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PREDICTION OF THE WEAR CHARACTERISTICS OF ZA-27/SiC NANOCOMPOSITES USING THE ARTIFICIAL NEURAL NETWORK

Aleksandar Vencl[1], Blaža Stojanović[2], Slavica Miladinović[3], Damjan Klobčar[4]

Abstract: The zinc-aluminium casting alloy ZA-27 is well-established and is a frequently used material for plain bearing sleeves. It has good physical, mechanical and tribological properties. Its tribological properties can be improved further by adding hard ceramic particles to the alloy. The tested nanocomposites were produced by the compocasting process with mechanical alloying preprocessing (ball milling). Three different amounts of SiC nanoparticles, with the same average size of 50 nm, were used as reinforcement, i.e. 0.2, 0.3 and 0.5 wt. %. Tests were performed on a block-on-disc tribometer (line contact) under lubricated sliding conditions, at two sliding speeds (0.25 and 1 m/s), two normal loads (40 and 100 N) and a sliding distance of 1000 m. The prediction of wear rate was performed with the use of an artificial neural network (ANN). After training the ANN with architecture 3-4-1, the regression coefficient for the network was 0.99973. The experimental values and values obtained by applying the Taguchi method were compared with the predicted values, showing that ANN is more efficient in predicting wear.

Key words: Artificial neural network, Nanocomposites, Nanoparticles, Wear, ZA-27 alloy

1 INTRODUCTION

The ZA-27 alloy [1] is a zinc-aluminium casting alloy which is a frequently used material for plain bearing sleeves. Although it has good physical, mechanical, corrosion and tribological properties, it can be improved further by adding hard ceramic particles to the alloy [2-6]. Nanocomposites are a relatively new kind of material that is made up of a matrix and nano-size reinforcements with substantially distinct physical and

[1] Full professor, Aleksandar Vencl, University of Belgrade, Faculty of Mechanical Engineering, Belgrade, Serbia, avencl@mas.bg.ac.rs (CA)
[2] Full professor, Blaža Stojanović, University of Kragujevac, Faculty of Engineering, Kragujevac, Serbia, blaza@kg.ac.rs
[3] Research assistant, Slavica Miladinović, University of Kragujevac, Faculty of Engineering, Kragujevac, Serbia, slavicam@kg.ac.rs
[4] Associate professor, Damjan Klobčar, University of Ljubljana, Faculty of Mechanical Engineering, Ljubljana, Slovenia, damjan.klobcar@fs.uni-lj.si

mechanical characteristics from the matrix. They can be made using a variety of processing techniques [7,8]. Due to the size of the reinforcement, surface characteristics rather than bulk qualities dominate the properties of nanocomposite materials. Furthermore, the nano-scale reduction in the size of the reinforcement phase increases the importance of particle interaction with dislocations, which, when combined with other strengthening effects found in microcomposites, results in improved mechanical properties.

The artificial neural network (ANN) is a computer programme that can simulate relationships between a set of input and output variables. Numerous ANNs have been used to solve challenging scientific and engineering issues in a variety of domains [9]. The ANN tends to mimic the operations of the human brain and transmits information via mutually connected nodes called neurons. It employs the black-box modelling principle, which, in contrast to white and grey-box modelling, permits the exclusion of physical information or equations that relate the relationship between the input and matching output without the loss of accuracy. Each ANN is made up of three layers: the input layer, the hidden layer, and the output layer. The number of neurons in the input layer is the same as the number of input factors, and the number of neurons in the output layer is the same as the number of output factors. The hidden layer, however, can have many layers and can have different numbers of neurons in each layer [10]. ANN is usually used with a high amount of input data, but it can be used successfully for small data sets as well. For example, the application of ANN for the prediction of the wear rate of vacuum casted ZA-27 alloy composites reinforced with marble dust was done based on 25 experiments [11], while in another example, the prediction of wear and coefficient of friction of ZA/ZrB_2 composite was done based on only 20 experiments [12]. For both investigations, ANN gave a good correlation between predicted and experimental values.

