Application of Artificial Intelligence Methods for Determination of Transients in the Power System

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***Abstract*--Numerous factors, including sudden load reductions, switching transient loads, lightning strikes, and malfunctions of control devices, can result in overvoltage. Overvoltage can harm associated power supply components and result in insulation failure, electronic component damage, flashovers, etc. A machine learning technique called a "neural network" estimates computation results that depend on a lot of inputs. For a variety of reasons, neural networks have recently been used to manage and optimize the power system. This paper presents an artificial neural network (ANN)-based approach to determining overvoltages in power systems. To simulate overvoltages, many simulations were performed in Electromagnetic Transient Program (EMTP). Variations of parameters of interest that have an influence on overvoltages were made using JavaScript that was connected to EMTP models. The extraction of characteristic parameters from overvoltage waveshape is a demanding task, and it was conducted in MATLAB, as was a overvoltage classification methodology based on neural networks. Results were presented and discussed.**

***Keywords*: artificial neural networks, lightning, modelling, overvoltages, switching, transmission line.**

I. Introduction

PROVIDING customers with a reliable and high-quality power supply is the major objective of the power system. Therefore, effective supervision and management of the power system are required. Electric power networks are evolving, and along with that, there are more potential issues that might occur. In addition to human resources, it is necessary to use computers and proper tools that provide quick analysis and reaction in order to respond to all potential scenarios in a professional manner.

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Artificial intelligence may significantly reduce the burden on operational staff while simultaneously increasing the effectiveness of problem solving and problem handling. This is one of the leading reasons behind the investigation and use of artificial intelligence in electrical engineering and power systems [1].

Unfortunately, power system outages are common. In most cases, it is necessary to turn off the power in the part of the power system where the fault has occurred. Transient events, which can have a variety of sources, are one of the main factors that contribute to failures. They can result in electrical failure of the power system's components, damage to the insulation of the power system's components, and a number of other adverse effects [2], [3].

Therefore, it would be important to observe, analyze, and classify surges in the power system to implement the appropriate management and operating changes for the system.

IEC 60071 and IEEE Std. 1894 classify voltage stresses based on the length of a power-frequency voltage or the form of an overvoltage and how they affect the insulation or the protective device. The classes include slow front overvoltages, fast front overvoltages, extremely fast front overvoltages, temporary front overvoltages, and mixed overvoltages [4], [5].

Switching overvoltages and lightning-caused fast front overvoltages are common in power systems, and they are taken into consideration for this work. The main idea was to evaluate the occurrence of these overvoltages using artificial intelligence. Two software packages EMTP and MATLAB, as well as JavaScript were employed to put the idea into practice.

This article's major contribution is a novel method for identifying overvoltages in power systems. This approach consists of a few steps, as follows:

- Modelling of power system components for transient studies in EMTP. This means developing two different models, one for switching overvoltages, and the other one for fast front overvoltages.
- Creating and deploying JavaScript to automate the simulation process and parametric analysis.
- Overvoltage feature extraction from generated overvoltage waveshape using harmonic analysis in MATLAB.
- Overvoltage classification using neural network in MATLAB.

The rest of the paper is organized as follows: Section II describes the basics of the artificial neural networks that were used for the purposes of this paper. Section III describes in detail the modeling procedure of power system components in EMTP as well as the overvoltage classification methodology.

Results and discussions are performed in Section IV, and the paper is concluded in Section V.

II. Artificial Neural Networks

In an attempt of making the improvements in deep learning procedures, one of the greatest subfields of data science, an artificial neuron (AN) was made. A potential of ANs reflects in handling a wide range of issues, including handwriting recognition, face detection, image recognition, finding optimal solution in specific case scenario, recognition of internal voltage in distribution network, fast assessments, classifications, and so forth.

In the simplest, AN represents single threshold gate capable to process inputs and create appropriate output [6]. The appearance of the artificial neuron is presented in Fig. 1.

