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Distribution Transformer Secondary Bushing Temperature Detection Device using Feed Forward Neural Network

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ABSTRAK

Transformator distribusi mengubah tegangan listrik tinggi menjadi rendah. Pada sekunder transformator, tegangan dan arus listrik cukup besar sehingga terjadi disipasi panas berlebihan karena timbulnya tahanan listrik pada titik koneksi sekunder transformator dengan kabel keluaran. Hal ini menyebabkan unbalance current dan overheat sehingga terjadi lost contact yang mengganggu pasokan listrik serta drop tegangan. Sayangnya pemeriksaan di lapangan dilakukan tiap enam bulan sekali padahal lost contact dapat terjadi sewaktu-waktu. Sehingga kami mengusulkan pengembangan alat deteksi overheat real-time pada bushing sekunder menggunakan metode klasifikasi suhu berbasis Feed Forward Neural Network (FFNN) yang dilengkapi dengan Internet of Things. FFNN berhasil mengklasifikasikan suhu dengan nilai 0 untuk suhu 30˚C-50˚C, nilai 0 untuk suhu 51˚C-90˚C yang memerlukan perbaikan, dan nilai satu untuk suhu di atas 90˚C dengan relay memutus, kemudian sistem mengirimkan notifikasi lost contact real-time. Sehingga alat ini meningkatkan keefektifan pemeriksaan dan dapat diterapkan guna mengurangi tindakan pemeriksaan secara langsung.

***Kata kunci**: Transformator Distribusi, Lost Contact, Internet of Things, Feed Forward Neural Network*

ABSTRACT

The distribution transformer turns high voltage into low voltage. On the secondary transformator, the voltage and current are sufficiently large that excessive heat dissipation occurs due to the appearance of electric retention at the point of secondary connection of the transformator to the output cable. This causes current imbalance and overheating, resulting in lost contact that disrupts power supply and voltage drop. Unfortunately, field inspections are carried out every six months and lost contact can occur at any time. So we suggested developing a real-time overheat detection tool on secondary bushing using a temperature classification method based on the Feed Forward Neural Network (FFNN) equipped with the Internet of Things. With FFNN, the system successfully classifies the temperature with a value of 0 for a temperature of 30˚C-50˚C, a value 0 for the temperature of 51°C-90˚C that requires repair, and a value 1 for a temperatur above 90˚C with a relay disconnect, then the system sends a real-time lost contact notification. Thus this tool increases the effectiveness of inspection and can be applied to reduce inspection actions directly.

***Keywords:** Distribution Transformer, Lost Contact, Internet of Things, Feed Forward Neural Network*

1. INTRODUCTION

Electricity is typically operated in line with its primary objective, which is to provide a power supply that is highly reliable and cost-efficient, with the expectation of reasonable continuity and quality. The increasing demand for electrical energy, driven by technological advancements, necessitates a corresponding improvement in the reliability of the power distribution system. Maintaining the reliability of an electrical distribution system is crucial for ensuring continuity and dependability in the supply of electricity **(Salim et al., 2021)**. PT.PLN (Perusahaan Listrik Negara), the state electricity company of Indonesia, plays a vital role in power generation and distribution across the country. The generated electrical energy is transmitted through transmission lines and subsequently distributed to consumers **(Purnomoadi et al., 2022).**

Bushings are composed of solid dielectric materials with multiple layers of metal and porcelain, each having different permittivity values. The characteristics of the electric field surrounding the bushing are influenced by these materials, leading to variations in the distribution of the electric field around the dielectric material, in accordance with the magnitude of the permittivity of the constituent materials of the **(AJ et al., 2018).** In the distribution system, various unforeseen disturbances can occur, negatively impacting the distribution process and resulting in a decline in service quality for consumers. One common disruption in the distribution system occurs in the low-voltage network (JTR). At PT.PLN, issues and failures are frequently observed, including challenges in identifying the condition of equipment in the JTR infrastructure. Among the critical components in the distribution system, transformers play a crucial role as they facilitate the transmission of electrical energy from the 20 kV network to consumers by stepping down the voltage to 220VAC **(Samangun et al., 2018)**.

