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Artificial neural network (ANN) approach to predicting micro hardness profile values of iron-based sintered alloys

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Abstract. *Recent interest in artificial neural networks has considerably extended their use in the field of powder metallurgy. Advanced in the paper is a model for predicting the micro hardness of sintered compacts made from iron powders and powder mixtures through the process of sintering performed in different atmospheres. The proposed model is based on three layer neural network with backpropagation learning algorithm. Specially developed software has been used to provide for the proper functioning of the neural network. Moreover, it should also be noted that the training data used to carry out the research has been collected by a laboratory controlled experimental testing. Finally, the paper concludes that the presented neural network model is applicable for hardness profile prediction of iron-based sintered alloys as confirmed by the experimental results.*

Keywords: PM sintered compacts, sintering atmosphere, heating rate, micro hardness, artificial neural network

1. Introduction

It is generally recognized that determining the mechanical properties of the PM sintered products significantly differs from the control which is exercised over the requirement-oriented design of cast parts. These pronounced differences are commonly associated with the presence of certain amounts of pores. The residual porosity in its turn exerts a powerful effect upon the mechanical property of hardness and its precise determination. Ascertaining the suitability of a given material and testing its hardness properties can be achieved through different micro hardness test methods. Employed for the purposes of this particular research was the Vickers method as the most preferred technique for measuring the micro hardness of sintered compacts. To conduct the laboratory testing a very small diamond indenter with pyramidal geometry has been forced into the surface of the specimen. Different loads were applied within the range of 20, 50 and 100g and the obtained impression was examined under a microscope and measured, with the final measurements being subsequently converted into a hardness number. A specific feature of this experiment was the performance of initial specimen surface preparations (grinding and polishing) in order to ensure a well-defined indentation allowing for higher accuracy of precise measurement (Callister, 2006).

Bearing in mind that obtaining micro hardness values is closely related to the preparation of special samples for microscopic observation, it becomes obvious that they cannot be seen as methods for system control.

There are, indeed, considerable numbers of studies in the existing literature with reference to the analytical prediction model for determining the mechanical properties of PM sintered compacts. Published examples indicate that artificial neuron network (ANN) can be effectively used to develop a working model for predicting the mechanical properties of materials and subsequently to carry out the required structural analysis (Cherian R., 2003) (Drandarevic, 2000) (Drnadaveric, 2005).

It is widely accepted that one of the key elements of the ANNs is their ability to learn through examples. Their example-based learning is organized in two main phases: training and generating outputs of new unknown inputs (Ohdar, 2003) (Sudhacar K, 2001).

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The present research makes extensive use of one of the most widely applied neural network models – namely that of the back propagation network which is, currently, the most prevalent, efficient, and the most suitable model for training complex multi-layered networks. To build such a neural network, the known information was fed in as input data, assigned were the connection weights within the network architecture, and the algorithm was implemented repeatedly until a perfectly satisfactory overall output was obtained. Accordingly, the weighted matrix ($w_{ji;}$ w_{kj}) of interconnections allows the neural networks to learn and remember. (Fausett, 1994), (Leonov & Nikolov, 2012).

The objective of the study is to provide a model of artificial neural network simulation to predict the micro hardness profile of sintered PM compacts.

2. Materials and experimental procedure

The selection of input parameters (fig.1) is of utmost importance for the construction of the neural network model. Therefore, all relevant parameters that may have a decisive impact upon the outcomes should be presented in the input data of the neural network.

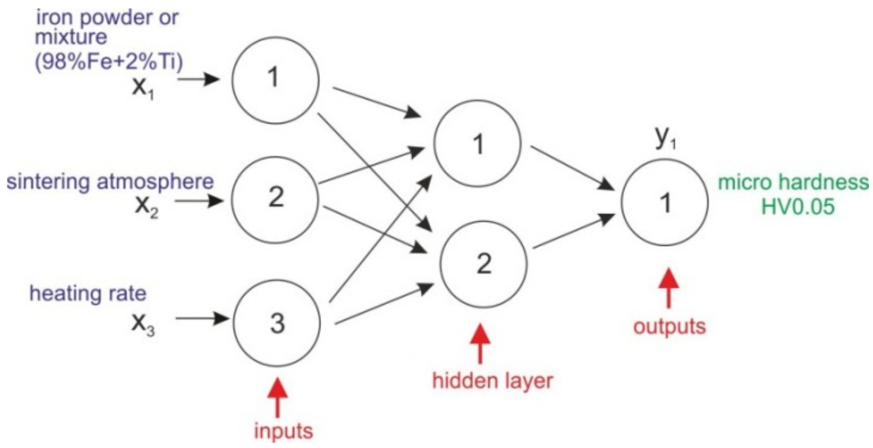

Fig. 1. Schematic model of ANN to simulate and predict the microhardness

The structure and properties of the sintered alloys being largely determined by the properties of the iron powders or mixtures and conditional upon the technological regimes of compaction and sintering, the input parameters used in this experimental study are: iron powder/mechanical mixture; sintering atmosphere and a range of heating rates relevant for a successful sintering process.

