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Penetration of DWT & ANFIS to Power Transmission Disturbances

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Abstract*—This study proposes a hybrid method to classify and estimate the location of short circuit disturbance on power transmission lines. The hybrid method uses Discrete Wavelet Transform (DWT) and Adaptive Neuro-Fuzzy Inference System (ANFIS). The transmission system is implemented in a real system, in which the electric power transmission system on the KP bus to the GS bus is with a length of 64 Km. The DWT is used to process information from each phase voltage and current transient signal as well as the zero-sequence current for one cycle after the disturbance has started. The ANFIS classification is designed to detect disturbance on each phase and ground in determining the type of short circuit disturbance. ANFIS estimation is used to measure the location of disturbances that occur on the transmission line. The training and testing data are generated by simulating the types of short circuit disturbance using software with variations in disturbance location and fault resistance. The result is that the disturbance classification is with 100% accuracy and the estimated disturbance location is with the lowest error of 0.0006% and the highest error is 0.03%.

***Keywords*—ANFIS, DWT, disturbance, hybrid techniques**

I. INTRODUCTION

The transmission line is a very important component in the electric power system. The transmission line of an electric power system must be able to guarantee the continuous availability of electrical energy for every load connected to the system because the transmission line is the link between the generating center and the load. The continuity of electric power distribution is often faced with disturbance problems that arise in the electric power system. One of the most common disturbances is short circuit faults. Therefore, these disturbances need to be detected, classified, and corrected as soon as possible.

Determining the fault location in the transmission system is very important to speed up the repair process. Quick fixes reduce customer complaints, system downtime, lost revenue, and repair costs. These factors are increasingly important for electricity supply companies in facing current market challenges. For this reason, it is necessary to develop an algorithm to provide an accurate and fast estimation of the disturbance location. Estimation of the location of disturbances in electric power transmission systems is generally based on methods that use the results of current and voltage measurements of the system frequency at the terminals connected to the transmission line that is experiencing interference.

This study uses a hybrid method to classify the types and estimate the location of short circuit disturbances. The hybrid method in this study is a combination of the wavelet transform method and the Adaptive Neuro-fuzzy Inference System (ANFIS). The wavelet transform used is the Discrete Wavelet Transform (DWT) to obtain information from transient signals when short circuit disturbances start to occur. The wavelet transform has an advantage over the Fourier transform in that the information is limited only to the frequency domain. Meanwhile, the information obtained from the wavelet transform can be in the form of frequency and time domains.

Processing of DWT results will be used as input in using ANFIS to classify the type and estimate the location of short circuit disturbances. By using ANFIS, the classification of types of disturbances is easier to do and has a high level of accuracy. Likewise in the use of ANFIS for estimating the location of short circuit disturbances. This method is tested for all types of disturbances, with different disturbance locations and disturbance resistance values on the transmission line.

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Saber S. B et.al conducted research using an Artificial Neural Network (ANN) to classify the type of disturbance and the location of the disturbance that occurs on the transmission line. From the research results it can be seen that using modular ANN can reduce training time and also increase the accuracy of ANN for the classification of disturbance types. From the research results it can also be seen that ANN, with current and voltage inputs is more accurate for estimating disturbance locations [1]. Further, Ahmed Saber et.al proposed implementing DWT with mother wavelet type Daubechies order 4 with a sampling frequency of 50 kHz and Support Vector Machine (SVM). The sum of the absolute values of the level 8 and 9 detail coefficients are used as input for SVM. The results obtained show that this method can correctly classify interference on parallel transmission lines [2]. Then, Ika Li W et.al conducted research on the estimation of the types and locations of disturbances in underground distribution channels. The research was carried out using different inputs, such as DC components, 50 Hz, 100-350 Hz, 400-1000 Hz, and 1050-1950 Hz. From the research, it is known that the 50 Hz input produces the smallest error for single phase-to-ground, between phase, and two phase-to-ground types of disturbances [3].

