Monitoring and Identification Electricity Load Using Artificial Neural Network

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***Abstract*— This study proposes a model that can be used for monitoring and identifying consumer electrical loads using Neural Network and Feed-Forward Backpropagation training methods. The modeling design is made in Simulink-Matlab software. The neural network training error obtained is 2.729%, then this is used for the identification process of electrical loads, which in this study used 21 load combinations. While the error test results obtained are 1.325476%. In this study, a new model is proposed for monitoring and identifying consumer electricity consumption by applying the concept of Non-Intrusive Load Monitoring (NILM) combined with the Artificial Neural Network (ANN) method.**

Keywords: Neural Network, Error. Electricity Load, Identification, Monitoring

I. Introduction

It is often heard that consumers of electricity, especially household consumers, complain because their electricity bills are too expensive, but not a few consumers are confused because the numbers printed on the electricity bill are too cheap. This is very likely to occur if the system for calculating the use of electrical energy is still done manually by PLN officials. Because it is done manually, this method has the disadvantage of the possibility of error.

Measuring electricity usage both analog and digital that is still used by household consumers can only record the use of electricity in every hour and the amount of electricity used is multiplied by the basic electricity tariff adjusted to the power installed in the housing. The electricity bill is only stated on the nominal amount of the bill to be paid by consumers without any details that include the use of electronic equipment for one month.

In this study, it is designed to monitor and identify the use of electrical energy from the use of electronic equipment in consumer homes in real time. Consumers can easily get information about how much electricity energy has been used. In this way, consumers can find and distinguish electronic devices that are wasteful of energy and save energy so that consumers can make effective savings. Non-Intrusive Load Monitoring (NILM) based monitoring system is a measurement method that only requires a voltage and current sensor [1-2]. With the implementation of NILM, the equipment used can be minimized, without reducing the accuracy of the monitoring results.

Artificial intelligence has been widely used and successful in system optimization. There have been many optimization systems that use intelligence methods [3]. Among them are Firefly Algorithm, Ant Colony Optimization, Imperialist Competitive Algorithm, Particle Swarm Optimization, Bat Algorithm, and others [4-6]. This study was designed using an intelligent algorithm based on Artificial Neural Network with the Feed-Forward Back propagation Neural Network (FFBNN) training method. Artificial Neural Network is a computational technique based on artificial intelligence that can recognize patterns, classification / identification, prediction, optimization, and function approaches [7]. The ability of back propagation neural networks to recognize patterns and identification can solve problems in monitoring and identifying the use of electrical energy with accurate results. The advantage of the artificial neural network is that the function used is non-linear, has high accuracy and does not have a model, so that with this artificial neural network method there is no need for assumptions from multivariate data that are normally distributed.

In several previous studies have investigated the burden of monitoring using NILM-based [8-10]. The study of the use of NILM devices for monitoring load usage is discuss in [10]. Implementation of NILM in monitoring loads for energy conservation is discuss in [11]. In some previous studies, monitoring of load usage is only limited to displaying information on the amount of electricity used, but does not provide information about which loads are operating. Then research on monitoring electrical loads is growing with the existence of intelligent methods [13-14]. This smart method is used as a method for identifying load usage based on some given inputs. Monitoring of load usage based on NILM and Neural Network is discuss, but this research was carried out offline [3]. Monitoring of load usage with a Neural Network based identification method, and the test results show a large error [14]. It examines the monitoring of load usage in industrial cases [15]. From some of these studies a reference for the author to discuss the implementation of an Artificial Neural Network intelligent algorithm for monitoring load usage with a modeling approach. The urgency of this research is needed in order to provide feedback to consumers in order to be able to manage electrical energy efficiently so that it can become a reliable energy management system.

