Artificial Neural Networks Prediction of Rubber Mechanical Properties in Aged and Nonaged State

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Abstract Artificial neural networks (ANN) have been used for characterization of rubber blend mixtures ageing and for prediction of mechanical properties according to chemical composition. Strength R_m and modulus M100 have been evaluated. The ANN application was tested by statistical function RMSE (root mean square error) and R^2 (coefficient of determination) which value for all predictions was higher than 0.93.

Keywords Rubber blends · Mechanical properties · Artificial neural networks

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1 Introduction

Several properties of rubber mixtures are strongly influenced by technology treatment and agents or fillers added to the rubber. Carbon black is an active filler which is used to increase the electrical and thermal properties because of its strong interactions with natural rubber. Plasticizers play an important technological role in rubber industry. Rubber is a multicomponent material, which is very sensitive to a lot of chemical species and mainly their technological treatment. For a multicomponent system inputs and outputs connected with optimization of chemistry or technological processes is useful to use an artificial neural network (ANN).

The study [1] proposed a novel approach to determine the fibre volume fraction in composites using vibration based on a non-destructive technique with a neural network. Currently, the volume fraction of a glass fibre/matrix based composite material is assessed using destructive techniques. Instead of changing or destroying the structure, a new non-destructive approach based on vibration analysis is proposed. Complete experimental protocols were developed to capture the vibration pattern. An auto-regressive model was developed as a feature extraction tool to classify the fibre volume fractions and as a pole tracking algorithm. The classification performances were within the range of 90–98%.

In [2] a back-propagation neural network was employed to conduct an approximation of a true stress-strain curve using the load-displacement experimental data of DP590, a high-strength material used in automobile bodies and chassis. The optimized interconnection weights are obtained with hidden layers and output layers of the BPN through intelligent learning and training of the experimental data; by using these weights, a mathematical model of the material's behaviour is suggested through this feed-forward neural network.

A decoupled computational homogenization method for nonlinear elastic materials was proposed using neural networks in [3]. In this method, the effective potential is represented as a response surface parameterized by the macroscopic strains and some microstructural parameters. The discrete values of the effective potential are computed by the finite element method through random sampling in the parameter space, and neural networks are used to approximate the surface response and to derive the macroscopic stress and tangent tensor components.

The article [4] deals with the experimental modal analysis of glass laminates plates with different shape and these results are compared with those obtained by applications of artificial neural networks (ANN) and the finite element method

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(FEM). It is presented the dependence of the generated mode frequency as a function of sample thickness as well as the sample shape (rounding) of glass laminate samples. The coincidence of both experimental and simulated results is very good.

In the paper [5] an application of artificial neural networks (ANN) on the relation between glass composition versus optical transmittance of the chosen glass systems is described. The excellent prediction ability of the ANN program shows a possibility to influence the glass composition to obtain the required optical properties.

The objective of the paper [6] is to classify each layer as coal, shale coal and shale depending upon the content of ash % and moisture % of the corresponding layer in coaly horizon. Hierarchical cluster analysis (HCA) is applied to classify the non-coal horizons and bands of identified coal seams of each well under the study area based on geophysical log responses: natural gamma ray (NG), high resolution density (HRD) and single point resistance (SPR). Hierarchical clustering separates the zones in a particular coal seam from five wells using the nature of the curve. These zones/clusters are further identified as coal, shale coal, shale in three wells using regression and a multilayer feed forward neural network.

In the study [7], an artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) models were used to predict the average permeate fluxes and sodium chloride rejection of waste brine nanofiltration process. A hybrid method was used as the training method of the ANFIS. The overall agreement between the ANFIS predictions and experimental data was excellent for both permeate flux and salt rejection ($r = 0.96$ and $r = 0.94$, respectively).

The aim of the work [8] is to develop a prediction method for renewable energy sources in order to achieve an intelligent management of a microgrid system and to promote the utilization of renewable energy in grid connected and isolated power systems. The proposed method is based on the multi-resolution analysis of the time-series by means of wavelet decomposition and artificial neural networks.

