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CHOSEN METHODS OF EXPERIMENTAL DATA EVALUATION

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Abstract: The paper deals with experimental data evaluation by artificial neural network as well as the phase space application at systems with changed physical state. In the experimental point of view we present the measurements of glass fibre laminates as well as tires modal analysis realized by electron speckle pattern interferometry (ESPI). Finally we discuss application of the phase space for evaluation of changes in physical state of rubber blends by introduction of holes as a structure of defect.

Key words: Artificial neural network, tires, glass laminates, rubber blends, defects.

1. Artificial neural networks

Neural networks are suitable for approximating complex mutual relations among different sensor-based data, especially among non-structured data, with a high grade of non-linearity, and with inaccurate and incomplete data. Neural networks are able to realize and appropriately express the general properties of data and the relations among them and on the contrary to suppress relationships which occur sporadically or are not sufficiently reliable and strong. Their usage enables the retrieval of relationships among the parameters of the process which cannot use common methods to trace the reason of their mutual interactions, large number and dynamics.

Learning is a basic and essential feature of neural networks. Knowledge is recorded especially through the strength of linkages between particular neurons. Linkages between neurons leading to a "correct answer" are strengthened and linkages leading to a "wrong answer" are weakened by means of the repeated exposure of examples describing the problem area. These examples create a so-called training set [1].

For all types of predictions neural networks are suitable to be used for their learning Backpropagation algorithms. This algorithm is convenient for multilayer feedforward network learning which is created minimally by three layers of neurons: input, output and at least one inner (hidden) layer (Figure 1). Between the two adjoining layers there is always a so-called total connection of neurons, thus each neuron of the lower layer is connected to all neurons of the higher layer. Learning in the neural network is realized by setting the values of synaptic weights w_{ij} between neurons, biases or inclines of activation functions of neurons. The adaptation at Backpropagation types of networks is also called „supervised learning“, when the neural network learns by comparing the actual and the required

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output and by setting the values of the synaptic weights so that the difference between the actual and the required output decreases [2].

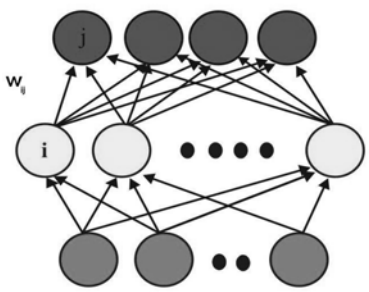

Fig. 1. *Topology of a multilayer feedforward neural network*

1.1. Prediction of mechanical properties of steel with exploitation of ANN

One of the fields where it is possible to exploit neural networks is predicting the mechanical properties of materials on the basis of their composition and preceding treatment. For proposing the optimal course of heat treatment therefore there must be taken into consideration both presently known physical- metallurgical knowledge, and also the experimental results and practical experiences acquired for various steel products from different types of steel. Different mechanisms have an influence on the final mechanical properties of steels, which are moreover in mutual interaction: the phase transformation, grain size, precipitates and dislocations. All these factors bring into the process a strong non-linearity and dependences of a superior degrees and very complicated creation of accurate models.

In the field of research oriented on metallurgical technologies control with the aim to optimize the industrial process and to increase a quality of materials by applying artificial intelligence elements, particular models of artificial multilayer neural networks for predicting material mechanical properties after heat treatment were designed and gradually tested.

These models predicted final mechanical properties as tensile strength *(R_m)*, yield strength *(R_e)*, elongation *(A)* and the area reduction *(Z)* of material on the basis of the knowledge of chemical steel composition and the conditions of heat treatment.

For learning and for verifying neural networks functionality data from a catalogue of experimental heats were used. The heats, which include all value parameters serving as inputs to a neural network from the catalogue, were chosen. The content of 10 elements of the chemical composition of steel and 6 possible resultant structures represented by a different cooling rate and drawing temperature are stated for each heat.

The temperatures of austenization and dwell time upon this temperature were the same at all heats: 880 °C for a period of 1 hour. All heats have also the same drawing time: 8 hours. Therefore these parameters were not included into the neural network input. The whole catalogue is divided into the two groups: the first group contains structural steels from grade 12 – 16 determined for hardening treatment. The second group Cr- Ni- Mo steels with a content 0.2–0.6 %C (carburizing, rotor, tool steels).

A neural network, whose output layer was created by 4 neurons, was designed (Figure 2). Neuron outputs represented the mechanical properties of steel: tensile strength *(R_m)*, yield strength *(R_e)*, elongation *(A)* and area reduction *(Z)*. An input layer was created by 12 neurons. Their values represent the basic parameters, which had an influence on the predicted mechanical properties value: 10 elements of chemical steel composition, the cooling rate *(V_i)* and drawing temperature *(T_i)*. The total number of patterns used for neural network learning was 273 (a training set) and the remaining 45 patterns served as a testing set.

