An ANN system to on-line detection of sag, swell and transient voltages

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Abstract. The analysis of power quality in electrical power systems includes the study of transient disturbances as frequency variations, sags, swells, flicker or interruptions. In this paper it is presented a measurement system of some transient disturbances based on Artificial Neural Networks. A feedforward network has been off-line trained to detect the initial time, the final time and the magnitude of voltage sags and swells. The designed system will be applied to detect transient voltage in electrical power systems. The performance of the designed measure method will be tested trough a simulation platform designed in ®Matlab/Simulink through the analysis of some practical cases.

Keywords

Electrical power quality, transient disturbances, measurement, artificial neural networks, feedforward

1. Introduction

The modern electrical equipment needs a high quality supply voltage. The problems appear with voltage disturbances as frequency variations, sags or dips, swells, flicker or voltage interruptions, [1,2]. For a suitable detection of the different disturbances [3], the adequate measurement method must be chosen.

The artificial neural networks (ANNs) had been applied successfully in several topics of the Electrical Engineering, including the detection of some voltage disturbances [4,5]. The calculation speed and parallelism are the main advantages of these techniques. In this work, a Feedforward ANN has been designed for transient disturbance measurements. Voltage sags and swells and transient voltage surge will be on-line detected. This fact is important because will be possible, i.e., a fast disconnection of sensible electrical devices when disturbance voltage occurs.

To probe the performance of designed measurement system, a feedforward network has been trained and simulated in a Matlab/Simulink platform. After an off-line training process using a Backpropagation algorithm, the network was connected to an electrical system for the on-line detection of supply voltage distrubances. The results of some practical cases will verify the suitable performance of the designed network.

2. Feedforward ANN architecture

The Artificial Neural Networks includes a large number of strongly connected elements: the artificial neurons, a biological neuron abstraction. The model of an artificial neuron in a schematic configuration is shown in figure 1

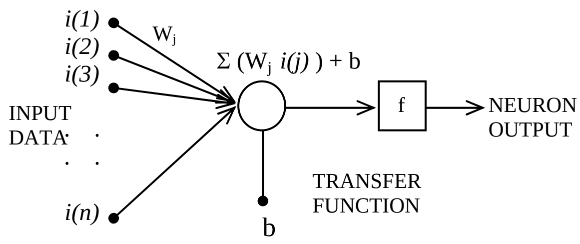


Fig. 1. Artificial Neuron Model

The input data *i(1), i(2), i(3), …, i(n)* flow through the synapses weights W_j. These weights amplify or attenuate the inputs signals before the addition at the node represented by a circle. The summed data flows to the output through a transfer function, f, which may be the threshold one, the sign one, the linear threshold one or the pure linear one. Otherwise, it may be a continuous non-linear function like the sigmoid one, the inverse tan one, the hyperbolic one or the gaussian one, according the application.

The neurons are interconnected creating different layers. The feedforward architecture is the most commonly adopted. The scheme is shown in figure 2.

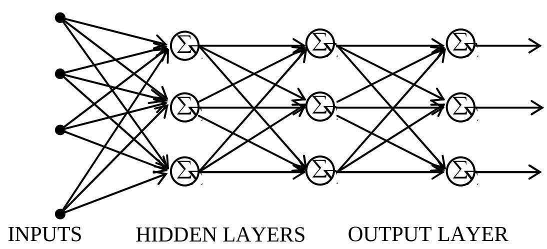


Fig. 2. Feedforward Neural Network Architecture

The feedforward ANN scheme includes the inputs, some hidden layers, an output layer and the outputs. In figure 2, the circles represent neurons. The number of output layer neurons is equal to the number of outputs. Thus, the feedforward architecture computes the input data in parallel way, faster than the sequential algorithm of the computers.

This network can be trained to give a desired pattern at the output, when the corresponding input data set is applied. This training process is carried out with a large number of input and output target data. These data can be obtained using a simulation platform or an experimental system. The training method most commonly used is the backpropagation algorithm. The network is initially untrained and is initialized with random weights.

