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Prediction of Powder Injection Molding Process Parameters Using Artificial Neural Networks

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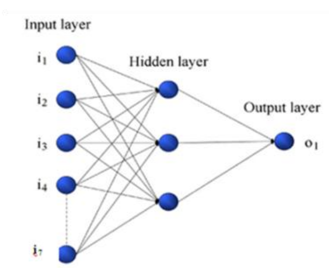
Graphical abstract



Abstract

The parameters of Powder Injection Molding (PIM) process were modeled by artificial neural networks (ANNs). The feed-forward multilayer perceptron was utilized and trained by back-propagation algorithm. Particle size, particle morphology, debinding time, and sintering temperature were taken into account and regarded as inputs of the ANN model. The outputs included relative density, wax loss, shrinkage, and hardness. The results obtained using the ANN model were in good agreement with the experimental data. In fact, they displayed an average R-value of 0.95 versus the experimental values. The optimum architecture of ANN was 7-4-1, in which the network was trained with Levenberg–Marquardt training algorithm. Thus, the ANN model can be used to evaluate, calculate, and forecast PIM process parameters.

Keywords: Artificial neural network; back propagation algorithm; powder injection molding; debinding; sintering

Abstrak

Parameter proses penyuntikan serbuk telah dimodelkan melalui rangkaian neural tiruan (ANN). Perceptron suapan ke hadapan berbilang dan algoritma rambatan telah digunakan. Saiz partikel, morfologi partikel, masa penyahikatan, suhu pensinteran dianggap sebagai data masuk model ANN. Kehilangan lilin, ketumpatan relatif, pengecutan dan kekerasan merupakan data keluar. Keputusan model ANN adalah setara dengan data ujikaji di mana ia menunjukkan purata nilai R 0.95 berbanding nilai eksperimen. struktur optimum ANN adalah 7-4-1 di rangkaian mana telah dilatih dengan algoritma Levenberg-Marquardt (LM). Oleh itu, Model ANN boleh digunakan untuk menilai, mengira dan meramalkan parameter PIM processs.

Kata kunci: Algoritma rambatan; ketumpatan pensinteran; penyuntikan serbuk; rangkaian neural tiruan

1.0 INTRODUCTION

The Powder Injection Molding (PIM) process has great advantages for the mass fabrication of complex geometry and discrete small components. First, compared with conventional manufacturing processes, reproducible and accurate shapes can be achieved at a considerably low manufacturing cost. Second, through the PIM process, complex shapes can be produced more easily than in the powder compaction process used for producing components with simple geometries. Third, densification increases when very fine powder is used in feedstock during the sintering process. In such a condition, high-performance components can be fabricated by material systems which are restricted to sintering using conventional processes. Furthermore, PIM process offers improved cleanliness, better element homogeneity, finer grain size, and more uniform distribution of precipitation phase [1]. The PIM process includes four main steps: mixing, injection molding, debinding, and sintering [2].

Recently, artificial neural networks (ANNs) have been utilized to investigate injection molding processes [3][4]. ANN can virtually estimate any function up to an arbitrary degree of accuracy. It has been used widely as an essentially semi-parametric regression estimator. Using neural network technology in the simulation of materials science engineering has shown a lot of promising results [5]. In an ANN, processing elements called neurons are linked to each other via connection weights. They are arranged in various layers that compose the network architecture.

The basic structure of feed-forward networks with multilayer networks consists of an input layer, one or more hidden layers, and an output layer. Input patterns from the external environment are received by the input layer neurons and then propagated to the first hidden layer neurons. In this layer, no data processing is done. Input values distributed from each of the input layer neurons are multiplied by each of the adjustable connection weights, thus linking the input layer neurons to the hidden layer of neurons. In the hidden layer, the weighted input values of each neuron are summed. A bias value is added as well. A nonlinear transfer function, such as sigmoid or hyperbolic tangent, passes the combined input value aimed at achieving the output value of the neuron. This output value is an input for the neurons placed in the following layer. Finally, the output layer neurons produce the output value of the network mode [6]. In the present investigation, efforts were exerted to develop a model to forecast PIM process parameters with a multilayer feed-forward network, as well as for the experimental verification of the same.

