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Detection and Classification of Voltage Variations Using Combined Envelope-Neural Network Based Approach

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Abstract— This paper presents a technique for detection and classification of short duration voltage variations including voltage sag, swell and interruption. The detection technique is based on envelope construction using Hilbert transform and classification using artificial neural network. The performance of the classifier is examined over several cases of synthetic voltage variation disturbances. Moreover, the performance of the classifier is tested on a simple distribution system subjected to a single-line-ground fault. The beginning and ending of the disturbance are also estimated. The simulation results show the robust capability of the proposed technique to accurately and rapidly classify voltage variation events.

Keywords— Artificial neural network, Envelope detection, Hilbert transform, Power quality, Voltage variations.

I. INTRODUCTION

Voltage variations are mainly caused by switching on/off of heavy loads such as motors and faults on the power system. Voltage sag/swell can cause a serious damage to sensitive loads and interruption of power systems. Technical surveys have shown that voltage sags and swells are the most dominant power quality (PQ) problem [1], [2]. Voltage variations including voltage sag (dip), swell and interruption are usually characterized by their magnitudes and durations. Voltage sag is defined as a decrease between 0.1 and 0.9 per unit (pu) in rms voltage or current, whereas voltage swell is defined as an increase between 1.1 pu and 1.8 pu in rms voltage or current at the power frequency for durations from 0.5 cycle to 1min. An interruption occurs when the supply voltage or load current falls to a value less than 0.1 pu for a time interval less than 1min [1], [2].

Mitigation techniques such as Dynamic Voltage Restorer (DVR) and Distribution Static Compensator (DSTATCOM) have been developed to overcome voltage variation problems. [3]-[5]. However, before any mitigation is applied, the voltage variation should be detected. Accordingly, several signal processing techniques have been developed for the detection and classification of voltage variations. Traditionally, RMS, Peak Detection and DFT have been applied [6], [7]. More advanced signal processing techniques based on Wavelet transform (WT), Hilbert transform (HT) and S-Transform combined with artificial neural networks (ANN) have been investigated for voltage variation detection and classification [8]-[16]. Using the properties of these transforms and the features of the distorted voltage signal along with ANN scheme, it is possible to extract features from the distorted signal and determine the type of voltage variations.

This paper aims to develop a simple yet powerful technique for fast voltage variation detection and classification by tracking the variation of the envelope of the voltage signal in real time. Envelope extraction combined with advanced signal processing techniques has been

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used for voltage flicker detection [17]-[20].
The paper is organized as follows. Section II presents the concepts of voltage envelope extraction using HT and voltage variation classification using ANN. In section III, training and testing of the ANN based classifier is discussed. In Section IV, simulation results of a case study are illustrated. Finally, Section V concludes the work presented in the paper.

II. ENVELOPE DETECTION AND CLASSIFICATION SCHEME

In this work an efficient combined HT-ANN based technique for voltage variation detection based on signal envelope extraction using HT and classification using ANN is proposed. A schematic diagram of the proposed detection and classification scheme of voltage variations is shown in Fig. 1. The proposed scheme stores a full-cycle of the voltage envelope samples and feeds them in series to the proposed ANN classifier. When a new input sample arrives, the oldest sample is discarded. The ANN classifier produces one output with four states: -1 (sag) or 0 (interruption) or 1 (swell) or 0.5 (normal). The input signal $v(t)$ is processed by anti-aliasing analog low-pass filter to remove high-frequency components and noise. The filtered continuous signal is then converted to discrete-time series $v(k)$ using an A-D converter by sampling the signal at a specific sampling frequency f_s. The digitized signal v_k is then processed by HT to obtain its Hilbert transform $v_H(k)$. The instantaneous envelope of $v(k)$ is extracted by computing the modulus $|y(k)|$.

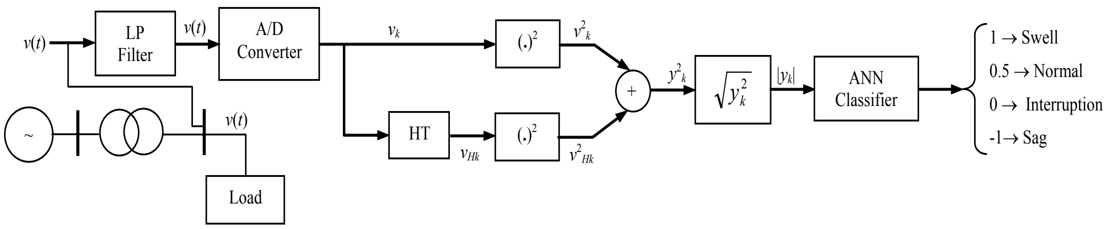


Fig. 1. Voltage variation detection and classification schematic diagram

A. Envelope Extraction Using Hilbert Transform

Hilbert transform is used in signal processing to construct the signal envelope by calculating the analytical representation of the continuous-time signal [18]. For a real-valued discrete sinusoidal voltage signal $v(t)$, the analytic signal $y(t)$ is defined as:

$$y(t)= v(t)+j\,H(v(t)) \tag{1}$$

where $H(v(t))$ denotes the HT of $v(t)$. If the Fourier transform of $v(t)$, $\mathbf{V}(\omega)= \mathrm{F}(v(t))$ is known, the Fourier transform $\mathbf{V_H}(\omega)= \mathrm{F}(v_H(t))$ can be obtained as:

$$\mathbf{V_H}(\omega) = -\frac{j\omega}{|\omega|}\mathbf{V}(\omega) \tag{2}$$

By calculating the inverse Fourier transform of $\mathbf{V_H}(\omega)$, $v_H(t)$ can be obtained.
For a single-frequency sinusoidal signal, $v(t)= \cos(\omega t)$, $v_H(t)= \sin(\omega t)$. If $v(t)= \sin(\omega t)$, then $v_H(t)= -\cos(\omega t)$. Subsequently, the envelope of the signal $v(t)$ can be calculated by computing the modulus $|y(k)|$ as given by (3):

$$|y(t)| = \sqrt{v(t)^2 + v_H(t)^2} \tag{3}$$

Similarly, for a discrete-time voltage signal, the instantaneous envelope of $v(k)$ can be defined as:

$$|y(k)| = \sqrt{v(k)^2 + v_H(k)^2}$$

B. Neural Network Classifier

Multilayer feedforward ANNs have been successfully used in solving many engineering problems such as function approximation, pattern recognition and classification and nonlinear mapping by selecting the output that best represents an unknown input pattern [12]-[14], [19]. Basically, an ANN consists of an input layer, one or more hidden layer(s) and an output layer. The hidden and output layers consist of sets of neurons that are fully connected to the neurons in the next layer. The number of neurons and hidden layers is problem-dependent and can be determined by trial and error till a goal performance is achieved [21]. The input layer receives the samples of the input signal and directly passes the signal to the neurons in the hidden layer after being modified by some weight coefficients. The neurons in the hidden layer send their weighed output to the neurons of the output layer. The weights of links to the hidden and output layers are determined by a process called training or learning, where a set of input patterns is admitted to the ANN along with the target output patterns. The weights are adjusted by a process called back propagation (BP) until an error measure representing the difference between the target and the predicted output of the ANN is minimized. The BP algorithm is an iterative gradient descent algorithm that adapts the weights; and the error is calculated and propagated backwards from the output to the hidden layer to the input. Usually, the mean square error (MSE) is minimized. The individual pattern error E_p of pattern p is calculated:

$$E_p = \frac{1}{2}\sum_k (t_k - o_k)^2 \tag{4}$$

where t_k is the target (desired) output; and O_k is the actual output of the neural network. The error E for all patterns is obtained as the sum of all individual patterns errors:

$$E = \sum_p E_p = E(W) \tag{5}$$

In this work, the architecture of the proposed ANN consists of an input layer with one input, a hidden layer with 10 neurons and an output layer with one neuron as shown in Fig. 2. The ANN classifier produces one output with four states: -1 (sag) or 0 (interruption) or 1 (swell) or 0.5 (normal).

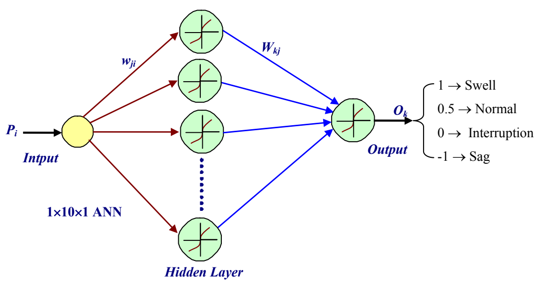


Fig. 2. Architecture of the proposed ANN classifier

The "*tansigmoid*" activation function has been used in both the hidden and output layers. The MATLAB levenberg-marquardt "*trainlm*" training algorithm has been used [22]. Upon completion of the training phase, the generalization capability of the proposed ANN classifier is examined using another set of testing input-output patterns which are different from the training input-output patterns.

III. NEURAL NETWORK TRAINING AND TESTING

A. Training Phase

A synthetic 50-Hz sinusoidal signal of the form:

$$v(t)= A_{sg}\cos(\omega_o t)u(t_{osg}-t_{fsg})+A_{sw}\cos(\omega_o t)u(t_{osw}-t_{fsw})+A_{in}\cos(\omega_o t)u(t_{oin}-t_{fin})$$

is generated for time duration of 26.7 seconds with multi levels of sag, swell and interruption disturbance events, where A_{sg}, A_{sw} and A_{in} are the amplitudes of the sag, swell and interruption events; t_{osg}, t_{osw} and t_{oin} are the beginning time of the sag, swell and interruption events; t_{fsg}, t_{fsw} and t_{fin} are the ending time of the sag, swell and interruption events.

The signal is sampled at a sampling rate of 600Hz, i.e. a sampling rate of 12 samples per 50-Hz cycle. Accordingly, a total number of 16000 samples is generated for training the proposed ANN classifier. Random amplitudes between 0.1-0.9 pu, 1.1-1.8 pu and 0-0.1 pu are generated for voltage sag, swell and interruption signals as shown in Fig. 3. The envelope of the training voltage signal is extracted as shown in Fig. 4 for a part of the training signal (3500) samples with the corresponding target values (-1, 0, 0.5, 1). The envelope is smoothed using the MATLAB "*smooth*" function which is basically a moving average based on a low-pass filter.

