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Neural networks application for modeling carbonizing process in fluidized bed

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ABSTRACT

Purpose: This paper presents neural network model used for designing the assumed curve of hardness after carbonizing car drive cross in fluidized bed. This process is very complicated and difficult as multi-parameters changes are non linear and car drive cross structure is non homogeneous [1-2]. This fact and lack of mathematical algorithms describing this process makes modeling required curve of hardness by traditional numerical methods difficult or even impossible. In this case it is possible to try using artificial neural network [3-7].

Design/methodology/approach: The neural network structure is designed and prepared by choosing input and output parameters of process. The method of learning and testing neural network, the way of limiting nets structure and minimizing learning and testing error are discussed.

Findings: Such prepared neural network model, after putting expected values of assumed hardness curve in output layer, can give answers to a lot of questions about running carbonizing process in fluidized bed.

Practical implications: The neural network model can be used to build control system capable of on-line controlling running process and supporting engineering decision in real time.

Originality/value: This paper presents different conception to obtain assumed material's hardness after carbonizing in fluidized bed. The specially prepared neural networks model could be a help for engineering decisions and may be used in designing carbonizing process in fluidized bed as well as in controlling changes of this process.

Keywords: Surface layer engineering; Neuron networks; Process modelling; Artificial intelligent

METHODOLOGY OF RESEARCH, ANALYSIS AND MODELLING

1. Introduction

The carbonizing process in fluidized bed is multi-parameters and complicated [1], because changes of parameters during this process have non linear characteristic, shown in Figure 1. The next problem is the lack of mathematical algorithms that could describe it. Using neural networks for modeling carbonizing in fluidized bed is caused by several nets' features: non linear character, ability to generalize the results of calculations for data out of training set and no need for mathematical algorithms describing influence changes input parameters on hardness [1,2]. The research are divided into tree stages:

- using special computer system to obtain training data set,
- designing and building neural network structure,
- minimizing model structure, training and testing error.

At present different carbonizing techniques are used in the thermo chemical treatment. One of this is carbonizing in fluidized bed. This is characterized by high coefficient heat and mass transfer. These techniques are very often used in researching institutes and small industrial plant [8-11].

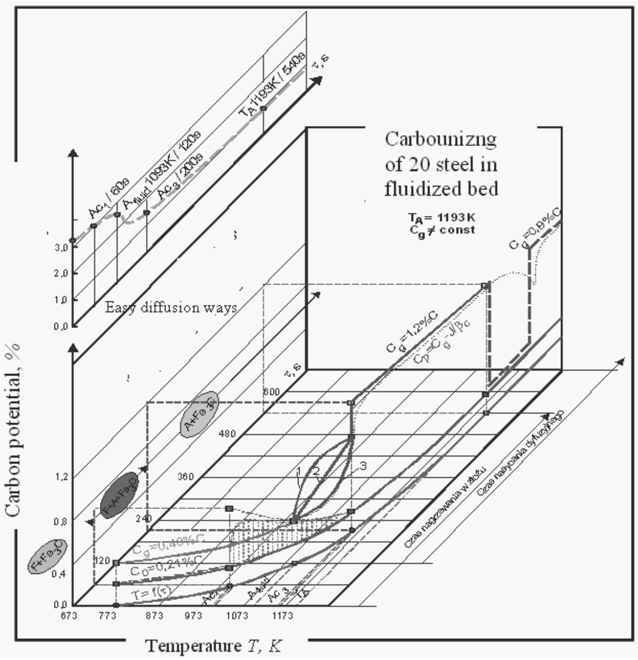

Fig. 1. Carbonizing process F-A/O-D in fluidized bed [1]

2. Description of the approach, work methodology, materials for research, assumptions, experiments etc.

During the first stage of research data are obtained and formatted for training and testing. This research are moved in Biomaterials and Surface Layer Research Institute. This institute administers special computer system, which is using for visualization and control thermo and thermo chemical treatment in fluidized bed [10-11]. This system enables high precision in dosage gas medium. Gas distribution station is used for controlling flows fife different gases and fluidized bed are shown in Fig. 2.