The backpropagation training process includes two phases: in the first one an input is presented to the network, that is propagated to the output. In each neuron of different layers is calculated.

$$\hat{y}(k) = f\,[\sum_{j}(W_j \cdot i(j)) + b] = f(v) \qquad (1)$$

In equation 1, v is the activation potential of the neuron and $\hat{y}\,(k)$ represents the neuron output at the iteration k. Thus, the network output $\hat{o}$ is obtained at the output layer.

In the second phase, the error between the desired output of the network and the real output, *e(k)*, is propagated to the back, adapting the network weights to minimize the addition of square errors in the output layer, $\varepsilon(k)$.

$$e(k) = o(k) - \hat{o}(k)\,, \quad \varepsilon(k) = \sum_{j \in O} e_j^2(k) \qquad (2)$$

Where *o(k)* is the desired output and *O* is the set of output neurons. In this phase, the neuron outputs remain constant, and the weights are changed according the following formula.

$$\Delta W_{ij}(k) = \eta \delta_j(k) y_i(k) \qquad (3)$$

W_{ij} represents the weight between the neurons i and j, η is the learning rate, $y_i(k)$ are neuron inputs that coincides with outputs of the preceding layer neurons, and $\delta_j(k)$ is the local gradient of the neuron, that is defined as

$$\delta_j(k) = -\frac{\partial \varepsilon(k)}{\partial v_j(k)} \qquad (4)$$

The initial output pattern is compared with the desired output pattern and the weights are adjusted by the algorithm to minimize the error $\varepsilon(k)$. The iterative process finishes when the error becomes near null.

In this work, the neural network has been designed with three inputs, corresponding to the voltage at three consecutive time instants *v(t)*, $v(t\text{-}\Delta t)$ and $v(t\text{-}2\Delta t)$, two hidden layers of 20 and 12 neurons with sigmoid transfer function, and an output layer with only one neuron with pure linear transfer function.

3. Simulation model

In this work, the proposed measurement system has been simulated using a ®Matlab/Simulink platform. The design, the off-line training process and the emulation of the ANN was developed using the Neural Network toolbox.

To carry out the network training process, a set of input voltage waveforms was generated. Voltage sags of length and depth known, figure 3, were added to sinusoidal voltage waveform. The training input data collection was completed with voltage sags of several lengths and depths. It was necessary, not only to include samples of several magnitude sags in the training data set, but also voltage sags of different initial and final instants, t_0 y t_1, to train correctly the network, and it can respond better to the presence of sags that can begin and finish at any time instant between a signal period.

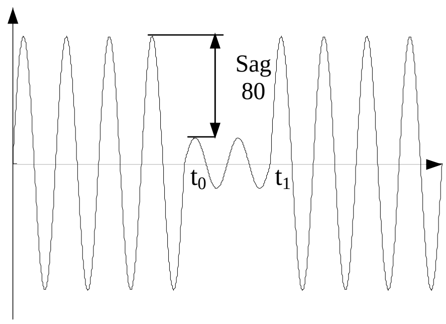


Fig. 3. Example of voltage sag

Figure 4 shows the Simulink diagram used to generate the network inputs.

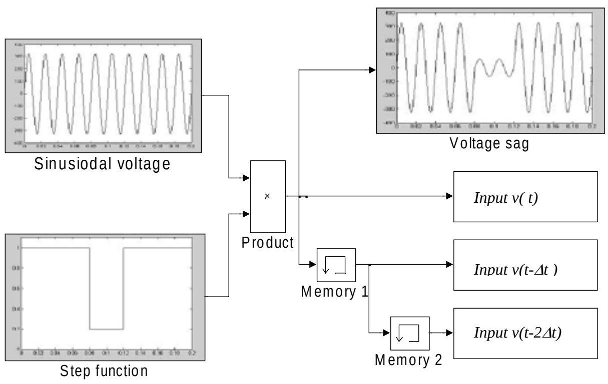


Fig. 4. Simulink diagram of input data generation

An incremental algorithm was applied to train the neural network, in which three inputs data are considered in each time step, corresponding to *v(t)*, $v(t\text{-}\Delta t)$ and $v(t\text{-}2\Delta t)$. Δt is the time step between two consecutive instants. The relative voltage amplitude was considered as desired network output. So, the output will be o =1 if the voltage has the nominal value and o = 0,2 when the voltage sag has a 80% depth.

