ASSESS THE RISK LEVEL OF POWER TRANSFORMER DUE SHORT-CIRCUIT FAULTS BASED ON ANFIS

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Abstract -- A power transformer is an electrical machine that converts electrical power at different voltage levels. Faults, occur in power transformers, inhibit electrical power distribution to the consumer. Protection, therefore, of the power transformers is essential in power systems reliability. The power system can be reliable if the protection devices work well when there is a fault. A hybrid intelligent technique, which is a combination of Artificial Neural Network (ANN) and Fuzzy known as Adaptive Neuro-Fuzzy Inference Systems (ANFIS), was used in this research. The objective of this paper is the simulation of differential relays as a protection device on power transformers using Matlab/Simulink. Performance of differential relays for power transformers protection is carried out with internal and external fault scenarios. The input data were classified into three different input for ANFIS such as internal and external 1, internal and external 2, internal, external 1, and external 2, respectively. The error results of ANFIS training for the type of fault internal and external 1 is $9.46*10^{-7}$, and types of fault internal and external 2 is $1.09*10^{-6}$ internal, external 1 and external 2 are $8.59*10^{-7}$. The results obtained from the simulation were accurate and shows that the ANFIS technique is an efficient method that gives less error and a great value. Finally, the technique can minimize faults with power transformers. Finally, to prove this method can reduce faults in the power transformer, the assess of this model has been carried out through the RMSE that has been generated which is zero.

Keywords: ANFIS; Differential relay; Power transformer; Resetting; Faults

INTRODUCTION

Fault diagnosis aims to estimate the occurrence faults in power systems using a hybrid intelligent technique, namely ANFIS. The problem is that the power transformer system does not detect short circuit fault caused by not working the relay properly as a protection device. Therefore, there is a need for an assessment of the protection relays on power transformers, wherein this study, the focus is differential relays. To reduce the fault occurred and the continuous supply of electricity, it is vital to recognize the type of fault before starting the recovery operation. Therefore, a fault diagnosis system intelligence is an alternative way to restore fault in protecting the system (Kim et al., 2019; Li, Wang, & Song, 2019; Kaur, Brar, & Leena, 2019).

ANFIS is a neuro-fuzzy adaptive inference system based on artificial intelligence techniques based on the Takagi-Sugeno model. ANFIS technique is a combination of two methods - the Fuzzy and Neural Networks,

designed to produce a new hybrid intelligent technology. By applying the ANFIS technique, it is expected to minimize short circuit fault in power transformers, both internal and external (Salama, Abdel-Latif, Ismail & Mousa, 2018; Ge et al., 2018; Lei et al., 2007).

There are several categories of ANFIS methods which are based on input learning, neural networks, fuzzification, and defuzzification. The Fuzzy method uses If-Then rules by having input and output exercises for the same data as the Back Propagation (BP) method of neural networks. If-Then rules on actual values can be trained with minimum operator requirements to calculate their suitability. This study will discuss several studies with the hybrid intelligent techniques related to fault diagnosis in power systems.

Fault diagnosis detects a fault in the power system using relay information and Circuit Breaker (CB). If the relay and CB failed to operate, then the backup protection will work, which requires a robust system of fault diagnosis

that might eliminate faults and helps protect the power system. Fault diagnosis becomes a complex decision process that is important for awakening several ways that can provide fault analysis. The diagnosis can be achieved with a fault diagnosis system for power systems using the Energy Management System (EMS).

In the electrical power system, it is a crucial element to achieve the continuity of electrical service from the power plant to consumers as end users. Protection systems need to be used to detect fault from power systems and isolate fault from components or protective devices to the system. The system can also function sufficiently to separate the mistake. The proposed method operates only using data obtained from substations consisting of voltage and three phase currents. An active fault diagnosis algorithm for modifying the operating mode has a complicated fault with the electric power system. Automatic retrieval of incomplete information will be uploaded to the control center in the electrical power system. This mechanism can lead to loss of information services in the control center. If one or more of the relays and CB do not function properly, the algorithm model is needed correctly to assess the fault (Zhangjun et at., 2012).

Liping Qu and Haohan Zhou have introduced a Support Vector Machine (SVM) method to analyze and diagnose transformer errors. Estimates of transformer errors are playing an essential role in the operation of power systems to be safe and stable. To detect an initial error on the transformer as early as possible, accumulation of error data, the SVM forecast model takes RBF using kernel functions and utilizes patterns to overcome data and to reduce imbalances. The final experimental results show that SVM makes a better diagnosis accuracy (Qu & Zhou, 2015).

