MATEC Web of Conferences **210**, 04030 (2018) https://doi.org/10.1051/matecconf/201821004030
CSCC 2018

Review on Artificial Intelligence Applications in Material Diagnostics and Technology

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Abstract. The paper presents the review of works devoted to the material engineering – diagnostic and technological application of artificial neural networks (ANN). This review has been realized by activities created in narrow connection with the industrial sphere, mainly as a constructive step to development of Industry 4.0 philosophy. The review covers different materials measurement and evaluation. There have been investigated such materials as rubber blends, laminates, optical glasses; and also survey covers degradation processes appeared in industrial applications as well as the material defect evaluation and wearing diagnostics. The last part of the review offers output concerning infrared technique application of ANN. This review can serve as an inspiration for new challenges.

1 Introduction

Neural networks assert increasingly in sphere of modelling and control of technological processes, where mostly appropriately complement analytic conventional models. Their application is advantageous especially for modelling and control of non-linear systems, where they can provide more accurate results contrary to so far used conventional approaches. They offer interesting approach in comparison with laborious classic methods of statistic data evaluation and at the same time they are able to describe more complex relations than these methods.

They are suitable for approximation of relations among sensor-based data, further they are able to simulate behaviour of systems with very complex internal structure and complicated external behaviour. They offer an ability to simulate dependences which can be hardly solved by classic methods of statistic data evaluation and they are able to express more complex relations than these methods. Typical property of ANN is their capability of learning on measured data and capability of generalization.

ANN results can be used for execution of a sensitivity analysis. The sensitivity analysis shows, how significantly each input value influences the output variable. This fact offers the technologists to find and influence main factors of product quality. In this review, we will analyse application of ANN in material engineering.

ANN technique is frequently used for material analysis and in some cases with success replaces destructive testing, for instance, also in fibre composites [1].

Calculations of true stress/strain curves in the automobile industry are realized with success in [2], where authors optimized interconnection weights obtained with hidden layers and output layers. And a mathematical model of the material's behaviour is suggested through this feed-forward neural network.

The work [3] applies the finite element method as well as ANN for description of surface stress in materials. Combination of ANN and FEM is applied for the study of dynamic properties of glass laminates with different material shaping [4].

Shape modes are presented for different vibrational excitation. ANN were used with success in optimization of composition of optical glasses [5] to obtain asked optical properties. Feed forward neural networks are used for classification of layers of coal, shale coal depending upon the content of both ash and moisture [6].

The work [7] deals with an application of ANN and a neuro-fuzzy interference system for rejection of permeate flux and salt content rejection. The multi resolution analysis of time dependent data sets obtained by Wavelet decomposition and analysed by ANN are applied on renewable energy sources management in [8].

A sound analysis statistical model was developed on the basis of deep neural networks. Using a new algorithm, authors attained results substantially improved to the conventional data [9].

Discoloration process analysis was used applying three intermediate layers, backpropagation learning algorithm, and sigmoid activation function implemented in FORTRAN. Three neurons in the intermediate layer gave the best results [10].

Plasticizers play an important role in rubber technology and dominantly influence blend mixing. The

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study [11-12] presents the influence of a plasticizer amount on chosen mechanical properties such as strength R_m, before and after aging on air which can influence final properties of blend and naturally also the final product. The used evaluation method is based on application of ANN that allows statistically analysing the applied technological processes influence on mechanical properties of blend. Some illustrating results are as follows.

Chemical composition of standard rubber mixture in PHR (parts per hundred of rubber) is shown in Table 1. The used rubber was SMR (Standard Malaysian rubber).

Reference rubber samples of the same composition described in Table 1 were mixed with oleic acid plasticizer, content of 1 PHR and 3 PHR together with weight percentage of Etoxon (2, 4, 6, 8, 10, 20, 30 wt. %). Etoxon is a surfactant (sodium 1-nonyl-2-(2-nonylphenoxy) benzene sulphate). These amphiphilic substances reduce the surface tension of the fluids and the interfacial tension in two liquids.

The sample aging was realized in open air for one month. The aim of this treatment is to study an influence of the open air on rubber chemistry changes. These changes subsequently influence mechanical properties of samples under investigation.

Table 1. Chemical composition of standard rubber mixture.

Ingredient	PHR
SMR	100
Sulphur	2
ZnO	5
Stearine	2
Sulfenax	2
N339 CB	50
Gumodex	10

ANN prediction was performed by Statistica 7 software. Artificial neural networks have been applied for teaching on results of selected mechanical properties versus both Etoxon and oleic acid amount. As input parameters of neural networks, we used an Etoxon amount as continuous neuron inputs and an oleic acid amount as categorical neuron inputs. Measured values of mechanical properties were used as continuous neuron outputs.

