Application of ANFIS in Decision-Making on the Smart Control Early Warning System for Tornadoes

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***Abstract*— A tornado is one weather process that arises due to atmospheric instability. A tornado is a strong wind, but not all strong winds are tornadoes. Tornadoes have a short time frequency but can result in no minor disaster because they can blow objects away and uproot trees. Due to the consequences, an early warning system is needed as an anticipation for the community in the affected areas so that it can help the community by warning early on of the occurrence of a tornado. The ANFIS (Adaptive Neuro Fuzzy Inference System) method is used to forecast the event of a tornado, and the parameters used are wind speed, ambient temperature, and ambient humidity. This study will compare the ANFIS method using hybrid and backpropagation algorithms. Using the backpropagation algorithm, an error of 0.42385 was produced during training and testing, and an average error of 136.54 was obtained. When using the hybrid algorithm, the error during training is 2.0781 x 10-5, and the average error during testing is 0.015%.**

Keywords* — *ANFIS ; Anemometer; DHT22; Early Warning System; Tornado.

I. INTRODUCTION

Tornadoes are a weather process that arises due to atmospheric instability. This category of wind is a strong wind, not all strong winds are tornadoes. Tornadoes have a short frequency but can cause quite large disasters because they can explode house tiles and uproot trees [1] - [4].

The tropical climate in Indonesia causes many natural disasters, one of which is tornadoes. Extreme weather conditions due to globalization are one of the causes of various disasters, especially tornadoes[5], [6]. With weather conditions like that, people cannot do anything to prevent tornadoes from occurring.

Therefore, society can only minimize the losses caused by tornadoes, both material and non-material victims[7], [8]. One way that can be done to reduce fatalities is to first detect the presence of tornadoes[9], [10].

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ANFIS is a hybrid model that integrates fuzzy logic and artificial neural networks. ANFIS is a dynamic network implementation that relies on a fuzzy inference system[11] - [14]. Combining these two technologies resulted in the creation of ANFIS, which has all the benefits of fuzzy logic control and neural networks. The ANFIS architecture uses a first-order Sugeno fuzzy inference system[15], [16]. The first order Sugeno fuzzy inference system is used because of its simplicity and ease of use. The ANFIS design consists of five layers: two input layers, rules, and output[17].

Therefore, an early warning system is needed to help residents provide early warning of the occurrence of a tornado[18], [19]. By using the ANFIS method, it is hoped that it can help in decision making. Where, the wind speed parameters used are based on the Beaufort scale, where a wind speed of 17-20 m/s can break tree trunks and cause trees to fall, and a speed of 24-32 m/s can cause minor damage to buildings.

II. STUDY LITERATURE

The research commenced with a comprehensive literature review, developing tools, and acquiring proficiency in the Adaptive Neuro-Fuzzy Inference System (ANFIS) technique. Subsequently, the learning outcomes of the method were evaluated, and the device was tested.

A. Tool Design

When designing this early warning tool, several components were used, such as an anemometer sensor to read wind speed, a DHT22 sensor to read environmental temperature and humidity, Arduino Mega as a microcontroller, and an LCD, which functions to display information on the reading results, of each sensor. And sirens as a warning when the condition is "Alert." Figure 1 is the electronic circuit of an early warning device.

B. DHT22 Sensor Calibration

Calibration was carried out on the DHT22 sensor and anemometer sensor by comparing the temperature output with a digital thermometer and the humidity output with a digital hygrometer[20], [21]. For thermometers and digital hygrometers. For both comparison tools, the HTC-2 type taffware brand is used, where the device has an accuracy of ±1oC for temperature readings and ±5% for humidity readings

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Figure 1. Electronic Circuit

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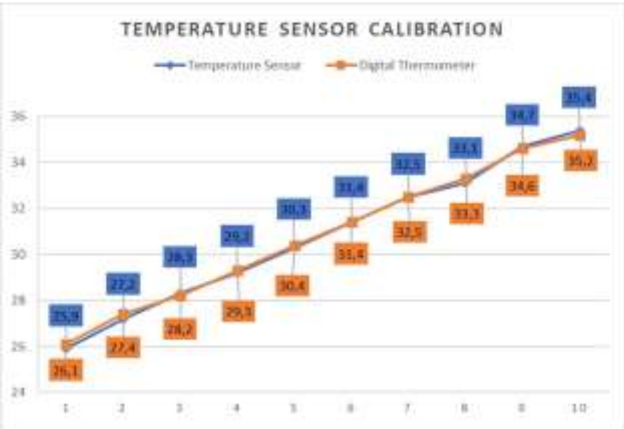