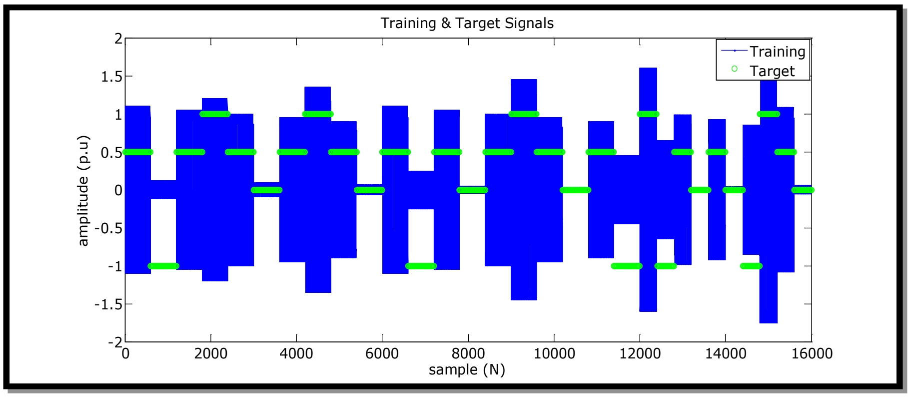


Fig. 3. Training voltage signal with multi-levels of sag, swell and interruption

The training performance of the proposed ANN classifier for the 16000 training samples is depicted in Fig. 5. Based on the examination of the training results, it can be seen that the ANN classifier shows excellent performance. Both targets and actual ANN outputs match each other with a high degree of accuracy. The training accuracy is also assessed in terms of the percentage of correctly classified samples to the total number of training samples. For a 1×10×1 ANN, an MSE of 0.0096 and training accuracy of 99.2% are achieved. Only 124 samples out of 16000 were miss-classified.

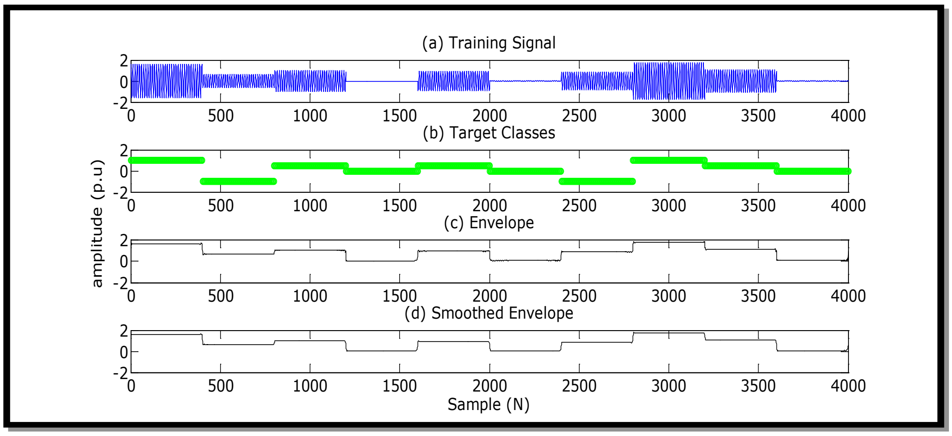


Fig. 4. Smoothed training envelop, input and output target pattern

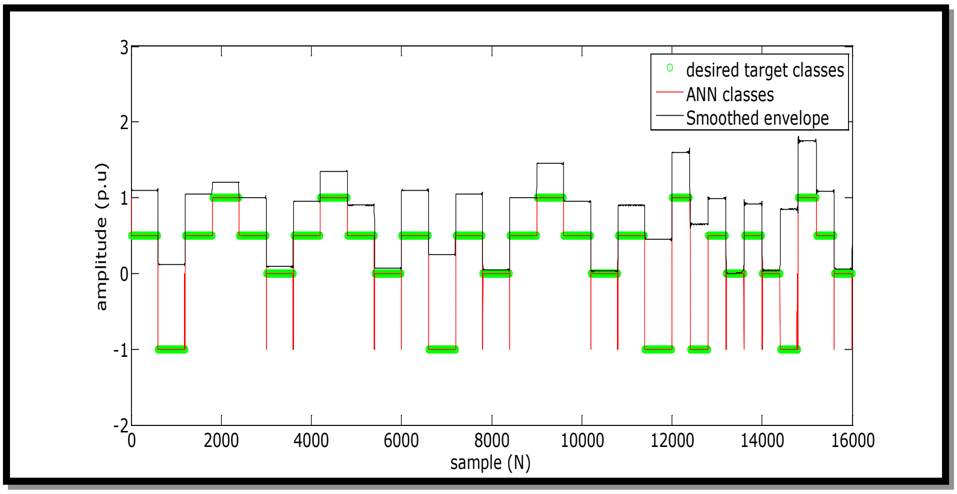
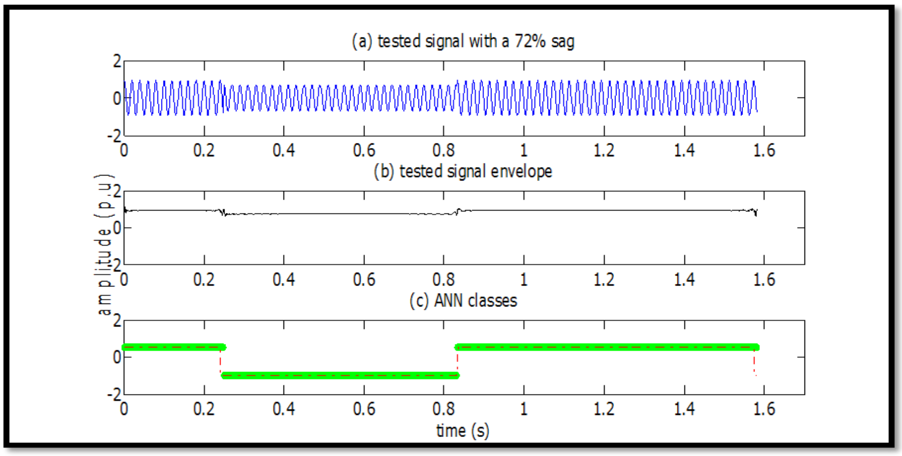


