NEURAL NETWORKS IN THE PROCESS OF DIAGNOSTICS

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SUMMARY

The contribution deals with the use of artificial intelligence methods in the life diagnostics of Relanex insulating material that is applied as insulation of electrical machine windings. For example, neural networks are one applicable method. The method belongs to the appropriate tools that provide the modelling, identification and simulation of technological systems and units. In such a case, the insulating material is used as a modelled and identified system. We have used the above-mentioned neural networks for the diagnostics of insulating materials that were programmed in Matlab 6 environment. All simulations and the values calculated were also obtained by means of this product.

Keywords: *diagnosis, artificial intelligence, neural network, insulating material*

1. INDRODUCTION

The life of insulating systems in electric rotary machines is strongly dependent upon electric and thermal properties of insulating material used. In this study, Relanex insulating material was used for the modelling and identification of the system. The life of such material will change during the life of an electric rotary machine, and this is a non-linear relationship. This non-linearity may be simulated by the appropriate artificial neural networks that, on the basis of the input data, will determine the output coefficient characterising the life of a machine. The input data are obtained by a non-destructive method which is characterised by diagnostic quantities Ba, Bv and Uk, including the output quantity, i.e. breakdown voltage U_p, which was adopted from literature [1].

For the modelling of insulating material, we have used a neural network that was trained by the Levenberg-Marquardt optimization method (LM). The Levenberg-Marqurdt optimization method belongs to the group of the standard optimization methods as well as the Newton's method or a non-linear solution by the least square method. Unlike the gradient methods, the

Levenberg-Marquardtova method is an approximation of the Newton's method. This optimization technique is much powerful compared to the gradient methods, however its disadvantage is in a higher PC memory capacity. In this paper, we have used a Neural Network toolbox, which incorporates a neural network with the Levenberg-Marquardt optimization method.

The neural network that was used as a model in the identification process of Renalex insulating material is illustrated in Fig. 1.

The most important assumption of the Levenberg-Marquardt method is the existence of the error function Err (w) which should be minimized in view of the weighing vector W of the neural network. The error Err is calculated from the following equation.

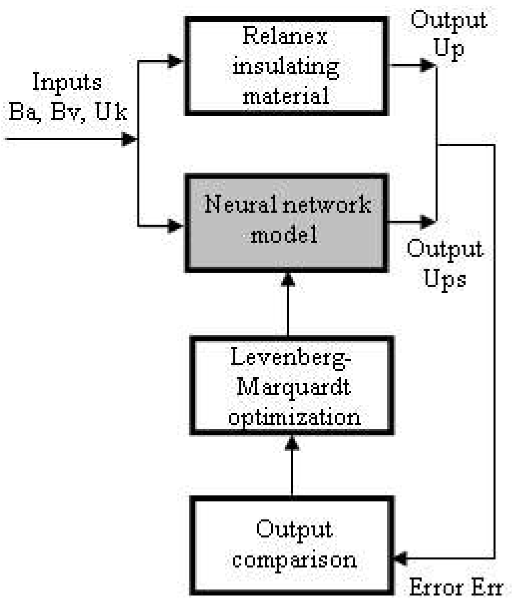

Fig. 1 The identification process of insulating material by a neural network

$$Err = \sum_{i=1}^{N} (Up - Ups)_i^2 \qquad (1)$$

with N = the number of elements in a training set, Up = a training/testing output that is measured at insulating material, and Ups = output which was determined by a neural network.

The architecture of a neural network is specified on the basis of the number of the input/output data. We have used a three-layer neural network that is the neural network with one hidden layer. The input layer involves three separate neurones for three input quantities, and the number of 6 and 7 neurones with the transfer function of hyperbolic tangent was selected in the hidden layer, and then the output layer of the neural network contains one output neurone with the linear transfer function.

Training data (see Fig. 2 and Fig. 3) forms 1,000 samples of the input/output data on which the neural network is trained. Considering a great time demand and difficulties to obtain the data, we have used a training data set of the sampling function that was created by the approximation of the data measured by the 10^{th} degree polynomial function. This method of obtaining the trai ning data was applied to provide a higher capability of generalization of the neural network to "unknown" test data.