For the purposes of the present ANN modeling, we have included experimental data on micro hardness (outputs) obtained from the values of different commercial iron powders (Dimitrov, Zlateva, Pieszonka, & Stoychev, 2011), (Mincheva, 2016), (Stoychev, Rusev, & Harizanova, 2002).

Commercial grades of iron powders (DistaloySA, DWP200, DP200, ASC100.29, SC100.26, AstaloyCrL) and mixtures with addition of titanium powder (98%Fe+2%Ti) were used to produce compacts (4x5x15mm) at compacting pressure of 600 MPa. The process of sintering was conducted in the horizontal NETZSCH 402E dilatometer under the effects of various flowing atmospheres: high purity nitrogen, hydrogen and mixture of hydrogen and nitrogen. The heating rates from RT up to the isothermal sintering temperature of 1120°C were: 2, 10 and 30°C/min. for 1 hour isothermal sintering time. All samples were cooled at 10°C/min.

The micro hardness of sintered compacts was measured by Vickers method using a load of 50g (HV0.05) and the measured average micro hardness values of some of the specimens are reported in table 1.

Considering the fact that ANNs work with quantitative characteristics, it is therefore necessary for the input-output data couple parameters to be submitted in digital format. Presented in table 2 is the encoding of the input parameters.

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Table 1. Part of the results

Materials	Sintering atmosphere	Heating rate ^{o}C/min	HV0.05
Distaloy+2%Ti	hydrogen	2	150
Distaloy+2%Ti	hydrogen	10	199
Distaloy+2%Ti	hydrogen	30	204
DWP+2%Ti	hydrogen	2	163
DWP+2%Ti	hydrogen	10	120
DWP+2%Ti	hydrogen	30	120
DP+2%Ti	hydrogen	2	135
DP+2%Ti	hydrogen	10	120
DP+2%Ti	hydrogen	30	130
ASC100.29+2%Ti	hydrogen	10	190
ASC100.29+2%Ti	hydrogen	30	195
ASC100.29	hydrogen	2	180
ASC100.29	hydrogen	10	150

Table 2. Encoding the Input Parameters

Powders/mixtures	code	atmosphere	code	Heating rate, ^{o}C/min	code
DistaloySA	1	Hydrogen (100%)	1	2	1
DWP200	2	Mix (H95%:N5%)	2	10	5
ASC100.29	3	Mix (H75%:N25%)	4	30	9
AstaloyCrL	4	Mix (H50%:H50%)	6		
SC100.26	5	Mix (H5%:N95%)	8		
DistaloySA+2%Ti	6	Nitrogen (100%)	9		
DWP+2%Ti	7				
DP200+2%Ti	8				
ASC100.29+2%Ti	9				

A specially developed software (Supervised Neural Network Prototype, fig.2) has been used to provide for the proper functioning of the neural network and compiled further has been a file with input and output parameters as regards the appropriate network training. The application runs from StartOnWindows.bat for Windows operating system.

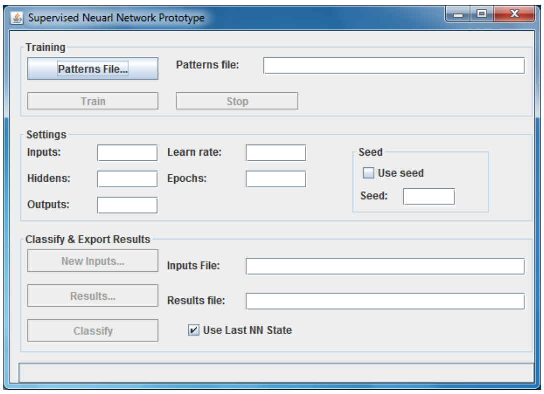

Fig. 2. Application at start-up

The work of the neural network consists of two main phases: learning /training/ and generating a new unknown input.