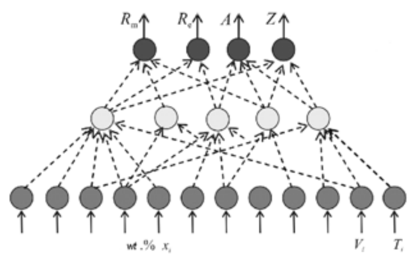

Fig. 2. *Multilayer feedforward neural network*

It was possible to distinguish two separate groups in analyzed heats according to their chemical composition. The first group is created of structural steels from a grade 12 – 16 determined for hardening treatment (below marked as „normal steels") and a second group steels of grade 16 (carburizing and rotor steels) and steel grade 19 (tool steels) with a higher content of Cr, Ni, Mo and V (below marked as „alloyed steels"). These groups were markedly distinguished in their resultant mechanical properties. For a possible comparison of the prediction quality from the standpoint of the content of alloying elements, the sets of input and output values of all heats were divided according to their chemical composition into two particular files.

The suggested network was able to satisfactorily predict the mechanical properties of structural steels of a grade 12 – 16 determined for hardening treatment with an average error at particular properties up to 7.5 %. The prediction results of steels grade 16 containing Cr, Ni, Mo, V and grade 19 were a little worse in the results. The average error for predicting particular properties was at the most 8.2 %. We can state that the model enables the prediction of mechanical steel properties with a sufficiently small error [1].

1.2. Application of ANN in Chosen Glass Laminates Properties Prediction

Another application deals with utilization of the artificial neural networks at the evaluation of chosen material's properties (sample thickness, sample shape) measured by electronic speckle pattern interferometry (ESPI). We have investigated the dependence of the generated mode frequency as a function of sample thickness as well as the sample shape of glass laminate samples. Obtained experimental results for differently shaped glass laminate samples are compared with those of artificial neural networks and finite element method (FEM) simulation. The coincidence of both experimental and simulated results is very good.

In the first step we have tested the mode frequency generation as a function of the sample thickness (0.8,1.05.1.35,1.65) mm. Sample with r = 0 is tetragonal and sample with r = 87,5mm is a disc, other diameters are as follows: (0,10,20,30,40,50,60, 70.87.5) mm.

The rate of inaccuracy between predicted and actual output represent a prediction error. In technical applications the error is mainly represented by following functions: relation for RMS error (Root Mean Squared), relation for REL_RMS error, R^2 – determination index.

For prediction of the resonance frequency in the dependence of the sample thickness data about sample thickness and type of mode (7 types of modes) were used as an input vector (8 neurons in the input layer). Output vector represented the resonance frequency (1 neuron in the output layer). The best results of prediction proved multilayer feedforward neural network with topology 8-3-1. Above mentioned prediction errors for this neural network are: RMS = 13,668 Hz, REL_RMS = 0,0226, R^2= 0,9986 (Figure 3).

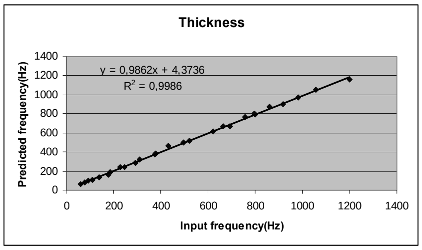

Fig. 3. *ANN prediction of resonance frequencies for different plate thickness*

For prediction of the resonance frequency in dependence of sample rounding data about sample rounding and type of mode (9 types of mode) were used as an input vector (10 neurons in the input layer). Output vector represented the resonance frequency (1 neuron in the output layer). The best results of prediction represented multilayer feedforward neural network with topology 10-7-1. Prediction errors for this neural network are: RMS = 2,743 Hz, REL_RMS = 0,0031, R2= 0,9999 (Figure 4).

The models of artificial neural networks for prediction of resonance frequencies of glass laminates were created. These models enable to predict glass laminates resonance frequencies with a sufficiently small error. Obtained experimental results for differently shaped glass laminate samples were compared with those of artificial neural networks and finite element method (FEM) simulation. The coincidence of both experimental and simulated results was very good.

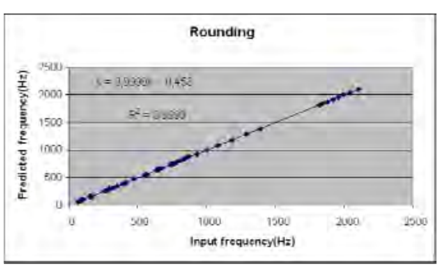

Fig. 4. *ANN prediction of resonance frequencies for different plate rounding*

1.3. ANN Application in Tires Modal Analysis

This application deals with using ANN at tires own frequencies prediction depending on a tire construction. Experimental data of own frequencies were obtained by electronic speckle pattern interferometry (ESPI) [4]. The presented ANN method applied on ESPI experimental data can effectively help constructors to optimize dimensions of tires from the point of view of their noise.

In the next part of the contribution we present comparison of measured and predicted own frequencies. An application that expects the tire parameters to serve as the input values was created as a sample of implementation. The parameters are the nominal width, profile number, rim diameter, load index and speed index. These parameters are used as input to the algorithm. The output is a predicted value of radial frequency and amplitude.

