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Application of neural network and genetic algorithm to powder metallurgy of pure iron

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ABSTRACT

In the present paper, soft computing techniques are applied to optimize the powder metallurgy processing of pure iron. An artificial neural network is trained to predict the stress resulting from a given trend in strain and sintering temperature. To prepare an appropriate model, pure iron powders are compacted and sintered at various temperatures. Subsequently, compression test is conducted at room temperature on the bulked samples. The sintering temperatures and the corresponding stress–strain records are used as sets of data for the training process. The performance of the network is verified by putting aside one set of data and testing the network against it. Eventually, by using a genetic algorithm, an optimization tool is created to predict the optimum sintering temperature for a desired stress–strain behavior. Comparison of the predicted and experimental data confirms the accuracy of the model.

1. Introduction

Powder metallurgy (PM) is one of the most promising methods for fabricating the near-net shape and complex parts because of its ability to eliminate the need for secondary operations. PM products offer a wide range of applications and give good dimensional tolerance for parts with complex geometries [1,2]. Conventionally, PM processing involves two main steps: cold compaction and sintering. During sintering, the bonding between particles is mainly formed by diffusion. Usually, PM products have an amount of porosity that strongly affects the mechanical properties of the material. The residual porosity arises from insufficient sintering temperature or sintering time [3]. Accordingly, there is an increasing interest to select an optimum sintering temperature to remove the porosity content and improve the mechanical properties. Optimization of powder processing by simulation or modeling is a challenging task because there are a large number of physical parameters to consider. In this context, utilization of soft computing appears to be an interesting practice, which is the aim of the present paper.

In recent years, soft computing methods have attracted researchers because of their ability to model and analyze complex problems that were previously difficult or impossible to solve. Neuro-fuzzy modeling, together with a new driving force from stochastic, gradient-free optimization techniques such as genetic algorithm, forms the constituents of the so-called soft computing [4]. Three well-known components of soft computing methods are artificial neural network, fuzzy logic and evolutionary computing. Artificial neural network and fuzzy logic have interested materials research community [5] to overcome such challenges as prediction of wear of materials [6,7], mechanical properties [8,9], corrosion behavior [10] welding parameters [11] and formability [12], among many other areas. Genetic algorithms have been used to solve optimization and design problems such as materials selection [13], forming [14] and casting [15]. There have also been some attempts to model the powder metallurgy via soft computing [16,17]; however, the effect of sintering temperature on mechanical properties has not been precisely modeled by such intelligent approaches.

This paper is an effort to predict the effect of sintering temperature on the mechanical properties of PM parts using an artificial neural network approach. The model predicts stress corresponding to a given trend in strain and sintering temperature. The result of the model gives the corresponding stress–strain curve, which provides the mechanical properties of the material. In addition, an attempt is made to apply a genetic algorithm for optimization and prediction of the sintering temperature for a desired stress–strain curve.

2. Materials and methods

The material used in this study was pure iron powder with the chemical composition summarized in Table 1. For compaction of powders, a cylindrical container with a central channel was designed and constructed. Dimensions of the channel were 20 mm in height and 10 in diameter. Compacted samples were obtained

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Table 1
Chemical composition of pure iron powder used in this study.

Element	Fe	Mn	Ni	Cu	S	Zn	Pb
wt.%	Balanced	0.05	0.05	0.02	0.02	0.01	0.002

by pouring powders into the die and cold pressing under the pressure of 1.2 GPa. Seven samples were compacted under the same conditions. For comparison, one of them was employed to be in compacted condition. The others were encapsulated into a quartz tube and sintered at temperatures 500, 600, 700, 800, 900 and 1000 °C for a period of one hour. The samples were sintered in a furnace and cooled inside the chamber to room temperature. To obtain the stress–strain data, compression tests were conducted at room temperature by a hydraulic press with the capacity of 20 tons. To investigate the level of porosity, scanning electron micrographs were taken on sections perpendicular to the pressing direction.

