IJSES

International Journal of Scientific Engineering and Science
Volume 8, Issue 12, pp. 14-18, 2024. ISSN (Online): 2456-7361

Distribution Power Loss Prediction of Unit Pelaksana Pelayanan Pelanggan Semarang (UP3) Using Artificial Neural Network Backpropagation

Rizko Andriansyah[1], Eka Nuryanto Budisusila[2], Agus Adhi Nugroho[3]
Faculty of Industrial Technology, Sultan Agung Islamic University
Jalan Raya Kaligawe KM.04 Semarang Indonesia 50112

Abstract— *PT. PLN (Persero) Unit Pelaksana Pelayanan Pelanggan (UP3 Semarang) is an electric power distribution unit in Central Java with the largest sales of electrical energy. One of the performances that is always a concern is the monthly distribution power loss. The amount of distribution power loss is manifested in percentage every month. The power loss rate of UP3 Semarang is between 6-6.5%. This month's power loss can only be known in the middle of the month in front of waiting for the results of the income report consisting of electricity account income, follow-up bills from customers who are subject to P2TL (Electricity Usage Control), negligence costs, transformer rentals, and others are considered too late to be used as a reference for policymakers related to power loss control. So, a prediction is needed to forecast the power loss rate in the future time period. This research using Matlab Software with the Backpropogation Artificial Neural Network method to predict the monthly power loss of PT. PLN (Persero) UP3 Semarang. Furthermore, in this process, it can provide data on the amount of monthly distribution power loss of any distribution unit in the next time period. From the results of research, analysis, design, manufacture and testing of application systems with backpropagation artificial neural networks, a 7-14-1 artificial neural network model with 7 input layers, 14 neurons in the hidden layer, and 1 output layer in this distribution power loss prediction, with a regression value of 0.9924 and RMSE 0.52525 so that the results of the test are considered good enough to be used as a power loss prediction in the future period.*

Keywords— *Distribution power loss prediction, artificial neural network, backpropagation, RMSE.*

I. INTRODUCTION

The problem faced by PLN today, especially for the distribution sector, is the amount of power loss, both technically and non-technically. Distribution power loss is a crucial problem, loss is the difference between the amount of electrical energy generated and the amount of electrical energy that has been used by customers. The distribution of electrical power through the distribution network from the power substation to the load center results in the loss of energy in the line due to turning into heat. This energy that turns into heat is often called grid power losses or grid energy shrinkage. This network energy loss is natural, so it cannot be avoided. Distribution electrical power losses include medium voltage networks to low voltage networks.

Power loss is an important discussion at this time because it is related to the quality of power that will be delivered to customers and opens up potential revenue for the company because the depreciation that occurs will reduce the potential for power sales by the company.

PT. PLN (Persero) Unit Pelaksana Pelayanan Pelanggan Semarang (UP3 Semarang) is an electric power distribution unit in Central Java with the largest sales of electrical energy. One of the performances that is always a concern is the loss of electrical energy. The amount of power loss is manifested in percentage every month. The power loss rate of UP3 Semarang is between 6-6.5%. This month's power loss can only be known in the middle of the month in front of waiting for the results of the income report consisting of electricity account income, follow-up bills from customers who are subject to P2TL (Electricity Usage Control), negligence costs, transformer rentals, and others are considered too late to be used as a reference for policymakers related to power loss control. So a prediction is needed to forecast the power loss rate in the future time period.

In the previous research, [1] used the *Fuzzy Logic* and *Feed Forward Neural Network* methods to predict short-term electrical power loss based on the load balance between phases and the magnitude of neutral current. In this research, the results of the calculation acquired MSE value 0.000131627 and the MAPE value 0.029797424%. So that by using the *Fuzzy Logic* method and *Feed Forward Neural Network* (F-FFNN), maximum and more accurate forecasting results are obtained for the next day.

