

Infrared Thermography of Fault Detection in Power Distribution System Equipment using Artificial Neural Network

Nurul Huda Ishak¹, Puteri Nur Syahirah Mohamad Mustafa², Iza Sazanita Isa³, Siti Solehah Md Ramli⁴ and Nur Darina Ahmad⁵

^{1,2,3,4,5}School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Cawangan Pulau Pinang, 13500 Permatang Pauh, Pulau Pinang, Malaysia¹

*corresponding author: ¹nurulhuda258@uitm.edu.my

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ABSTRACT

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Repair and maintenance in power distribution is an important factor that affects the continuous productivity services and power efficiency in electrical supply systems. Thermographic inspection has been often used as a maintenance tool, as it allows detection of early-stage failure from the system in electrical distribution. Failure in the system can lead to catastrophic failure like a high-voltage arc fault. The presence of fault is caused by the higher temperature of the instrument that leads to the formation of hotspots. The use of infrared inspection is useful in detecting the hotspot that is hardly noticeable. It helps to overcome the problems that arise during operation and maintenance in the distribution systems. In this research, a fault detection system is proposed with the application of Artificial Neural Network (ANN) in identifying faults on electrical equipment. This method was trained by using the temperature parameter on the IR images taken from TNB Distribution. As a result, it will lead to faults detection. Thus, the purpose of this project is to ensure the correct recommendation of corrective actions in the maintenance procedure of the electrical system. The actions to the detection of faults taken are based on the results of the temperature measured. The neural network training performance for the temperature of hotspot detection was developed with a minimum error of 0.00084165 MSE at epoch 39. The study shows the best-fitting allows detection of early-stage failure. It can be concluded that the current method in conducting the prediction process by using Thermographic inspection is suitable for electrical equipment based on the training result.

Keywords: Artificial Neural Network (ANN), thermographic inspection, failure, fault, hotspot.

1. INTRODUCTION

Preventive maintenance of electrical components is called the monitoring of electrical components in power substations according to historical working capability data, previous component failure data, and mean time to failure (MTTF) component output [1]. In this approach, reliable equipment or installation efficiency depends on the standard and quality of pre-service [2]. Thermography has a benefit over traditional systems in that it allows maintenance procedures to be performed without shutting down the system. In-service failure or equipment breakdown under operating conditions of the facilities or structure. To prevent such situations, the use of thermal imaging or thermography technology is an alternative way to perform predictive maintenance of electrical equipment [3]. Efficient and detailed NDT assessment techniques are essential to ensure the safe function of multiple equipment and

facilities in an industrial environment. This is applicable in the analysis of service life, acceptability, and danger, as well as the reduction or even removal of human error.

Condition-based monitored (CBM) is a maintenance strategy that is used to monitor the actual condition of the electrical equipment to come out with the decision that needs to be done. Based on the paper by Young Zaidey and colleagues, they state that the key aim is to arrive at a cost-effective approach by implementing effective asset management on the application of CBM [7]. The work of Mildad Niaz Azari and colleagues also state that especially with the rise of multiple loads over time, as well as the high cost and difficulty of power network expansion, it appears that developing proper strategies to maintain existing lines operating at full efficiency is critical [4]. Thermographic inspection has often been used as a maintenance tool, as it allows detection of early-stage failure from the system in electrical distribution. Failure in the system can lead to catastrophic failure like a high-voltage arc fault. There is an early warning that gives time to plan a corrective procedure if any parameter drifts away from the standard, preventing the issue from progressing to a point of complete failure [5]. The image of electrical equipment at the distribution substation was taken manually by using an Infrared Thermographic Camera. For identification of failures of a targeted Electrical Equipment in the system through Thermographic image, a monitoring system was developed [6]. Based on the study conducted by Young Zaidey and colleagues, they present that TNB's experience through diagnostic approach and transformer health index formulation in conducting condition evaluation and life management programs on distribution power transformers is also based on one of the fault detection stages which is screening the thermal performance [7]. The samples of targeted Electrical Equipment image at Electrical distribution are taken from the TNB Distribution as shown.