In the paper [9], authors investigated the ensemble of deep neural networks (DNNs) by using an acoustic environment classification (AEC) technique for the statistical model-based voice activity detection (VAD). From an investigation of the statistical model-based VAD, it is known that the traditional decision rule is based on the geometric mean of the likelihood ratio or the support vector machine (SVM), which is a shallow model with zero or one hidden layer. The approach for VAD was evaluated in terms of objective measures and showed significant improvement compared to the conventional algorithm.

The study [10] describes the application of TiO_2, ZnO, TiO_2-ZnO-based systems modified with 1.5 and 2.5% wt. Fe using the impregnation method for the maxilon blue 5G dye discoloration. Specific surface area (BET method), X-ray diffraction, thermogravimetric analysis, and photoacoustic spectroscopy characterization techniques were used in this work. A neural model was developed for each studied catalyst with three intermediate layers, backpropagation learning algorithm, and sigmoid activation function implemented in FORTRAN. The three models presented the best results with three neurons in the intermediate layer. Therefore, the neural networks can be successfully employed to model the discoloration process involving the synthesized catalyst (R^2 varying between 0.98 and 0.99).

In this paper we solve by ANN the optimization of plasticizer amount on chosen mechanical properties such as strength R_m and modulus M100 before and after aging on air.

2 Theoretical Assumptions

Artificial neural networks are used for materials properties prediction when analytical mathematical approximation cannot be found. From this very robust mathematical tool material properties can be predicted.

Artificial neural networks use different topologies that in most cases consist with three or four layers. In these networks three types of neurons occur that are:

- input neurons
- hidden neurons
- output neurons.

Input neurons have the information about parameters that change in our datasheet such as material composition, thermal treatment information and others.

Output neurons correspond to material properties that we want to predict.

Some part of the input neurons is used for training and another part for generalizing.

Advantages of neural networks are as follows:

- Neural network can teach
- Neural network can generalize.

Disadvantages are as follows:

- Neural networks need very much values of one or more parameters that change in every dataset as input.

The ANN usage is tested by statistical parameters RMSE and R^2 which are defined by Eqs. (1) and (2)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - o_i)^2}{n.(n-1)}}. \quad (1)$$

$$R^2 = \left(\frac{E(y).E(o)}{E(y.o)}\right)^2 \quad (2)$$

where y_i represent i-th measured value of selected parameter, o_i represent i-th predicted value of selected parameter corresponding to i-th measured value, n is the total number of input values, E(y) represent statistical mean value of inputs, E(o) is the statistical mean value of predicted values and E(y.o) is the mean value of multiplification of predicted and measured values in the same point.

3 Experimental Procedures

3.1 *Used Samples*

Chemical composition of standard rubber mixture in DSK (one part of component per 100 part of rubber) is shown in Table 1.

3.2 *Ageing Conditions*

Conditions of ageing are shown in Table 2.

3.3 *Experimental Values*

3.3.1 Measured Properties

Measured values of tensile strength and moduli M100 of samples with 1DSK oleic acid and surfactant Etoxon are shown in Table 3.

The measured values of tensile strength and moduli M100 versus Etoxon amount for the rubber blend with 3DSK oleic acid and non-aged state are shown in Table 4.

The measured values of tensile strength and moduluses M100, versus Etoxon amount with 1DSK oleic acid after ageing are shown in Table 5.

The measured values of tensile strength and moduluses M100 versus Etoxon amount of samples with 3DSK oleic acid after ageing are shown in Table 6.

Table 1 Chemical composition of standard rubber mixture

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

Table 2 Ageing conditions of samples

Environment	Time
Air	1 month

Table 3 Measured values of R_m and M100 versus Etoxon amount for1DSK oleic acid mixtures (non-aged state)

Etoxon amount (%)	R_m (MPa)	M100 (MPa)
0	17	3.60
2	18.01	3.80
4	18.71	4.10
6	19	4.20
8	19.28	4.30
10	19.83	4.60
20	20.50	5.10
30	21.90	5.50

Table 4 Measured values of R_m and M100 versus Etoxon amount for3 DSK oleic acid mixtures (non-aged state)