The difference in this research tries to predict the monthly power loss of the distribution unit of PT. PLN based on 7 types of input data for neural networks and monthly power loss data as output or target data. As input data are medium voltage network length (JTM), low voltage network length (JTR), number of installed distribution transformers, the capacity of installed distribution transformer, substation output voltage value, total amount of electrical power sales and home connection length (SR).

The calculation of power loss in the electrical distribution network is a very complex. The calculation of the energy loss of the distribution network can only be done through the process of measuring energy that is passed over a certain period of time on each component of the distribution system. This of course requires a lot of energy meters that will be used and cause loss. The causes of the large loss in the distribution network include the natural state of the network itself, such as the length of the network which tends to increasing, the load that exceeds the ability to conduct cross-sectional currents which can worsen the technical loss of the electric power

International Journal of Scientific Engineering and Science
Volume 8, Issue 12, pp. 14-18, 2024. ISSN (Online): 2456-7361

network [2]. This technical loss cannot be eliminated because it is a congenital or lost condition that occurs due to engineering reasons where the power loss turns into heat in the High Voltage (JTT) network, Substation (GI), Medium Voltage Network (JTM), Distribution Substation (GD), Low Voltage Network (JTR), Home Connection (SR) and Measuring and Limiting Devices (APP)

II. METHOD

A. *Research Object*

The study area in this research was distribution power system.

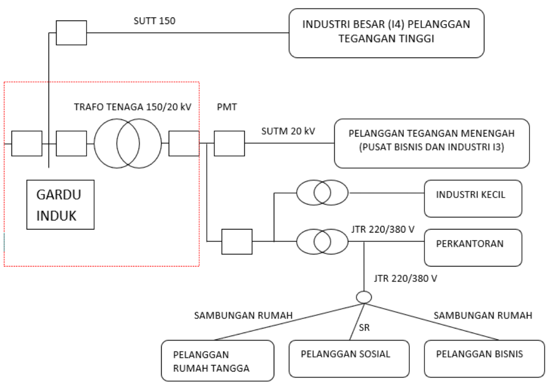

Fig. 1. Distribution electrical power system

B. *Data Collection*

Data collection is the beginning step in this research. Table 3.1 displays the data that the researcher has obtained from various sources. Furthermore, it is used as a parameter to predict the number of loss of electricity distribution from a Customer Service Implementation Unit at PT. PLN (Persero). According to the basic theory of electricity, the seven data data below contribute to the loss of electricity power in an electric power distribution system. The data taken is data that is updated every month from January 2018 to December 2023.

1. Previous monthly distribution power loss.

   Monthly power loss of distribution sector is expressed in percentage. It is percentage of the electrical energy loss from the amount of electricity sold in gigawatt hours in a month. It used as an output or target data of artificial neural network training.

2. Medium voltage and low voltage network lengths.

   One of the parameters that determines the magnitude of the technical loss of the distribution system is the loss of voltage due to the value of conductor resistance, both in medium and low voltage networks, both low voltage networks (JTR) and home connections (SR).

3. Number of installed distribution transformers and its total capacity

   The Distribution Transformers were installed to convert medium voltage (20 kV) to low voltage (220/380 V). Then the low voltage electricity is distributed to the consumers. Losses in distribution transformers are caused by copper losses and core losses (Risnandar 2022). The power losses are directly proportional to the nominal square of the current and impedance, so that the higher the current flowing, the higher the power loss in the electrical component

