# Artificial Neural Network Based Backup Differential Protection of Generator-Transformer Unit

H. Balaga and D. N. Vishwakarma Department of Electrical Engineering, Indian Institute of Technology (BHU) Varanasi, Varanasi, India Email: {harish.balaga.rs.eee, dnv.eee}@iitbhu.ac.in

H. Nath

Department of Electrical and Instrumentation Engineering, Thapar University, Patiala, India Email: harshitnath@yahoo.com

Abstract—This paper presents the use of Artificial Neural Networks (ANN) as a pattern classifier for the combined differential protection of generator-transformer unit with an aim to build a backup protection system to improve the overall reliability of the system. The proposed neural network model is trained and tested with an efficient Resilient Back propagation (RPROP) algorithm and Genetic Algorithm. The results are then compared. The neural network model makes the discrimination between operating conditions (like normal, magnetizing inrush, overexcitation conditions in transformer) and internal faults in transformer and generator based on the differential current waveform patterns. The proposed method is independent of amplitudes of the waveforms. Various normal and internal fault conditions of the transformer and generator are simulated using toolboxes in MATLAB/SIMULINK in order to obtain the differential current data used for the training and testing of the ANN.

*Index Terms*—artificial neural networks, differential protection, genetic algorithm, pattern recognition, resilient back propagation, unit protection

# I. INTRODUCTION

Transformer and generator are the most essential elements of the power system with their protection importance. Since last three decades, researchers have been working on this particular topic and rose to many new methods but mostly concentrated on individual protection system. There are varieties of protective relays to provide reliable and secure transformer protection, of which the differential relays are found to be more effective [1] in fault discrimination than the old harmonic restraint techniques. The differential relays should be designed in a manner that it does not mal-operate during magnetizing inrush and over excitation conditions of transformer. The inrush currents generated after fault clearance are also to be considered, as in [2], while designing the relay. Most of the methods follow a deterministic approach, relying on fixed threshold.

The ANN-based algorithms have been successfully implemented in many pattern or signature recognition problems, as they can detect healthy conditions of generator and transformer based on recognizing their wave shapes, more precisely, by differentiating them from the fault current wave shapes [3]-[5]. In [6], Neural Network Principle Component Analysis along with Radial Basis Function Neural Networks is used as pattern classifier. In other words, this technique makes the decision based on the current signature verification which is more accurate than traditional harmonic restraint based techniques used for the protection of transformer. This technique could produce the tripping signal in the event of internal fault within 15ms after fault occurrence. Optimal Probabilistic Neural Network (PNN) used in [7] as the core classifier to discriminate between inrush and internal fault. Particle Swarm Optimization is used to obtain optimal smoothing factor for PNN. PNN requires larger storage for exemplar patterns & it is more difficult to train owing to numerical difficulties.

A new approach based on decision tree for discrimination between inrush and internal fault with better accuracy is presented in [8]. This method claims to take processing time of 0.02sec (1 cycle) with classification accuracy of 97.77%. Similarly, ANN based techniques have been used for the protection of generator too. One such scheme with simple ANN is presented in [9] for stator winding protection. Three parallel ANNs have been used in this scheme for classifying three different fault cases. Another such scheme is presented in [10] where two separate ANNs are used for fault detection and fault classification. An advanced version of this method using fuzzy logic in combination with ANN is presented in [11]. In both cases, fault waveforms are simulated using direct phase quantities method. A practical protection scheme is implemented in [12] with ANN developed on a digital signal processor (DSP).

Although the importance of combined/unit protection systems has been identified in late nineties, very few have carried out research on unit protection systems since then. A hybrid protection scheme is presented in [13] for the

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protection of generator-transformer unit considering most of the fault types. This scheme is developed using three microprocessors based on conventional harmonic restraint circuit method. This gave a base idea for unit protection systems. Later, two ANN based techniques were presented in [14], [15] in combination with conventional methods with a fault detection time of 20ms approximately. In both cases, ANN had been trained with back propagation algorithm. A ground fault unit protection system is presented in [16] considering only the ground faults occurring in generator.

