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Discrimination of Power Transformer Differential Protection Using Bpn Neural Algorithm

GAJENDRA KUMAR G, M.Tech (Power System Engineering), PRIST University, Thanjavur,

ABSTRACT

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 different fault protection. The increased growth in power systems both in size and complexity has brought the need for fast and reliable protection scheme for major equipments like transformer. The power transformer protective relay should block the tripping during magnetizing inrush and rapidly initiate the tripping during internal faults .In this paper, First we review the concept of describe the magnetizing inrush current and over- excitation phenomena as they belong to the causes of the protection male-operation .Many methods have been used to discriminate magnetizing inrush from internal faults in power transformers. Most of them follow a deterministic approach, i.e. they rely on an index and fixed threshold. This article proposes for Identification of Inrush Current & Internal Fault Current power transformer for proper protection scheme. In the proposed algorithm, is Feed Forward Back Propagation Network (BPN) are used 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 FFBPN is faster, stable and more reliable recognition of transformer inrush and internal fault condition.

Key Words :Inrush Current, Back Propagation Network,

INTRODUCTION

In power systems one of the most important equipment is Power transformer. Power transformers are different in size, type, and connection. They function as system nodes to connect different voltage levels and have vital importance in maintaining continuity and reliability of the power supply. 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. It is also well recognized that the current differential relays performance could be affected by different factors such as inrush current, over excitation, transformer tap change and current transformers mismatch. 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. Many methods have been used to discriminate magnetizing inrush from internal faults in power transformers. Most of them follow a deterministic approach, i.e. they rely on an index and fixed threshold. This article proposes for Identification of Inrush Current & Internal Fault Current power transformer for proper protection scheme. In the proposed algorithm, is Feed Forward Back Propagation Network (BPN) are used as a classifier and address the challenging task of detecting magnetizing inrush & internal fault current . Medium & large power transformers are very important and vital component of electric power systems. Due to its importance and cost, its protection needs to be addressed properly. The protection should be fast and reliable. Proper continuous monitoring of power transformer can provide early

Warning of electrical failure and can prevent catastrophic losses. It can minimize damages and enhanced the reliability of power supply. Accordingly, high expectations are imposed on power transformer protective relays. Expectations from protective relays include dependability (no missing operations), security (no false tripping), speed of operation (short fault clearing time) and stability. Differential relaying principle is used for protection of medium and large power transformers. This superior approach compares the currents at all terminals of the protected transformer by computing and monitoring a differential (unbalance) current. The value of differential current greater than no-load value indicates an internal fault. Magnetizing inrush occurs in transformer at the time of large change in voltages, whenever, polarity and magnitude of residual flux do not agree with polarity and magnitude of ideal instantaneous value of steady-state flux.

POWER TRANSFORMER PROTECTION PRINCIPLES

Power Transformers are a critical and expensive component of the power system. Due to the long lead time for repair of and replacement of transformers, a major goal of transformer protection is limiting the damage to a faulted transformer. Some protection functions, such as over excitation protection and temperature-based protection may aid this goal by identifying operating conditions that may cause transformer failure. The comprehensive transformer protection provided by multiple function protective relays is appropriate for critical transformers of all applications.

INTERNAL FAULTS IN POWER TRANSFORMER

The principle faults which occurs inside a power transformer are categorized

- Insulation breakdown between winding and earth.
- Insulation breakdown in between different phases
- Insulation breakdown in between adjacent turns i.e. inter - turn fault
- Transformer core fault.
- Internal Earth Faults in Power Transformer
- Internal Earth Faults in a Star connected winding with neutral point earthed through an impedance

MAGNETIZING INRUSH AND INTERNAL FAULT CURRENT

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Under normal operation circumstance, the iron core of transformer works in the unsaturation state, the relative magnetic conductivity is tremendous , and the excitation inductance of winding is also tremendous, sothe excitation current is tiny, which is not more than 2%-10% of rated current. When the no-load transformer throws in or voltage recovers after external fault is cleared ,because of iron core ,relative conductivity is nearly 0. Seldom parts of primary side current, most parts are into excitation inrush . So excitation inrush current only flow into one side of transformer, the amplitude is probably 6-8 times of rated current. And it causes protection equipment error operation. Internal fault is various fault occurring inside of the transformer tank, including the short circuit between the phase winding, single-phase inter-turn short circuit, single phase ground short circuits, its turn to turn short-circuit problems accounted for a large ratio . Harmful to internal faults, because the high temperature electric arc short-circuit currents will not only damage the winding insulation, burning core, but will also heat insulating materials and decomposition of transformer oil , which will produce large amounts of gas which may cause the transformer tank explosion

DIFFERENTIAL PROTECTION IN TRANSFORMERS

INTRODUCTION

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 against phase-to-phase faults.