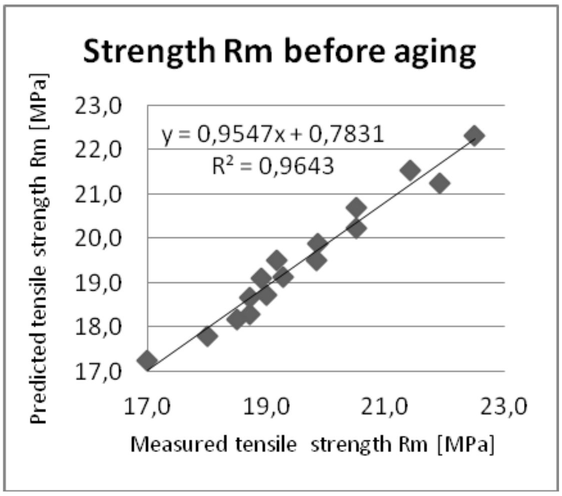
Statistica Neural Networks software enables execution of a sensitivity analysis and creation of response graphs. The sensitivity analysis shows how significantly each input value influences the output value and the response graphs express an influence of the chosen parameter on the output value.

Statistica Neural Networks conducts the sensitivity analysis by treating each input variable in turn as if it were "unavailable". Every model defines a missing value substitution procedure which is used to allow predictions to be made in the absence of values for one or more inputs. To define sensitivity of a particular variable, we first run the network on a set of test cases and accumulated the network error. Then we run the network again using the same cases, but this time replacing the observed values with the value estimated by the missing value procedure, and again accumulated the network error.

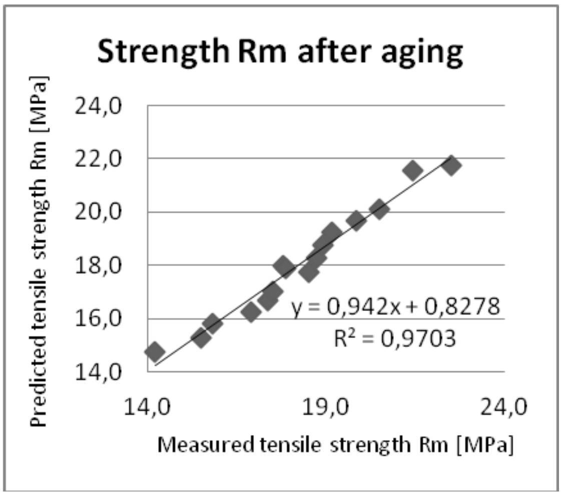
Given that we have effectively removed some information that is presumably used by the network (i.e. one of its input variables), we would reasonably expect some deterioration in error to occur. The basic measure of sensitivity is the ratio of the error with missing value substitution to the original error. The more sensitive the network is to a particular input, the greater the deterioration we can expect, and therefore the greater the ratio.

If the ratio is one or lower, then making the variable "unavailable" either has no effect on the performance of the network or actually enhances it. Results for the aged and non-aged state were learned in two independent stages. Because of used concentrations of Etoxon equal to 0, 2, 4, 6, 8, 10, 20, 30 wt.% and two concentrations of oleic acid equal to 1 PHR and 3 PHR, the neural networks for both aged and non-aged state were learned on the 16 input neurons.

Total analysed neural networks for each variable and each state were equal to 10 neural networks from which we used best 5 neural networks. Criterion to selected retained networks was lowest error. Used networks were linear, PNN or GRNN (general regression neural network), Radial Basis function, three-layer and four-layer perceptron type. As the best neural network, we used a neural network at which the correlation between the real measured and ANN approximated network were closest to 1 by sustaining the root mean square error between the measured and approximated values closest to zero. Measured and predicted data of physical values under investigations presented in Fig. 1.



a)



b)

Fig. 1. Comparison of predicted and measured **tensile strength** R_m a) before and b) after aging.

Table 2. Ratio parameter for tensile strength before aging.

Neural network	Oleic Acid Ratio	Etoxon Ratio
MLP 2:2-16-8-1:1	1,434(8,4%)	4,725(91,6%)

Table 3. Ratio parameter for tensile strength after aging.

Neural network	Oleic acid ratio	Etoxon ratio
MLP 2:2-16-13-1:1	7.282 (67.3%)	5.073 (32.7%)

Table 3 shows the network as the most sensitive to the Etoxon weight percentage amount (in the non-aged state). On the other hand, after aging, the dominant influence on rubber mixture plays Oleic acid as we can see it in Table 3. The reason of this fact is probably caused by degradation of sulphur crosslinking enhanced by Etoxon (dodecyloxyethyl sulphate [13].

A process of ANN application on measured data so offers the interesting possibility of "technological tuning".

In the paper [14], there is presented application of an artificial neural network on a relation between glass composition versus optical transmittance of the chosen glass systems of Sb_2O_3 - $PbCl_2$ and Sb_2O_3 – PbO – M_2O, where M was Na, K and Li, respectively. This paper is a prolongation of theoretical and experimental works connected with metallurgical outputs [15-18].