Our previous study [13] demonstrated that nano-size reinforcement led to a finer structure in the nanocomposites matrix and improvement of basic mechanical properties (hardness and compressive yield strength). Erosive wear properties were also slightly improved due to the increase in ductility of nanocomposites [14], as well as the sliding wear resistance in lubricated conditions [15]. In this paper, we apply ANN to the experimentally acquired wear values to see if it can predict them with acceptable accuracy.

2 EXPERIMENTAL DETAILS

2.1 Materials and wear testing

The chemical composition of the matrix material, zinc-aluminium alloy ZA-27, was according to the ASTM standard [1]. Three nanocomposites with 0.2, 0.3, and 0.5 wt. % SiC (particle size < 50 nm) were produced through the compocasting process with mechanical alloying pre-processing (ball milling). Prior to the compocasting technique, ball milling was used to mechanically alloy matrix alloy metal chips with nanoparticles. The apparatus used for semi-solid processing is described elsewhere [15], as well as the production process parameters and a detailed description of the experimental procedure [13,14].

Experimental research of the wear characteristics was carried out under lubricated sliding conditions, on a tribometer with a block-on-disc contact geometry. Lubrication was provided by gear oil (ISO VG 220, ISO L-CKC/CKD). The blocks were produced from tested nanocomposites, while the discs were made of hardened and tempered steel 42CrMo4. The tests were conducted over a 1000 m sliding distance at sliding speeds of 0.5 and 1 m/s and normal loads of 40 and 100 N. The wear scars on the blocks were measured after each test to calculate the wear volume.

2.2 Artificial neural network (ANN) model

The ANN simulation starts with a "training" process in which a set of inputs are applied to the network and the resulting set of outputs is compared to known values. The training is performed until the error between the output and known values reach some predefined value. This means that ANN may take a long time to be ready for use. Once it has been trained, the network can be used to predict the output for inputs that were not in the training data set. ANNs are reliable for prediction within the trained data range, but not for prediction beyond the trained data range [17].

In this study, a feed-forward backpropagation multilayer ANN is employed. Training and testing of the ANN are conducted using the software MATLAB R2016a. The logarithmic sigmoid transfer function (logsig) and linear transfer function (purelin) are used as activation transfer functions, while the Levenberg-Marquardt backpropagation algorithm (trainlm) is used as the training algorithm. Several ANN architectures have been tested (3-3-1, 3-4-1 and 3-10-1) in order to get the one with the best prediction accuracy. One hidden layer was chosen due to a small data set and low complexity of the experiment (investigation) [18]. Ultimately, the developed ANN had architecture 3-4-1 (Fig. 1), which means it had three inputs (SiC amount, sliding speed, and normal load), 4 neurons in one hidden layer, and one output (wear rate).

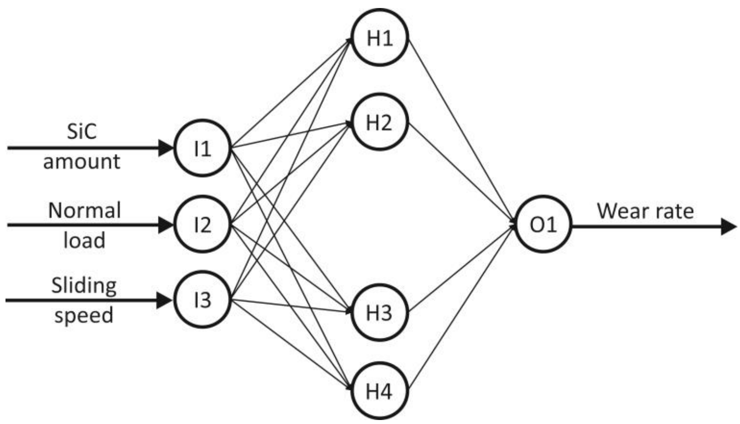

Figure 1. *Architecture of the developed feed-forward backpropagation multilayer ANN*

3 RESULTS AND DISCUSSION

The values of the used parameters in the input layer of the modelled ANN were shown in Table 1. The experimental output values [15], which were used for training, validation and testing of the ANN, are also shown in Table 1. An ANN was trained using 70 % of the data, while 15 % was used for testing and 15 % for validation. The performance and accuracy of the used ANN model are evaluated through statistical indicators such as mean square error (MSE) and regression coefficient (*R*) [17,19]. The closer the MSE value gets to zero, the better the accuracy of the model is. On the other hand, the ideal value for *R* is 1, and the closer it gets to one, the better correlation between the two groups of data (target and output values) is.