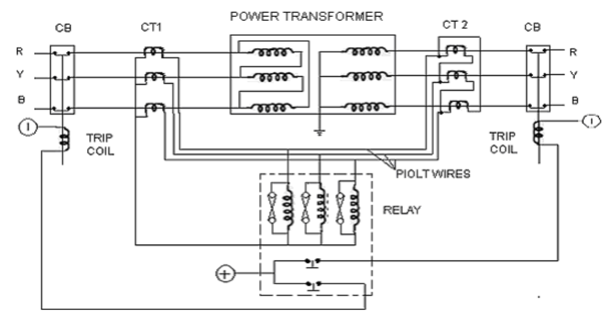
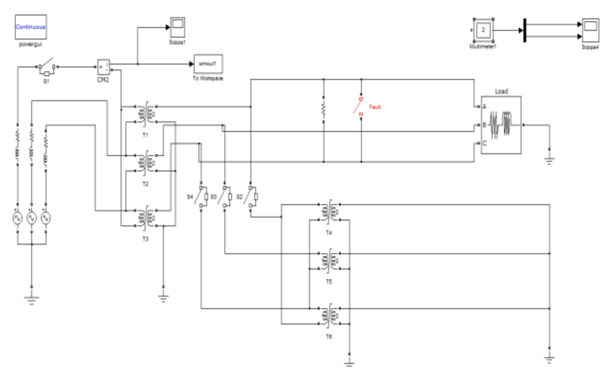
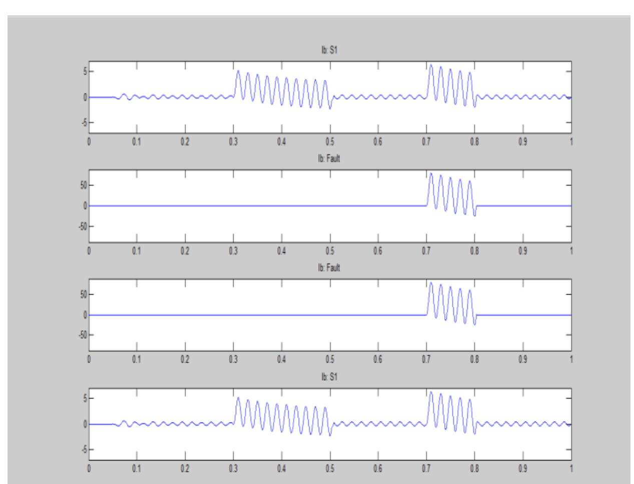


fig 8

SYSTEM ARCHITECHTURE

Inrush & Fault Current





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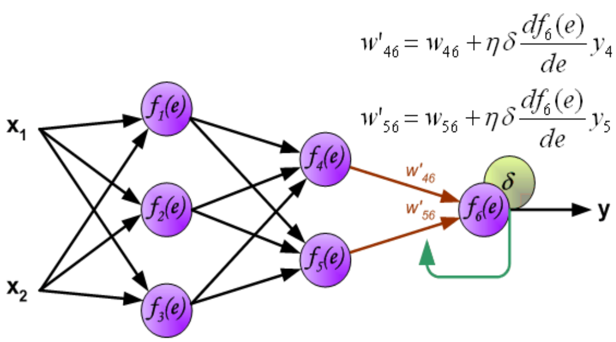
BACK PROPAGATION ALGORITHM

Back propagation is a form of supervised learning for multi-layer nets, also known as the generalized delta rule. Error data at the output layer is back propagated to earlier ones,allowing incoming weights to these layers to be updated. It is most often used as training algorithm in current neural network applications. The back propagation algorithm was developed by Paul Werbos in 1974 and rediscovered independently by Rumelhart and Parker. Since its rediscovery, the back propagation algorithm has been widely used as a learning algorithm in feed forward multilayer neural networks.

BACK PROPAGATION PROCESS

The process then starts by applying the first input pattern Xk and the corresponding target output Tk. The input causes a response to the neurons of the first layer, which in turn cause a response to the neurons of the next layer, and so on, until a response is obtained at the output layer



That response is then compared with the target response,and the difference(the error signal) is calculated. From the error difference at the output neurons, the algorithm computes the rate at which the error changes as the activity level of the neuron changes. So far, the calculations were computed forward (i.e., from the input layer to the output layer). Now, the algorithm steps back one layer before that output layer and recalculate the weights of the output layer (the weights between the last hidden layer and the neurons of the output layer) so that the output error is minimized. The algorithm next calculates the error output at the last hidden layer and computes new values for its weights (the weights between the last and next-to-last hidden layers).

IMPLEMENTATION OF BACK PROPAGATION ALGORITHM

The back-propagation algorithm consists of the following steps:

- Each Input is then multiplied by a weight that would either inhibit the input or excite the input. The weighted sum of then inputs in then calculated

First, it computes the total weighted input Xj, using the formula:

$$X_j = \sum_i y_i W_{ij}$$

Where yi is the activity level of the jth unit in the previous layer and Wij is the weight of the connection between the ith and the jth unit.

Then the weighed Xj is passed through a sigmoid function that would scale the output in between a 0 and 1.

- Next, the unit calculates the activity yj using some function of the total weighted input. Typically we use the sigmoid function:

$$y_j = \frac{1}{1 + e^{-x_j}}$$

Once the output is calculated, it is compared with the required output and the total Error E is computed.

