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Journal of Soft Computing Exploration

Homepage: https://shmpublisher.com/index.php/joscex

JOSCEX

p-ISSN: 2746-7686
e-ISSN: 2746-0991

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Design of ANFIS system to detect the condition of generator set model P22-6 based on Omron CJ1M PLC

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Article Info

Article history:

Received Jul 27, 2024
Revised Aug 9, 2024
Accepted Aug 21, 2024

Keywords:

ANFIS
Generator Set
Monitoring
Temperature
RPM
Vibration

ABSTRACT

The application of machine monitoring systems is currently increasingly needed, one of which is on generators. Generator sets are one of the important elements in providing energy needed in company operations. However, to ensure optimal performance and prevent unexpected engine damage, careful monitoring of the generator set's operational conditions is required, especially of key variables such as temperature, rotation speed, and engine vibration. The purpose of this study is to identify the condition of the generator set using three parameters. In this research, adaptive neuro fuzzy inference system (ANFIS) is used as a tool to model the relationship between inputs (temperature, speed, and vibration) and outputs (engine condition). The dataset for normal conditions amounted to 25 data and for abnormal conditions amounted to 25 data. From this data, an RMSE of 0.000032 was obtained in the 3-3-5 membership function structure with a trapezoidal type membership function. And at the stage of applying fuzzy to the Omron PLC, the RMSE is 0. Simulations are carried out to test the effectiveness of ANFIS in predicting machine conditions based on monitored parameters.

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https://doi.org/10.52465/joscex.v5i3.435

1. INTRODUCTION

In the modern industrial era, the sustainability and reliability of electricity resources is a very important aspect to maintain the operational continuity of various industrial facilities. The use of generator sets or Genset, both diesel and gasoline fueled, has been widely used both as the main power plant and backup power plant. The working principle of generators to generate electricity is based on the work of combustion engines, which produce electric power when the generator rotates [1]. Generator sets (gensets) play a key role in providing a reliable and efficient backup power source. However, as with all industrial machinery, gensets are also susceptible to various operational issues that can affect their performance, including excessive temperature rise, unstable rotation speed and excessive vibration. Therefore, a careful and accurate monitoring system is required to ensure the generator set is operating in optimal conditions and prevent unexpected breakdowns.

An adaptive network-based fuzzy inference system (ANFIS) is a cross between an artificial neural network (ANN) and a fuzzy inference system (FIS). It is a powerful universal approach that eliminates the requirement for manual optimization of fuzzy systems by automatically tuning the system parameters using neural network techniques. It combines the advantages of ANN and FIS, thereby improving system performance without operator intervention. Given a given input/output dataset, this integrated neuro-fuzzy system builds a fuzzy inference system whose membership function parameters are tuned using the back-propagation algorithm alone, or combined with a least squares estimator [2]. This research aims to develop and simulate the application of Adaptive Neuro-Fuzzy Inference System (ANFIS) on a generator engine monitoring system with a focus on three main parameters namely temperature, speed, and vibration. ANFIS is a modeling method that combines artificial intelligence and fuzzy logic to identify complex relationships between system inputs and outputs. By using ANFIS, it is expected to create a model that is able to predict the condition of the generator engine based on data from sensors that measure these three parameters. ANFIS is capable of self-learning based on the input-output pairs provided, allowing it to automatically create fuzzy controllers based on the data. This reduces the reliance on expert knowledge required for traditional fuzzy control. This research also includes an accuracy comparison between ANFIS and Sugeno fuzzy. The performance of both methods will be observed when faced with the exact same environment [3].

