Modelling of Dimensional Changes During Sintering

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Abstract:
An approach to modelling the behaviour of dimensions of PM parts during the sintering process for the prediction of dimensional changes is given. The model is developed on the basis of significant process factors by applying a multilayer neural network architecture with the backpropagation learning algorithm. Results of the simulation in the form of diagrams and tables are presented. The presented model gives better results than the one based on statistical analysis of experimental data, i.e. less total mean approximation errors of the part dimensions for 11.4%. A practical result of the model is the determination of compact dimensions to compensate for dimensional changes during sintering.

Keywords: Modeling; Sintering, PM parts; Neural networks; Back-propagation algorithm.

1. Introduction

Development of new materials with designed characteristics has been an ancient desire and aim [1]. In that sense numerous predictive methods have been developed, both for processing and properties of unique materials [2]. Representatives of the Belgrade sintering school contributed significantly in this effort with numerous scientific work in this field [3-5]. Most of them were successfully implemented in practical applications.

A dimensional change of a heated powder body occurs during sintering for most materials. Both volumetric and linear shrinkage occur during reduction of porosity and growth of the product density. The source of the driving forces of the shrinking process is the tendency of the system towards reduction of the free energy, which is possible only on account of the reduction of the entire surface. The process itself develops through three stages, between which there are no sharp limits (Fig. 1):

In the early stage the velocity of consolidation depends on the processes which elapse in the contact area. Pore filling with metal is provided thanks to the great relative movement of particles and their volume deformation.

The density of the power body in the transition stage is sufficiently large and if porosity is uniform, consolidation is also uniform through the entire volume of the heated body. Pores make-up a unique ensemble.

In the final stage of sintering individual pores are closed because of Rauleigh instability. Small pores shrink and larger ones get larger by diffusion so the total volume of the pores remains essentially unchanged. Pore coarsening is possible even if porosity (overall)

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is reduced.

If the powder body is heated to and kept at a certain temperature, then shrinkage occurs quickly initially, and slows down progressively until it finally stops. At subsequent temperature increase the speed of consolidation rises again initially and slows down again. This happens for every temperature increase. That is connected to the supply of system free energy which depends on the value of the surface particles and on the total quantity of vacancies per surface unit or per volume unit.

[Fig. 1 Growth scheme of interparticle contacts and spheroidizing of pores because of atom surface diffusion: a) before sintering, b) after sintering]

During sintering of multicomponent systems the process of consolidation depends on the character of the phase diagram. With unlimited mutual solubility of components the volume heterodiffusion has the highest importance. Sintering in systems with limited solubility and in the absence of the mutual influence of components depends a lot on the component with the largest concentration in the mixture.

Modelling of the dimensional changes during sintering within the process of the production of PM parts from cold compaction in a closed die is presented. During sintering many factors appear, which influence change of dimensions and by that, the final tolerances of a part (temperature, sintering time, type of the protection atmosphere, regimes of pre-heating and cooling, kind of transport). In this paper the objective was to examine the influence of geometry and dimensions of a part to the change of these dimensions during sintering.

The modelling was performed by means of artificial neural networks (NNs). A multilayer NN with the backpropagation learning algorithm was used, which gave the best results in the process modelling, compared to standard procedures.

Modelling by NNs is used in most fields of PM production:
- Elastic behaviour of green compacts with die compacted samples was investigated in [6].
- In [7] a survey is given explaining the concepts involved in NN modelling and its application to various aspects of PM manufacturing.
- Rheological behaviour of PIM feedstock. This involved utilization of a large amount of experimental data to train NNs to predict the rheological behaviour of feedstock made from specified powders and binders [8].
- In [9], an artificial NN approach for exploring the prediction of the PM process parameters, particularly sinter-forged density of metal powder perform, is derived.
- [10] describes research that has been conducted into artificial intelligence techniques for solving the “inverse problem”, for assisting with materials selection.
- Materials and process parameter selection are performed using a hybrid system employing Bayesian NNs and heuristics [11].
- The artificial NN methodology, presented in [12], has been developed for a selection of powder and process parameters for PM part manufacturing.
- Accuracy modelling of powder metallurgy parts, based on the multilayer NN [13].
2. Model

The model is applied here for self-lubrication bearings, made of P4013Z bronze. The sintering process parameters were kept constant in the experiments (temperature, time of sintering and protective atmosphere). The model works in an inverse way. As input factors, dimensions and density of the sintered parts are measured, and output characteristics are dimensions of the compacts, based of which, dimensions of the compaction tool can be determined, i.e. the elements necessary for projecting the manufacture process.