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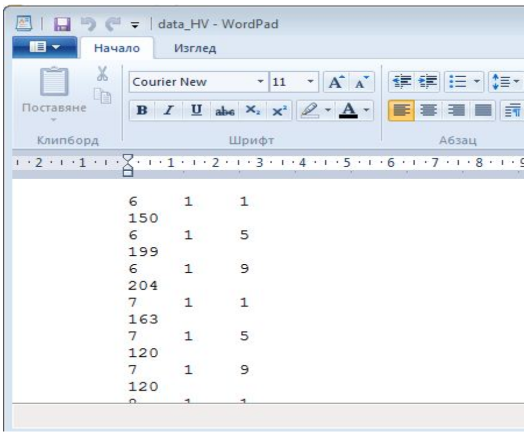
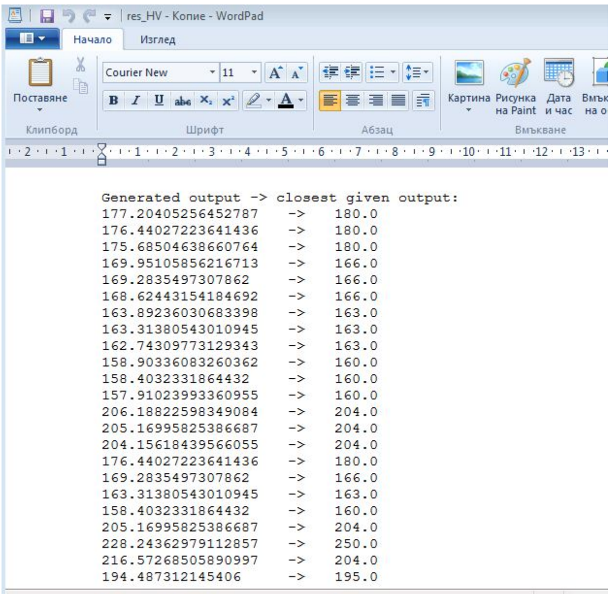
In. fig. 3 is shown WordPad text document with data for training the neuronal network. For example, the numbers from the first line are inputs parameters /material, atmosphere, heating rate/, and the number from the second line is output parameter /hardness/.



```
6     1     1
150
6     1     5
199
6     1     9
204
7     1     1
163
7     1     5
120
7     1     9
120
```

Fig. 3. File with data for training the ANN

Gradually, through sustained instructions the neural network is considered well-structured and ready to be used for classification or prediction by generating the output data in the submitted new unknown input data values.



```
Generated output -> closest given output:
177.20405256452787    ->    180.0
176.44027223641436    ->    180.0
175.68504638660764    ->    180.0
169.95105856216713    ->    166.0
169.2835497307862     ->    166.0
168.62443154184692    ->    166.0
163.89236030683398    ->    163.0
163.31380543010945    ->    163.0
162.74309773129343    ->    163.0
158.90336083260362    ->    160.0
158.4032331864432     ->    160.0
157.91023993360955    ->    160.0
206.18822598349084    ->    204.0
205.16995825386687    ->    204.0
204.15618439566055    ->    204.0
176.44027223641436    ->    180.0
169.2835497307862     ->    166.0
163.31380543010945    ->    163.0
158.4032331864432     ->    160.0
205.16995825386687    ->    204.0
228.24362979112857    ->    250.0
216.57268505890997    ->    204.0
194.487312145406      ->    195.0
```

Fig. 4. Generated outputs of micro hardness

The sample items in fig.4 with the generated test outcomes and the comparative diagram fig.5 show that the data obtained on micro hardness is close to the experimental results, and yet, a slight discrepancy occurred between the closest results and the generated outputs due to the overall "statistical" feature of the design model.

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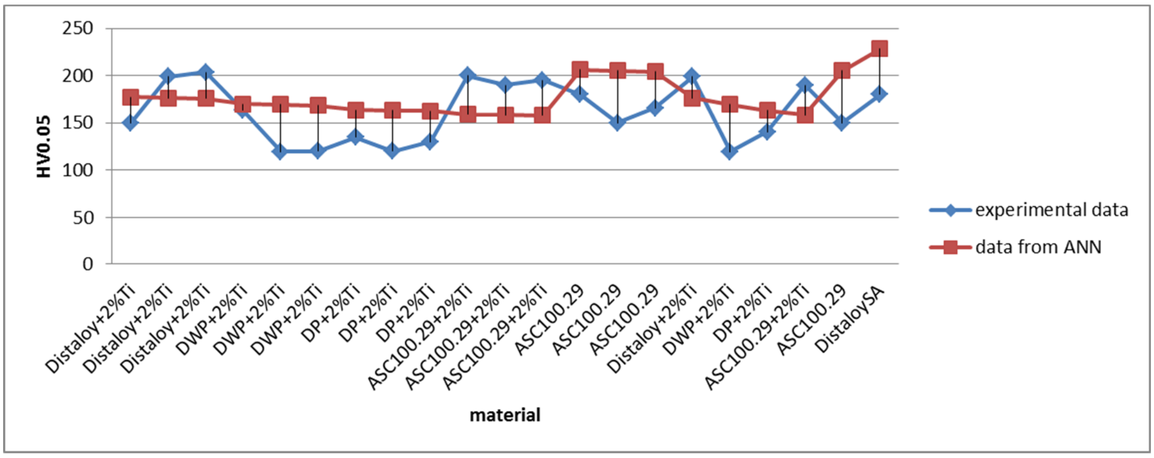

Fig. 5. Comparative chart with ANN data and experimental values

3. Conclusion

A neural network model has been developed along with the respective software application for simulation and prediction of the micro-hardness profile values through the process of sintering of different types of PM sintered alloys conducted under conditions of different sintering environments and controlled heating rates.

After the training process, the fully developed ANN-based model shows a strong potential for better simulation and prediction of the micro hardness profile values of the studied materials.

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