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Prediction for Dry Sliding Wear in P/M Alloy: A back-propagation ANN approach

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ABSTRACT

An artificial neural network (ANN) based model was developed, trained and evaluated for studying the dry sliding wear behavior of Fe-2%Ni based powder metallurgy (P/M) alloy as a function of heat treatment. The P/M alloy in the as-sintered (designated AS, hardness 7 HRC) as well as in the hardened and tempered at 813 K (designated HT1), and at 593 K (designated HT2) conditions having hardness 30 HRC and 40 HRC respectively were investigated for their wear behavior. Several different ANN back-propagation models with different layers/slabs connections, weights with various weight updating methods, and activation functions including logistic, symmetric logistic, linear, Gaussian, and Gaussian complement were trained. The presented ANN back-propagation model with logistic activation function exhibited the excellent statistical performance both in the training and evaluation phases. The wear rate was found to decrease initially and remain almost constant with increasing sliding distance in all the samples. This was consistent with the experimental observations. Based on the ANN trained model, wear rate predictions were made for higher hardness (60 HRC) for steel with varying percent of carbon contents (0.3%, 0.4% and 0.6%). Since, the ANN trained model exhibited excellent comparison with the experimental results, it will provide a useful predictor for dry sliding wear rates in powder metallurgy alloys.

KEYWORDS

Wear rate; artificial neural network (ANN); powder metallurgy (P/M) alloy; dry sliding wear; sliding distance

INTRODUCTION

Artificial Neural Networks (ANNs) are revolutionary computing paradigms that try to mimic the biological brain. These ANNs are modeling techniques that are especially useful to address problems where solutions are not clearly formulated [1] or where the relationships between inputs and outputs are not sufficiently known. ANNs have the ability to learn by example. Patterns in a series of input and output values of example cases are recognized. This acquired "knowledge" can then be used by the ANN to predict unknown output values for a given set of input values. Alternatively, ANNs can also be used for classification. In this case, the Artificial Neural Networks' output is a discrete category to which the item described by the input values belongs. ANNs are composed of simple interconnected elements called processing elements (PEs) or artificial neurons that act as microprocessors. Each PE has an input and an output side. The connections are on the input side correspond to the dendrites of the biological original and provide the input from other PEs while the connections on the output side correspond to the axon and transmit the output. Synapses are mimicked by providing connection weights between the various PEs and transfer functions or thresholds within the PEs. Figure 1 illustrates a simple processing element of an ANN with three arbitrary numbers of inputs and outputs [2].

