High speed transmission line fault classification using an Elman neural network

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Detection and classification of a fault on a transmission line is essential to the proper performance of a power system. It would be desirable to develop a high speed and accurate approach to determine the fault type for different power system conditions. To classify single-phase, two-phase or three-phase faults on a given line, neural network abilities could be considered as a solution. To demonstrate the applicability of this solution, neural network technique is employed and a novel Elman recurrent network is designed and trained. Details of the design procedure and the results of performance studies with the proposed network are given and analyzed in this paper. System simulation studies show that the proposed approach is able to detect and classify a fault on a transmission line rapidly and correctly. It is suitable to be used in an ultra high-speed transmission line protection scheme.

يقدم هذا البحث طريقة جديدة لمعرفة وتشخيص سريع للأعطال التى تحدث فى خطوط نقل القوى الكهربية والتى يمكن أن تكون آحادية الفازات أو ثنائية أو ثلاثية . وتعتمد الطريقة المقترحة فى البحث على نوع جديد من الخلايا العصبية يسمى المان والذى يعد من أنسب الخلايا العصبية التى تتعامل مع الدوال المتغيرة مع الزمن ، وبذلك يمكنها التعامل بكفاءة عالية مع الجهود والتيارات الخاصة بخطوط نقل القوى الكهربية . ويمكن لهذه النوعية الجديدة من الخلايا العصبية أن تتعرف على العطل وتشخصه فى أقل من ٢ ميلى ثانية مما يتيح سرعة أكبر فى فصل العطل وتجنب الأضرار التى تنتج من هذه الأعطال . ويحتوى البحث على شرح كامل لهذه النوعية من الخلايا العصبية وكيفية تمرينها لتشخيص العطل وأيضا النتائج التى تدل على الدقة والسرعة العالية فى تحديد وتشخيص الأعطال .

Keywords: Transmission lines protection, Fault classification, Elman recurrent neural networks

1. Introduction

Artificial Neural Networks (ANN) are systems that are inspired by biological neural networks. Artificial neural networks have proved to be a vital tool in applications related to power systems due to the non-linearity of the system [1]. Contributions to the field vary from neural algorithms for different applications to dedicated hardware impleme-ntations. One of the areas of power systems engineering that gained more attention with use of ANN is distance protection. The solutions based on ANN use different methods to increase performance in terms of speed of operation and efficiency. Dalestein et al. is one of the early researchers that applied ANN in distance protection [2-4]. In this work Multi-layer Feed-forward Neural Networks (MFNN) are used for the purpose of fault detection, fault classification, fault direction identification and fault location. The neural network used for fault classification in [2] was trained using the back propagation learning algorithm. For the purpose of training the MFNN to classify the fault, the entire training process needed around 500 cycles and 24 hours computing time on a PC using 2268 simulated faults which mounted to 45360 different training patterns. The neural network used for fault classification consists of 30 inputs (in the form of five consecutive samples of currents and voltages for each line), two hidden layers, 20 neurons in the first layer and 15 neurons in the second hidden layer and an output layer with 11 nodes. Coury et al. describe an ANN solution for the Transmission Line (TL) protection [5]. A two layered MFNN architecture with magnitudes of currents and voltages as inputs and a trip/no trip signal as the output is presented. They use back-propagation algorithm for training the ANN and employ 2000 simulated faults, covering different fault conditions, for training.

They claim the ANN considerably improves the protection system efficiency. A training time of 2 CPU hours is reported in [5]. The solution, though attractive in terms of improvement in efficiency, requires a large number of simulated faults for training.

The prototypical use of neural networks is in the structural pattern recognition. In such a task, the network uses a collection of features presented to it to classify the input feature patterns into different classes. In the MFNN method, the network is presented with all relevant information simultaneously and its output is based on the currently presented input pattern, with no regard to its previous output. In contrast, temporal pattern recognition involves processing of patterns that evolve over time and its output depends on the current input pattern as well as its previous output. Hence, neural networks with temporal pattern recognition may be more suitable for patterns that vary over time.

Samples of phase voltage and current waveforms are usually used as inputs to the neural network. The voltage and current are time-varying signals. Therefore, a network with temporal processing abilities could be considered. In the present work, an Elman recurrent neural network is proposed for fault classification on transmission lines. The ANN based algorithm is tested to evaluate the performance of the proposed method in terms of accuracy, robustness and speed. Some of the test results are included in this paper.

