

APPLICATION OF ARTIFICIAL INTELLIGENCE METHODS FOR PREDICTION OF STEEL MECHANICAL PROPERTIES

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The target of the contribution is to outline possibilities of applying artificial neural networks for the prediction of mechanical steel properties after heat treatment and to judge their perspective use in this field. The achieved models enable the prediction of final mechanical material properties on the basis of decisive parameters influencing these properties. By applying artificial intelligence methods in combination with mathematic-physical analysis methods it will be possible to create facilities for designing a system of the continuous rationalization of existing and also newly developing industrial technologies.

Key words: metallurgy, steel, mechanical properties, neural networks, model

Rabljenje metode umjetne inteligencije za predmnijevanje mehaničkih svojstava čelika. Nakana članka je očivid mogućnosti rabljenja umjetne neuralne mreže za predmnijevanje mehaničkih svojstava čelika poslije vruće obrade i ocijena njezine perspektivne primjene u tom polju. Ostvareni model omogućuje predmnijevanje završnih mehaničkih svojstava materijala na temelju zahtijevanih parametara. Primjenom metode umjetne inteligencije u sprezi sa matematičko-fizikalnim analizama, omogućen je jednostavniji pristup oblikovanju sustava neprekidne racionalizacije postojećih, a također i novog razvitka industrijskih tehnologija.

Ključne riječi: metalurgija, čelik, mehanička svojstva, neuralne mreže, model

INTRODUCTION

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. Final steel product manufacture properties of a given size and form depend on their chemical composition, on steel technology, the type of semi-product, formation and heat treatment technology. Steel and forming technology have a considerable importance from a steel product final properties point of view because together with the chemical composition and so-called steel purity they create the basis of the properties of these materials. These properties however can be partially influenced by heat treatment. Inappropriately selected or executed heat treatment technology thus can be also the cause of not achieving the manufacture properties of steel products are [1].

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.

The theoretical knowledge of physical metallurgy does not express comprehensively all physical variables, which influence the resultant product's manufacture quality. Therefore, the data files contained in IRA and ARA steel diagrams of different chemical compositions are the basic tool for heat treatment. It is possible to treat these data statistically and thus acquire empiric relations, which serve for predicting the course of partial processes proceeding in heat treatment. These relations have been obtained so far on the basis of the regression analysis of measured data. The real possibility of predicting different steel parameters with the use of artificial intelligence elements is presently offered. By suitably connecting these results with knowledge of physical metallurgy and with practical data about heat treatment, it is possible to obtain the groundwork for creating a semi-empiric model of heat treatment [2].

The aim of the paper is to outline the possibilities of applying artificial neural networks for the prediction of mechanical steel properties after heat treatment and to judge their perspective use in this field.

ARTIFICIAL NEURAL NETWORKS

Neural networks use the distributed parallel processing of information during the execution of calculations, which means that information recording, processing and

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transferring are carried out by means of the whole neural network, and then by means of particular memory places. 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 [3].

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 can not use common methods to trace the reason of their mutual interactions, large number and dynamics.

A disadvantage of neural network application is the danger of network overtraining when a neural network fixates exceedingly on training data and it loses the capability of generalization and further there is an uncertainty if it is possible to achieve the required results because it is not possible to estimate beforehand the size of an error which is strongly dependent on network parameters and on training data. It is necessary to verify experimentally the usability of neural networks in any field and to try to retrieve optimal parameters by way of experiment, experience and intuition to achieve the best possible results [4].

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

The rate of inaccuracy between the predicated and actual output represents a prediction error. In technical applications the error is mainly represented by the following relations [5]:

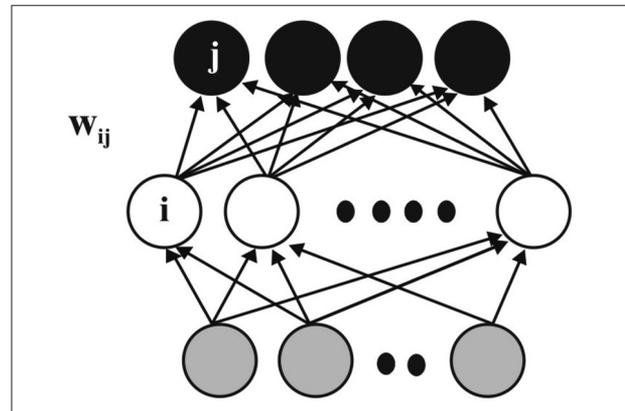


Figure 1. Topology of a multilayer feedforward neural network

- The relation for RMS error calculation (Root Mean Squared) – it does not compensate for units used

$$\text{RMS} = \sqrt{\frac{\sum_{i=0}^{i=n-1} (y_i - o_i)}{n - 1}} \quad (1)$$

- The relation for REL_RMS error calculation – it compensates for units used

$$\text{REL_RMS} = \sqrt{\frac{\sum_{i=0}^{i=n-1} (y_i - o_i)^2}{\sum_{i=0}^{i=n-1} (y_i)^2}} \quad (2)$$

where: n - number of patterns of a training or test set, y_i - predicted outputs, o_i - measured outputs.