ANFIS is a hybrid learning method that is able to build input-output based on human knowledge by selecting the appropriate membership function. ANFIS is a hybrid method between fuzzy logic and ANN, each of which has advantages. The advantage of fuzzy logic is the application of rules to model human knowledge from a qualitative aspect. The advantage of ANN is that it does not require mathematical modeling for pattern recognition and the learning process. ANN is also able to work based on historical data so that it can make predictions from the data. ANFIS has the advantages of fuzzy logic and ANN because ANFIS is a combination of both. ANFIS is an effective method for making predictions because it has a smaller error rate when compared to ANN [4]. The ANFIS method was chosen because basically the Neural Network can learn from previous experience/data. Just like Neural Network, Fuzzy Logic can provide function calculation without mathematical modeling as the output depends on the input. In addition, Neuro-Fuzzy has the low-level learning and computational power of a Neural Network as well as the advantage of high-level human like thinking of Fuzzy systems, thus making them better for non-linear prediction problems [5].

Fuzzy logic is able to model the qualitative aspects of human knowledge and make decisions as humans do by applying a rule base. Meanwhile, neural networks are artificial representations of the human brain that will simulate the learning process in the human brain. By combining the two, the method will be able to cover their respective weaknesses where the complicated and long decision-making process by fuzzy logic can be automated by the thinking process carried out by neural networks [6]. This simulation aims to test the effectiveness of ANFIS in predicting generator conditions, which is expected to provide valuable input in the development of a more sophisticated and responsive monitoring system. Thus, the results of this study can contribute to improving the reliability and operational efficiency of generators, which in turn will support the continuity of industrial operations that depend on a stable and reliable source of electrical power.

2. METHOD

Adaptive Neuro Fuzzy Inference System (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) is a network based on fuzzy inference system. ANFIS parameters can be separated into two, namely premise and consequent parameters that can be adapted with hybrid training. Hybrid training is done in two steps, namely forward and backward steps. ANFIS is a combination of fuzzy inference system mechanisms described in a neural network architecture. The inference system used is the first-order Takagi-Sugeno-Kang (TSK) model fuzzy inference system with consideration of simplicity and ease of computation. The ANFIS method has a structure consisting of 5 layers, each of which has a different function as shown below.

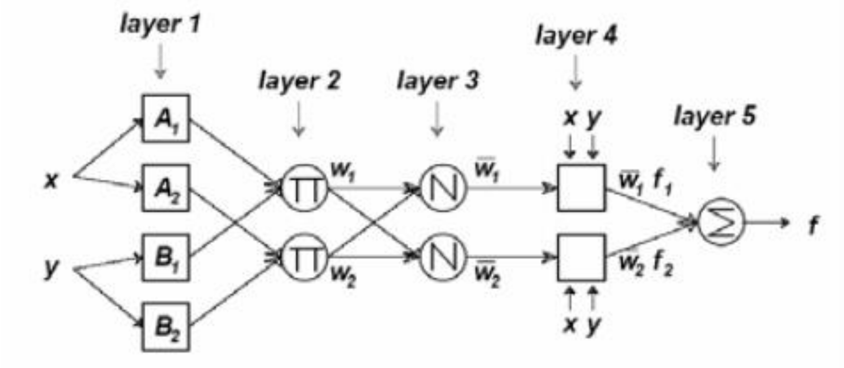

Figure 1. Structure of ANFIS

The first layer represents the input variables, which are A1, A2, B1, and B2. These are the firm input values that the ANFIS system will use to perform inference. The second layer is a fuzzification process where the explicit input values are converted into fuzzy membership values. Each node in this layer represents a membership function, such as W1 and W2, which determines the degree of membership of the input value in the corresponding fuzzy set. This third layer represents the fuzzy rules of the ANFIS system. Each node in this layer corresponds to a particular rule, and the relationships between nodes represent the antecedents and consequences of the rules. The fourth layer normalizes the activating powers of the fuzzy rules, ensuring that the sum of the normalized activating powers is equal to 1. The fifth layer is the defuzzification layer where the normalized activating powers are combined with the consequent parameters (f1 and f2) to produce the final strict output value. The defuzzification process converts the fuzzy output into a strict value. With ANFIS, a control system equivalent to the TSK model fuzzy controller can be created. ANFIS is trained using the backpropagation algorithm. The limitation of ANFIS is that it cannot be applied to systems with multivariable outputs.