The training process of the neural network was carried out helped by the Neural Network Matlab toolbox, using the *trainlm* function. Different network topologies were issues. Figure 5 shows the error evolution during the training process using an ANN with 8, 4 and 1 neurons and figure 6 using an ANN with 20, 12 and 1 neurons, the topology that has been adopted in this work.

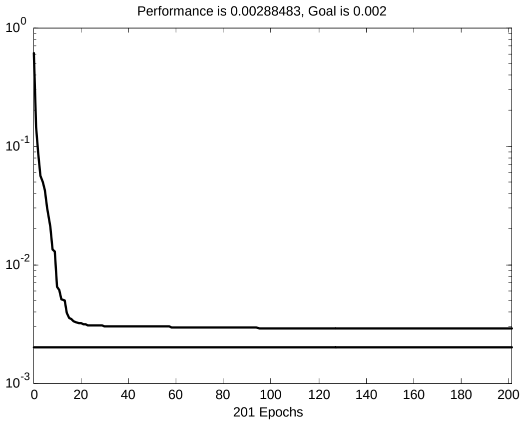


Fig. 5. Error evolution during the training process of neural network with 8, 4 and 1 neurons.

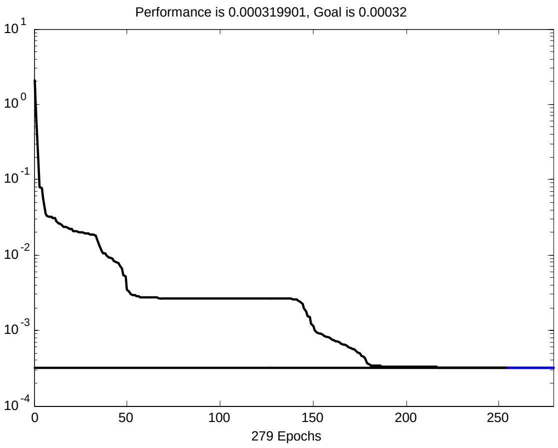


Fig. 6. Error evolution during the training process of neural network with 20, 12 and 1 neurons.

In the first case the maximum error didn't became small, and in the second case the maximum error was minor than 0,032 %.

In a first design, the neural network responded with a considerable peak when the input signal is crossing by zero. An improved training process has been carried out to correct this behaviour. Sinusoidal wave samples with different phases were utilised. Thus, the neural network responds in a better way with very small waves.

The new training process is more robust, and the behaviour of the neural network is adequate with signals including any phase. Besides, it is possible to detect disturbances minor significant. Figure 7 shows the error evolution in the final training process developed.

After this training process, a Simulink block with *sim* function is used to issue the designed measurement system in different situations.

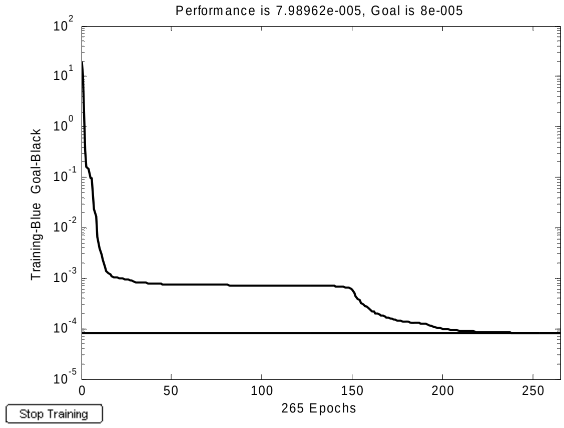


Fig. 7. Error evolution during the training process with out-of-phase samples

4.   Results of practical cases

A. Detection of ideal sags

After the network training process, the measurement system performance was tested in the presence of three voltage sags of 69%, 44% and 18% which happens in different time instants. The voltage waveforms are shown in figure 8, and the results of the designed measurement system are shown in figure 9.

