International Journal of Research
Available at https://edupediapublications.org/journals
E-ISSN: 2348-6848
P-ISSN: 2348-795X
Volume 05 Issue 15
May 2018

A Novel Differential Protection for Power Transformer Using Radial Basis Function Neural Network

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ABSTRACT :

This paper presents A novel method used for Differential Protection in power transformer. In a power system, transformers and other electrical equipment need to be protected not only from short circuit, but also from abnormal operating conditions, such as over loading, and differential fault protection. The power transformer protective relay should block the tripping during magnetizing inrush and rapidly initiate the tripping during internal faults. Many methods have been used to discriminate magnetizing inrush from internal faults in power transformers. Most of them follow a deterministic approach, This article proposes for power transformer differential protection & the proposed algorithm are the Radial Basis Function Neural Network (RBFNN) as a classifier and address the challenging task of detecting magnetizing inrush from internal fault. The algorithm is evaluated using simulation performed with MATLAB. The results confirm that the RBFNN is faster, stable and more reliable recognition of transformer inrush and internal fault condition.

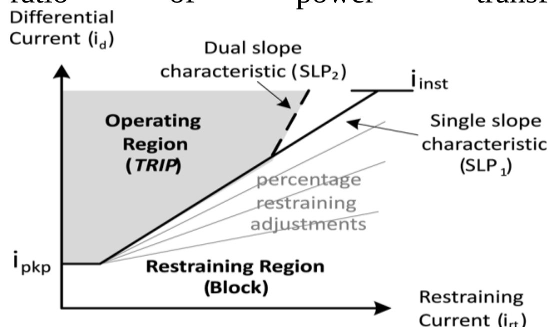
Keywords **:*Inrush current, Differential protection, Radial Basis Neural Network, MATLAB***

I.INTRODUCTION

In power systems one of the most important equipment is Power transformer. Power transformers are different in size, type, and connection. Any unscheduled repair work, Especially replacement of a faulty transformer is very expensive and time consuming. Theoretically, differential protection provides the best overall protection for a power transformer. In principle, this protection scheme makes use of current difference flowing through the different terminals of transformer so as to distinguish between internal and external faults.[4] The conventional differential protection schemes might encounter difficulties and mal operations in some cases. They are not capable to distinguish between internal faults and other abnormal events in all conditions correctly. Many methods have been used to discriminate magnetizing inrush from internal faults in power transformers. The use of standard transformer differential protection for such applications is considered impossible in the protective relaying standards and practices currently applied This article proposes for power transformer differential protection and address the challenging task of detecting magnetizing inrush from internal fault. Generally, discriminate between magnetizing inrush condition and fault condition .The method consists of distinguishing magnetizing inrush and over-excitation condition from internal fault condition on the basis of waveform identification. This method was carried out by utilizing the differential current peaks, dead angle, and the length of time intervals during which the differential current is near zero. In this paper, simple decision making methods based on the Radial Basis Function Neural Network (RBFNN) [9]are proposed for discriminating internal faults from inrush current. The algorithm has been developed by considering different behaviors of the differential current under internal fault and inrush condition. The MATLAB extracts the relevant features from the differential current and reduces a training data set to a lower dimension. The algorithm was proven MATLAB simulations considering distinct scenarios as changes in transformer load, source impedance, CT ratio, ruminant flux, etc RBFNN based classifier is also presented in distinguishing between magnetizing inrush and internal fault condition of power transformer. The proposed method has been observed as the best solution for power transformer differential protection.

DIFFERENTIAL PROTECTION IN TRANSFORMERS

The differential protection used for transformers is based on the principle of current circulation. This type of protection is mostly used for transformers as this responds not only to inter turn fault but also provides protection In a power transformer, the currents in primary and secondary are to be compared As these two currents are usually different, therefore the use of identical transformers will give differential current and operate the relay even under no load conditions.[10] The difference in magnitude of currents in primary and secondary of power transformers is compensated by different turns ratios of C.T.s. If T is the turn's ratio of power transformer,