II. Research Methods

A. Hardware Design

1. Prototype

The hardware design consists of one current sensor, a signal conditioning circuit (rectifier), an arduino uno

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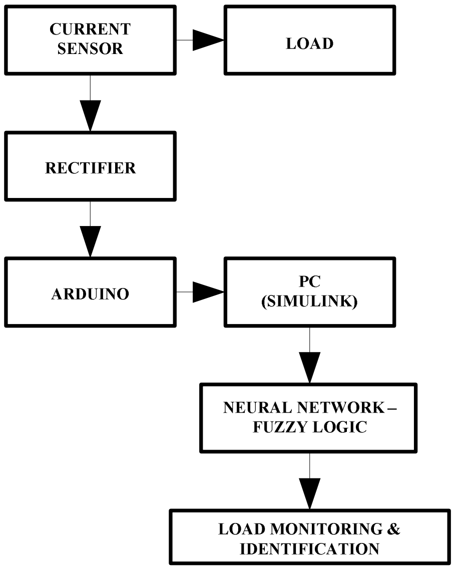

Fig 1. Testing Scheme

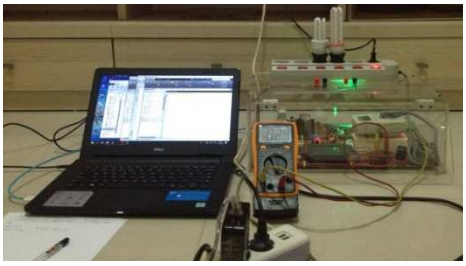

Fig 2. Testing Prototype

interface device, a laptop and five electronic devices as a load consisting of a TV, a lamp, a refrigerator, a fan, and a drinking water heater (dispenser). The following figure shows the testing scheme and prototype of the testing tool.

2. Power Supply and Signal Conditioning Circuits

The current signal measured by the ACS712 current sensor in this study is the AC current signal. The current signal must be converted to a DC current signal first. It is intended that the current signal received by Arduino Uno is stable or does not contain much noise. The power supply designed in this study will issue a constant voltage of 5 volts.

3. Current Sensor Module

The current sensor used here is ACS712 with a maximum current of 20 Amperes. Current sensor is used to detect current usage at load.

4. Arduino Module

The signal output from the current sensor is an analog signal, therefore a converter is needed to convert this signal to digital. In this research, the Arduino Mega 2560 module will be used as an analog to digital signal (ADC) converter.

B. Load State

The current characteristics of each load are shown in the following figure. Total load is 5 single loads and 16 combination loads. Taking the sampling data of each load will later be used as neural network training. Load data used as many as 20 samples or for 20 seconds. Each load combination is written with state, which is then used as an identification method by the neural network algorithm. The following table shows the load classification and current characteristics of each load combination.

TABLE I. LOAD CLASSIFICATION

State	Load	State	Load	State	Load
1	Lamp	8	TV + Lamp + Fan	15	Disp + Lamp + Fan
2	TV	9	Refrig + Lamp + Fan	16	Refrig+Disp+TV
3	Lamp + TV	10	Refrig + Lamp + TV	17	Disp+Lamp+Fan+ TV
4	Fan	11	Dispenser	18	Refrig + Disp + Fan
5	Lamp + Fan	12	Disp + Lamp	19	Refrig + Lamp + Fan + Disp
6	TV+Fan	13	Refrig + Disp	20	Refrig+Fan+ TV + Disp
7	Refrig	14	Refrig + Disp + Lamp	21	Refrig+Lamp+ Fan + Disp +TV

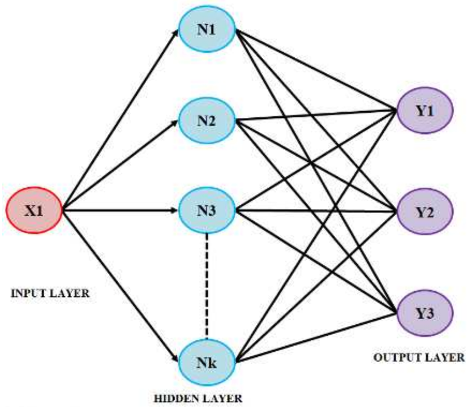

Fig. 3. Neural Network Structure

C. Artificial Neural Network Modeling

The next procedure for training networks that have been made, this procedure will require time, because it takes several training or experiments in conducting training, until the error obtained is small. The backpropagation neural network algorithm architecture consists of an input layer, a hidden layer, and an output layer. The backpropagation neural network structure is shown in Figure 3.