Intelligent hybrid techniques have also been introduced in research into power protection in transmission. This hybrid technique is an ANFIS technique that is applied for distance relay protection, especially for transmission lines. When a fault occurs during identification on a transmission line caused by an unwanted fault, the power delivery to the consumer does not work correctly. Therefore, they have provided alternative solutions to fix this problem. The transmission line impedance has determined how long distance relays will protect the channel distance. Simulation results have shown that excellent testing results can contribute to alternative algorithms that have good performance to protect the system in the transmission line (Azriyenni & Mustafa, 2015).

Gang Peng et al. has presented a diagnostic method for electrical equipment compatible with using multilayer fuzzy vectors. This method mining information about equipment features using the fuzzy logic method, many vector support tools use multilayer features as input and determining the class of devices that are problematic by contributing to the voting method. Through the application of algorithms in fault diagnosis using circuit breakers and transformers, explain this method can overcome abnormal data. Therefore, overcoming the sensor difficulties for unusual conditions and increasing the accuracy of equipment diagnosis (Peng et al., 2017).

Azriyenni et al. in his research have examined the Backpropagation of Neural Networks to detect the location of a fault in the 150 kV transmission line. Distance relay is one of the protective equipment that becomes the object of research for protection devices that often used in power system transmission. The Backpropagation of neural networks is a computational model that uses the training process can be used to solve the problem of the limitations of distance relay protection work. The Backpropagation also does not have limited impedance range settings. When the output gives the wrong result, the weight can be minimized and the response from the error. The Backpropagation technique has proven that the output is closer to the correct value. Therefore, The Backpropagation structure successfully detects the fault location and identifies the output current and CB status that trip (Azriyenni & Dame, 2017; Azriyenni et al., 2014).

Soloot et al. have presented internal faults in transformers in many of the failure cases. Developing a method to detect the location of internal short circuits inside the transformer winding can be helpful for a more cost-effective repair and enhancing the transformer design. Frequency response analysis can estimate the location of an internal fault inside the winding. The results showed that there are systematic changes in the frequency response of High Voltages (HV) to Low Voltage (LV) or vice-versa when the position of the internal fault moves from input layers of the winding to the output layers. The input impedance from HV and LV terminals are not sensitive to the location of short circuits in the frequency range of 10 kHz-10 MHz (Soloot et al., 2015).

In the last few years, intelligent techniques are a method that is often used in providing alternative solutions to solving problems in forecasting fault in the power system. This study will propose a fault modeling using a differential relay to protect the power transformer via Matlab/Simulink. Differential relay performance is also used to simulate short circuit fault internal and external faults. The application of the ANFIS

technique for forecasting the intended power transformer system minimizes internal and external fault in the power transformer. ANFIS differential relay can assess fault with input data, that is; the fault of Internal, External 1, and External 2 at RMSE values that are very accurate, which is zero. The ANFIS model is run using the Membership Function (MF) Gbell and triangle. Comparisons will be made between the two MF to reach the target of correct errors, and to reach the precise error target, and several iterations are carried out as much as possible.

METHOD
The Power Transformer
A short-circuit occurs at the power transformer; the short-circuit current can flow through the windings. This current is several times the rated current of the transformer. Due to this increased short-circuit current, the transformer winding is prone to undergo mechanical fatigue due to the electromagnetic forces, which are proportional to the square of the short-circuit current. Several methods have been described for short circuit interference in power transformers. The method of using the probability of a Monte Carlo simulation for external fault has also been introduced by Flores et al. (2008).

The electric power system built has one generator unit, two measuring transformer units, and a 25 MVA power transformer using differential relays. Fig. 1 shows a single line diagram model of a power transformer using differential relays, which will be simulated when a fault occurs. Simulations of fault occur at three points of fault location, which consists of; internal fault, external fault one, and external fault two. A few faults will be simulated with a type of short circuit faults: there are; one phase to ground fault (AG), two phases to the ground (BCG), phase to phase (BC), and three phases (ABC).
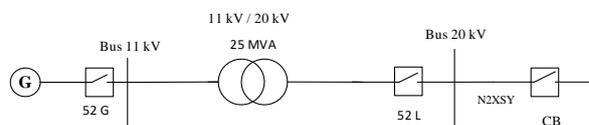