Distribution transformers often experience disruptions such as lost contact in the secondary side connectors, especially in step-down. Lost contact is often caused by high temperatures in transformer bushings. Bushings act as conductors to distribute electricity to consumers and are coated with insulators to protect against short circuits between the bushing conductors and the transformer tank **(Xie et al., 2022).** The standard temperature for the secondary side bushing connector of a transformer is specified in the PLN SPLN D3.021-1:2020, adhering to the IEC60137 requirements. Currently, PLN personnel have to physically inspect each connection point on transformers in the field to determine the level of heat, which is a time-consuming process due to the large number of transformers and their diverse locations. PT.PLN still faces challenges in identifying lost contacts from customers **(Almanda & Ardiansyah, 2021).**

To address this problem, a device is proposed to simplify the work of PT. PLN personnel. The research involves the creation of a monitoring tool capable of measuring the temperature of the secondary side of distribution transformers. The device will display the temperature data on an IoT application, serving as a means to alert personnel when the temperature exceeds the nominal limit for bushing connectors. According to the IEC60137 standard, the maximum permissible temperature for the connector is 90°C **(Gu et al., 2020).** By utilizing this system, personnel can monitor the temperature conditions of transformers in real-time through the IoT application. The collected temperature data will be classified into binary parameters (1 or 0) using the Feed-Forward Neural Network (FFNN) method. The output classification will then be used as input for a relay. If the implemented system detects overheating of the transformer, it will generate notifications on the Blynk application **(Yuvaraju et al., 2023).** The objective of this final project is to assist PT.PLN in minimizing overheating issues in distribution transformers, thereby facilitating remote monitoring without the need for physical visits to the locations. The monitored data can also be utilized for maintenance purposes.

2. METHODS

The focus of this research is to design an early detection system for the secondary bushing of distribution transformers to prevent lost contact. This system utilizes temperature and voltage parameters as indicators of faults. During the research implementation phase, the concept design is carried out according to the block diagram shown in Figure 1. This will facilitate the analysis, data collection, and drawing of conclusions required for this research.

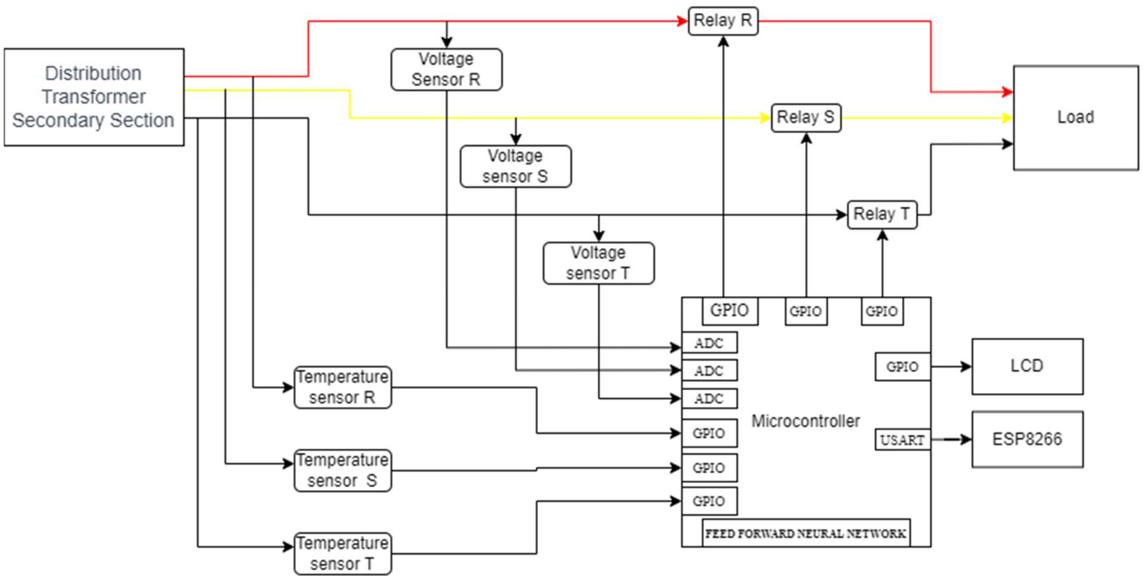

Figure 1. Block Diagram of The System

In general, the working principle of the block diagram based on Figure 1. The temperature sensor reads the temperature at the bushing connector on the secondary side of the transformer. It is then processed by the STM32F407VG microcontroller using the feed-forward neural network (FFNN) method to classify the output as either 1 or 0. If the output is 1, indicating a certain condition, the relay is automatically activated, causing a disconnection in the power supply network. Voltage sensors are installed in each phase to measure the voltage, enabling the detection of any lost contact. The temperature and voltage sensor readings are transmitted through the ESP8266 module, which is connected to the microcontroller. This allows the data to be displayed on an IoT platform and stored as a data logger.

2.1 Temperature Sensor

Monitoring the temperature in power substations is essential due to various factors that can cause equipment malfunctions and damage **(Rahmadani et al., 2022)**. Therefore, it is crucial to monitor substation temperature as it significantly impacts the overall condition and performance of the equipment **(Usamentiaga et al., 2018)**. The temperature sensor is used to measure the heat parameter of the distribution transformer's bushing. The sensor is placed in close proximity to the bushing to accurately capture its temperature. The sensor is connected to a microcontroller or microprocessor unit, which acts as the central processing unit for the monitoring system.