The following is the overall network display that will be created. The following figure shows the best training process that has been carried out with several trials. From the results of the experiment it was found that the iteration / repetition process was carried out 7 times iteration. From the results of the training can be seen, obtained training errors in the following table. Neural network algorithm test results obtained a very small error that is equal to 2.729%.

D. Modeling Load Indicator

In this study used 5 types of loads, with 16 load combinations. To make it easier for users to see the results of monitoring and identification, in addition to measuring features that can be directly read, then the load indicator is being made. For modeling the load indicator using the block lamp feature on Simulink. The following figure shows a modeling example for a lamp load indicator, with the number of states consisting of 0, 1, 3, 5, 8, 9, 10, 12, 14, 15, 17, 19, and 21. For full results in the following table.

TABLE II NEURAL NETWORK TESTING RESULTS

Target	Testing	Error
1	1,055084	-0,05508
2	1,9809	0,0191
3	3,038783	-0,03878
4	3,959806	0,040194
5	5,03793	-0,03793
6	6,039857	-0,03986
7	6,984805	0,015195
8	7,84137	0,15863
9	9,008224	-0,00822
10	10,00183	-0,00183
11	11,12062	-0,12062
12	12,0017	-0,0017
13	13,29339	-0,29339
14	14,37946	-0,37946
15	14,97999	0,020011
16	16,24371	-0,24371
17	16,92442	0,07558
18	18,43965	-0,43965
19	18,81863	0,181372
20	19,96177	0,038235
21	20,46117	0,538833
Total		2,729

TABLE III. STATE CLASSIFICATION LOAD INDICATOR

Load	State
Lamp	0, 1, 3, 5, 8, 9, 10, 12, 14, 15, 17, 19, 21
TV	0, 2, 3, 6, 8, 10, 16, 17, 20, 21
Fan	0, 4, 5, 6, 8, 9, 10, 15, 17, 18, 19, 20, 21
Refrigerator	0, 7, 9, 10, 13, 14, 16, 18, 19, 20, 21
Dispenser	0, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21

E. System Modeling

The neural network that has been made is then modeled so that the response system can be seen in recognizing the pattern of the load or identification of the load. The following figure is the initial design of networks that will be modeled on Simulink. To do the modeling, Matlab software is used as an interface with Arduino devices. This tool is designed to monitor and identify electrical equipment; therefore the input of this research is consumer electrical equipment. To carry out the identification process using a current sensor. Then the output of this tool is the identification of the electrical equipment used.

III. RESULTS AND ANALYSIS

After sampling the flow data of each load, then proceed with the creation of the Neural Network algorithm for the identification method in the MATLAB software, then the results of the algorithm are converted into blocks for further use for modeling the system in Simulink. Furthermore, testing is done to test the Neural Network algorithm and the system that has been made for monitoring and identification. There are 21 states / load combinations tested and explained in this discussion chapter.

Load Testing 1

The first test case load 1 is testing the lamp load. The results of the identification of the neural network algorithm obtained the results of current monitoring of 0.05865 A, with a Neural Network output of 1,071 and an error of 7.1%.

Load Testing 2

The second test on load case 2 is testing on TV load. The results of the identification of the neural network algorithm

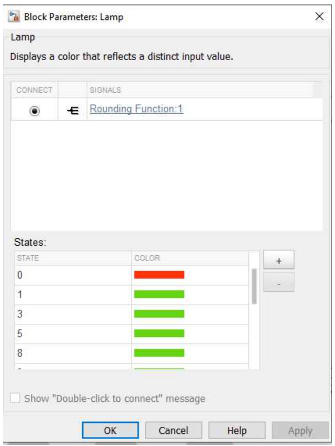

Fig 4. Lamp Indicators for Lamp Loads Gambar 3. Indikator Lamp Untuk Beban Lampu

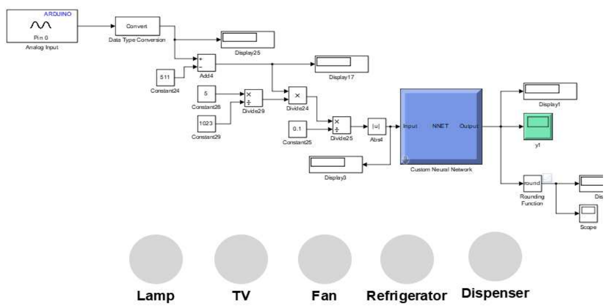

Fig 5. System Modeling

obtained the results of current monitoring of 0.1857 A, with a Neural Network output of 2.043 and an error of 4.3%.