Base on previous studies related to the classification and estimation of disturbance locations in electric power transmission systems, this study will develop a hybrid technique for the classification and estimation of disturbance locations in transmission systems, namely a combination of the DWT and ANFIS methods. This hybrid technique is expected to add improvements in terms of accuracy in determining the classification of disturbance types and estimation of disturbance locations in electric power transmission systems.

Transformation of Discrete Wavelet

Wavelet transform has the ability to analyze various types of disturbances with information obtained from the frequency domain and time domain. Wavelet transform is very useful in detecting and processing various data disturbances because it is sensitive to signal irregularities [4]. Wavelet transforms can be divided into two types; they are continuous wavelet transform and discrete wavelet transform. Continuous wavelets are used to calculate the signal transition from a modular signal at any time to the desired scale. The window scale has a modifiable mode. By giving a wave of $f(t)$, continuous wavelet transform can be calculated as follows [5], [6].

$$TWK(f,a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} \quad f(t)\varphi^* \frac{(t-b)}{a}dt \qquad (1)$$

Where a dan b are scale constant and transition constant (time shift), TWK (f,a,b) is the coefficient of TWK, and φ is an artificial wavelet. The signal input of $f(t)$ has been rearranged using displacement parameters and time expansion to the proper scale. The discrete wavelet transform is considered a relatively easy implementation compared to the continuous wavelet transform. The DWT wave coefficient can be obtained by applying the DWT as the following equation [7].

$$TWD(f.m.k) = \frac{1}{\sqrt{a_0^m}}\sum_k \quad f(k)\varphi^*\left[\frac{n-ka_0^m}{a_0^m}\right] \qquad (2)$$

Where parameters a and b in equation (6) are replaced as a_0^m, ka_0^m, k and m are positive integers. DWT divides the wave signal into two parts using filtering techniques and down-sampling operations. The input signal waveform is divided into two parts; the low-frequency signal is known as the approximation and the high-frequency part as the detail. In the wavelet transform, the mother wavelet is used to process the original signal. Mother wavelets are of various types such as Haar, Daubechies, Coiflets, Symlets, etc. The most widely used mother wavelet is Daubechies, which is usually written *dbN*, where N is the orde, and db denotes the name of the mother wavelet Daubechies [8], [9]. The decomposition process in DWT with an output in the form of an approximation that is used as DWT input for the next level. The signal is first sent to a high-pass filter and a low-pass filter and then part of each output is taken as a sample [10].

Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is an adaptive network based on a fuzzy inference system. ANFIS is a combination of an Artificial Neural Network (ANN) and Fuzzy Inference System (FIS). The ANFIS parameters can be separated into two; they are premise parameters and consequence parameters which can be adapted with a hybrid learning algorithm. ANFIS has a structure with 5 layers. Figure 3 is an ANFIS architecture with 2 inputs: x, y, and one output in f. There are two rules in Sugeno Model. These two rules can be seen in equation 3 and equation 4, while the ANFIS output is calculated using equation 5 [11].

If x is A_1 *and* y is B_1,

$$f_1 = p_1x + p_1y + r_1 \qquad (3)$$

If x is A_2 *and* y is B_2,

$$f_2 = p_2x + p_2y + r_2 \qquad (4)$$

$$f = \frac{w_1f_1 + w_2f_2}{w_1 + w_2} = \underline{w_1}f_1 + \underline{w_2}f_2 \qquad (5)$$

The SIF used is the fuzzy inference system model of Tagaki-Sugeno-Kang (TSK) first order with considerations of simplicity and ease of computation. Layer 1 is called the fuzzification layer. All nodes in this layer are adaptive nodes (parameters can change). The layer 1 activation function can be calculated by equations 6 and 7 [12].