Many of the proposed algorithms produced good results in terms of accuracy. A better algorithm can always improve the reliability of the protection scheme. However, use of a backup protection system improves the reliability and functionality of protection devices. This paper presents a model of decision system based on ANN considering the generator-transformer unit as the protected object. All the internal fault conditions of transformer and generator have been simulated to generate the required database for the training of ANN. Also, few cases of faults are generated using the method given in [10]. These cases are used only during testing of the networks. The developed ANN has been trained and tested with RPROP and Genetic Algorithm and the results are compared. During this process, various architectures of ANN have been tested by varying the number of hidden neurons and keeping the number of input and output neurons fixed. Detailed description about these inputs and outputs is discussed in later sections.

# II. POWER SYSTEM SIMULATION FOR PATTERN GENERATION

A three-phase power system including a 200MVA, 13.8kV Generator and a 200MVA 13.8/132kV  $\Delta$ -Yg Transformer along with a 150 km transmission line has been used to produce the required test and training patterns. Fig. 1 shows the scheme of the unit protection system and Fig. 2 shows the power system model created by means of MATLAB Simulink software. Different types of faults are created at different locations. All the generator faults are assumed to occur at 100% of the stator winding. Also, inrush current and over excitation conditions are simulated at different voltage angles and with different loads. The generated waveforms are then sampled to feed the neural networks to be tested with two different sampling rates.



Figure 1. Differential protection scheme of generator - transformer unit



Figure 2. Simulated three-phase power system model

# III. NEURAL NETWORK DESIGN AND SIMULATION

The first step to formulate the problem is identification of proper input and output set. Various architectures and combination of input sets were attempted to arrive at the final configuration with a goal of maximum accuracy. Keeping the number of outputs fixed at 2, the number of input neurons and the number of hidden neurons are varied on trial and error basis until it produced minimum error. Two configurations are finalized for testing after many trials, ANN1, 30-12-2 neurons and ANN2, 48-12-2. For ANN1, each of the differential currents (of each phase) is typically represented in discrete form as a set of 20 uniformly spaced (in time) samples obtained over a data window of one cycle i.e. at the sampling frequency of 1000Hz. For ANN2, a set of 16 samples are obtained over a data window of one cycle i.e. at the sampling frequency of 800Hz. These samples are used for training and testing the developed neural networks.

Both the proposed ANNs generate 2 outputs to represent 4 classifications as shown in Table I. The basic architecture of the ANN is shown in Fig. 3.



Figure 3. ANN architecture

TABLE I. TARGET OUTPUT CASES OF THE ANN

$O_1$	O <sub>2</sub>	Output case
0	0	Normal
0	1	Transformer Inrush
1	0	Transformer Over Excitation
1	1	Internal Fault in Transformer/Generator

### IV. ANN TRAINING ALGORITHMS

#### A. Resilient Backpropagation (RPROP) Algorithm

Resilient Backpropagation is a modification of the ordinary gradient descent back-propagation. To overcome the inherent disadvantages of pure gradient-descent, Resilient Backpropagation (RPROP). This algorithm was pioneered by Martin Riedmiller [17]. The basic principle of RPROP is to eliminate the harmful influence of the size of the partial derivative on the weight step. As a consequence, only sign of the derivative is considered to indicate the direction of the weight update but not the magnitude.

The update value for each weight and bias is increased by a factor  $\Delta$  whenever the derivative of the performance function with respect to that weight has the same sign for two successive iterations. The update value is decreased by a factor  $\Delta$  whenever the derivative with respect to that weight changes sign from the previous iteration. If the derivative is zero, then the update value remains the same. Whenever the weights are oscillating, the weight change will be reduced. In such case, the update value  $\Delta_{ij}$  is decreased by a factor  $\eta^-$ . If the derivative retains its sign, the update value is slightly increased in order to accelerate convergence in shallow regions. This is shown in mathematical form by (1) and (2) [17]. The size of the weight change is exclusively determined by

$$\Delta w_{ij}(t) = \begin{cases} -\Delta_{ij}(t), if \frac{\partial E(t)}{\partial w_{ij}} > 0 \\ +\Delta_{ij}(t), if \frac{\partial E(t)}{\partial w_{ij}} < 0 \\ 0, else \end{cases}$$
(1)

It should be noted, that by replacing the  $\Delta_{ij}$  by a constant update-value  $\Delta$ , (1) yields the so-called 'Manhattan'-update rule.

