A NEURO-FUZZY TECHNIQUE FOR DISCRIMINATION BETWEEN INTERNAL FAULTS AND MAGNETIZING INRUSH CURRENTS IN TRANSFORMERS

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ABSTRACT. This paper presents the application of the fuzzy-neuro method to investigate transformer inrush current. Recently, the frequency environment of power systems has been made more complicated and the magnitude of the second harmonic in inrush current has been decreased because of the improvement of cast steel. Therefore, traditional approaches will likely mal-operate in the case of magnetizing inrush with low second component and internal faults with high second harmonic. The proposed scheme enhances the inrush detection sensitivity of conventional techniques by using a fuzzy-neuro approach. Details of the design procedure and the results of performance studies with the proposed detector are given in the paper. The results of performance studies show that the proposed algorithm is fast and accurate.

1. Introduction

The phenomenon of magnetizing inrush is a transient condition, which occurs primarily when a transformer is energized. It is not a fault condition, and therefore, it does not necessitate the operation of protection system, which, to the contrary, must remain stable during the inrush transient. This requirement imposes certain difficulties on the design of protective systems for transformers [3].

To this day, the differential current protection principle remains the most popular protection principle for power transformers. This principle has been proved to be a reliable method. To ensure correct operation of the differential current relay, an important preliminary task is to identify the inrush current.

There are many identification methods. The most popular method is the second harmonic component of three phase currents. The second harmonic is very low if the transformer is connected to a long transmission line. Also, there are cases in which the presence of differential currents cannot make a clear distinction between fault and inrush [2]-[15]-[20]-[22]. A new relaying technique with high degree of reliability is required for flexibility in spite of change of condition in power system.

Recently, to advance the conventional approaches, several new AI (artificial-intelligence) features for protective relaying have been developed [4]-[11]. A number of applications of ANNs to power system protection have been reported so far [8]-[10-12] including differential protection for power transformers [7]-[13]-[16-18].

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Also, differential protective relay based on fuzzy logic are proposed for solving some of problems of power transformer protection by researchers [4]-[6]-[21]. Most of these approaches are liable to mal-operate in the case of magnetizing inrush with low second harmonic component and internal faults with high second harmonic component.

This paper presents a fuzzy-neuro application for an inrush detector in the differential protection of three-phase power transformers. The different conditions are considered as different patterns and fuzzy-neuro algorithms will be used to recognize these patterns. Utilization of fuzzy-neuro algorithms in pattern recognition of such a transformer enables it to be robust against specific phenomena related to the three-phase power transformers and provides a better response and consequently improves relay performance in comparison with traditional approaches. In this paper, the ability of the fuzzy-neuro to operate in a high sensitivity manner against both inrush current with and without internal faults will be shown.

2. Simulation of the Power System to Prepare the Patterns

A three-phase 230/63 kV power system including a 60-km transmission line, as shown in Figure 1, has been used to produce the required test and training patterns. The simulation was done by means of PSCAD/EMTDC software package [19]. The power transformer was simulated using the transformer model reported in [9]. Different internal winding faults have been simulated using this model. Here the transformer connection is considered as delta-star. Table 1 presents the data associated with this power system. The current transformer has been also modeled as shown in Figure 1 and its parameters are shown in Table 2. This component models a current transformer based on the Jiles-Atherton theory of ferromagnetic hysteresis. The effects of saturation, hysteresis, remnance and minor loop formation are modeled based on the physics of the magnetic material [19]. The accuracy of CT model based on the Jiles-Atherton theory of ferromagnetic hysteresis has been checked by means of many tests in [1]. The test results confirm a high degree of accuracy for this CT model. CT ratios are chosen as 1000:1 and 250:1 for secondary and primary of the transformer, respectively.

The combinations of system conditions, shown in Table 3, have been produced using this system to train the fuzzy syatem. As can be seen, all types of the terminal faults and internal winding faults have been considered. Also, they involve inrush current with and without internal faults and different remnant fluxes in the power transformer core. The effect of CT saturation is also studied.