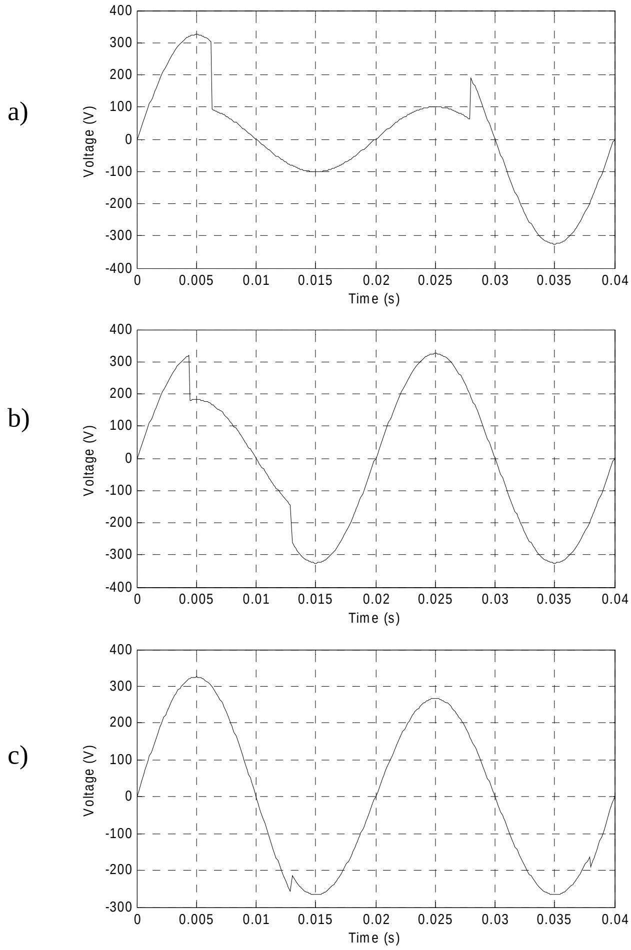


Fig. 8. Voltage waveforms of the three voltage sags

a)

b)

c)

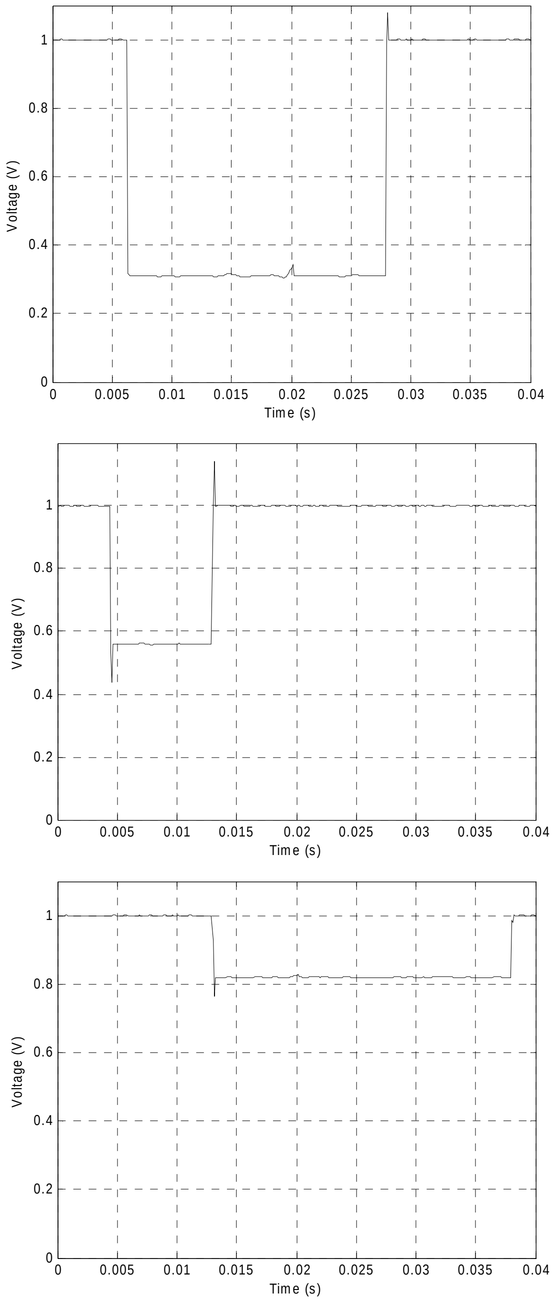


Fig. 9. Output of the network in the presence of a) 69%, b) 44% and c) 18% voltage sags

It can be appreciated that the network works in a suitable form, detecting the voltage sag, including the initial and final instant, and the duration of the sag.