$$O_{1,i} = \mu_{Ai}\ (x) \text{ for i = 1, 2} \qquad (6)$$

$$O_{1,i} = \mu_{Bi-2}\ (y) \text{ for i = 3, 4} \qquad (7)$$

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Membership function of (μ) used is *Generalized Bell* (GBell) which can be calculated by equation 8 [13].

$$\mu_A\,(X) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \quad (8)$$

a, b, and c as the parameter set, parameters in this layer are called adaptive premise parameters, i.e. parameters that can change. For layer 2, all nodes in this layer are non-adaptive (fixed parameters). The output is the product (AND operator) of all inputs for this layer. The output of layer 2 ANFIS can be calculated using equation 9 [14].

$$O_{2,i} = w_i = \mu_{Ai}(x)\;.\;\mu_{Bi}(y) \text{ for i = 1, 2} \quad (9)$$

For layer 3, all nodes in this layer are non-adaptive nodes (fixed parameters). The output in this layer is called the normalized activation degree function, which is the ratio of the output of the ith node in the previous layer to all the outputs of the previous layer. The ANFIS layer 3 output can be calculated using equation 10 [15].

$$O_{3,1} = w_i = \frac{w_i}{w_1+w_2} \text{ for i = 1, 2} \quad (10)$$

For layer 4, all nodes in this layer are adaptive nodes (parameters can change). The output of layer 4 ANFIS can be calculated using equation 11 [16].

$$O_{4,i} = \underline{w_i} f_i = \underline{w_i}\,(p_i x + q_i y + r_i) \quad (11)$$

For layer 5, there is only one fixed node in this layer whose function is to add up all inputs. The output of layer 5 ANFIS can be calculated using equation 12 [17].

$$O_{5,i} = \Sigma_i \underline{w_i} f_i \quad (12)$$

The hybrid learning algorithm is carried out in two steps: they are the forward step and the backward step. In the forward step, the premise parameters remain, while the consequence parameters are identified using the Least Square Estimator (LSE) method. The backward step of the error signal between the desired output and the actual output is propagated backward, while the premise parameters are updated using the Error Back-Propagation (EBP) method. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) is usually used in model evaluation studies. RMSE is a squared scaling rule that also measures the size of the average error. That is the square root of the average of the squared differences between the actual and predicted values. Whereas MAE measures the average magnitude of error in a set of predictions, without considering the direction.

TABLE 1. HYBRID LEARNING PROCESS ON ANFIS

	Forward Stage	Backward Stage
Premise Parameters	Fixed	Gradient descent
Parameter Error	LSE	Fixed
Signal	Output Node	Error Signal

That is the average on the test sample of the absolute difference between the actual and predicted values where all the differences in each data have the same weight. The RMSE and MAE equation formulas from the amount of data as much as n can be seen below [18].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - y_i')^2} \quad (13)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - y_i'| \quad (14)$$

II. METHODOLOGY

In this paper, the research was conducted using electric power transmission system data obtained from PT. PLN (Persero) Central Sumatra Load Regulatory Unit. Then, modeling the electric power transmission system data uses the software. Furthermore, a short circuit disturbance simulation is carried out in the modeling with variations in the form of disturbance type, disturbance location, and disturbance resistance. Then the data obtained from the short circuit disturbance simulation in the form of disturbance voltage and current signals will be processed using DWT. The processed results from DWT are used as input to ANFIS for the classification and estimation of disturbance locations.

The electric power transmission system used as the research object is a transmission line that starts from the KP, BG, and GS. On the KP bus, there are three synchronous generator units as generators. The KP bus also receives 136 MW of power from the PY bus. Each bus in this system has a load with a different capacity. The GS bus has a capacitor bank with a capacity of 50 MVAr to prevent a voltage drop. Short circuit disturbances are placed on the transmission line between the KP Substation and GS which has a line length of 64 km. Figure 4 displays a single-line diagram of the transmission system of the research object. There are 3 buses KP bus, BG bus, and GS bus. The voltage and current signals obtained from the disturbance simulation results using software with a sampling frequency of 50 kHz will be processed using the TWD function which is a feature in the software. Then, the voltage and current data are taken for one cycle after the disturbance occurs. The wavelet decomposition sequence with a sampling frequency of 50 kHz can be seen in Table 2. Determination of the mother wavelet used in the DWT process for current signals is Daubechies 4, because it produces better classification

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accuracy and smaller error values in estimating disturbance locations compared to other mother wavelets [19], and is very effective for analyzing transient signals [20].

