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M. SZOTA*, J. JASINSKI*

MODELING OF MICROHARDNESS OF CARBONIZED CHOSEN CAR PARTS USING AN ARTIFICIAL NEURAL NETWORK TOOL

ZASTOSOWANIE SZTUCZNYCH SIECI NEURONOWYCH DO MODELOWANIA MIKROTWARDOŚCI WARSTW NAWĘGLONYCH WYBRANYCH CZĘŚCI SAMOCHODOWYCH

This paper presents the possibility of using neural networks model for designing a carbonizing process in a fluidized bed. This process is complex and difficult as multi-parameter changes are non-linear and a car drive cross structure is non-homogeneous. This fact and lack of mathematical algorithms describing this process make modeling properties of drive elements by traditional numerical methods difficult or even impossible. In this case, it is possible to use an artificial neural network. Using neural networks for modeling of carbonizing in a fluidized bed is caused by several net features: non-linear character, the ability to generalize the results of calculations different from the learning data set, lack of need of mathematical algorithms describing influence of input parameters changes on modeling materials properties.

The neural network structure is designed and specially prepared by choosing input and output parameters of the process. The method of neural network learning and testing, the way of limiting net structure and minimizing learning and testing error are discussed. Such prepared neural network model, after putting desirable values of car cross driving properties in the output layer, can give answers to a lot of questions about carbonizing process in a fluidized bed. The practical implications of the neural network models are the possibility of using them to build control system capable of on- line process control and supporting engineering decision in real time. The originality of this research is a new idea to obtain desirable materials properties after carbonizing in a fluidized bed. The specially prepared neural network model could be a help for engineering decisions and may be used in designing carbonizing process in a fluidized bed as well as in controlling changes of this process.

Keywords: neural network modeling, artificial intelligence, materials engineering

Praca ta prezentuje możliwości zastosowania modelu na bazie sztucznej sieci neuronowej do modelowania nawęglania w złożu fluidalnym. Proces ten jest skomplikowany i wielo-parametryczny, a zmiany poszczególnych jego parametrów są nieliniowe. Fakt ten oraz brak algorytmów matematycznych opisujących wpływ parametrów procesu nawęglania na właściwości mechaniczne elementów po nawęglaniu utrudnia, a niejednokrotnie uniemożliwia zastosowanie tradycyjnych metod symulacji numerycznej. W tym przypadku, było uzasadnionym podjęcie próby zastosowania sztucznej inteligencji do modelowania tego procesu.

Przedstawiona w pracy struktura sztucznej sieci neuronowej została zaprojektowana dla wybranych parametrów oraz wielkości modelowanych procesu nawęglania w złożu fluidalnym.

W pracy zostały omówione metody uczenia i testowania sztucznej sieci neuronowej, redukcji jej struktury oraz minimalizacji błędu uczenia i testowania. Model neuronowy przygotowany w omówiony sposób może odpowiedzieć na wiele pytań dotyczących parametrów procesu nawęglania. W przyszłości istnieje możliwość zastosowania opisanego modelu do budowy systemu wspomagającego decyzję inżynierską i kontrolującego proces nawęglania w czasie rzeczywistym.

1. Introduction

The carbonizing process in a fluidized bed is multi-parameter and complex [1, 2], because changes of parameters during this process have non-linear characteristics, shown in Fig. 1. The next problem is the lack of mathematical algorithms that could describe it. Neural networks can be used for modeling of carbonizing in a fluidized bed thanks to their three basic features such as:

- non-linear character,
- ability to generalize the results of calculations for data out of the training set,

* FACULTY OF MATERIALS PROCESSING TECHNOLOGY AND APPLIED PHYSICS, CZĘSTOCHOWA UNIVERSITY OF TECHNOLOGY, 42-200 CZĘSTOCHOWA, 19 ARMII KRAJOWEJ AV., POLAND

- no need for mathematical algorithms describing the influence of changes in input parameters on modeled materials properties [3–7].

The research is divided into eight stages:

- choosing modeled properties of materials,
- choosing heat treatment parameters to prepare data input vector,
- using a special computer system to obtain a training data set,
- designing and building a neural network structure,
- minimizing a model structure and a learning error,
- minimizing a testing error,
- using a neural network model for the prediction of material carbon layer thickness after heat treatment in a fluidized bed,
- practical verification of the modeling results quality.

