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Using Fuzzy ARTmap Neural Network for Determination of Partial Discharge Location in Power Transformers

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Abstract--**Techniques for locating a partial discharge source are of major importance in both the maintenance and repair of a transformer. This paper presents a novel approach to identify partial discharge locations in transformer winding using neural network. In this paper for simulation and detection of partial discharge, detail model of transformer is used. With modeling of partial discharge impulse source in EMTP software, this phenomenon is implemented in different points of transformer winding. Then produced current in both ends of winding is measured and use for training and test of neural network. In actual, obtained current signals is with noise. Thus in this paper the performance of the Fuzzy ARTmap neural network for correct determination of partial discharge location in power transformer with considering different noises on simulated current signals for simulation of actual conditions is surveyed. The most important characteristics of neural networks are capabilities to learning and predict the various patterns and other is capability to provide a fast responsible for input patterns. The neural network used here for simulation patterns trainings and testing of the partial discharge in power transformer winding is Fuzzy ARTmap.**

Index Terms—**Detailed model, Fuzzy ARTmap neural network, Partial discharge, Transformer.**

I. Introduction

PARTIAL Discharges (PD) are well known as a source for insulation degradation and a major source of insulation failure in power transformers [1]. Power transformers play a major part in electricity transmission and [2]. The capital cost of a transformer is extremely high and the economic penalties incurred by transformer failure, and the resulting outage costs, are considerable. If insulation deterioration caused by Partial Discharge (PD) activity can be detected at an early stage, then incipient insulation faults can be identified and preventive maintenance measures taken [3]. Therefore, many researches in PD location detection are done. PD detection is classified into acoustic and electrical methods. Electrical method is based on the taking created impulses in cavity of transformer insulation. Assessment of PD in electrical method is possible by using current transducers which is connected to measurement terminals. In this method many different ways is used or now studying i.e., tip-up, dielectric loss analysing, inductive probes, pulse detecting and analysing and transformer methods and etc.

The vantage point of the acoustic method is the simple locating algorithm but the sensitivity is very low. On the other side complicated structure of power transformers is caused difficult finding PD with due attention to propagation velocity of acoustic waves resulting from PD. Therefore, in recent years concentration of researches is on electrical method. In all researches, the PD current impulses is injected into the different point of the winding and produced signals in the neutral and ending point of the winding is recorded. With analysing of these signals, location of PD is detected. Locating of the PD is performed by transfer function [4], zeroes and poles of signals frequency spectrum [3], wavelet and neural network [5]. In this paper a novel approach to finding location of PD using Fuzzy ARTmap neural network is proposed.

II. Partial Discharge and Modelling

PD are localized ionization within electrical insulation that are caused by a high electrical field. They occur in part of the insulation system and are limited in extent, so they do not immediately cause full insulation breakdown.

PD acts similar to an impulse current source [6]. Thus, the depicted circuit in Fig. 1 is used for modeling of PD in the EMTP software. The value of shown elements in Fig. 1 is specified in [7].

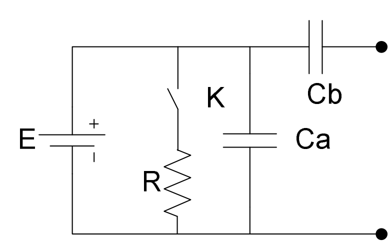

Fig. 1. Circuit for PD pulse modelling

Fig. 2 depicts the produced waveform by the circuit which is shown in Fig. 1. The PD impulse is used for this paper simulation is similar to specifications and results of

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experimental tests[8] which rise time and fall time is approximately 5 nsec and 15 nsec respectively (refer Fig. 2).

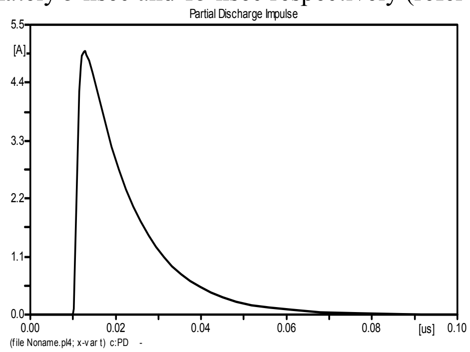


Fig. 2. PD current impulse

III. DETAILED MODEL WITH CONSIDERING PD

The equivalent circuit diagram of the test objects beyond 10 kHz is shown in Fig. 3. A winding unit can contain one disk, two disks or several numbers of turns. The number of units is a modelling parameter and the chosen value is a compromise between the accuracy and the complexity. For the sake of simplicity only three winding units of the double disk high voltage winding are shown in Fig. 3. Only one layer with three winding units have been shown for the low voltage winding in Fig. 3, too. This model is called Detailed Model (DM).