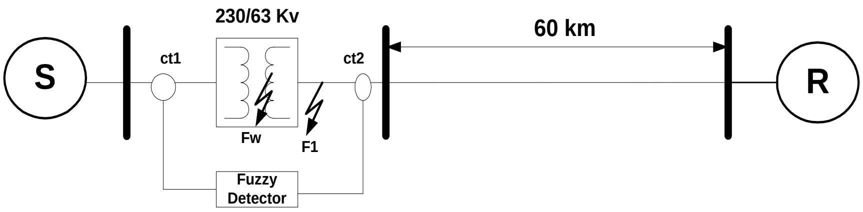

FIGURE 1. Simulated Power System Model

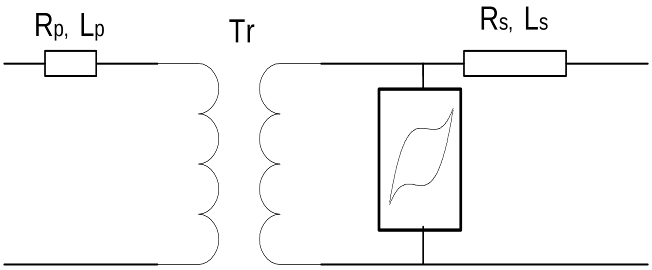

FIGURE 2. Current Transformer Circuit Diagram

Transformer Reactance (P.U.)	j 0.13
Line Impedance (+ and – sequences) Ω/km	0.072 + j 0.416
Line Impedance (zero sequence) Ω/km	0.346 + j 1.066

TABLE 1. Simulated Power System Parameters

Secondary winding resistance and leakage inductance (Ω)	0.5, 8×10^{-4}
Turn ratio	2000:1
Area (m^2)	6.5×10^{-4}
Path length (m)	0.5
Frequency (Hz)	50
Rated voltage (kV)	230

TABLE 2. Simulated Current Transformer Parameters

System conditions		Fault: AG, BG, ABC, … at points F1, F2 and F3 Inrush: In Different Voltage angle with different remnant flux
Internal winding faults	Turn to turn fault	Different percentage of winding
	Turn to ground fault	Different percentage of winding
Voltage angle		0, 30, 60, and 90
Remnant flux in Transformer Core		-80% - 80%
Source Impedance Ω		12-42
Remnant flux in CT Core		-80% - 80%
Power angle (deg)		-10_10

TABLE 3. Patterns Data Generation

3. **Determination of the Characteristics of the Inrush Current**

The classical second harmonic restraint compares the magnitude of the second harmonic with the magnitude of the fundamental frequency component.

The proposed technique is based on the concept of symmetrical components of the second harmonic. The symmetrical components can provide better recognition between magnetizing inrush currents and internal fault currents.

The symmetrical components technique is a powerful tool for analysing power networks under unbalanced operations. Symmetrical components allow unbalanced phase quantities such as currents and voltages to be replaced by three separately balanced symmetrical components. Based on this theory, three-phase unbalanced phasors of a three-phase system can be resolved into three balanced systems of phasors as follows:

1- Positive-sequence components consisting of a set of balanced three-phase components with a phase sequence a-b-c and exit during all system conditions.

2- Negative-sequence components consisting of a set of balanced three-phase components with a phase sequence a-c-b and exit during unbalanced conditions.

3- Zero-sequence components consisting of three single-phase components, all equal in magnitude and with the same phase angles and exit when ground is involved in an unbalanced condition.

In order to evaluate the recognition power of the quality symmetrical component method, the power system in Figure 1 has been used and the amplitude ratio of the second and the first harmonics has been derived. The performed simulations have shown improved identification ability of the inrush current.

To illustrate this, Figures 3-7 show the amplitude ratio of symmetrical components between the second and first harmonics for two inrush cases and two internal faults.

As seen from these figures, the values of the symmetrical component ratios of inrush cases are quite different from the values of the symmetrical component ratios of internal faults. These ratios can be used to identify inrush cases.