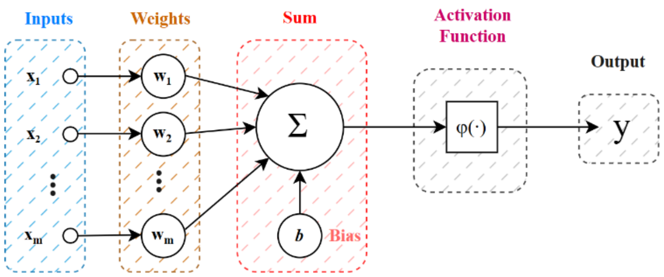

Fig. 1. Artificial neuron

In the case of an AN, the signals which come to the input are summed up (x_1, x_2, ..., x_m), taking into account the weighting factor for each input parameter (w_1, w_2, ..., w_m). After addition with the AN's bias value, output triggers only if the calculation result exceeds certain threshold. The activation principle is solely based on activation function φ(·) used at the gate.

Combining ANs on the basis of similar working mechanism, creates grid capable for data manipulation, named perceptron [7]. In a present comprehension, a perceptron can be perceived as simple single-layer or multi-layer network of ANs. This paper shows performance of the single-layer perceptron and how those results compare to the ones obtained with more complex installations.

The foundation of neural networks lies in the idea that connections between neurons are not equally weighted. Based on its inputs, a neuron produces an output while taking the connections' strength with the previous one into account. By this concept, principle of the natural neural network is integrated into artificial neural networks (ANNs). Certain mathematical functions are used to form the output of neurons. This process is repeated throughout the entire structure of neurons, making the network "learn" to solve a variety of issues by using algorithms that mimic or replicate the operations of actual neurons [6].

Trying to reproduce information propagation paths with the processing of data, ANs are mainly based on supervised learning. For the quality functioning of ANNs, it is necessary to determine the strengths (weights) of the connections between neurons. This is obtained with training artificial neural networks by sending them a large set of data with known outcomes (solutions). Following this procedure, optimal strengths (weights) of connections between neurons are obtained.

The representation of ANNs is shown in Fig. 2. It consists of multiple layer structure containing inputs, outputs and inner hidden layer(s). Fig. 2 shows a network where all the neurons of one layer (first with weights w_{11}, w_{12}, ... w_{m1}, ... w_{mp}) are connected to the neurons of the next layer, the second with the third and so forth as this represents a fully connected network. The type of problem being solved determines the neural network's topology and the connections between its layers.

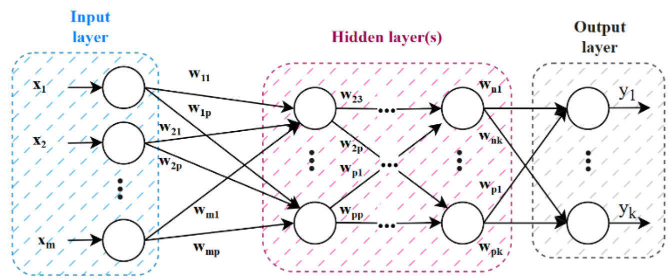

Fig. 2. Artificial neural network

More than the single-layered perceptron stated earlier, two other types of networks have been used in this paper. Feedforward neural network (FFNN) could consist minimum of the three layers (single hidden layer) as in [8], or differently organized multi-layered network with alternating nodes in each layer as in [9]. This paper shows results for ANNs with single and multiple hidden layers, as well as the results from neural networks with radial basis. The latter mentioned, represents network which contain a radial activation function in each ANs and propagation principle of FFNN as in [10].

III. Modelling Procedure

Two software tools, EMTP and MATLAB, were used to obtain proper modeling of all power system elements and all analyzed phenomena, as well as for data analysis and result presentation. Parametric analyses were conducted using self-developed Java Script that is linked with EMTP to automatize simulating process due to many simulations. Block diagram of neural network training and proposed classification methodology is shown in Fig. 3.