The ANN outputs are s = 0,31 for the first sag, s = 0,56 for the second sag, and s = 0,82 for the third sag.

Three voltage inputs at t, $t\text{-}\Delta t$ and $t\text{-}2\Delta t$ times are needed to guarantee an adequate dynamic response of the neural network. For this application, it is chosen a value of Δt = 0,1 ms, and the answer time of the neural network results 0,2 ms. The simple time must be the same that those used in the training process for a correct working of the network. To detect more rapid disturbances will be necessary considerer other Δt values.

The network was tested in the presence of micro sags of small lengths. Figure 10 shows the behaviour of the network in the presence of microsags of 0,3 ms.

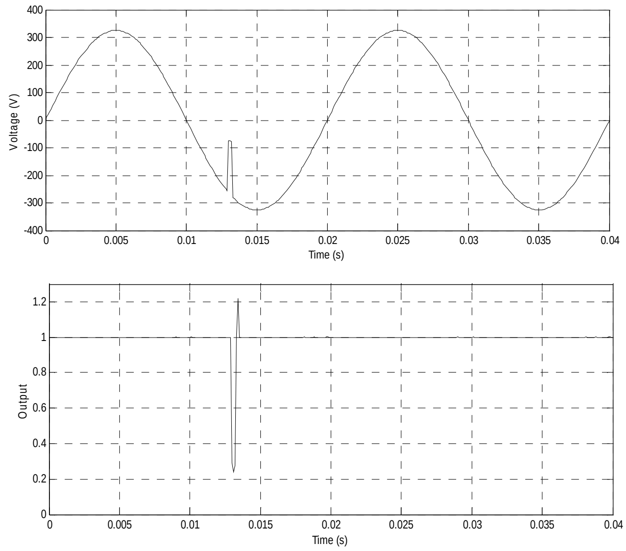


Fig. 10. Voltage waveform with a microsag and output of the neural network

B. Detection of ideal swells

The neural network was too trained to detect voltage swells. The training process was very similar that those used for the detection of sags. As example, figure 11 shows the results when a 205% swell occurs. The ANN output is 2,05.

a)

b)

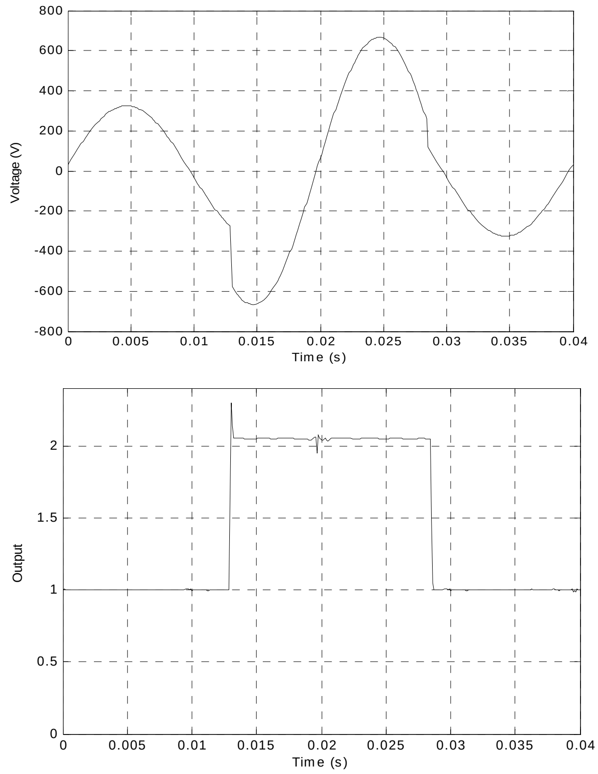


Fig. 11. a) Ideal voltage swell and b) output of the network

C. Detection of transient voltages

The neural network has been applied to detect voltage transients. The analysis of the error signal between the original voltage and the network output is very large when the transient is fast. This is because the neural network estimates very good only sinusoidal waveforms. Therefore, the initial and final instants of the transient can be correctly determined by means of the study of the square error, in a similar way as some network analyzers works.