Figure 2. Graph of Temperature Sensor Calibration Results

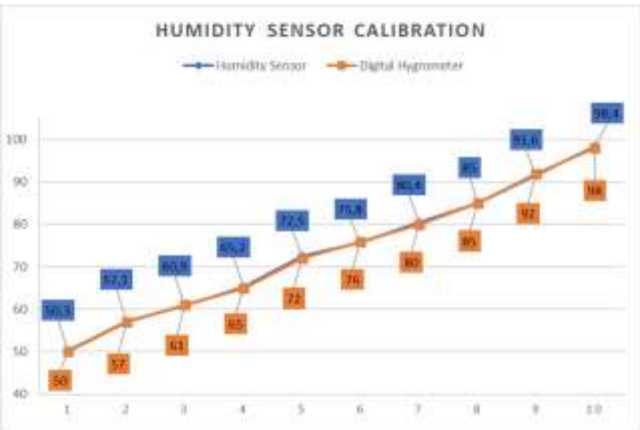


Figure 3. Humidity Sensor Calibration Results Graph

Figure 2 illustrates a graph of temperature sensor calibration outcomes using a digital thermometer. The calibration findings indicate an average inaccuracy of ±0.4%. Figure 3 is a graph of the effects of calibration of the humidity sensor with a digital hygrometer, where the calibration results show an average error of ±0.35%. The average error of the temperature sensor and humidity sensor is relatively small, so it can be ensured that the sensor readings are based on the surrounding environment's temperature and humidity.

C. Anemometer Sensor Calibration

The anemometer sensor that will be used uses a rotary encoder sensor, where the reading results from the sensor are in the form of Revolutions Per Minute (RPM) and will then be converted into wind speed in units of Meters per Second (m/s)[22], [23]. The anemometer sensor test compares the sensor's readings with those of a digital anemometer. This ensures that the sensor data accurately corresponds to the wind speed in the immediate vicinity. The calibration results of the anemometer sensor with a digital anemometer are presented in Figure 4. The results of this calibration show an average error of ±1.29%. These results are quite small.

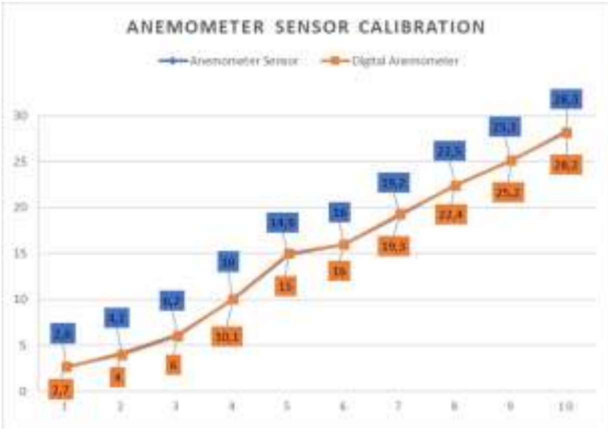


Figure 4. Graph of Anemometer Sensor Calibration Results

D. Design of Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS and fuzzy logic controllers can solve highly nonlinier and time-sensitive problems. ANFIS requires fewer membership rules than a fuzzy logic controller, automatically reducing controller execution time. This model was developed with the Takagi-Sugeno fuzzy inference system[24], [25]. Therefore, it is possible to increase system resilience. These parameters modify and train the membership function using a hybrid algorithm.

The ANFIS estimator has two components contruction and training[10], [26]. The structure parameters are output membership fuction. Membersip function are usually triangular, gausian, or trapezoid. In this case the membership is use triangular. Each node is designated as an input to the first layer, and the output signal is passed to the next layer.

$$O_1, i = \mu_{Ai}(x), \;\; for\ i = 1,2, or \qquad (1)$$

$$O_1, i = \mu_{Bi-2}(y), \;\; for\ i = 3,4 \qquad (2)$$

Membership function values are multiplied in the second layer to determine the burning intensity the rule of fuzzy. Therefore, the output is the result of the input.

$$O_{2,i} = w_i = \mu_{Ai}\,(x).\,\mu_{Bi}\,(y)\ ; i = 1,2 \qquad (3)$$

Within the third layer, the firepower of each rule is standardized, and the proportion of the firepower of each rule to the total sum of all rules is computed.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1+w_2}; i = 1,2 \quad (4)$$

The output of the third layer is multiplied by the corresponding parameters defined in the fourth layer.