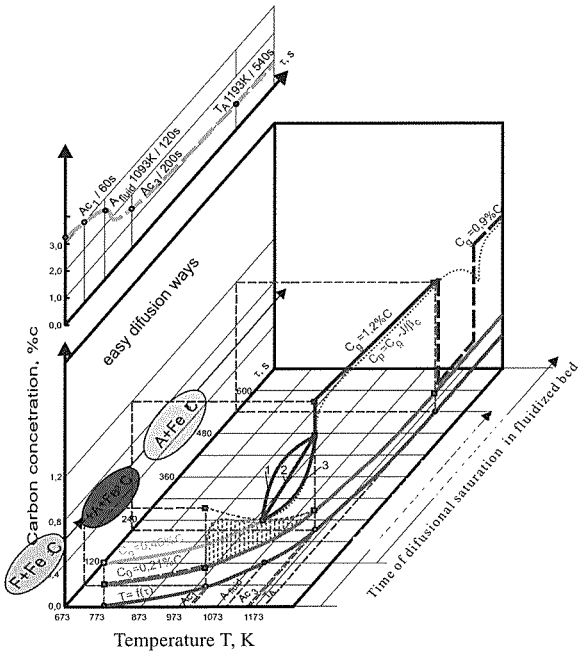

Fig. 1. The carbonizing process F-A/O-D in a fluidized bed [1]

At present different carbonizing techniques are used in the thermo chemical treatment. One of them is carbonizing in a fluidized bed. It is characterized by high coefficients of heat and mass transfer. These techniques are very often used in research institutes and small industrial plants [1, 8, 9].

2. Research material

2.1. Macrostructure of material cross-section

The material for this research has been provided by the industrial plant, which produces car drive crosses used in a lot of car models. The main problem in designing car drive cross surface layer properties, its non-homogeneous metallographic, which is presented in Figures 2, 3.

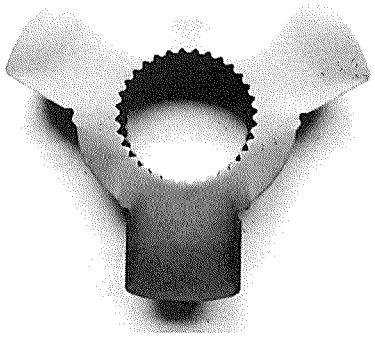

Fig. 2. Macrostructure of material cross-section, etched by Fry with visible fluid lines in scale 1:1

2.2. Microstructure of material cross-section

Non-homogeneous metallographic structure in car drive crosses causes difficulty in designing the carbonizing process, because it is difficult to obtain the same thickness of a carbonized layer.

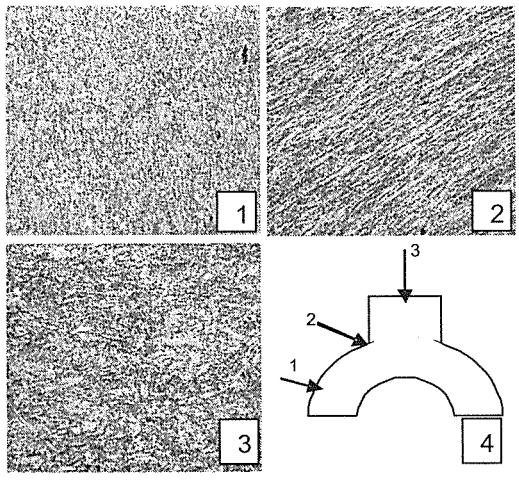

Fig. 3. 3.1-3.3 micro-structure cross-section etched by Nital in scale 1:50 in areas shown in picture 3.4

The surface hardness before the carbonizing process in places chosen in Figure 3 is shown in Table 1.

TABLE 1

Surface hardness of research elements

Places	Hardness [HV]
1	274.7
2	340.8
3	246.5

3. Research work methodology

3.1. Neural network structure

Modeling the process using neural networks can be started with designing the structure of the network. The characteristic features of neural nets are a number of layers and a number of neurons in each layer. The number of neurons in input layer and the number of input parameters are usually equal. For steel the carbonizing process in a fluidized bed: n = 13. Neural networks inputs are described by data inputs variables, such as:

x_1 – τ_{Pod} heating time,
x_2 – τ_A austenitizing time,
x_3 – $\tau_{Chł}$ cooling time,
x_4 – τ_{Odp} tempering time,
x_5 – T_{Wej} batch temperature,
x_6 – T_A austenitizing temperature,
x_7 – $T_{Chł}$ cooling temperature,
x_8 – T_{Odp} tempering temperature,
x_9 – atmosphere type,
x_{10} – α_p air excess coefficient,
x_{11} – cooling type,
x_{12} – batch length,
x_{13} – batch width.