2. Problem description

Fig. 1 shows the main components of a digital relay used to protect a TL. Faults on TL need to be detected, classified and located accurately and cleared as fast as possible. In this framework the most important point is fast and reliable fault classification. A fundamental part of a protective relay is a selector module. This module classifies whether a single phase, two phases or three phases are involved in a fault. In addition, a selector module has also to classify the "normal state" of the power system (no fault, load jump, etc). Using very high speed protective relay systems, a selector module

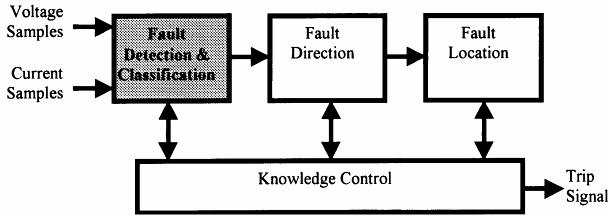

Fig. 1. Typical modules of a protective relay.

should make an accurate decision in less than 2 ms to obtain a trip signal as fast as possible. Estimation times of conventional methods are prohibitively long.

Identifying the faulted phase can allow for selected phase tripping instead of tripping all three phases. This practice increases system stability during faults. Moreover, if a suitable technique is applied to differentiate between arcing (transient) and non-arcing (permanent) faults, autoreclosure can be safely applied after arc extinction while autoreclosure is prohibited in case of permanent fault [6].

Hence, this paper focuses on the design of a reliable and fast acting Elman based ANN fault detector and classifier module. The other modules shown in fig. 1 are the subjects of future work to be published later.

3. Temporal pattern recognition

3.1. Temporal processing

Time is clearly an important factor in many of the cognitive tasks encountered in practice. It is inextricably bound up with many behaviors, which express themselves as temporal sequences. Thus, the question of how to represent time in connectionist models is very important. In particular, how one can extend the design of a feed forward network so that it assumes a time-varying form and therefore will be able to deal with time-varying signals and sequences more efficiently. The answer to these questions is to allow time to be represented by the effect it has on signal processing. This means providing the mapping network dynamic properties that make it responsive to time varying signals [7].

In short, for a neural network to be dynamic, it must be given memory [8]. One way to accomplish this requirement is to introduce time delay into the synaptic structure of the network in one form or another. One popular technique which uses time delays is the Time Delay Neural Network (TDNN). The TDNN is a MFNN whose hidden and output neurons are replicated across time [9].

The TDNN topology is in fact embodied in a feed forward network in which each synapse is represented by a Finite-duration Impulse Response (FIR) filter. This latter network is referred to as FIR neural network. The FIR neural network uses temporal model of the neuron to construct a feed forward network. A FIR ANN is used in [10] for the purpose of fault detection, classification and direction estimation for a high voltage TL. It is shown in [10] that the FIR ANN response to a fault is 2.5 ms and that in general it is reliable. However, the FIR ANN proposed contains a large number of neurons, as it has 45 neurons in the first hidden layer, 35 in the second hidden layer and 5 output neurons. Moreover, the number of time delay units is 5 for the first hidden layer, 2 for the second and 2 for the output layer.

Another way in which a neural network can assume dynamic behavior is to make it recurrent, that is, to build feedback into its structure. The recurrent connections allow the hidden units of the network to see their own previous output, so that the subsequent behavior can be shaped by previous response. These recurrent connections are what give the network memory. A few different types of recurrent networks have been proposed by different researchers, including Real-Time Recurrent Network [11], Partially Recurrent Network [12] and Elman Network [8]. The difference between these networks lies in their structures and the way they handle the feedback.

3. 2. Elman network

In parallel-distributed processing models, the processing of sequential inputs has been accomplished in several ways. The most common solution is to attempt to parallelize time by giving it spatial representation. This approach does not easily distinguish relative temporal position from absolute temporal position [8]. A better approach would be to represent time implicitly rather than explicitly. That is, time is represented by the effect it has on processing and not as an additional dimension of the input.

Elman network is a two-layer feed forward network with the addition of a recurrent connection from the output of the hidden layer to its input. The delay in this connection stores values from the previous time step, which can be used in the current time step. This feedback path allows the Elman network to learn to recognize and generate temporal patterns, as well as spatial patterns.

The architecture of Elman network is shown in fig. 2. The network is augmented at the input level by additional units, called context units. These units are also hidden in the sense that they interact exclusively with other nodes internal to the network, and not the outside world [8].

