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PREDICTION OF WEAR BEHAVIOR IN POROUS SINTERED STEELS: ARTIFICIAL NEURAL NETWORK APPROACH

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Abstract

Due to the increasing usage of powder metallurgy (PM), there is a demand to evaluate and improve the mechanical properties of PM parts. One of the most important mechanical properties is wear behavior, especially in parts that are in contact with each other. Therefore, the choice of materials and select manufacturing parameters are very important to achieve proper wear behavior. So, prediction of wear resistance is important in PM parts. In this paper, we try to investigate and predict the wear resistance (volume loss) of PM porous steels according to the affecting factors such as: density, force and sliding distance by artificial neural network (ANN). ANN training was done by a multilayer perceptron procedure. The comparison of the results estimated by the ANN with the experimental data shows their proper matching. This issue confirms the efficiency of using method for prediction of wear resistance in PM steel parts.

Keywords: Wear Behavior, Powder Metallurgy Steels, Artificial Neural Network.

INTRODUCTION

The economic factors, the production value, proper quality and gaining of market share are important issues that need to be addressed in order to manufacture parts in today's developing industry. Among the various methods, powder metallurgy (PM) is an efficient process for manufacturing the parts, given the aforementioned aspects. Powder metallurgy is a method for manufacturing metal and ceramic parts which is essentially based on the compaction of powder materials and sintering them below the melting temperature. Economic justification of the use of powder metallurgy is based on the production circulation. Therefore, the use of powder metallurgy is important in the production of automobile parts since this industry has a remarkable annual circulation of production [1, 2].

Powder metallurgy steels are widely used to operate under sliding, rolling or abrasive wear conditions such as gears and teeth. For this reason a deep understanding of their tribological behaviour is very important [3]. The wear of a solid surface is caused by contact with another surface. This process takes place by a mechanical contact between two surfaces. In powder metallurgy steels, porosity and microstructure are the most important factors which control the wear behaviour. Other factors that affect wear behaviour include: alloy elements, wear rate and coating [1]. The wear phenomenon has various mechanisms which include: abrasive, adhesive wear and surface fatigue.

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The phenomenon of a wear is one of the problems that the industry has been facing for a long time and it has been a major part of the destruction in the industry [4]. Given the expansion of the use of parts manufactured by PM method, it is of great importance to control the wear behaviour of these parts. On the other hand, performing experimental wear tests and manufacturing standard samples are two costly processes. According to these issues, using solutions that can predict the wear resistance of PM components without performing empirical tests and by using valid data in this area will be very promising.

Artificial neural networks (ANN) are new computing systems that recognize the algorithm through existing information processing. Then, the ANN can predict the output responses through complex systems. This system, inspired by biological neural networks, consists of a large number of processing elements called neurons. Using computer programming, one can design a data structure that works like neurons. In order to develop a training algorithm, one should create a network of interconnected neurons and train the network by applying this algorithm [5].

In this research, an artificial neural network is used to predict the wear behaviour of steels that produced by powder metallurgy process. For this purpose, multi-layered perceptron synthetic method has been used for network training. As mentioned earlier, density, force and slid distance are among the most important factors affecting the wear resistance of powder metallurgy parts; therefore, these factors are regarded as inputs, while the lost volume (estimated values) is regarded as artificial neural network output.

RESEARCH METHODOLOGY

In this paper, 60 data prepared for processing in the neural network were used. Data were collected by an empirical test performed using dry wear test on porous powder metallurgy steels [6]. It should be pointed out that the data use to involve low-alloy steel containing carbon, Cr and Mn.

In this paper, to predict the wear resistance of Fe-C-Cr-Mn steel the multilayered perceptron neural network, which contains 5 neurons in the hidden layer, have been used. Figure 1 shows the structure of the neural network with a single hidden layer. The bond strength between the two neurons is represented by weight (w_{ij}). The Equations (1) and (2) indicate the relationship between the input, the hidden layer and the output. The three-layered network demonstrated in Figure 1 has an input layer, an output layer and a hidden layer [7].