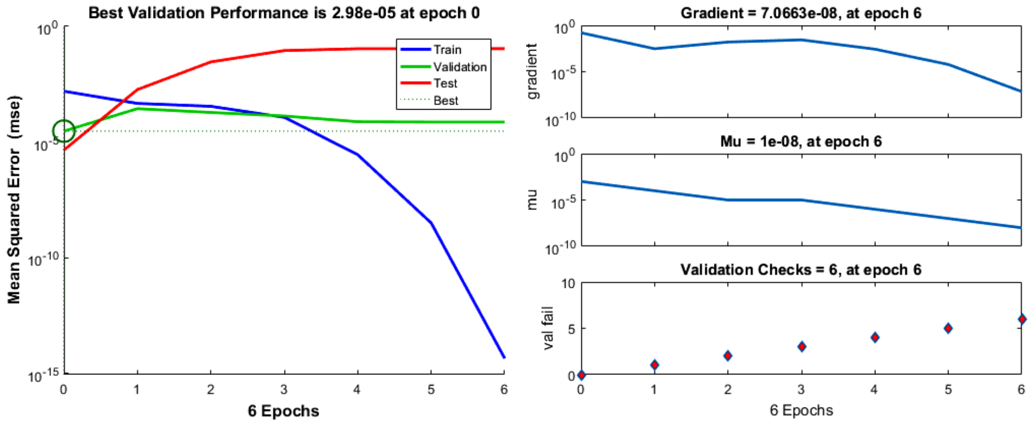

Figure 2. *Performance of the modelled ANN – mean square error and training state plots*