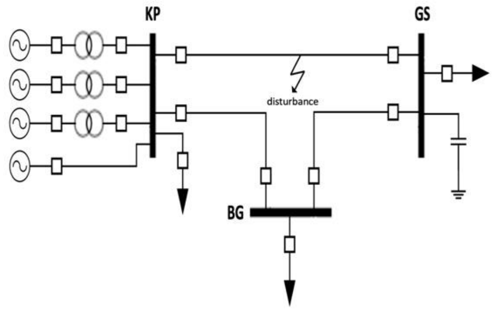

Fig. 1. Single-line electrical power transmission system

TABLE 2. A SEQUENCE OF WAVELET DECOMPOSITION WITH A SAMPLING FREQUENCY OF 50 KHZ

Level	Approximation	Detail
1	0 – 12.5 kHz	12.5 – 25 kHz
2	0 – 6.25 kHz	6.25 – 12.5 kHz
3	0 – 3.125 kHz	3.125 – 6.25 kHz
4	0 – 1.563 kHz	1.563 – 3.125 kHz
5	0 – 781 Hz	781 – 1.563 kHz
6	0 – 391 Hz	391 – 781 Hz
7	0 – 195 Hz	195 – 391 Hz
8	0 – 98 Hz	98 – 195 Hz
9	0 – 49 Hz	49 – 98 Hz

TABLE 3. SIMULATION PARAMETERS FOR TESTING ANFIS CLASSIFICATION AND ESTIMATION OF DISTURBANCE LOCATIONS

Identification	Disturbance	L (%)	R (Ω)	D (°)
Classification and Estimation	FT	1,6, 5,6, 9,6, …, 93,6, 97.6	50	45
	FF			
	FFT			
	FFF			

The voltage and current data for one cycle after a disturbance occurs, then the TWD output at detail level 8 (D8) and detail level 9 (D9) is calculated for the RMS value to be used as input in ANFIS. Then the network selection is carried out for the best ANFIS results in ANFIS classification and ANFIS estimation of disturbance locations. Next, a re-test was carried out on the selected ANFIS with different inputs from the ANFIS training and testing data as shown in Table 3. Finally, the accuracy and error obtained from the test results using the ANFIS classification and estimation of the selected disturbance location are calculated.

Design of ANFIS Classification

ANFIS classification of disturbance types is made by using ANFIS which classifies disturbances on each phase and ground which work in parallel. When there is a disturbance in a phase, the ANFIS will provide information in the form of a disturbance in that phase. Likewise, if there is a disturbance to the ground, then ANFIS will read through the zero sequences current signal and provide information on the disturbance according to the zero sequences current value trained on ANFIS. By combining all the information obtained from the classification of disturbances that occur on each phase and ground using ANFIS, we can find out the short circuit disturbances that occur on the transmission line. The ANFIS structure for the classification of disorders can be seen in Figure 1.

Figure 1 is the structure of the ANFIS network for the classification of disturbance. The red box is the input of the ANFIS classification of disturbance, the blue circle is the number of membership functions where there are ten membership functions for each input. The resulting output is information in the form of the presence or absence of disturbance in the phase and ground. ANFIS classification of disturbance was given input in the form of variations in the RMS values of the current signal coefficients D8 and D9 from each simulation result. The input is varied as:

- 2 RMS of the detail coefficient of the phase current signal A
- 2 RMS of the detail coefficient of the phase current signal B
- 2 RMS of the detail coefficient of the phase current signal C
- 2 RMS signal detail coefficients of zero sequence current

For each ANFIS that classifies disturbances on phases A, B, and C, the disturbance current samples for each phase are used as input. For the classification of ground disturbances to be used as input is a zero-sequence current sample.