Figure 1 shows the Thermographic captured image that shows the result of the parameter of data temperature of the targeted image [8]. When an area of targeted electrical equipment is situated together under the same conditions of temperature, moisture, and other environmental conditions, an object with a high emissivity will appear hotter than an object with a low emissivity in a bright yellow colour. The work of Yasaswi and colleagues in 2015 states that the scanning system can be done without any physical contact between the test body and the measuring system [9]. It should be remembered that the issue of this approach requires the detection of the target location function. Each location focuses on the image stabilization, the identification, and persistence of the target in the camera's field of view, and the data processing method [4]. The work of Taib and colleagues state that an important aspect is to understand the concept of temperature rise detection, its characteristics, and detection in the process of Thermographic [2]. The fieldwork proposes the extraction of characteristics relating to the thermal conditions of the equipment and the environment [10]. The general concept of thermal imaging is that when electrical installations fail, the temperature rises. Temperature is one of the most important parameters that should be given priority consideration in maintenance because higher temperatures result in an indication of losses of energy in the form of heat. By raising the resistance, the produced heat causes more degeneration, which in turn leads to more heat. The study conducted by Shilpa, undersized conductors, loose connections, or excessive current flow due to an electrical fault may all cause unwanted heat generation [11]. The paper also states that Thermographic is a non-contact technology that assists in the detection of potential trouble areas in electrical installations by detecting "hot spots." The undetectable hotspot normally exponentially feeds on itself until the total devastation of the equipment is the result.

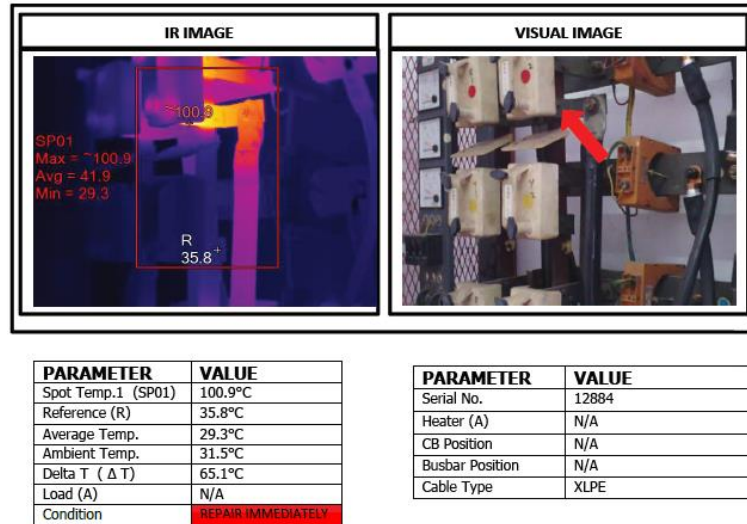


Figure 1: Thermographic Captured Image

In this analysis, through a systematic sequence of Thermographic images targeted in the electrical distribution system, the artificial neural network (ANN) technique is trained by applying the temperature parameter obtained from IR image processing. The benefit of utilising a neural network is that it learns to recognise patterns in each collection and can manage very complicated interactions. Then, defect diagnosis is one of the key areas where ANNs have been applied with promising results, with similar success in complex nonlinear system control and identification. The ANN imitates the human brain capabilities. Therefore, a model was developed to stimulate the classifier's outcomes based on the already known output of the training model. The input and output data were analysed during this supervised phase. As stated by Harsh Kukreja and colleagues, the brain has the incredible capacity to interpret incomplete, ambiguous, and hazy details and draw its own conclusions [12]. Hence, faults in the electrical equipment installation can be identified by the detection of the hotspots.

2. METHODOLOGY

A set of temperature condition-based monitor defect data was collected from TNB Distribution on electrical equipment at different substations. After collecting the data, the method of Artificial Neural Network is being applied and MATLAB R2016b software is used to carry out a process for data prediction. Then, the condition of the hotspot detection is seen throughout the training performance of the neural network. Data collection, examination, and interpretation are completely automated, according to a study conducted by Soib Taib and colleagues, to improve accuracy and lessen the impact of human mistakes and wrong diagnoses [2].