Load Testing 3

The third test on load case 3 is testing on the load of lights and TVs. The results of the identification of the neural network algorithm obtained the results of current monitoring of 0.259 A, with a Neural Network output of 3.023 and an error of 2.3%.

Load Testing 4

The fourth test on case load 4 is testing on fan load. The results of the identification of the neural network algorithm obtained the results of current monitoring of 0.3177 A, with a Neural Network output of 4.103 and an error of 10.3%.

Load Testing 5

The fifth test on case load 5 is testing on the lamp and fan loads. The results of the identification of the neural network algorithm obtained the results of current monitoring of 0.3763 A, with a Neural Network output of 5.153 and an error of 15.3%.

Load Testing 6

The sixth test on case load 6 is testing on TV and fan loads. The results of the identification of the neural network algorithm obtained the results of current monitoring of 0.4252 A, with a Neural Network output of 6,159 and an error of 15.9%.

Load Testing 7

The seventh test is carried out on case load 7, namely testing on the TV and fan loads. The results of the identification of the neural network algorithm obtained the results of current monitoring of 0.4692 A, with a Neural Network output of 7.2 and an error of 20%.

Load Testing 8

The eighth test on case load 8 is the test on the load of lamps, TVs and fans. The results of the identification of the neural network algorithm obtained the results of current monitoring of 0.5034 A, with a Neural Network output of 7.903 and an error of 9.7%.

Load Testing 9

The ninth test on load case 9 is testing on the load of lamps, fans, and refrigerators. The results of the identification of the neural network algorithm obtained the results of monitoring the flow of 0.7136 A, with a Neural Network output of 9,012 and an error of 1.2%.

Load Testing 10

The tenth test on case load 10 is testing on the load of lamps, TVs, fans, and refrigerators. The results of the identification of the neural network algorithm obtained the results of current monitoring of 0.8796 A, with a Neural Network output of 10.21 and an error of 21%.

Load Testing 11

The eleventh test on case load 11 is testing on the dispenser load. The results of the identification of the neural network algorithm obtained the results of current monitoring of 1,696 A, with a Neural Network output of 11.27 and an error of 27%.

Load Testing 12

The twelfth test was carried out in case load 12, that is, testing on lamp loads and dispensers. The results of the identification of the neural network algorithm obtained the results of current monitoring of 1,735 A, with a Neural Network output of 11.95 and an error of 5%.

Load Testing 13

The thirteenth test on case load 13 is the test on the load of the refrigerator and dispenser. The results of the identification of the neural network algorithm obtained the results of current monitoring of 1,999 A, with a Neural Network output of 13.42 and an error of 42%.

Load Testing 14

The fourteenth test on case load 14 is testing on the load of lamps, refrigerators and dispensers. The results of identification of the neural network algorithm obtained the results of current monitoring of 2,019 A, with a Neural Network output of 13.75 and an error of 25%.

Load Testing 15

The fifteenth test on load case 15 is testing on the load of lamps, fans and dispensers. The results of the identification of the neural network algorithm obtained the results of current monitoring of 2,072 A, with a Neural Network output of 14.83 and an error of 7.1%.

Load Testing 16

The sixteenth test on case load 16 is testing on the load of TV, refrigerator and dispenser. The results of the identification of the neural network algorithm obtained the results of current monitoring of 2.19 A, with a Neural Network output of 16.34 and an error of 34%.

Load Testing 17

Seventeenth test on case load 17, namely testing on the load of lamps, TVs, fans and dispensers. The results of the identification of the neural network algorithm obtained the results of current monitoring of 2,224 A, with a Neural Network output of 16.71 and an error of 29%.

Load Testing 18

The eighteenth test on case load 18 is testing on the load of fans, refrigerators and dispensers. The results of the identification of the neural network algorithm obtained the results of current monitoring of 2,322 A, with a Neural Network output of 18.21 and an error of 21%.