Design of ANFIS Estimation

ANFIS estimation of disturbance location is made to estimate the location of disturbance for each type of disturbance and provides the output in the form of the distance of the disturbance location. Each type of disturbance has a different ANFIS network estimation of the location of the disturbance. The disturbance simulated are FT and FFF. In designing ANFIS, the estimation of the location of this disturbance will be carried out by varying the input to ANFIS. As for the types of membership functions used in ANFIS: generalized bell and gauss with a total of 3 membership functions. The aim is to obtain and select better accuracy results for ANFIS training in the estimation of disturbance locations. The training process is carried out in 100 iterations with a training error tolerance value of 0. The ANFIS structure for estimating disturbance can be seen in Figure 2.

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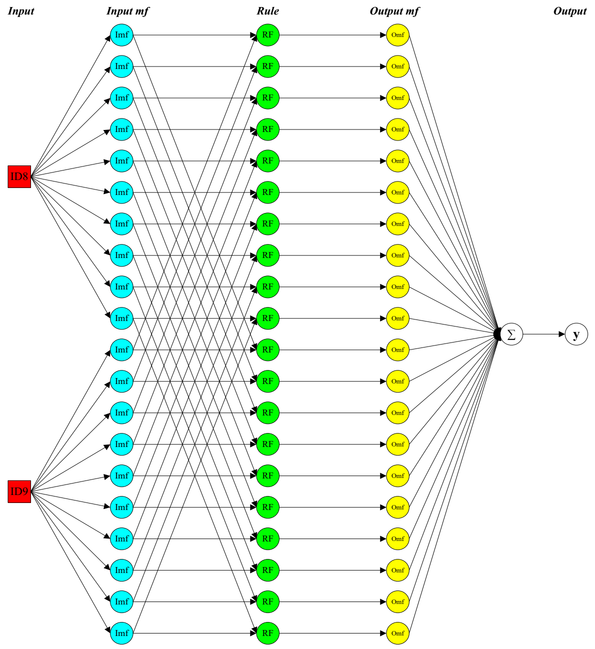

Fig 2. Structure of ANFIS Classification

Figure 2 is the structure of the ANFIS network for the estimation of disturbance location. The red boxed part is the input from ANFIS estimated disturbance location, and the blue circled part is the number of membership functions where there are three membership functions for each input. The resulting output is information in the form of the distance to the disturbance location. The ANFIS disturbance estimation location is given 6 inputs, which are the RMS value of the D9 coefficient of the voltage and current signals after the disturbance on each phase. Input from ANFIS estimated disturbance location can be formulated as follows:

$$X_{FL} = [VD9_A, VD9_B, VD9_C, ID9_A, ID9_B, ID9_C]$$

III. Results and Discussion

Table 4 and Table 5 are comparisons of RMSE and MAE from the test results of each ANFIS classification and estimation of disturbance locations. After training and testing on various types of ANFIS classification and estimation of disturbance locations, then the output results for each ANFIS are seen. The ANFIS to be used is selected based on the output of the ANFIS, namely by looking at the smallest RMSE and MAE values in the classification and estimation of the location of the disturbance from each ANFIS. The results of selecting the ANFIS network used are shown in Table 6.