System Diagram Block

The research concept is the basis for designing and developing systems. By having an understanding of the system this research can use a structured framework. This research has three stages, namely input, process, and output. Each stage has a different function. At the input there are several components used, namely temperature sensors, speed sensors, vibration sensors, two push buttons for start and stop, and emergency switches. For the process stage, there are two processes, namely processing through ESP32 and through a Programmable Logic Controller (PLC) which is then connected to the MAD42 module of the Omron CJ1M PLC to read analog and digital signals from ESP32 which can then be processed by the Omron CJ1M PLC. In the output section there are several components to produce output from processing, namely two indicator lights, buzzers, HMI, relays, and web servers as well as output from ESP32 in the form of signal output.

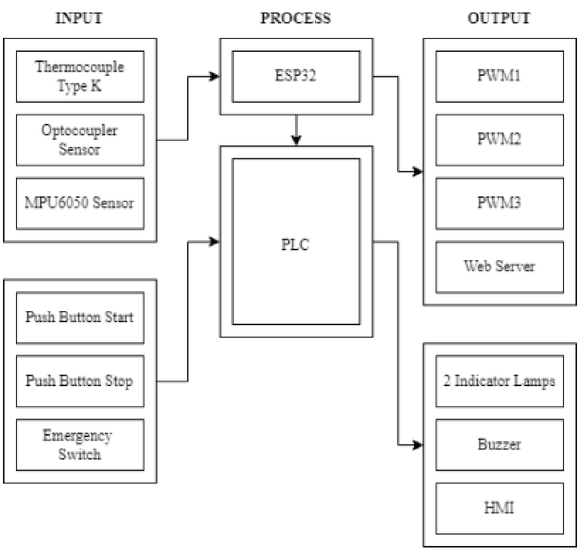

Figure 2. Block diagram

In the system block diagram, there is a division for each stage. In the input there are two parts of input that will enter into different processing. Likewise, the processing process has two processes and the output also has two outputs. The first input containing sensors will enter into the process carried out by the ESP32 which from the microcontroller reads the output in the form of temperature, speed, and vibration values from the engine where the value is then entered and data training is carried out into the adaptive neuro fuzzy inference system (ANFIS) program which is run using matrix laboratory software (MATLAB). The results obtained from the training are in the form of a fuzzy inference system (FIS) file which at this training stage is selected which one has an RMSE value with a minimum value. FIS which has a minimum RMSE value then the fuzzy form is entered into software called CX-Programmer which is used for PLC programming. After training in the software, the ESP32 that has been connected to three sensors, namely the temperature sensor, speed sensor, and vibration sensor, is connected to the MAD42 module of the Omron CJ1M PLC because it is used in reading pulse width modulation (PWM) signals which are then processed by the Omron CJ1M PLC to enter the ANFIS method implemented in the PLC ladder diagram. For the input used in the PLC process, there are two push buttons for start and stop, as well as an emergency switch. At the output of the PLC there are 2 indicator lights that are used to determine the condition of the generator if it is normal, the green indicator light will be on but if it is abnormal, the indicator light is red and the buzzer will turn on. There are two outputs for the interface of each process, namely the webserver and Human Machine Interface (HMI).

Research Stages

The research stage is a planning flow in the implementation of research. This stage is carried out as the first step in the implementation of research so as to achieve the objectives of making this research. This section discusses problem identification, literature study, needs analysis and system design, hardware manufacturing and software manufacturing as well as analysis and discussion. The research flow can be seen in the figure below.