As the input variables, there were identified concentrations of the following source substances: Sb_2O_3, $PbCl_2$ $PbCO_3$, Na_2CO_3, K_2CO_3, Li_2CO_3 and wavelength. One output variable has been marked as the transmittance. The scheme of input and output variables related to the neural network is shown in Fig. 2.

Software Statistica – Neural Networks was used for the creation of artificial neural networks. Data file had to be modified before the creation of artificial neural networks so that it could be used in the above-mentioned software. The total amount of data was randomly divided into three parts: training, testing and validation. This is necessary for proper learning and verification of the accuracy of the prediction of a created artificial neural network (Fig. 3). Several artificial neural networks with varying structure and parameters were created on the basis of adjusted data. The one that had the best results of learning has been selected for the prediction of defects. It was three-layer network with topology 7-10-1. This means that the input layer contains 7 neurons, the hidden layer 4 and the output layer one neuron (Fig. 2).

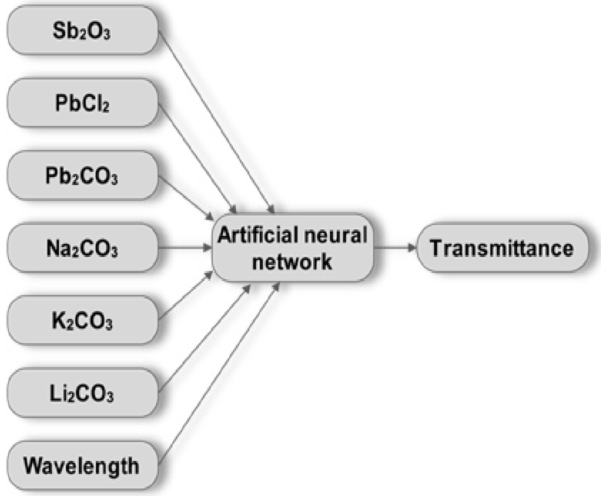


Fig. 2. Structure of input and output data.

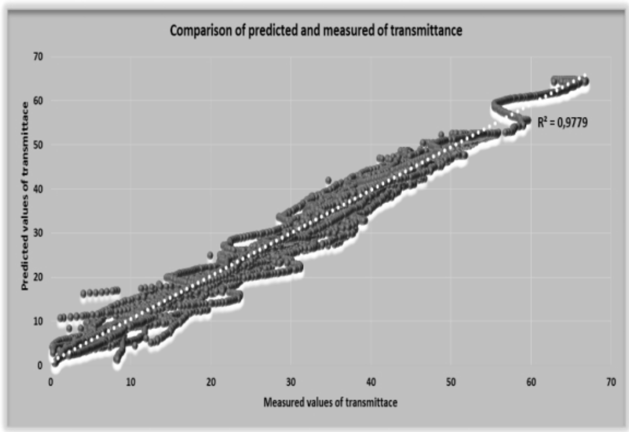


Fig. 3. Evaluation of ANN.

Prediction errors of the chosen neural network model are RMS = 2.28 and REL_RMS = 0.068.

Furthermore, sensitivity analysis was realized for this neural network. ANN shows a new possibility for the determination of the relative importance of distinguished chemical ingredients in tested samples.

Sensitivity analysis showed that $PbCl_2$, Sb_2O_3 were variables with the greatest influence on the system. On the other hand, $PbCO_3$, Li_2CO_3, K_2CO_3 are variables, which have a relatively small effect on the system. The overview of the sensitivity analysis and the significances is in the Table 4.

Table 4. Sensitivity analysis.

Variable	Relative importance of the variables
$PbCl_2$	119,62
Sb_2O_3	103,10
$PbCO_3$	70,10
$Na_2\ CO_3$	59,91
$K_2\ CO_3$	49,77

A line analysis of technological processes which can substantially influence the product quality plays important role [19]. This work deals with crystallizers diagnostics, which are a part of continuous casting devices. Main focus is on technical diagnostics of crystallizer. A crystallizer is a special device which can dissipate redundant heat from liquid steel and force it to solidification in a predefined profile. In the crystallizer, a surface steel layer will be solidified and feed in the direction of crystallizers output. This process is going together with many unwanted effects, like abrasion of crystallizers walls. The inner wall state is very important quantity, which is closely observed. Too worn crystallizers' walls did not dissipate redundant heat well and they are prone to outbreak or to unwanted cracks by heat tension in the surface layer. Technical diagnostics of the desks surface is very time consuming process, which requires taking out the crystallizer and dismantling it. Goal of this effort was to verify, if there is a possibility to find out the state of crystallizer without a necessity of taking it out of its bearing. Diagnostics are based on vibration spectrum analysis, obtained while crystallizer runs. In the first phase, we dealt with a vibration spectrum analysis of the crystallizer's model. Vibrations were excited artificially, with help of a striker. Single strikes were driven by PLC Siemens.