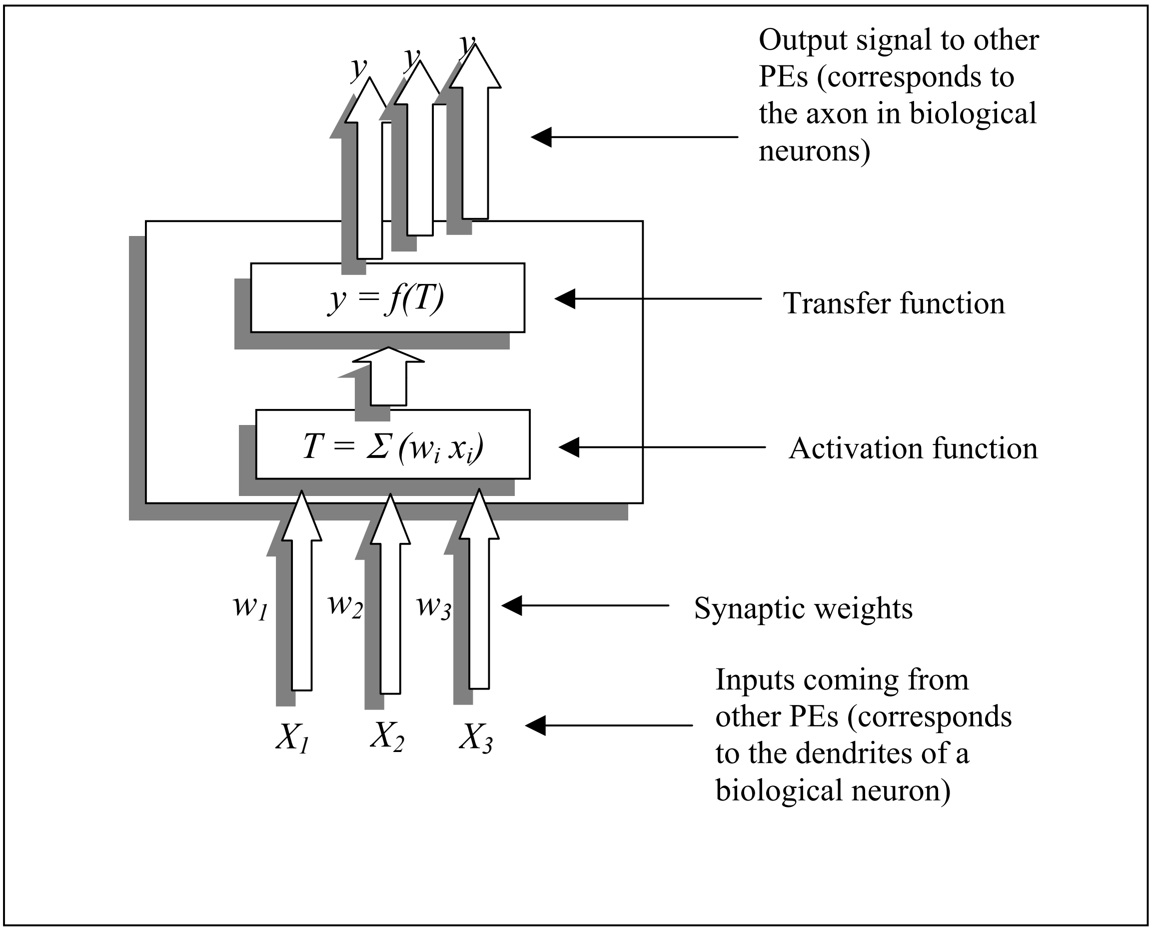

Figure 1 Processing element of an ANN model with three arbitrary numbers of inputs and outputs

The activation of the PE results from the sum of the weighted inputs and can be negative, zero, or positive. This is due to the synaptic weights, which represent excitatory synapses when positive (w_i>0) or inhibitory ones when negative (w_i<0). The PEs output is computed by applying the transfer function to the activation, which as a result of the synaptic weights, can be negative, zero, or positive. The type of transfer function to be used depends on the type of ANN to be designed. Currently, back-propagation is the most popular, effective and easy to learn model for complex networks [2,3]. To develop a back-propagation neural network, a developer inputs known information, assigns weight to the connections within the network architecture, and runs in the networks repeatedly until the output is satisfactorily accurate. The weighted matrix of interconnections allows the neural networks to learn and remember [4]. In essence, back propagation training adapts a gradient-descent approach of adjusting the ANN weights. During training, an ANN is presented with the data thousands of times (called cycles). After each cycle, the error between the ANN outputs and the actual outputs are propagated backward to adjust the weights in a manner that is mathematically guaranteed to converge [5].

The powder metallurgy processing has the advantage of forming near net shaped components. The advantages of producing complex shapes with close dimensional control at high density (porosity <2%) are the distinct advantages of this process. There is no published research data in the area of artificial neural network for predicting the wear behavior for P/M alloys. Hence artificial intelligence approach has been used in the present study so that the recent investigation [6] on wear behavior of P/M alloys can be interpreted over a wide range of processing/design parameters.