Figure 1. Single line diagram of the power transformer

Fig. 2 explains that the differential relay configuration needs to be done to provide protection to the power transformer and improve relay performance. CT limits the input of CT_1 and CT_2 for the protection area. On the 11 kV side, the transformer is connected in delta, and the voltage side of 20 kV is connected in a star.
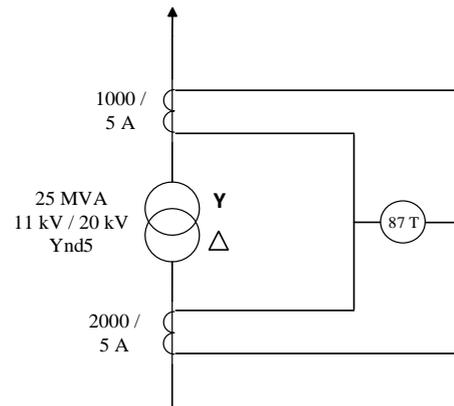

Figure 2. Differential Relay Configuration

This transformer has a Ynd5 connection group vector which will experience a phase shift of 150 degrees. To ensure the current phase angle is shifted, the relationship of the current transformer is designed differently.

Mismatch Error
The calculation of ratio the CT_1 on the 11 kV side is 2000 to 5, and the CT_2 ratio on the 20 kV side is 1000 to 5. Because of differences, there will be an error in reading the difference in current, voltage, and phase shift on the primary and secondary side of the power transformer. To calculate the previous mismatch error, calculate the ideal CT value of one side of the power transformer. For example for the voltage side of 20 kV (CT_2), the ideal value is 2000/5 * (11 kV) / (20 kV). Then, the CT_2 ratio on the voltage side is 20 kV when the maximum load is 1100 to 5. The ratio of CT used on the side of 20 kV is 1000 to 5, and ideally, CT for the side of 20 kV is 1100 to 5. The mismatch error for differential relays is 1100 / 1000n = 1.1%.

Thus, the differential relay error in securing the power transformer from the fault is 1.1%. This mismatch error in the differential relay can be corrected by increasing or decreasing the tap on CT. Mismatch errors are expected to be as small as possible, so that differential relay protection works optimally to protect power transformers. The condition of differential relay sensitivity in operation mismatch error cannot be more than 5%. This requirement is determined for protection to maintain the electric power system from fault optimally.

The internal fault is the location of the fault that is in the protection zone of the differential relay, which is limited between CT_1 and CT_2. An external fault is the location of the fault that is outside the differential protection zone that is outside CT_1 and CT_2. External fault one is simulated to occur before CT_1. External fault two is simulated after CT_2. This design aims to

produce two external faults to improve differential relay performance. The duration of the fault simulation carried out in this simulation is 0.2 seconds. So the timing of the fault starts at (2/50) * 0.2 = 0.04 seconds, then the fault occurs at 0.04 seconds. Fig. 3 shows the modeling of internal and external fault that using differential relay simulated via Matlab/Simulink

The setting membership functions using Gbell by entering MF [3 3 3 3 3 3]. Fig. 4 shows

the ANFIS structure having six entries. These six inputs are composed of current fault on CT_1 and CT_2, namely; I_A, I_B, I_C. The input of the membership function is each of the three membership functions, so the total number of membership functions is 18. For fuzzy rules that run as many as 729 for Input Membership Function (IMF) and Output Membership Function (OMF) and output targets, that is 1.

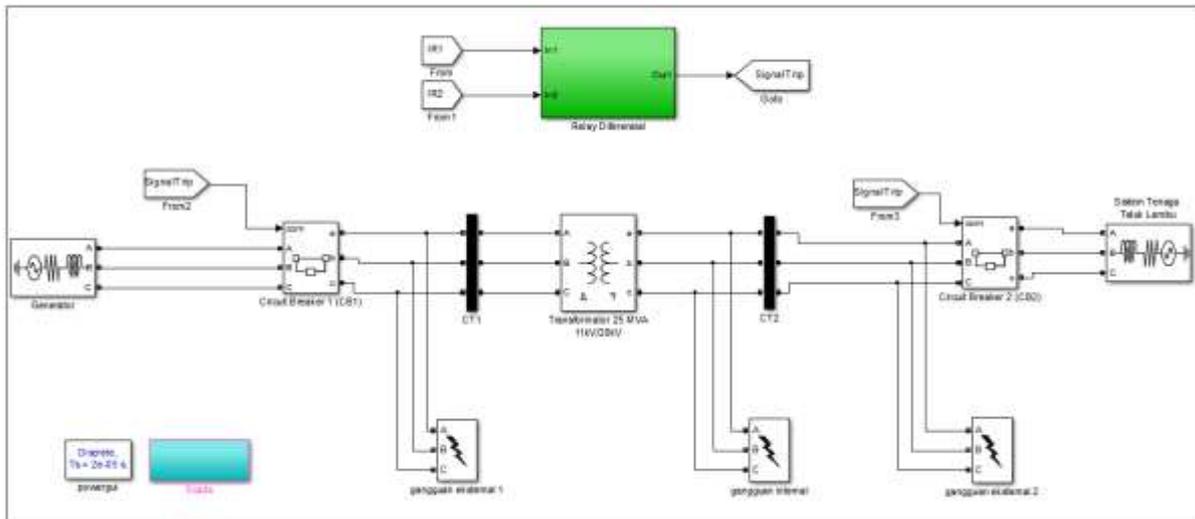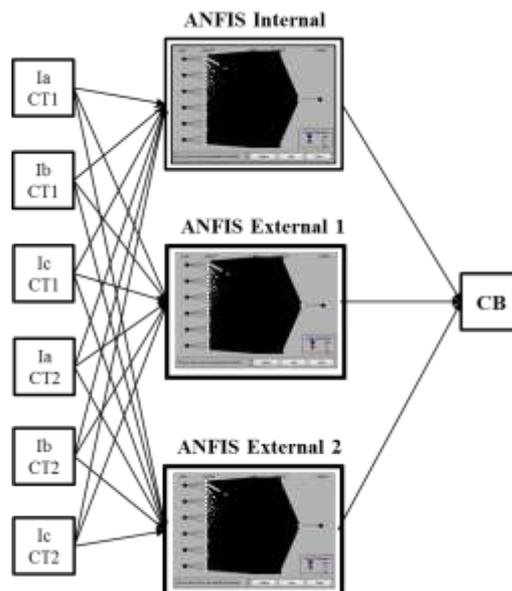Figure 3. Modeling of internal and external fault using differential relay simulated via Matlab/Simulink