The diagnostics are made by software analysis of vibration spectrums respectively of acoustics emission. These emissions can cause occurrence of an unexpected situation. A principle of this method is an analysis of spectrum of gained signal, its processing in the Matlab environment and subsequent verification in Statistica software. The last step is the most important, because thanks to it we are able to tell, with certain confidence, in which state the examined object occurs. If the initial neural network has good starting data, it is able to analyse other samples and with successfulness over 70% tell, in which state the current objet remains, eventually if occurs a critical (limiting) state (untighten screws in critical spots and so on). Data from an accelerometer (microphone) are evaluated in the Matlab environment and a special filter is applied on them.

Data were registered continuously in one block (9 strikes with 2s interval). In the first step, it was necessary to isolate single strikes and extract them into the alternative matrix. On every single data record, there was applied a Fast Fourier transform (FFT). As a result, we obtained power spectral density (PSD) of each pulse. Every PSD was further stored into another matrix. Some vibrations on the specific frequencies go through without any major changes, but the others are highly suppressed. In the spectrum, there were so included many relevant data, which have to be necessarily filtered off (Fig. 4).

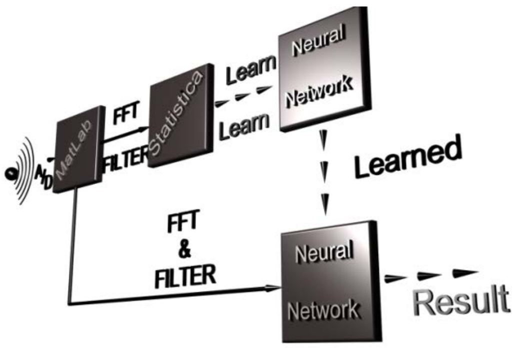


Fig. 4. Block schema of the data acquisition.

Attention was focused on the frequencies, which present highest amplitude in its area. The designed filter passes through the record of every impulse and searches for specific values of single spectra component. For another PSD analysis, the position of the peaks is very important, to be more precise, frequencies, which belong to them. It is relatively difficult to determine Location of these anomalies, because signal spectrum has an odd curve. After the application of classic algorithm for finding the maximum $(f(x\text{-}1) < \max > f(x\text{+}1))$, there were obtained hundreds of data, which have to necessarily evaluated. Some peaks were very close to each other, other on the contrary dominate some specific empty area and has very low amplitude. Therefore, it was necessary to develop filter, which could consider amplitude of the peak regarding to its surroundings. The newly designed filter is capable of eliminating these anomalies. It passes through the record and for the highest amplitude in the current area, the local maximum, is capable of verifying, whether it is really the highest. This interval is optional and its value is inversely proportional to the maximum count in the record. This interval can be expressed as insensitiveness. This value tells us on which interval the local maximum has to be valid, in order to admit and store its position. This algorithm was inspired by human perception. With some simplification, we can say that perception of particular extremes depends on their position compared with other values. If we have two sharp local maxims side by side, it is possible to ignore them, even if their amplitudes are very high. On the other hand, if the local maximum is alone and even if it has much lower amplitude compared with the global maximum, it is perceived sharply. Obtaining relevant peaks from PSD is the key process. It is only its position, which guarantees correct learning of artificial neural network, eventually back detection and indication of the result. In present time, a flag is assigned to every local maximum, which tells how long current maximum is the maximum. In future the algorithm will be extend into possibility to work in narrow band and choose local maximums more precisely than now.

It is important to remove ubiquity noise from signal record. To make this possible, local maximums with amplitude lower than 7% (an empirically discovered value) of the global maximum were removed. After this final touch, the picture became clear and readable and could be proceed to another processing with the help of a neural network. The used filter is still being improved and shortly will enable reaching even better results.

Atmospheric corrosion of metal materials exposed under atmospheric conditions depends on various factors such as local temperature, relative humidity, an amount of precipitation, pH of rainfall, concentration of main pollutants and exposition time [20]. As these factors are very complex, exact relation for mathematical description of atmospheric corrosion of various metals are not known so far. Classical analytical and mathematical functions have the limited use for description of this type of a strongly non-linear system depending on various meteorological-chemical factors and interaction between them and on material parameters. Nowadays there is a certain chance to predict a corrosion loss of materials by ANN [21].

Data about local temperature, relative humidity, amount of precipitation, pH of rainfall, air pollution by sulphur dioxide and exposition time were used as an input vector. Corrosion weight loss of structural carbon steel represented the output vector (Fig. 5 and Fig.6).