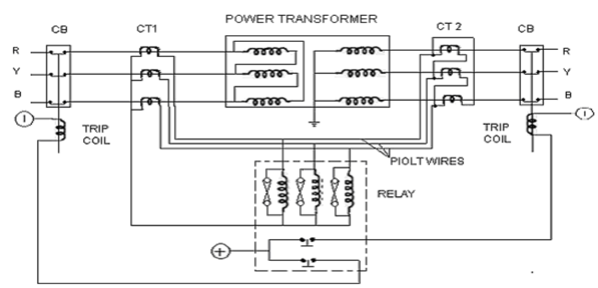


fig 8

. then the turns ration of C.T.s on lv side is made T times the turn's ration of the C.T.s on hv side. When this condition is fulfilled the secondary's of the two C.T.s will carry same current under normal conditions.[13] And thus no current will flow through the relay and it remains inoperative. In order to understand the phase difference in the two sides consider The primary is connected in delta and the set of current transformers CT1 is connected in star, while the secondary is connected in star and the set of current transformers CT2 is connected in delta. Fig 9 illustrates the vector diagram in reference to primary and secondary sides of current transformer. IRP, IYP and IBP are the

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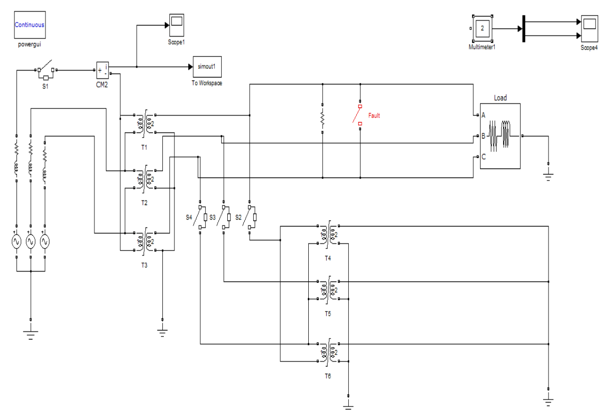
phase currents in the primary side, while IR is the line current on the same side in line R the corresponding secondary current of current transformers CT1 on the primary side is in phase with IR and is represented as IRS. the current in the secondary side of the power transformer is represented as IR, IY and IB , the phase current in the secondary winding of the current transformers CT2 is represented as I'R, I'Y and I'B the current in pilot wire of CT2 is represented as IRS.

POWER SYSTEM SIMULATION

To obtain the required current signals for investigation of the merit of the proposed algorithm, a part of a power system consisting of a power transformer and relevant CTs with transmission lines on the both sides of the transformer are modeled using MATLAB SIMULINK software that is shown in Fig. . So the required current signals for a digital differential protection can be provided. The proposed power system consists of a 500-MVA and 400/230-kV transformer and the distributed model for the transmission lines is used. A long 400-kV line in parallel with the transformer distorts the faulty current waveform. Different cases of inrush current and fault current are simulated. Different cases of inrush current are simulated by varying those major parameters that influencing the characteristics of this current. These parameters are the residual core flux of single phase transformers , the voltage angle of switching phase a, switching in the case of close or open secondary, the high or low power supply connected to transformer and knee of the core magnetic characteristic. Different cases of fault currents are also simulated where the major factors affecting the characteristics of the current are considered.