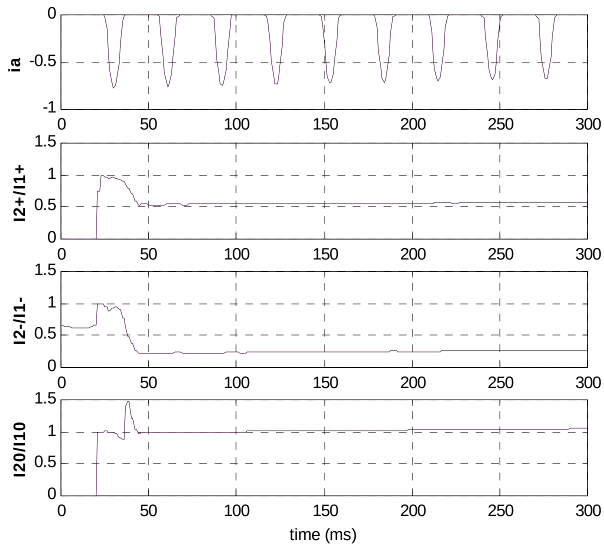

FIGURE 3. Inrush Current with Closing Angle 135 Degrees

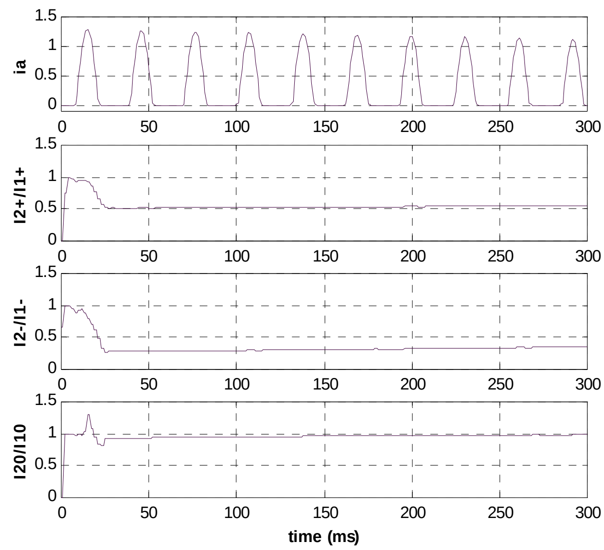

FIGURE 4. Inrush Current with Closing Angle 0 Degree

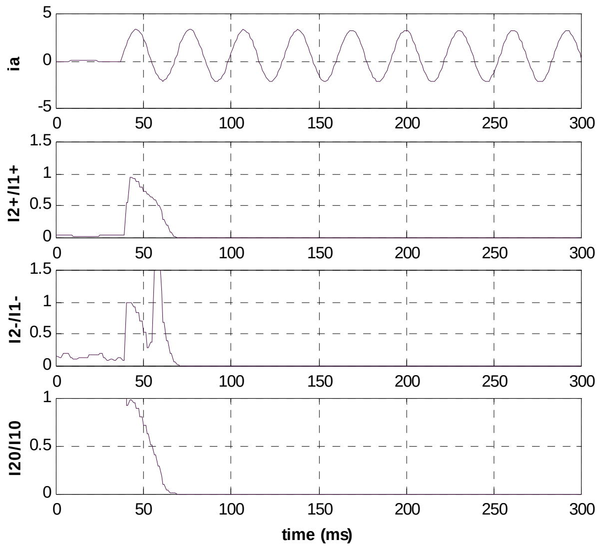

FIGURE 5. Internal ABG Fault with Inception Angle 90 Degrees

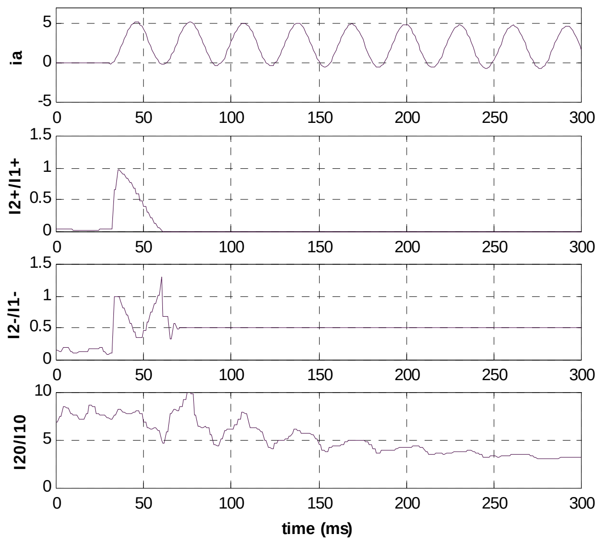

FIGURE 6. Internal ABCG Fault with Inception Angle 0 Degree

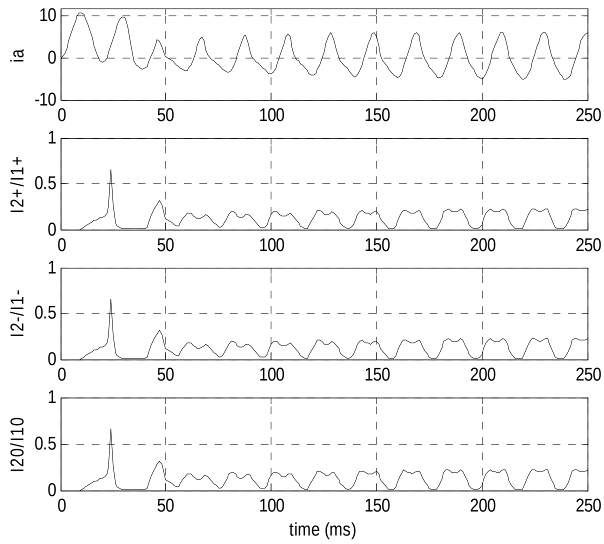

FIGURE 7. Internal AG Fault with CT Saturation

4. **Fuzzy-neuro Techniques**

In this paper, the architecture of adaptive fuzzy network has been utilized. In general, fuzzy sets and neural networks deal efficiently with the two very distinct areas of information processing. Fuzzy sets are good at various aspects of uncertain knowledge representation, while fuzzy-neuro is an efficient structure capable of learning from examples. Both techniques have their advantages and disadvantages, and they can also be complementary [14].