2.1 Primary Data Collection

The image of electrical equipment for identification of failures of targeted electrical equipment in the system through Thermographic image, the monitoring system was developed [6]. The most common way is to capture images using thermal cameras for data acquisition, where the radiation is transformed into a thermal image [10]. The targeted electrical equipment visual and IR image and result of parameter temperature samples of LVDB, transformer, and switchgear are shown [8]. 30 images were used in this research. The number of IR images taken for

detecting the hotspot region is the same, which is the capture is focused on target equipment (blue phase cable). Besides, IR image also captures the other cable image to compare the temperature value. The results on the IR image are taken in Figure 2.



Figure 2: Visual Images from Six Different Positions of Interest

Figure 2 shows some of the visual images from six different positions of interest taken from TNB distribution, Sungai Petani. The image then will be analyzed by using a Thermographic camera.

Figure 3 shows the results of the IR image taken. The figure shows the infrared image of the targeted electrical equipment in the distribution substation.

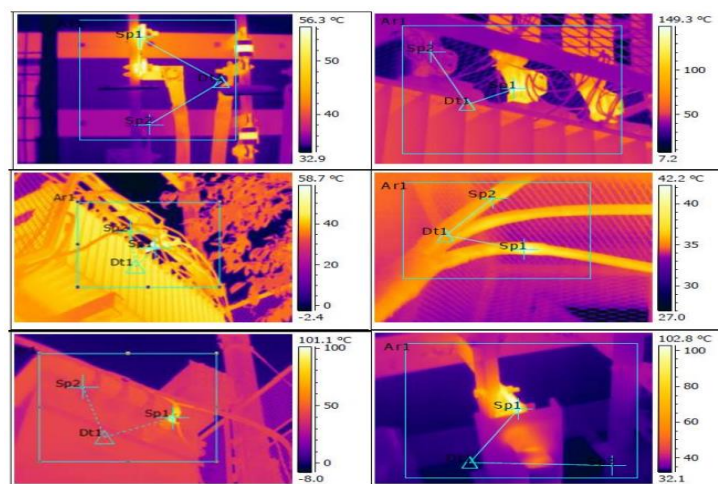


Figure 3: Image from Six Different Positions of Interest Obtained with Infrared Thermal Camera

2.2 Image Temperature Fault Identification

The different colours of the temperature scale reflect the equipment's various temperature spots. In an infrared image, heating components are usually detected as red or brighter coloured regions. Detecting the intensity of radiation in the infrared region of the electromagnetic spectrum to determine the temperature distribution on the surface of the seen object. As a result

of the characteristic of these cameras, each part of an image's colour is graded based on its temperature [4].

2.3 Artificial Neural Network (ANN)

ANNs are input-output models based on biological neuron characteristics [13]. The artificial neural network is a method for pattern detection that replicates the human brain's capacity to identify and predict different kinds of patterns [14]. They also state that ANN training corresponds to the minimization of a predefined error function.

Figure 4 shows the schematic diagram of the Artificial Neural Network with one layer. The ANN consists of an input layer, hidden layer, and output layer. The parameter of the data targeted image that is used in the ANN simulation is described in Table 1. A various number of neurons will be tested on the hidden layer of the training ANN. The number of neurons to include in the input and hidden layers is one of the most important considerations when training a neural network. Then, for the given input, this output is compared to the desired output. The error is propagated back from the output layer to the hidden layer, and from the hidden layer to the input layer, based on this variance. Trial and error are a method that will be applied to test each of the neurons until the best validation performance achieves with a minimum value of mean square error (MSE).

