Recognizing of Partial Discharges with Neural Network

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ABSTRACT: Recognizing of partial discharges is the basic method for controlling the quality of insulation materials and insulation elements. The paper describes the phenomenon of partial discharges and consequences that appear due to exceeded values of partial discharges. Given are principles of detection and measurement of partial discharges, together with the indication of some problems that cam emerge in the analysis of measurement results. Recognizing of partial discharges was realized with an artificial neural network, and it is included in the monitoring system of the device during operation. In the monitoring system not only this function will be included, but also detection of failures that will serve as a basis for functioning of protective system. This will enable prompt acting of protective relays in due time.

KEYWORDS: neural networks, partial discharges, insulators, bushings, electrical switchgears, covered conductors

INTRODUCTION

The quality of insulation materials (insulation of conductors, etc.) and insulation elements (insulators, bushings, etc.) is crucial for achieving the reliable operation of the electric power system. Their quality is measured with measurements of partial discharges. These measurements can be performed on new, in factory completely assembled elements that are ready to be used in the power system. Such elements are destroyed during the measurements. The existing elements of the electric power system in medium and high voltage networks, such as switching devices in substations, are already in operation. There are many insulation elements that can be the cause of a failure that affects the reliability of operation. The researchers have in the recent years intensively thinking about finding a reliable method of detection of partial discharges. Given were many concrete proposals for testing the voltage measurement transformers with synthetic pitch, e.g. Lupo(1998), for controlling the quality of cables, e.g. Ilstad (1997), for diagnostics of aging of the entire insulation system, e.g. Contin (1998). More and more authors try to solve the problem with the inclusion of artificial intelligence, mostly through the application of neural networks and fuzzy logic. Neural networks are nowadays used for control, identification and classification of patterns, load forecasting, etc. Chathan (1997). Neural networks have already been applied also in the field of partial discharges, e.g. Shihab (1994), in monitoring systems of substations, Lim (1998), and in a neuro-fuzzy model of partial discharges for monitoring and diagnostics of insulation.

PARTIAL DISCHARGES

Insulation material is always exposed to an electric field. Due to various reasons, such as inconsistency in manufacturing, aging of material, etc., the structure of material is not homogenous. This is the reason why under exposure to an electric field, at some points of insulation material electric field strength may exceed dielectric strength of this material. In such cases partial discharges occur in these overloaded parts of insulation. Partial discharges significantly deteriorate insulation capability of material, which can lead to its destruction. This, of course, results in a failure of the device and consequently in many cases in a supply interruption. It is possible to detect the presence of partial discharges visually and audibly, but it is much more difficult to measure their precise strength and to localize at which places in material they actually appear.

Partial discharges occur inside solid dielectric materials. They cause current and voltage impulses that can be measured with an adequate measurement method. These impulses are characterized by their amplitude, phase angle and their degree of recurrence within a certain period of time. These parameters of impulses are characteristic for each insulation material, therefore on the basis of them it is possible to localize where in the device partial discharges occur. There are various measurement methods, prescribed also by IEC 60270. Concerning the accuracy and sensitivity of measurement

it should be stressed that many external and internal factors affect the measurement, especially due to small amplitude of partial discharge impulses. These disturbances can be divided in two groups. In the first group there are disturbances that appear when electric current does not flow through the device (turning neighboring circuits on or off, measurement instruments, high frequency signals, etc.), while in the second group there are disturbances that occur when current flows through the device (testing transformer, connections, bad grounding, etc.). These disturbances have to be well known if we wish to neutralize them with the measurement method.
Our task was to acquire as much quality patterns of partial discharges for various insulation elements as possible. The high voltage laboratory is entirely encircled by a metal screen (Faraday's cage), with filters in all electricity supply circuits. The connections between measured object and measurement instruments were made by coaxial cables, all exposed metal parts were screened (semicircular and circular shape). With all these measures it was possible to minimize the impact of disturbances (to a few percents of measured value).