A 110 kV transmission line was modelled in EMTP. Two different models were developed, one for simulating switching overvoltages and the other one for simulating fast front transients. This section describes both models in detail. Also, surge arresters are modelled in both the cases, but some simulations are performed with surge arresters and some of them without using surge arresters.

Parameters that were varied for the simulation of fast front overvoltages:

- lightning stroke parameters (peak value, front and tail time),
- stroke location (the distance from the beginning to the end of the transmission line),
- stroke to the shield wire or phase conductor,
- value of voltage when lightning strikes

- and the presence of surge arresters.

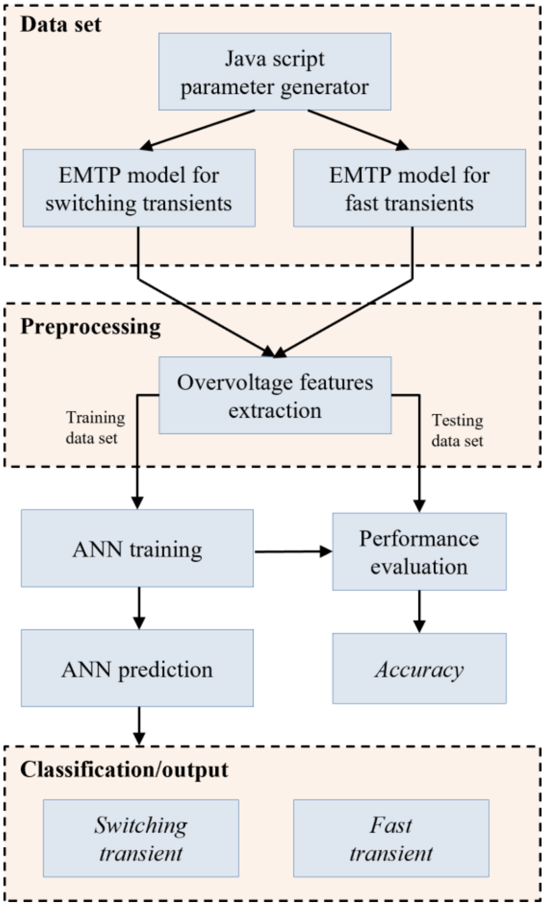

Fig. 3. Block diagram of neural network training and classification methodology

For simulation of switching overvoltages, the following parameters were varied:

- types of short circuits that cause switching operations (one phase, two phase and three phase short circuit),
- distance of short circuit from substation,
- value of voltage when switching operations occurs,
- and presence of surge arresters.

Overvoltages of interest were recorded in all three phases and in all simulations. Furthermore, overvoltages were analyzed using MATLAB, and characteristic parameters were determined, including amount of overvoltage, duration, and harmonic analyses. MATLAB was also used for the implementation of neural networks for detecting overvoltages in power systems.

A. Modelling in EMTP

Two models that were developed in EMTP are:

- Model I for simulating switching overvoltages due to switching on transmission line, switching off transmission line, and due to automatic reclosing operation, which was initiated due to fault along the line;
- Model II for simulating fast front transients that are caused by lightning.

All simulations were run using three-phase models, but single-line schemes for the modelled parts of the system are shown in Fig. 4 and Fig. 5 for better illustration and presentation.

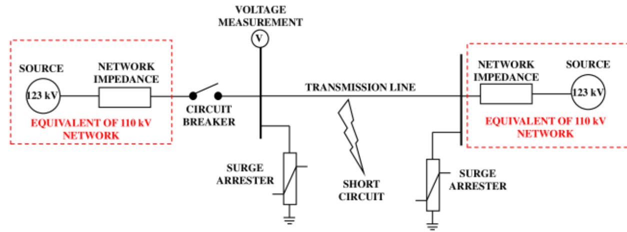

Fig. 4. Single-line scheme for simulating switching transients (model I)

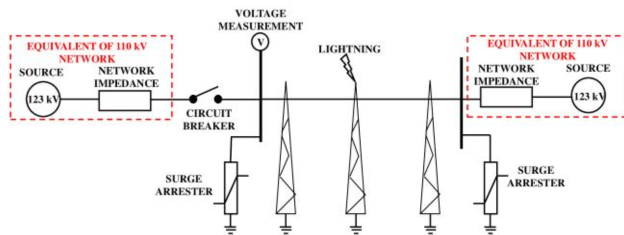

Fig. 5. Single-line scheme for simulating fast front transients (model II)

Model I consists of 110 kV transmission line and substations on both ends of the transmission line. In this model, parts of the power system are modeled as follows.