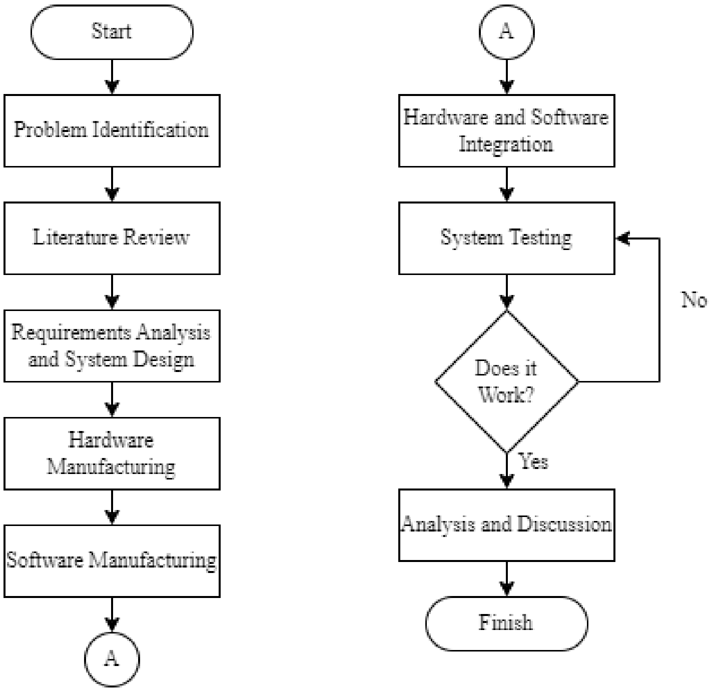

Figure 3. Research flow chart

This research starts from problem identification then looking for previous research so that it can determine the needs and design of the system which will be used to make hardware and software. After both are made, then enter the integration process between hardware and software and test the entire system if successful, then proceed with analysis and discussion, but if it is not successful, the system is tested again. Data collection is carried out when the integration between hardware and software is successful. The ANFIS method is entered when the data has been collected and then training is carried out using the software.

3. RESULTS AND DISCUSSIONS

Test Data

Test data is obtained from the test results of temperature sensors, speed sensors, and vibration sensors placed on the outside of the generator. In this study using a generator set model P22-6 which can be used to generate electricity. The following is the shape of the generator used in this study.

Figure 4. Generator set model P22-6

The initial step in testing the ANFIS method is to use training data derived from the test results of temperature sensors, speed sensors, and vibration sensors recorded at each time interval. The resulting output is a condition between normal or abnormal. The training data that has been collected will be processed and analyzed using software.

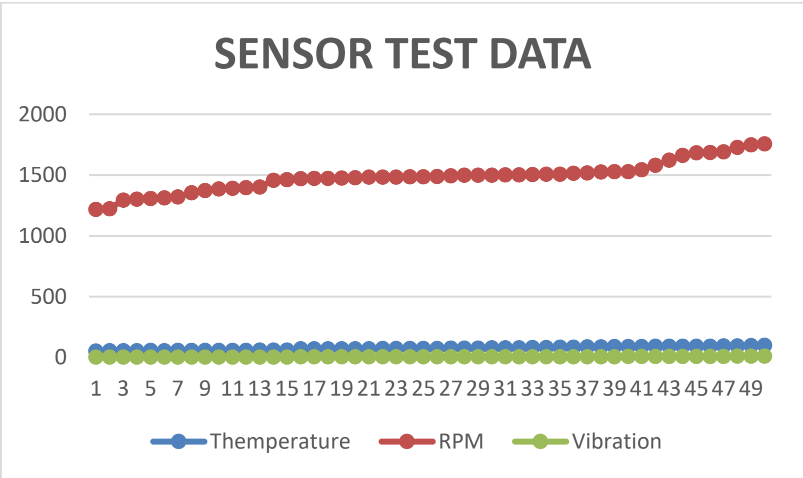

Figure 5. Sensor testing data chart

The table above is the test data from the temperature, speed, and vibration sensors that come out of the serial monitor and are validated using their respective measuring instruments such as temperature using a measuring instrument, namely a thermogun, speed using a tachometer for validation with a tool and vibration using a vibration meter to measure vibration and validated with the sensor output results so that the error results appear. The graph above displays the readings from each sensor and gets as much as 50 data. Where the temperature has a range between 53-100 degrees Celsius, then for RPM speed has a range between 1218-1758 RPM. Vibration has a range between 3-10 mm / s.

ANFIS Testing Using Fuzzy

This test uses MATLAB as supporting software and the first step in testing ANFIS using fuzzy is to enter existing test data into the fuzzy program to get the lowest RMSE value. The following is a flowchart of ANFIS testing using fuzzy.

