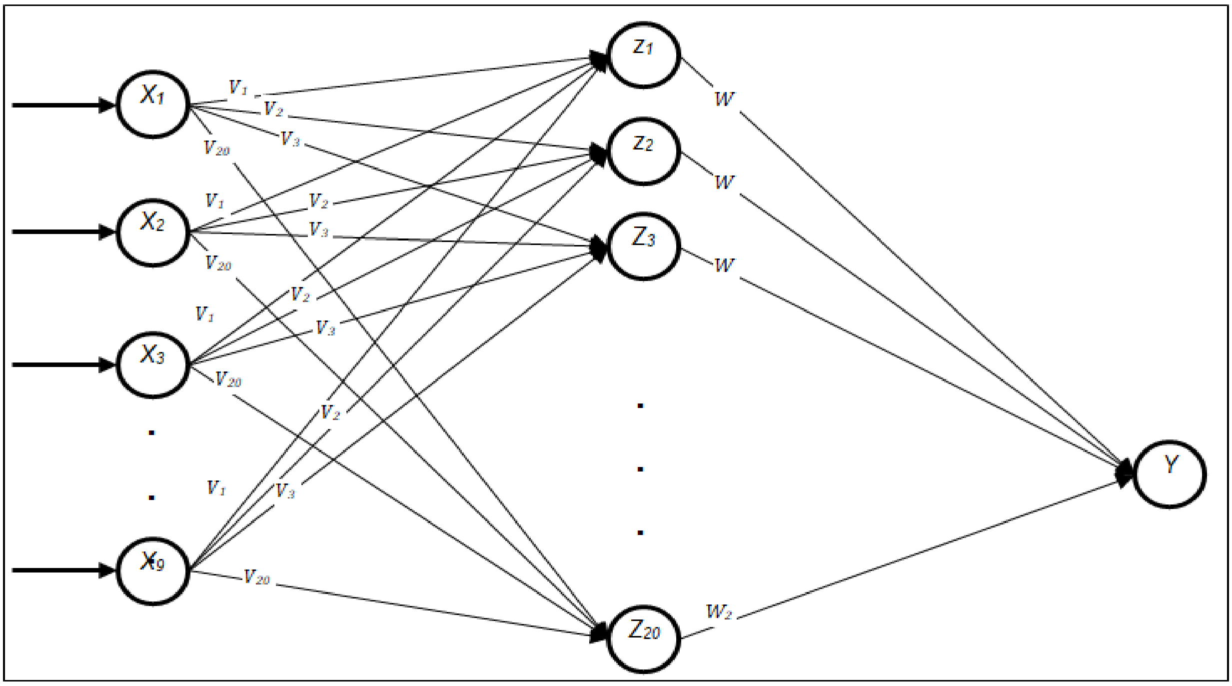

Figure 1. ANN architecture X1, X2, X3, … X9 are input layers (9 inputs), Z1, Z2, Z3, … Z20 are hidden layers (20 neurons), Y are outer layers, V and W are the weight on the layer).

Table 1. Parameters of ANN.

Model	Many hidden layers	Many neurons in hidden layer	Activation function	
			Hidden layer	*Outer layer*
Model-1	1	20	Hyperbolic tangent	Linear
Model-2	2	20	Hyperbolic tangent	Linear
Model-3	3	20	Hyperbolic tangent	Linear
Model-4	1	7	Hyperbolic tangent	Linear
Model-5	1	12	Hyperbolic tangent	Linear

Model	Many hidden layers	Many neurons in hidden layer	Activation function	
			Hidden layer	***Outer layer***
Model-6	1	20	Logistic sigmoid	Linear
Model-7	2	20	Logistic sigmoid	Linear

The forecasting input data from previous publications [37] are used to build predictor matrices and construct the STLF model using ANN to obtain the best performance. The training iteration process must converge, and the training process will be stopped if the following conditions occur: (1) the specified performance has been achieved, (2) exceeds the specified max value, (3) validation performance increases beyond the specified max_fail value set (calculated from the last time a validation performance decreased).