Transmission line sections are modelled as constant parameter (CP) lines. To permit connection between the fault and the middle of the span for phase conductors, the phase conductors are subdivided into a number of segments.

In the model I a 110 kV network is represented with a three-phase source with a maximum line voltage of 123 kV and positive and zero-sequence impedances. Coefficient α is ratio of reactance X to the resistance R of analyzed power system, it is given by (1) and values are selected according to the [11].

$$\alpha = \frac{X}{R} \tag{1}$$

Then, positive and zero-sequence Z_d and Z_0 respectively, are calculated according to equations given in [12]:

$$Z_d = \frac{U_{max}^2}{S_{tpsc}} = \frac{U_{max}}{\sqrt{3} I_{tpsc}} \tag{2}$$

$$Z_0 = U_{max}^2 \left(\frac{3}{S_{spsc}} - \frac{2}{S_{tpsc}} \right) = \frac{U_{max}}{\sqrt{3}} \left(\frac{3}{I_{spsc}} - \frac{2}{I_{tpsc}} \right) \tag{3}$$

where U_{max} is maximum equipment voltage, S_{tpsc} and I_{tpsc} are three-phase short circuit power and current, S_{spsc} and I_{spsc} are single-phase short circuit power and current.

Sequence data: zero resistance R_0 and positive resistance R_d as well as zero reactance X_0 and positive reactance X_d can be calculated based on (1), (2) and (3).

$$R_d = \frac{Z_d}{\sqrt{1 + \alpha^2}} \tag{4}$$

$$X_d = \alpha R_d \tag{5}$$

$$R_0 = \frac{Z_0}{\sqrt{1 + \alpha^2}} \tag{6}$$

$$X_0 = \alpha R_0 \tag{7}$$

The circuit breaker is modeled as an ideal switch. Phase voltage measurements were performed behind the circuit breaker, that is, at the beginning of the transmission line.

In both model I and model II surge arresters were modelled with following characteristics.

- Rated voltage: 108 kVrms
- MCOV: 86 kV
- IEC class: II
- Nominal discharge current: 10 kA

The nonlinear behavior of the line surge arrester is represented by the current-voltage (U–I) characteristic from [13].

Model II, used for simulating fast front transients, is based on model I with additional elements. The substations are represented as the voltage sources with a impedance, as it is explained in model I. Towers, insulators, phase conductors, shield wire, line surge arresters, and tower footing resistance are some of the components used to represent the transmission line. The 110 kV transmission line under investigation has 144 towers and is 42.09 kilometers long. A line or span between two towers is assumed to have a mean length of 300 meters. The soil resistivity is 1200 Ωm, while the tower footing resistance value is adjusted to account for the fact that the line's footing resistance varies throughout its path.

There are four sections that represent each tower. The first section of the tower is the segment between the bottom crossarm and the ground, and the second segment is the section between the top of the tower and the top crossarm. Sections in between the crossarms make up the third and fourth parts. In EMTP software first section is modelled as single phase CP line element.

Inductance branches are used as models for three other sections. On the tower top, transient calculations were achievable using this method. The tower shape theory is used to compute tower surge impedance [14]. According to the section length, tower surge impedance, and propagation speed, branch inductances are calculated. The velocity of light was assumed to be the same as the wave propagation speed on the tower.

The Air Gap elements are used to simulate the insulators. This model operates based on the equal area flashover model and details of this model can be found in [15].