2.2 Transformer Temperature Rise

The temperature rise caused by heat in the transformer winding usually occurs due to loading. This is due to the current in the winding and the induction of the iron. Every increase of about 9°C from the permissible limit will result in reduced life or increase in life loss value. Excessive temperature increase in transformer windings can cause lost contact in the phase wire connection (schoen cable) with the terminal bushing. This can interfere with the performance of the transformer and cause a decrease in the quality and reliability of the electricity generated **(Akbari & Rezaei-Zare, 2021).**

One of the methods used to check the temperature of equipment components is by using a Thermal Camera or Thermovision, shown in Figure 2. This measurement utilizes infrared radiation emitted by thermal imagers, allowing the thermal imager display to indicate the temperature of the measured equipment **(Simko et al., 2018).** In the evaluation of thermovision measurements, a calculation table is used to classify the condition of the measured equipment and determine the necessary maintenance actions based on Table 1.

Table 1. Parameters and Recommendations For Thermovision On Terminals

No	Temperature	Recommendations
1	30°C -50°C	Under normal conditions, the next measurement will be conducted according to the schedule.
2	51°C-90°C	Immediate repairs are necessary.
3	> 90	Emergency condition.

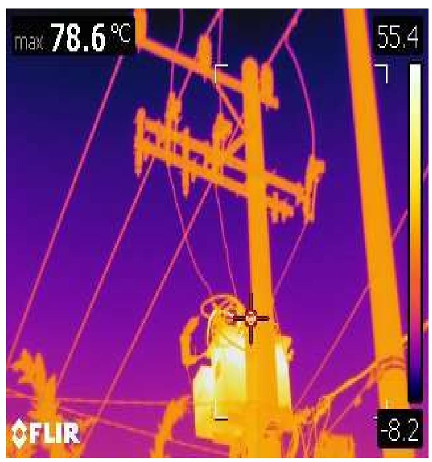

Figure 2. Measurement Results With Thermovision

2.3 Feed Forward Neural Network

Artificial Neural Network (ANN) is a modeling method inspired by the functioning of neurons in the human brain. Neurons in the human brain are interconnected to transmit information. Based on Figure 3, the structure of an Artificial Neural Network (ANN) as composed of an input layer, hidden layer(s), and an output layer **(Habibi et al., 2020).** In the case of Feed Forward Neural Network (FFNN), the training process is segregated into two stages: the forward pass and the backward pass. During the forward pass, the network processes the input data by multiplying the input values with the weights and biases, and applying activation functions **(Wahjono et al., 2020)**. This process is repeated until the final output is obtained. In the backward pass, also known as backpropagation, the network adjusts the weights and biases based on the calculated error. The error is computed by comparing the network's output with the expected output or target values. By propagating the error backwards through the network, new values for the weights and biases are obtained, aiming to minimize the error **(Zuraidah et al., 2021).**

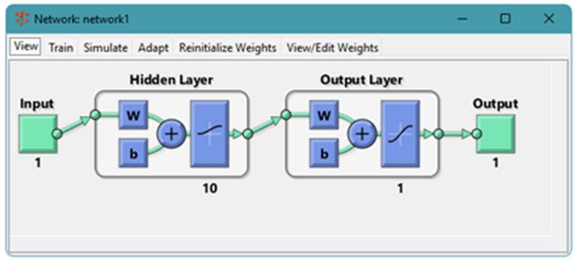

Figure 3. Network Feed Forward Neural Network

The implementation of the FFNN method in this research is to classify input temperature data and produce an output that will control the SSR (Solid State Relay). By using the FFNN algorithm, the system can identify whether the temperature exceeds a certain limit and take appropriate action to maintain the reliability and safety of the electricity distribution system. The FFNN method involves a data search stage from the initial training process. Then the data is studied using the Neural Network Tool (NNTool) feature in MATLAB. So that the value of the bias and weight can be obtained that will be used in the system. The training was carried out using a simulation on the MATLAB Simulink software. The resulting training data is 361 temperature characteristic data from the range of 0˚C to 180˚C. The output or target of FFNN is binary logic, namely 1 or 0, which will produce a decision according to the predetermined logic. Some of the training data representatives that will be used in this system are shown in Table 2.