ANN BACKPROPAGATION MODEL

The neural network used for the proposed model was developed with NeuroShell 2 software by Ward Systems Group, Inc., using a back-propagation architecture with multi- layers jump connections, where every layer (slab) is linked to every previous layer. The network was trained for wear rate. The inputs were sliding distance (500 through 6000 m), hardness (7 HRC, and 40 HRC), and carbon contents (0.3% and 0.4%), and outputs were the wear rate. The number of hidden neurons, for which the logistic activation function, $f(x)=1/\{1+ exp(-x)\}$ was used, was determined according to the following formula [7]:

Number of hidden neurons = 0.5(Inputs + Outputs) + √(Number of training patterns)

Training data for the neural network training was obtained from the recent research work [6]. In the research dry sliding wear rate tests were carried out on a standard pin-on-disc machine. The data consisted of variation of wear rates with sliding distance as a function of heat treatments. Three different heat treatments were used which were: (1) AS, as-sintered, (2) HT1, hardened and tempered at 813 K, and (3) HT2, hardened and tempered at 593 K. Materials with two different carbon contents of 0.3% and 0.4% were tested. The training sets (total 100 experimental data points) included data corresponding to heat treatments 'AS' and 'HT2', and data corresponding to 'HT1' treatment (total 50 experimental data points) were used to evaluate the trained model.

Training ANN model

Network training is an act of continuously adjusting their connection weights until they reach unique values that allow the network to produce outputs that are close enough to the desired outputs. This can be compared with the human brain, which basically learns from experience. The strength of connection between the neurons is stored as a weight-value for the specific connection. The system learns new knowledge by adjusting these connection weights. The learning ability of a neural network is determined by its architecture and by the algorithmic method chosen for training. The training method usually consists of one of three schemes:
(1) Unsupervised learning where no sample outputs are provided to the network against which it can measure its predictive performance for a given set of inputs. The hidden neurons must find a way to organize themselves without help from the outside.
(2) Reinforcement learning where the connections among the neurons in the hidden layer are randomly arranged, then reshuffled as the network is told how close it is to solving the problem. Reinforcement learning is also called supervised learning, because it requires a teacher. The teacher may be a training set of data or an observer who grades the performance of the network results.
Both unsupervised and reinforcement suffers from relative slowness and inefficiency relying on a random shuffling to find the proper connection weights.
(3) Back propagation method is proven highly successful in training of multi-layered neural nets. The network is not just given reinforcement for how it is doing on a task. Information about errors is also filtered back through the system and is used to adjust the connection weights between the layers, thus improving performance.

The accuracy of the developed model, therefore, depends on these weights. Once optimum weights are reached, the weights and biased values encode the network's state of knowledge. Thereafter, using the network on new cases is merely a matter of simple mathematical manipulation of these values.

In the present research, several different ANN back-propagation trial models with different layers/slabs connections, weights and activation functions (including linear, Tanh, Tanh15, Sine, Symmetric Logistic, Gaussian, Gaussian Complement, etc.) were trained. In addition, pattern selections including "Rotation" and "Random" were used with weight updates using Vanilla, Momentum and TurboProp. The presented ANN back-propagation model with logistic activation function, "Rotation" for pattern selection, and "TurboProp" for weight updates was the best one among all other trials, which converges very rapidly to reach the excellent statistical performance (as illustrated in System Performance). Figure 2 demonstrates the graphical comparisons between the actual experimental data and the network predicted output during training and evaluation phases. They clearly demonstrate very good agreement between the actual and predicted performance.