The shield wires and the phase conductors are subdivided into number of segments. Each segment is presented with a multiphase CP line (three phases and shield wire).

To permit connection between the current source and the middle of the span for the shield wire and the phase conductors, each span of 300 m is split into two segments. The subcircuit element that represents the transmission line section is made up of a number of tower subcircuit components, including spans, line surge arresters, grounding footing resistances, and the associated pins (for connection with other elements).

Lightning stroke is modelled with so called CIGRE model that is incorporated into EMTP. Lightning current parameters that were varied in simulations are:

- Current peak;
- Front time;
- Tail time;
- Steepness.

Lighting strokes to shield wire and phase conductors were simulated and position of lightning stroke along the line was also changed.

Overvoltage waveshapes simulated in EMTP due to switching operation, lightning stroke to shield wire and phase conductor are presented in Fig. 6. To make overvoltages more noticeable, Fig. 6 shows a single-phase representation.

On graphs in Fig. 6 are shown different types of the waveshapes of simulated overvolages:

1. On the first graph is shown overvoltage on one of phases due to lightning stroke to shield wire (parameters of stroke: I_{max} = 40 kA, t_f = 2 μs, t_h = 75 μs, S_m = 30 kA/μs, distance 5 km)
2. On second graph is shown overvoltage due to lightning stroke to phase conductor (parameters of stroke: I_{max} = 31 kA, t_f = 3 μs, t_h = 75 μs, S_m = 26 kA/μs, distance 5 km)
3. On third graph is shown overvoltage due to switching on of transmission line.

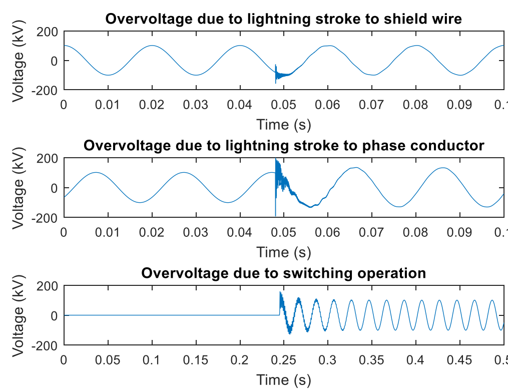

Fig. 6. Overvoltage waveshapes simulated in EMTP

B. Parameters for determination of transients

There are two types of overvoltages of interest, and these are switching and fast front overvoltages. These two types of overvoltages have different considerably features which include overvoltage peak, overvoltage duration and front and tail time.

For the purpose of neural network training and testing following set of features were selected and extracted from simulation results:

- Amount of overvoltage (in per unit);
- Duration of overvoltage;
- Total harmonic distortion (THD) factor.

Total harmonic distortion (THD) is often used as a measurement of harmonic distortion of signal. It is defined as the ratio of the sum of the powers of all harmonic components to the power of the fundamental frequency.

THD is calculated based on harmonic analysis using equation:

$$THD = \frac{1}{V_1}\sqrt{\sum_{k=2}^{N} V_k^2} \quad (8)$$

where V_k is RMS voltage of k-th harmonic.

Selected features are calculated from the simulated voltage signal. The code that specifies these signal parameters has been created in MATLAB and it is based on harmonic analyses.

IV. Results and Analyses

The results of artificial neural networks in MATLAB and their analysis from the point of view of efficiency and accuracy are presented below. The total number of examples used for training and testing is 1000, of which 650 are switching overvoltages (350 transmission line switching on overvoltages and 300 transmission line switching off overvoltages) and 350 fast front overvoltages. The codes are written in such a way as to enter the number of examples to be used in training and testing (equal number from each type). Examples for training and testing are chosen randomly each time the code is run.

This section will present the results of artificial neural networks used to distinguish switching (designation S in table 1) and lightning (designation A in table 1) overvoltages. The three types of artificial neural networks were used to classify overvoltages:

- Perceptron;
- Feedforward neural networks;
- Neural networks with radial basis.