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i \left(p_i x + q_i y + r_i\right) \quad (5)$$

The fifth layer calculates the output by adding up all the incoming signals.

$$O_{5,i} = \sum_i \bar{w}_i f_i = \frac{\sum_i \bar{w}_i f_i}{\sum_i w_i} \quad (6)$$

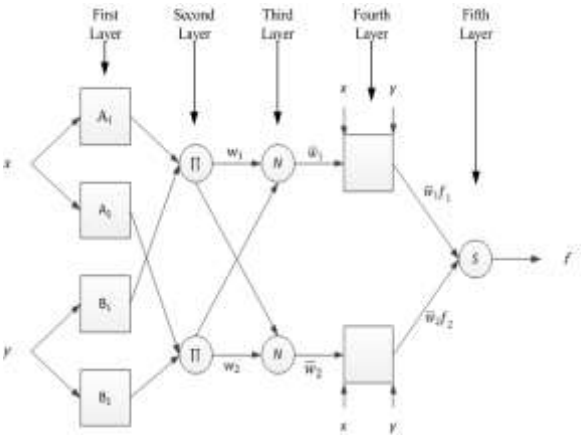
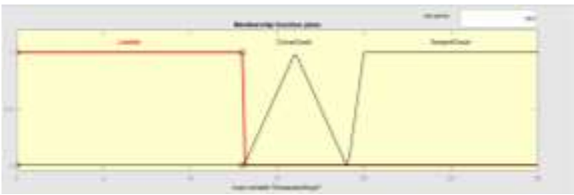
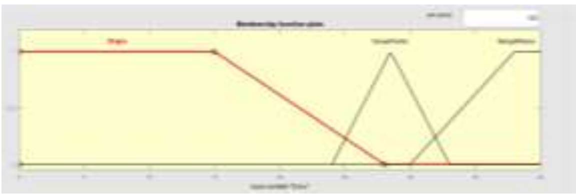


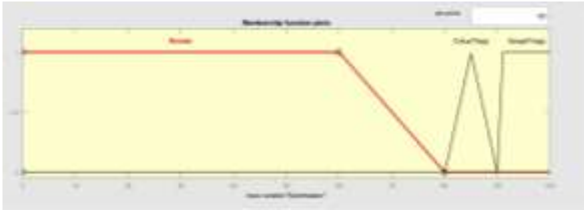
Figure 5 ANFIS Layer Structure



(a)



(b)



(c)

Figure 6. Membership Functions (a) Wind Speed (b) Temperature (c) Humidity

Hidden layers are triggered offline via error feedback; the fuzzy inference system is assumed to have three inputs and one output. There are three functions associated with each input. The ANFIS model based on the Sugeno inference system consists of three principles. This feature implements the principle of product inference to the initial layer (fuzzification level). The normalized fuzzifier output represents the potential of each rule. Utilizing the Sugeno model, the output is defuzzified.

Each node is designated input to the first layer, and the output signal is passed to the next layer. The ANFIS system design was carried out using the Graphical User Interface (GUI) in MATLAB[15], [17], [27]. 500 data are used for each condition during training, so the total data that will be used during training is 1500 input data and 1500 output data. A total of 30 input and 30 output data are used for testing. For the parameters that will be used in the MF input, the "trapmf" type is used, for the MF output parameters, the "constant" type is used.

TABLE I
WIND SPEED, TEMPERATURE AND HUMIDITY PARAMETER FOR EACH CONDITION

Condition	Parameter			
	Wind Velocity (m/s)	**Temperature (ºC)**	**Humidity (%)**	**Target**
Safe	0 - 13	15 - 28	60 - 80	0,1
Alert	14 - 19	24 - 33	81 - 90	0,2
Danger	20 - 30	30 - 38	91 - 100	0,3

For the number of MFs used, as many as 3, the error tolerance is 0, and the epoch (iterations) are 100. The algorithms that will be used are backpropagation and hybrid. Figure 6 is the architecture of ANFIS that has been designed. Table 1 shows each condition's wind speed, temperature, and environmental humidity parameters.