Fig. 2. Fluidized bed and gas distribution station PGIMP-1 [10]

This station is controlled by special computer system. This system is built of one PC computer using Windows NT operation system and InTouch 7.1 software, which main interfaces are shown in Figs. 3 and 4. It is connected with GE Fanuc drivers system, which are connected with gas distribution station and used for gas dosage.

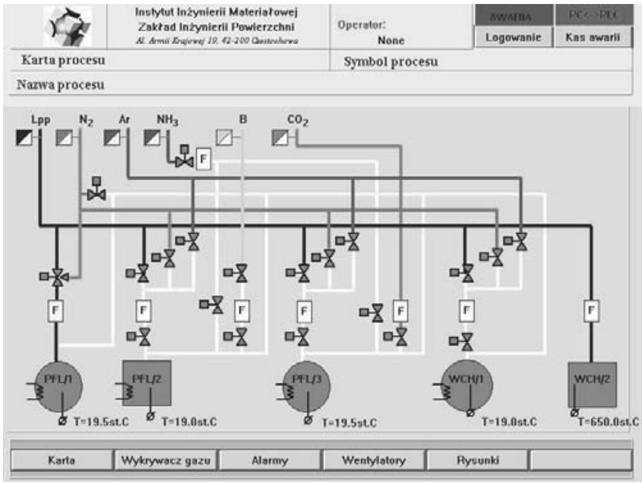

Fig. 3. Main interface of gases distribution [11]

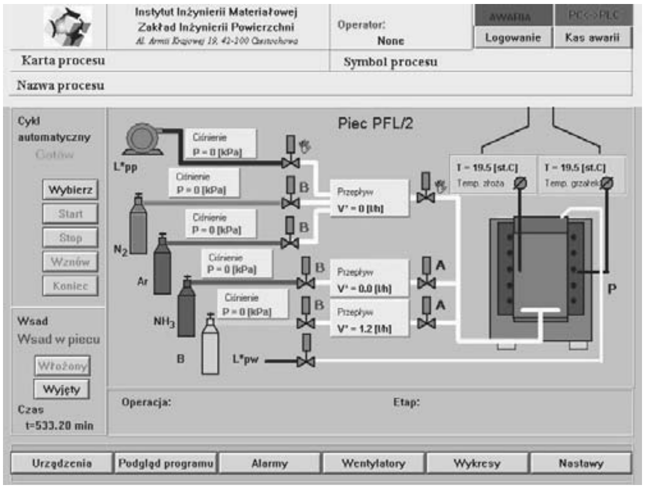

Fig. 4. Parameters of one with fluidized beds [11]

Material for this research is provided by Visteon Industrial plant, witch produced car drive cross used in a lot car models. The main problem during car drive cross structure designed is non homogenous metallographic structure in car drive cross provide to Visteon, what is presented in Figs. 5-7.

Non homogenous metallographic structure in car drive cross causes difficulty designed carbonizing process, because is very hart obtain the same assumed hardness and thickness carbonizing layer in all material's parts. The comparison of materials properties in one place of car cross drive (Fig. 6) to another places from Fig. 6 is presented in Figures 8 and 9.

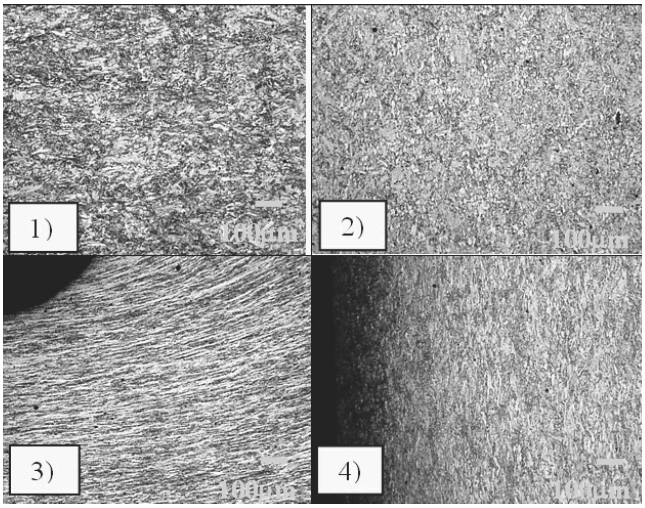

Fig. 5. Micro-structure cross-section of car drive cross etched Nital in scale 1:50 in places shown in Figure 6

