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Fault Classification with Artificial Neural Networks based on the Application of Teager Energy Operator

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ABSTRACT: In this paper frequency and voltage signals are obtained from NE 39 bus test system using DigSILENT Power Factory software. Signals obtained in the fault conditionsare analyzed with Teager Energy Operator (TEO). Simulated fault types are generator outage, transmission line outage and short circuit. This paper proposes application of artificial neural networks based on TEO input values for the fault classification task. Classification of the faults simulated through this work is done with Artificial Neural Networks in MATLAB as multiclassification. Different ANN structures and input data types have been analyzed in order to compare achieved performance. Designed network is tested on data provided with application of Teager-Huang transform as well.

Keywords: power dynamics, fault classification, Teager energy operator, Teager-Huang transform,artificial neural networks

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I. INTRODUCTION

Transmission lines are one of the most important power system components since they connect generation and distribution part of the system. Unexpected failures that they are exposed to can interrupt reliability of the total power system. Function of the protective systems is to prevent propagation of the faults from the location where fault occurred to the other parts of the system. Neural pattern networks have shown proven powerful applications as fault classifiers [1]. Various researchers identified that there is potential to use artificial neural networks (ANN) for identification and classification tasks. In designing neural networks it is necessary to achieve trade-off between the number of hidden layer neurons, computational time and generalized efficiency. Number of the neurons affects the network in a way that small number of neurons may result in unsufficient accuracy while large number of neurons result in problem of increased processing time [2]. ANN features selection of input parameters is one of the main challenging tasks in ANN since it affects network performance and network dimension. Irregularity in this selection can make network structure more complicated [3]. In training part of the ANN algorithm network is learning how the input values are mapped to output values in obtainment of the appropriate model [4].

Configuration of the network is still designed through various trials and errors in order to find appropriate design for the particular engineering issue. Each connection weight and each processing unit bias have been updating according to the achieved error between actual and target data output[5]. The ease of the implementation and possibility for generalization of the problems brought artificial intelligence techniques to wide application in fault classification and localisation. In this paper ANN is used for classification of three different fault types: generator outage, transmission line outage and short circuit in NE 39 bus test system. Voltage and frequency signals have been analyzed with Teager Energy Operator (TEO). Second input type is extracted from the application of Teager - Huang Transform (THT).

II. RELATED WORK

Aim of [6] was to create fault classification and location algorithms that will be fast, reliable and accurate. Inputs for ANN algorithm are current signals. Features are extracted with discrete Fourier transform (DFT) and discrete Wavelet transform (DWT) from current signals of different fault types at different locations. Input layer is constituted of 12 neurons (three phase currents x four features) [6].In [7] analysis is done on small part of Croation transmission system constituted of single-circuit 110 kV transmission line. Fault location is determined with application of the ANN. Structure of the ANN network is [24 3 2 2]. Input data is composed of amplitudes and angles of current and voltage phasors at both line ends and output data contains fault location and faut impedance. Training part of ANN includes 80% of data, validation part 10% and testing part 10%.

In [3] current signals are used as input parameters in ANN training using Back Propagation algorithm for diagnosis of the fault in a distributed motor network. Different number of nodes where tested in network structure for calculation of the network performance. The best Mean Squared Error performance is achieved with structure of 10 neurons in hidden layer and 4 neurons in output layer.Detection and classification of the faults at transmission line based on DWT and back-propagation neural network with Clarke's transformation is presented in [4]. Applied mother wavelet was Daubechies4. Network configuration that achieved the best results was 12-24-48-4. Input is constituted of 12 samples of output currents. Short-circuit faults in power transmission lines were detected, classified and located in [8]. Features for the ANN inputs were extracted from voltage and curent signals with application of DWT. Classification and identification of the fault area are based on S-transform and support vector machines (SVM). In [1] several faults were tested in their detection, classification snd localisation with ANN. Inputs for the network are three phase voltages and three phases currents. Output represents four fault categories with variables 0 or 1. Different structures of the network were tested. With experiments of trials and errors the best performance was achieved with structure that includes two hidden layers with 5 and 4 neurons, respectively.