2.0 MATERIALS AND METHODS

2.1 Network Database

The performance of an ANN model is based on the data set utilized for its training. In this study, as detailed in the literature [7],[8], three different kinds of 90/10 bronze powders, namely, powders called OSP (9 µm, Spherical), W50 (13 µm, Irregular), and W100 (75 µm, Irregular), were used. Nine blends of bronze powder were prepared to study the effect of particle size and shape of the powder on the PIM process through mixing different amounts powders. The feedstock was achieved by mixing different mixtures of powder at 170 °C for 30 min using a wax–polyethylene (50/50, *vol.* %) binder. Feedstocks were fabricated in a Thermo HAAKE twin screw extruder at 170 ºC. Then, injection was molded at this temperature to produce the green parts. The debinding was conducted in two steps: first, the green components were used as solvents which were debinded in hexane, establishing the optimal conditions to eliminate the paraffin wax. Next, thermal debinding was driven in the hydrogen atmosphere at 600 ºC using a heating rate of 1 ºC/min to ensure that the brown parts from all feedstocks were free of defects. In the last stage, components were sintered in a tubular furnace with hydrogen atmosphere (purity 99.999%) at a gas flow rate of 3 L/min. The thermal cycle consisted of a heating ramp at 10 ºC/min, with a sintering temperature in the interval from 800 to 870 ºC, plateau for 60 min, and cooling ramp at 15 ºC/min to room temperature. Densities were determined by the Archimedes water immersion method, whereas the porosity was evaluated using an image analyzer device [7],[8].

2.2 Network Architecture

In this section, a trained two-layer, feed-forward network model via Levenberg–Marquardt (LM) training algorithm was presented in the ANN model. The experimental results were used to model a network by calibration and validation. The main objective was to incorporate seven input and one output parameters in the network models. Parameters such as particle size, particle morphology, particle percentage for bimodal powders, debinding time, and sintering time were selected as input variables. The model output variables were wax loss, sintering density, and shrinkage. The selected model architecture is shown in Figure 1. A data set for every output, including 85 data samples obtained from the experimental studies, was used for the training, testing, and validation phases of the network models. Data subsets of training, testing, and validation were achieved by dividing the available data set into 60%, 20%, and 20%. From the available data set, a sample from the data was selected randomly to make a data subset. The program utilized in running the network models was obtained from the Matlab software toolbox.

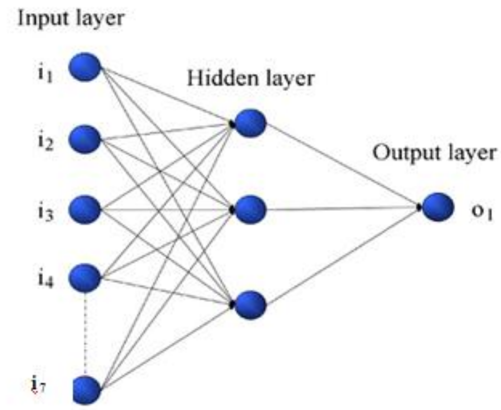


Figure 1 Neural network architecture used in this study [9]

To identify the best network model, transfer functions of pure linear and logarithmic sigmoid were tried as activation functions for the output and hidden layer neurons. In such an investigation, the optimal parameters of the network were identified by comparing the results achieved from the network model with the experimental result forecasted values based on the minimum sum of the mean square error (MSE) presented in Eq. 1.

$$\mathrm{MSE} = \frac{1}{p}\sum_{J=1}^{p}\left[y_j^d - y_j^0\right]^2 \qquad (1)$$

Where y^d is the desired response, y^o is the output response from the ANN, and p is the pattern presented.

3.0 RESULT AND DISCUSSION

Any complex nonlinear function can be estimated using the multilayer feed-forward network models, which consist of a hidden layer provided sufficiently in the many hidden layer neurons available. Accordingly, a multilayer feed-forward network model with a hidden layer was utilized. The results for the wax loss using the different neurons in the hidden layer are shown in Figure. 2 and 3. Figure 2 shows the changes in the amount prediction of the network results of wax loss through the application of various neuron values in the hidden layer between 1 and 20. Several trends were obvious. In $R_{testing}$, the highest R-value was related to the time when 2 to 4 neurons were applied in the hidden layer. The values of linear regression were 0.992 and 0.995. However, these values fell to approximately 0.929, as indicated in Figure 2 by 18. Nevertheless, this R-value dropped steadily as the neuron amount increased, ranging from 12 to 18. Moreover, with regard to the neurons ranging from 8 to 12, nearly an unchanged state was observed.