The second step of RPROP learning is to determine the new update-values  $\Delta_{ii}(t)$ .

$$\Delta_{ij}(t) = \begin{cases} \eta^{+} \Delta_{ij}(t-1), if \frac{\partial E(t-1)}{\partial w_{ij}} * \frac{\partial E(t)}{\partial w_{ij}} > 0\\ \eta^{-} \Delta_{ij}(t-1), if \frac{\partial E(t-1)}{\partial w_{ij}} * \frac{\partial E(t)}{\partial w_{ij}} < 0\\ \Delta_{ij}(t-1), else \end{cases}$$
(2)

where  $0<\eta^-<1<\eta^+$  RPROP is generally much faster than the standard steepest descent algorithm as it converges quickly and it is said to be the best training algorithm for pattern recognition & classification problems [18].

#### B. GA Based Training of ANN

The genetic algorithm (GA) is a well known optimization technique based on the principles of genetics and natural selection and doesn't require derivative information for optimization. Unlike back propagation algorithm, it provides global minima of optimization function. In the proposed method, GA has been used for finding weights and biases of Artificial Neural Network. Then the next part is to define a fitness function which can be used as an evaluation function to optimize the weight set. The fitness function used here is mean square error (MSE), which has been obtained by applying all training sets (Input and Target) for each weight set in the population. The algorithm of fitness function used with GA is given below.

Let  $(I_i, T_i)$ , i=1, 2, ...N, where  $I_i=(I_{1i}, I_{2i}...I_{ii})$  and  $T_i=(T_{1i}, T_{2i}, ...T_{ni})$  represents the input-output pairs of the problem to be solved by ANN with configuration 1-m-n.

For each chromosome  $C_i=1, 2, ...p$  belonging to the current population  $P_i$  whose size is p

Extract weights and biases from C<sub>i</sub>

Keeping theses weights and biases setting train the ANN for N input instances;

Calculate error  $E_i$  for each input instance using  $E_i=T_{ji}$ -O<sub>ii</sub>; where Oi is the output vector calculated by ANN;

Find root mean square MSE of the errors  $E_i$ , i=1, 2, ...N

Output fitness value F=MSE; }

# C. Training and Testing of ANN

Both the ANNs are trained separately with both above algorithms. During RPROP based training, 10% sets of total samples are used for validation and another 10% are used for testing purpose. During GA based training, the ANN is trained by optimizing the weights and biases of the network to minimize MSE. The total number of variables is calculated as given below.

No. of variables = input weights + input biases + layer weights + layer biases

$$=(I*H) + H + (H*O) + O$$
  
 $=(I + O + 1)*H + O$ 

where I = No. of inputs; H = No. of Hidden neurons; O = No. of outputs.

Once the training process is completed the network is ready for testing. The network is then fed with new samples that are not used for training. For this purpose few test cases of generator have been developed using the direct phase quantities method given in [10]. For transformer fault cases, database is created in MATLAB only.

## V. NETWORK PERFORMANCE AND NUMERICAL RESULTS

The designed ANN has been trained and tested with Resilient Back Propagation (RPROP) algorithm and Genetic Algorithm (GA). The graphical representations of the training errors for both architectures are given in Fig. 4-Fig. 7. Table II shows the performance errors for all cases. As one can find from these results, the RPROP algorithm produced better results than GA with the present network architecture. Further, ANN1 with 30 inputs (half cycle data) give less error than the ANN2 with 48 inputs (full cycle data). However, further decreasing the inputs didn't produce good results as the data less than half cycle is insufficient to reproduce the required wave shape to take the decision.