TABLE I: Supporting data of distribution power loss

Tahun	Bulan	Panjang JTM (kms)	Panjang JTR (kms)	Jumlah Trafo (unit)	KVA Trafo (kVA)	KMS SR (kms)	Tegangan Operasi PMT Outgoing (Volt)	Penjualan (kWh)	hilang distribusi (%)
2018	Jan	3133,86	4190,81	13912	850410	24805,26	20500	315916310	5,89
	Feb	3148,01	4194,26	13949	855676	24842,86	20500	284346437	4,47
	Mar	3149,41	4197,71	13970	857769	24880,46	20500	323612958	5,79
	Apr	3152,29	4201,15	14011	860818	24918,06	20500	331200571	5,14
	Mei	3155,68	4204,60	14055	863943	24955,66	20500	337812287	6,90
	Jun	3157,23	4208,05	14093	866373	24993,3	20500	293097090	6,32
	Jul	3159,51	4211,50	14102	868143	25075,05	20500	332211718	8,98
	Agust	3164,10	4214,94	14150	872228	25156,8	20500	328623453	9,13
	Sep	3168,79	4218,39	14192	876183	25248,87	20500	326052787	9,34
	Okt	3171,34	4221,84	14230	879858	25340,94	20500	352778866	8,53
	Nop	3183,28	4225,29	14282	884688	25433,01	20500	341511416	7,68
	Des	3183,31	4228,73	14326	890558	25529,22	20500	337596349	6,63
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
2023	Jan	3303,42	4391,37	16148	1034419	29804,22	20500	337224145	7,05
	Feb	3306,34	4393,76	16156	1034979	29871,69	20500	315719682	4,64
	Mar	3312,91	4401,29	16167	1035629	29929,77	20500	362113959	7,83
	Apr	3320,11	4405,99	16177	1036179	29986,44	20500	328596528	6,94
	Mei	3326,14	4410,49	16189	1036779	30036,48	20500	373376660	7,55
	Jun	3330,67	4414,85	16201	1037479	30096,33	20500	363052242	6,85
	Jul	3333,36	4417,43	16210	1037979	30135,48	21000	369193499	5,57
	Agust	3335,27	4419,31	16220	1038799	30170,7	21000	379921633	6,02
	Sep	3336,87	4421,20	16236	1039599	30292,23	21000	371145608	5,95
	Okt	3338,50	4422,97	16251	1040769	30330,12	21000	401794356	7,11
	Nop	3339,64	4424,32	16262	1041419	30371,28	21000	393426960	4,79
	Des	3340,78	4425,67	16273	1042069	30412,44	21000	373539935	5,90

4. Operation voltage of feeder 20 kV

   The operating voltage in a distribution system determines the voltage drop value at the end of the line. In theory, the higher the nominal voltage of an electric power circuit line system, the smaller the voltage drop value at the end of the line.

III. DATA PREPARATION

Data normalization is the conversion of data from its original value into numbers that have a range of 0 to 1 (normalization). This is to facilitate the process of research or data processing where each data set has a different range of numbers. The following is the normalization formula:

$$X' = \frac{X - Xmin}{Xmax - Xmin} * (BA - BB) + BB$$

Keterangan :

X' = Normalization
X = data values to be normalized
Xmin = minimum value
Xmax = maximum value
BA = Upper limit (1)
BB = Lower limit (0)

IV. ARTIFICIAL NEURAL NETWORK

A. *Artificial Neural Network Backpropagation*

According to Siswanto (Siswanto 2018), *Neural Network* is an information processing system based on the philosophy of the neural behavior structure of creatures. NN has the advantage of solving technical problems. First, NN does not need programming about *the input* and *output* relationships. Rather,

International Journal of Scientific Engineering and Science
Volume 8, Issue 12, pp. 14-18, 2024. ISSN (Online): 2456-7361

they will learn the desired response by themselves by training. This is very important in order to eliminate most of the programming costs. Second, NN can improve responses by learning. That's because NNs are designed to evaluate and adapt to new response criteria. Third, NN works as the sum of all *input* signals with the inputs not necessarily the same. This means that NN will be able to recognize a person even though that person is different from when they were first recognized or NN will recognize a word even if it is spoken by different people. All of this is certainly very difficult to do with ordinary digital computer.

Backpropagation is the most commonly used neural network learning method. This method compares the predicted value of the network with each example through an iterative process using a set of sample data (training data). The weight of the relationships in the network is modified on each process to minimize the Mean Square Error (MSE) value between the predicted value of the network and the actual value. The modification of the NN relationship is carried out in reverse, from the output layer to the first layer of the hidden layer, so this method is called backpropagation (Novita 2013).