Table 2. Feed Forward Neural Network Learning Data

Suhu (ºC)	Target
0	0
10	0
20	0
30	0
40	0
50	0
60	0
70	0
80	0
90	0
100	1
110	1
120	1
130	1
140	1
150	1
160	1
170	1
180	1

In this research, 2 layers were used, namely 1 hiden layer with 10 neurons using the logsig function. The next layer is the output layer with the same number of neurons, namely 10 neurons using the tantig function. The neural network training process lasts for 1000 iterations using the lavenberg-marquadt training method. The result of the training process is in the form of a regression plot with a value of R=1, which means that the ANN created is identical enough to the data being trained, so that the ANN can be used as a relay to turn on. The following results of the ANN regression plot graph can be seen in Figure 4. From the results of the regression plot graph, the structure of the ANN algorithm diagram appears as shown in Figure 5

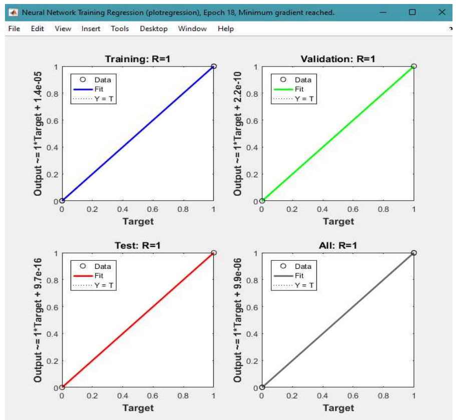

Figure 4. Feed Forward Neural Network Regression Plots

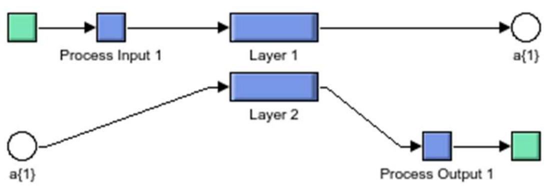

Figure 5. Feed Forward Neural Network Algorithm Diagram

The structure of the FFNN network diagram is shown in Figure 5 which consists of several constituent components namely, Process Input 1; layer 1; Layer 2 and Process Output 1. Of the four main process components of the ERNN network above, then they are discussed in more detail to obtain Equations (1-6) **(Prasetyo et al., 2020).** In the input process for learning artificial neural networks, data normalization is carried out with the aim of producing a data representation that has a smaller value than the original data, but without losing its characteristics. The data normalization (xn) process can be calculated using Equation (1).

$$xn = \frac{2(\mathrm{x}-D_{\min(input)})}{(D_{\max(input)}-D_{\min(input)})-1} \quad (1)$$

The variables D_{min} and D_{max} are the maximum and minimum value limits of the temperature input, while X is set to data input. The goal of the normalization is to standardize the input values so that they can be processed by a neural network. Furthermore, the output of process input 1 will be forwarded to layer 1 and then go to layer 2 in the neural network, which can be seen in Figure 6.

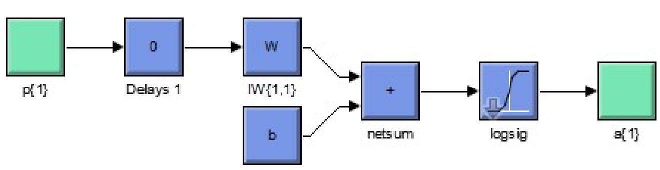

Figure 6. Simulink Layer 1 Diagrams

In Figure 6 is part of the Layer 1 block. This block can alternatively be referred to as a hidden layer, and it comprises three primary function blocks: weight (W), bias (B), and the logsig activation function. The function of Layer 1 is to receive input data from outside and forward it to the next layer in the network. In layer 1, calculations can be performed using Equation (2).

$$y_n = x_n w_n + b_n \tag{2}$$

To calculate the output of n (yn) neurons in layer 1, by multiplying the input data (xn) with the appropriate weight (wn) then adding the bias value (bn). The result of the calculation value will be converted into a value with a range of 0 – 1 by the logsig activation function. The logsig activation can be calculated using Equation (3).

$$logsig(n) = \frac{1}{1+\exp^{-n}} \tag{3}$$

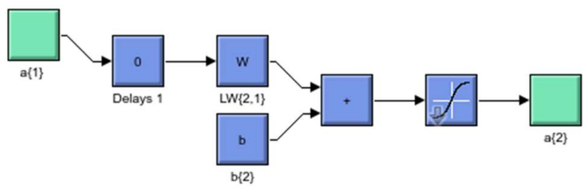

Figure 7. Simulink Layer 2 Diagrams

In Figure 7, layer 2 represents the content of the output layer block, comprising a single neuron responsible for computing the output based on inputs received from the calculations performed in layer 1 or the hidden layer, so that initially 10 output data will then become 1 output data and is translated by the Equation (4).

$$y = x1w1 + x2w2 + x3w3 \ldots\ x_n w_n b_n \tag{4}$$

The tansig activation function is utilized in the calculation of the activation function at the output layer. The tansig function is used to standardize the calculation results of the weight calculation results and can be a value with a range of -1 to 1. The tansig function is expressed in the Equation (5).