The acquired database for prediction of noise contained 83 cases. Due to the absence of values in case of some variables, the database had been modified and included only 69 cases. These facts were subsequently adjusted to a form suitable for the application of neural network. The whole database was divided into the data to be used for the network learning (training and validation set) and the data to be later used to check the prediction accuracy, i.e. the generalization ability of the neural network (test set). Artificial neural networks were subsequently designed and trained on the basis of the adjusted data. The best prediction results were achieved by a three-layer perceptron neural network of 5-11-2. Comparison of measured and predicted data for the amplitude and for the frequency is shown on Figure 5 and Figure 6.

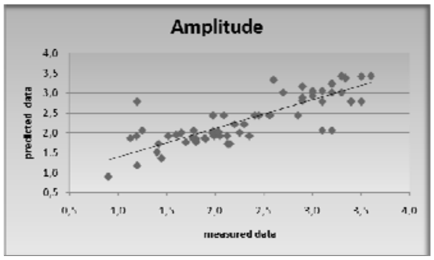

Fig. 5. *Comparison of measured and predicted amplitude data*

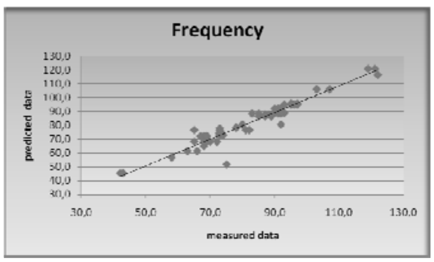

Fig. 6. *Comparison of measured and predicted frequency data*

The functional neuronal model was created for prediction of frequency and amplitude of self-sustained tire oscillations. The model is capable of providing satisfactory prediction of frequency of tires with a mean square error RMS = 4.314 Hz and amplitude of self-sustained tire oscillation with an RMS error = 0.397 μm. The presented results and the experience acquired with applications of neural networks in material research show that their utilization in this area is very promising. Application of ANN in tires modal analysis is very useful tool for tire designers.

In the next part of our contribution we will analyze the influence of artificial defects in rubber blends [5]. The philosophy of the experiment is as follows. The sample located on the top of the shaker is submitted to the sum (at the up movement of the shaker) of gravity and inertial forces and to difference of both in the case of down movement of the shaker. So we obtain the periodical changes of the amplitude of forced oscillations.

The net model with a hole is in Figure 7. It is clearly seen from all presented results that used physical model of forced oscillation acting on the rubber blend with macro defect is valid.

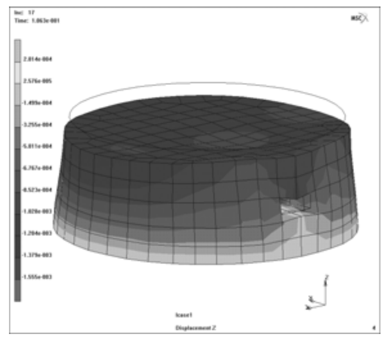

Fig. 7. *Net model of a sample with a hole*

To proof these results obtained by FEM simulation we experimentally measured the influence of defect on the viscoelastic parameters describing the mechanical properties of rubber blend, such as complex Young's modulus.

In the Figure 8 the amplitude of forced oscillations versus frequency is plotted. It is seen from the plot that the changes of the amplitude caused by presence of defects are apparent but they could be clearer. To find the solution for this situation we assumed the idea of representation of obtained experimental results in other axes system, which could better reflect dynamic properties of viscoelastic system.

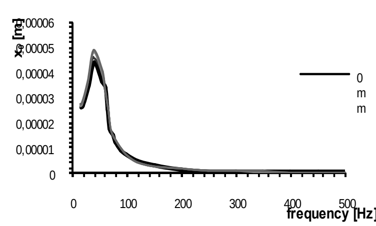

Fig. 8. *Experimental amplitude versus frequency of different defects*

It is well known that dynamic state of the system is fully described by 3N values of momentum of movement and 3N values of displacement (N is a number of mass points). These 6N values create the representation of dynamic system in phase space. Such representation of results has an advantage in the fact that all changes in the amplitude trend are in described case enhanced through their derivatives which are present in the momentum of movement. Evaluated changes in the sample quality are much more visible in this representation and have the expected "butterfly shape" well known from the chaos theory. Results of such representation are plotted in Figure 9.

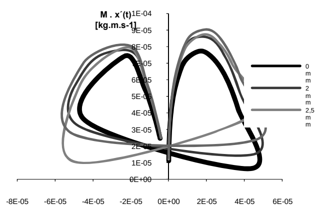

Fig. 9. *The momentum of movement versus displacement of blend with different defects size*

To broaden the application of such representation of results of dynamic measurements of rubber blends we tested the influence of rubber blend preparation on dynamic properties of forced oscillations for three blends of the same composition, as well but with difference in mixing technology of one of them. It is clearly seen (Figure 10) that two blends (black and red) have the phase diagrams practically identical but one of them differs substantially form the previous ones. According to presented results such representation in phase space can serve as a quick quality test of technological uniformity.

Fig. 10. *The momentum of movement dependence versus displacement of three samples of the same quality*

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