Findings and Discussion

Forecast input data obtained in previous studies, such as weather forecast data on the day to be forecasted, historical load data for the previous day, and historical load data for the last seven days [37], are used to produce a predictor matrix. The STLF model development phase includes the ANN training process and testing using historical data. The period for sharing the recorded data is five years for the training data set and one year for the test data set.

As training input, a training data set is used with time series data for six years, where the time series interval is per half hour or equal to 105,216-time series data, and produces a predictor matrix measuring (105,216 x 9). This training data is intended for good results, but data sharing must be emphasized, so the network gets sufficient training data [4]. The problem of overtraining (excessive training data) will cause the network to memorize the input data rather than generalize it. The insufficient data for the training process will cause the network to be unable to learn the data scatter well. On the other hand, too much data for the training process will slow down the convergence process.

The training target is the recorded load variable in the time series data equal to or equal to 105,216 targets. In the early stages of training, initial weights are assigned randomly, and a weight matrix is assigned to the input network in a matrix (20 x 11). The proposed model consists of 8 clusters, each with its forecasting model. The weights and biases are updated during the training process according to the Levenberg-Marquardt algorithm. The activation function in the hidden layer is a sigmoid logistic function, while the linear function is used in the outer layer. The average training process involves epochs ranging from 90-380 epochs. The training performance is finally achieved at the end of the training process. It is measured using the Mean Squared Error (MSE) performance function. The performance value during the training process for cluster-1 is shown in **Figure 2**.

Based on the training process, it can be concluded that the concept of load forecasting in the electrical system is dynamic, so the forecasting model must also be dynamic [12]. Training needs to be reworked to get a better-performing forecasting model [13]. Historical data that grows daily, with customer growth and energy demand growth, the pattern of seasonal data will also change. The need for training is conditional and can be observed daily through indications of decreasing forecasting performance.

Testing the short-term load forecasting model is believed to provide better forecasting performance and has significant benefits. In this paper, the forecasting performance values of several models that have been tested are shown in **Table 2**. The electrical load forecasting accuracy level is reviewed based on MSE, MAPE, and MAE. The smaller the MSE, MAPE, and MAE values, the better the forecasting accuracy [4]. **Table 2** shows the lowest level of forecasting accuracy in model-6, where the MSE value is 430.85 MW2, MAE 15.07 MW, and MAPE 2.81%.

In addition to weather and customer factors, factors affecting forecasting performance are the parameters that build the ANN model. These parameters are the pattern of the series of neurons in the network (network architecture), the determination of weights in the training process, and the function to process input to the next layer [37]. The results of the forecasting trials are plotted in graphical form and illustrated in **Figure 3**.

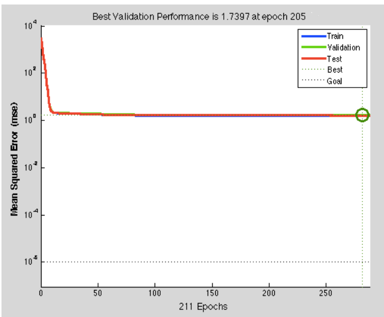

Figure 2. Performance values during the training process.

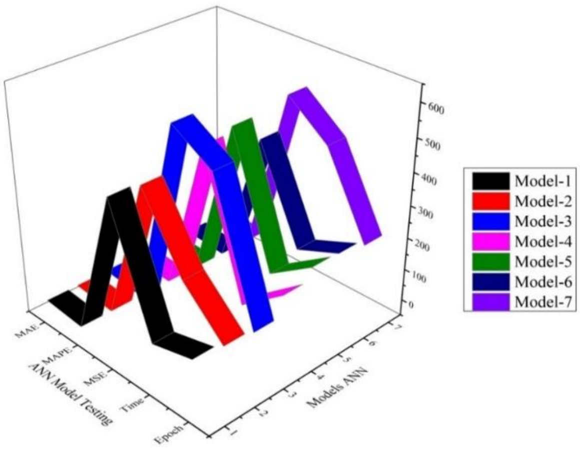

Figure 3. Graph of STLF test results on several ANN models.

