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REVIEW ON FAULT DETECTION USING ANN AND WAVELET TRANSFORM FOR POWER TRANSFORMER

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ABSTRACT

The need for a reliable supply of electrical energy for the requirements of the modern world in all fields has increased significantly, requiring the fault less operation of electrical systems. The overriding objective is to minimize the frequency and duration of unexpected failures associated with power transformers with peak demand, including reliability requirements related to zero bias and operating speed with the ability to detect and eliminate errors in a short time. The second harmonic restrain principle has been used in industrial applications for many years using the Discrete Fourier Transform (DFT) and often encounters the problems unable to identify magnetizing inrush state internal fault and longer restrain time. Therefore, artificial neural network (ANN), a powerful tool of artificial intelligence (AI), capable of mimicking and automating knowledge, has been proposed to detect and analyze types of defects under normal and fault conditions.

KEYWORDS- ***Power Transformer, Artificial Neural Network, Wavelet Transform, Differential Protection.***

INTRODUCTION

The safety of large power transformers is very tough task in electrical power system. The peak demand includes the necessities of reliability related to no false tripping, and working speed with short fault detection and clearing time. The protective machine includes instruments that recognize the fault, identifies its position, sense some additional abnormal fault like running conditions, and initiate the inceptive steps of the opening circuit breakers to detach the defective device of the power system. The vital purpose to reduce the frequency and length of undesirable outages associated with power transformers places additional burden on protecting relays to perform impeccably and seamlessly. The real magnitude of fault based on resistance to flow as well as assorted impedance amid the fault and the source of power supply. Total impedance contains fault resistance, line conductor resistance and reactance, transformer impedance, the circuit reactance, and generating station impedance. The standard distance relay settings are totally basis on a determined network outline with the worst fault consequences.

For transformer which are above 10MVA capacity, the differential protection system is used to protect the transformer in power system. Whereas, the overcurrent protection is used for transformers below 10MVA. Still, when transformer operates at No-Load condition it creates a large inrush current. This inrush current contains a continuous large DC component, rich in harmonics and takes a large peak value around 6-30 times its rated value. Because of this condition, there is current loop unbalancing of differential relay which cause false tripping. To avoid unnecessary tripping due to inrush current, a method using the second harmonic component of the current waveform is commonly used. However, this method cannot provide a complete solution to the inrush current.

LITERATURE REVIEW

Differential protection has long been used as the principal protection for power transformers, which are critical components in the operation and management of power systems. As a result, precise event detection and rapid fault clearing are critical. Traditional differential protection, while capable of accurately distinguishing external from internal faults to the protection zone delineated by current transformers (CT), may be unable to detect internal faults from inrush currents that develop as a result of power transformer energizations.[1]

Since its introduction [2], the digital differential relay has been greatly developed, and it was first presented for industrial use in 1988 [3]. Since 1958, the phenomenon of inrush current has been studied [4-9]. In the event of a magnetizing inrush, the second harmonic component of the transformer is utilized to prevent the differential relay from malfunctioning. The ratio of the second harmonic power spectrum to the fundamental power spectrum, based on an autoregressive algorithm, was utilized to determine the magnetizing inrush current [10-11].

The employment of a harmonic restraint technique to safeguard a power transformer has resulted in a wavelet-based algorithm for numerical differential protection. This programmed distinguishes internal defects utilizing magnetizing inrush and overexcited inrush in a precise and computationally efficient manner. This algorithm is essentially a numerical filter that reproduced the fundamental

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frequency component, as well as the second and fifth harmonic components for the differential current, in order to provide operating and restraining signals. This method creates its coefficient only using addition and subtraction procedures, avoiding the time-consuming calculations of multiplication and division. When compared to a DFT-based technique, the computing complexity of the algorithm provided here is additions and subtractions [12]. The vector difference is shown as a differential quantity in differential relay, whereas the vector sum is shown as a restrain quantity [13].

WAVELET TRANSFORM

The Fourier transform can be used to examine the signal's frequency components. The Fourier transform, on the other hand, is mute about when a specific frequency arises. The short-time Fourier transform (STFT) finds a spectrogram, which contains both time and frequency information, using a sliding window. The length of the window in the STFT, on the other hand, is constant for all frequencies. Wavelet transform (WT) facilitates the analysis of signals with localized impulses and oscillations by focusing on short time intervals for high-frequency components and lengthy intervals for low-frequency components. As a result, wavelet decomposition is perfect for analyzing transitory signals and providing a much better current characterization and discrimination.

The signal to be analyzed is multiplied with a wavelet function termed mother wavelet in wavelet analysis, similar to how it is multiplied with a window function in STFT. With each spectral component, the width of the wavelet function changes in WT. During the analysis, higher frequencies are given less time and lower frequencies are given more time. The WT provides good time resolution for high frequencies and good frequency resolution for low frequencies.

Because it is based on sub-band coding, the Discrete Wavelet Transform (DWT) provides faster analysis than the continuous wavelet transform. In DWT, digital filtering techniques allow the digital signal to be represented on a time scale. The signal analysis method consists of passing a signal through filters with various cutoff frequencies at various scales.