Load Testing 19

Nineteenth testing on case load 19 is testing on the load of lamps, fans, refrigerators and dispensers. The result of the identification of the neural network algorithm is that the current monitoring results are 2,346 A, with a Neural Network output of 18.51 and an error of 49%.

Load Testing 20

The twentieth test on case load 20 is testing on the load of TV, fan, refrigerator and dispenser. The results of the identification of the neural network algorithm obtained the results of current monitoring of 2,542 A, with a Neural Network output of 20.48 and an error of 48%.

Load Testing 21

Twenty one tests on case load 21, namely testing on the load of lamps, TVs, fans, refrigerators and dispensers. The results of the identification of the neural network algorithm obtained the results of current monitoring of 2,581 A, with a Neural Network output of 20.77 and an error of 23%.

From the results of monitoring with several load combinations the error characteristics are obtained between the input data and the results of current monitoring. The complete results are shown in table 4. The biggest error of monitoring load current is in the 20th test which is 4.2%, while the smallest error is in the 8th test which is 0.34%. Monitoring results are shown in figures 6 and 7.

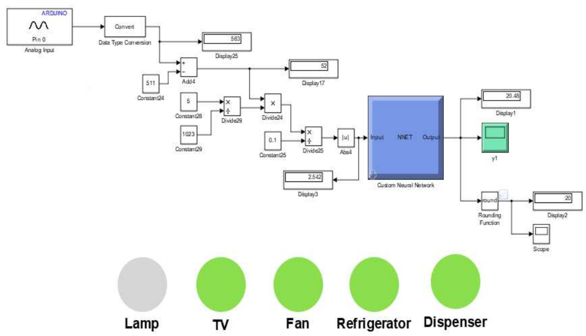

Fig 6. Monitoring and Identification of the 20th Test

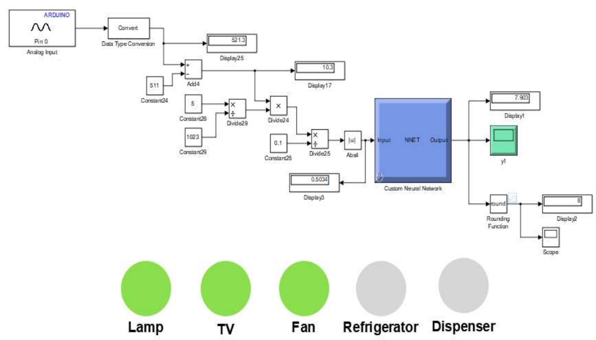

Fig 7. Monitoring and Identification of the 8th Test

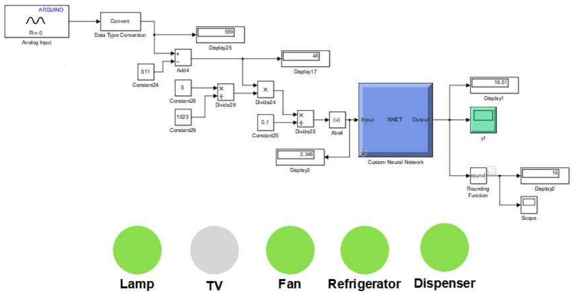

Fig 8. Monitoring and Identification of the 19th Test

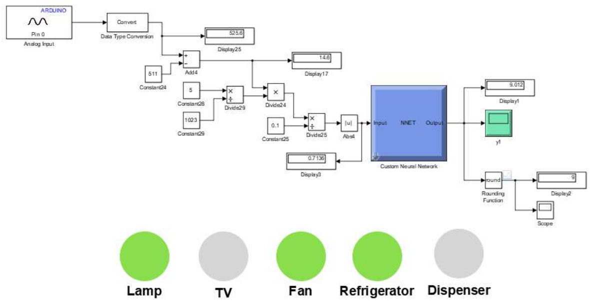

Fig 9. Monitoring and Identification of the 9th Test

TABLE IV. COMPARISON OF TEST RESULTS

No	Monitoring			Identifikasi		
	Input	Testing	Error (%)	Target	Testing	Error (%)
1	0.05	0.05865	0,865	1	1.071	7,1
2	0.18	0.1857	0,57	2	2.043	4,3
3	0.25	0.259	0,9	3	3.023	2,3
4	0.31	0.3177	0,77	4	4.103	10,3
5	0.37	0.3763	0,63	5	5,153	15,3
6	0.42	0.4252	0,52	6	6.159	15,9
7	0.46	0.4692	0,92	7	7.2	20
8	0.5	0.5034	0,34	8	7.903	9,7
9	0.71	0.7136	0,36	9	9.012	1,2
10	0.87	0.8796	0,96	10	10.21	21
11	1.69	1.696	0,6	11	11.27	27
12	1.74	1.735	0,5	12	11.95	5