Adaptive fuzzy network is inflected in three basic elements: fuzzification, fuzzy inference and defuzzification. In neural nets, the weights between the input and the first hidden layer as well as the last hidden layer and output layer, determine the input/output behavior. In a fuzzy system, these parameters are found in the fuzzification and defuzzification routines and can thus be trained. Calculated degrees of membership in the rule layers are according to IF-THEN rules. The network uses the least-squares method and the back propagation gradient descent method to learn from the data sets, and find a suitable adaptive fuzzy network [5]. A fuzzy technologies map is shown in Figure 8.

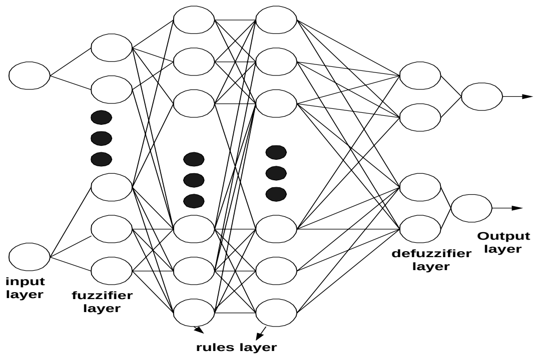

FIGURE 8. Neuro Fuzzy Technologies Map a Neural Net to a Fuzzy Neuro System

5. Design of Fuzzy-neuro Inrush Detector

Figure 9 shows the block diagram of the proposed inrush detector. First, primary and secondary three phase current input signals were processed by 2nd-order low-pass Butterworth filters. The anti-aliasing filters had a cut-off frequency of 450 Hz. Then, the magnitudes of harmonics of symmetrical components of current were obtained by the DFT algorithm.