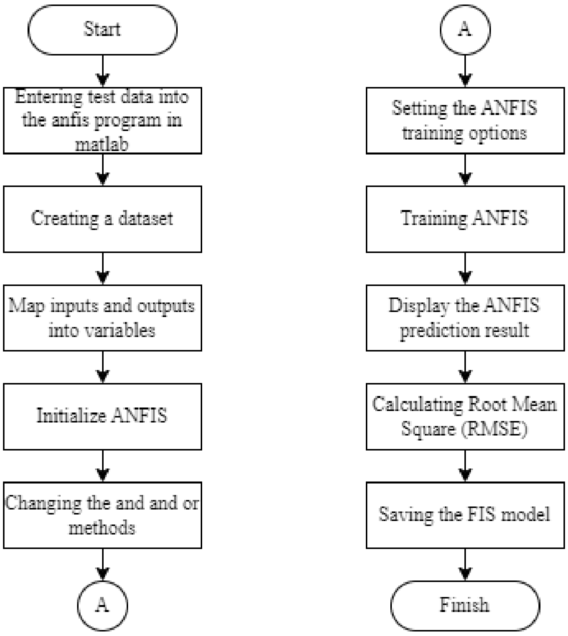

Figure 6. Fuzzy testing flowchart

In the flowchart above, the stage starts with entering test data into the ANFIS program in Matlab. Furthermore, the data is processed into a dataset of x1, x2, x3, and y. Then map the dataset into input and output variables. The next stage is to initialize ANFIS where this testing is carried out by changing the number of membership functions to three pieces with odd values. The next process is to change the OR method so that in the FIS file the AND and OR methods become min and max this is done so that the logic operation is more flexible and realistic. After that, setting the ANFIS training option is used to determine the number of epochs or iterations that will be run during training, in this case, ANFIS is trained for 1000 iterations. Next is to train ANFIS using input and output data and training options that have been determined. For ANFIS prediction results in this test are displayed in the form of a graph where there is original data and ANFIS results. The command window will display the minimum RMSE value for each test and after that, the test will be saved into the FIS file. To find out the smallest RMSE value, testing was carried out 10 times by changing the value of the membership function and the results can be seen in the Table 1.

Table 1. RMSE Value Data

Test Data	**Number Membership Function**	**Membership Function Type**	**RMSE**
1	3 3 3	Trapmf	0,016933
2	5 5 5	Trapmf	0,000063
3	3 3 5	Trapmf	0,000032
4	3 5 5	Trapmf	0,000102
5	5 3 3	Trapmf	0,043392
6	5 5 3	Trapmf	0,000910
7	3 3 3	Trimf	0,001930
8	5 5 5	Trimf	0,000034
9	3 3 5	Trimf	0,000524
10	3 5 5	Trimf	0,000190

From the tests that have been carried out, the lowest error value is obtained by using a 3-3-5 membership function using the trapmf membership function type which produces a minimum training RMSE of 0.000032. So, for testing in this study will use the 3-3-5 membership function.