Table 2. Forecasting performance.

Model	MSE (MW2)	MAE (MW)	MAPE (%)
Model-1	463.27	15.63	2.91
Model-2	454.31	15.65	2.91
Model-3	587.79	17.36	3.18
Model-4	488.4	16.2	3.02
Model-5	505.97	16.46	3.07
Model-6	430.85	15.07	2.81
Model-7	526.7	16.83	3.1

Figure 3 shows the five test results used as the basis for obtaining the best ANN model. The five quantities are the number of iterations in training (the number of epochs), the length of the training time (in minutes), and the value of forecasting performance, including MSE, MAPE, and MAE. The five experimental quantities use different units. The magnitude of the value of the test results is shown on the same vertical axis, so the differences in some parameters are not visible. The five experimental results are plotted separately in a histogram, as shown in **Figures 4** to **8**.

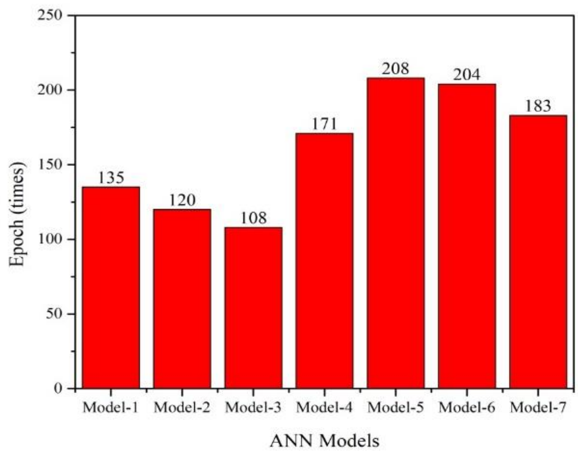

Figure 4. Graph of the number of epochs in several ANN models.

Figure 4 shows the number of epochs in several ANN models. The least number of epochs is in Model-3 with the ANN architecture model (9-20-20-20-1), which is 108. Meanwhile, Model-5 has as many as 208 epochs with the ANN architecture model (9-12-1). Both models use the same transfer function, including the hyperbolic tangent. The results show that the number of hidden layers and neurons in the hidden layer does not affect the number of epochs in training.

The length of the training process (time) is shown in **Figure 5**. Model-3 with the ANN architecture model (9-20-20-20-1) requires the most comprehensive training process, which is 510.52 minutes. Meanwhile, Model-4 requires the fastest training process time is 68.02 minutes, with the ANN architecture model (9-7-1). Model-3 and Model-4 also use the same transfer function, including the hyperbolic tangent function. In this case, the number of hidden layers affects the length of the training process. The more hidden layers, the longer the training process will be. Likewise, the number of neurons in the hidden layer affects the length of the training process.

The forecasting performance of MSE, MAPE, and MAE is shown in **Figure 6**, **Figure 7**, and **Figure 8**. It appears that the trend is the same in each ANN model. It means that for all MSE, MAPE, and MAE performance values, the best result is Model-6 with the ANN architecture model (9-20-1). Meanwhile, the worst outcome is Model-3 with the ANN architecture model (9-20-20-20-1).

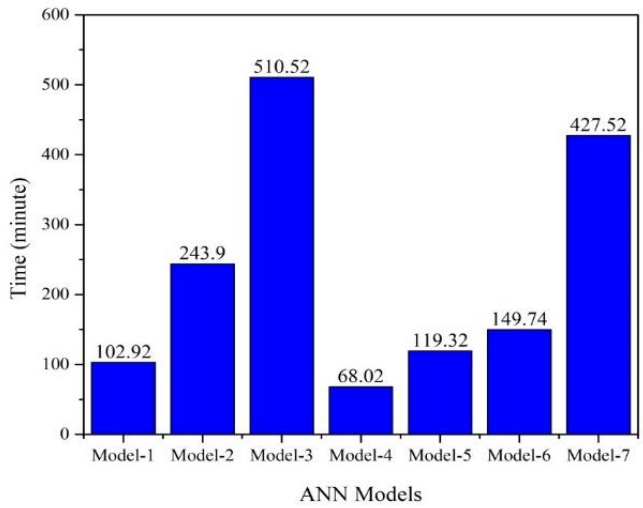

Figure 5. Graph of training time on several ANN models.