ARTIFICIAL NEURAL NETWORK

The artificial neural network represents a parallel, multi-layer information processing structure, which enables the inclusion of expert knowledge into the processing, recognition and classification of signals. The characteristic feature of the artificial neural network is that it considers the accumulated knowledge acquired during training, and responds to new events in the most appropriate manner, given the experiences gained during the training process. The model of the artificial neural network is determined according to network architecture, transfer function and learning rule. Corresponding weights and connection scheme define the architecture. We have decided to use a three-layer neural network. With three layers of neurons, this can be done for any inside field, in other words, any non-linear function can be approximated e.g. Lippmann (1987). Figure 1 shows the structure of a three-layer ANN, where **X** is the ANN input training matrix, $\mathbf{W}^{[s]}$ are the weight matrices, $\mathbf{F}^{[s]}$ is the matrix of transfer functions, $\mathbf{b}^{[s]}$ is the bias vector for individual neural layers s=1,2,3 while **y** is the calculated output vector and **d** is the target output vector in ANN training. There were S_1 neurons in the first layer, S_2 in the second layer and one neuron in the third. The effectiveness of including the artificial neural network depends on the quality of the training procedure. We have used the error backpropagation method. The objective of the training process is to adjust all neural network weights to obtain minimal deviations between the target and calculated ANN outputs in relation to the mean value of all input samples. The criterion function for the sum square errors is minimized according to the standard gradient procedure e.g. Pihler (1997).

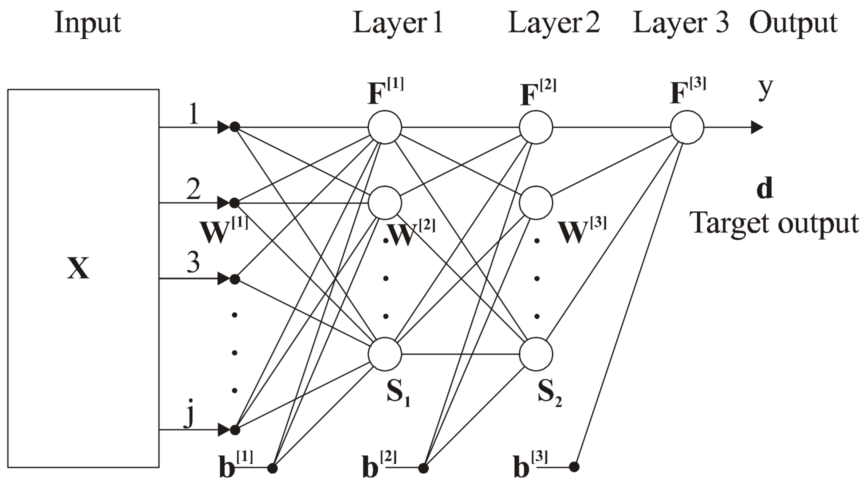

Figure1: Three-layer ANN Structure

We have used the artificial neural network for recognizing the partial discharges. To make ANN to perform the designated tasks successfully, we must select the characteristic input patterns for training, and an appropriate learning rule. The quality of training is then determined by testing the trained neural net.

TRAINING PROCESS

Characteristic examples of partial discharges are discharges in solid dielectric materials, such as in insulators, bushings, potheads, insulated conductors, etc. For the success of training process it is essential to have enough characteristic

patterns of partial discharges. They were obtained partially as results of simulations on a mathematical model, and partially with measurements on the above mentioned power system insulation elements.
Figure 2 shows the shape of partial discharges in an insulator. The time window of measurement was 20 ms – one period of power frequency waveform – and it contains 50 samplings. Measurements were also performed with 40, 100, 200 and 500 samplings per time window. Decision on the number of samplings per time window has to comprise consideration on possibilities of the measurement hardware for on-line sampling during operation of the measured device. It is theoretically possible to measure the patterns with which the neural network is learnt, with the above stated sampling rates.