Etoxon amount (%)	R_m (MPa)	M100 (MPa)
0	18.50	3.90
2	18.72	4.10
4	18.90	4.20
6	19.16	4.30
8	19.85	4.70
10	20.50	5.10
20	21.42	5.40
30	22.49	5.70

Table 5 Measured values of R_m and M100 versus Etoxon amount for1 DSK oleic acid mixtures (aged state)

Etoxon amount (%)	R_m (MPa)	M100 (MPa)
0	14.21	4.20
2	15.50	4.50
4	15.81	4.70
6	16.90	5.30
8	17.35	5.50
10	17.50	5.60
20	17.80	5.70
30	17.86	6.10

Table 6 Measured values of R_m and M100 versus Etoxon amount for 3 DSK oleic acid mixtures (aged state)

Etoxon amount (%)	R_m (MPa)	M100 (MPa)
0	17	5
2	17.21	5.10
4	17.44	5.30
6	17.66	5.50
8	18	5.70
10	18.16	5.70
20	18.55	6.20
30	19.12	6.40

3.3.2 ANN Prediction

The ANN prediction was performed by the Statistica 7 software. DSK content of oleic acid and ETOXON have been used as input neurons.

Functions of predicted tensile strength as function of measured tensile strength are shown in Figs. 1 and 2. Functions of predicted M100 value as function of measured M100 value are shown in Figs. 3 and 4.

Figures 1, 2, 3 and 4 show very good correlation between measured and ANN predicted values. Statistical parameters of ANN predictions for tensile strength R_m, moduli M100 are shown in Tables 7 and 8.

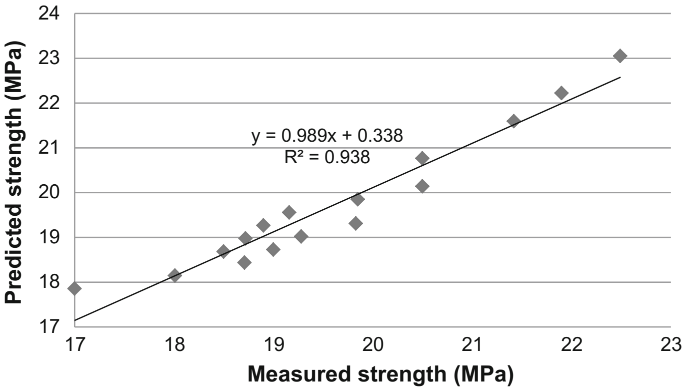

Fig. 1 Predicted versus measured values of R_m for oleic acid mixtures before ageing process

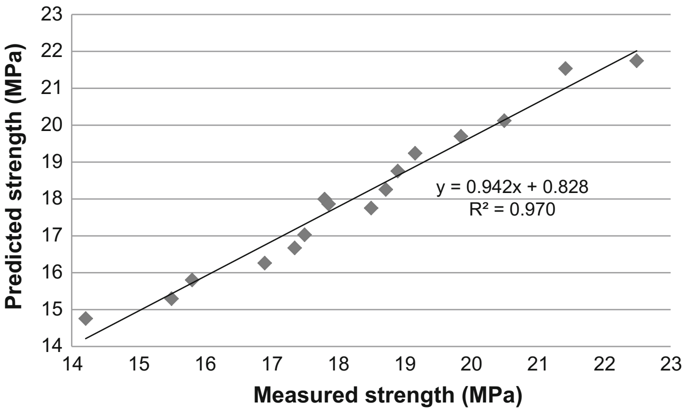

Fig. 2 Predicted versus measured values of R_m for oleic acid mixtures after ageing process