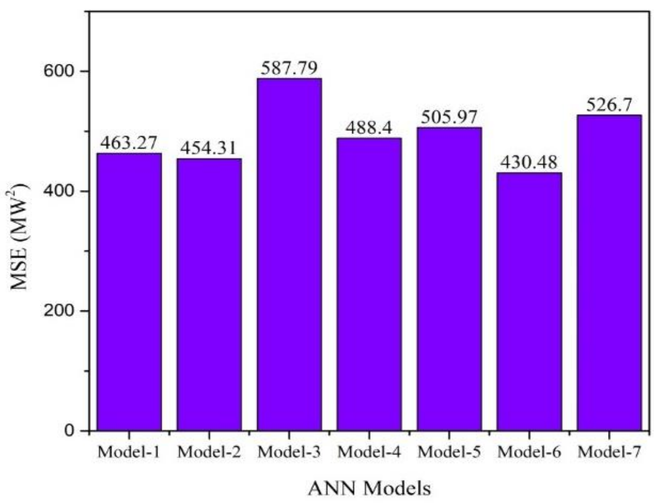

Figure 6. Graph of MSE values in several ANN models.

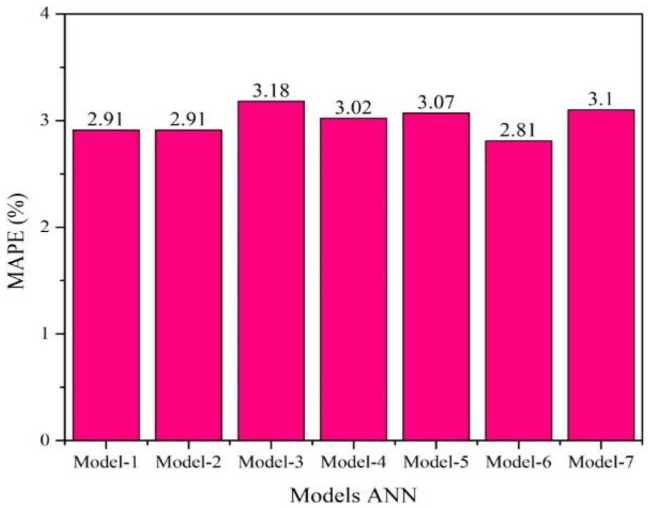

Figure 7. Graph of MAPE values in several ANN models.

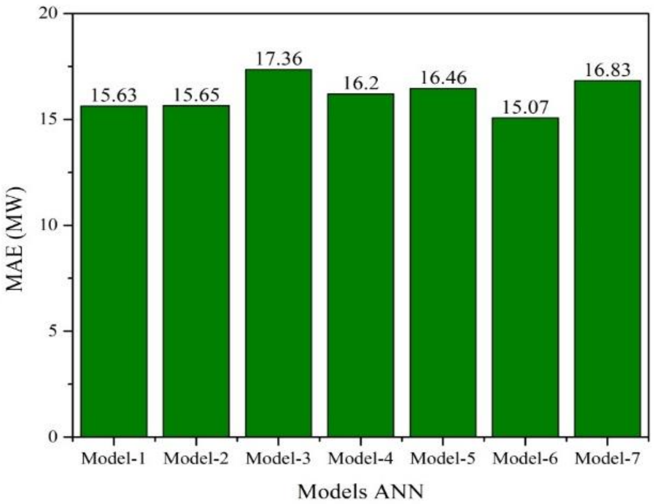

Figure 8. Graph of MAE values in several ANN models.

Based on the activation function used, it describes that the activation function in this study has little effect on the results of forecasting performance. The proof is illustrated by comparing the results of the forecasting performance of Model-1 and Model-6, which have the same ANN architecture (9-20-1). The difference between these models is in the activation function. The activation function used in Model-1 is the hyperbolic tangent, while in Model-6, the activation function is logistic sigmoid. The test results of the forecasting model prove that Model-6 has slightly better forecasting performance than Model-1.

