NEURAL NETWORKS IN POWDER METALLURGY

Dragoljub Drndarevic, Milovan Milivojevic
High Business Technical School, Uzice, Serbia, skola@vpts.edu.rs

Abstract: A neural network approach in modelling and its application at powder metallurgy processes is given. The model is based on experimental data applying multilayer neural network, whose massive parallelism and multipath structure give best results. Powder metallurgy process with powder cold compacting in closed tool with the variants is given in short. The basic principle of modelling of a process unknown behaviour is shown and development of neural network model is described. Simulation results showed that neural network models give less approximation error then statistical procedure, which is in conventional application. Practical significance of the presented procedure is in better prediction of output characteristics (mechanical properties, tool dimensions etc.). In the example prediction of the dimensional changes during sintering using neural networks is given.

<u>Keywords</u>: Process modelling, Powder metallurgy, Neural networks, Backpropagation learning algorithm

1. INTRODUCTION

Artificial neural networks, or simply neural networks (NNs), represent a parallel distributed connection of many simple elements (neurons) performing data processing. The structure of artificial NNs is based on understanding the biological nervous systems. NNs have good characteristics in regard to fault tolerance and noise robustness, as well as to incomplete data. In according to these characteristics NNs are very powerful method for modelling and optimization in different kind of processes with large number of influential factors and where effect of these factors on final process characteristics are complex with high nonlinearity.

Application of NN modelling in various of powder metallurgy (PM) processes is given in [1-3]. In [1] an artificial neural network model has been developed for the prediction of the effects of the manufacturing parameters on the density and porosity of powder metallurgy Al–Cu–Mg/B_4Cp composites. In [2] modelling principles with one kind of neural networks – backpropagation learning algorithm with examples is given. In the paper [3], a two stage hydrometallurgical treatment of eudialyte concentrate was investigated with Artificial Neural Networks and the other methods.

2. POWDER METALLURGY PROCESS WITH POWDER COMPACTING IN CLOSED TOOL

The process in which the forming is carrying out by cold compacting in closed tool, which is treated in this paper, has more variants as shown in Figure 1. All variants of the process include the operations of powder preparing and mixing, compacting and sintering, after which a part of final shape, dimensions and other characteristics is obtained. The final part can be obtained also after sizing operation and/or additional operations. In order to increase density in some variants, two or three sintering and sizing operations, or repressing, are combined. In the last phase, one or more additional operations can be used, depending on the final part demands. In the course of sintering and sizing operations, the change of dimensions and shape occurs. The same applies to compacting operation, if the volume of powder freely filled in the die is observed as the fictious part before compacting. At compacting and sizing, an elastic tool deformation and part springback are present, occurring after the part leaves tool.
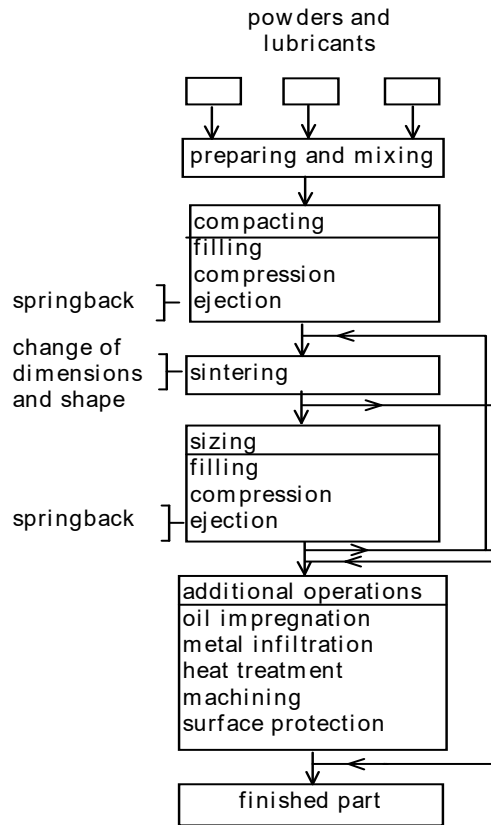
Figure 1: Diagram of powder metallurgy process with powder compacting in closed tool