The size of the output layer is equal to the number of searched parameters. In this case the number of neurons in the output layer is divided into four sections shown in Figure 4. The first three sections which describes the distribution of microhardness in chosen places shown in Figure 3, are presented in Table 2.

TABLE 21
First three sections of the output layer of a neural network

Distance from surface [μm]	Neurons is the output layer of a neural network describing microhardness for corresponding depths		
	Section 1	Section 2	Section 3
10	y_1	y_9	y_{17}
50	y_2	y_{10}	y_{18}
100	y_3	y_{11}	y_{19}
150	y_4	y_{12}	y_{20}
200	y_5	y_{13}	y_{21}
250	y_6	y_{14}	y_{22}
300	y_7	y_{15}	y_{23}
350	y_8	y_{16}	y_{24}

The fourth section in the output layer is built of three neurons which describe carbon layer thickness after the carbonizing process in chosen places:

y_{25} – carbon layer thickness in place 1 shown in Figure 3
y_{26} – carbon layer thickness in place 2 shown in Figure 3
y_{27} – carbon layer thickness in place 3 shown in Figure 3.

This way make possible compared layout of microhardness in three characteristic places of research material, this fact was very important for this element's producer. The main difficult was obtained the similar mechanical properties in this places.

After fixing the input and the output layer structure the next step is designing the inside layers of the model. As mathematic algorithms describing correlations between vectors x_n and y_k are not known it is necessary to use an unconventional way of building the neural nets. It is based on information about output and input.

Theoretically the problem of choosing neural structure is restricted to approximation of multi-variable function for given vector x_n [3]. The case discussed in this paper concerns multi-dimensional input vector and continuous activation function. Building that kind of neural network model is defined by Kołmogorow statement [12]. He proved that in order to obtain k-dimensional output vector y_k for n-dimensional input vector x_n and continuous activation function, using one hidden layer neural network built of 2n+1 neurons is sufficient. It is shown in Figure 4.

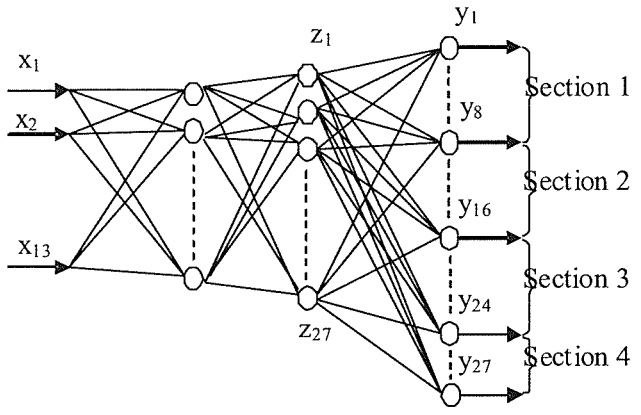

Fig. 4. Structure of neural network for modeling thickness in accordance with Kolmogorow statement

Where:

$X = [x_1, x_2, ..., x_n]$ – n-dimensional input vector,
$Y = [y_1, y_2, ..., y_k]$ – k-dimensional output vector,
$z_1, z_2, ..., z_{2n+1}$ – hidden layer neurons.

Kołmogorow didn't define activation function algorithm, because it is chosen for a particular process likewise then number of hidden layers. In accordance with Kolmogorow, the number of hidden layer changes in range from n to 3n.

3.2. Learning and testing data

In order to use the designed neural network in practice it should be taught by learning data set. The size of learning data set and the size of artificial neural network was depended on the expected generalization degree,

which is the correct answer of model for the input data different from the data of learning set. Neural networks taught by learning set should be hundred times bigger than the number of adapted parameters of network (the quantity of synaptic weights connecting artificial neurons) would have better generalized qualities. If those proportions are disturbed, the network has reproduction abilities. In order to obtain the best approximation qualities for a designed model it is necessary to minimize the number of adapted parameters of network and, in consequence, minimize $E_G(w)$ – generalization error (1):