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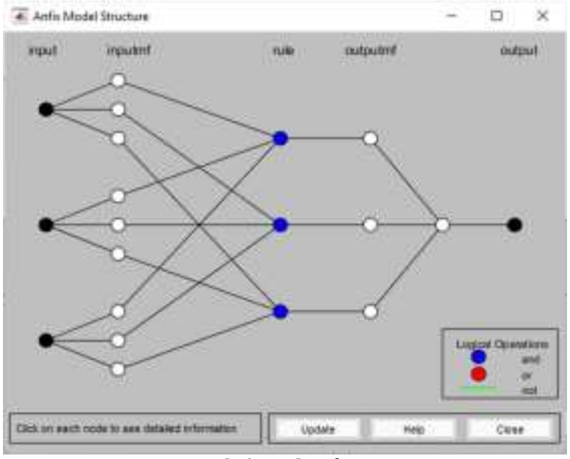

Figure 6. ANFIS architecture

III. *METHODOLOGY*

To achieve research results, several stages will be carried out sequentially. This is done to achieve the objectives of the research, these stages are based on Figure 7 diagram of research stages, namely:

Figure 7. Research Stage Diagram

A. Study of literature

Conduct a study on the basics of the smart control early warning system for tornadoes by looking for references related to tornadoes, cup anemometer sensors, temperature, humidity sensors, and finally, the ANFIS algorithm, where these references become a reference for obtaining research results.

B. Tool Making and Design

This stage is where the researcher designs the tools that will be made. The researcher carried out the design using AutoCAD 2012 software. After the procedure, the next stage was directly making the tool.

C. ANFIS Algorithm Design

After the tool was created, the researchers designed the ANFIS algorithm which would be used to process data taken by the cup anemometer sensor and temperature and humidity sensors. After the data from the sensor is processed using ANFIS, the output results are in several conditions such as Safe, Alert and Danger.

At this stage several experiments were carried out by designing ANFIS using different algorithms. In the first experiment it will be carried out using the backpropagation algorithm and in the second experiment it will be carried out using a hybrid algorithm.

D. Algorithm and Tool Testing

At this stage, testing was carried out on the ANFIS method using the backpropagation algorithm and hybrid algorithm. From these experiments, a comparison will be made with the test error level, the smallest test error level will be used for testing the tool.

If the tools and program are in accordance with the researcher's plan, the tools will be tested on a laboratory scale. Where testing is carried out in the laboratory by adjusting the conditions of wind speed, temperature and humidity according to the parameters that have been created.

At this stage it is also ensured that the tool can work correctly and with the desired output. At this stage, trial and error is also carried out to determine the accuracy of the data that will be used.

E. Data Collection and Analysis

Furthermore, after it was confirmed that the tool was functioning properly and correctly, the researcher collected the data needed to analyze the performance of the tool that had been made. Then the researcher carried out an analysis of the data that had been taken.

F. Conclusion

At this stage, the researcher makes a report after all the data the researcher wants has been achieved. After that, conclusions are drawn based on the results of data collection and analysis of the performance of the tools created.

IV. RESULTS AND DISCUSSION

This section will discuss the training results of the ANFIS method with hybrid and backpropagation algorithms, each algorithm's testing results, and the entire tool's testing.

A. ANFIS Training and Testing

The error tolerance in the first experiment using the backpropagation algorithm was 0, and the number of epochs (iterations) was 100. Figure 8 is the result of training using the backpropagation algorithm, where after training with these parameters an error of 0.42385 was obtained at the 100th epoch. Figure 9 is a comparison graph of the output value with the desired target value, with an average test error of ±136.54%. With an average test error of that size, it states that using the backpropagation algorithm is still less accurate.

The second experiment used a hybrid algorithm with an error tolerance of 0 and 100 epochs. Figure 10 is the result of training using a hybrid algorithm. It can be seen that after training with these parameters, an error of 2.0781×10^{-5} was obtained at the 100th epoch. Figure 11 compares the output and desired target values with an average test error of ±0.015%. Based on the second training experiment using the hybrid algorithm, it was very accurate compared to the first experiment, because the testing error value in the second experiment was much smaller compared to the first experiment using the bacpropagation algorithm.