Fig. 5. Comparison between the target and ANN actual outputs

B. Testing Phase

The generalization capability of the proposed ANN classifier is examined using nine different input-output testing pattern sets of synthetic voltage signals. Each signal is constructed by embedding a short duration segment of sag, swell or interruption disturbance within a voltage signal of normal level. Three segments of 72%, 55% and 25% voltage sag levels, three segments of 170%, 140% and 120% voltage swell levels and three segments of 7%, 5% and 2% voltage interruption levels are generated as shown in Fig. 6-8. The numbers of samples, beginning and ending times and duration intervals of each disturbance event are tabulated in Tables 1-3. The simulation results for nine cases of voltage sag, swell and interruption are depicted in Fig. 6-8, respectively. The simulation results of the testing phase reveal that the high accuracy of detection and classification of the proposed ANN are satisfied over a wide range of voltage variations and durations.



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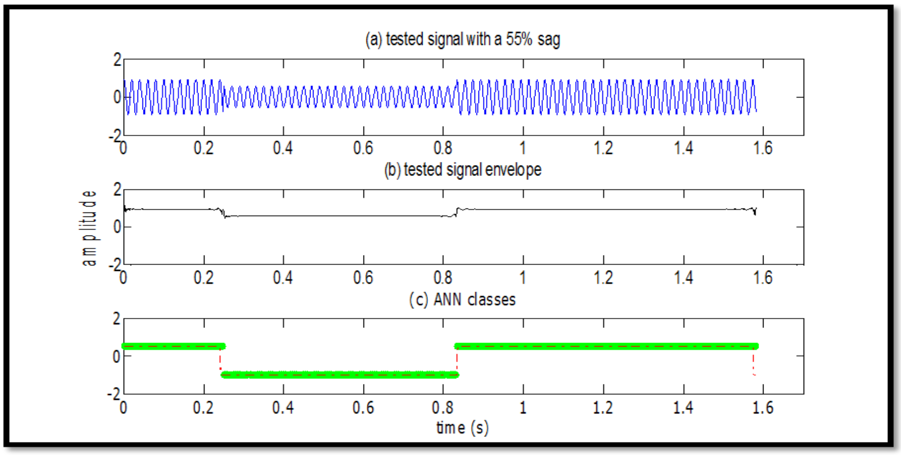

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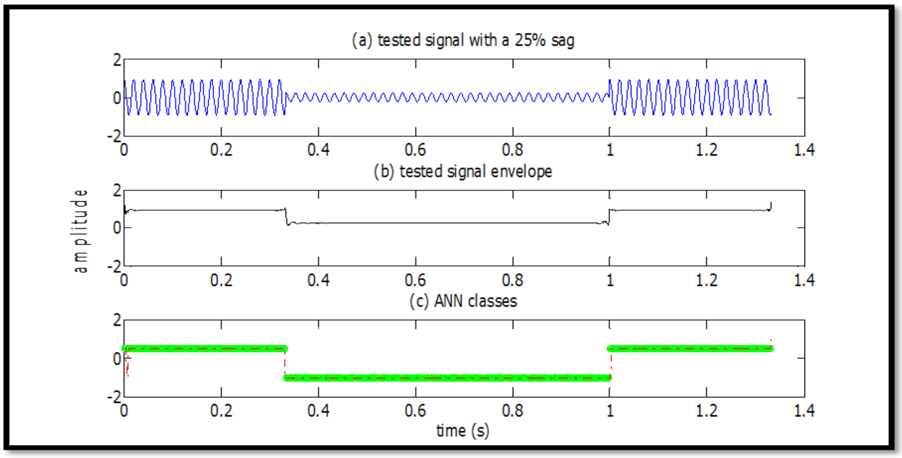

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Fig. 6. Comparison between target and ANN: a) actual outputs-72% voltage sag, b) actual outputs-55% voltage sag, c) actual outputs-25% voltage sag