3. NEURAL NETWORKS

Different kinds of NNs are used in process modelling [4]. In the most cases multilayer NN is used, which give best results. General architecture of multilayer NN is shown in Figure 2. It consists of an input layer with N processing elements, H "hidden" layers with $N_1, N_2, ..., N_H$ processing elements, respectively, and an output layer with M processing elements.
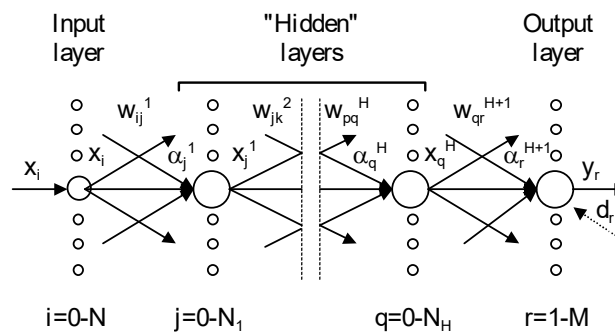

Figure 2: General architecture of multilayer neural network

For learning multilayer NN with Backpropagation algorithm [5] is used. The learning process is iterative. An iteration consists of two passes - forward and backward. In the forward pass, the real values of network outputs $y_1, y_2, ..., y_M$ are determined. It starts from the first layer representing the input layer in which no processing of the input signals $x_1, x_2, ..., x_N$ is performed, but only the fanout of signals towards all processing elements of the second layer. Processing elements in the second layer, i. e. the first "hidden" layer, processes the input signals in the following way: the total input α_j^1 in processing element j is the weighted sum of all inputs, where w_{ij}^1 represents the weight of interaction of processing element i and j between the input and the first "hidden" layer:

$$\alpha_j^1 = \sum_{i=0}^{N} x_i w_{ij}^1 \ , \quad j = 1, 2, \ldots, N_1 \tag{1}$$

The output x_j^1 from the processing element j in the first "hidden" layer is obtained applying the corresponding transfer function to the total obtained input α_j^1. With this kind of NN, a sigmoidal transfer function is mostly applied.

$$x_j^1 = \frac{1}{1 + e^{-\alpha_j^1}} \tag{2}$$

Continuing the same procedure forward through all layers, using equations (1,2), the NN outputs y_r, $r=1,2,\ldots,M$, are obtained.

In the backward pass, a correction of weights is performed with the aim to reduce the output error. The output error means the difference between the desired, i. e. experimental output d_r and the real network output y_r, and it is determined in the form of mean square error :

$$E_r = \frac{1}{2} \lim_{P \to \infty} \frac{1}{P} \sum_{t=1}^{P} \left(d_r^t - y_r^t \right)^2 , \quad r = 1, 2, \ldots, M \tag{3}$$

where $t=1,2,\ldots,P$ is number of pairs of input/output data, i. e. iterations, at network learning.

Applying the gradient method to the output mean square error, the weight corrections is performed in each iteration for the given input/output pair, decreasing the deviation of the real from desired output value until it reaches the minimum error in accordance with chosen criterion. The correction of weights w_{mn}^h between processing elements m and n in two arbitrary layers $h-1$ and h in iteration $t+1$, is performed according to :

$$w_{mn}^h(t+1) = w_{mn}^h(t) + \eta \delta_n^h x_m^{h-1} \tag{4}$$

where:

η - learning term

δ_n^h - the error factor for processing element n in h layer.

The weights correction is performed by the output error backpropagation from output to input layer.