Accuracy of classification, defined as number of correctly classified test examples in relation to total number of testing examples, was used for evaluation of neural network performance. The influence of the number of training examples and neural network parameters on the results will be presented.

Perceptron

Since perceptron is a single-neuron neural network, only the influence of the number of training examples is shown in table 1.

TABLE I
Perceptron Results

Attempt	Number of examples for training	Number of examples for testing	Number of incorrect	Accuracy (%)
1	S-20 A-20	S-5 A-5	0	100
2	S-50 A-50	S-10 A-10	0	100
3	S-50 A-50	S-20 A-20	0	100
4	S-100 A-100	S-30 A-30	0	100
5	S-100 A-100	S-50 A-50	S-2	98
6	S-100 A-100	S-100 A-100	0	100
7	S-100 A-100	S-130 A-130	0	100
8	S-100 A-100	S-150 A-150	S-7 A-1	97.33

Feedforward neural networks

In FFNN number of hidden layers and the number of neurons in the hidden layers that were adjusted and influence of these parameters on accuracy of classification is presented. Size of training dataset was also evaluated.

FFNN with one hidden layer was investigated first, with number of neurons in range from 1 to 100. Training and testing of NN was performed four times with different size datasets: from smallest, containing 40 training and 10 testing examples, to largest containing 300 training and 200 testing examples. In all training cases, performance of NN was evaluated using accuracy shown on Fig. 7-10.