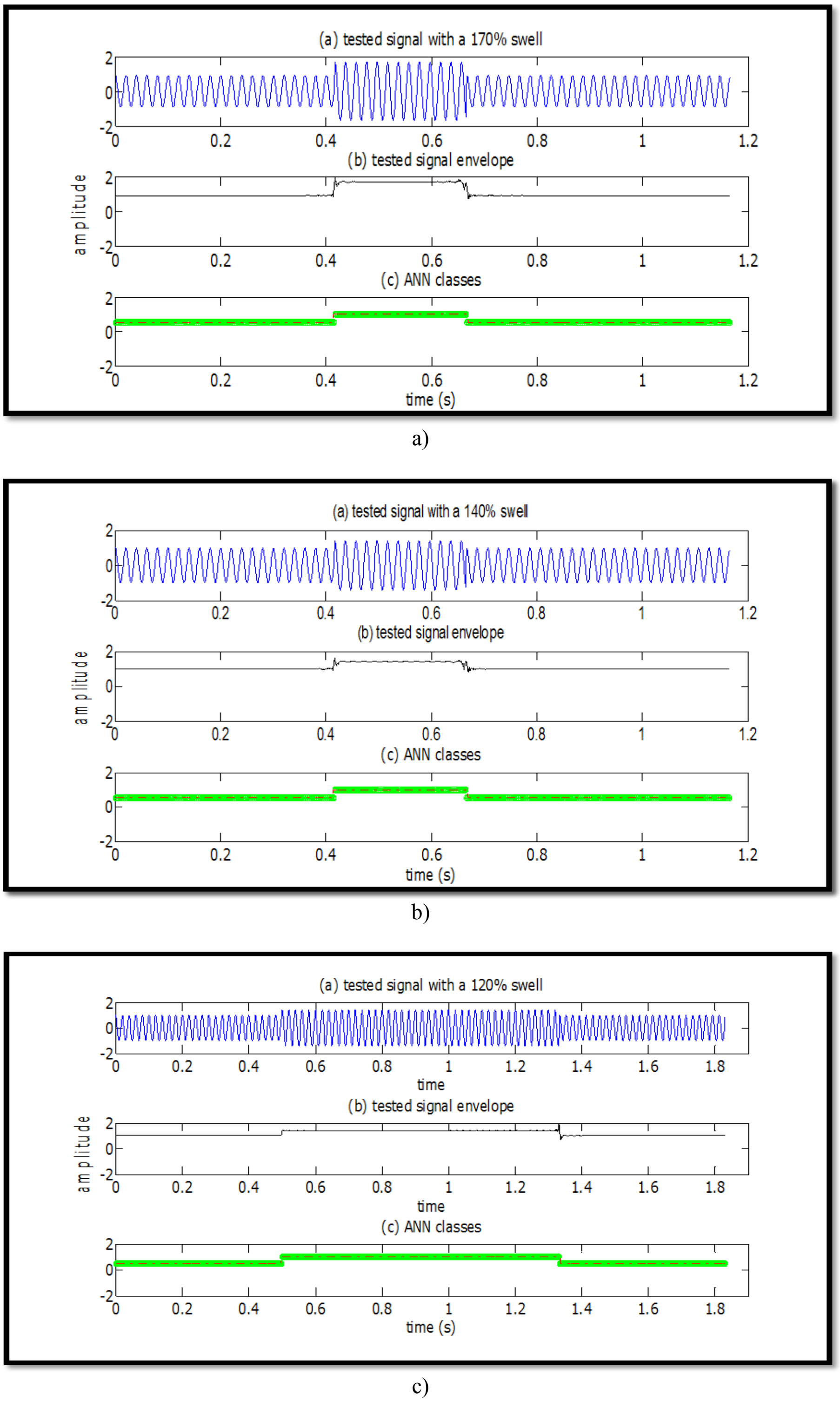
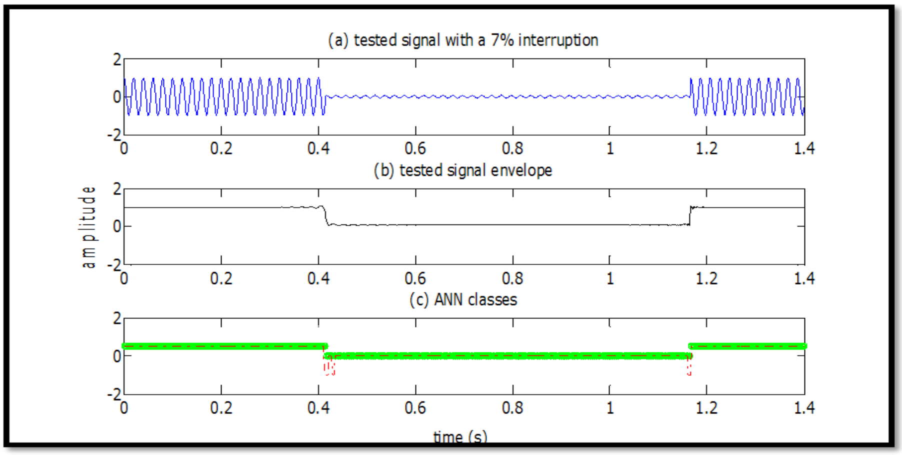


Fig. 7. Comparison between target and ANN: a) actual outputs-170% voltage swell, b) actual outputs-140% voltage swell, c) actual outputs-120% voltage swell