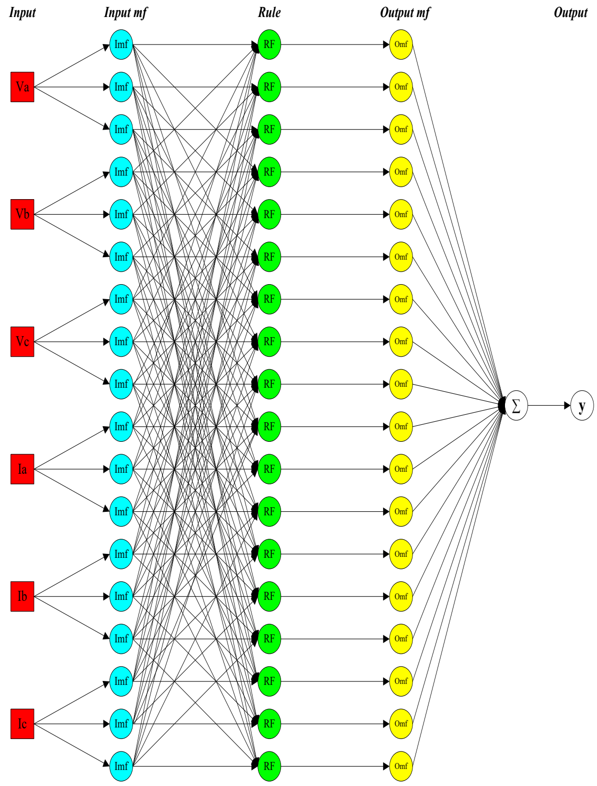

Fig. 3. Structure of ANFIS location estimation

TABLE 4. COMPARISON OF RMSE AND MAE OF ANFIS DISTURBANCE CLASSIFICATION

No	Net Code	RMSE	MAE
1	FCA1	0.001058	0.000403
2	FCA2	0.001728	0.000408
3	FCB1	0.000461	0.000271
4	FCB2	0.003285	0.000454
5	FCC1	0.001074	0.000576
6	FCC2	0.000403	0.000283
7	FCG1	0.000724	0.000099
8	FCG2	0.000923	0.000117

Table 4 and Table 5 are comparisons of RMSE and MAE from the test results of each ANFIS classification and estimation of disturbance locations. After training and testing on various types of ANFIS classification and estimation of disturbance locations, then the output results for each ANFIS are seen. The ANFIS to be used is selected based on the output of the ANFIS, namely by looking at the smallest RMSE and MAE values in the classification and estimation of the location of the disturbance from each ANFIS. The results of selecting the ANFIS network used are shown in Table 6.

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TABLE 5. COMPARISON OF RMSE AND MAE OF ANFIS TEST ESTIMATION OF DISTURBANCE LOCATIONS

No	Net Code	RMSE	MAE
1	FLAG1	0.027835	0.022561
2	FLAG2	0.060488	0.043865
3	FLBG1	0.044998	0.032314
4	FLBG2	0.057077	0.042393
5	FLCG1	0.021440	0.015247
6	FLCG2	0.025668	0.020017
7	FLAB1	0.021700	0.016029
8	FLAB2	0.031829	0.024150
9	FLAC1	0.039927	0.022348
10	FLAC2	0.022982	0.016008
11	FLBC1	0.060020	0.037147
12	FLBC2	0.090362	0.062569
13	FLABG1	0.013161	0.009917
14	FLABG2	0.031725	0.020344
15	FLACG1	0.023947	0.016975
16	FLACG2	0.027912	0.021601
17	FLBCG1	0.031361	0.019761
18	FLBCG2	0.031423	0.024422
19	FLABC1	0.010469	0.007704
20	FLABC2	0.010469	0.007704