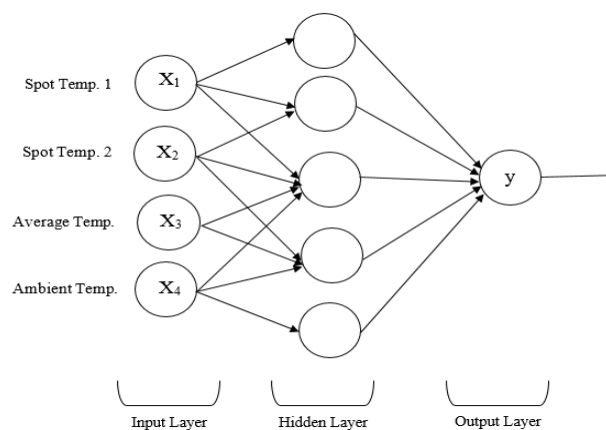


Figure 4: Schematic Diagram Artificial Neural Network

Figure 5 shows the process of training the Artificial Neural Network. Firstly, the feedforward neural network propagates the input of the temperature parameter and the output obtained from the training model will be compared with the actual output. Then, an ANN will be trained to identify the hotspot detection of electrical equipment temperature.

After training the network, the neural network algorithm is generated and capable of capturing the well fit network properties for the model. Table 2 shows the summary of the artificial neural network model that was used to estimate the presence of the hotspots in the electrical equipment.

Table 1: Parameter description of the electrical equipment

Parameter	Description	Used as
Spot temp 1 (spo1)	The target temperature of electrical equipment (For example:the connection between cable lux and the copper of the busbar)	Input
Reference (spo2)	Temperature is taken of other different places fromtarget equipment of the same type	Input
Average temperature	The sum of spo1 and spo2 divide into two	Input
Ambient temperature	Surrounding temperature of target equipment	Input
Condition	Decision made after considering the parameterobtained	Output

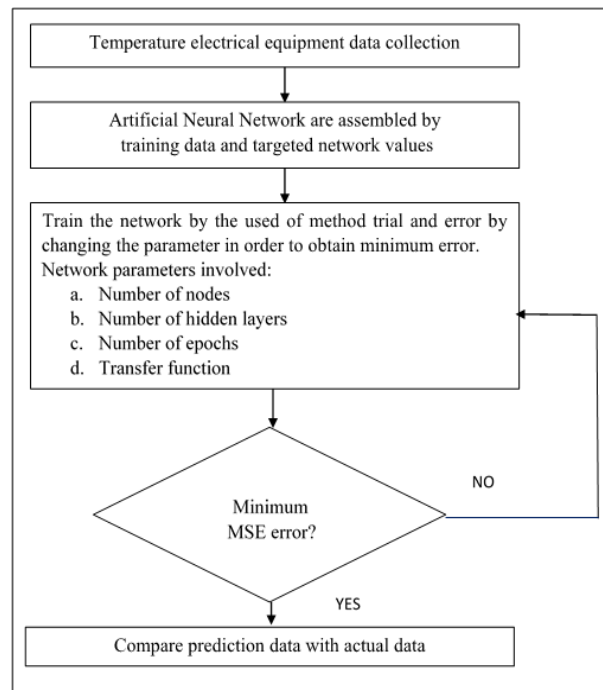


Figure 5: Training Artificial Neural Network

Table 2: Neural Network Overall Review

Neural network	
Neural network type	Multi-layer feedforward network
Learning algorithm	Levenberg-Marquardt
Hidden layer	single
Hidden neurons	Temperature parameter: <ol style="list-style-type: none"> 1. Spot temperature 1 2. Spot temperature 2 3. Average temperature 4. Ambient temperature
Output neuron	Hotspot condition
Data division	400 training data, 100 validation, 150

The ANN is based on supervised learning. The supervised-learning classifier process must learn to predict future output based on the already known correct output [15]. It learns to recognize

the pattern in the data textually which is the value of the temperature parameter. Supervised training tries to keep back a collection of data to be used to assess the system after it has completed its training to track the network decision to decide whether the system is effectively memorizing its data parameters in any non-significant way. It studies the system and takes action accordingly to maximize the probability of success [16].