$$tansig(n) = \frac{2}{1+exp^{-2+n}} - 1 \tag{5}$$

Denormalization in ANN is a process to return data that has been normalized to its initial scale. This is done to obtain predictive results that are understandable and useful in everyday life. The output value of data denormalization can be expressed by Equation (6).

$$\mathrm{De} = (tansig(y) + 1)x\,\frac{(D_{\max(output)} - D_{\min\,(output)}}{2} + D_{\min\,(output)} \tag{6}$$

Denormalization is the final result of calculations using the feed forward neural network method. In this calculation, two trial samples were taken. Two temperature values are given as input to the ANN, namely 90°C and 100°C. After going through the mathematical calculation process, the ANN output is a logical value of 0.000508444 and 1.

2.4 Internet of Things (IoT)

This research is equipped with a feature to display a database using IoT, where the IoT function serves as a database platform using Blynk IoT. By connecting Blynk IoT with ESP8266, there are several processes to connect ESP8266 with Blynk IoT. Blynk is an iOS and Android platform utilized to remotely control Arduino modules, Raspberry Pi, Wemos, and comparable devices via the internet **(Rifadil et al., 2022).** This application permits remote management of hardware devices, enabling the display and storage of sensor data, along with the execution of diverse and captivating tasks **(Rakhmawati et al., 2019).** It facilitates remote control and monitoring from anywhere, as long as an internet connection is established.

Figure 8. Block Diagram of IoT

Based on Figure 8, can be seen a diagram block of sensor reading data collected by the microcontroller that is sent through a series of co-communications with the Wi-Fi module ESP8266.then processed through the cloud blynk server that serves as an intermediary of communication between the IoT device with the mobile application Blynk, the mobile blync application is useful to denote notifications and will also be sent to google sheets as a database storage as data storage.with the presence of technology in the form of iot useful to monitor an object,especially in this study to monitor the heat of the secondary bushing of the distribution transformation.

3. RESULTS AND DISCUSS

In this research, two types of testing were conducted: simulation testing and overall system integration testing. Simulation testing was performed using the MATLAB application to determine the classification values of the feed-forward neural network. As for the overall system hardware integration testing, it was carried out as planned.

3.1 Simulation Test

This integration testing is conducted to determine the reliability of the system, whether the designed and implemented system is functioning properly as planned from the beginning, which is when the temperature reaches 90 degrees, the relay will disconnect.

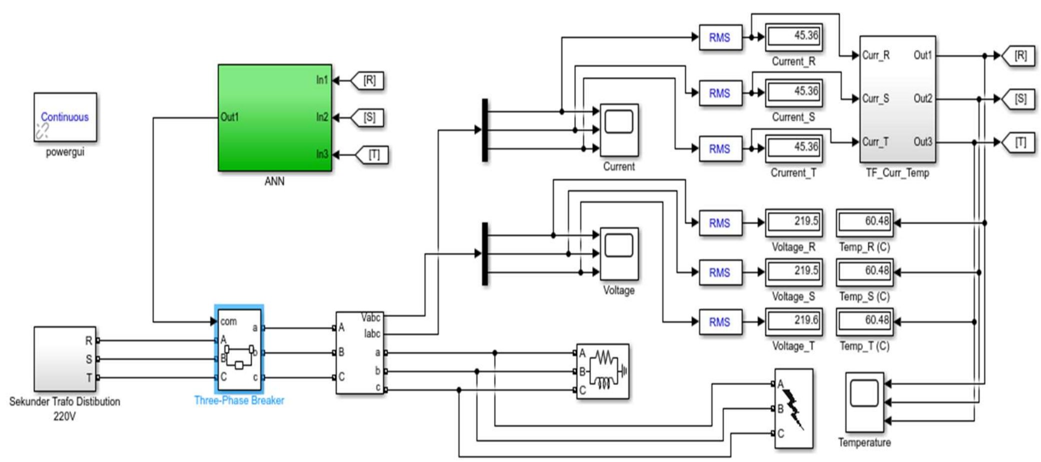

Figure 9. System Integration Circuit in Matlab

As seen in Figure 9, the simulation above represents the system integration circuitry in the MATLAB application. This simulation is used to compare the results of relay disconnection time obtained in open loop mode, without control, with close loop mode using the Feed-forward neural network method. The graph of relay disconnection in open loop condition can be seen in Figure 9, while the application of the feed-forward neural network method for temperature classification can be seen in Figure 10.