SIMULATION RESULT

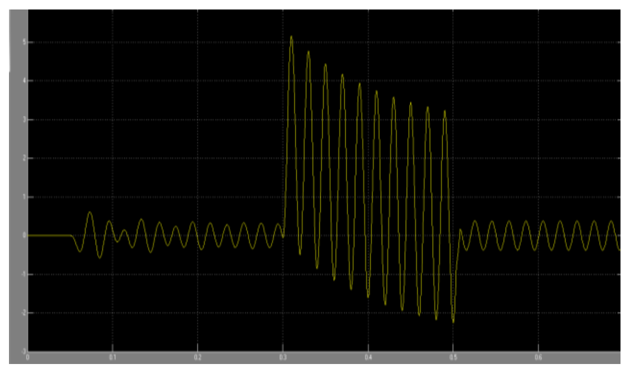


Fig-1 Simulation result for fault Current

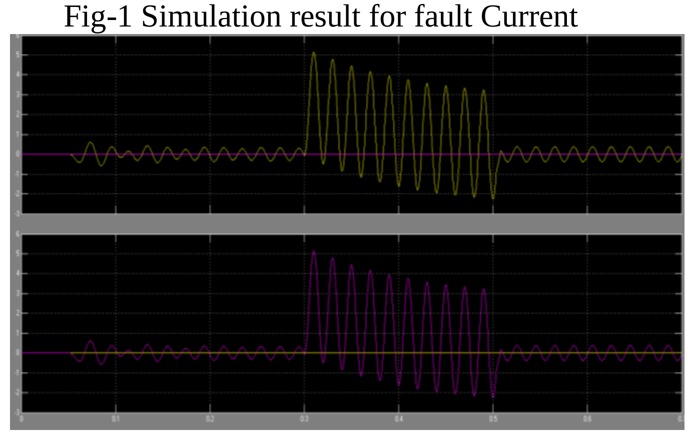


Fig-2 Simulation for Inrush & Fault Current

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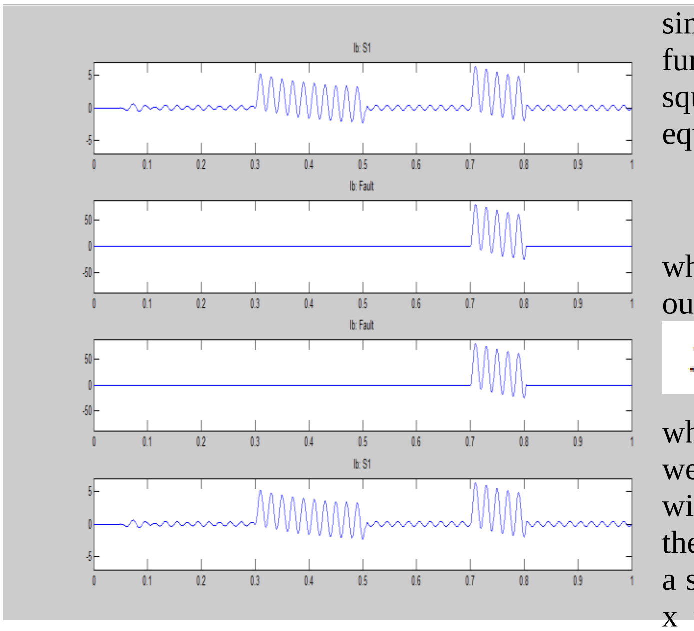

RADIAL BASIS NEURAL NETWORK(RBFN)

Radial Basis Function Network (RBFN) is especial type of feed forward neural network with an input layer used as sensing unit containing n neurons through which input vector x e Rn is fed to a single hidden layer having q number of RBF-type hidden neurons and an output layer, containing L neurons. In RBF neural network model the activation of hidden unit is determined by using the radial distance between the input vector and prototype vector. Generally, Euclidean norm is used to measure the radial distance.[16] The network is designed to perform a nonlinear mapping from input space to the hidden space, followed by a linear mapping from the hidden space to the output space. The Performances of RBF network critically depends on the choice of nonlinear activation function, the centers and width factor.[13] The centers in RBF network should be selected to minimize the total distance between the data and the centers so that the centers can properly represent the data. A simple and widely adopted square error cost function is used for network training. The square error E is defined in the following equation:

$$E = \frac{1}{2}\sum_{k=1}^{L}(d_k - y_k)^2$$

where dk is the desired output and yk is the output of neuron k given by:

$$y_k = (w_k)^T \cdot \Phi$$

where $w_k = [w_{k1}, w_{k2}, \ldots, w_{kq}]^T$ T are the weights connecting the RBF hidden neurons with the output neurons and Φ is the output of the hidden layer. Each hidden neuron represents a single RBF and computes a kernel function of x using any one of the activation function as mentioned in this section where cj = (cj1, cj2,. . ., cjn) and bj = (βj1, βj2, . . .,βjn) are the center and width factor of the jth hidden neuron, respectively.

$$\Phi_j = \exp\left(-\frac{1}{2}\sum_{i=1}^{n}\left(\frac{x_i - c_{ji}}{\beta_{ji}}\right)^2\right)$$

IX.NETWORK TOPOLOGY & TRAINING

The systematic diagram of three layered radial basis function neural network is shown in Fig..2.The response of kernel function utilized by hidden layer neuron of RBFNN is local in nature. The number of neurons in hidden layer is fixed heuristically. The sigmoid type of activation function used in multilayer feed forward networks to train with back-propagation, does not yield the approximating capabilities for RBF networks

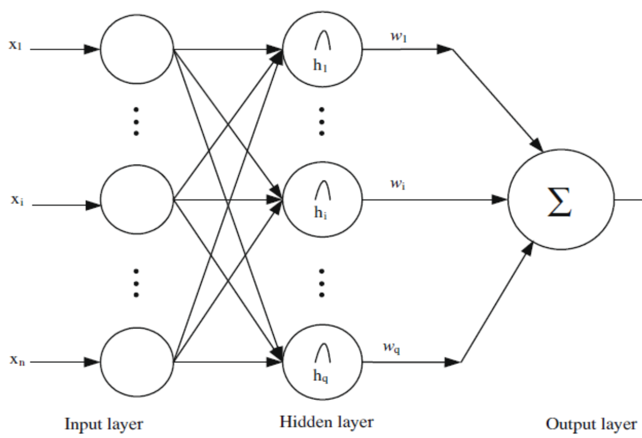

Fig. 2. Typical radial basis function neural network architecture.