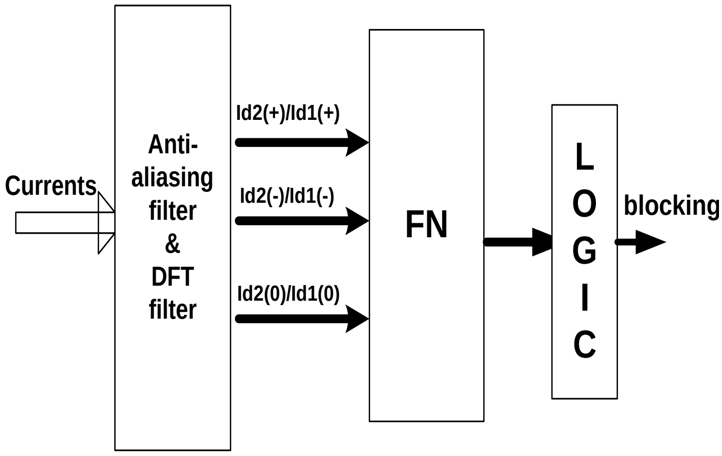

FIGURE 9. The Structure of the Proposed Inrush Detector

As can be seen, the detector consists of a FN unit. Also a logical unit is embedded into this structure to provide the appropriate blocking commands based on the output of the previous unit. The inputs of this unit consist of the second harmonic component of the different sequence differential current to the first harmonic component of the differential current ratio.

5.1 Training

An adaptive fuzzy network was chosen to process the input data set. In this work the Takagi-Sugeno model with multiple inputs and a single output is used. This model is composed of linguistic variables in the premise part and polynominal variables in the consequent part. The generic fuzzy rule used under this scheme has the following structure:

R^1: IF x is A_1 and y is B_1 and z is C_1 THEN $f_1=p_1x+q_1y+r_1z+o_1$

R^2: IF x is A_2 and y is B_2 and z is C_2 THEN $f_2=p_2x+q_2y+r_2z+o_2$

R^3: IF x is A_3 and y is B_3 and z is C_3 THEN $f_3=p_3x+q_3y+r_3z+o_3$

Where x, y and z are inputs, A_i, B_i, C_i are membership functions, and p_i, q_i, r_i, o_i are consequent parameters. In the learning procedure, the forward pass learning estimates the consequent parameters and backward pass learning updates the premise parameters.

$Id2_{(+)}/Id1_{(+)}$, $Id2_{(-)}/Id1_{(-)}$ and $Id2_{(0)}/Id1_{(0)}$ are considered as input vector to the network. Where, $Id2_{(+)}$, $Id2_{(-)}$ and $Id2_{(0)}$ are positive, negative and zero sequences of second harmonic of differential current respectively and $Id1_{(+)}$, $Id1_{(-)}$ and $Id1_{(0)}$ are positive, negative and zero sequences of basic component of differential current respectively. An output in final layer was chosen for the network. If only an inrush phenomenon occurs, the detector output must be 1, otherwise, it must be 0.

The training sets include data for different types of shunt faults, different fault inception angles, inrush current with and without internal faults and at different conditions of the system.

Membership functions and suitable fuzzy rules were obtained by a data set resulting from the simulation. For training, Matlab software was used. The parameters associated with the membership functions will change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the neuro fuzzy system models the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimization routines can be applied to adjust the parameters so as to reduce some error measure (usually defined by the sum of the squared difference between actual and desired outputs).

As shown in Figure 10, final membership functions of inputs are guessing functions. Membership functions include three functions (low, medium and high). The fuzzy- neuro applied is assumed to produce output equal to 1 for INRUSH patterns and 0 for other conditions. For classification purposes, a threshold value set to 0.5 is introduced. All cases for which the FN output is lower than 0.5 are classified as NO-INRUSH and those for which the treshould is exceeded are recognized as INRUSH cases and a blocking signal is produced. The FN uses the least-squares method and the back propagation gradient descent method to learn from the data sets, and hence find a suitable adaptive fuzzy network.

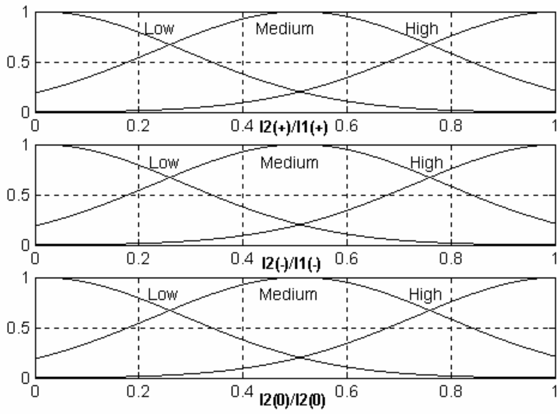

FIGURE 10. Membership Functions of Inputs of Unit

Training fuzzy rules are shown in Table 4. All the rules are derived from the training of the fuzzy-neuro model based on the prior database.