To develop the accuracy of the detection of hotspots using a Thermographic camera of the targeted electrical equipment, multilayer artificial neural networks are constructed with the temperature as an input of the training network. The model of Multilayer Perceptron (MLP) traces the input collection to output collection [16]. It consists of several layers of nodes and links each node to the next node. Each processing unit in the MLP functions with a non-linear activation feature.

2.4 Mean Square Error (MSE)

Mean Square Error is a measurement that will be managed to perform and obtain the best Artificial Neural Network model performance [17]. Acceptable neural networks are referring to the minimum value of the Mean Square error. The mean squared is advantageous when the error increases as the square of the deviation, which ensures that huge errors are highly weighted [18].

3. RESULT AND DISCUSSION

Referring to the previous study that has been done, the potential of a neural network with one hidden layer is attempting to deal with most of the complex functions [19]. The training network is trying with a different number of neurons, and then evaluating how well it did on the new test data.

The training of ANN has been done by using 400 data of temperature parameters and 100 data used for validation. For testing the input model that has been trained, 150 data is used. The training process has been trained from neuron '1' in the hidden layer until neuron '20' by using the transfer function 'tansig'. The training is done until the minimum MSE value reaches 0.00084165 at epoch 39. The comparison of the results obtained has been shown in Figure 8. The overall neural network output is represented in Figure 5. From the result, the best validation by using multilayer ANN with Levenberg-Marquardt (LM) occurred at epoch 39 followed by 0.00084165 of mean square error (MSE). The comparison value of MSE has been taken at each increment number of neurons. Table 3 showed the result taken of each neuron after training the network model. The model trained at neuron 18 results in the least MSE value which is 0.00084165.

Figure 6 shows the neural network training tool. Once it stopped, the outcome plot can be opened from the model. The neural network architecture shows the model has a two-layer feed-forward network with sigmoid hidden neurons and a linear type of output neurons. The training of (trainml) shows the model training function that updates weight and bias value according to the Levenberg-marquardt optimization. This is the often fastest backpropagation. Which this model provided clear data and sufficiently neurons in its hidden layer, it may match arbitrarily well with multi-dimensional mapping issues.

Table 3: Result of MSE and Epoch Set

Number of Neurons	Mean Square Error (MSE) value	epoch
1	0.037974	17
2	0.047141	10
3	0.050958	21
4	0.039481	5
5	0.056856	8
6	0.014465	50
7	0.036687	38
8	0.0088294	13
9	0.041769	11
10	0.014002	59
11	0.015948	14
12	0.016337	23
13	0.0083606	32
14	0.035988	7
15	0.035856	11
16	0.011934	14
17	0.026691	5
18	0.00084165	39
19	0.022914	18
20	0.044549	5

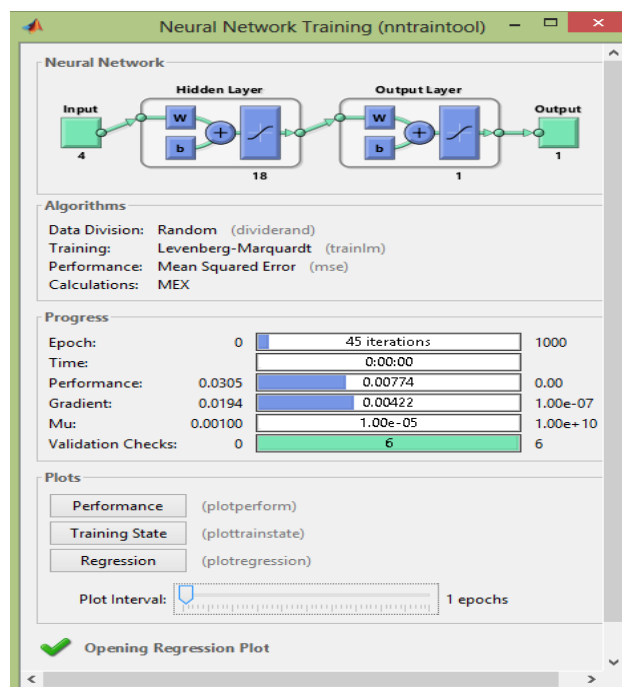


Figure 6: Neural Network Tool

Figure 7 shows the best validation train performance of the training model. The plot shows the minimum of MSE which is 0.00084165 at epoch 39. This low MSE at the end of the training shows that the model's estimate of the test values and actual test value of the training set have become very close to each other.