The augmented input units, including both the input units and the context units activate the hidden units. The hidden units feed forward to activate the output units as well as they feedback to activate the context units. The number of context units is equal to the number of hidden units. Activations are copied from hidden layer to the context layer on a one-for-one basis with fixed weights of 1.0. The context unit values at time step $t + 1$ are exactly the same as the hidden unit values at time step t. Therefore, the context units provide the network with memory.

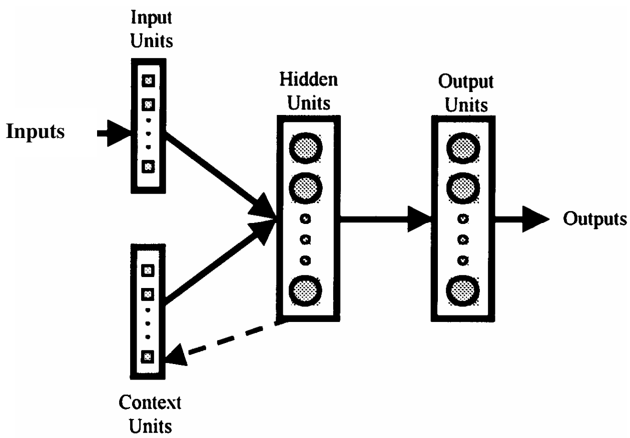

Fig. 2. Elman network architecture. Solid lines represent the trainable connections and the dashed line represents fixed weight recurrent connections.

4. The proposed Elman network design

An Elman recurrent ANN was designed to act as the fault detection and classification module of a TL relaying system. Details of the design procedure are given below.

4.1. Power system model

The training data set of an ANN should contain the necessary information to generalize the problem. Using the electromagnetic transient program PSCAD/EMTDC [13], a typical 500 kV single circuit transmission system of the type encountered in Egypt, Fig. 3, was simulated and the input/output pair patterns for training and testing the network were generated. The parameters of the Sending End (SE), Receiving End (RE) and their Short Circuit Levels (SCL) are as shown in fig. 3.

Training patterns were generated by simulating different types of faults on the power system. Fault location, fault resistance and fault inception time were changed to obtain training patterns belonging to a wide range of different conditions of the power system. Faults including high amount of resistance, up to 70 ohms, were also considered.

4.2. Feature extraction

Neural networks have the ability to classify different input patterns into desired output classes. The application of a pattern classification technique requires a selection of features that contain the information needed to discriminate between classes, and which permit efficient computation to limit the amount of the required training data and size of the network.

The voltage and current waveforms are the most available information in power systems. The sampled normalized voltage and current signals measured at the relay location are considered as the input data to the ANN. To ensure that the network is able to detect and classify the fault in a timely fashion, voltage and current waveforms are sampled at a rate of 64 samples/cycle (sampling rate is 3200 Hz). This sampling rate is compatible with the sampling rate commonly used in high-speed digital relays.

The fault voltage and current waveforms may undergo some changes in their frequency spectrum, due to the capacitor voltage transformers and current transformers in-addition-to the anti-aliasing filters, before they are finally introduced to the ANN based digital relay. Fig. 4 shows the frequency response of a typical Capacitor Voltage Transformer (CVT) [14]. The frequency spectrum of a typical Current Transformer (CT) can be represented by a wide band second order Butterworth filter, which attenuates partially the dc component and the high frequency noise [15]. However, it should be noted that the Butterworth filter representation of a CT excludes the saturation phenomenon that can occur in a CT. Hence, the above mentioned frequency spectrums for both the CVT and CT, together with a low pass anti-aliasing filter with a cut-off frequency at 1600 Hz, have been included in the PSCAD/EMTDC simulation of the power system shown in fig. 3. In fig. 5 the filtered 3-phase voltage and current waveforms, for a phase-to-phase fault (phases *a* and *c*) occurring after 0.517 s time mark at 10 km from SE, are shown. The Elman ANN was trained using the filtered voltage and current samples in order to match as close as possible actual values fed to a relay.

4.3. Network structure and training

For the ANN to detect and classify a fault, it should be able to indicate a "normal state" during a no fault condition. Once a fault occurs the ANN should indicate which phase or phases are involved in the fault. In order to reduce the number of output neurons as much as possible, which further reflects in a

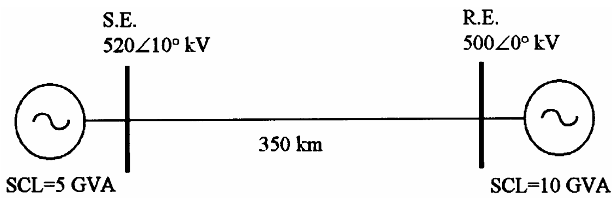

Fig. 3. 500 kV transmission system (part of Egypt national grid).