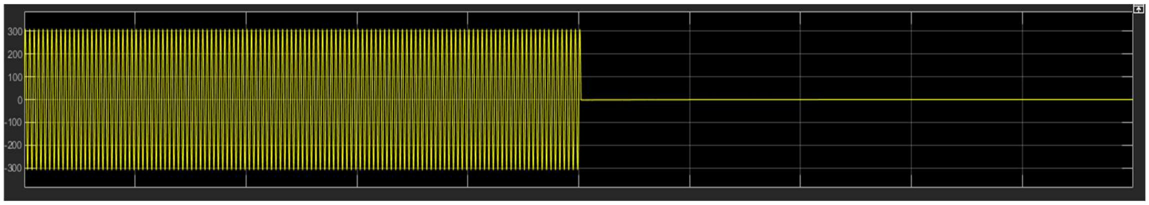

Figure 10. Graph of Relay Disconnection Time in Open Loop Mode

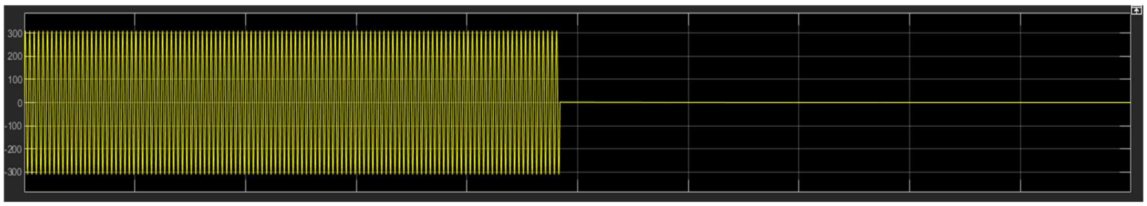

Figure 11. Graph of Relay Disconnection Time with Feed Forward Neural Network

The above figure represents the results of the testing conducted when the temperature exceeds 90 degrees, which is the threshold for triggering the relay to disconnect. Figure 10 illustrates the open loop condition where the relay disconnects at 2.5 seconds, while Figure 11, utilizing the feed-forward neural network, shows the relay disconnecting at 2.3 seconds. This demonstrates that the feed-forward neural network is able to achieve a faster response time, reducing it by 0.2 seconds.

3.2 Testing Temperature Sensor

The accuracy testing of the MAX6675 temperature sensor was performed by collecting temperature data from the MAX6675 sensor. A thermogun and a thermometer were used as reference devices for comparison. Testing the temperature sensor is shown in Figure 12.

Figure 12. Testing Temperature Sensor Compared to Thermometers And Thermoguns

Table 3. The Results of Temperature Measurements using The MAX6675

No	Phase	Max6675 (˚C)	Thermoguns (˚C)	Thermometers (˚C)
1	Phase R	30	29	31
		49	50	50
		101	100	99
2	Phase S	30	30	30
		50	51	51
		102	100	100
3	Phase T	30	30	29
		50	49	50
		100	100	98

From the Table 3, you can see the comparison between the temperature readings of the MAX6675, thermogun, and thermometer at each phase. For example, in phase R, the temperature reading of the MAX6675 is 30°C, while the temperature read from the thermogun is 29°C, and the temperature reading from a thermometer is 31°C. By comparing temperature data from the three devices, the accuracy of the MAX6675 temperature sensor in measuring temperature compared to thermometers and thermoguns can be assessed.

3.3 System Integration Hardware Result

The hardware integration testing in this research focuses on testing the protection against lost contact occurring in the secondary bushing of the distribution transformer. The voltage source used for the hardware testing in this research is an AC power source from the local power grid, with a voltage of 220 V. The testing is conducted using a 10 W lamp load for each phase. Figure 13 is a system integration testing diagram.