To overcome the local minima and increase the weight convergence speed, the "momentum" version of backpropagation algorithm is used. One of its forms is:

$$w_{mn}^h(t+1) = w_{mn}^h(t) + \eta \delta_n^h x_m^{h-1} + \mu \left[w_{mn}^h(t) - w_{mn}^h(t-1) \right] \tag{5}$$

where μ is momentum term.

4. MODELLING PRINCIPLES

The principal elements of the process model based on NN generally contain input data, NN architecture and learning algorithm. The basic stages, i.e. process modelling activities, are shown in Figure 3. The activity flow chart of process modelling can be divided into two parts. In the first stage, based on prior process analysis, the selection of significant factors is performed and the model architecture with learning algorithm defined, while, in the second stage, the experimental program is formed and computing program is generated to be used for learning and testing of the model. In the case of unsatisfactory test results an intervention is possible on three levels (shown in Figure 3.).
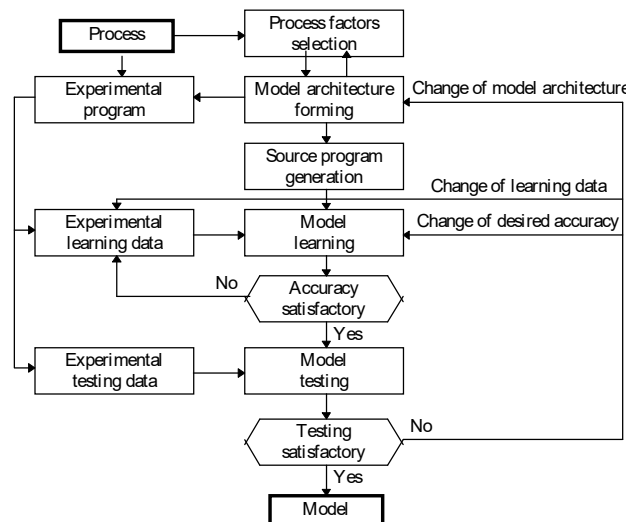
Figure 3: Development of the process model based on neural networks

5. EXAMPLE

Prediction of the dimensional changes during sintering within the process of the production of the PM parts with cold compaction in a closed die is given. The dimensions model was formed for particular kind of sintered parts - self-lubricating bearings, whose shapes, dimensions and tolerances were defined by the standard of ISO 2795 and [6] (Figure 4). For the material of bearings the bronze P4013Z was used.
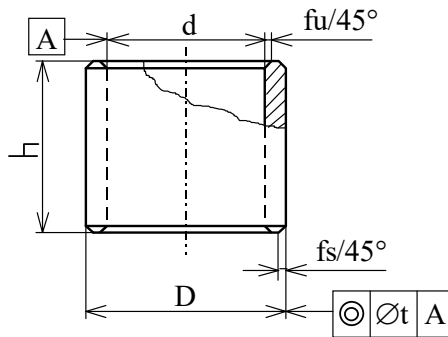
Measure	Tolerance		Interval
	D≤50	D>50	
d	H7	H8	1-60
D	r6*	r7*	3-72
h	js13		1-70
t	IT9	IT10	

* according to [6] (is not given in ISO 2795)

Figure 4: The measures and the tolerances of bearings

The experimental program included 53 kinds of bearings, three series of each (internal diameter being 3-60 mm, outside diameter 5.5-70 mm and height 6-50 mm). The regimes of the sintering process for the given material during obtaining of the experimental data were constant and they are given in Table 1. The measured values processing was performed statistically, by calculating the mean value and standard deviation for each series, with assumed normal distribution.