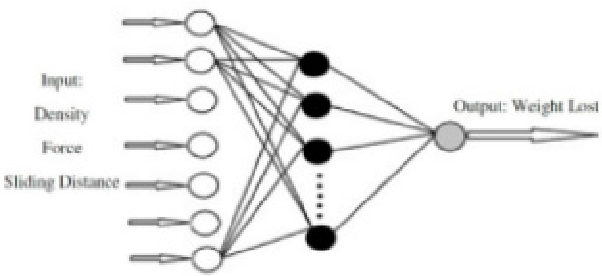

Fig 1. The structure of a perceptron neural network with a hidden layer [7].

$$a_1 = f_1(IW_{1.1} \times P + B_1) \quad (1)$$
$$a_2 = f_2(LW_{1.1} \times P + B_2) \quad (2)$$

The coding process was performed by MATLAB for artificial neural networks. Input and output data were normalized in order to better train the network in the interval [-1, 1], using the Equation (3) [5].

$$x_n = \frac{(x - Min\ x)}{(Max\ x - Min\ X) \times 2} - 1 x_n = \frac{(x - Min\ x)}{(Max\ x - Min\ X) \times 2} - 1 \quad (3)$$

In order to train the network and to test the accuracy of the program, 48 data (80% of the data) and 12 data (20% of the data) were used, respectively. The activation function in the network structure is known as Tangent Sigmoid function, shown in Equation (4) [8]. In order to minimize the output error of the neural network, the mean square error (MSE) is used which is shown in Equation (5).

$$tansig\ (n) = \frac{2}{(1 + exp(-2n))} - 1 tansig\ (n) = \frac{2}{(1 + exp(-2n))} - 1 \quad (4)$$

Where $n = w_{ij} \times u_i + b_i$.

$$MSE = \frac{1}{n} \sum_{j=1}^{n} (t_j - O_j)^2 MSE = \frac{1}{n} \sum_{j=1}^{n} (t_j - O_j)^2 \quad (5)$$

In the Equation (5), t, O and n represent the target value, output value, and the number of artificial neural networks outputs, respectively.

RESULT AND DISCUSSION

The results of artificial neural network training are as follows: The reason why the network is stopped is the number of iterations of the network (Epoch). The mean square error in the network training stage was 0.0078, while it was calculated to be 0.011 for the network test. The number of network training iterations, the network performance, the network derivative and the Mu is 1000, 0.00783, (at 0.000554 and 1×10^{-4}, respectively).

The Figure 2 shows the output normalization (Ytr) and the network training output (YtrNet), which are demonstrated by the red circle and the blue square, respectively. Figure 3 indicates the output normalization (Yts) and the network test output (YtsNet), which are represented again with red circles and blue squares. As shown in Figures 2 and 3, the output diagram and the training diagrams are relatively consistent which indicates the proper training and testing of the network up to this stage.

Figures 4 and 5 show the training and testing of the neural network, respectively. This includes the normalized value of the predicted fatigue limit based on the normalized value of the actual fatigue limit. The line plotted in Figures 4 and 5 shows the ideal state. The higher the density around the axis plotted, the better the prediction of the network.

The Figure 6 shows the mean squared error diagram based on the number of network training iterations. The diagram shows that the mean square error has the lowest value in 1000 iterations. The regression diagram is presented in the Figure 7. This diagram shows the deviation or regression from the ideal state, which is R = 1. This quantity corresponds to 0.97912. In the diagram, the closer the data diagram to the regression line, the better the training of the diagram. It ultimately indicates that the predicted values have a slight difference with the actual values obtained from the experimental test.

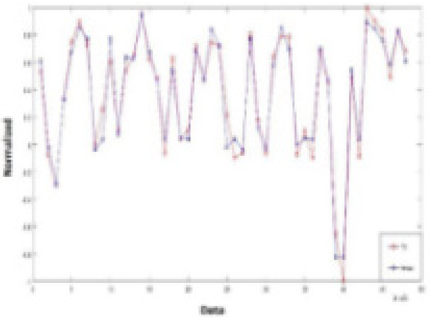

Fig.2. The output diagram and network training output.