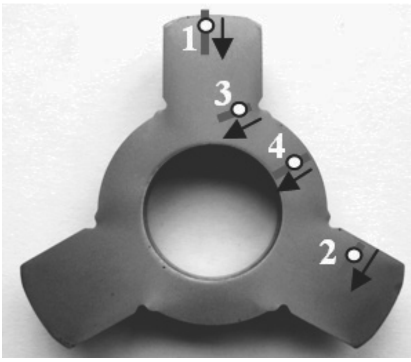

Fig. 6. Cross-section of car drive in which are shown characteristic places, scale 1:2

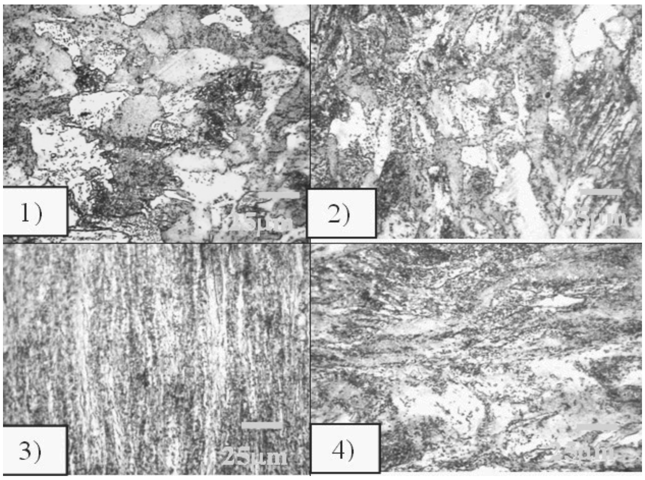

Fig. 7. Micro-structure cross-section of car drive cross etched Nital in scale 1:500 in places shown in Figure 6

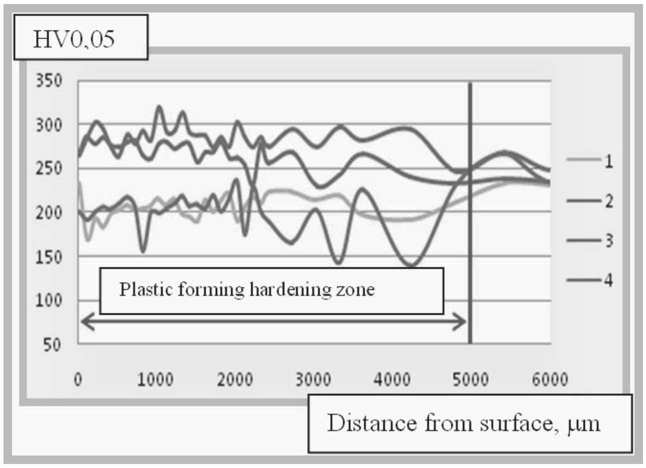

Fig. 8. Distribution of microhardness in paces shown in Fig. 6, before carbonizing in fluidized bed