Training

The design and training of an RBFNN consist of the following three steps:

i. Determining the center,

ii. Determining the widths,

iii. Determining the weights.

The above first two parameters of the RBFNN are determined by unsupervised learning methods. The centers are determined by using C-means clustering technique. The width factor can be determined by two methods, i.e. given as fixed center method and Moody and Darken method. The fixed center method is given as:

$$\beta = \frac{d_{\max}}{\sqrt{2M}}$$

where M is the number of centers and dmax is the maximum distance between chosen centers. Moody and Darken [23] proposed width factor βj by r-nearest neighbor heuristic:

$$\beta_j = \frac{1}{r}\sqrt{\left(\sum_{i=1}^{r} ||c_i - c_j||^2\right)}$$

where ci is nearest neighbor of centers cj and a suggested value for r is 2.

Nabil Benoudjit et al. [24] suggested the optimal width factor as

$$\forall_j, \quad \beta_j = s\beta_i^c$$

where bci is the standard deviation of each data cluster obtained by Eq. (8) and s is the width scaling factor.In this paper, the above mentioned three parameters of RBFNN are designed by considering C-means clustering and optimal width factor. The weights are calculated by a supervised, single-shot process using pseudo-inverse matrices or Singular Value Decomposition (SVD) method.

X. RESULT PERFORMANCE

Descrimination

FAULT	INRUSH	NORMAL
-1.4089	-0.0620	-0.0337
-1.3506	-0.0620	0.0106
-1.2545	-0.0620	0.0548
-1.1216	-0.0619	0.0981
-0.9537	-0.0619	0.1402
-0.7526	-0.0619	0.1802
-0.5208	-0.0619	0.2178
-0.2610	-0.0618	0.2523
0.0237	-0.0618	0.2833
0.3299	-0.0618	0.3104
0.6542	-0.0617	0.3331
0.9926	-0.0617	0.3512
1.3412	-0.0617	0.3644
1.6959	-0.0617	0.3726
2.0525	-0.0616	0.3755
2.4070	-0.0616	0.3733
2.7550	-0.0616	0.3658
3.0926	-0.0615	0.3532
3.4158	-0.0615	0.3357
3.7208	-0.0614	0.3136

FAULT	INRUSH	NORMAI
-1.3506	-0.0620	0.0106
-1.2545	-0.0620	0.0548
-1.1216	-0.0619	0.0981
-0.9537	-0.0619	0.1402
-0.7526	-0.0619	0.1802
-0.5208	-0.0619	0.2178
-0.2610	-0.0618	0.2523
0.0237	-0.0618	0.2833
0.3299	-0.0618	0.3104
0.6542	-0.0617	0.3331
0.9926	-0.0617	0.3512
1.3412	-0.0617	0.3644
1.6959	-0.0617	0.3726
2.0525	-0.0616	0.3755
2.4070	-0.0616	0.3733
2.7550	-0.0616	0.3658
3.0926	-0.0615	0.3532
3.4158	-0.0615	0.3357
3.7208	-0.0614	0.3136
4.0040	-0.0614	0.2871

XI.CLASSIFIED TARGET RESULT

Y =FAULT	INRUSH	NORMAL
0	0.0000	1.0000

1.0000	1.0000	1.0000
1.0000	-0.0000	1.0000

CONCLUSION

This work presents a new approach in differential protection for power transformer vastly improved performance over conventional techniques. Shape identification technique and independent of the harmonics contained in differential current which is quite suitable in case of modern power transformers that use high-permeability low coercion core materials. The conventional harmonic restraint technique may fail because high second harmonic components are generated during internal faults and low second-harmonic components are generated during magnetizing inrush with such core materials. In the proposed new algorithm will used for Radial Basis Function Neural Network approach It does not require choosing any coefficient or threshold values. This is another advantage of the method. The ability of the new method will demonstrate by simulating various cases on a typical power system and the proposed algorithm is also tested offline using data collected from a prototype laboratory three-phase power transformer.

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