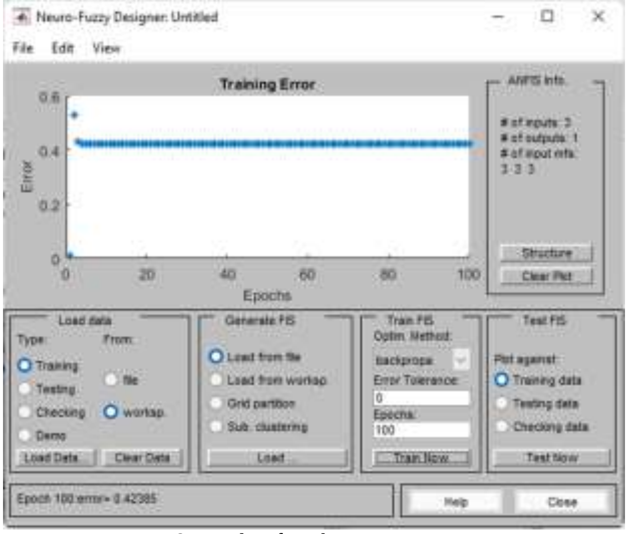

Figure 8. Results of Backpropagation Training

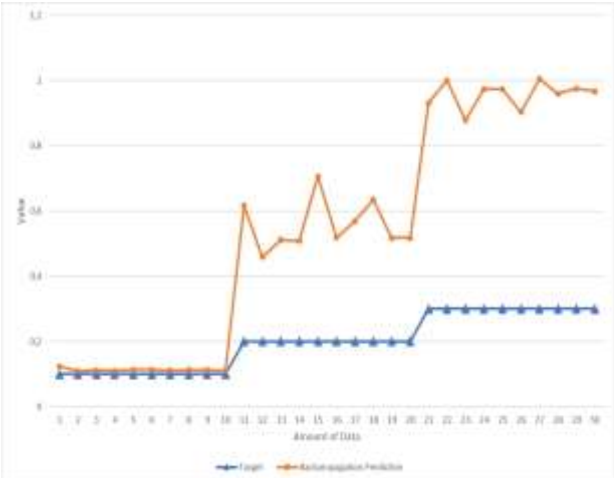

Figure 9. Comparison Graph Of Output Values And Target Values Using The Backpropagation Algorithm

Figure 11 shows that in the "Safe" condition with a target value of 0.1 the graphic results coincide, whereas in this condition ANFIS can map the input and output values very accurately. In the "Alert" condition with a target value of 0.2 and the "Danger" condition with a target value of 0.3, the test results appear to have shifted quite far from the desired target value, so that in this condition ANFIS is still very inaccurate for mapping input and output values which are desired. These results show that when ANFIS using the backpropagation algorithm is given input values in these conditions it is still not accurate for mapping as a whole.

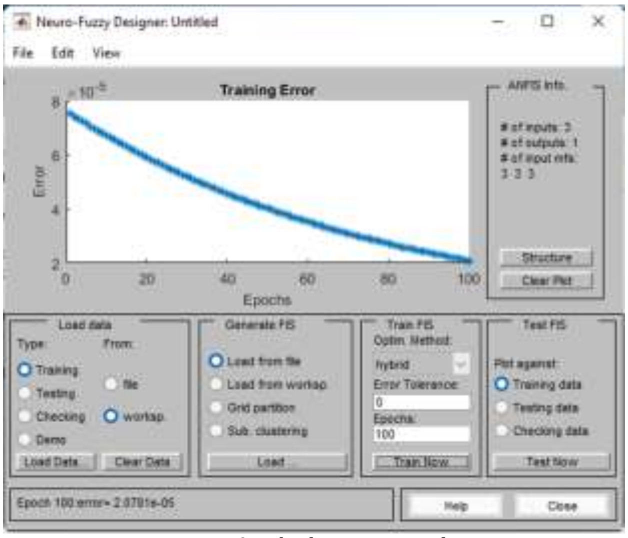

Figure 10 Hybrid Training Results

From Figure 11, you can see that the graph between the target value and the ANFIS results is designed to coincide. This means that the ANFIS that we trained using a hybrid algorithm can map input and output values very accurately.