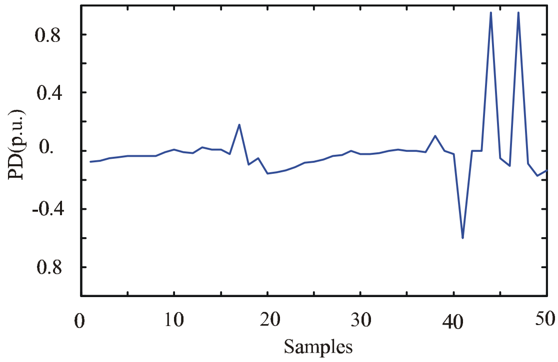

Figure 2: Shape of partial discharges in insulator

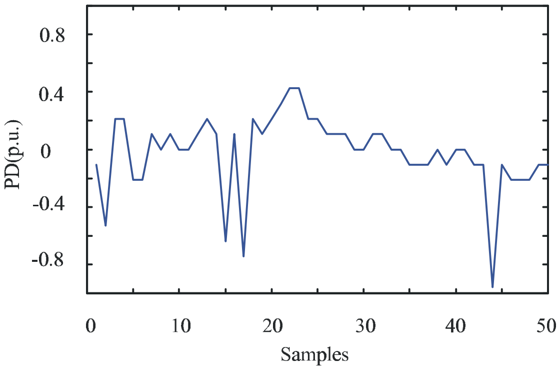

Figure 3: Shape of partial discharges in bushing

Figure 3 shows partial discharges in a bushing. Values of partial discharges in all cases significantly exceed maximum permitted values for each element. In these cases the value for target output d=1 is set. From such a pattern an input vector with the number of elements equal to the number of samples, is composed. It is also necessary to compose the input vectors containing measured signals of partial discharges with values much below the permitted values. These signals in real terms do not represent, therefore their target output is set to d=0. In the composition of patterns for learning it is also necessary to take into account differently scaled values within the per unit system. It is also important to consider different values of phase angle, since the moment of arising of partial discharges signal depends on it.
In this way composed vectors form the set of training patterns **X –** input matrix of patterns.
Training with the error backpropagation learning rule consists of the following sequences:

1. Initialization of all weights $w_{ij}^{[s]}$ and bias $b_{ij}^{[s]}$ with small, randomly selected initial values;
2. Calculation of output vectors **y** for all input training vectors according to the equation:

$$\mathbf{y} = \mathbf{F}^{[3]}\left[\mathbf{W}^{[3]} \cdot \mathbf{F}^{[2]}\left[\mathbf{W}^{[2]} \cdot \mathbf{F}^{[1]}\left[\mathbf{W}^{[1]} \cdot \mathbf{x}\right]\right]\right]; \quad (1)$$

   Non-linear sigmoid transfer functions were used. Figure 1 also shows bias **b** which is included in the weights **W** of equation (1);

3 Calculation of the network error vector and the sum squared error for all the input vectors. Stop if the sum square error for all training vectors is less than the error goal, or if the specified maximum number of epochs has been reached, otherwise continue. Reverse calculation of partial errors with the help of previously determined target vector **d**, and weight changes for all neuron layers;

4 Calculation of each layer's new weight matrix (learning phase).

One learning epoch includes procedures described in steps 2 to 4. We have used an improved method of error backpropagation – learning by finding the global minimum and adaptive learning rate.
Training results are presented with the set of 50 input current patterns (100 input training vectors **x** that contain signals of partial discharges in insulators, bushings, conductors and other elements). Each input vector **x** is assigned a target output, which defines whether a certain signal represents partial discharges or not. In the first hidden layer, there were 15 neurons, the second hidden layer comprised 4 neurons, and in the output layer there was one neuron.
Figure 4 shows error and learning speed for the above described combination of neurons and input training patterns.

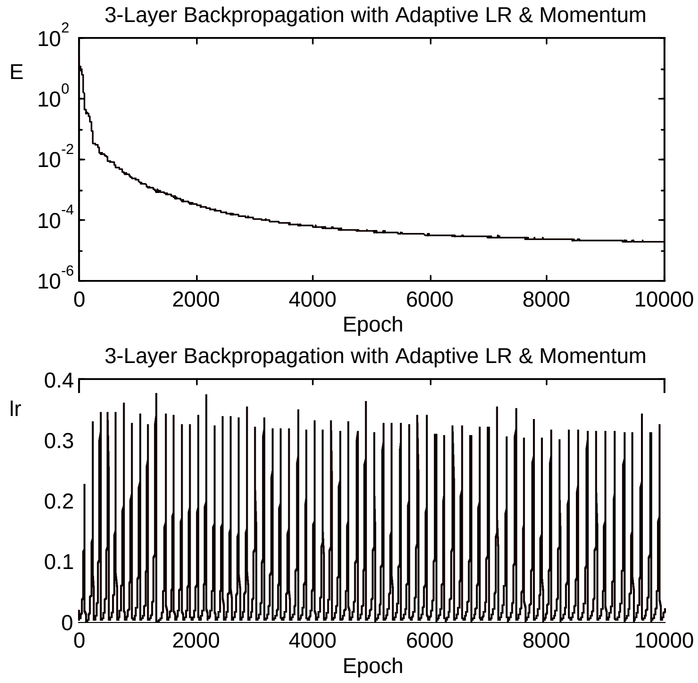

Figure 4: Error and learning speed for 10000 learning epochs

RESULT OF LABORATORY TEST

Quality of recognition of signals caused by partial discharges increases with decreasing the sum of squares of errors E. This is achieved with increasing the number of learning epochs, number of neurons in each layer of the neural network, and number of input training patterns.