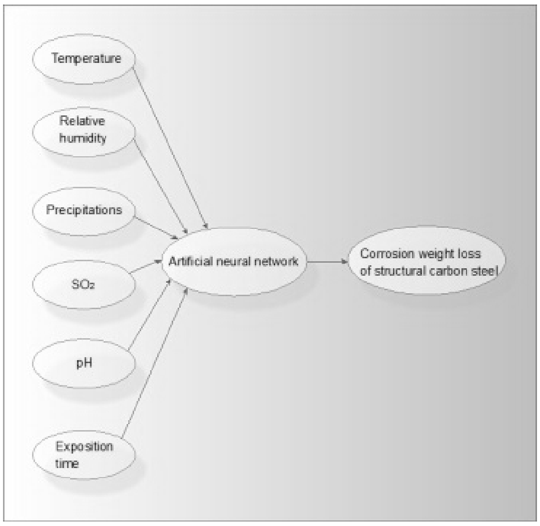


Fig. 5. Structure of input and output data.

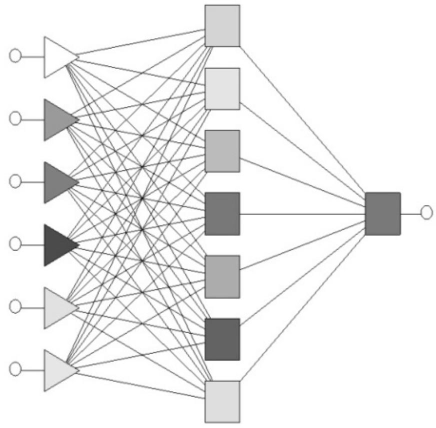


Fig. 6. Structure of ANN (topology 6-7-1).

Results of the sensitive analysis are shown on Table 5. It was found that air pollution by sulphur dioxide and exposition time has the most influence on corrosion weight loss of structural carbon steel.

Table 5. Sensitivity analysis.

Variable	Relative importance of the variables
SO_2	48,25
Exposition time	42,58
pH	13,45
Relative humidity	2,85
Precipitations	2,51
Temperature	1,29

The detection of internal defects in rolled products is performed using ultrasound control of cooled rolled products; therefore this is a very complicated and extensive problem. The model developed using ANN for prediction of defects in rolled products appears as an alternative to traditional methods, such as statistical regression analysis, and it is able to express more complex relations than these methods. The model predicts internal defects of rolled products on the basis of the input parameters such as chemical composition and selected technological operations. [22]

The subject of the neural network application was a data set formed by 150 continuously cast round blooms with a diameter of 525 mm made from low-alloyed steel 25CrMo4. Those blooms were hot rolled to square billets of 260x260 mm after heating in a soaking pit. All billets were controlled by an ultrasonic device after cooling down to ambient temperature. In our paper, the billets were divided into two groups (with and without internal defects). A concrete data file intended for the creation of artificial neural networks consisted of 153 cases. The total number of variables in this file was 21. 20 of the total number of variables were used as inputs into the artificial neural network. The input variables were: "Casting speed, Coefficient of heat transfer from the mould, Heating time, Heating temperature, Electromagnetic mixing in the mould, Tundish Exchange, Metallurgical length" and "Chemical composition". There was only one output variable named "Ultrasound findings". This variable contained information whether there was a defect based on a combination of the input parameters or not. The expression of the number of cases showing a defect and the cases without any defect are presented using a histogram in Fig. 7. Structure of ANN is presented in Fig. 8.

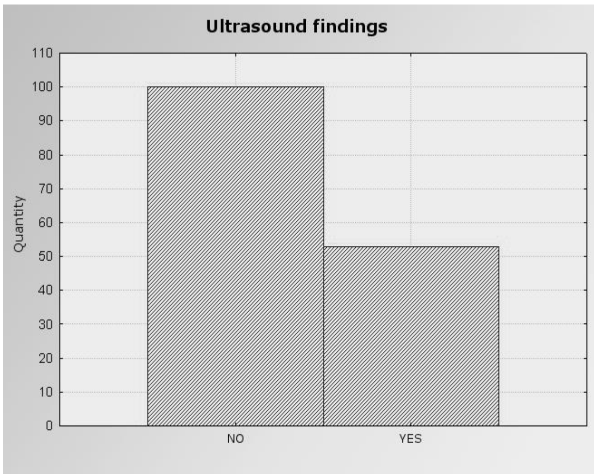


Fig. 7. Histogram of output variables.

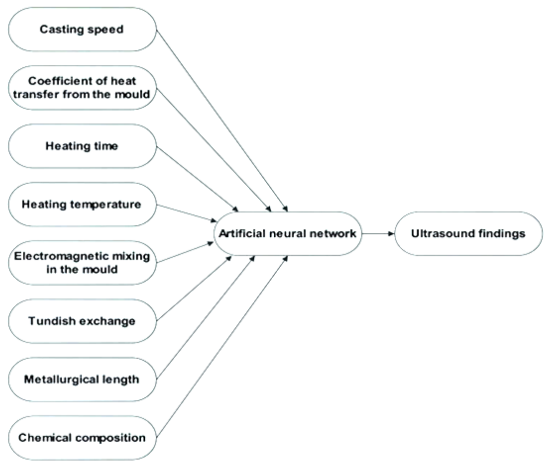


Fig. 8. Structure of input and output data.