Once trained, the FN performance was tested using test patterns that were different from the training patterns. Some of the simulation results are presented in the next section.

IF			THEN
$Id2_{(+)}/I1_{(+)}$	$Id2_{(-)}/Id1_{(-)}$	$Id2_{(0)}/Id1_{(0)}$	Output
High	Low|High|Me	Low|High|Me	BLK
Medium	Low	Low	BLK
Low	Low|High|Me	Low|High|Me	NO_BLK
Medium	High	High	NO_BLK
Medium	Medium	Medium	NO_BLK

TABLE 4. Fuzzy Rules
(BLK: Blocking, NO_BLK: No Blocking)

5.2 Test Results

A validation data set consisting of about 200 different states was generated using the power system model shown in Figure 1. For different conditions of the validation set, fault type, fault inception time, closing angle source impedance and remnant flux were changed to investigate the effects of these factors on the performance of the proposed algorithm.

The proposed inrush detector for several different power system conditions is presented in Table 5 and Table 6. Table 5 shows the test results of the detector for different inrush currents with different conditions. These conditions include inrush with and without fault with different closing angles and remnant fluxes. Table 5 shows that the detector has detected inrush conditions correctly. For cases where internal fault and inrush have both occurred , the output has been NO_BLK.

DISTURBANCE	CLOSING ANGLE (deg)	REMNANT FLUX (%)	OUTPUT
INRUSH	0	-60	BLK
	45	50	BLK
	135	-40	BLK
	180	35	BLK
	60	-75	BLK
	30	45	BLK
INTERNAL FAULT WITH INRUSH	INCEP. ANGLE (deg)	TYPE FAULT	OUTPUT
	0	AG	NO_BLK
	30	Turn -Turn	NO_BLK
	90	ACG	NO_BLK
	180	Turn-Ground	NO_BLK
	60	BCG	NO_BLK

TABLE 5. Inrush Detector Operation Test Results

Table 6 shows the test results of the detector for different internal faults including internal faults with CT saturation, winding faults and terminal faults. As shown in Table 6, the detector performs quite reliably for all conditions. The detector has responded correctly and remained stable, even when internal faults with CT saturation has occurred.

The detector output for a few cases with different power system conditions is presented in this section. The main emphasis is on checking the detector's performance under different power system conditions. In general, the detector performance is accurate and suitable.

The performance of the newly designed inrush detector is further evaluated by comparing its results with the results obtained from a conventional digital differential relay. Initial results indicate that, in general, the proposed detector performs faster and more reliably. More studies are being conducted under a wide range of system conditions.

INTERNAL FAULT WITH CT SATURATION	INCEPTION ANGLE (deg)	TYPE FAULT	OUTPUT
	90	AG	NO_BLK
	60	ACG	NO_BLK
	65	BCG	NO_BLK
	135	ABCG	NO_BLK
	180	CG	NO_BLK
	120	ABC	NO_BLK
	45	AG	NO_BLK
WINDING FAULT	percentage of winding	TYPE FAULT	OUTPUT
	15.8	Turn to Turn	NO_BLK
	3.14	Turn to Ground	NO_BLK
	6.34	Turn to Ground	NO_BLK
	9.45	Turn to Ground	NO_BLK
	39.3	Turn to Turn	NO_BLK
TERMINAL FAULT	INCEPTION ANGLE (deg)	TYPE FAULT	OUTPUT
	45	AG	NO_BLK
	90	ABCG	NO_BLK
	-45	AC	NO_BLK
	-90	ABG	NO_BLK
	135	ABC	NO_BLK

TABLE 6. Inrush Detector Operation Test Results for Different Faults

6. **Conclusion**

This paper presents a new inrush detector algorithm for differential protection of power transformer based on the fuzzy-neuro method. The results show that the proposed fuzzy-neuro based inrush detector represents a proper action. It can operate with proper sensitivity and even when internal faults with CT saturation occur. Thus, the use of fuzzy-neuro can make it possible to extend the use of reliable and sensitive differential relays to power transformer protection.

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