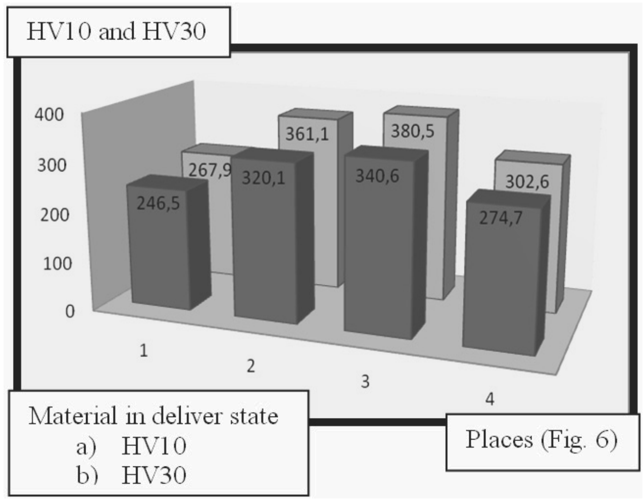

Fig. 9. Comparison of surface hardness HV30 in one paces shown in Fig. 6, to another before carbonizing in fluidized bed

Modeling the process using neural networks can be started from designing the structure of the network. The characteristic features of neural nets are: the number of layers, the number of neurons in each layer and kinds of neural connections. The number of neurons in input layer and the number of input parameters are usually equal. For carbonizing steel process in fluidized bed n = 13. Particular neural networks inputs are ascribed particular variables data input. The size of output layer is equal with number of searched parameters. In this case number of neurons in output layer equals eight.

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. Neural connections are determined on the grounds of the identification of process rules and weights.

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 Fig. 10.

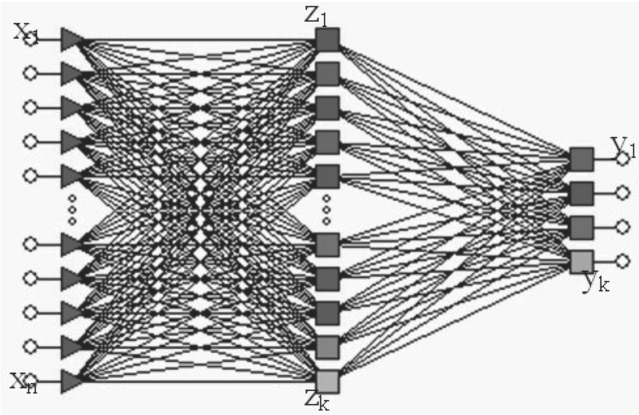

Fig. 10. Structure of neural network MPL 43:43-87-4:4 using for modeling microhardness

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 the number of neurons in hidden layers which changes in range from n to 3n.

In order to use the designed neural network in practice it should be taught by learning data set. The size of learning data set depends 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 one far 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 will have only 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):

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

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 will cause the increase of learning error $E_L(w)$, whose range from maximum $E_G(w)$ to minimum $E_G(w)$ behaves similarly to $E_G(w)$. 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 in able faster selection of network structure. 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 $E_L(w)$, whose 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 (Fig. 11).

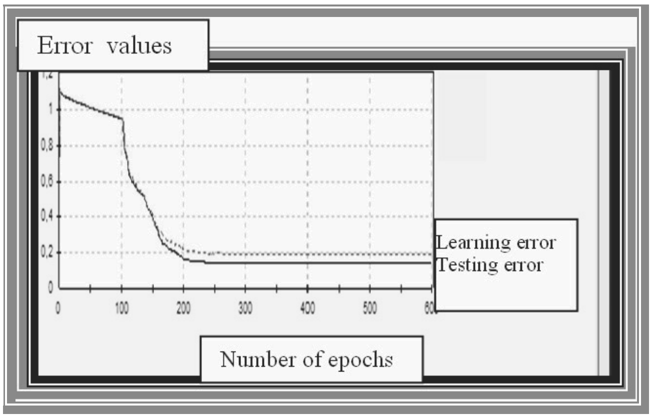

Fig. 11. Changes of MPL 43:43-87-4:4 learning and testing error

3. Description of achieved results of own researches

The method proposed in the paper makes to possible obtain assumed curve of car drives cross hardness after carbonizing process in fluidized bed, which is build with eight approximated point. This eight point is different for places shown in the Fig. 6.