Table 1: Process regimes for manufacture of bearings

Powder preparation	Mixing time	5-10 min
	Mixing velocity	18-20 min^{-1}
Compaction	Pressure	$(1.9-3.5)10^4$ Ncm^{-2}
	Velocity	Const. (for mechanical press)
	Max. pressure time	Const. (for mechanical press)
Sintering	Temperature	780º C
	Time	6 min
	Protection atmosphere	Dissociated ammonia (75%H_2+25%N_2)
Sizing	Pressure	≈30% of compacting pressure
	Deformation ratio	Δd_m=+0.12%, ΔD_m=+0.27%, Δh_m=+3.6%

The process is observed inversely. As input factors, dimensions and density of the sintered parts are taken, and output characteristics are dimensions of the compacts, on the basic of which, dimensions of the compaction tool can be determined, i. e. the elements necessary for projecting manufacture process. Based on the experimental data, a model of dimensional changes of the part during sintering is formed. As a model, a multilayer neural network is used, the architecture of which is shown in the Figure 5.
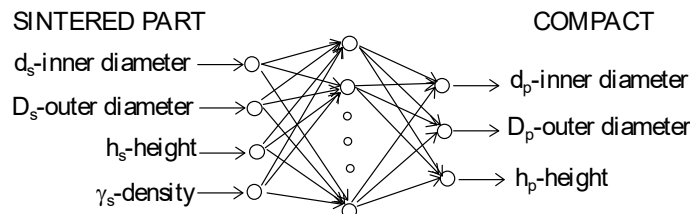

Figure 5: The architecture of the model of dimensional changes during sintering

The set of input, i. e. experimental data is divided in the way that approximately 3/4 of the accidentally chosen data are used for learning and 1/4 for testing. By optimization as per the criterion of the minimum error of testing and minimum number of learning cycles, the parameters of the model are obtained as follows: learning rate term 0.9, momentum term 0.4, the interval of the initial weights ±0.3 and the number of processing elements in the hidden layer 4.

By the simulation of the model with the optimal parameters in the set of the experimental data for testing, the outputs are obtained, i. e. dimensions of the part after compaction, for the given dimensions of the sintered part. Based on the input experimental data and the obtained outputs, the coefficients which represent relative change of the corresponding dimensions during sintering are obtained as follows:

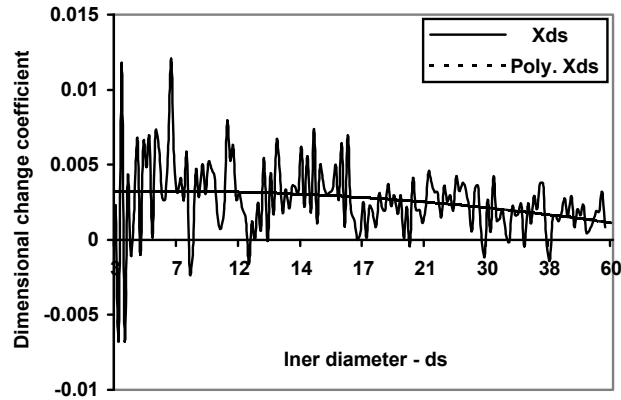$$Xds = \frac{dp - ds}{ds} \; ; \; XDs = \frac{Dp - Ds}{Ds} \; ; \; Xhs = \frac{hp - hs}{hs}$$

Figure 6: Change coefficient of inner diameter

A relative change of the inner diameter *Xds* for the bearings with *ds* = 3-60mm is shown in the Figure 6. Next to the real curve, its polynomial approximation is given. It is observed that the coefficient *Xds* decreases with diameter increasing. Coefficient of the outer diameter *XDs* slowly increases with increasing *Ds*, and coefficient of the height *Xhs* behaves similarly as *Xds* (it is not shown). The mean values of the dimensional changes during sintering is given in the Table 2., where the sign gives direction of the change in relation to the supposed direction in the equation given above.