TABLE 6. ANFIS FOR THE CLASSIFICATION AND ESTIMATION OF LOCATIONS

No	ANFIS Network	Net Code
1	Classification of disturbances in phase A	FCA1
2	Classification of disturbances in phase B	FCB1
3	Classification of disturbances in phase C	FCC2
4	Classification of disturbances on the ground	FCG1
5	Estimation of the location of the type of disturbance of AG	FLAG1
6	Estimation of the location of the type of disturbance of BG	FLBG1
7	Estimation of the location of the type of disturbance of CG	FLCG1
8	Estimation of the location of the type of disturbance of AB	FLAB1
9	Estimation of the location of the type of disturbance of AC	FLAC2
10	Estimation of the location of the type of disturbance of BC	FLBC1
11	Estimation of the location of the type of disturbance of ABG	FLABG1
12	Estimation of the location of the type of disturbance of ACG	FLACG1
13	Estimation of the location of the type of disturbance of BCG	FLBCG1
14	Estimation of the location of the type of disturbance of ABC	FLABC1

TABLE 7. THE ANFIS STRUCTURE IS USED FOR THE CLASSIFICATION AND ESTIMATION OF LOCATIONS

Disturbance Type	Error (%)		
	Average	Max	Min
AG	0.000605	0.002612	0.000002
BG	0.000865	0.003601	0.000016
CG	0.001145	0.003001	0.000064
AB	0.007382	0.024944	0.000384
AC	0.029827	0.107867	0.000469
BC	0.001452	0.005280	0.000026
ABG	0.002798	0.010721	0.000074
ACG	0.002586	0.007653	0.000084
BCG	0.001158	0.003627	0.000037
ABC	0.007240	0.015574	0.000133

In ANFIS, the disturbance classification can determine the presence of disturbances on each phase and ground correctly according to the type of disturbance that occurs so that the accuracy of ANFIS disturbance classification is 100% without any errors. While ANFIS estimates the location of disturbance for each type of disturbance, the error value can be calculated from the ANFIS results as shown in Table 7. Table 7 is the result of calculating the error in estimating the disturbance location for various simulated disturbance. The disturbance that occur are AG, BG, CG, AB, AC, BC, ABG, ACG, BCG, and ABC. In the test results from ANFIS, the estimation of the location of the disturbance, the smallest average test error generated by the ANFIS network, the estimation of the location of AG type disturbance, which is 0.000605%, while the largest average error is generated by the network estimation of the location of AC type disturbance, which is equal to 0.029827%. The results of calculating the RMSE and MAE values from the test can be seen in Figure 4. The red line shows the RMSE calculation results, while the blue line shows the MAE calculation results. It can be seen from the ANFIS network that the estimated disturbance location have the smallest RMSE and MAE values, which are in the AG disturbance of 0.0006 and 0.00039. Meanwhile, those with the largest RMSE and MAE values are located in AC disturbance of 0.2786 and 0.01909.

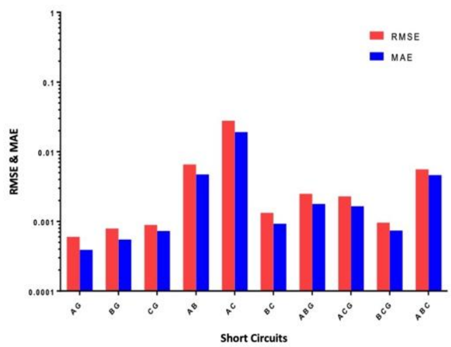

Fig. 4. RMSE and MAE ANFIS testing of location estimation.

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IV. CONCLUSION

Based on the results of the design and analysis of ANFIS as a classification of disturbances and estimation of disturbance locations in the electric power transmission system from the KP, BG, and GS buses, several conclusions can be drawn. Firstly, in ANFIS disturbance classification that has been selected can correctly determine the presence of disturbance on each phase and ground according to the type of disturbance that occurs so that the accuracy of ANFIS disturbance classification is 100%. Secondly, the lowest average testing error is generated by the ANFIS network estimation of the selected disturbance location: AG type disturbance of 0.0006% with RMSE 0.0006 and MAE 0.00039, while the largest average error is generated by the estimated ANFIS network. At last, the location of the AC-type disturbance is 0.029827% with an RMSE of 0.02786 and MAE of 0.01909.

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