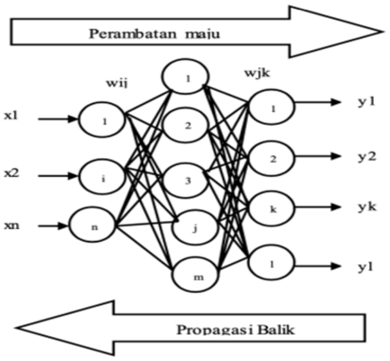

Fig. 2. Neural Network Backpropagation

There are 2 *stopping conditions* in *the backpropagation algorithm*:

a. *Error < Maximum error*
The training will stop if the value of the MSE is less than or equal to the predetermined error limit.

b. *Epoch > Maximum Epoch*
Training will stop if the maximum iteration condition has been reached (Tambun et al. 2018).

B. Neural Network Architecture

In general, *the Backpropagation* network architecture consists of three layers, that is the input layer, the hidden layer, and the output layer. The procedure for deciding the quantity of neurons in the input layer and output layer is straightforward as it is based on the number of inputs and the expected number of outputs. This is different as the number of neurons in the hidden layer. Deciding how many neurons to use in the hidden layer is one of the most important properties of neural networks. If the number of neurons is too small, the network cannot model complex data and the results may not be acceptable. The use of too many neurons will not only increase training time, but also decrease the performance of the network. Therefore, many researchers conduct experiments to determine the optimal number of neurons. The count of neurons utilized during the data training phase is a critical factor in building the Back Propagation network framework to achieve high accuracy (Suprajitno 2022).

C. Neural Network Parameter

Some of the parameters of neural network training (Nadia Chandra Devi 2018):

1. *Epoch*
Epoch indicates the number of iterations/steps required by a neural network to meet certain criteria that are determined so that it stops.
2. Target *error*
The error target is the target of the network performance value (*error*).
3. *Learning Rate* (*Lr*)
The learning speed is affected by the learning *rate parameter*. To be able to achieve the *convergence condition*, the selection of *the learning rate* is very influential in learning, if the *learning rate* is too small it takes a long time to approach the minimum *error*, but if the *learning rate* is too large the update weight will exceed the minimum error and the weight will oscillate. The selection *of learning rate* with a value range of 0-1 is done manually and there is no standard method in determining good parameter values. When JST has oscillated and stuck at the minimum locale, the method used is to stop learning and reset the neural network parameters.[9]
Ratio to increase learning rate, a ratio that is useful as a multiplier factor to increase learning rate if the learning rate is too low.
Ratio to reduce learning rate, a ratio that is useful as a multiplier factor to reduce the learning rate if the existing learning rate is too high.
4. Number of neurons in the hidden *layer*
Neural networks have an input layer and an output layer. Between the two layers, there is a layer called the hidden *layer*. The purpose of this layer is to allow the neural network to produce the expected output of the given input. A good starting point is a single hidden layer with the number of neurons equal to twice the input layer (Nadia Chandra Devi 2018). Determining the number of hidden neurons is an important part of determining the network architecture because it will have a significant effect on the final result.
5. The maximum failure is the largest invalidity allowed. Maximum failure is required if the algorithm is accompanied by validity (optional). Iterations will be stopped when the number of failures exceeds the maximum number of failures.
6. The minimum gradient is the root of the sum of the squares of all the smallest gradients (input weight, layer weight, refractive weight) allowed. Iteration will be stopped when the square root value of all these gradients is less than the minimum gradient.
7. Performance objectives (performance function value targets). Iteration is stopped when the performance function value is less than or equal to the target performance.

Volume 8, Issue 12, pp. 14-18, 2024.

International Journal of Scientific Engineering and Science
ISSN (Online): 2456-7361

8. The maximum uplift is the maximum value of the allowable increment of errors, between the current error and the previous error.
9. Maximum time for training, this parameter indicates the maximum time allowed to conduct training. Iterations will be stopped if the training time exceeds the maximum time.