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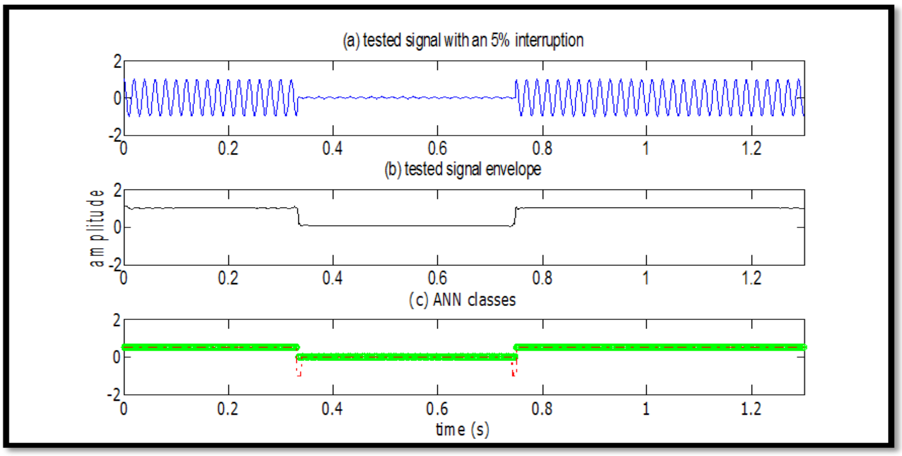

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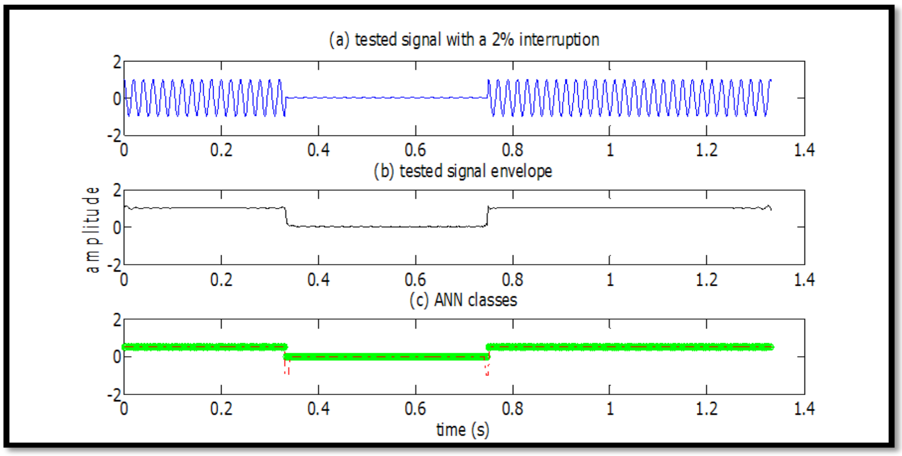


c)

Fig. 8. Comparison between target and ANN: a) actual outputs-7% voltage interruption, b) actual outputs-5% voltage interruption, c) actual outputs-2% voltage interruption

TABLE 1
ANN CLASSIFICATION ACCURACY OF VOLTAGE SAG CASE

Sag Level	Item	Target	Actual Output	%Accuracy
72%	Number of Samples	350	347	99.1
	Beginning Time (s)	0.250	0.243	97.3
	Ending Time (s)	0.833	0.822	98.7
	Sag Duration (s)	0.583	0.579	99.3
55%	Number of Samples	350	361	96.9
	Beginning Time (s)	0.250	0.243	97.3
	Ending Time (s)	0.833	0.845	98.6
	Sag Duration (s)	0.583	0.602	96.7
25%	Number of Samples	400	407	98.3
	Beginning Time (s)	0.333	0.333	100
	Ending Time (s)	1.000	1.008	99.2
	Sag Duration (s)	0.667	0.675	99.2

TABLE 2
ANN CLASSIFICATION ACCURACY OF VOLTAGE SWELL CASES

Swell Level	Item	Target	Actual Output	%Accuracy
170%	Number of Samples	150	153	98.0
	Beginning Time (s)	0.416	0.415	99.8
	Ending Time (s)	0.667	0.670	99.7
	Sag Duration (s)	0.250	0.255	98.0
140%	Number of Samples	150	154	98.0
	Beginning Time (s)	0.416	0.415	99.8
	Ending Time (s)	0.667	0.672	99.3
	Sag Duration (s)	0.250	0.257	97.2
120%	Number of Samples	500	503	99.4
	Beginning Time (s)	0.500	0.500	100
	Ending Time (s)	1.333	1.338	99.6
	Sag Duration (s)	0.833	0.838	99.4

TABLE 3
ANN CLASSIFICATION ACCURACY OF VOLTAGE INTERRUPTION CASES

Interruption Level	Item	Target	Actual Output	%Accuracy
7%	Number of Samples	450	454	99.1
	Beginning Time (s)	0.416	0.413	99.4
	Ending Time (s)	1.166	1.17	99.3
	Sag Duration (s)	0.75	0.757	99.3
5%	Number of Samples	250	252	99.2
	Beginning Time (s)	0.333	0.331	99.4
	Ending Time (s)	0.750	0.755	99.3
	Sag Duration (s)	0.417	0.424	98.3
2%	Number of Samples	250	252	99.2
	Beginning Time (s)	0.333	0.331	99.4
	Ending Time (s)	0.750	0.755	99.3
	Sag Duration (s)	0.417	0.424	98.3

IV. SIMULATION RESULTS

In this section, the detection and classification performance of the proposed method for a voltage variation event is simulated for a single-line-ground fault (SLGF) disturbance on phase *A* of a simple 33/0.4kV distribution system as shown in Fig. 9. The fault is initiated at *t*=0.4s and cleared after 0.4s. The time-oscilligrams of the three phase voltages *A*, *B* and *C* are shown in Fig. 10, where a voltage interruption appears on phase A compared with 173% voltage swell in phases B and C, respectively.