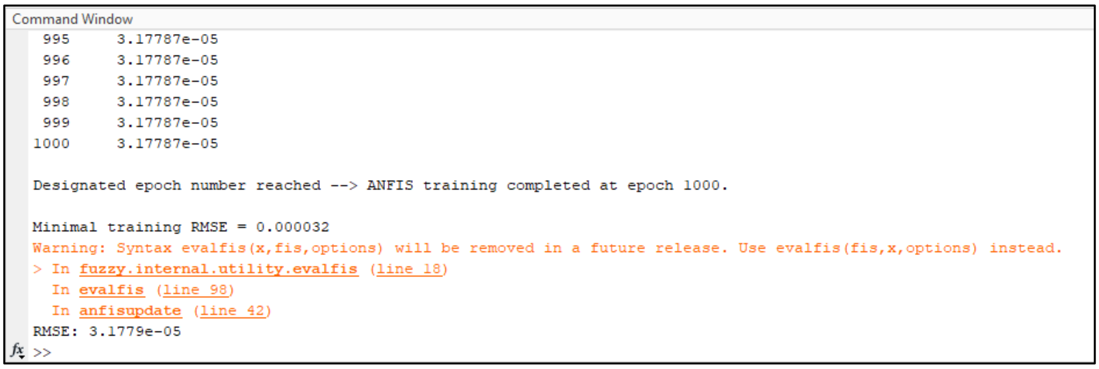

Figure 7. Display of RMSE testing results using MATLAB

In the Figure 7, the RMSE value of the training data is generated for the first time after the data is obtained from the ESP32 output which reads the values of the three sensors, namely the temperature sensor, speed sensor, and vibration sensor. The data is then input into an excel file which is input into the program that will be run using MATLAB. The training results also produce a graphical form that can be seen in the figure below.

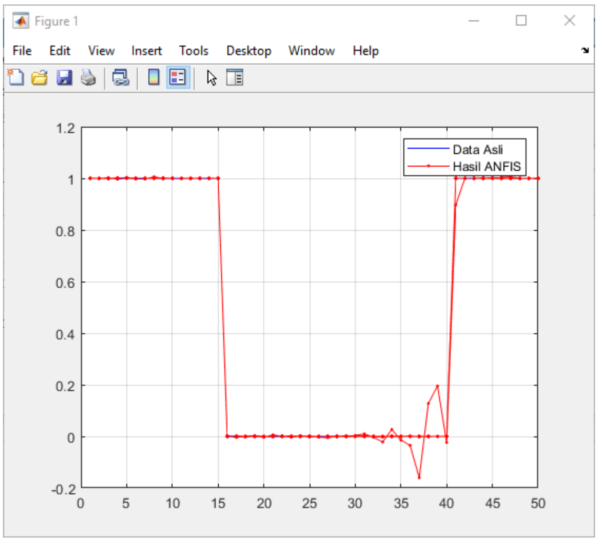

Figure 8. Training result chart

The Figure 8 is a graph of test results through MATLAB software using existing test data. The graph contains the value of the original data and the ANFIS results. Through the program that has been run, new data is generated in the form of a fuzzy inference system (FIS) file that already contains a membership function according to the lowest RMSE value selected from training 10 times before. The next step is to open the FIS file by using the fuzzy call in the MATLAB command window.

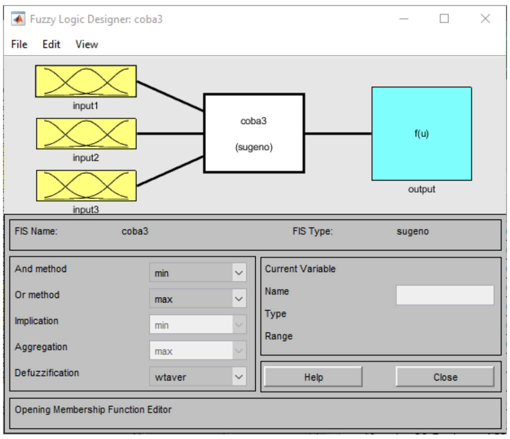

Figure 10. Fuzzy inference system

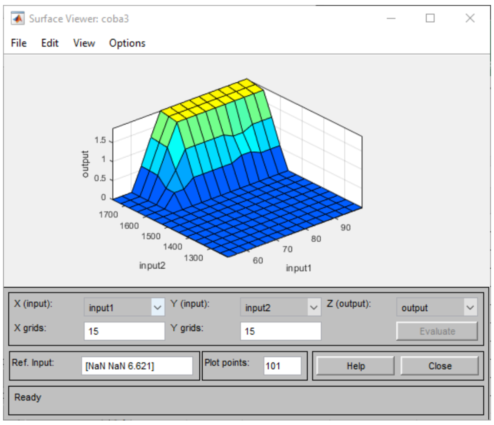

Figure 9. Surface view

Fuzzy that has been opened will bring up three inputs and one output with each input having five membership functions and there are 125 membership functions for the output result. This fuzzy result has 125 rule-based systems that can help in programming the function blocks. The figure above also displays the surface of the running FIS. The fuzzy surface is a visualization of how fuzzy rules are used to determine the output value based on a combination of input values. This display is three-dimensional showing how the fuzzy rule surface changes according to the input variation.