- Once the activities of all output units have been determined, the network computes the error E, which is defined by the expression:

$$E = \frac{1}{2} \sum_j (y_j - d_j)^2$$

where y j is the activity level of the ith unit in the top layer and dj is the desired output of the ith unit. Now the error is propagated backwards. Compute how fast the error changes as the activity of an output unit is changed. This error derivative (EA) is the difference between the actual and the desired activity.

$$EA_j = \frac{\partial E}{\partial y_j} = y_j - d_j$$

Compute how fast the error changes as the total input received by an output unit is changed. This quantity (EI) is the answer from step 1 multiplied by the rate at which the output of a unit changes as its total input is changed.

$$EI_j = \frac{\partial E}{\partial x_j} = \frac{\partial E}{\partial y_j} \times \frac{dy_j}{dx_j} = EA_j y_j (1 - y_j)$$

Compute how fast the error changes as a weight on the connection into an output unit is changed. This quantity (EW) is the answer from step 2 multiplied by the activity level of the unit from which the connection emanates.

$$EW_{ij} = \frac{\partial E}{dW_{ij}} = \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{dW_{ij}} = EI_j y_i$$

Compute how fast the error changes as the activity of a unit in the previous layer is changed. This crucial step allows back propagation to be applied to multi-layer networks. When the activity of a unit in the previous layer changes, it affects the activities of all the output units to which it is connected. So to compute the overall effect on the error, we add together all these separate effects on output units. But each effect is simple to calculate. It is the answer in step 2 multiplied by the weight on the connection to that output unit.

$$EA_i = \frac{\partial E}{\partial y_i} = \sum_j \frac{\partial E}{\partial x_j} \times \frac{\partial x_j}{\partial y_i} = \sum_j EI_j W_{ij}$$

TESTING PERFORMANCE

INPUT DATAS

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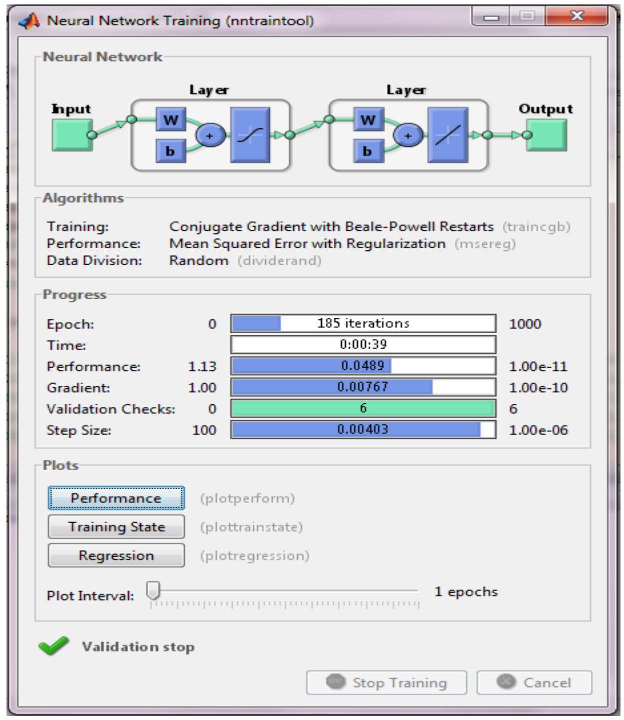
S.NO	DESCRIPTION	Normal Current	Inrush Current	Line to Ground Fault	Line to Line Fault
1.	MEAN	-0.0054	14	1.805	5.4520
2.	STD	1.942	11.790	10.85	72.300
3.	MAX.NORM	10.234	38.670	24.88	203.50
4.	THD	0.123	23.660	0.510	0.9700

TARGET

S.NO	DESCRIPTION	Normal Current	Inrush Current	Line to Ground Fault	Line to Line Fault
1.	TARGET OUTPUT	1.0	2.0	3.0	4.0

TRAINING PERFORMANCE



RESULT INDENTIFICATION

S.NO	DESCRIPTION	Normal Current	Inrush Current	Line to Ground Fault	Line to Line Fault
1.	TRAINED OUTPUT	1.0034	2.0643	3.0524	4.0139

CONCLUSION

This work presents a new approach in differential protection for power transformer vastly improved performance over conventional techniques. 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 previous algorithm was used for Radial Basis Function Neural Network approach. It does not require choosing any coefficient or threshold values. It was analyzed by the taking the values are magnitude parameter of the inrush & fault current. But sometimes the magnitude of the inrush & Fault current has same, so classification performance error was presented. In this phase to improve the performance & rectify error by analyzing of Mean , Standard Deviation , Maximum Norm & THD values are taken from the inrush & fault current. And also approach by the new algorithm of Feed Forward Back Propagation Neural algorithm was performed. The ability of the new method will demonstrate by simulating various cases on a typical power system and the proposed algorithm is also tested data collected from a simulation model. In this new algorithm is performance was very vital. The proposed approach is considered a general tool because it can be easy implemented on the popular MATLAB software. Moreover, the approach is considered a flexible tool. We expect this work providing useful reference to electric power industry.

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