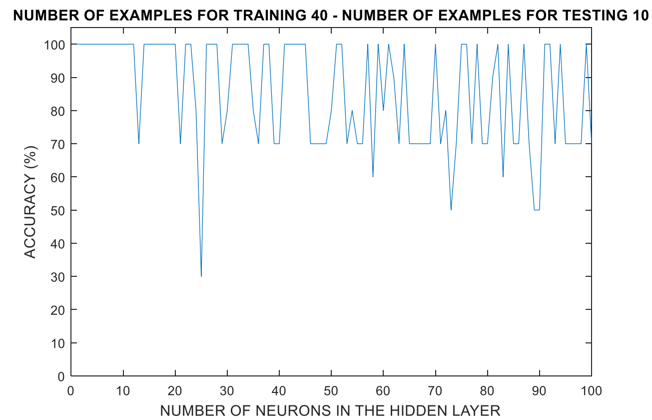

Fig. 7. Feedforward NN with one hidden layer – case 1

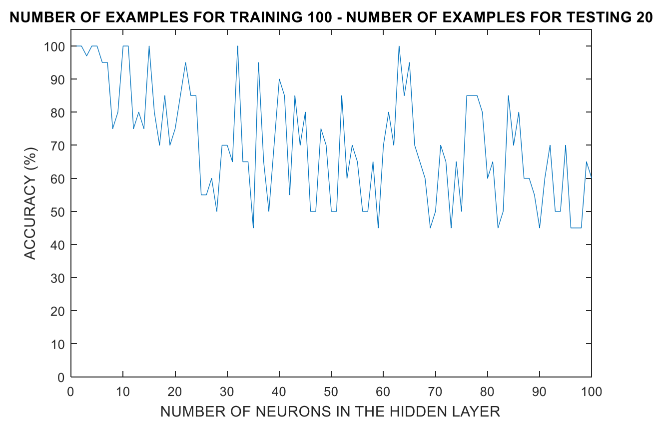

Fig. 8. Feedforward NN with one hidden layer – case 2

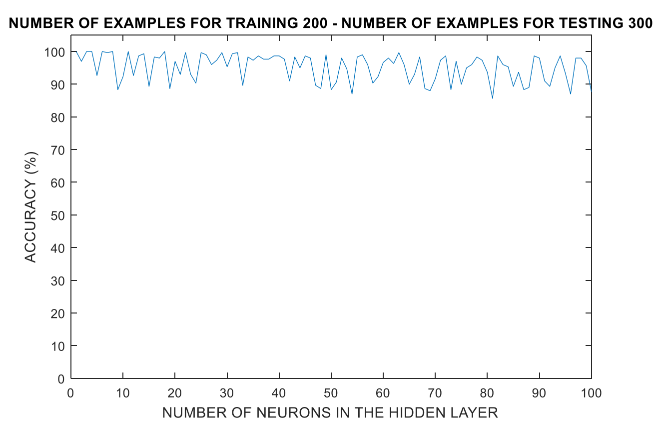

Fig. 9. Feedforward NN with one hidden layer – case 3

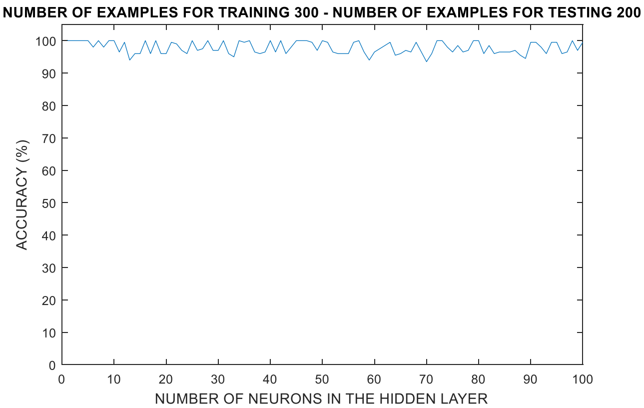

Fig. 10. Feedforward NN with one hidden layer – case 4

From obtained results, in all cases maximal classification accuracy is reached with relatively low number of neurons in hidden layer (1-5 neurons in layer). In general, for more than 10 neurons in hidden layer accuracy becomes considerably variable, likely due to overfitting. Also, when using less than 10 neurons in hidden layer high accuracy is achieved regardless of size of training dataset – there is no significant increase in accuracy with increase in size of training dataset.

FFNN with two hidden layers is also investigated. Number of neurons in first layer was variable (from 1 to 5, based on best results from FFNN with one hidden layer) and number of neurons in second layer was set in range from 1 to 100. Due to larger number of neurons maximum size training dataset containing 300 examples was used. The Fig. 11 shows classification accuracy obtained with this FFNN structure.

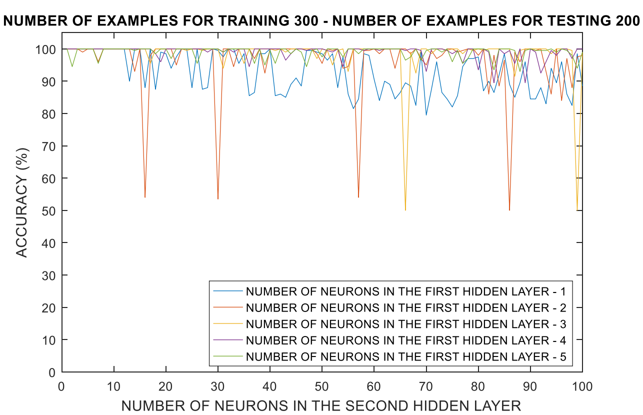

Fig. 11. Feedforward NN with two hidden layers

As in previous case, it can be noticed that high accuracy is achieved if there is a smaller number of neurons in the second hidden layer. For more than 10 neurons in second layer neural network is overfitted, and accuracy of classification is seriously diminished.

Neural networks with radial basis

In neural networks with radial basis, it is important to specify two parameters for activation function and simulation. Two parameters are spread constant and the maximal number of neurons. Spread constant affects on the process of designing of neural network and the response space of the hidden neuron, [16]. Too high or too low values of spread constant inhibit good function generalization.

For neural network with radial basis with constant maximal number of neurons, influence of the spread constant in the range 0 to 1 on classification accuracy is shown on Fig 12. This type of neural network has one hidden layer.