The test data (see Fig. 5) involves 61 samples of the input/output data that was obtained by the non-destructive measurement on Relanex insulating material and which is "unknown" because the neural network has not been trained for such data. The neural network generalizes the appropriate output Ups.

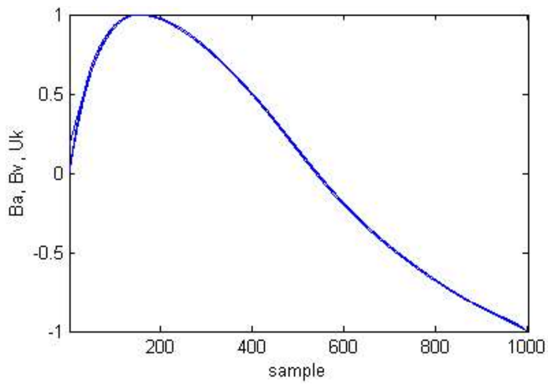

Fig. 2 Normalized input training data

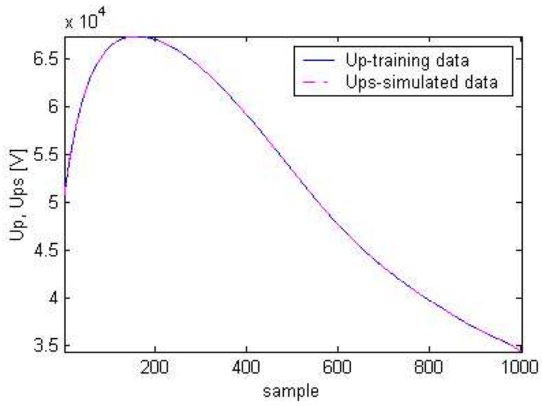

Fig. 3 The curve of output Up and simulated output Ups for the neural network with 7 neurones in a hidden layer

Because inputs Ba, Bv and Uk and the output Up are included in the sets with the ranges of significantly different values, the neural network has not been able to train. Hence before the training itself the trained data Ba, Bv and Uk was normalized in the range of [-1; 1] (see Fig. 2, 3 and 5), and this method was also used to normalize the required output Up. With the values of the training data modified in this way, there are not any problems on the input of the neural network. After training the neural network and during the simulation with the training and testing data, it is necessary to denormalize the output of the neural network according to the original range of the values on the trained output Up. The output denormalization of the neural network gives a simulated output Ups which has its unit as for breakdown voltage Up measured with the real material samples. The normalization and denormalization data processes are illustrated in Fig. 2 and their application is necessary for both the training and testing data.

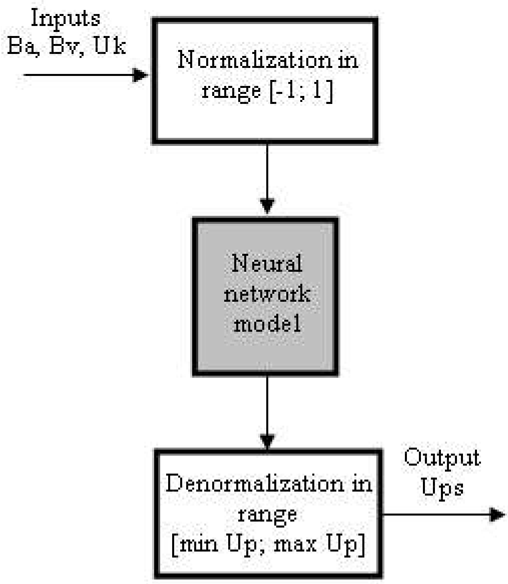

Fig. 4 Normalization and denormalization of the input/output data

In the case of this neural network, the training and testing data is different, which means that the neural network is jeopardized by the effect called "over-training" reducing the capability of generalization during the processing of unknown test data. Over-training of the neural network is demonstrated in such a way that the neural network trained for a lower error of the training data shows a higher error of the test data compared to the neural network trained for the lower error of the training data. This phenomenon has been verified during the identification process and recorded in Tab. 1 and 2 and in chart no. 8.

To remove this phenomenon, it is necessary that all weights and biases of neurones would be recorded and stored in compliance with the training sequence. For each step of training, we also carried out the simulation of the test data for the neural network with all stored weights and biases. The neural network which shows the minimum mean absolute error (see Tab. 1 and 2) for the simulation of "unknown" test data is considered as an optimized neural network.