V. TRAINING STAGE

In this experiment, several training sessions were carried out on the artificial neural network model with 4 training parameters, namely *training function*, *Error goal*, *Epoch, and Learning rate*. From several experiments, the trainlm algorithm provides the best network training results with the smallest RMSE value. The best performance of the network at the time of the error goal is determined at a value of $1e^{-6}$ with *an epoch* determined at 1000 and *a learning rate* of 0.1.

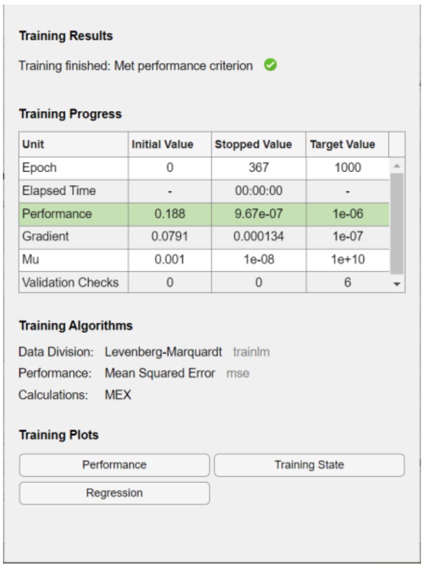

Fig. 4. Training results for distribution loss prediction

Figure 4 shows that the training of the *backpropagation* artificial neural network stops when *the performance* reaches *the best validation performance* value of $09.67e^{-07}$ at the 367th *epoch* of 1000. In the *training plots window*, there are performance, *training, and regression plots,* these three plots will show the results of the training in the form of graphs. The neural network modeling after training has a correlation coefficient (R) between *output* and target = 0.9999 as shown in figure 4.5 below.

- The number of neurons in the hidden layer is 14 nodes
- *The learning rate* (*Ir*) aims to accelerate the rate of its iteration. The result of this discussion for *Ir* is that if the Ir value is too large, the algorithm becomes less stable and reaches the local minimum point, which is zero (0) error. If *the error* is zero (0), it means that there is no weight correction so that the training process is not optimal. In this study, *Ir* 0.1 was used.
- *Epoch* (iteration) aims to indicate the maximum number of iterations in training. In this study, an *epoch* value of 1000 was used to get good results.
- *Goal* is the setting of the goal parameter used to determine the limit of the MSE value so that the iteration stops. In this study, a goal of $^{1e-06}$ was used. If the goal is achieved, then on the *performance graph* the MSE must be less than or equal to 0.000001.

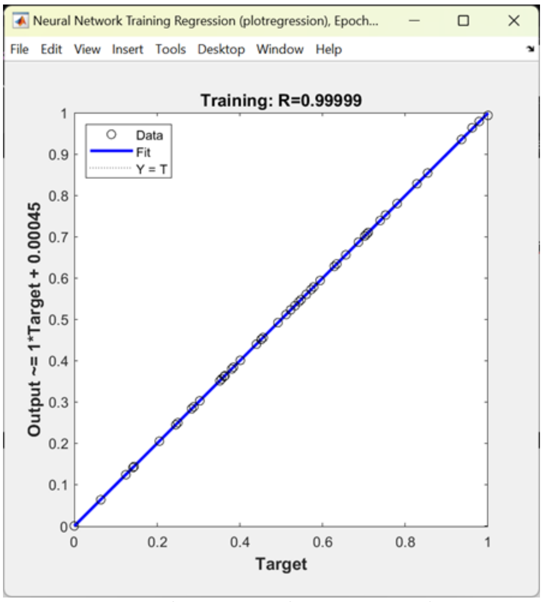

Fig. 5. Graph of evaluation of correlation coefisien (R)

The use of this model got *an MSE value* of 9.6737e-7 as seen in figure 5.