Table 2: Mean values of the dimensional change coefficients

Xds	XDs	Xhs
$2.616 \cdot 10^{-3}$	$-1.453 \cdot 10^{-4}$	$-1.796 \cdot 10^{-4}$

The results of the model simulation in the form of the output errors are given in the Figure 7.

a)   b)
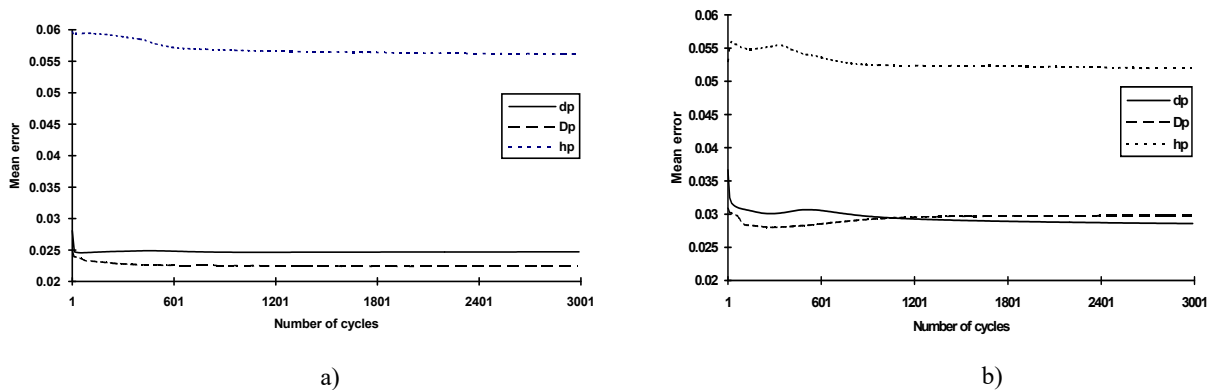
Figure 7: The learning errors (a) and testing errors (b) of the part dimensions model

The results of model simulation, were compared with the statistical processing of experimental data. The comparison results are given in [7] and they show that NN based model gives lower mean error of every output, and lower total mean error for 11.4% than obtained by statistical procedure.

6. CONCLUSIONS

A neural network approach in modelling and its application at powder metallurgy processes is given. The model is based on experimental data applying multilayer neural network with Backpropagation learning algorithm. The basic

principle of modelling of a process unknown behaviour is shown and development of neural network model is described.

The advantages of modelling methods using NNs in comparison with statistical procedure and other applicable methods (regressive analysis, cubic spline) are in including the greater number of factors and their interactivity, simultaneous obtaining of greater number of outputs, more common functional forms and iterative approach to solution.

Practical significance of the presented procedure is that the model, i.e. trained NN, for another input data (new material, for example) from the range in which learning was performed or from its surroundings (since the model is capable of extrapolation apart from interpolation), gives outputs with a similar average error as for data set used for learning.

The presented methodology can be applied in all processes of the PM field, to the different kinds of parts, materials and process regimes.

REFERENCES

[1] Varol T., Canakci A., Ozsahin S., Modeling of the Prediction of Densification Behavior of Powder Metallurgy Al–Cu–Mg/B$_4$C Composites Using Artificial Neural Networks, Acta metallurgica Sinica, Volume 28, Issue 2, February 2015: 182–195.

[2] Drndarevic D., Milivojevic M., Modelling with neural networks, Journal of Mechatronics, Vol. 2., No. 2., June 2014: 143-146.

[3] Ma Y., Stopic S., Gronen L., Milivojevic M., Obradovic S., Friedrich B., Neural Network Modeling for the Extraction of Rare Earth Elements from Eudialyte Concentrate by Dry Digestion and Leaching, , Metals, 8, 267, 2018: 1-22.

[4] Rumelhart D. E., Hinton G. E., Williams R. J., Learning representation by back-propagating errors, Nature, Vol. 323, 1986: 533-536.

[5] Hecht- Nielsen R., Neurocomputing, Reading MA, Addison-Wesley, 1990.

[6] Catalogs of Company Standards of "Sinter", Uzice.

[7] Drndarevic D., B. Reljin B., Accuracy modelling of powder metallurgy process using backpropagation neural networks Powder Metallurgy, Vol. 43, No. 1, 2000: 25-29.