3. Neural network and genetic algorithm

Neural networks are composed of simple elements operating in parallel (neurons). These elements are inspired by biological nervous systems. As in the nature, the network function is determined largely by the connections between the elements. One can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Typically, neural networks are adjusted or trained, so that a particular input leads to a specific target (supervised training). The network is adjusted, based on a comparison between the output and the target, until the network output approximates the target. Commonly, many input/target pairs are needed to train a network. Other networks can be obtained from unsupervised training techniques or from direct design methods. In unsupervised learning, the weights and biases are modified in response to network inputs only. There are no target outputs available. Most of these algorithms perform clustering operations. They categorize the input patterns into a finite number of classes [18].

The multi-layer feed-forward back-propagation neural network is the most well known and widely used network in engineering applications. It can easily be implemented and trained faster than other types of networks. It can efficiently solve many types of problems correctly. This network operates in two steps. First, the data are fed into the input layer and processed by transfer functions through the layers until the network's response is computed at the output layer. Second, the network's response is compared to the target and an error is generated. Based on this error signal, connection weights between layer neurons are updated until the network reaches a pre-defined performance goal. The classical back-propagation algorithm is fairly slow. Therefore, several heuristic techniques were developed to accelerate the convergence of this algorithm. The basic back-propagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient) where the performance function (usually mean square error) decreases more rapidly.

Genetic algorithm, from a practical point of view, is capable of optimizing the design parameters incorporated into a specified fitness function to accomplish a goal fitness quantity. The key feature of genetic algorithms and other similar methodologies is that they are derivative-free. In fact, the stochastic nature of the algorithm with dynamic evaluation of the fitness function turns it into a powerful systematic random search engine. This approach is an alternative to inefficient derivative-based methods. This extends its ability to a wide range of applications.

4. Methodology

One goal of the paper is to construct a model, capable of predicting the stress trend according to the variation in strain and sintering temperature. Artificial neural network is selected as the primary modeling tool to carry out the task. It is supplied by the temperature and strain data as independent variables (input arguments) and the corresponding stress data as the dependent variable (target argument). Feed-forward architecture with a Levenberg–Marquardt back-propagation training algorithm is utilized to develop the model. A sensitivity analysis is conducted on the hidden layers and neurons. Results demonstrate that a network with 15 neurons in its first hidden layer and 10 neurons in the second hidden layer gives the smallest error. Table 2 represents various settings in adjustment of network and training parameters.

To evaluate the performance of the artificial neural network model, the data is separated into two divisions: The first, which is used in the training process, includes 83% of the total data and is equivalent to 776 data lines. The rest is put aside for validating and blind testing the trained network. This data set consists of 162 samples. Making use of a secondary new data set in order to validate and test the model assists in evaluating the generalization ability of the trained network. In the present work, the whole strain–stress behavior corresponding to the sintering temperature of 900 °C was taken as the testing set. This makes the validity check of the network stricter as the network is presented with a completely new trend, unseen in the training process.

Another goal of the paper is to assemble a system that can efficiently estimate the optimal sintering temperature of a specified strain–stress behavior. To achieve this goal, genetic algorithm seems to be the most useful. A program is developed to facilitate the procedure. It takes two input vectors, one as the intended strain quantities and the other as the stress trends. It then searches the space of possible solutions created by the neural model to find the optimal temperature. The genetic optimization finds the optimal temperature by minimizing the error (fitness) function. The error function is defined as the mean square error (MSE) among all the predicted stress values and the desired values by

$$\text{Error Function} = \frac{1}{N}\sum_{i=1}^{N}(p_i - d_i)^2 \tag{1}$$

Table 2
Settings used in the development of the neural network.

Network type	Training function	Layer no.	Neuron no.			Transfer function		
			Layer #1	Layer #2	Layer #3	Layer #1	Layer #2	Layer #3
FFBP	TRAINLM	3	15	10	1	TANSIG	TANSIG	PURELIN
Performance function	Epochs	max fail	mem_reduc	min_grad	mu	mu_inc	mu_dec	mu_max
MSE	300	50	1	1×10^{-10}	20	8	1×10^{-3}	1×10^{10}

FFBP: Feed-Forward Backpropagation.
TRAINLM: Levenberg–Marquardt training.
MSE: Mean square error.