2. RESULTS OF THE IDENTIFICATION AND SIMULATION

The results of the identification and simulation of insulating materials for the neural network with six neurones in a hidden layer are recorded in Tab. 1, while the neural networks with seven neurones in a hidden layer are shown in Tab. 2.

Tab. 1 The simulation of the neural network with 6 neurones in a hidden layer

Tested with the data measured				
	Absolute error		Relative error	
	Max.	Mean	Max.	Mean
Minimum error value	288.1 V	90.4 V	0.638 %	0.178 %
Training step with minimum error	4 steps	5 steps	5 steps	2655 steps
3,000 training steps of neural network				
	Absolute error		Relative error	
	Max.	Mean	Max.	Mean
Tested with the training data	1.7 V	0.2 V	0.005 %	5e-4 %
Tested with the data measured	622.6 V	93.5 V	0.999 %	0.180 %
5 training steps of neural network				
	Absolute error		Relative error	
	Max.	Mean	Max.	Mean
Tested with the training data	79.8 V	22.8 V	0.232 %	0.047 %
Tested with the data measured	333.1 V	90.4 V	0.683 %	0.186 %

Tables illustrate the results of the simulation of the training and test data in the final step of the neural network training, and even for the step with the minimum absolute mean error Err.

In charts and figures, the curves of the training and test data, the outputs given by the neural network with seven neurones in a hidden layer and the curves of the mean absolute error are illustrated.

Tab. 2 The simulation of the neural network with 7 neurones in a hidden layer

Tested with the data measured				
	Absolute error		Relative error	
	Max.	Mean	Max.	Mean
Minimum error value	261.5 V	75.5 V	0.470 %	0.147 %
Training step with minimum error	26 steps	5 steps	19 steps	6 steps
3,000 training steps of neural network				
	Absolute error		Relative error	
	Max.	Mean	Max.	Mean
Tested with the training data	1.7 V	0.3 V	0.003 %	6e-4 %
Tested with the data measured	387.6 V	103.5 V	0.621 %	0.200 %
5 training steps of neural network				
	Absolute error		Relative error	
	Max.	Mean	Max.	Mean
Tested with the training data	139.7 V	25.6 V	0.274 %	0.048 %
Tested with the data measured	321.1 V	75.7 V	0.622 %	0.148 %

3. CONCLUSION

This paper describes the artificial intelligence application in the diagnostics of the life of insulating material for windings in electric rotary machines. To identify the system, we used the neural networks with the optimizing Levenberg-Marquardt algorithm that in our case represents a modelling tool. The identification process of insulating material is shown in Fig. 1. During the identification, the neural network (with 6 and 7 hidden neurones) was trained via the training set, which was formed from threeinput quantities Ba, Bv and Uk and one output quantity Up. On the basis of the input quantities, the neural network generalizes the simulated output quantity Ups with a certain error in relation to the expected value Up. After training, we carried out the simulation by means of the training/test data sets

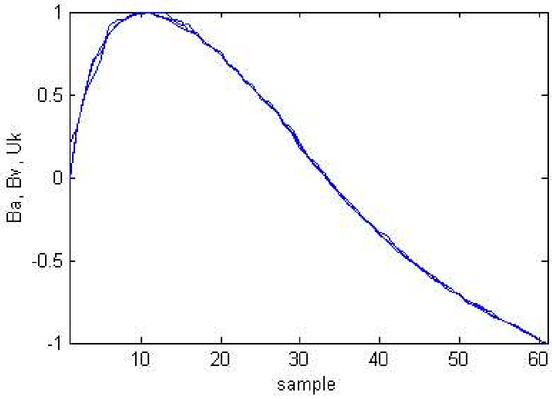

Fig. 5 The normalized test data - inputs in the neural network with 7 neurones in a hidden layer