Fault identification algorithm in [9] is also based on application of DWT in combination with ANN. Output of the network is in the form of four neurons that represents phases (A, B, C) and ground. Number of the neurons in hidden layer is 8. ANN in [2] is used for fault classification in HVDC and it has dc link current as input. The firing angle of the rectifier is used as target data. With this paper authors manage to provide trade-off with large input data size and minimum number of the neurons in hidden layer. In [10] ANN is used for fault classification of phase to phase fault. Haar wavelet is used for features extraction from voltage and current signals. Extracted features are approximated coefficients and detailed coefficients. Input data for ANN is standard deviation of approximated coefficients. In order to achieve better performance different variations of total number of layers and transfer functions are tested. The best performance is obtained with three layers and 'tansig' transfer function. Faults on high voltage power lines are classified in [11]. Structure of ANN is [12 10 6 3]. Input layer is consisted of 12 neurons. There are two hidden layers consisted of 10 and 6 neurons, respectively. Number of neurons in output layers is 3 in terms of three fault causes: lightning, fire and bird.

With trials and errors it is shown in [5] that network with eight or more neurons are sufficient for this application of ANN in fault classification and detection in medium voltage dc shipboard power systems. Network is designed with nine inputs (extracted features) and two outputs. Different methods have been tested for provided data. Designed network is general for usage in different fault and operating conditions. Some of the highlighted contributions in this paper is that variation of electrical parameters do not affect method performance.For the purpose of power system fault identification different fault signals were generated through simulations performed in [12]. Fault signals are analyzed with multi-wavelet packets and extracted fetaures are used for ANN input. Network output are ten fault types. Number of the neurons in hidden layer is chosen empirically and set to the value two times bigger than input layer. The potential application of Teager Energy Operator (TEO) and Discrete Energy Separation algorithm (DESA) in combination with Kalman filter, Hilber Transform and Wavelet transform for the power system control and the practical areas is highlighted in [13]. In mentioned paper TEO and DESA are applied in detection of different distortions of voltage waveform.

III. TEAGER - HUANG TRANSFORM (THT)

DESA is an alternative approach to Hilber Huang Transform (HHT) in determination of the instantaneous amplitude and frequency in a way that it estimates the required energy in signal generation and then perform separation into instantaneous components [14].By appling TEO to discrete signal $x_i(n)$sampled with a sampling period T and to its difference $y_i(n) = x_i(n) - x_i(n-1)$discrete energy separation algorithm is defined in this formulation:

$$\Omega_i(n) = \arccos\left(1 - \frac{\Psi_d[y_i(n)] + \Psi_d[y_i(n+1)]}{4\Psi_d[x_i(n)]}\right)$$

$$A_i(n) = \sqrt{\frac{\Psi_d[x_i(n)]}{1 - \left(1 - \frac{\Psi_d[y_i(n)] + \Psi_d[y_i(n+1)]}{4\Psi_d[x_i(n)]}\right)^2}}$$

Where $\Omega_i(n) = \omega_i(n)T$ and ψ_d TEO in the form$\psi_d[x(n)] = x^2(n) - x(n-1)x(n+1)$.

DESA definition is related to single-component signals and its proper application to multi-component signal includes filtering for decomposition into monochromatic components [15].

The separation of the signal into different signal components is possible to achieve with Empirical Mode Decomposition (EMD). EMD thus can perform multiband filtering and isolate IMFs selecting the highest frequency oscillation remained in the signal [16].EMD decomposes original signal into IMFs giving:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r$$ (c_i-IMF; r residue).

THT algorithm can be divided into two parts. EMD is first used to extract IMFs from the signal. Then DESA is applied to the extracted IMFs in order to obtain instantaneous amplitudes and frequencies. TEO in THT is applied with the expression:

$$TE_{THT} = \sum_{j=1}^{M+1} TEO(IMF_n^j)$$

Where M is number of IMF's and n is number of samples [17]. Application of the TEO in THT includes sum of product of squared instananeous amplitude and squared instananeous frequency of every sample n.