In figure 12, a voltage transient signal used as example to test the neural network behaviour is shown. A transient period is beginning at instant 45 ms.

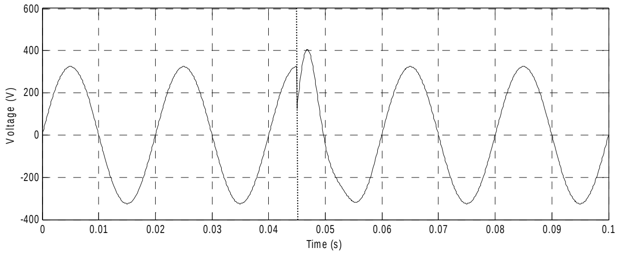


Fig. 12. Voltage transient signal

Figure 13 presents the estimated signal of the neural network and the error between that signal and the real one.

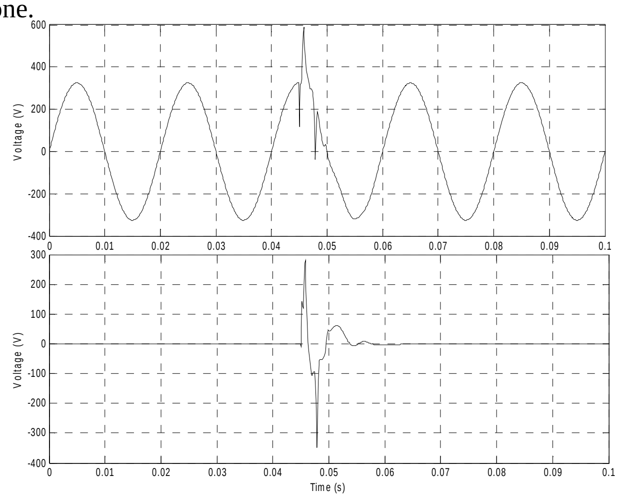


Fig. 13. Estimated and error signal of the neural network

Figure 14 shows the square error used for the detection of the initial and final times. The initial instant is calculated when the square error is major than a threshold. The final instant was calculated when the square error turn down the threshold. In the example, it was measured 45,1 ms as initial time.

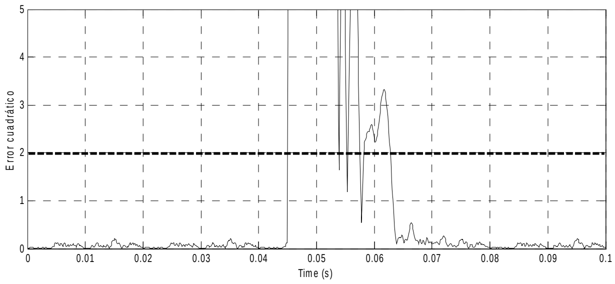


Fig. 14. Square error signal

D. Electric Power System application

Finally, the performance of the neural network with the occurrence of a fault in an electric power system was tested. That power system is represented en figure 15 and it was simulated in Matlab/Simulink helped by SimPowerSystem blockset.

The system includes a 20 kV voltage source connected to a 20kV/400V transformer. Two loads are supplied trough a distribution line. The first load is localized in the middle of the line, with the addition of a capacitor bank to improve de power factor. The second load is connected at the end of the line with another capacitor bank. A three-phase fault occurs in the point of connection of the second load. The initial instant of the fault is 16,67 ms and the final instant is 133,3 ms.

The voltage V_{RN}, figure 16a, was measured at the point of connection of the first load. The neural network detected initial and final time and the magnitude of the voltage sag (figure 16b).

In figure 16, the voltage at the measurement point and the output of neural network are presented in per unit values.