ANFIS Testing Using Function Blocks

This test uses CX-Programmer software which is used to run the ladder diagram on the PLC. To run the ladder diagram in this study using function blocks to input the available data such as entering three inputs into the function blocks and one output into the function blocks. Furthermore, entering data from fuzzy that has been done before into the function blocks. The following is a flowchart of ANFIS testing using function blocks.

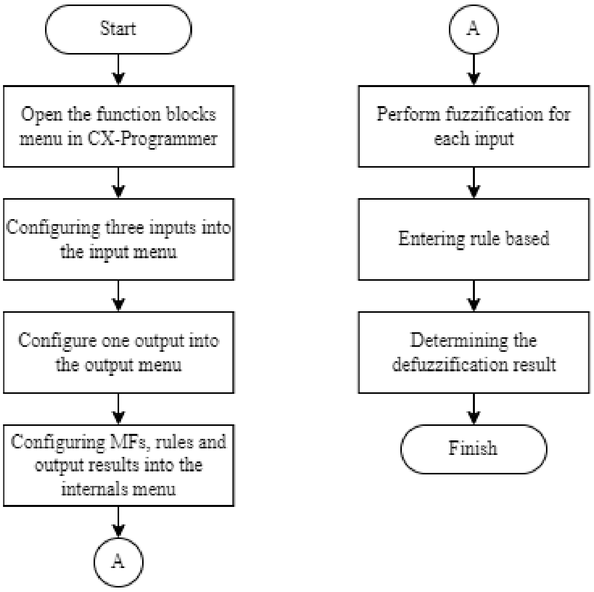

Figure 11. Function blocks testing flowchart

In the flowchart above, the stage starts from opening the function blocks menu in the CX-Programmer software, followed by configuring three inputs and one output into the input and output menu on the function blocks menu. Then configure the membership function which in this test amounted to 11 MFs, for rule based amounted to 45 rules, and for output results amounted to 45. After doing these things, the fuzzification process is carried out for each input, and enter the rule based that has been made before. The last stage is to determine the defuzzification results by summing the rule based and output results.

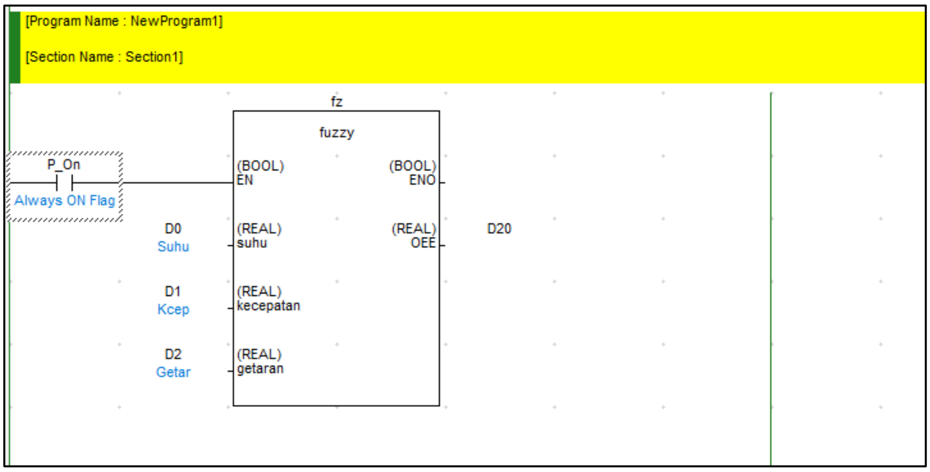

Figure 12. Ladder diagram result display using CX-programmer

The picture above is a ladder diagram of this research, there are three inputs, namely temperature, speed, and vibration and one output in the form of conditioning. After configuring and other stages in the function blocks, the next stage is inputting data in the ladder diagram.