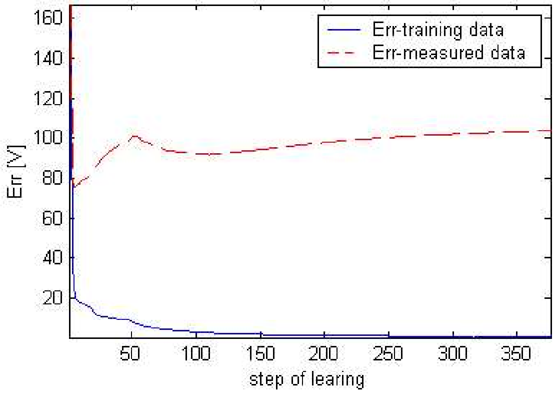

Fig. 8 The phenomenon of "over-training" in the 5^{th} step of training of the neural network with 7 neurones in a hidden layer

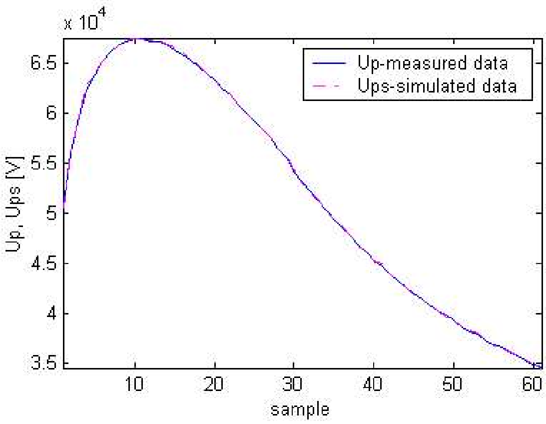

Fig. 6 Output Up and simulated output Ups for the neural network with 7 neurones - 3,000 steps of training

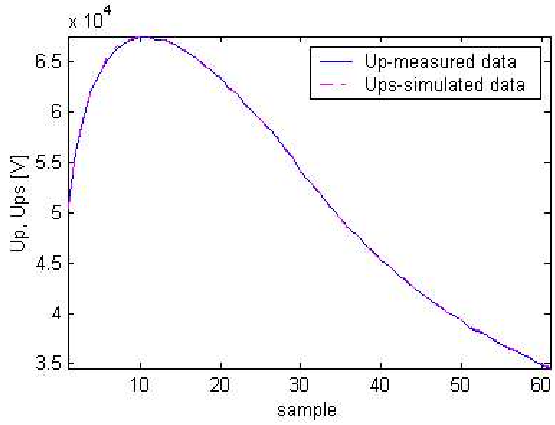

Fig. 9 Output Up and simulated output Ups for the neural network with 7 neurones, i.e. 5 steps of training

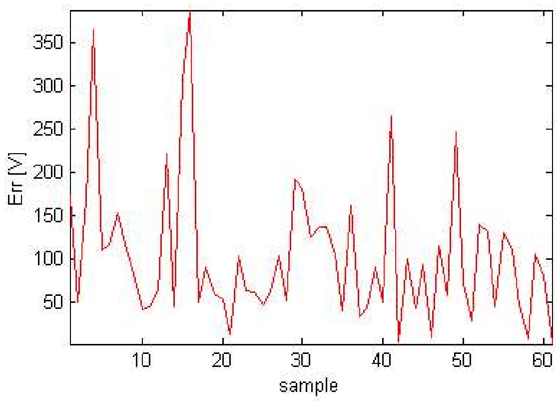

Fig. 7 The absolute error of the simulation of the neural network with 7 neurones in a hidden layers - 3,000 steps of training

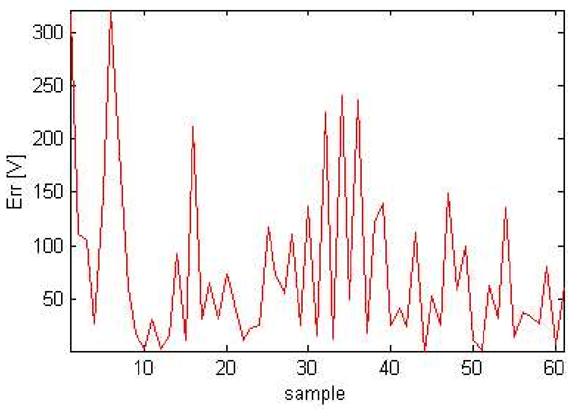

Fig. 10 The absolute error of simulation in the neural network with 7 neurones of a hidden layer, i.e. 5 steps of training