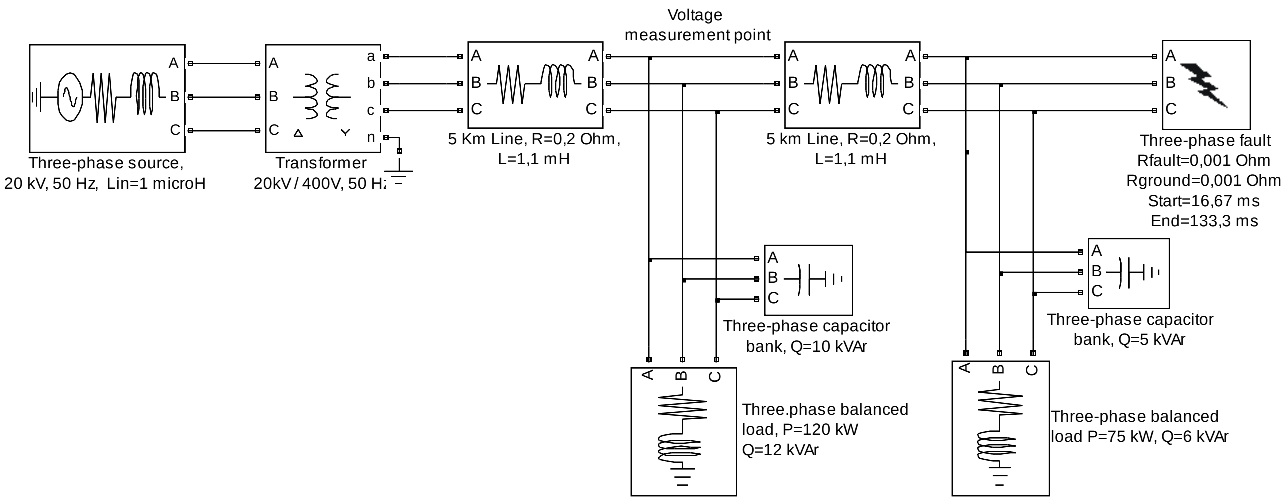
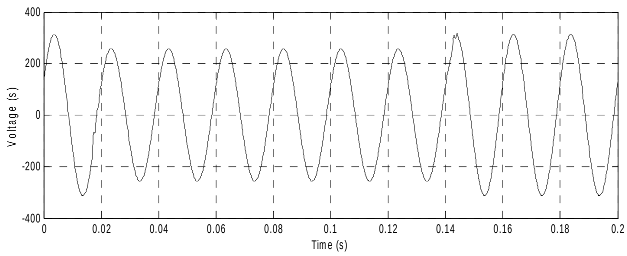
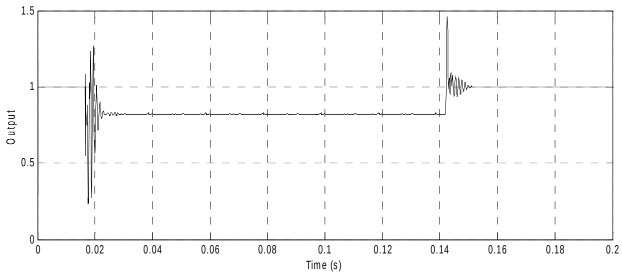


Fig. 15. Simulink scheme of the simulated electric power system



a)



b)

Fig. 16. Estimated voltage and per unit output of the neural network

The measured voltage during the sag is 181,8 V and the neural network output is *o*=0,82. The output of the network presents oscillations at the beginning and at the end of the sag during the transient periods.

5. Conclusions

A procedure to measure on-line voltage disturbances using artificial neural networks has been presented. A feedforward neural network has been designed and trained with a backpropagation method, using input/output data supplied with computer simulations. To have an adequate dynamic response of the disturbance detection system, three inputs were considered for the neural network, the voltage at instant t, and at two preceding instants, $t-\Delta t$ and $t-2\Delta t$.

The neural network was satisfactorily tested for the detection and measurement of different voltage sags and swells and for the detection of transient voltages in electrical power systems.

The proposed measurement system can detect disturbances with duration of 0,2 ms. The detection delay is 0,1 ms approximately in this work using a 10 kHz sampled waveforms in the training process. This method could be applied to faster phenomenon detection with the adequate ANN training process.

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