Figure 4. Structure of power transformer system

RESULTS AND DISCUSSION

Results and Discussion should be a The simulation of short circuit fault for the location of

an internal fault in the protection zone using differential relays that is the area between CT_1 and CT_2. The differential relay will provide information

on the trip signal to CB at 0.0437 seconds. By the differential relay working principle that sends a trip to CB command because the differential current is greater than the current setting. It can be observed that the secondary currents of CT_1 and CT_2 values decrease to a time of 0.0566 seconds. In the analysis of the value of the differential current for each fault, the value of the differential current is compared with the current value of the setting. The internal fault of power transformers, differential relays will operate if:

$$I_{set} < I_d = \text{differential relay operated}$$

The external 1 and external 2 faults including fault outside the differential relay protection area, the differential relay does not operate if:

$$I_{set} > I_d = \text{differential relay not operated}$$

Table 1 has shown that differential current (I_d) is the difference between secondary current CT_1 and CT_2 in differential relays. I_{set} for an internal fault is obtained 2.805 A. I_{set} for an

external fault is obtained 11.22 A. The differential relay operates when internal fault and does not operate on the external fault.

In this section, we will explain the simulation of the results of fault outside the protected area for a differential relay. The fault simulation is carried out via software; this data will be used as an input for training data to the ANFIS, as seen in Table 1. Table 2 shows the simulation results of fault in 25 MVA power transformers that run with various types of fault and fault locations. Then, the simulation produces short circuit data, which is used as an input data of ANFIS. The data of short circuit fault is carried out for faults - internal, an external one, and external two. The data is generated as input for ANFIS and simulation of a fault in the power transformer. The data has been trained and tested through ANFIS; the more iterations are carried out the smaller error rate. Each group input analyzed in the ANFIS and, it has been run with two membership functions (membership of Gbell and triangle). These results can improve the accuracy of the ANFIS technique and provide excellent recommendations on power transformers.

Table 1. Differential Current Setting

Type of Fault	Fault Location	Differential Current (Ampere)			Current Setting (Ampere)	CB
		A	B	C		
AG	Internal	14.29	3.92	2.37	2.805	1
BCG		2.23	9.61	3.93		1
BC		2.211	5.26	6.08		1
ABC		12.18	13.56	3.8		1
AG	External 1	0.29	1.135	1.47	11.22	0
BCG		1.22	1.38	0.98		0
BC		0.47	1.54	0.94		0
ABC		1.53	1.08	1.62		0
AG	External 2	0.33	0.87	1.16		0
BCG		0.62	0.945	0.484		0
BC		0.62	0.97	0.685		0
ABC		1.075	0.67	0.98		0