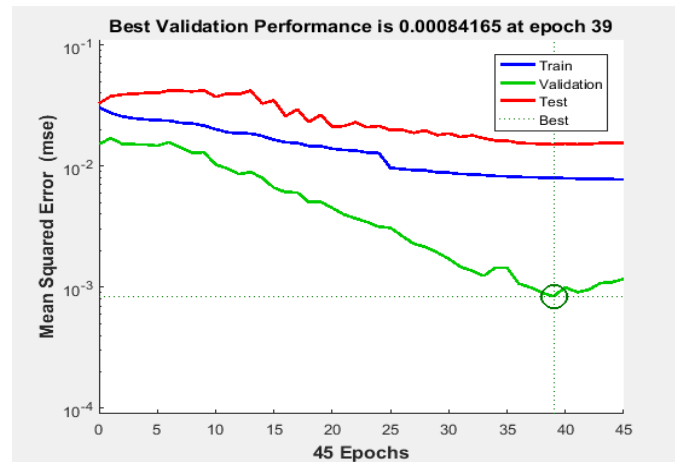


Figure 7: Best Validation Training Performance

Figure 8 shows the neural network training state of the ANN model which presents three different types of graph plots. The title of each plot shows the final values. The training state figure represents the difference between the testing and training dataset of the model. The first plot shows the progression of the minimum gradient of 0.0042155. The second one shows the Mu is increased and decreased with the epoch. The last plot indicates that during the training, after receiving the validation MSE value in the output graph, it will immediately stop at 45 iterations. As mentioned by [20], the gradient value represents the tangent of the graph. It indicates there is a high rate of increase for the considering function. Mu is the control parameter for the back-propagation neural network. The choice of Mu directly affects the error convergence. Validation check is used to terminate the learning of neural networks.

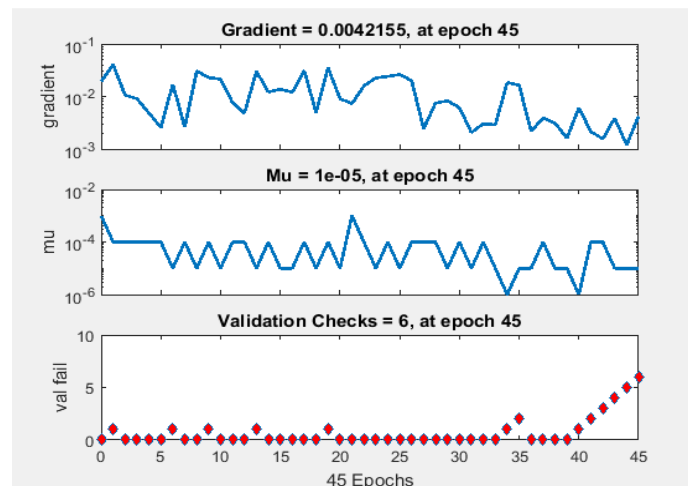


Figure 8: Neural Network Training State

Figure 9 shows the neural network training regression of the model. The regression plots display the network output with terms to targets of training, validation, and test. The data should fall along the 45-degree line for a better match. From the above figure, the output of the model 0 and 1 fall near along the line where the network outputs are identical to the predictions.