The signal resolution, which is a measure of the amount of detail information in the signal, is determined by filtering operations, whereas the scale is determined by up and down sampling processes. When a signal is down sampled, the sampling rate is reduced, and when a signal is up sampled, the sampling rate is increased. In one algorithm called the Mallat algorithm or Mallat-tree decomposition, the DWT is computed by consecutive low pass and high pass filtering of the time-domain signal in one algorithm called the Mallat algorithm or Mallat-tree decomposition, as shown in Fig 1. High pass (H0) and low pass (G0) filters are used to separate an original signal into two halves of the frequency spectrum.

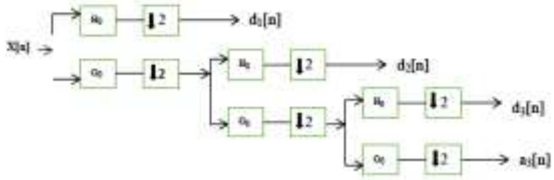

Fig 1: DWT implementation

ARTIFICIAL NEURAL NETWORK

A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two aspects: First is knowledge required by the network from its environment through a learning process. And second is connection strengths, known as synaptic weights, are used to store the acquired knowledge.

Features of Neural Networks:

a) Robustness and fault tolerance
b) Flexibility
c) Ability to deal with a variety of data situations
d) Collective computation

The model of an artificial neuron on computer that closely matches a biological neuron is given by an op-amp summer-like configuration. The artificial neuron is also called a processing element, a neurode, a node, or a cell. The input signals are normally continuous variables instead of discrete pulses that occur in a natural neuron. Each of the input signals flows through a gain or weight, called synaptic weight or connection strength whose function is analogous to that of the synaptic junction in a natural neuron. The weights can be positive (excitory) or negative (inhibitory) corresponding to acceleration or inhibition respectively. The summing node accumulates all the input-weighted signals and then passes to the output through the transfer function, which is usually nonlinear. The motivation to explore new computing models based on ANNs is to solve pattern recognition tasks that may sometimes involve complex optical and acoustical patterns also. It is impossible to derive logical rules for such problems for applying the well-known AI methods. It is also difficult to divide a pattern recognition task into subtasks, so that each of them could be handled on a separate processor. Thus, the inadequacies of the logic-based artificial intelligence and the limitations of the sequential computing have led to the concept of parallel and distributed processing through ANN. A remarkable feature of ANNs is that it can deal with data that are not only noisy, but also fuzzy, inconsistent and probabilistic, just as human beings do. All this is due to the associative and distributed nature of the stored information and the redundancy in the information storage due to large size of the network.

The process of modifying the weights in the connections with the objective of achieving the expected output is called training a network. The internal process carried out during training is called learning. Training is grouped into three categories.

A) Supervised Training: Training by a teacher.
B) Unsupervised Training: There is no external teacher or critic to oversee the training process.
C) Reinforced Training or Neuro dynamic Programming: The

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training of an input-output mapping is performed through continued interaction with the environment in order to minimize a scalar index of performance.

A. Multi-layer Feed Forward NN

MLF neural networks, trained with a back-propagation learning algorithm, are the most popular neural networks. The basic multilayer feed forward network contains three layers: input, output and hidden. This type of neural network has one input layer, one output layer and any number of hidden layers in between the former two layers. Each network layer contains processing units called nodes or neurons. Each node in a network layer will send its output to all the nodes of the next layer.

In the input layer the nodes receive signals from the outside world. The input layer of the neural network serves as an interface that takes information from the outside world and transmits that to the internal processing units of the network, analogous to a human's interface parts such as our eyes' retina and our fingers' sensing cells. Similarly, the output layer of the neural network serves as an interface that sends information from the neural network's internal processing units to the external world. The nodes in the hidden layer are the neural network's processing units. The number of hidden layers and the numbers of neurons in each hidden layer depend on the network design considerations. The input layer transmits the signal to the hidden layer, and the hidden layer in turn transmits the signals to the output layer. There is no self, lateral or feedback conversion of neurons.

B. Back Propagation Training Algorithm

Back Propagation (BP) learning algorithm is used to train the multi-layer feed- forward neural network. Signals are received at the input layer, pass through the hidden layer, and reach to the output layer, and then fed to the input layer again for learning. The learning process primarily involves determination of connection weights and patterns of connections. The BP neural network approximates the non-linear relationship between the input and the output by adjusting the weight values internally instead of giving the function expression explicitly. Further, the BP neural network can be generalized for the input that is not included in the training patterns. The BP algorithm looks for minimum of error function in weight space using the method of gradient descent. The combination of weights that minimizes the error function is considered to be a solution to the learning problem. The training algorithm of back propagation involves four stages. i.e.

i. Initialization of weights
ii. Feed forward
iii. Back propagation of errors
iv. Updation of the weights and biases

CONCLUSION

The performance of neural networks has been found to outperform traditional approaches, which need precise sensing devices, expensive equipment, and an expert operator or engineer, according to the research and analysis presented in this paper. The ANN's classification ability, together with advanced signal processing techniques, paves the way for smart relays for power transformer protection that operate in a fraction of the time and with high accuracy.

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