Fuzzy Validation with Diagram Ladder

Validation is done to determine the suitability of the results issued from each test. In this test using the ANFIS method where there are two tests using fuzzy and ladder diagrams.

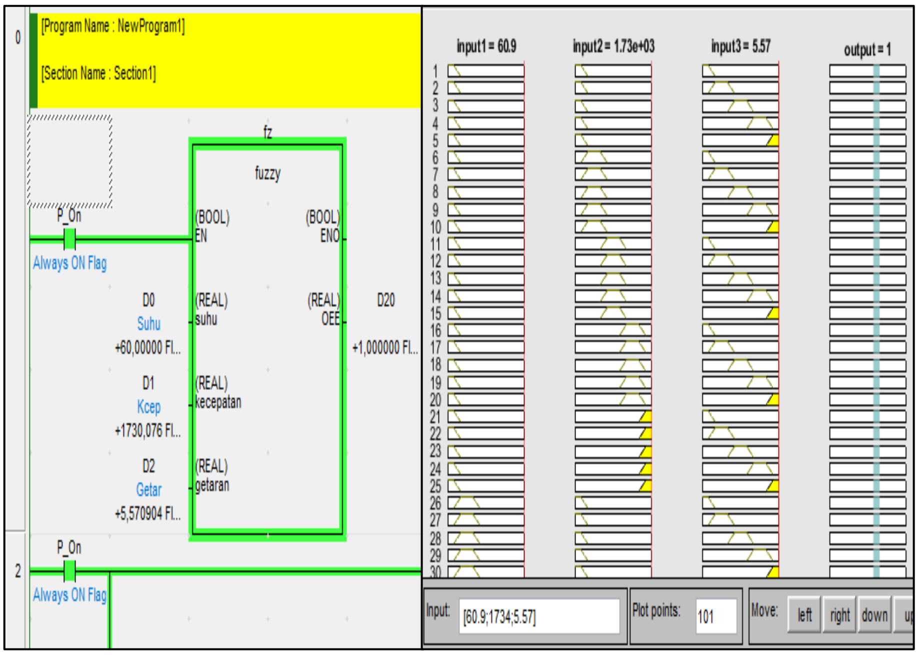

Figure 13. Display of fuzzy and ladder diagram testing validation results

In the picture above is a test using a ladder diagram on the CX-Programmer and a test using fuzzy in Matlab. In these tests using the same data, namely for temperature 60, speed 1730 and for vibration 5.57. In this test the output is in the form of conditioning where 0 is a normal condition and 1 is an abnormal condition. Below is a table of validation results from fuzzy and ladder diagram testing. Where fuzzy is run using MATLAB and ladder diagrams are run using CX-Programmer. And the following results were obtained:

Table 2. Fuzzy and ladder diagram testing validation results

Temperature Testing	**Speed Testing**	**Vibration Testing**	**Fuzzy Output**	**Ladder Output**	**Error (%)**
45,2	423	3,3	0	0	0
46,1	992	3,4	0	0	0
49,3	1215	3,5	0	0	0
50,6	1320	3,7	0	0	0
51,3	1398	4,1	0	0	0
51,9	1463	4,2	0	0	0
52,5	1536	4,3	0	0	0
55,4	1591	4,3	0	0	0
58,1	1642	4,6	0	0	0
60	1730	5,57	1	1	0

4. CONCLUSION

This research successfully developed and simulated a generator engine monitoring system using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method that focuses on temperature, speed, and vibration. ANFIS effectively predicts the condition of the generator engine with the lowest RMSE value of 0.000032 using a 3-3-5 membership function. Implementation in CX-Programmer through ladder diagrams and function blocks allows integration with PLC control systems, proving that the monitoring system can be well applied in industrial environments. Validation results between fuzzy testing in Matlab and ladder diagrams in CX-Programmer show consistent results with RMSE during training of 0.000032 and RMSE during ladder implementation of 0. This system improves the reliability and operational efficiency of generator engines through early detection of abnormal conditions.

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