The selected model with better forecasting performance for the South Sulawesi, Southeast Sulawesi, and West Sulawesi area, Indonesia, is Model-6 with the ANN architecture model (9-20-1). The parameters used in Model-6 are having one hidden layer, 20 neurons in the hidden layer, and the activation function used is a logistic sigmoid and linear function. Sigmoid logistics is a transfer function from the input layer to the hidden layer, while the linear function is a function from the hidden layer to the outer layer. Considerations for selecting the ANN model based on the best performance value from the test results using a test data set [4, 13]. Although the number of iterations during the training process is not the best, the training time is relatively short and acceptable. Furthermore, it is not an obstacle for computing technology on hardware in today's era. Focus on forecasting performance is prioritized, considering the potential for efficiency to finance electricity system operations that can be achieved.

Conclusion

STLF using weather and seasonal data through the proposed method improves forecasting performance. The proposed method can present the value of weather data that represents the electrical system and is used as input for the forecasting model, which is very suitable to be applied in Indonesia with an extensive electrical system and fluctuating weather conditions. The proposed model produces an absolute average of forecasting errors of 15.07 MW (represented by the value of MAE = 15.07 MW), an average square of forecasting error of 430.48 MW2 (represented by the value of MSE = 430.48 MW2), and the absolute mean percentage of forecasting errors is 2.81% (represented by the MAPE value = 2.81%). In the PLN electricity system in South Sulawesi, Southeast Sulawesi, and West Sulawesi, the best ANN model is a model with ANN architecture (9-20-1) using activation functions, including sigmoid logistics and linear functions. The method used can be implemented to large electrical systems with fluctuating and very diverse weather conditions. Thus, this provides an opportunity to improve the operational efficiency of the electrical system and respond to future challenges to trends in utility companies.

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References

[1] S. Fan and L. Chen, "Short-term load forecasting based on an adaptive hybrid method," *IEEE Transactions on Power Systems*, vol. 21, no. 1, pp. 392–401, 2006.

[2] S. K. Sheikh and M. G. Unde, "S -t l f ann t," *International Journal of Engineering Sciences & Emerging Technologies*, vol. 1, no. 2, pp. 97–107, 2012.

[3] H. K. Alfares and M. Nazeeruddin, "Electric load forecasting: Literature survey and classification of methods," *Int J Syst Sci*, vol. 33, no. 1, pp. 23–34, 2002, doi: 10.1080/00207720110067421.

[4] J. Sun, H. Dong, Y. Gao, Y. Fang, and Y. Kong, "The Short-Term Load Forecasting Using an Artificial Neural Network Approach with Periodic and Nonperiodic Factors: A Case Study of Tai'an, Shandong Province, China," *Comput Intell Neurosci*, vol. 2021, 2021, doi: 10.1155/2021/1502932.

[5] Z. Shafiei Chafi and H. Afrakhte, "Short-Term Load Forecasting using Neural Network and Particle Swarm Optimization (PSO) Algorithm," *Math Probl Eng*, vol. 2021, 2021, doi: 10.1155/2021/5598267.

[6] H. M. Al-Hamadi and S. A. Soliman, "Short-term electric load forecasting based on Kalman filtering algorithm with moving window weather and load model," *Electric Power Systems Research*, vol. 68, no. 1, pp. 47–59, 2004, doi: 10.1016/S0378-7796(03)00150-0.

[7] Y. Shen, Y. Ma, S. Deng, C.-J. Huang, and P.-H. Kuo, "An ensemble model based on deep learning and data preprocessing for short-term electrical load forecasting," *Sustainability*, vol. 13, no. 4, p. 1694, 2021.

[8] 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," *International Journal of Engineering Science and Innovative Technology (IJESIT)*, vol. 1, no. 2, pp. 45–53, 2012.