$$E_G(w) \leqslant E_L(w) + \varepsilon\left(\frac{p}{h}, E_L\right), \tag{1}$$

where: E_L – learning error (2), ε – range of trust, h – the number of all synaptic weights

$$E_L(w) = \sum_{k=1}^{p} E(y_k(w), d_k). \tag{2}$$

When the generalization error increases, the model becomes interpolator for which all input signals, different from those of the training set are rejected as a measure background. In order to avoid that it is necessary to minimize the generalization error by means of either building bigger training set or limiting the network structure. However limiting the network structure excessive cause the increase of learning error $E_L(w)$, which similarly to $E_G(w)$ when it goes from maximum to minimum. Before it reaches minimum $E_G(w)$ starts behaving in the other way (it increases in contrast to decreasing $E_L(w)$). This quality can be used in searching minimum $E_G(w)$, because it could make the selection of network structure faster. Direct observation of $E_G(w)$ is very time-consuming, because searching its minimum needs checking error $E_G(w)$ for fully learned network each time. A better solution is observing error $E_L(w)$, which changes can be observed continuously during teaching the network. In this case the structure of networks could be corrected each time after stopping teaching process with the constant control value of learning set, because too big a learning set causes the re-increase the generalization error.

3.3. Results of neural network modeling

Obtained results are presented in Figures 5, 6, 7.

Such prepared artificial neural network make possible predicts values of microhardness in particular depth with average validation error in range 4.5-6.8%. This results was satisfactory for producer of this kind of car elements. The neural network prepares in this way may be used to design assumed carbon layer thickness of cross driver carbonized in a fluidized bed.

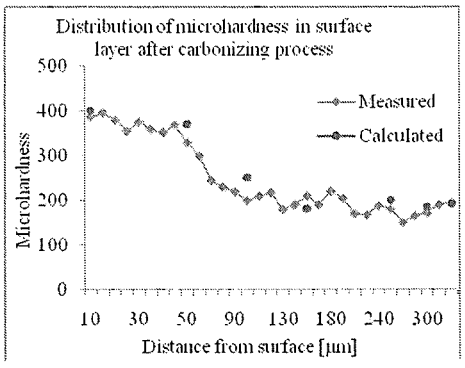

Fig. 5. Comparison of the assumed and calculated curve of hardness for place 1 shown in fig. 3.4

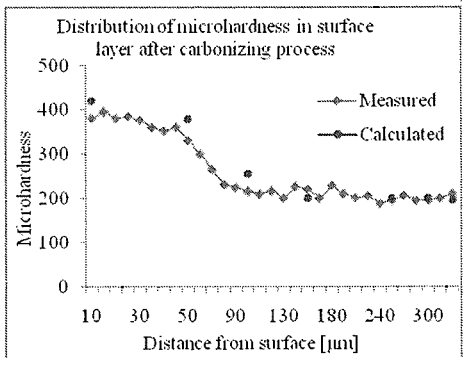

Fig. 6. Comparison of the assumed and calculated curve of hardness for place 2 shown in fig. 3.4

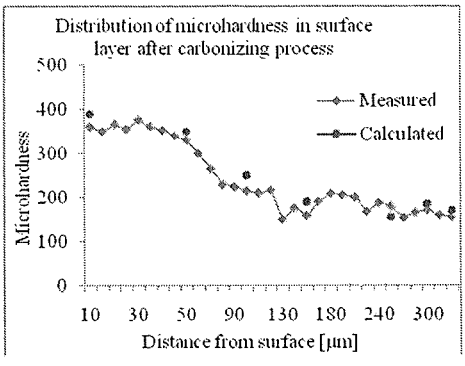

Fig. 7. Comparison of the assumed and calculated curve of hardness for place 3 shown in fig. 3.4

4. Conclusions

Neural network developed and used in this research is able to modeling distribution of microhardness in surface layer after the carbonizing process in a fluidized bed. In accordance with empirical obtained distribution of microhardness, carbon layer thickness of cross driver is computed. After compared this results with results obtained by neural network modeling, error of prediction is computed.

This research will be continued to complex solve this subject and applied it in Industrial plant. The goal is to obtain possibly the same distribution of microhardness in all places of car drive after the carbonizing process. The final solution will be special computer system, which will be connected in real time [13] with heat medium and gas distribution station. This connection and special work application make to possible to add new date in training and testing data. Connection of this system whit heat treatment control system makes to possible on-line control running process [14–15] and support engineering decision in real time.

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