This analysis has shown that from the total number of 153 cases, 53 cases were indicated as cases with a defect, while 100 cases were without a defect. A scheme of the input and output variables related to the neural network is illustrated in Fig. 8. Data with the best learning results were selected for the prediction of defects. They included a three-layer perceptron network with 22-18-2 topology. This means that the input layer contained 22 neurons; the hidden layer 18 and the output layer 2 neurons. Data with the best learning results were selected for the prediction of defects. Summary of the results of particular neural network is presented in Table 6.

Table 6. Summary of the results of particular neural network.

	Ultrasound findings - YES	Ultrasound findings - NO	Ultrasound findings - ALL
Altogether	53.00	100.00	153.00
Correctly	41.00	91.00	132.00
Incorrectly	12.00	9.00	21.00
Correctly (%)	77.36	91.00	86.27
Incorrectly (%)	22.64	9.00	13.73

The work [23] deals with the experimental modal analysis of glass laminated plates with different shape and these results are compared with those obtained by applications of the artificial neural networks ANN and finite element method (FEM) simulation.

For the mode frequency measurements, the standard ESPI (Electronic speckle interferometry) device was used [24]. In the first step we have tested the mode frequency generation as a function of the sample thickness. Table 7 describes the sample shape and dimensions for experiments with different rounding. The sample with r = 0 is tetragonal and the sample with r = 87,5mm is a disc. The sample thickness influence on generated modes is presented in Table 7.

Table 7. Sample rounding values.

Sample Number	1	2	3	4	5	6	7	8	9
Sample Rounding [mm]	0	10	20	30	40	50	60	70	87,5

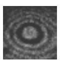
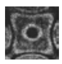
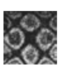
In the first step of our analysis we focus attention on the finite element method application and its comparison with ESPI mode measurements. Results are collected in Table 8 (ESPI). Corresponding mode shapes are presented in all cases.

The measured ESPI values are higher than computed ones (FEM) in the first mode only. These observations could be caused by model imperfections as well as material's constants indefiniteness of the model and the real body respectively. A maximum observed percentage difference for the first mode is 27 percent (thickness 0.8). All other differences are smaller than this value.

For prediction of the resonance frequency depending upon 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). The output vector represented the resonance frequency (1 neuron in the output layer). The best results of prediction proved a multilayer feed forward 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, 9983.

The optimization of the technological processes control is usually connected with mathematical models usage. Most of technical instruments for control at the level of own technology are not customized for the hard mathematical operations solving; besides of that, the computation with qualitatively precise models of the dynamic systems is very time consuming and together with the real time optimization is not really solvable. On the other hand, the mathematical description of artificial neural networks is very simple and the algorithms of the learned ANN are easily implemented into existing technological processes control means. For successful using of the models on the basis of ANN, the ANN needs to be rationally learned on the data that occupy all eventual variants which could occur in the real process including malfunction and crash states. But such data are not practically possible to get from a real technological process. There is a possibility of off-line ANN learning with using data given by simulations based on high precision mathematical models and by this way to get a hybrid model. By the suitable organization, it is secured that ANN will also react correctly to such situations which are highly exceptional in real control conditions. Authors present the philosophy and the possibilities of this hybrid models usage on several practical processes [25].

Table 8. Resonance frequencies measured by ESPI.

		Sample thickness h [mm]			
	ESPI mode shape	**0,8**	**1,05**	**1,35**	**1,65**
Resonance frequency [Hz]	1 	61	78	93	112
	2 	138	187	228	293
	3 	179	248	309	378
	4 	374	522	663	800
	5 	432	620	758	919
	6 	498	694	861	1058

Under hybrid model idea, there is mostly imagined a model, where a part of the computation is executed based on the mathematical-physical basis and other with artificial neural network exploitation. This model could be signed as a parallel hybrid model. Mathematical-physical models seem to be advantageous for generating a large amount of alternatives of real object behaviour and data acquired by this way are then used for artificial neural network learning. This approach could be named as a serial hybrid model. The main reason for serial hybrid models application is an effective advantage of computation exploitation on one side and effort to eliminate their characteristic disadvantages on the other side. Originally, the idea of serial hybrid models has been invented in an effort to find an effective solution for on-line control of material complex heating and cooling processes intended for forming; it can also be used for hybrid models creation in other industrial parts.