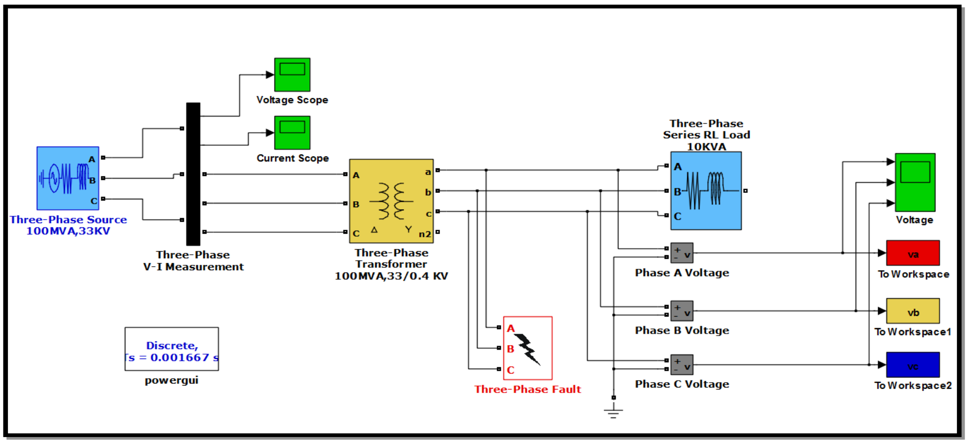


Fig. 9. Simulation of a SLGF on a distribution system

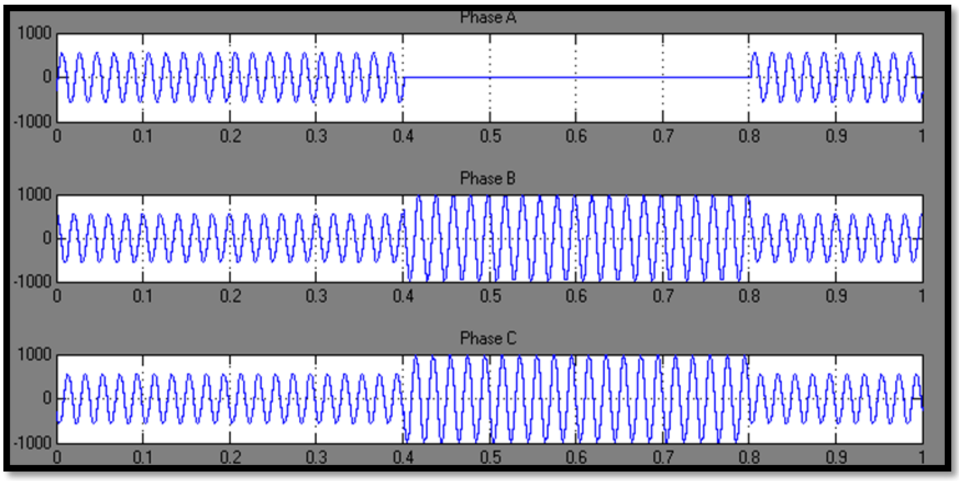
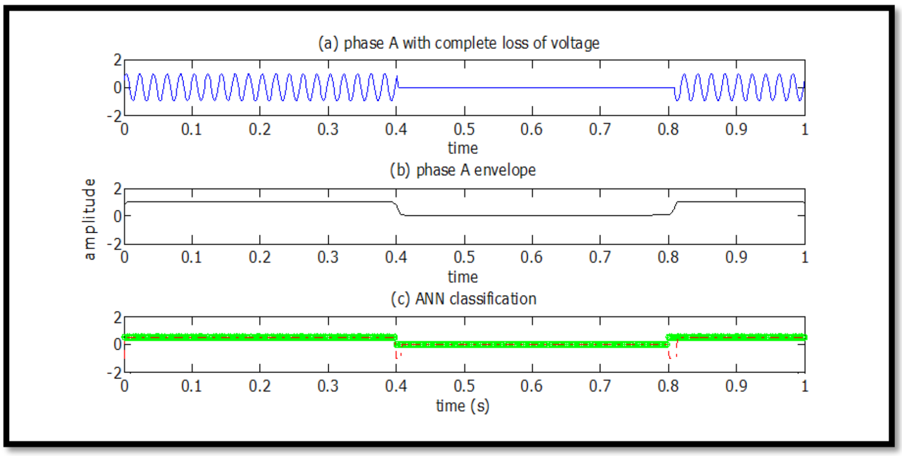


Fig. 10. Time-oscilligrams of phases A, B and C for SLGF

The three oscilligrams are introduced to the proposed voltage envelope detection-ANN classification scheme. The results of classification simulations are illustrated in Fig. 11a, 11b and 11c and Table 4. Simulation results demonstrate the excellent performance of the proposed ANN classifier in detecting and classifying the voltage variation type; it as well estimates time durations with an average accuracy of 98%.