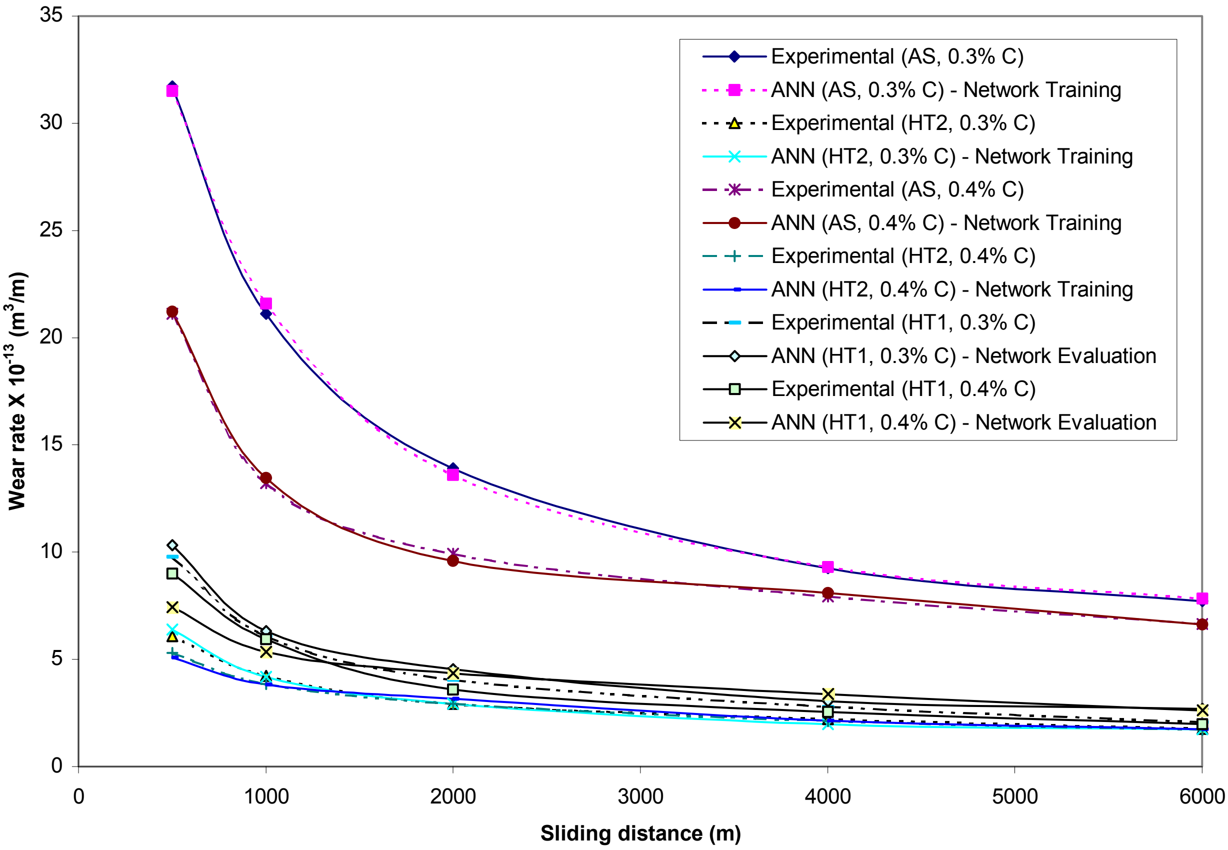

Figure 2 Wear rate vs. sliding distance - ANN training and evaluation performance

System Performance

The neural network used for the presented model demonstrated an excellent statistical performance as indicated by the R^2 and r values. During network training, R^2 was obtained as 0.9993 and 0.9237 during network evaluation, which were very close to 1.0 indicating a very good fit between the actual and the network prediction. R^2 is a statistical indicator usually applied to multiple regression analysis, and can be calculated using the following formulae [7]:

$$R^2 = 1 - (SSE/SS_{yy})$$

Where $SSE = \Sigma (y - \hat{y})^2$, $SS_{yy} = \Sigma (y - \bar{y})^2$, y is the actual value, $\hat{y}$ is the predicted value of y, and $\bar{y}$ is the mean of the y values.

The correlation coefficient, r is a statistical measure of the strength of the relationship between the actual vs. predicted outputs. The r coefficient can range from -1 to +1. It will show a stronger positive linear relationship when r is closer to +1, and a stronger negative linear relationship when r is closer to -1. During network training, *r* values were obtained as 0.9997, and 0.9699 during network evaluation, which were very close to +1.0 indicating a very good fit between the actual and the network prediction. The following formulae [7] were used to calculate r:

$$r = SS_{xy} / \sqrt{(SS_{xx}\, SS_{yy})}$$

Where

$$SS_{xy} = \Sigma xy - (1/n)\{(\Sigma x)(\Sigma y)\}$$

$$SS_{xx} = \Sigma x^2 - (1/n)(\Sigma x)^2$$

$$SS_{yy} = \Sigma y^2 - (1/n)(\Sigma y)^2$$

where *n* equals the number of patterns, *x* refers to the set of actual outputs, and *y* refers to the predicted outputs.