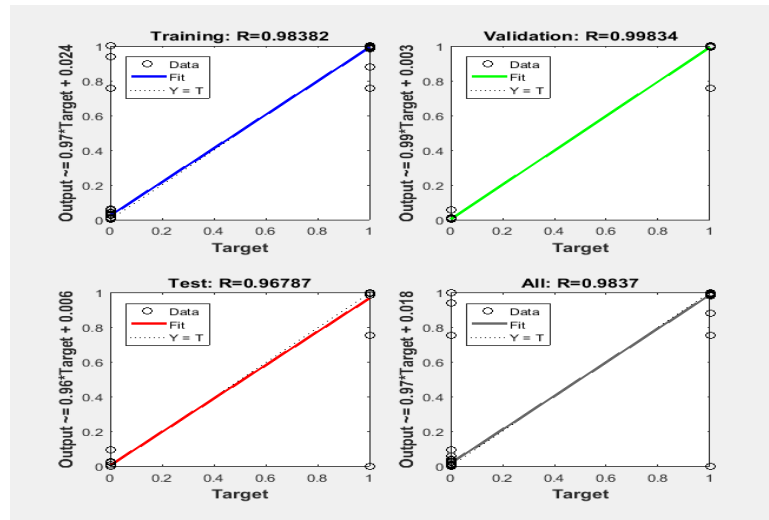


Figure 9: Neural Network Training Regression

Figure 10 shows the temperature of equipment prediction comparison between the actual and predicted output of the trained model. The x-axis shows the 150 samples of the electrical equipment data temperature, and the y-axis shows the estimation results of the equipment condition. The blue line represented the output of the actual result of the data while the red line represented the prediction output from the neural network model at the training of 18 neurons in a single hidden layer. From the figure, since the output of the condition is represented by 0 and 1, the model testing output is seen to be fitted at the range between 0 and 1. Based on the well-matched result with a minimum MSE of 0.00084165, indicate that the system built shows its efficiency. Therefore, the accurate and efficient performance of ANN is predicted when 18 neurons in the hidden layer are used.

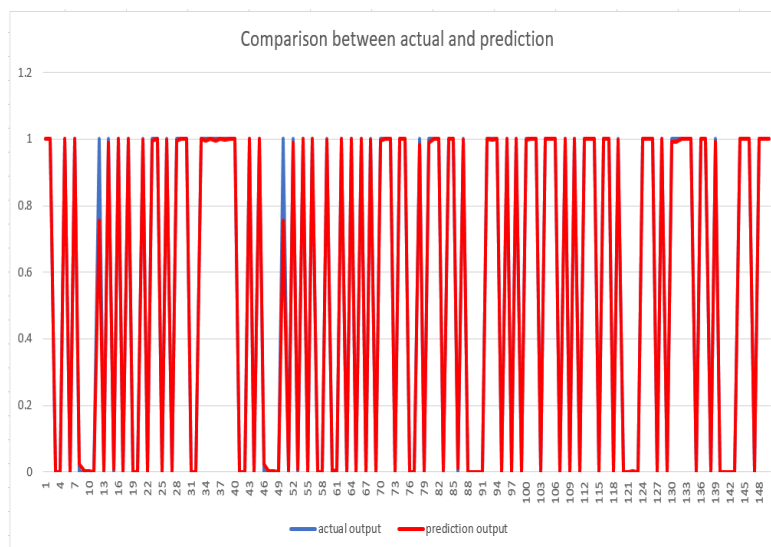


Figure 10: ANN Temperature of Equipment Prediction Results

4. CONCLUSION

The development of the Artificial Neural Network is used in designing a model that can be trained to come out with the decision of the condition on the temperature of targeted electrical equipment. From the result obtained, it shows that the developed training data enable ANN to predict the output for the testing dataset. The result shows when the prediction output of the training model gives the best fitting to the actual value with a minimum MSE of 0.00084165. This shows that it can allow the detection of the early-stage failure by thermal abnormality. Hence, ANN helps to analyze the current methods used in defect monitoring of repair and maintenance.

From the study done, this concludes that using a Thermographic camera in the detection of hotspots from the temperature result helps to minimize partial and complete failure. This can minimize the business interruption and the action to avoid any costly disasters to the equipment. The method also benefits in performing the maintenance as it can lessen the chances of disruption to the normal operation. Additional power can be safely routed through the equipment if the temperature is below operating limits. The reduction of higher critical level thermal abnormalities is due to its early detection and addressing through programmed outages, taking corrective measures to prevent the abnormality of the system performance could evolve to a worse critical level.

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