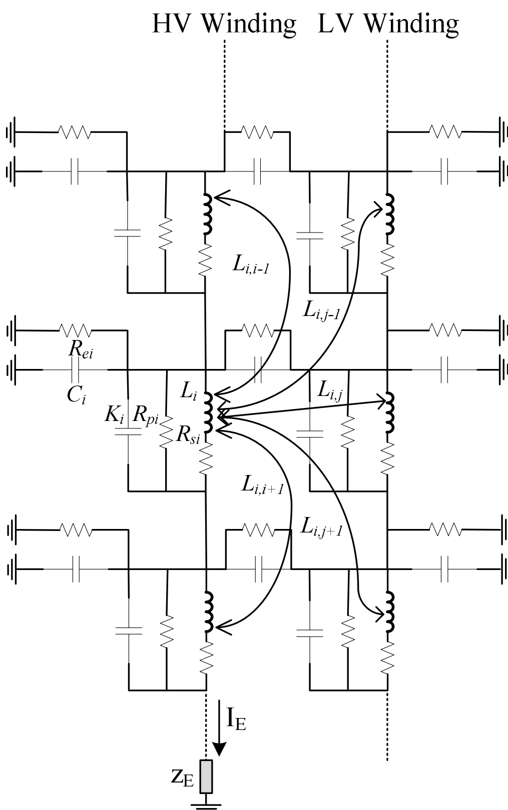


Fig. 3. DM of a two winding transformer

The elements of the circuit diagram are defined in [9]. Using this model, it is possible to calculate node voltages and branch currents in the time as well as in the frequency domain. Due to the frequency dependence behaviour of the resistive elements (R_{pi}, R_{ei} *and* R_{si}) the calculation in the frequency domain is preferable.

IV. FUZZY ARTMAP NEURAL NETWORK

For the purpose of training and testing, in this paper Adaptive Resonance Theory (ART) neural networks have been used. In general, this family of neural networks include ART1, ART2 [10], ART3 [11], ARTmap [12], Fuzzy ART [13] and Fuzzy ARTmap [14]. ART1 and ARTmap categorize the binary input patterns while, Fuzzy ARTmap are also capable to categorize analogue patterns.

Fuzzy ARTmap is an incremental supervised learning algorithm which combines fuzzy logic and Adaptive Resonance Theory (ART) neural network for recognition of pattern categories and multidimensional maps in response to input vectors presented in an arbitrary order. It realizes a new minmax learning rule which conjointly minimizes predictive error and maximizes code compression, and therefore gives generalization. This is achieved by a match tracking process that increase the ART vigilance parameter (fuzzy degree of membership of the input with respect to the category templates) by the minimum amount needed to correct a predictive error (PE). The Fuzzy ARTmap neural network is composed of two Fuzzy ART modules [14], i.e. *fuzzy* ART_a and *fuzzy* ART_b, which are depicted in Fig. 4 and are essentially the same as those described by Carpenter et al.

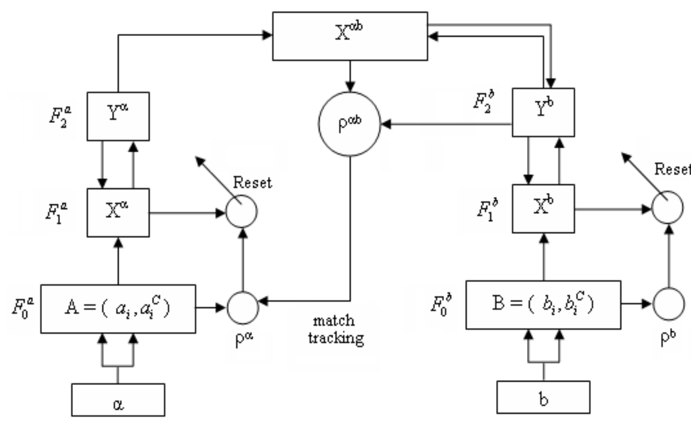


Fig. 4. Typical Fuzzy ARTmap

The interactions mediated by the map field F^{ab} operationally characterized as follows.