IV. ARTIFICIAL NEURAL NETWORK STRUCTURE

Idea for the structure of the artificial neural networks is based on the neurons role in human's brain [18]. Classification of the faults simulated through this work is done with Artificial Neural Networks in MATLAB as multiclassification. Multiclassification task in ANN is performed with designing pattern recognition neural network. These networks are feedforward networks trained to classify inputs according to target classes. Target data is presented in form of vectors of zero values except value 1 in vector element which represents associated class (Figure 1).

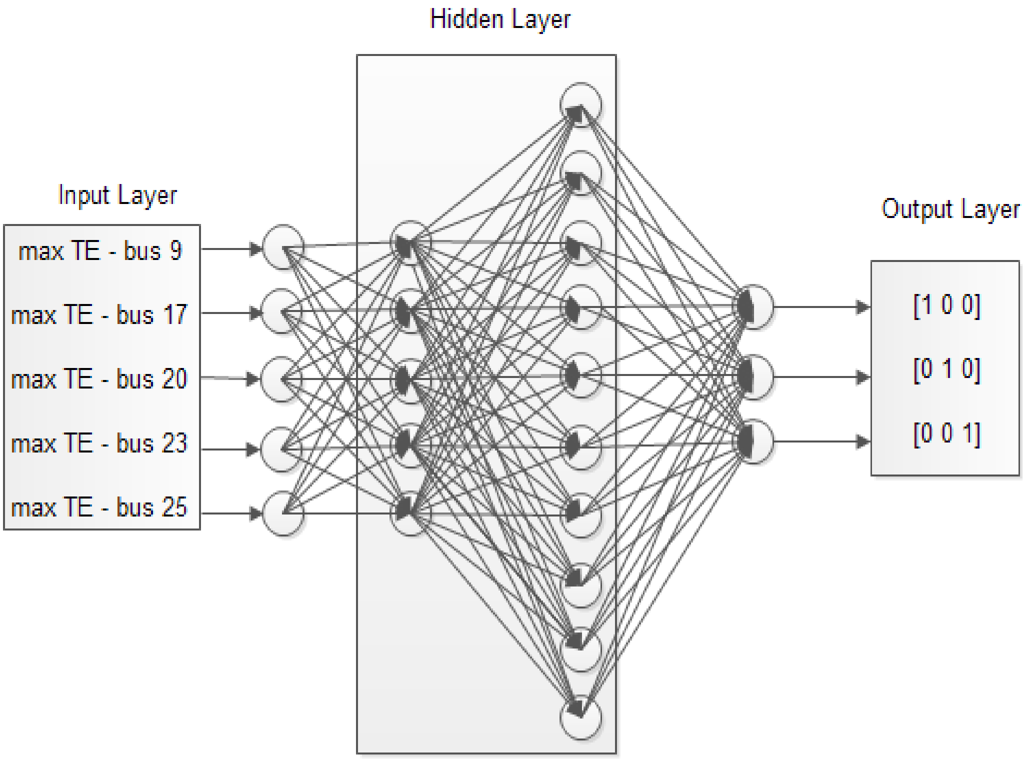

Fig. 1: ANN Architecture

Simulations should be classified to three different fault types indicating that form of the target data in this application is vector composed of three elements. Each element represents specific class in terms of the type of the simulated fault. Vectors are set as:

1 0 0 – generator outage
0 1 0 - transmission line outage

0 0 1 - short circuit.

One of the measures how well the neural network fit the data is the classification confusion matrix. It determines the percentages of correct and incorrect classifications. Defined value is confusion value that represents fraction of the samples that are misclassified. Network data is composed of 81 values for each of the inputs to the designed network. After analysis of the voltage and frequency signals with TEO maximum Teager energy values for signals from five selected buses (buses 9, 17, 20, 23 and 25) are extracted (Figure 2).