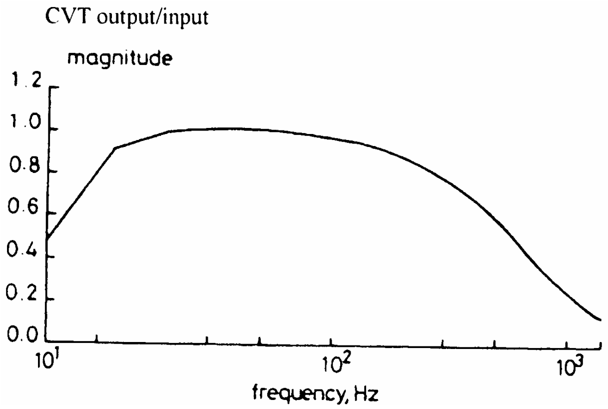

Fig. 4. CVT frequency response.

Table 1
Elman neural network outputs

Output neuron 1	Output neuron 2	Output neuron 3	Fault classification
-1	-1	-1	Normal state
1	-1	-1	Phase *a*
-1	1	-1	Phase *b*
-1	-1	1	Phase *c*
1	1	-1	Phases *a,b*
1	-1	1	Phases *a,c*
-1	1	1	Phases *b,c*
1	1	1	Phases *a,b,c*

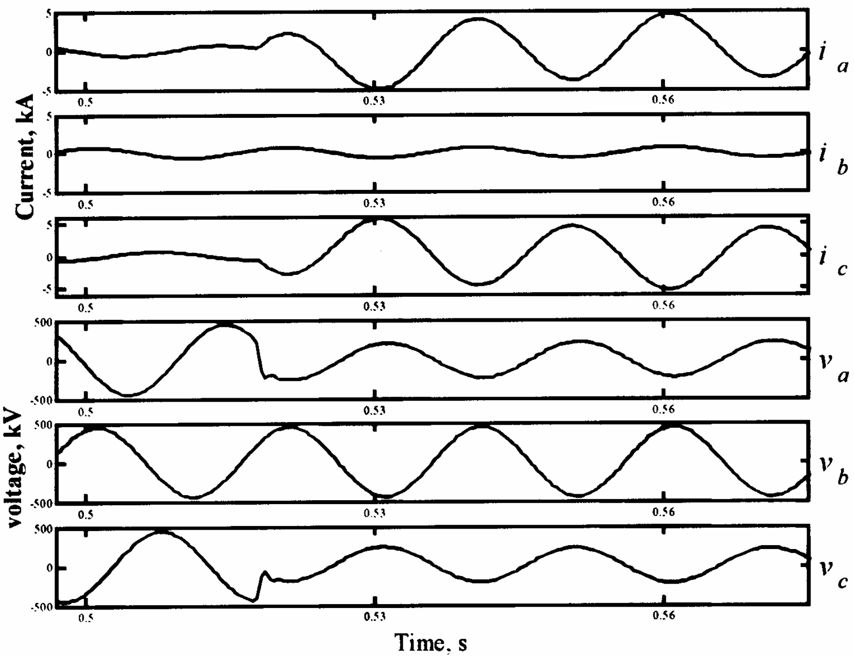

Fig. 5. 3-phase voltage and current waveforms for a phase-to-phase fault (phases *a* and *c*) occurring after 0.517 s time mark at 10 km from SE.

smaller structure for a neural network, and still obtain all the required output, it has been decided to have 3 output neurons only. In table 1 all the outputs of the proposed Elman ANN based fault detector and classifier module are shown.

A few different network structures, all having three outputs but with a different number of inputs and different number of neurons in the hidden layer, were considered and trained. Training patterns were generated by simulating different types of faults using the power system shown in fig. 3. Independent test patterns were also generated to validate the networks' performance. The tansig nonlinear function was chosen for both hidden and output layers of the network in order to achieve the requirements shown in table 1 [7].