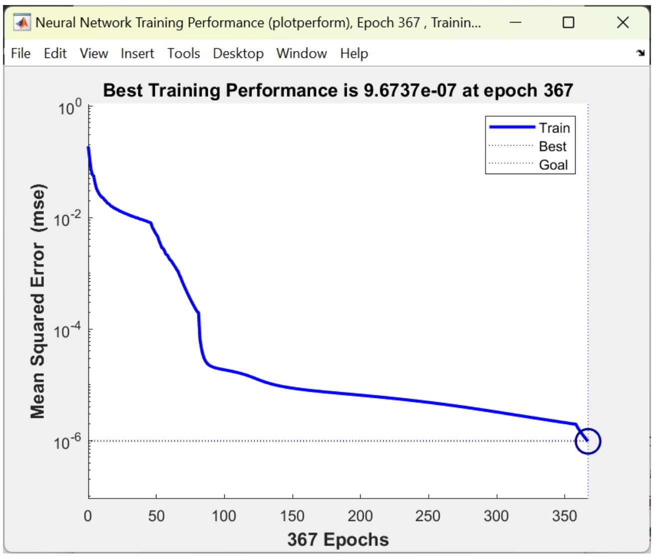

Fig. 6. *MSE Output vs* power loss prediction target graph

Figure 6 shows that the error indicator is very small, which is below the set error target. When the goal is achieved, the *MSE performance* graph must be less than or equal to the goal (Hasan & Fatta 2019).

This shows that the network is able to produce predictions that are close to the expected target. So that modeling like this can be used. The final evaluation of the results of the study obtained an SSE = 4.6434e-05 and RMSE = 0.00098355

International Journal of Scientific Engineering and Science
Volume 8, Issue 12, pp. 14-18, 2024. ISSN (Online): 2456-7361

Research on prediction of distribution loss using artificial neural networks *backpropagation* with this kind of supporting data is a new thing. Based on the results of the training process that has been carried out, it produces a good output where *the error* value is quite small, namely the RMSE value = 0.00098355 with the network architecture used 7-14-1, with *a learning rate* of 0.1, *the trainlm algorithm*, and the binary sigmoid activation function (logsig). Based on the results of the training, a model was obtained that was declared good for the model testing stage. The error result obtained during the test was an RMSE value of 0.52525. If the *error* value of the test stage is compared to the *error value* at the training stage, then there is a considerable difference. However, it is still within the tolerance of the error limit of a prediction model. So that the prediction value of the loss of the distribution of PLN units will result in a fluctuating number of losses.

VI. DATA PREDICTION

The following are the results of the running program distribution loss prediction using new data taking input and output data for October.

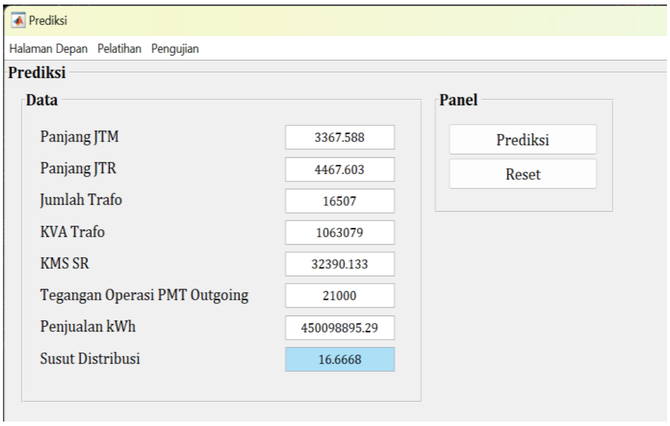

Fig. 7. Network prediction results for supporting data for October 2024

Here is a table that displays the prediction results using data from January – October 2024