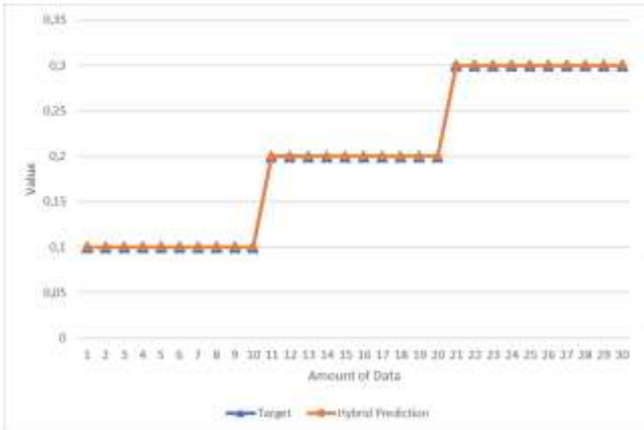

Figure 11 Graph of Comparison of Output Values and Target Values Using the Hybrid Algorithm

B. *Tool Testing*

The ANFIS approach will be employed for training and testing after calibrating each sensor. Carry out tool testing to analyze the performance and success rate of the methods and tools that have been designed. The ANFIS method with a hybrid algorithm will be used from the training results because, during training, an error of 2.0781 x 10-5 was produced with an average testing error of ±0.015%.

The reading results from each sensor will be processed on the Arduino MEGA using the ANFIS method. Then, the task results from each sensor and the current conditions of the

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process output of the method used will be displayed on the LCD. During "Alert" and "Danger" conditions, the siren will sound to warn the public. Table 2 is the test results data.

TABLE II
EQUIPMENT TESTING DATA

Wind Velocity (m/s)	Temperature (ºC)	Humidity (%)	Target	Condition
3,39	25,79	89,83	0,099	Safe
3,89	25,89	90,03	0,099	Safe
4,62	27,93	80,65	0,099	Safe
4,83	28,79	80,90	0,099	Safe
6,50	37,68	69,10	0,099	Safe
10,74	26,93	61,15	0,099	Safe
12,44	30,77	60,46	0,099	Safe
10,74	31,32	61,05	0,099	Safe
10,74	26,93	61,15	0,099	Safe
12,44	30,77	60,46	0,099	Safe
15,83	25,99	90,08	0,2	Alert
15,83	25,99	89,93	0,2	Alert
17,53	26,81	89,09	0,2	Alert
18,66	25,99	89,78	0,199	Alert
19,23	25,99	89,73	0,202	Alert
18,92	30,54	83,96	0,2	Alert
16,96	26,93	84,15	0,2	Alert
16,96	27,40	86,52	0,2	Alert
17,53	27,16	86,82	0,2	Alert
15,83	28,65	84,85	0,2	Alert
20,92	26,30	93,98	0.3	Danger
23,75	26,46	91,61	0.3	Danger
23,18	26,57	91,66	0.3	Danger
22,62	26,61	90,33	0.3	Danger
23,18	26,57	90,42	0.3	Danger
21,49	35,40	95,02	0.3	Danger
24,32	37,44	96,00	0.3	Danger
26,01	38,70	96,20	0.3	Danger
24,88	36,11	96,89	0.3	Danger
26,58	36,82	95,51	0.3	Danger

V. CONCLUSION

The anemometer sensor and DHT22 sensor can provide data regarding current environmental conditions. Based on test findings, all sensors meet the desired specifications. The anemometer sensor has an average error of ±1.29%, while the DHT22 sensor has an average error of ±0.4% for temperature readings and ±0.4% for humidity measurements. The average error is ±0.35%. With an average reading error of that size, it is very accurate for reading wind speed, temperature and environmental humidity.

Based on the results of experiments using the backpropagation algorithm, it is still less accurate because the test error is ±136.54%. And in experiments using the hybrid algorithm, it can be ensured that it is very accurate because the test error obtained is ±0.015%, smaller than the backpropagation algorithm.

Based on the test results of the tool, it can be seen that using the ANFIS method with a hybrid algorithm can determine each safe, alert and dangerous condition very accurately based on the parameters of wind speed, temperature and environmental humidity.

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