In the paper [26], there was shown that cooling curves for specimens, which vary in shape, have the same character and therefore is sufficient when an artificial neural network would predict not a cooling curve, but corresponding time transformation coefficient (TTC) only, by the reciprocal value of which the physically measured (referential) cooling curve of known shape must be transformed; therefore the time course of the cooling predicted curve for specimens of required dimensions is acquired. In a real-time cooling process of two geometrically different steel specimens intended for rolling process, two cooling curves were acquired by means of maximum surface temperature measurement. For correct artificial neural network learning, this count is insufficient. Therefore it is effective to use a mathematical-physical three-dimensional model of heat diffusion spread in material which results from Fourier partial differential equation: Model parameters could be defined based on identification of both measured cooling curves, on which mathematical-physical models were also verified. From Fig. 9, it is obvious that prediction by means of an artificial neural network exhibits a good relationship with mathematical model results (maximum error does not exceed 5%, which represents 2 s as the maximum error of determining the cooling down time).

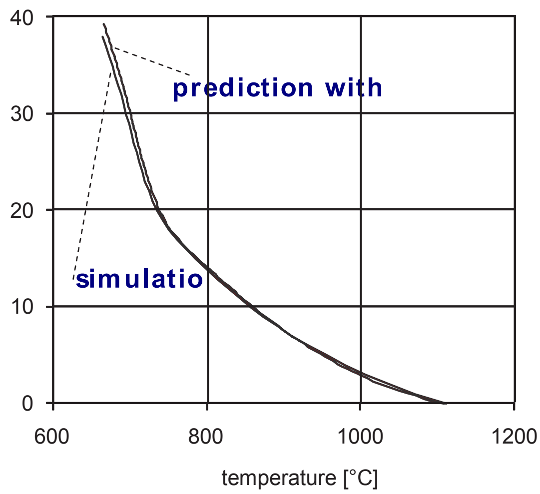


Fig. 9. Accuracy of prediction.

In the next part of the contribution, we present comparison of the measured and predicted own frequencies (OF) of tires. 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 the input to the algorithm. The output is a predicted value of radial frequency and amplitude of own frequencies. In the papers [27, 28], we present results of ESPI measurements of tires own frequencies depending on tire construction parameters as well as ANN application of ESPI data for own frequencies and own amplitudes prediction depending on the chosen tire construction parameters. 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 a 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 topology (5 input neurons, 11 in the hidden layer and 2 outputs). Results are presented in the graphic form in Fig.10 [27].

To test the reliability of the chosen network, we have evaluated next 120 tires and obtained also the same network configuration with statistical data SSE = 526.127, RMS =1218, R^2 = 0.985. For a third group containing 98 tires, we obtained values SSE =723.221, RMS= 962, R^2 = 0.988 at the same network configuration. These results clearly show reliability of the chosen network.

Further input parameters of the neural network were enlarged. Radial static stiffness, circumferential static stiffness, lateral static stiffness, static torsional stiffness have been added as input data. The results of this analysis show independency of the radial frequency on the static torsional stiffness. In other presented cases, the assumed dependence is decreasing.

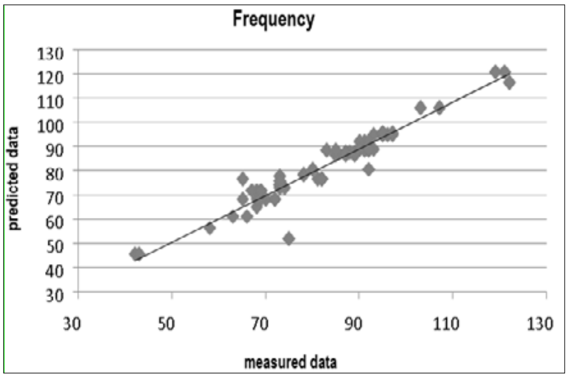


Fig. 10. Comparison of measured and predicted frequency data obtained by ESPI and ANN.

Thermovision outputs are usually thermograms with a form of a quasi-coloured imaging record of the observed temperature field [29-32]. A thermogram is usually registered and presented in a form of an electronic or printed image. The character of such a document is for informational purposes only, and real temperature values are difficult to detect. The exploitation of neural networks is advantageous if it is necessary to express complex mutual relations among sensor-based data. More accurate results of the predictions of different metallurgical parameters with the exploitation of neural networks are based on the fact that the application of neural networks enables the assignment of relations among process parameters which cannot be traced using common methods due to their mutual interactions, the considerable amount of data, dynamics and the thus ensuing time demands.