A. ART_a and ART_b

Inputs to ART_a and ART_b are in the complement code form: for ART_a ‘$I = A = (a,a^c)$ and for ART_b ‘$I = B = (b,b^c)$ (See Fig. 4). Variables in ART_a or ART_b are designated by subscript “a” and “b” respectively. For ART_a, let $x^a = \{x_1^a,...,x_{2Ma}^a\}$ denote the F_1^a output vector, let $y^a = \{y_1^a,...,y_{Na}^a\}$ denote F_2^a, and let $w_j^a = \{w_{j1}^a,...,w_{j2Ma}^a\}$ denote the j^{th} ART_a weight vector. For ART_b, let $x^b = \{x_1^b,...,x_{2Mb}^b\}$ denote the F_1^b output vector and let $y^b = \{y_1^b,...,y_{Nb}^b\}$ denote F_2^b. And let $w_k^b = \{w_{k1}^b,...,w_{k2Mb}^b\}$ denote the k^{th} ART_b weight vector. For the map field, let $x^{ab} = \{x_1^{ab},...,x_{Na}^{ab}\}$ denote the F^{ab} output vector, and let $w_j^{ab} = \{w_{j1}^{ab},\dots,w_{jNb}^{ab}\}$ denote the weight vector from the j^{th} F_2^a node to F^{ab}. Vectors x^a, y^a, x^b, y^b, and x^{ab} are set to 0 between input presentations.

B. Map field activation

The map field F^{ab} is activated whenever one of the ART_a or ART_b categories is active. If node J of F_2^a is chosen, then its weights w_j^{ab} activate F^{ab}. If K in F_2^b is active, then node K in F^{ab} is activated by one-to-one pathways between F_2^b and F^{ab}. If both ART_a and ART_b are active, then F^{ab} becomes active only if ART_a predicts the same category as ART_b via the weights w_j^{ab}. The F^{ab} output vector x^{ab} obeys the following:

$$\begin{cases} y^b \wedge w_j^{ab} & \text{If the } j^{th} F_2^a \text{ is active and } F_2^b \text{ is active.} \\ w_j^{ab} & \text{If the } j^{th} F_2^a \text{ is active and } F_2^b \text{ is inactive.} \\ y^b & \text{If the } j^{th} F_2^a \text{ is inactive and } F_2^b \text{ is active.} \\ 0 & \text{If the } j^{th} F_2^a \text{ is inactive and } F_2^b \text{ is inactive.} \end{cases} \quad (1)$$

From (1), $x^{ab} = 0$ if the prediction w_j^{ab} is disconfirmed by y^b. Even such a mismatch triggers and ART_a search for a better category, as follows.

C. Match tracking

At the start of each input presentation, the ART_a vigilance parameter ρ_a equals to baseline vigilance ρ_a. The map field vigilance parameter is ρ_{ab}

$$If \quad |\mathrm{x}^{ab}| < \rho_{ab}\cdot|y^b| \quad (2)$$

The ρ_a is increased until it is slightly larger than $|A \wedge w_j^a||A|^{-1}$, where A is the input to F_1^a, in complement coding form, and

$$|x^a| = |A \wedge w_j^a| < \rho_a |A| \quad (3)$$

where J is the index of active F_2^a node.

When this occurs, ART_a search leads either to activation of another F_2^a node J with:

$$|x^a| = |A \wedge w_j^a| \geq \rho_a |A| \quad (4)$$

and

$$\left|x^a\right| = \left|y^b \wedge w_j^{ab}\right| \geq \rho_a \left|y^b\right| \quad (5)$$

Or, if no such nodes exist, i.e. the input pattern to F_2^a layer does not match any pattern: the input pattern is classified as a new pattern.

V. Case Study

DM of transformer is used for PD simulation in EMTP and this PD model is considered between transformer winding and earth, as aforesaid in previous sections.

A. Transformer specification

The used transformer is 35kV/220kV and 50MVA. Windings dimensions and model of the transformer tank are detailed in [15].

HV winding of the simulating transformer consist of 56 discs. The first 6 two-discs is interleaved type and the 22 other two-disc is inverted type. Dimensions of all two-discs are presented in Table I.