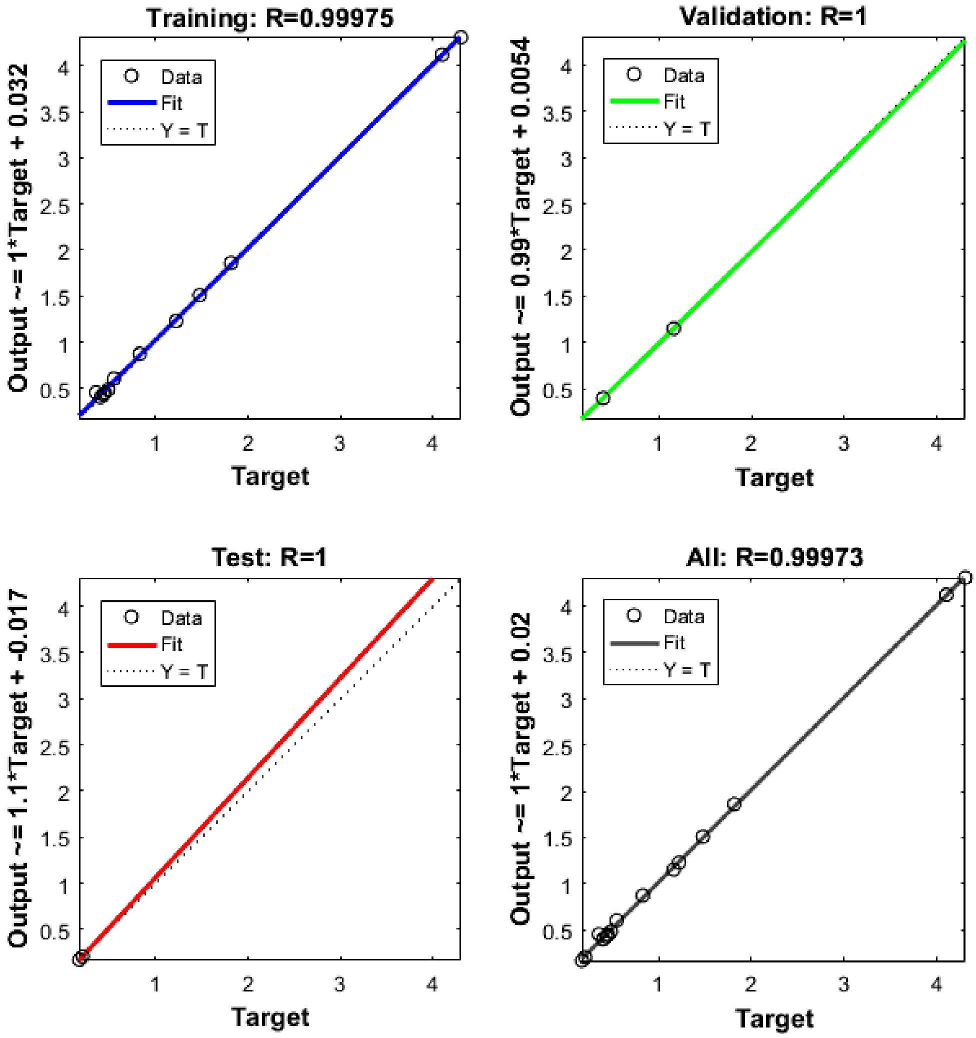

Figure 3. *Accuracy of the modelled ANN – regression analysis of different phases*

The performance of the modelled ANN is shown in Figure 2, and it can be noticed that the mean square error (MSE) for training initially has a high value and then decreases to a very small value as the number of epochs increases. This means that the ANN's training process is being performed correctly. Even though training continues until epoch 6, the best validation performance is achieved at epoch 0 with a value of 0.0000298. The training state of ANN (Fig. 2) shows that the final value of the gradient coefficient at epoch 6 is very close to zero, i.e. 7.0663×10^{-8}.

Regression analysis of the modelled ANN is performed and the regression coefficient for training, validation and testing, as well as the overall regression coefficient of the network, was obtained and shown in Figure 3. The overall regression coefficient of the network was very close to 1 (R = 0.99973), indicating a good fit and good agreement between the experimental results and the ANN model prediction.

Based on the developed mathematical model, using modelled ANN, it is possible to predict the wear rate of the nanocomposites within the limits of the experiment (trained data range). The values of the wear rate predicted with ANN are presented in Table 1 and compared with the experimental data. The deviation (error) of the predicted values from the experimentally measured values is expressed through their difference, which is also calculated as the percentage increase/decrease. Although there was a small number of data for ANN training (only 12 data), these differences were very small and the average error was only 3.38 %.

Table 1. *Input layer values, experimental data and predicted ANN output values of the composite wear rate*

Sample no.	*SiC amount, wt. %*	*Sliding speed, m/s*	*Normal load, N*	*Wear rate x 10^{-4}, mm^3/m*			
				experimentally measured	*predicted with ANN*	*error*	*± error, %*
1	*0.0*	*0.25*	*40*	*1.815*	*1.861*	*-0.045*	*2.49*
2	*0.0*	*0.25*	*100*	*4.304*	*4.303*	*0.000*	*0.01*
3	*0.0*	*1.00*	*40*	*1.476*	*1.510*	*-0.034*	*2.30*
4	*0.0*	*1.00*	*100*	*4.099*	*4.117*	*-0.018*	*0.44*
5	*0.2*	*0.25*	*40*	*0.436*	*0.432*	*0.004*	*0.87*
6	*0.2*	*0.25*	*100*	*1.221*	*1.230*	*-0.009*	*0.78*
7	*0.2*	*1.00*	*40*	*0.486*	*0.487*	*-0.001*	*0.15*
8	*0.2*	*1.00*	*100*	*0.548*	*0.606*	*-0.058*	*10.53*
9	*0.3*	*0.25*	*40*	*0.402*	*0.403*	*-0.001*	*0.22*
10	*0.3*	*0.25*	*100*	*1.162*	*1.154*	*0.008*	*0.66*
11	*0.3*	*1.00*	*40*	*0.356*	*0.456*	*-0.099*	*27.80*
12	*0.3*	*1.00*	*100*	*0.452*	*0.451*	*0.001*	*0.20*
13	*0.5*	*0.25*	*40*	*0.209*	*0.209*	*0.000*	*0.08*
14	*0.5*	*0.25*	*100*	*0.828*	*0.874*	*-0.046*	*5.55*
15	*0.5*	*1.00*	*40*	*0.174*	*0.171*	*0.003*	*1.72*
16	*0.5*	*1.00*	*100*	*0.404*	*0.405*	*-0.001*	*0.25*
						Average ± error, %	*3.38*