Based on the experimental data, a model of dimension changes of the part during sintering is formed. A multilayer neural network is used, the architecture of which is shown in Fig. 2. The architecture of the model consists of an input layer, one (or more) "hidden" layers and an output layer. Each layer consists of processing elements, whereas the number of processing elements of input and output layers corresponds to the number of the chosen input factors and output characteristics of the part, respectively, while the number of the processing elements in the hidden layer is arbitrary.

Fig. 2 The architecture of the model of dimensional changes during sintering

The modelling process consists of learning and testing stages. Learning is an iterative process in which the coefficients (weights) of the model are determined. During testing with the obtained weights, for the corresponding input data, the requested characteristics are obtained. With the aim of determining accuracy, i.e., errors of the model, the values of the obtained characteristics can be compared to the corresponding experimental values.

A standard backpropagation algorithm with a correction of weights after every iteration and with the moment term is applied. Within the simulation programme, the preparation of inputs, i.e., experimental data, has been performed (randomization of order, division of the entire input set into a training data set and test data set, parameterization and normalization of data), as well as generation of the initial weight values and definition of the accuracy criterion.

The experimental data are divided so that approximately 3/4 of the randomly chosen data are used for learning and 1/4 for testing. By optimization of the criterion of minimum error of testing and minimum number of learning cycles, the parameters of the model were 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.

3. Results

Simulation with optimal parameters in the set of the experimental data for testing, provides the dimensions of the part after compaction, for the specified dimensions of the sintered part. Based on the input experimental data and the obtained outputs, coefficients which represent the relative change of the corresponding dimensions during sintering are obtained as follows:
Fig. 3 shows the dimensional change coefficients. A relative change of the inner diameter $Xds$ for the bearings with $ds = 3-60$mm is shown in Fig. 3a. Next to the real curve, its polynomial approximation of a second degree is given. It is observed that the coefficient $Xds$ decreases with diameter increasing. Coefficient of the outer diameter $XDs$ slowly increases with increasing $Ds$ (Fig. 3b), and coefficient of the height $Xhs$ behaves similarly as $Xds$ (Fig. 3c).

Fig. 3 Dimensional change coefficients

The mean values of the dimensional changes during sintering are given in Tab. I, where the sign gives the direction of the change in relation to the supposed direction in the equation given above.

<table>
<thead>
<tr>
<th></th>
<th>$Xds$</th>
<th>$XDs$</th>
<th>$Xhs$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>$2.616\cdot10^{-3}$</td>
<td>$-1.453\cdot10^{-4}$</td>
<td>$-1.796\cdot10^{-4}$</td>
</tr>
</tbody>
</table>

The results of the model simulation in the form of the output errors are given in Fig. 4. The errors represent mean values of the absolute deviations of the model outputs from the desired ones, i.e., experimental values of the outputs. The diagrams in Fig. 4 display the change of learning and testing errors in the 3 dimensions for 3000 cycles of training, which are enough because the convergence after that number of cycles is very slow. The change of the learning errors with increasing cycles of training is given in Fig. 4a. The learning errors, after a relatively rapid decrease in the beginning of training, and varying in the next stage, after approximately 600 cycles begin to converge. The testing errors behave in a similar way.
(Fig. 4b). It is observed that the error of modelling of the compact height is considerably bigger from the error of inner and outer diameters. Apart from that, the learning error at the compact height is bigger than the testing error, which implies that the noise of the process is bigger at this dimension.

![Graph](image)

**Fig. 4** Learning errors (a) and testing errors (b) of the part dimensions model

Detailed information of possible approximation with the model based on NN is shown in Table II. Network output values, obtained from testing corresponding data sets and, for the purpose of comparison of the experimental output values from the same set, are given (k is the ordinal number of the experiment).