Consecutive samples of three phase voltages and currents are usually chosen as inputs to the neural network [2-5, 10]. The appropriate input data window length is a major factor, which should be considered. In [2] each phase voltage and current was represented by its 5 consecutive samples (data window of 5 ms) and a 30 input MFNN with two hidden layers was designed. The Elman network has some kind of memory in its structure. Therefore, compared with the previously proposed 30 inputs network it should be able to use a smaller size of window and less number of inputs to cover the necessary input information to the network.

Various networks considered were trained to detect and classify a fault on a TL. The network that showed satisfactory results, while not having a big size, had just 24 inputs (4 consecutive samples of all three phase currents and voltages), 24 hidden neurons and 3 output neurons. The data window used in this case is only 1.25 ms.

The Elman ANN was trained using 120 different fault and normal state cases. Each case has 2 consecutive cycles; the first cycle is a pre-fault normal operation while the remaining cycle represents a fault. As each cycle is represented by 64 samples, so each case consists of 128 samples. The total training patterns were thus 15360. The back propagation algorithm as indicated in [7,8] was used for training the Elman ANN. However, the weights of the recurrent connections, fig. 2, are fixed at 1 and are not subjected to adjustment.

It should be noted that the proposed Elman ANN has a much smaller size than the MFNN fault classifier proposed in [2]. As it has 24 inputs, 24 hidden neurons and only 3 output neurons, while the MFNN has 30 inputs, 20 neurons in the first hidden layer, 15 neurons in the second hidden layer and 11 output neurons. Moreover, the Elman ANN required only 15360 training patterns to train, but the MFNN required 45360 patterns to train. Also the data window of the Elman network is 1.25 ms while that of the MFNN is 5 ms. Comparing the Elman ANN proposed in this paper with the other ANN proposed in [2,5,10], it is found that it has the smallest size and smallest data window, in-addition-to the least number of training patterns.

The trained network was tested with different independent test patterns and promising results were obtained. The results obtained indicate that the proposed network is able to detect and classify the fault very fast and reliably. Some of the simulation results are presented in the next section.

5. Simulation results

The proposed Elman network was tested with a set of 100 different faults including very extreme cases like faults at the far end of the TL with high amount of fault resistance. In all cases the network was able to detect and classify the fault accurately. The network output for a few faults with different power system conditions is presented in this section.

The output of the network for different types of faults on the TL is shown in fig. 6. Fault location was 300 km from the relay location at the SE, with fault resistance of 10 Ω and fault inception time of 20.6 ms, which correspond to sample number 66. For each fault, the output of the recurrent network is represented for the prefault condition and then during the first three cycles after the fault inception. Different faults involve different phases and ground as well. Fault type *ag* indicates a single phase to ground fault (phase *a* to ground), while fault type *bc* indicates a phase to phase fault (phases *b* and *c*). This figure shows that the detection and classification is very fast and reliable. The output of the network is stable for 3 cycles after fault inception, although the network was trained with the data samples of the first cycle after fault inception.

A feed forward network structure classifies different input patterns independently. The order in which the patterns are presented to the network is not considered. There is a possibility that for some extreme cases two consecutive input patterns would be classified into different classes. During such extreme cases the network output may become oscillatory [1-4]. To further increase the reliability of a network, a post processing output averager is usually used [2-5] to smooth up the output of the feed forward neural network. For the recurrent network, the output of the network depends on the present input as well as the previous history of the inputs. Its track is smooth; it does not jump from one region to another region. The output smoothly increases/decreases from zero towards 1 or -1. For the recurrent network, therefore, averaging would not be necessary and it can be used as a stand-alone unit.

There are 3 neurons in the output layer, where each neuron is associated with one phase as indicated in table 1. So, it has been decided that the neuron output with a value higher than zero will be interpreted as a faulted phase. For the faults presented in fig. 6, it takes at most 5 samples and at least 3 samples for the output of the recurrent network to classify the fault. On average the fault classifier module needs less than 2 ms after fault inception to detect and classify the fault.

The next set of simulation results test the performance of the Elman network for faults at the far end of the protection area with 70 Ω fault resistance. Different faults were applied at 335 km from the relay location and the results are shown in fig. 7. It shows that the network performed correctly for the far end faults even in the presence of very high amount of fault resistance.