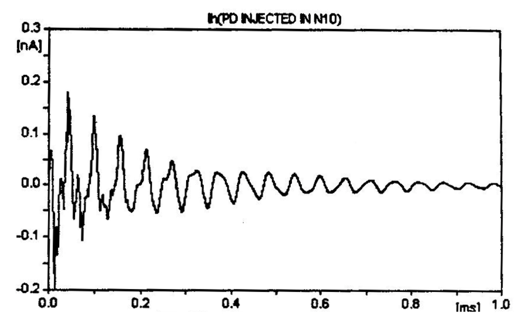
TABLE I

TECHNICAL SPECIFICATION OF HV WINDING

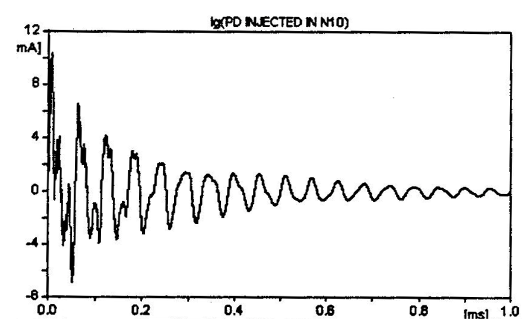
Winding Type	Num of Discs	Disc Number from-to	Num. of turns in each disc	Height × Width
Interleaved	4	01-05	$13\frac{18}{20}$	3.0×15.0
Interleaved	8	05-13	$12\frac{18}{20}$	2.8×13.2
Inverted	4	13-17	$15\frac{18}{20}$	2.5×17.0
Inverted	28	17-45	$19\frac{17}{20}$	2.0×23.0
Inverted	9	45-54	$19\frac{18}{20}$	2.0×17.0
Inverted	3	54-56	$15\frac{18}{20}$	2.5×17.0
Total	56		1005	

B. simulation results

PD source is placed in different points of the winding and produced current in terminals of the winding is recorded. Fig. 5a and Fig. 5b show the current in end and neutral points of the winding with regard to injection of the PD impulse into the 10^{th} node of the DM.



(a)



(b)

Fig. 5. Current waveform resulting from PD injection in 10^{th} node of DM, (a). in end point of winding, (b). in neutral point of winding

C. Fuzzy ARTmap training

In order to train the neural networks there is a need for measured training patterns. The current of both sides of the winding is used for learning of Fuzzy ARTmap neural network. This neural network is implemented in MATLB software. Used DM consists of 40 nodes. Thus all simulated states are 40. For training of neural network 30 of them is used. This low number of data sets is because of the EMTP limitation for number of the mutual inductances.

D. Test of Fuzzy ARTmap

As mentioned, necessary simulations of transformer are done in EMTP and the results is used for input data for the Fuzzy ARTmap neural network in MATLAB. Result of the Fuzzy ARTmap neural network testing is shown in Table II.

TABLE II

RESULTS OF NEURAL NETWORK TESTING

Training Rate	Vigilance Parameter	Num. of Clusters	Accuracy (%)
0.9	0.9	29	90
	0.95	65	100
	0.98	201	90
0.88	0.9	30	100
	0.95	69	100
	0.98	230	100
0.85	0.9	29	80
	0.95	68	90
	0.95	213	90

As it is shown in table II, the best PD location accuracy is reached 100 percent for 0.88 of training rate, 0.9, 0.95, and 0.98 for mapfield vigilance parameters. The obtained number of clusters is 30, 69, and 230 respectively. The reason of this matter is lack of the parameters which are used for training and test of Fuzzy ARTmap neural network because of EMTP limitation.

VI. CONCLUSION

In this paper Fuzzy ARTmap neural network is proposed for locating of PD in power transformers. Rate of learning and the accuracy of this method have a great improvement comparing other neural networks used for this purpose. Furthermore, the automatic optimization of vigilance parameter of *fuzzy* ART_a can be assumed as other advantage of the proposed method. DM of transformer is used for PD simulation in EMTP and this PD model is considered between transformer winding and earth. A study on parameters selection is presented in this paper and the results show highly dependency of these parameters. In this paper in has been shown that Fuzzy ARTmap neural network response to the signals with considering noise is acceptable and the results have highly accurate. This method can be used as a general solution for locating of partial discharge in power transformers, provided the parameters value of detailed model of transformers to be selected accurately.

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