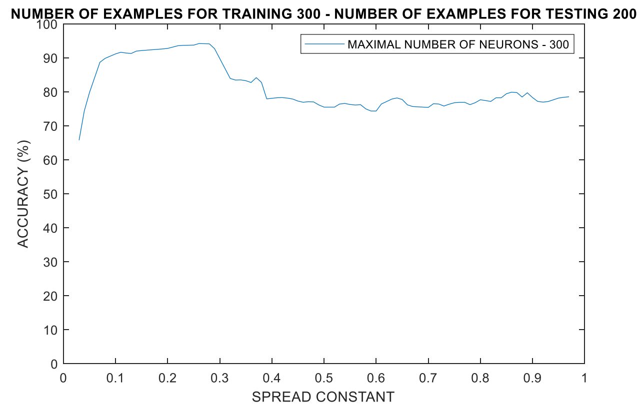

Fig. 12. NN with radial basis – changing of spread constant

The highest accuracy was obtained for a spread constant of 0.265. The Fig. 13. shows the results when the maximum number of neurons was varied in range from 10 to 1000 with the spread constant set to value of 0.265.

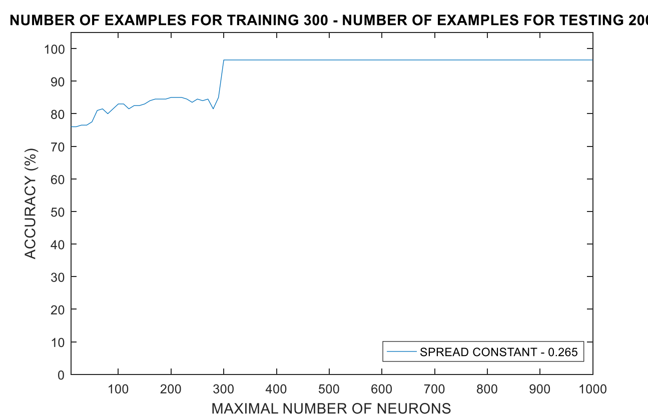

Fig. 13. NN with radial basis – changing of maximal number of neurons

Default mean square error was reached for 300 neurons, and the radial neural networks always interrupted the process of increasing the number of neurons when they reach default mean square error. Maximum accuracy is 95.5% for all cases where the maximum number of neurons is greater than 300.

Based on the presented results, it is concluded that neural networks are very successful for purpose of distinguishing switching and fast atmospheric overvoltages. Perceptron shows in most cases 100% accuracy. In the case of more complex neural networks, high accuracy can be obtained with relatively small number of hidden layers and the number of neurons in each of them.

Based on Fig. 7 - 11, the highest accuracy is obtained for a smaller number of hidden layers (one or two), each of which has up to 5 neurons (100% accuracy is achieved). In neural networks with radial activation function (according to Fig. 12-13), the highest accuracy is 95.5%.

V. Conclusions

The primary contribution of this study is a novel method based on artificial neural networks for classification of overvoltages in power systems. In this method, measured voltage is used to classify overvoltages into two distinct groups: switching and fast (atmospheric) transients.

For the purpose of method evaluation, the overvoltages were simulated in the EMTP-RV software package from which the voltage signals were imported and further processed in MATLAB. Three features of simulated signals were selected as input parameters for neural network training and testing: overvoltage peak value, duration of overvoltage, and THD factor. These three features were shown to be most relevant for high accuracy of classification.

Three types of neural networks available in MATLAB were used to perform classification and all gave satisfactory results. It is concluded that relatively simple neural networks with small number of neurons can be used for this task. Also, these neural networks can achieve high accuracy of classification when trained with relatively small training datasets (up to 300, depending on NN complexity). Based on the results presented in chapter IV, it can be concluded that the artificial neural networks performed their task very well, they distinguished the switching and fast front overvoltages with high degree of accuracy.

Adding more features of overvoltage signal to input of neural network could further improve results and extend capabilities of classification to include more types of overvoltages. Future work might include improvements to accurately identify and classify all types of transients in power systems. Also, for the future work authors have a plan to train neural networks based on overvoltages measurements in the power system.

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