PREDICTION OF STEEL MECHANICAL PROPERTIES

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 [6]. 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 pe-

riod 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.

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.

Modeling neural network was performed using MATLAB - Neural Network Toolbox software. For particular neural network models the quality of network adaptation to the submitted patterns and generalization scale were observed.

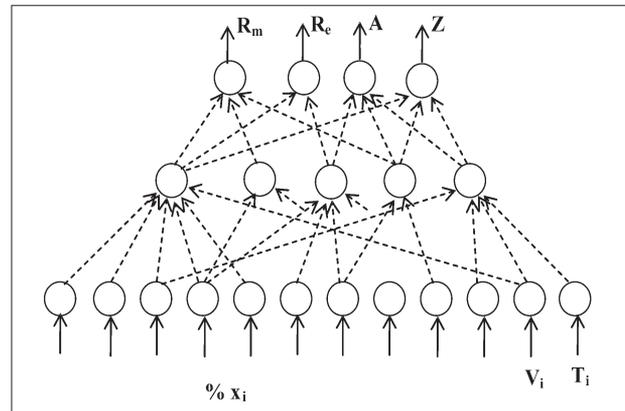


Figure 2. Multilayer feedforward neural network

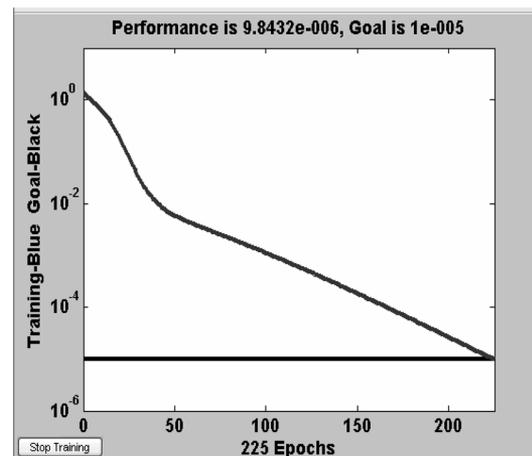


Figure 3. Time behavior of total mean squared error during the learning of the neural network

Time behavior of the total mean squared error during network learning is represented in Figure 2. Total mean squared error development during the learning of the neural network is illustrated in Figure 3. The best results of predicting the mechanical properties proven neural network models, whose topology and prediction errors RMS and REL_RMS are calculated according to relations (1) a (2), are showed in Tables 1 and 2.

Table 1. RMS errors for selected network topologies

Steels	Topology	RMS			
		R_e	R_m	A	Z
		/ MPa		/ %	
Normal and alloyed	12-3-5-4	82.73	62.40	1.67	4.1
Only normal	12-3-4	33.07	36.25	1.44	4.9
Only alloyed	12-3-3-4	98.70	61.96	1.45	4.8

Table 2. REL_RMS errors for selected network topologies

Steels	Topology	REL_RMS			
		R_e	R_m	A	Z
		[1]			
Normal and alloyed	12-3-5-4	0.099	0.065	0.083	0.064
Only normal	12-3-4	0.036	0.047	0.066	0.079
Only alloyed	12-3-3-4	0.107	0.059	0.076	0.075

The suggested network was able to satisfactorily predicate 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 %. However, these heats were represented in a training set by a smaller number of patterns.

CONCLUSION

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.

A model of a neural network for predicting the final mechanical steel properties was created. The model enables the prediction of mechanical steel properties with a sufficiently small error. After evaluating the achieved results, we can state that the exploitation of neural networks is advantageous, if it is necessary to express complex mutual relations among sensor-based data and thus also for predicting the mechanical properties of steels. Neural networks are able to be realized and appropriately express the general properties of data and 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 parameters of the process which with the use of common methods are not possible to trace due to their mutual interactions, great amount and dynamics.

By suitably connecting the achieved results with the knowledge of physical metallurgy, it will be possible to obtain the groundwork for creating a semi-empiric model of heat treatment which can become the foundation for a system of continuously rationalizing existing and also newly developing industrial technologies.

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Note: The responsible person for English language is the author Z. Jančíková.