where the test set was obtained in a real insulating system. This data set was unknown for the neural network to which it was not trained. Before using the neural network, it was necessary to normalize both the training and even test data in compliance with Fig. 4 due to high differences of the values (in orders). The phenomenon of over-training (see Fig. 8) that is typical for the simulations with "unknown" test data was eliminated by a record of the weight and bias matrix in each step of training. In our case, the phenomenon of over-training occurred during the 5th training step. Thus, the simulation was performed for each training step. The neural network with the minimum absolute mean error of the training in view of the expected value up may be considered as an optimally configured neural network. The results of the simulation of the neural networks with 6 and 7 neurones in a hidden layer are shown in Tab. 1 and 2. For example, the values of absolute and relative errors during the simulations with the training and test data in the final step (3,000 steps) and even in the step with the minimum mean absolute error (5 steps) are illustrated in Tab. 2. Moreover, the table includes the minimum values of the absolute/relative errors during the complete training process and the training steps in which the values were achieved. The curves of the simulations with the training and test data for the neural network with 7 hidden neurones are illustrated in figures 2 to 10. Fig. 2 illustrates the normalized training inputs Ba, Bv and Uk; and the training output Up and the simulated output Ups are shown in Fig. 3. The normalized input test data is shown in Fig. 5. In Fig. 6, we can see the simulated output Ups and the expected output Up in the final training step. The curve of the absolute mean errors in this training step is illustrated in Fig. 7. The simulated output Ups of the 5th training step is shown in Fig. 9, that is the step with the minimum mean absolute error and with the curve over the complete test set illustrated in Fig. 10.

The application of neural networks in the diagnostics of the life of insulating systems is possible, and in practical terms fully applicable, because during the identification of insulating material we have achieved the mean absolute error of 75.7V. This is 0.158 percent error in view of the expected value Up with its real value ranging in tens kV.

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BIOGRAPHY

Miloš Hammer (Doc, Ing., CSc.) was born in Nové Město na Moravě, Czech Republic of 16 June 16,1953. Doc. Hammer graduated from Brno Technical University, Electrotechnical Faculty in the branch of electrical material technology. This discipline was focused on physics and the technology of electrotechnical and electronic materials, electrical insulating technology of materials and the technology and the construction of electrical machines and instruments. He received the research degree of „Candidate of Technical Sciences - CSc." in the same branch in 1986, and he was appointed as Senior Lecturer in the branch of electrical technology in machinery in 1989. After four-year practice in industry, he has been working at Faculty of Machinery Engineering, Brno Technical University since 1981. When he had entered the faculty, he was involved in solving many research tasks as a project manager or a participant who solved the problem. The problems were focused on technology, development a verification of new insulating and magnetic materials which were used for the production of electrical rotary machines. Furthermore, the topics were focused on reliability of electrical machines, mainly searching for the methods of their assessment. Doc. Hammer has studied the diagnostics of insulating systems of electrical machines since 1991. This resulted in the elaboration and the verification in practical terms of many diagnostic methods that enable to specify both the conditions of insulating materials of electrical machine windings and the prognosis of their life by non-destructive methods. Recently, doc. Hammer has applied the theory of fuzzy sets for the establishment of mathematical models for technical phenomena and processes, and furthermore, he concentrated on neuron networks which can be used in technical diagnostics, system modelling and the prediction of their life.

Tomáš Kozlovský was born on 8.1.1977 in Boskovice, Czech Republic. In 2000 he graduated (Ing.) at the department of Automatization and Measurement of the Faculty of Electrical Engineering and Informatics at Brno University of Technology. His thesis was „Neural networks in process of identification". Since 2001 he is studying his PhD. in Institute of Production Machines, Systems and Robotics of the Faculty of Mechanical Engineering at Brno University of Technology. His scientific research is focusing in the field of diagnostics and artificial intelligence. The main point is an application of methods of artificial intelligence for the lifetime diagnostics of insulating systems in electric rotary machines. Ing. Kozlovsky deals with lifetime diagnostics and lifetime prediction by neural networks, fuzzy systems, expert systems and hybrid systems. The another interest is with genetic algorithms used for optimization of non-linear models and diagnostics models. The results of projects which were solved by Ing. Kozlovsky are publicated in many domestic and international scientific conferences.