Each thermogram pixel is characteristic in its colour that corresponds to the temperature in this pixel. Colour is preferably expressed by the brightness of three fundamental colour components, known under the R, G and B definition. Thermovision software consists of some algorithm that binds the measured temperature with a specific RGB brightness. This algorithm differs as well as the number and diversity of exploited colours with various camera types. That is the reason why the same thermograms of the same object measured by various cameras differ from each other. It is necessary to find the typical and functional parameters:

$$T = f\,(R,\ G,\ B) \qquad (1)$$

A specific function is usually not known, so it seems to be useful to replace a real function with a mathematical description represented by ANN. Learning of a neural network is carried out based on data acquired from the colour scale that accompanies thermograms. An example of such a scale is in Fig. 11. From Fig. 11, it is apparent that each temperature from the minimal to maximal value, the values of which are part of the scale, is uniquely assigned by unique colour. The temperature scale from the minimum to the maximum is linear. It is easy to create software that allows a random spot inside the scale to be assigned to temperature and colour components of the RGB picture.

Fig. 11. Thermogram scale used for learning, validation and testing of an artificial neural network.

Now, based on data acquisition, it is possible to learn an artificial neural network uniquely and with sufficient accuracy to assign corresponding temperature to each R, G and B colour combination. A three-layer neural network has been used with teacher learning, and with the Back propagation learning algorithm. The application of the software Statistica Neural Networks has been used for neural network creation [9], [10], [11]. Topology 3-5-1 (see Fig. 12) has been used for its simplicity that exhibited a similar accuracy as other ANN with more complicated topology.

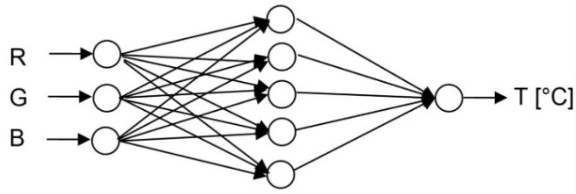


Fig. 12. Used topology of the artificial neural network.

For thermogram backward analysis, a computer program has been created, the design of which is visible in Fig. 13.

The interaction with the program is simple and intuitive. It is easy to supply the thermogram analysis program with other useful statistical computing and reproduction based on user demands. An example might be a graphical shape of a quantum thermogram that is a graph analogy with isolines. Such a projection can be obtained by pressing the button “To Quantize”. The result of a thermogram quantum of a heated material can be seen in Fig. 14.

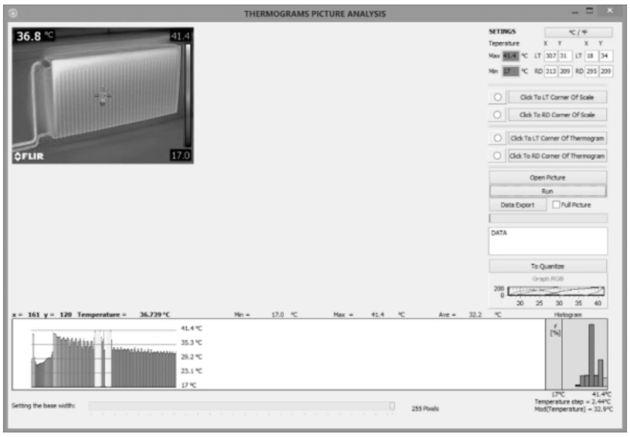


Fig. 13. Design of software for thermogram.

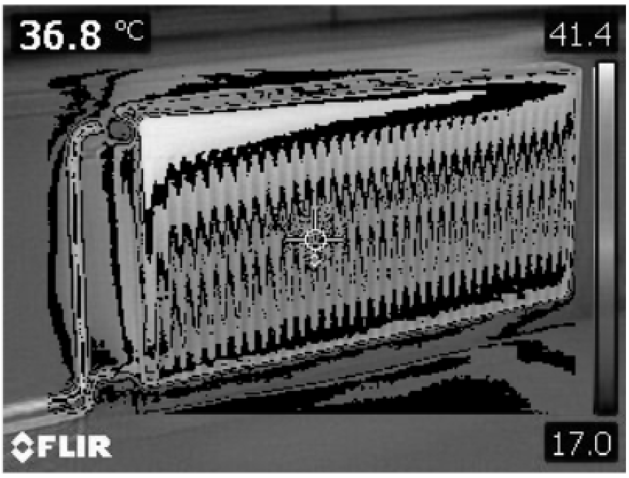


Fig. 14. The result of a thermogram quantum of a heated material backward analysis.

2 Conclusion

Presented analysis of materials realized by ANN show a relatively large spectrum of problems which can be solved by ANN. For material engineers, it offers clever “tuning” of chemical and physical properties of materials according to demands of product properties. According to prediction ability of ANN, we can also spread our knowledge to domains which are difficultly reached by experimental methods. What is also very useful is evaluation of fatigue processes defect appearance, material wear appearing in industrial processes as well as the product properties testing. Evaluation of thermal data acquisition by ANN offers also interesting application in measuring technique.

This work was supported by Ministry of Education, Youth and Sports, Czech Republic in the framework of the projects SP2018/65 and SP2018/109.

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