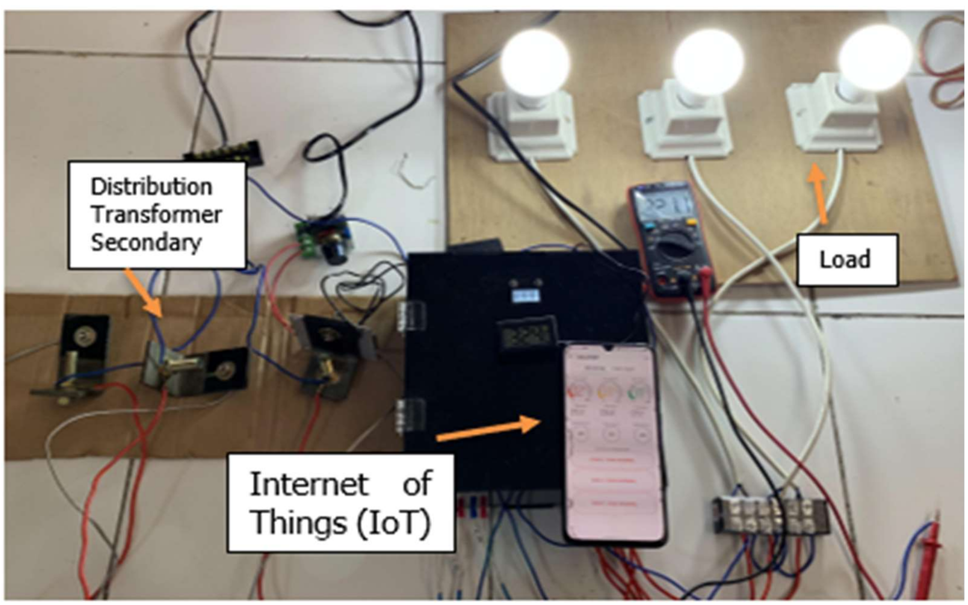

Figure 13. The Process of Integration Testing

Table 4. Hardware Testing Condition Phase R Disruption

Temperature (˚C)			Voltage (V)			Relay			lightbulb		
R	**S**	**T**	**R**	**S**	**T**	**R**	**S**	**T**	**R**	**S**	**T**
32	30	30	228	228	228	1	1	1	On	On	On
42	30	30	227	227	227	1	1	1	On	On	On
52	29	30	227	228	228	1	1	1	On	On	On
62	30	30	227	228	227	1	1	1	On	On	On
72	29	30	227	228	227	1	1	1	On	On	On
82	30	29	228	228	228	1	1	1	On	On	On
88	30	29	225	225	225	1	1	1	On	On	On
89	30	30	225	225	225	1	1	1	On	On	On
90	30	30	225	225	225	1	1	1	On	On	On
91	29	29	155	226	225	0	1	1	Off	On	On
92	29	30	155	226	226	0	1	1	Off	On	On
93	30	30	155	226	225	0	1	1	Off	On	On

From the Table 4, during the testing with the introduction of a fault using a disturbance module, which includes a heater to heat the plate on the secondary bushing and a dimmer to adjust the AC voltage value to control the heater, it can be observed that when a fault is introduced to one phase, the other phases are not affected due to the incorrect installation of the heater on only one phase. Based on the test results, in the first row, the temperature is 32˚C, the voltage is 228 V, and the relay status is 1 (indicating that the relay is activated). As a result, the load (lamp) is turned on (ON). When the temperature and voltage remain the same in the following rows, the relay status and load condition also remain consistent, with the lamp staying on (ON). In the tenth row, when the temperature reaches 91˚C and the voltage remains 155 V, the relay status changes to 0 (indicating that the relay is deactivated). As a result, the load (lamp) is turned off (OFF). Similarly, in the eleventh and twelfth rows, with the temperature above 90˚C and voltage at 155 V, the relay status remains 0 and the load condition is off (OFF). The table represents the relationship betfween temperature, voltage, relay status, and load condition (lamp) based on the provided conditions. By training the FFNN, the measured temperature from the bushing size can generate values that can activate the relay. Thus, the use of this method can classify the temperature magnitude and control the relay device based on the obtained classification results.

One of the corrective steps that can be taken is to tighten the bolts used to prevent lost contact. It is important to deal with this emergency immediately in order to maintain safety and prevent serious damage to the power system. By using the information provided through the Blynk platform in an IoT system. Storage test results from IoT refers to the evaluation and analysis of data storage capabilities and performance in an Internet of Things (IoT) system. In IoT, devices generate and collect vast amounts of data, which needs to be stored securely and efficiently for further processing and analysis.