[9] M. Buhari and S. S. Adamu, "Short-term load forecasting using artificial neural network," *Lecture Notes in Engineering and Computer Science*, vol. 2195, no. March, pp. 83–88, 2012, doi: 10.1109/icit.2000.854220.

[10] A. K. Fard and M.-R. Akbari-Zadeh, "A hybrid method based on wavelet, ANN and ARIMA model for short-term load forecasting," *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 26, no. 2, pp. 167–182, 2014.

[11] J. Zhang, Y.-M. Wei, D. Li, Z. Tan, and J. Zhou, "Short term electricity load forecasting using a hybrid model," *Energy*, vol. 158, pp. 774–781, 2018.

[12] M. O. Okelola and S. Ayanlade, "An Artificial Neural Network Approach to Short-Term Load An Artificial Neural Network Approach to Short-Term Load Forecasting For Nigerian Electrical Power Network," no. April 2022, 2021, doi: 10.17605/OSF.IO/539DV.

[13] A. I. Arvanitidis, D. Bargiotas, A. Daskalopulu, V. M. Laitsos, and L. H. Tsoukalas, "Enhanced short-term load forecasting using artificial neural networks," *Energies (Basel)*, vol. 14, no. 22, Nov. 2021, doi: 10.3390/en14227788.

[14] A. Yang, W. Li, and X. Yang, “Short-term electricity load forecasting based on feature selection and Least Squares Support Vector Machines,” *Knowl Based Syst*, vol. 163, pp. 159–173, 2019.

[15] H. Dong, Y. Gao, Y. Fang, M. Liu, and Y. Kong, “The short-term load forecasting for special days based on bagged regression trees in qingdao, China,” *Comput Intell Neurosci*, vol. 2021, 2021.

[16] G. Dudek, “Short-term load forecasting using random forests,” in *Intelligent Systems’ 2014*, Springer, 2015, pp. 821–828.

[17] M. N. JYOTHI, V. DINAKAR, and N. S. S. R. TEJA, “Narx Based Short Term Wind Power Forecasting Model,” *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 4, no. 4, p. 129, 2015, doi: 10.11591/ijai.v4.i4.pp129-138.

[18] R. v Kanth and G. v Marutheswar, “Distribution System Short-TermLoad & Frequency Forecasting (STLFF) for OptimalUI C harges : ANeural-Wavelet based Approach,” *International Journal of Application or Innovation in Engineering & Management (IJAIEM)*, vol. 2, no. 7, pp. 142–147, 2013.

[19] S. Annamareddi, S. Gopinathan, and B. Dora, “A simple hybrid model for short-term load forecasting,” *Journal of Engineering (United States)*, vol. 2013, 2013, doi: 10.1155/2013/760860.

[20] K. S. Rawat and G. H. Massiha, “Hardware Implementation of FIR Neural Network for Applications in Time Series Data Prediction,” *TELKOMNIKA Indonesian Journal of Electrical Engineering*, vol. 14, no. 1, pp. 130–139, 2015, doi: 10.11591/telkomnika.v14i1.7272.

[21] A. Baliyan, K. Gaurav, and S. Kumar Mishra, “A review of short term load forecasting using artificial neural network models,” in *Procedia Computer Science*, 2015, vol. 48, no. C, pp. 121–125. doi: 10.1016/j.procs.2015.04.160.

[22] S. A. Ilić, S. M. Vukmirović, A. M. Erdeljan, and F. J. Kulić, “Hybrid artificial neural network system for short-term load forecasting,” *Thermal Science*, vol. 16, no. SUPPL. 1, 2012, doi: 10.2298/TSCI120130073I.

[23] L. Hernandez, C. Baladrón, J. M. Aguiar, B. Carro, A. J. Sanchez-Esguevillas, and J. Lloret, “Short-term load forecasting for microgrids based on artificial neural networks,” *Energies (Basel)*, vol. 6, no. 3, pp. 1385–1408, 2013, doi: 10.3390/en6031385.

[24] L. Hernández *et al.*, “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.