An optimum number of hidden layer neurons needs to be designed to accurately forecast a parameter via ANN. To date, there exists no theory on the number of hidden layer neuron for a particular problem reported. The usage of a few numbers of neurons and the slight rise of the number of neurons are considered the best approach in seeking the optimum number of hidden neurons. At the starting point of the process, one neuron was selected for the hidden layer. Then, the number of neurons rose in every step. For every step, two neurons were added until a considerable improvement was observed. The tried network models were contrasted based on the sum of the MSE. An ANN model containing four neurons in the hidden layer achieved the best performance in the process. The presentation of the training data set involving input–output data pairs was carried out by training the network models. To adjust the connection weights during the training phase, the difference between the target output (CS) and the actual measured output (CS predicted) was used, and the overall MSE of the training samples was reduced to below a given value or until the maximum epoch number was reached. Parameter values utilized in the chosen network models can be summarized as follows:

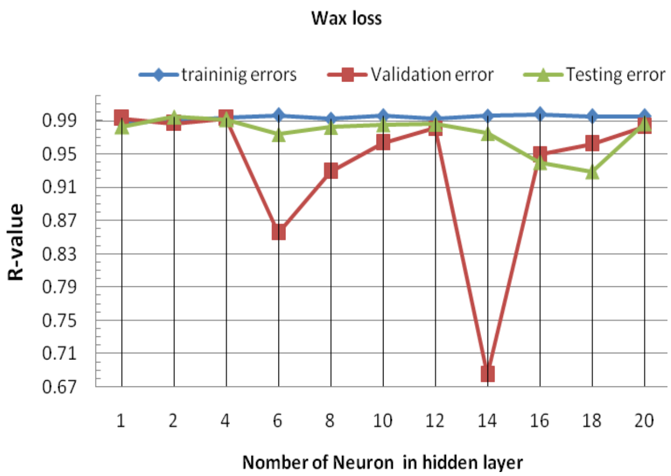
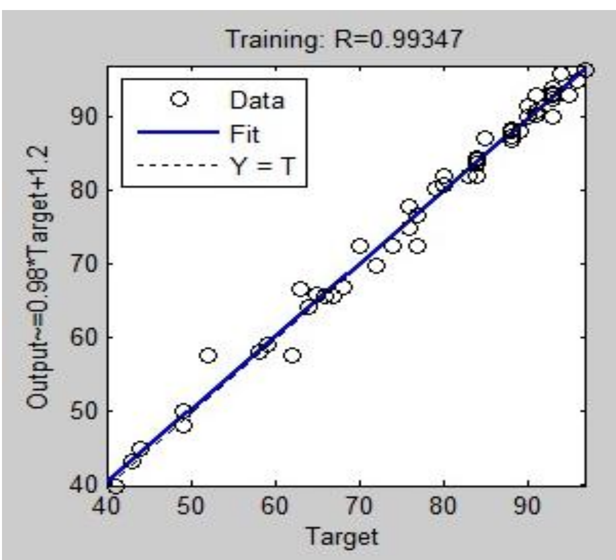
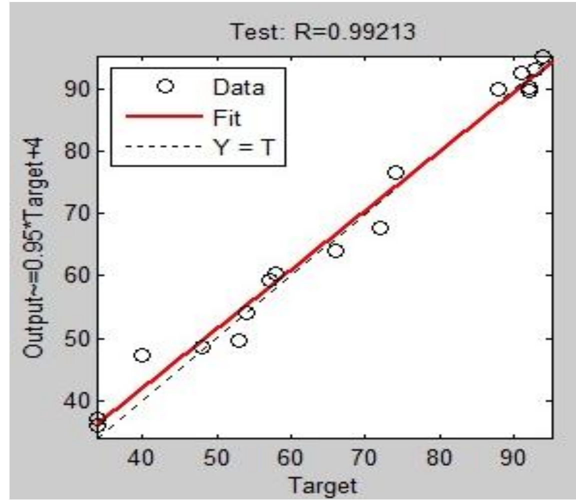


Figure 2 R-Value for different neuron numbers in wax loss

Number of input layer neurons = 7, Number of hidden layer = 1, Number of hidden layer neurons = 4, Number of output layer neurons = 1, Performance goal = 0.0001.