Figs. 12-14 present comparison of the required curve of car driving cross hardness after carbonizing process with the curves calculated.

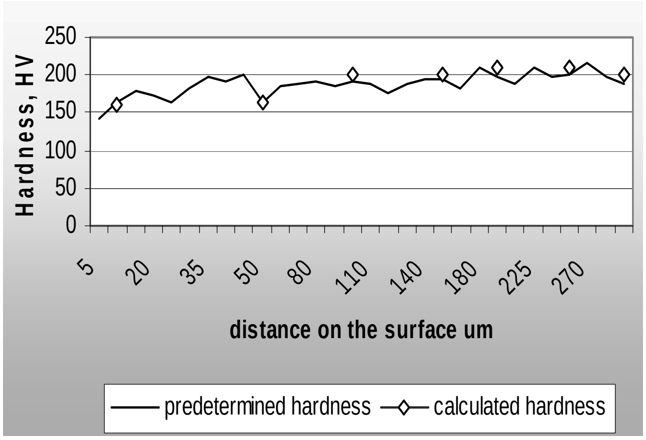

Fig. 12. Comparison of the assumed and calculated curve of hardness for place 1 shown in Fig. 5

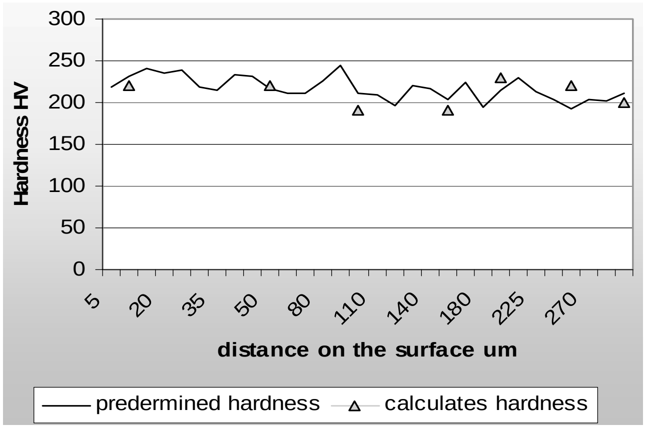

Fig. 13. Comparison of the assumed and calculated curve of hardness for place 2 shown in Fig. 5

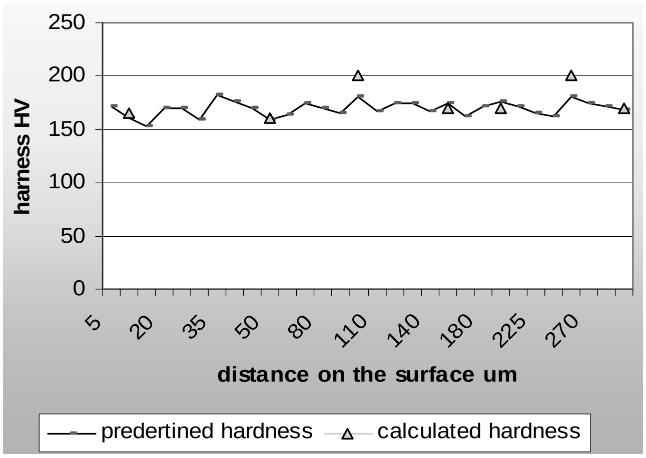

Fig. 14. Comparison of the assumed and calculated curve of hardness for place 3 shown in Fig. 5

4. Conclusions

Such prepared neural network model, after putting expected values of assumed hardness curve in output layer, can provide give answers to a lot of questions about running carbonizing process in fluidized bed. The information obtained in this way can be used in practice by engineering designed running carbonizing process and property of final products. This research will be continued to complex solve this subject and applied it in Industrial plant. The final solve this problem will be special computer system, which will be connected in real time with heat medium and gas distribution station [13]. This connect and special work application to make possible adding new date in training and testing data. Connect this system whit heat treatment control system makes to possible on-line control running process and support engineering decision in real time [14-15].

Acknowledgements

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