PREDICTION OF WEAR RATE

Based on the ANN trained model, wear rates were predicted as a function of sliding distance for P/M steel having hardness 60 HRC and carbon contents at 0.3%, 0.4%, and 0.6% as shown in Figure 3. It may be observed that the wear rate is sensitive and decreasing with the increase in carbon content up to about 4000 m sliding distance. Beyond a sliding distance of 4000 m, the wear rate remains constant and the same

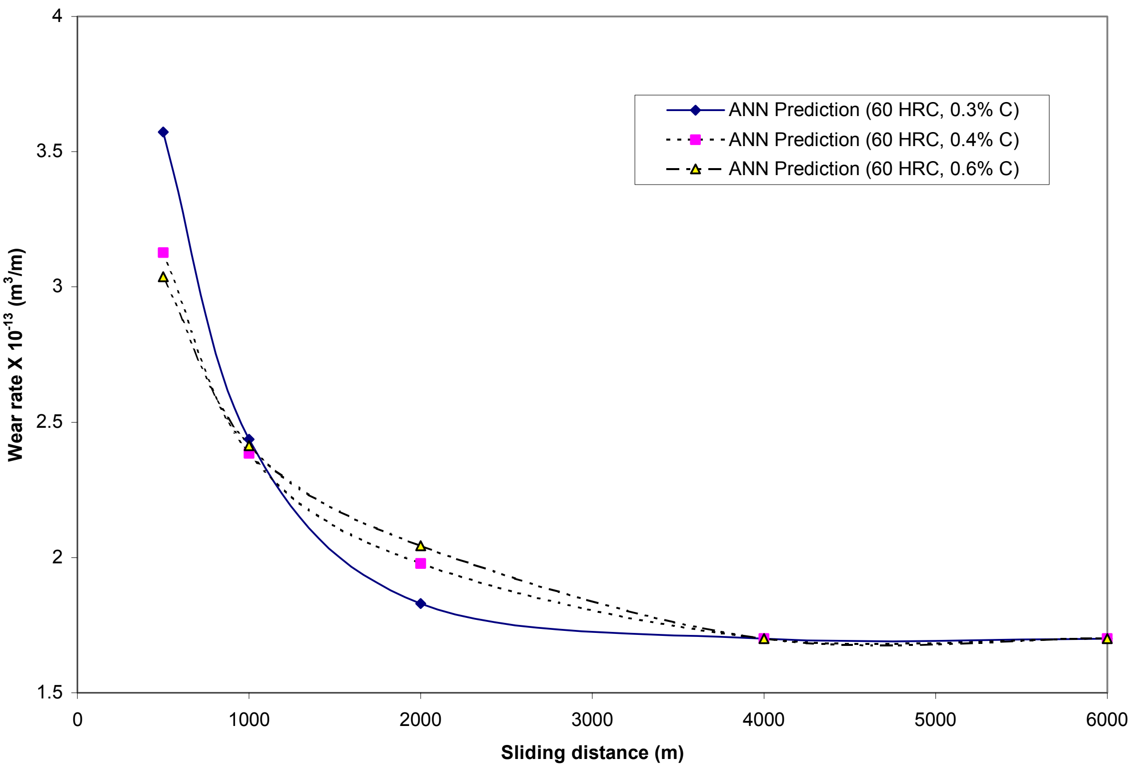

Figure 3 ANN network predicted wear rate vs. sliding distance

irrespective of the carbon contents. Figure 3 clearly predicts that the P/M alloy with 0.6% carbon content and 60 HRC hardness has the minimum wear rate (i.e. having maximum wear resistance) as compared to the other cases having lower carbon contents (0.4% & 0.3%). This is a valid observation since the addition of carbon usually contributes to improved hardness (by forming interstitial solid solution of carbon in iron lattice) in steel and thereby resulting in improved wear resistance property.

CONCLUSIONS

ANN Back-propagation model developed for studying the dry sliding wear behavior of powder metallurgy (P/M) alloys exhibited results consistent with the experimental findings. The prediction of wear behavior for P/M steel at higher hardness and/or higher carbon content is accurate and reliable with the expected trend. Hence, the present ANN based model can be used successfully over a wide range/combination of wear properties in P/M steel.

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