The higher is number of input training patterns, the more successful is learning, therefore it is necessary to compose as much as possible training patterns.

Learning is also improved with increasing the number of learning epochs. The tests have shown that the results are adequate if the number of epochs is higher than 10000. The difference of sum of square errors between 5000 and 10000 learning epochs is 20 % at the same number of neurons.

Increasing the number of neurons in each hidden layer of the neural network also improves learning. Variation of number of neurons in the first layer from 5 to 20 and in the second layer from 2 to 6 has shown that the first layer has to contain at least 10, and the second at least 3 neurons.

Verification of training results is performed so that the ANN is first tested with training patterns, which were used in training, then with samples which were not used in training. This testing is performed so that the ANN gives **y** outputs (1) for the entire set of input patterns **x**, for which the values of **W** and **b** are the ANN training result. If the ANN output $y < 0.5$, then signal was not caused by partial discharges, while the value of $y \geq 0.5$ signifies partial discharges.

In the recognition of partial discharges for patterns which were used in training, the ANN correctly recognized all 100 input training vectors. Values of ANN output for patterns that represented the partial discharges were in the range of 0.75 to 1.2, and for patterns not represented, the partial discharges was between -0.15 and 0.35. In testing with patterns that were not used in training, the ANN incorrectly recognized 3.5% of patterns represented in the partial discharges and about 6% of other patterns. It should be pointed out that the output values for these incorrectly recognized patterns were between 0.4 and 1.4 for partial discharges, and between -0.1 and 0.7 for all other patterns.

After the process of training the neural network has been finished, the input data, necessary for operation of logical unit of monitoring of a switchgear and substation, as shown in Figure 5, are prepared. The main purpose of monitoring is to follow on-line what is happening in the device (sampling of various signals in certain time windows) and to send these data via appropriate interfaces to a personal computer. The computer all the time compares current data from the device with previously off-line learnt values of neural network algorithms, which recognize whether a certain signal is a result of partial discharges or not. The decision of the comparison unit triggers an alarm or turns the device immediately off. The proposed logical unit will also contain other sensors for various defects and different kinds of protective relaying.

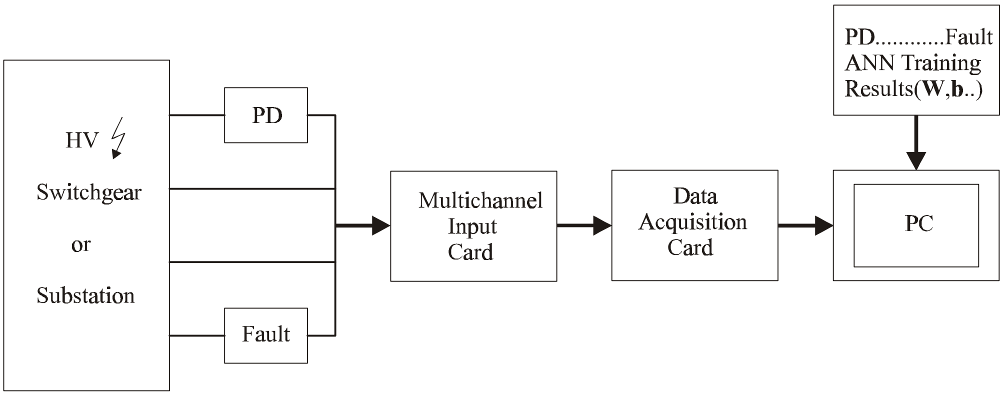

Figure 5: Logical unit of on-line operating monitoring system

CONCLUSION

The paper describes recognition of partial discharges signals with artificial neural networks. The backpropagation learning rule was used for three layer perceptron. Patterns for training were obtained with simulations on a mathematical model of partial discharges, and mostly with measurements on power system insulation elements. The best results were achieved in learning of the neural network with fifteen neurons in first layer, four neurons in second layer and one neuron in third layer. With regard to the obtained results of tested samples that were not included in the process of learning, it can be concluded that the number of patterns for learning will have to be increased. Sampling of measured samples will have to be harmonized with hardware that will be used in practical implementation of the project.

The paper also presents concept of the logical unit for on-line monitoring of operation of the entire switchgear or substation. The basic idea is to improve operational reliability of devices through preventive acting that would early enough detect circumstances that may lead to a failure with undesirable consequences. This would essentially reduce the time when a device is not available for operation.

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