Table III gives the time taken for training in each case. Apart from better accuracy, RPROP took very less time for training when compared to GA as it converges quickly. The training time also depends on the processor used in the PC. Present methods are implemented on the latest Intel core i7 processor based system. To further increase the training speed of the GA algorithm, parallel processing technology has been used with the help of parallel processing toolbox available in MATLAB. This allows GA to use best speed of multi-core technology of the processor. The Intel i7 processor has 8 cores which can be used in 12 clusters or workers mode.

It is worth mentioning that both algorithms (RPROP and GA) take almost same time to detect the occurrence of fault, i.e., about 10ms for ANN1 and about 13ms for ANN2. This time is calculated based on the number of the sample at which the ANN produce a value above 0.98 at the output for a target value of '1' after the first sample of the fault wave is fed to it. Although the results are not very good when the method is applied as a primary protection system, the results can be considered satisfactory when this system is used as a backup protection unit, which generally operates after some delay from the primary protection unit.

TABLE II. PERFORMANCE ERRORS OF BOTH ANNS

ANN	Best Performance Error		
Architecture	RPROP Trained ANN	GA trained ANN	
30-12-2	0.0306	0.0409191	
48-12-2	0.069228	0.0761089	

TABLE III. TRAINING TIMES

ANN	Time taken for training (minutes)		
Architecture	RPROP Trained ANN	GA trained ANN	
30-12-2	4	330	
48-12-2	6	425	



Figure 4. Performances of 30-12-2 ANN trained with RPROP









Figure 7. Performances of 48-12-2 ANN trained with GA

## VI. CONCLUSION

In this paper, an artificial neural network based pattern recognition method has been presented for the backup protection of Generator-Transformer unit. After many trials, two topologies of the network are finalized, one with half cycle data input and the other with full cycle data input fed in moving window format. Both topologies are trained separately with Resilient Backpropagation algorithm (RPROP) and Genetic Algorithm (GA) for all the possible cases of simulated data under different operating conditions of transformer and generator. After comparing the results, it is found that the ANN with half cycle data input is found more suitable than the remaining 3 combinations in terms of accuracy, training speed, precision and speed in fault detection. The RPROP based pattern recognition method is efficient in solving classification problems and a differential relay can be considered as a classifier which identifies what kind of event occurs on the power system network.

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Harish Balaga is currently Assistant Professor at GMRIT, Rajam. He has submitted his Ph.D. thesis at the Indian Institute of Technology (BHU) Varanasi, India. He obtained his B.E. (Electronics and Instrumentation Engineering) from Andhra University and M.Tech (Control Systems) from the National Institute of Technology Kurukshetra, India. His area of research interest is Applications of Microcomputers and Artificial Intelligence to

Power Systems. He has contributed research papers in IEEE and other International Conferences. He is student members of IET and IEEE.



Harshit Nath is presently a final year student of BE in Electrical Engineering at Thapar University, Patiala, India. He has undergone practical internship training at HVDC Back to Back Substation of Power Grid Corporation of India. His area of research interest is Applications of Microcomputers and Artificial Intelligence to Power Systems. He has worked on Applications of Artificial Intelligence to Power System Protection at IIT (BHU),

Varanasi during summer vacations. He has contributed research papers in IEEE and other International Conferences. He is student members of IET and IEEE.



**Devendra Nath Vishwakarma** is currently Professor of Electrical Engineering at the Indian Institute of Technology (BHU) Varanasi, India. He obtained his B.Sc. (Engineering), M.Sc. (Engineering) and Ph.D. from Patna University, Patna. He had earlier served as associate professor of electrical engineering at the Bihar College of Engineering, Patna (Presently National Institute of Technology Patna). He has a

teaching and research experience of over 35 years and has contributed about 65 papers to various national and international journals and conferences. He is coauthor of the book, "Power System Protection and Switchgear" published by McGraw Hill education (India) private limited. He is a senior member of IEEE (USA), a fellow of the Institution of Engineers (India) and a fellow of the Institution of Electronics and Telecommunication Engineers.