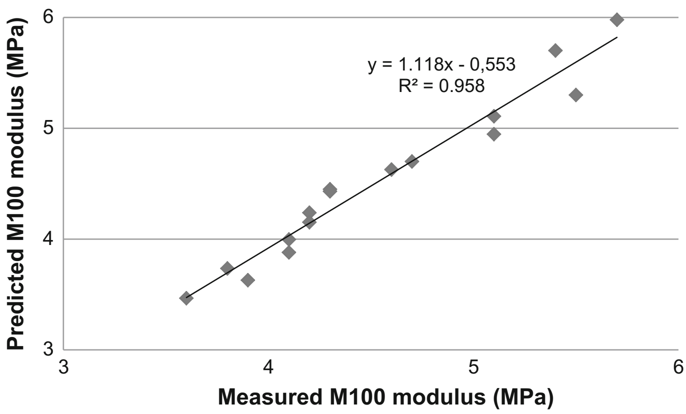

Fig. 3 Predicted versus measured values of M100 for oleic acid mixtures before ageing process

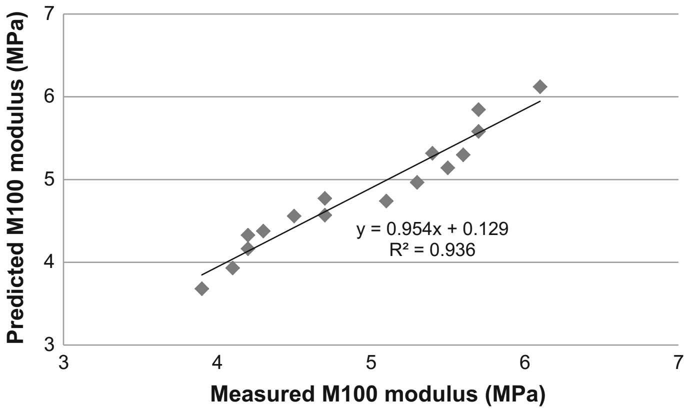

Fig. 4 Predicted versus measured values of M100 for oleic acid mixtures after ageing process

Table 7 Statistical parameters of ANN predictions for tensile strength R_m

State	RMSE	R^2
Before ageing	0.080	0.938
After ageing	0.112	0.970

Table 8 Statistical parameters of ANN predictions for modulus M100

State	RMSE	R^2
Before ageing	0.042	0.958
After ageing	0.051	0.936

4 Conclusions

From presented results of ANN prediction we can draw following conclusions.

– ANN can predict chosen mechanical values of rubber mixtures with combination of both plasticizer and ETOXON surfactant amount,
– ANN can predict values also after ageing process.

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References

1. Farhana NIE, Majid MSA, Paulraj MP et al (2016) A novel vibration based non-destructive testing for predicting glass fibre/matrix volume fraction in composites using a neural network model. Compos Struct 144:96–107
2. Doh J, Lee SU, Lee J (2016) Back-propagation neural network-based approximate analysis of true stress-strain behaviors of high-strength metallic material. J Mech Sci Technol 30:1233–1241
3. Le BA, Yvonnet J, He QC (2015) Computational homogenization of nonlinear elastic materials using neural networks. Int J Numer Meth Eng 104:1061–1084
4. Seidl D, Koštial P, Jančíková Z et al (2011) Modal analysis—measurements versus fem and artificial neural networks simulation. Commun Comput Inf Sci 188:170–175
5. Jančíková Z, Minárik S, Bošák O et al (2014) The neural network analysis of optical glasses transmittance. In: International carpatian control conference, IEEE, 345 E 47th St, New york
6. Ghosh S, Chatterjee R, Shanker P (2016) Estimation of ash, moisture content and detection of coal lithofacies from well logs using regression and artificial neural network modelling. Fuel 177:279–287
7. Salehi F, Razavi SMA (2016) Modeling of waste brine nanofiltration process using artificial neural network and adaptive neuro-fuzzy inference system. Desalin Water Treat 31:14369–14378
8. Doucoure B, Agbossou K, Cardenas A (2016) Time series prediction using artificial wavelet neural network and multi-resolution analysis: application to wind speed data. Renew Energy 92:202–211
9. Hwang I, Park HM, Chang JH (2016) Ensemble of deep neural networks using acoustic environment classification for statistical model-based voice activity detection. Comput Speech Lang 38:1–12
10. Lenzi GG, Evangelista RF, Duarte ER et al (2016) Photocatalytic degradation of textile reactive dye using artificial neural network modeling approach. Desalin Water Treat 30: 14132–14144