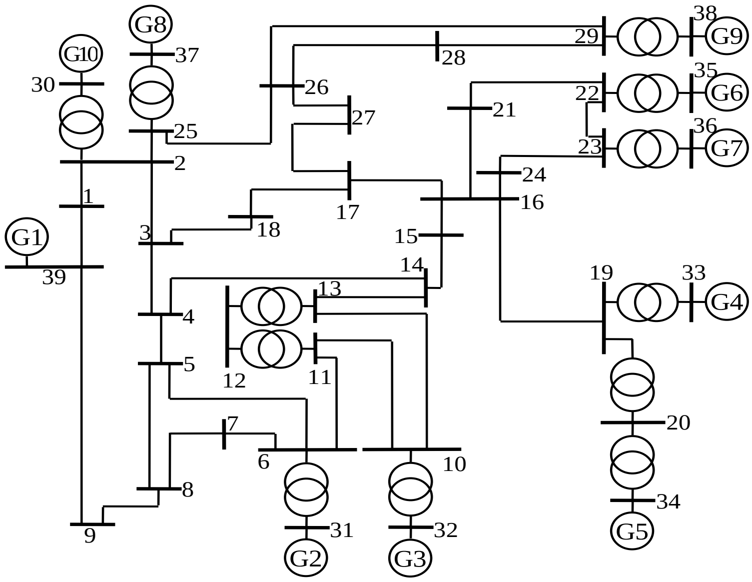

Fig. 2: NE 39 bus test system[19]

Train data is composed of 70% of total data and network is tested on the 30% of each input. Number of the neurons in the hidden layers was changing accordingly with enhanced network performance. Final selected size was 5 in first and 10 neurons for second hidden layer. Output layers number is 3 presenting three categories of the simulated faults.

V. RESULTS AND DISCUSSION

The task of the fault classification is to determine type of the fault that occured in the system. Different structures of the ANN input were tested through this work and achieved performance each of them is presented. Designed network is tested with output of the THT algorithm as well. Input variable is maximum value of applied DESA to the voltage and frequency signal with the highest value of Teager energy for specific simulated fault. With the structure of the hidden layers as [5 10] achived performance has a value of 39,39 %. In order to try to improve achieved performance different size of hidden layers is tested. Performance values according to the neurons number in the hidden layers are listed in Table I.

TABLE I: ANN Performance with THT Algorithm

Frequency and Voltage Signals			
Number	**Input Matrix**	**Hidden Layers**	**ANN Performance**
1	2 x 111	[5 10]	39,39 %
2	2 x 111	[5 50]	51,51%
3	2 x 111	[5 60]	39,39 %
4	2 x 111	[5 70]	45,45%

Performance values is improved with changing number of the hidden layers but still doesn't represent satisfactory value of network performance.Performed classification with base TEO algorithm can be organized as three parts: frequency signals input, voltage signals input and frequency voltage signals common input.

TABLE II: ANN Performance with Base TEO Algorithm

Frequency and Voltage Signals				
No	**Input Data**	**Input Signals**	**Input Matrix**	**ANN Performance**
1	max TE – bus 9, max TE – bus 17, max TE – bus 20, max TE – bus 23, max TE – bus 25	Voltage	5 x 81	87,5 %
2		Frequency	5 x 81	70,83 %
3		Voltage and frequency	5 x 162	62,5 %

The best performance among three tested input structures (Table II) is achieved in the case when voltage signals from five selected buses in the system were analyzed – 87,5%. When data was extracted only from frequency signals performance value was lower. The last structure includes frequency and voltage signals as common input what provided the lowest performance value of designed ANN.

VI. CONCLUSIONS

In this paper fault classification task is obtained with application of ANN. Different ANN structures and input data types have been analyzed in order to compare achieved performance. Designed ANN structures differ in the number of neurons in the hidden layer. The best performance among performed experiments is achieved for the case of five input variables for obtained voltage signals with [5 10] hidden layer structure. Future work should include Hilbert Huang Transform for signal analysis and definition of specific filters that will overcome restrictions for TEO in terms of possible negative values.

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