Table 5. Data Logger Test Results from IoT

Date	Time	Phase			Voltage			Condition
		R (˚C)	S (˚C)	T (˚C)	R (V)	S (V)	T (V)	
22/06/2023	16.39.22	30	30	30	227.8	227.9	228.0	Under normal conditions
22/06/2023	16.39.38	32	29	30	227.7	227.9	227.8	Under normal conditions
22/06/2023	16.41.04	40	29	29	227.9	228.1	228.0	Under normal conditions
22/06/2023	16.41.08	42	30	30	227.0	227.4	227.4	Under normal conditions
22/06/2023	16.42.24	49	30	30	228.4	228.9	228.7	Under normal conditions
22/06/2023	16.42.35	50	29	29	227.5	228.1	227.8	Under normal conditions
22/06/2023	16.42.38	51	29	30	227.9	228.1	228.0	Immediate repairs are necessary
22/06/2023	16.42.42	52	29	30	227.7	228.1	228.0	Immediate repairs are necessary
22/06/2023	16.44.16	61	30	30	228.0	228.3	228.0	Immediate repairs are necessary
22/06/2023	16.44.19	62	30	30	227.8	228.2	227.9	Immediate repairs are necessary
22/06/2023	16.46.12	72	29	30	228.1	228.5	228.2	Immediate repairs are necessary
22/06/2023	16.46.16	74	30	30	228.4	228.8	228.5	Immediate repairs are necessary
22/06/2023	16.47.39	82	30	29	227.7	228.3	227.9	Immediate repairs are necessary
22/06/2023	16.47.43	83	30	30	227.9	228.3	228.1	Immediate repairs are necessary
22/06/2023	16.48.43	88	29	30	225.4	225.7	225.5	Immediate repairs are necessary
22/06/2023	16.48.53	89	30	30	225.2	225.6	225.4	Immediate repairs are necessary
22/06/2023	16.48.57	90	30	30	225.4	225.9	225.7	Immediate repairs are necessary
22/06/2023	16.49.01	90	30	30	225.4	225.7	225.6	Immediate repairs are necessary
22/06/2023	16.49.05	91	30	30	174.2	226.2	225.9	Emergency condition
22/06/2023	16.49.08	90	30	30	154.9	226.1	225.7	Immediate repairs are necessary
22/06/2023	16.49.12	90	29	29	155.0	225.9	225.8	Immediate repairs are necessary
22/06/2023	16.49.16	90	29	30	155.0	226.0	225.7	Immediate repairs are necessary
22/06/2023	16.49.20	92	30	30	155.1	225.8	225.7	Emergency condition
22/06/2023	16.49.28	91	29	29	155.2	226.0	225.7	Emergency condition
22/06/2023	16.49.32	92	30	30	155.6	226.3	226.1	Emergency condition
22/06/2023	16.49.36	92	29	30	155.6	226.5	226.2	Emergency condition
22/06/2023	16.49.40	93	29	30	155.7	226.5	226.1	Emergency condition

From the results of the Table 5 above is the loger data carried out on June 22, 2023 that where the testing for the load given disruption in the phase R at around 16:00 am can be seen at 45°C - 50°C then it will be read conditions are still in normal condition and when it starts 51°C-90°C then the conditions read is to be repaired!, and when the temperature starts from 91°C – 93°C it will be read emergency and can be seen for the voltage read after the working relay will read 155 V. Figure 14 shows the application of the Blynk platform in detecting secondary transformer bushing conditions.

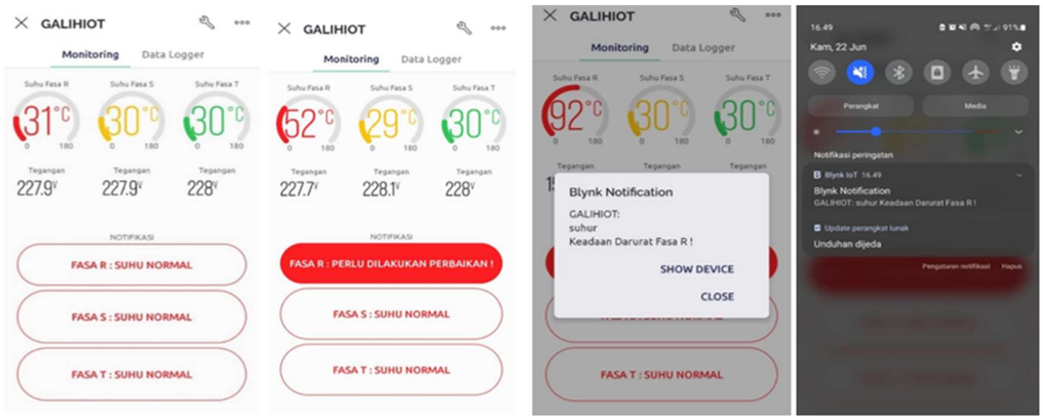

Figure 14. Blynk IoT Display

By using the information provided through the Blynk platform in the IoT system, real-time monitoring can be carried out and appropriate action taken according to detected conditions. One of the corrective steps that can be done is to tighten the bolts used so that there is no loss of contact (lost contact).

4. CONCLUSION

The results of the study showed that the device operates successfully when the temperature of 30°C-50°C FFNN is 0 with the relay not working still in normal condition, 51°C-90°C FNN is zero with the Relay is not working but requires repair, and the temperature > 90°C FFNN value is 1 with relay working in an emergency. This system demonstrates the effectiveness of FFNN in accurately classifying temperature and preventing contact loss. Thus, the system has the reliability of the distribution transformator by detecting temperature disturbances earlier. By using the information provided through the Blynk platform in the IoT system, real-time monitoring can be carried out and appropriate action taken according to detected conditions. In this research, the scope is limited by testing the system on a prototype bushing. In future research works, this system can be developed and applied to the actual conditions of distribution transformer secondary bushings, incorporating more precise temperature sensors and more real-time data transmission communication protocols.

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