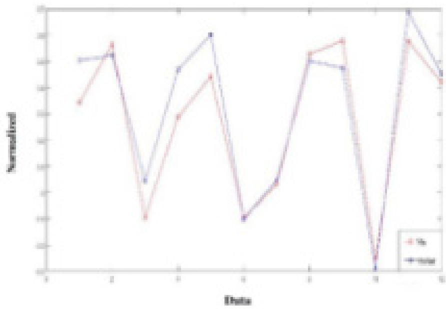

Fig.3. The output diagram and network test output.

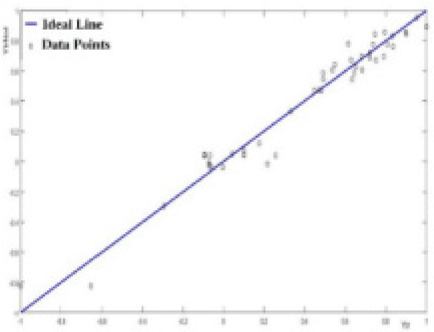

Fig.4. The normalized value of the predicted fatigue limit based on the normalized value of the actual fatigue limit in the network training process.

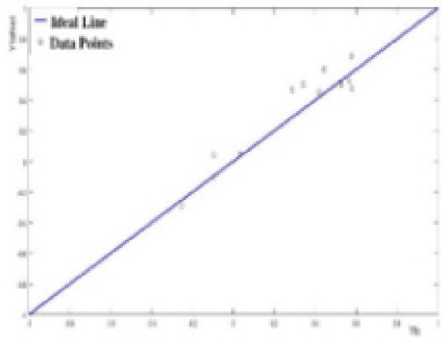

Fig.5. The normalized value of the predicted fatigue limit based on the normalized value of the actual fatigue limit in the network testing process.

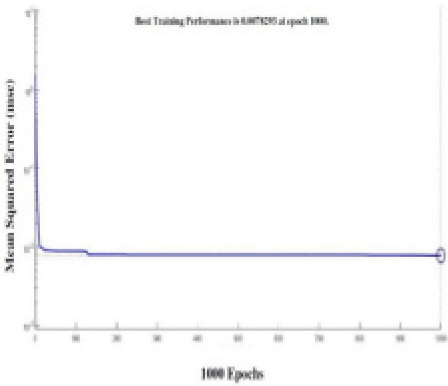

Fig.6. Mean square error diagram based on the number of network training iterations.

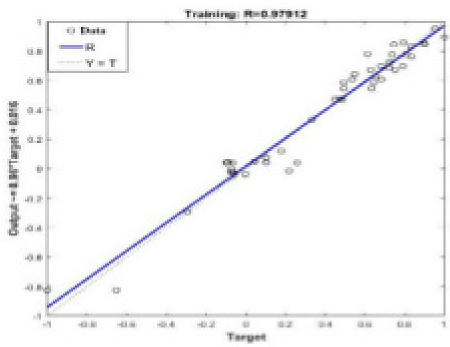

Fig.7. Regression diagram.

CONCLUSION

Wear resistance is one of the most important factors in the failure of industrial materials. The experimental tests are performed to measure this feature at a high cost. Therefore, artificial intelligence applications are used to predict the features of different parts. In this study, an artificial neural network was designed to estimate the rate of wear based on density, slide distance and force. The neural network was optimized with 5 neurons in the hidden layer. Furthermore, 48 data and 12 data were used in the training and the test processes, respectively. The accuracy of the network was measured during the test and training with the mean square error value. The Tangent Sigmoid function was used in the structure of this network (hidden layer cells). In order to facilitate the processing, data were normalized and then used in the hidden layer. According to the results, the used neural network is able to accurately estimate and predict the wear rate of the PM steels.

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