(a)



(b)

Figure 3 Comparison of experimentally measured and ANN-predicted values of thermal conductivity for a) training data set b) test data set in 7- 4 -1 model

Figure 4 shows the whole result of the best network for forecasting, debinding, and sintering parameters, including wax loss, shrinkage, and sintering density, along with amount of R in training, testing, and validation process.

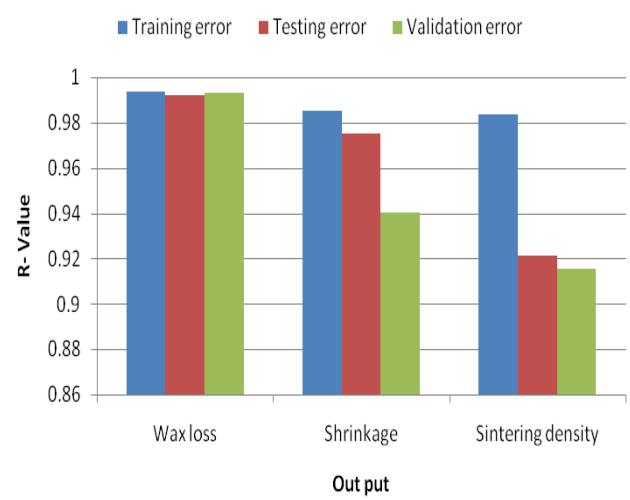


Figure 4 Result of training, testing and validation errors on the out put data set

As seen in this graph, among the output parameters, wax loss achieved the highest R-value based on the training, validation, and testing errors. This finding showed that the achieved architecture for the wax loss parameter was more valid than the other parameters. If the network is trained accurately, the function relating the input variables to the output variables can be modelled as well. It can also be used for forecasting in places where the output is not observed. Such ability is labelled as generalization. The test set is taken to evaluate the generalization capability of the trained network.

The prevention of overtraining the network during training is very important because it gives rise to an increase on the error rate of new unknown data compared with the error rate on the training data. The best technique in selecting the iteration number (training epochs) is the early stopping method. The validation data set is used to measure the error rate for it when the network is being trained. This procedure was used in the present work, as shown in Figure 5. When the error in the measurement begins to increase, the training process must be stopped by the independent validation set. This stop criterion is likely to provide the best error rate in the new data, similar to the test data set [10].

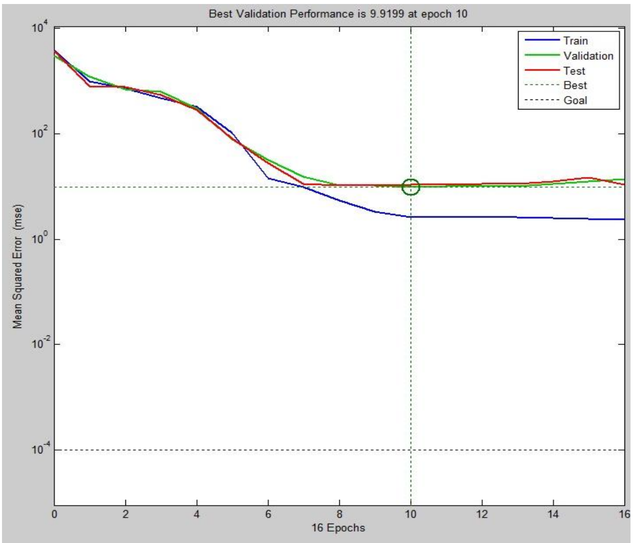


Figure 5 Schematic representation of the stopping technique used in 7-20-1 model for wax loss

■4.0 CONCLUSION

This study developed a model using ANN in forecasting wax loss, shrinkage, and sintering density in terms of PIM process parameters. The developed network displayed good performance. The network results were in good agreement with the experimental data. The optimum architecture of ANN was 7-4-1, achieved through trial and error procedure. The multilayer feed-forward perceptron network models were trained with LM training algorithm, which forecasted outputs with the most R-value over 0.995 by applying four neurons in the hidden layer. The achieved architecture in the wax loss parameter was more valid because it contained the highest R-value of training, validation, and testing steps. To obtain the best result from the ANN models, the input parameters should be well defined, so all properties affecting the amount of output are shown.

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