13	1.99	1.999	0,9	13	13.42	42
14	2.05	2.019	3,1	14	13.75	25
15	2.08	2.072	0,8	15	14.83	17
16	2.18	2.19	1	16	16.34	34
17	2.24	2.224	1,6	17	16.71	29
18	2.34	2.322	1,8	18	18.21	21
19	2.38	2.346	3,4	19	18.51	49
20	2.5	2.542	4,2	20	20.48	48
21	2.55	2.581	3,1	21	20.77	23
Total			1,325476			20,3381

From the results of testing several load combinations obtained the characteristics of monitoring and identification of the load current, the test results are shown in table 4 below. The biggest error is in the 19th test that is equal to 49%, while the test with the smallest error is the 9th which is equal to 1.2%. The test results are displayed in the figure 8 and 9 below.

From the comparison test table, the average load current monitoring error is 1.325476%, while for error load identification using the Neural Network algorithm the average error is 20.33381%. This research uses a new modeling for monitoring and identifying load currents with the concept of Non-Intrusive Load Monitoring (NILM) with the ACS712 current sensor combined with intelligent methods based on Artificial Neural Network (ANN) with training methods based on Feed-Forward Bakppropagation. To see the comparison of each test, the comparison results are also displayed in the following figure, where Figure 11 shows the comparison.

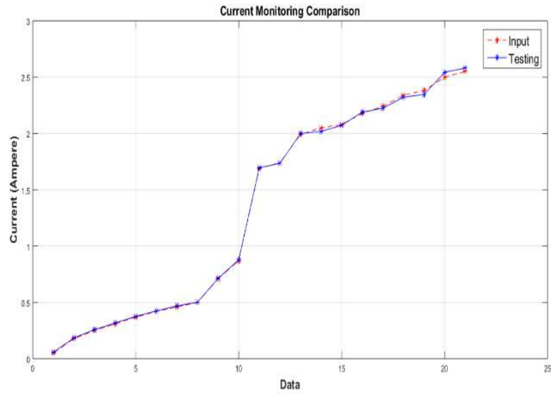

Fig 10. Comparison of Load Current Monitoring

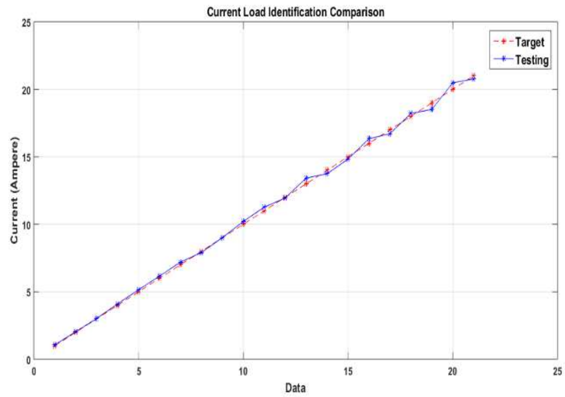

Fig 11. Comparison of Load Current Identification

IV. CONCLUSION

In this study, a model is proposed to monitor and identify the type of load used with the Neural Network.The training error obtained is 2.729%, in other words the identification process using a neural network is accurate enough to identify 21 types of load combinations.

While the average error for testing is 1.325476%. This research proposes a model for monitoring and identifying electrical loads with the concept of Non-Intrusive Load Monitoring (NILM), namely the ACS712 current sensor combined with an intelligent method based on Artificial Neural Network (ANN) with a training method based on Feed-Forward Bakpropagation.

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