Fig. 8 shows the output of the network for different faults during about five cycles after the inception of a fault. The sending end source impedance was reduced by a factor of 5. Outputs of the network in all cases classify the fault correctly. The fault detection and classification is very fast. The output of the network is stable, although the network was not trained with the data samples of reduced

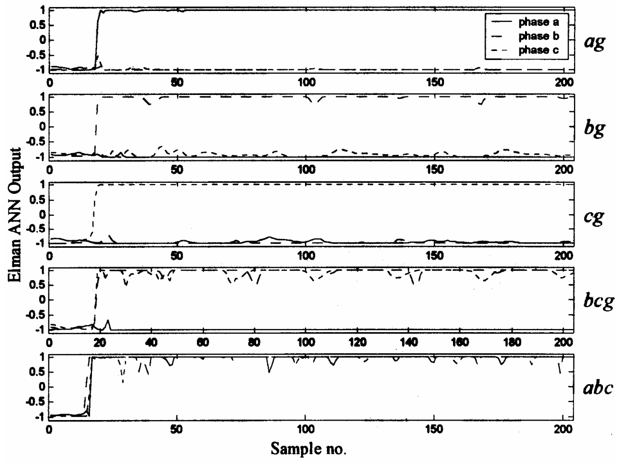

Fig. 7. Elman network response to faults at 335 km from SE, fault resistance is 70 Ω and fault inception time is 5 ms (sample number 16).

source impedance at the sending end. This study demonstrates that the proposed method is not affected by the variation of the source impedance. This means that the Elman network can work accurately for other transmission systems without the need for further training.

The results presented demonstrate the performance of the network for some extreme fault cases. In general, the network performs better and faster for more usual cases such as low resistance faults around the middle of the protected area.

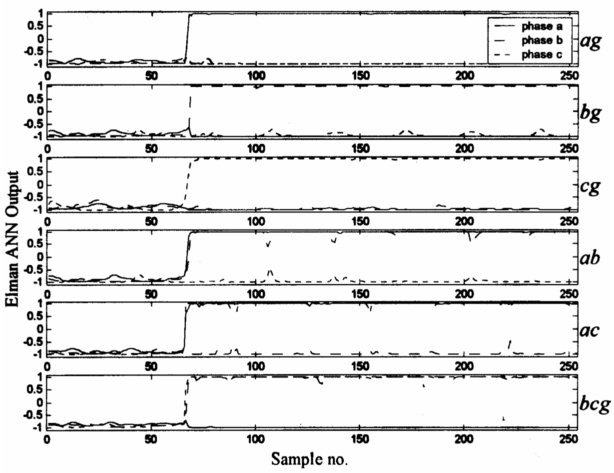

Fig. 6. Elman network response to faults at 300 km from SE, fault resistance is 10 Ω and fault inception time is 20.6 ms (sample number 66).

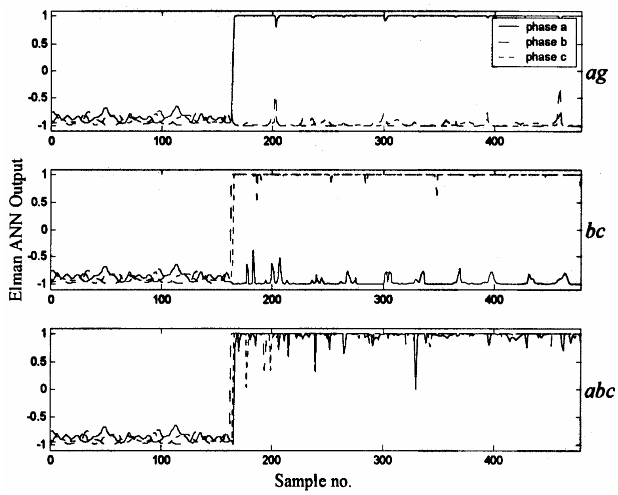

Fig. 8. Elman network response to faults at 200 km from SE, fault resistance is zero and fault inception time is 51.5 ms (sample number 164).

6. Conclusions

A novel fault detection and classification module for protecting transmission lines is described in this paper. The proposed approach is based on the use of recurrent neural network technique. The recurrent connections provide the neural network with memory. The designed neural network uses samples of all three phase voltages and currents from one end of the line to classify the fault. The classification module network is extensively tested by independent test fault patterns and promising results are obtained. The performance of the Elman network is also checked for faults including high amount of resistance. Extensive studies indicate that the network is able to classify faults in less than 2 ms. The classification is not affected by the type and location of the fault, the variation of the source impedance and the presence of fault resistance. The results show that the network is very powerful in processing the voltage and current temporal input signals. Elman neural network based approach can thus be successfully used as a part of a new generation of high-speed relays for power systems.

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