<table>
<thead>
<tr>
<th>k</th>
<th>Model outputs (exp.)</th>
<th>Desired (exp.) outputs</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>dp</td>
<td>Dp</td>
</tr>
<tr>
<td>2</td>
<td>30.162</td>
<td>35.166</td>
</tr>
<tr>
<td>38</td>
<td>20.053</td>
<td>30.139</td>
</tr>
<tr>
<td>39</td>
<td>60.135</td>
<td>70.081</td>
</tr>
</tbody>
</table>

The results of model simulation, given in this paper, were compared to the standard procedure of modelling, based on statistical processing of experimental data. This procedure is carried out by backward movement, from the sintered part dimensions to compaction, taking into consideration dimensional changes during sintering. Dimensional change coefficients, based on the learning data set used with NN, were determined. Compact dimensions were determined for the testing data set using the obtained coefficients. The same form of the mean error as the one of the NN was used for comparison.

The comparison results are given in Tab. III. The results show that the NN based model gives a lower mean error of every output, and a lower total mean error for 11.4% than obtained by the statistical procedure. This was achieved by including a greater number of significant factors and their interdependence, as well as by having an iterative approach to the solution.
Tab. III Mean errors of the prediction for the statistical procedure and the NN model

<table>
<thead>
<tr>
<th>Model</th>
<th>$d_p$</th>
<th>$D_p$</th>
<th>$h_p$</th>
<th>$\Sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>With the statistical procedure</td>
<td>0.03315</td>
<td>0.03271</td>
<td>0.05867</td>
<td>0.12453</td>
</tr>
<tr>
<td>With NN</td>
<td>0.02858</td>
<td>0.02977</td>
<td>0.05198</td>
<td>0.11033</td>
</tr>
</tbody>
</table>

4. Conclusions

A modelling procedure and results of dimensional changes during sintering using multilayer neural networks and the backpropagation learning algorithm are presented.

In developing of the model, the advantages of the neural networks are used for identification of the unknown behaviour of a process with a great number of influential factors (the tolerance of error, robustness to noise and incomplete data and approximation ability of high nonlinear systems). With a parallel processing structure a required interdependence of the inputs and simultaneous forming of a greater number of outputs are achieved.

The limitations and deficiencies of the given modelling procedure result from the general characteristics of the backpropagation algorithm requiring a relatively large amount of input data with a random distribution, as well as a great number of iterations for obtaining satisfactory results. The disadvantage of the displayed modelling procedure is that the obtained results are useful only for the given material.

A practical significance of the prediction of dimensional changes during sintering is in determination of the dimensions of the compact for the required dimensions of the sintered part and a kind of a material, for the in advance set regimes of the process. By means of the dimensions of the compact, dimensions of the compaction tool can be determined, in order to get a final part of the necessary dimensions as a result.

5. References


Резюме: С целью прогнозирования изменения размеров ПМ образцов в процессе спекания, в данной работе представлен подход к моделированию поведения размеров. Модель разработана на основе существенных факторов процесса с применением архитектуры многослойной нейронной сети и backpropagation алгоритма учения. Результаты симуляции представлены на диаграммах и в таблицах. Полученная модель показывает результаты, которые лучше модели основанной на статистической обработке экспериментальных данных. Эффективность моделирования на практике — определение размеров прессовок, учитывая изменения размеров в процессе спекания.

Ключевые слова: Моделирование, спекание, образцы ПМ.

Садржај: Дат је један приступ моделовању понашања димензија ПМ делова у процесу синтеровања у циљу прогнозирања димензијалних промена. Модел је развијен на бази суштинских фактора процеса са применом архитектуре вишеслојне неуронске мреже и backpropagation алгоритма учења. Резултати симулације су приказане у облику дијаграма и табела. Добијени модел даје боље резултате од модела базираног на статистичкој обради експерименталних података. Практични ефекти моделовања су у одређивању димензија отпреска с обзиром на димензијалне промене при синтеровању.

Кључне речи: моделовање, синтеровање, ПМ делови.