Table 2. Input Data of ANFIS in Short Circuit Simulation

Type of Fault	Fault Location	Current of CT_1 (Ampere)			Current of CT_2 (Ampere)			CB
		A	B	C	A	B	C	
AG	Internal	1753,788	1258,317	595,200	4143,470	395,265	734,939	1
BCG		998,600	1377,215	1789,889	555,582	2984,624	3526,392	1
BC		432,497	1398,640	1789,890	327,332	2258,289	2575,818	1
ABC		2636,700	2460,660	1789,889	4144,438	2985,005	3527,691	1
AG	External 1	2072,550	1524,915	668,710	1138,776	327,340	843,791	0
BCG		1042,780	2361,103	2464,134	780,413	1520,751	990,807	0
BC		595,185	2107,809	2683,976	492,057	1520,751	1037,604	0
ABC		4072,786	3614,873	2939,647	2243,474	1520,751	2003,175	0
AG	External 2	1753,786	1258,317	595,197	946,626	359,280	734,954	0
BCG		998,600	1377,215	1789,889	555,598	906,463	831,645	0
BC		998,497	1398,639	1789,889	327,350	1011,142	696,765	0
ABC		2636,698	2460,660	1789,889	1490,458	1059,754	1260,205	0

ANFIS training data for internal, external one and external two faults that are run using Matlab is a combination of internal & external one fault, internal & external two, and internal, external one & internal two as shown in Table 2. Initialization of initial values for techniques ANFIS is run for data training. The results of the training begin training data on iterations 30, 50, 80, 100, 130, 150, 180, 200, and 230. Observation of the error values in each training iteration of the data is carried out seven times. The error analysis carried out at each stage with the lowest error value is

produced, at 200 iterations with an error value of $8.59*10^{-7}$.

Table 3 shows the accuracy of ANFIS can be calculated using the Root Mean Square Error (RMSE). The RMSE is the least square root error value of a simulation, where, y_i' is the actual target value, y_i' is the predicted output value, and n is the amount of data. The RMSE equation is as follows:

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

Table 3. The result of ANFIS for various fault

Input Data	Type of Fault	Fault Location	Target	Internal & External 1 Faults	Internal & External 2 Faults	Internal, External 1, dan External 2 Faults
				Output of ANFIS	Output of ANFIS	Output of ANFIS
1	AG	Internal	1	1	1	1
2	BCG		1	1	1	1
3	BC		1	1	1	1
4	ABC		1	1	1	1
5	AG	External 1	0	0	-	0
6	BCG		0	0	-	0
7	BC		0	0	-	0
8	ABC		0	0	-	0
9	AG	External 2	0	-	0	0
10	BCG		0	-	0	0
11	BC		0	-	0	0
12	ABC		0	-	0	0
RMSE				0	0	0

Table 4 Comparison error of membership function between Gbell and triangle for Internal, External 1, and External 2 faults

Iteration	Error (pu)	
	GBell	Triangle
30	0,0000018972	0,0000020678
50	0,0000016721	0,0000020653
80	0,0000014223	0,0000020614
100	0,0000012236	0,0000020576
130	0,0000010641	0,0000020576
150	0,00000094961	0,0000020576
180	0,00000086146	0,0000020576
200	**0,00000085893**	**0,0000020576**
230	0,00000085893	0,0000020576

The error percent is valued by calculating the difference between the actual target and the ANFIS output value and divided by the real value. The ANFIS technique for securing power transformers using differential relays results in good forecasting of fault, cause the value of RMSE is very small. This analysis can be suggested that the lower the RMSE, the higher the success rate of applying the ANFIS technique.

Table 4 shows the error value from the ANFIS training via Matlab. The membership function Gbell had the smallest error value is

$8.6*10^{-7}$. The Gbell membership function training obtained the smallest error value in training with 200 iterations.

When, the membership function triangle, the smallest error value was obtained at $2.06*10^{-6}$. The triangle membership function training got the lowest error value at 100 iterations. Based on training data that has been run for internal, external 1 and external 2 faults, it can be observed that the smallest error value generated is the membership function Gbell.

CONCLUSION

The ANFIS technique has been applied to predict fault with 25 MVA power transformers with a short circuit current data. The calculated resetting current of the differential relay is 2.805 Amperes to secure the internal fault of 11.22 Ampere and can work properly. The results of the error concluded that the more the number of iterations the smaller the errors obtained. For internal and external fault 1 the target error has been reached in the 180 iterations (Gbell). For internal and external fault 2, the target error has been achieved at 230 iterations (Gbell). The internal, external 1, and external 2 faults the target error has been reached in the 130 iterations (Gbell). Therefore, from the simulation results via ANFIS, it was concluded that Gbell membership function is better than the triangle membership for three short circuit fault scenarios. Finally, ANFIS differential relays can predict for all types of faults at excellent and accurate RMSE, which is zero. This ANFIS method has also been run by using other relays such as; distance relays that have been explained in the literature review above, and then this method is very accurate and efficient to be applied in terms of the assessment of errors tested.

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