[25] S. Rodygina, V. Lyubchenko, and A. Rodygin, “Efficiency of Using Artificial Neural Network for Short-Term Load Forecasting,” *Applied Mechanics and Materials*, vol. 792, pp. 312–316, 2015, doi: 10.4028/www.scientific.net/amm.792.312.

[26] C. Ge, L. Wang, and H. Wang, “Power system short-term load forecasting based on fuzzy neural network,” *Research Journal of Applied Sciences, Engineering and Technology*, vol. 6, no. 16, pp. 2972–2975, 2013, doi: 10.19026/rjaset.6.3680.

[27] Y. Y. Hsu, T. T. Tung, H. C. Yeh, and C. N. Lu, “Two-Stage Artificial Neural Network Model for Short-Term Load Forecasting,” *IFAC-PapersOnLine*, vol. 51, no. 28, pp. 678–683, 2018, doi: 10.1016/j.ifacol.2018.11.783.

[28] I. Samuel, T. Ojewola, A. Awelewa, and P. Amaize, “Short-Term Load Forecasting Using The Time Series And Artificial Neural Network Methods,” *IOSR Journal of Electrical and Electronics Engineering Ver. III*, vol. 11, no. 1, pp. 2278–1676, 2016, doi: 10.9790/1676-11137281.

[29] S. Singh, S. Hussain, and M. A. Bazaz, “Short term load forecasting using artificial neural network,” *2017 4th International Conference on Image Information Processing, ICIIP 2017*, vol. 2018-Janua, no. December, pp. 159–163, 2018, doi: 10.1109/ICIIP.2017.8313703.

[30] H. Patel, “Application of Artificial Neural Network for Short Term Load Forecasting,” *International Journal of Advance Engineering and Research Development*, vol. 2, no. 04, 2015, doi: 10.21090/ijaerd.020439.

[31] H. Dong, Y. Gao, X. Meng, and Y. Fang, “A multifactorial short-term load forecasting model combined with periodic and non-periodic features-a case study of qingdao, China,” *IEEE Access*, vol. 8, pp. 67416–67425, 2020.

[32] G. Veljanovski, M. Atanasovski, M. Kostov, and P. Popovski, *Application of Neural Networks for Short Term Load Forecasting in Power System of North Macedonia*. 2020. [Online]. Available: https://www.wunderground.com/history.

[33] P. Ray, D. P. Mishra, and R. K. Lenka, "Short term load forecasting by artificial neural network," *2016 International Conference on Next Generation Intelligent Systems, ICNGIS 2016*, no. September, 2017, doi: 10.1109/ICNGIS.2016.7854003.

[34] S. A. W. Dinata, M. Azka, P. Hasanah, S. Suhartono, and M. D. H. Gamal, "Comparison of Short-Term Load Forecasting Based on Kalimantan Data," *Indonesian Journal of Statistics and Its Applications*, vol. 5, no. 2, pp. 243–259, 2021.

[35] T. E. Putri, A. A. Firdaus, and W. I. Sabilla, "Short-Term Forecasting of Electricity Consumption Revenue on Java-Bali Electricity System using Jordan Recurrent Neural Network," *Journal of Information Systems Engineering and Business Intelligence*, vol. 4, no. 2, pp. 96–105, 2018.

[36] E. N. Yaqin *et al.*, "Short Term Load Forecasting for Weekends in Indonesia: Comparison of Three Methods," in *IOP Conference Series: Materials Science and Engineering*, 2018, vol. 288, no. 1, p. 012119.

[37] S. J. A. Sumarauw, E. Winarko, and R. Wardoyo, "Weighting Customers'data for More Accurate Short-Term Load Forecast," *J Theor Appl Inf Technol*, vol. 90, no. 2, p. 23, 2016.

[38] T. Tumiran, S. Sarjiya, L. M. Putranto, E. N. Putra, R. F. S. Budi, and C. F. Nugraha, "Long-Term Electricity Demand Forecast Using Multivariate Regression and End-Use Method: A Study Case of Maluku-Papua Electricity System," in *2021 International Conference on Technology and Policy in Energy and Electric Power (ICT-PEP)*, 2021, pp. 258–263.