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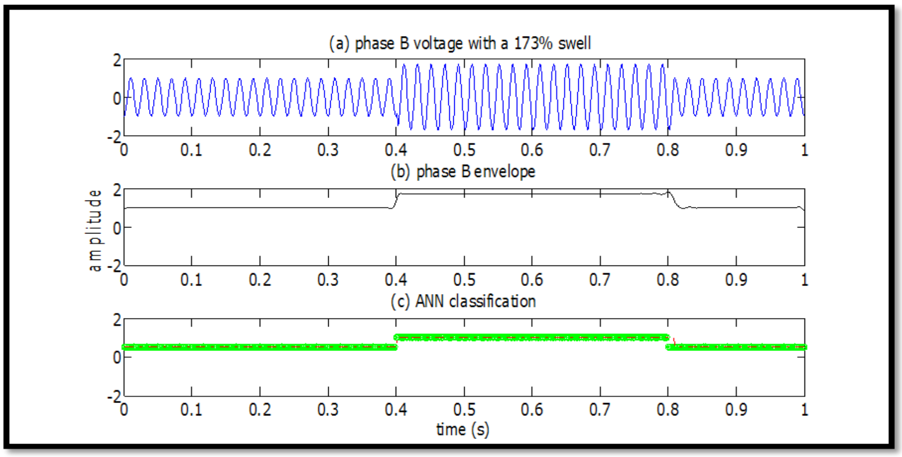

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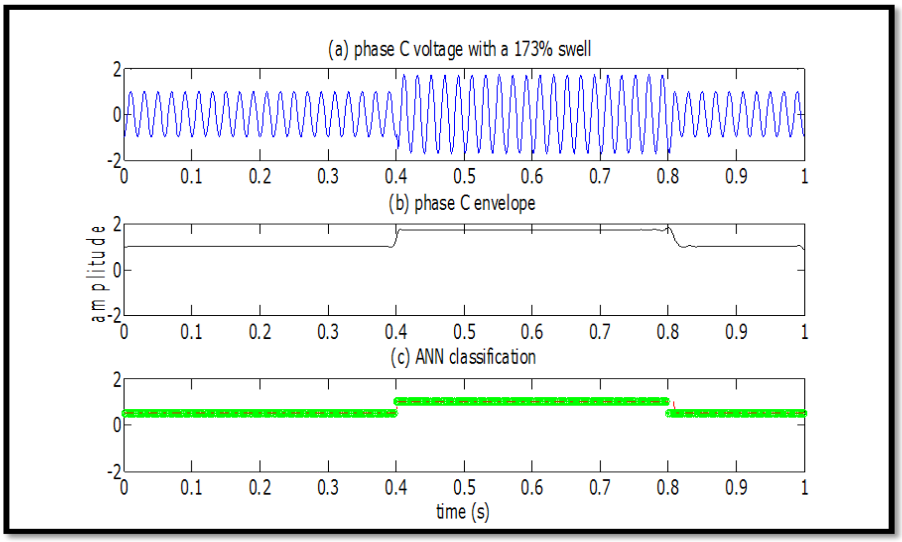

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Fig. 11. a) Time-oscilligrams of phase *A* for SLGF on phase *A*, b) voltage swell-oscilligram of phase *B* for SLGF on phase *A*, c) voltage swell-oscilligram of phase *C* for SLGF on phase *A*

TABLE 4
ANN CLASSIFICATION ACCURACY OF VOLTAGE VARIATIONS FOR SLGF ON PHASE *A*

Event	Item	Target	Actual Output	%Accuracy
Phase *A* 0% Interruption	Number of Samples	240	249	96.3
	Beginning Time (s)	0.400	0.401	99.9
	Ending Time (s)	0.800	0.816	98.0
	Sag Duration (s)	0.400	0.415	96.3
Phase *B* 173% Swell	Number of Samples	240	245	97.9
	Beginning Time (s)	0.400	0.403	99.3
	Ending Time (s)	0.800	0.812	98.5
	Sag Duration (s)	0.400	0.409	97.75
Phase *C* 173% Swell	Number of Samples	240	245	97.9
	Beginning Time (s)	0.400	0.403	99.3
	Ending Time (s)	0.800	0.812	98.5
	Sag Duration (s)	0.400	0.409	97.8

V. CONCLUSION

In this paper, an efficient envelope-ANN based technique for detection and classification of sag, swell or interruption voltage variations along with their time durations is developed. The envelope of the signal is developed using HT. A feed forward ANN with BP training is also developed for the classification of the voltage variation. The proposed ANN classifier consists of one input, 10 hidden neurons and one output neuron. Computer simulations of the training phase have shown high classification accuracy up to 99.2%. Likewise, high accuracy up to 98.6% has been achieved for several cases of voltage variations in the testing phase. The simulation results reveal that the proposed envelope detection-ANN based classifier technique provides a powerful technique for fast and effective classification of voltage variations and estimation of the beginning, ending and duration times of the voltage variation.

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