TABLE II: Results of distribution power loss prediction using new data

on	JTM Length	JTR Length	Sum Trafo	KVA Trafo	SR length	PMT Outgoing Operating Voltage	kWh sales	Power loss	Prediction Test Results
n	3343.20	4427.26	16280	1042689	31122.63	21000	409,391,297.80	7.01	14.9013
b	3343.91	4428.19	16292	1043709	31259.43	21000	372,002,638.61	6.06	12.4633
ar	3345.35	4429.62	16307	1044879	31302.81	21000	400,932,237.97	6.33	14.8937
r	3346.65	4430.48	16315	1045479	31344.39	21000	371,671,711.23	6.51	12.5038
ei	3347.50	4430.83	16344	1047254	31428.26	21000	432,531,667.40	6.71	16.8853
n	3352.09	4439.72	16239	1037064	31512.13	21000	406,209,266.10	6.15	15.0043
l	3355.55	4443.78	16323	1047864	31553.71	21000	421,549,819.06	6.02	14.3749
ist	3359.00	4450.52	16373	1051764	31637.58	21000	423,751,475.76	6.03	14.7965
p	3363.43	4454.71	16440	1056714	31680.96	21000	414,777,541.77	6.01	4.25281
t	3367.59	4467.60	16507	1063079	32390.13	21000	450,098,895.29	6.10	16.6668

VII. RESULT AND DISCUSSION

From the results of research, analysis, design, manufacture and testing of application systems with backpropagation artificial neural networks in this prediction of distribution loss, the following conclusions are obtained:

1. Artificial neural networks can predict the value of the distribution loss according to the research object, namely the UP3 Semarang distribution loss using new supporting data for the period January – October 2024 as shown in table 4.3 because there is a difference between the results of the training stage error and the error during the test.
2. The application of the Backpropagation algorithm to predict the loss of this distribution resulted in a regression value of 0.9924 and RMSE of 0.52525 in epoch 367 so that the results of the test are precise enough to be used as a consideration to predict the loss in the future period.
3. A 7-14-1 artificial neural network architecture model with 7 input layers, 14 neurons in the hidden layer, and 1 output layer, as a pattern that can be used to predict loss in all Electricity Distribution Management Units

REFERENCE

[1] Puguh, “Peramalan Susut Energi Jangka Pendek Menggunakan Metode Fuzzy Logic Dan Feed Forward Neural Network Berdasarkan Keseimbangan Beban,” *J. Tek. Elektro Unnesa*, vol. 10, no. 2, pp. 453–462, 2021.

[2] Syukri, “Analisa perhitungan susut teknis di pt. Pln (persero) rayon singkil,” *J. Elekri*, vol. 16, p. 15, 2024.

[3] M. A. Risnandar, “Analisis rugi daya trafo distribusi pada penyulang tamansari kota tasikmalaya,” *JEEE*, vol. 4, no. 1, pp. 13–19, 2022.

[4] Siswanto, “Prediksi Lama Studi Mahasiswa Menggunakan Jaringan Syaraf Tiruan Metode Backpropagation,” *FTEKNIK*, vol. 5, pp. 5–10, 2018.

[5] A. Novita, “Prediksi Pergerakan Harga Saham Pada Bank Terbesar Di Indonesia Dengan Metode Backpropagation Neural Network,” pp. 965–972, 2013.

[6] M. S. Tambun, M. T. Furqon, and A. W. Widodo, “Penerapan Algoritme Jaringan Syaraf Tiruan Backpropagation pada Pengklasifikasian Status Gizi Balita,” vol. 2, no. 9, pp. 3074–3080, 2018.

[7] H. Suprajitno, “The Formula Study in Determining the Best Number of Neurons in Neural Network Backpropagation Architecture with Three Hidden Layers,” vol. 5, no. 158, pp. 397–402, 2022.

[8] Nadia Chandra Devi, “Penentuan Akurasi Algoritma...,” *Fak. Tek. Dan Sains Ump*, pp. 5–19, 2018.

[9] C. D. Suhendra and A. C. Saputra, “Penentuan Parameter Learning Rate Selama Pembelajaran Jaringan Syaraf Tiruan,” vol. 14, no. 2, pp. 202–212, 2020.

[10] N. F. Hasan and H. Al Fatta, “Peramalan Jumlah Penjualan Menggunakan Jaringan Syaraf Tiruan Backpropagation Pada Perusahaan Air Minum Dalam Kemasan,” vol. 5, pp. 179–188, 2019.