The accuracy of the ANN prediction was compared with the prediction obtained with the Taguchi method [15], for the same experimental set of data, and presented in Figure 4. It can be noticed that, in both cases, there is a good correlation between experimental and predicted values and both prediction methods can be used with high reliability. However, values obtained by the modelled ANN are closer to experimental values; therefore, it can be concluded that in this case, the ANN is more efficient in predicting wear rate.

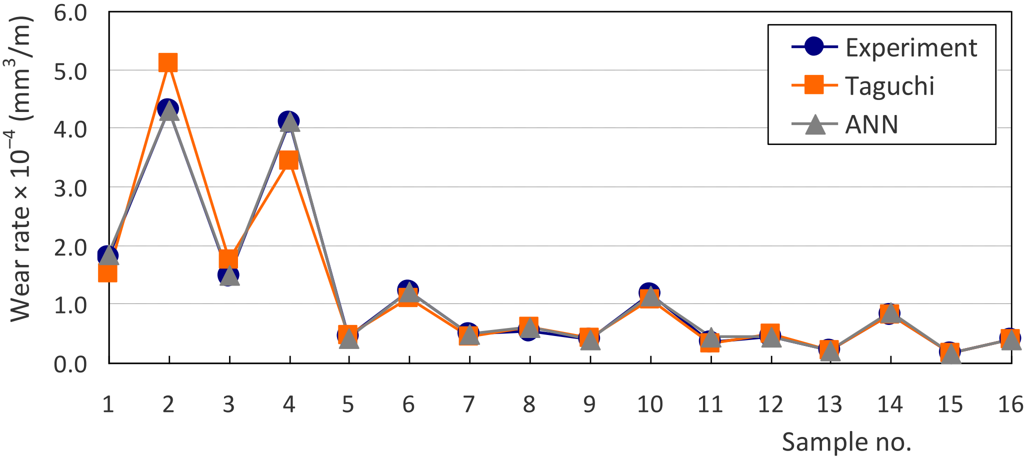

Figure 4. *Comparison of experimental, Taguchi and ANN results*

4 CONCLUSIONS

In this study, ANN was used to investigate and predict how the SiC nanoparticles, sliding speed and normal load affect the wear rate of ZA-27/SiC nanocomposites. The optimal architecture for the modelled ANN was 3-4-1, i.e. the one with three inputs (SiC amount, sliding speed, and normal load), 4 neurons in one hidden layer, and one output (wear rate). The ANN model was developed using the software MATLAB R2016a.

When compared to the experimental measurements, the results predicted by the ANN model are adequate, i.e. the regression coefficient was very close to 1 (R = 0.99973), and the average error was less than 3.38 %. Therefore, testing time and cost can be reduced by obtaining satisfactory results using the developed ANN rather than measuring them.

By comparing the two predicting methods (Taguchi and ANN), it can be concluded that ANN, in this case, is more efficient in the prediction of wear rate since their predicted values are closer to the experimentally measured values. In future research, some other machine learning techniques like random forest, gradient boosting and decision trees could be applied and then compared to ANN, because these techniques are suitable for small data sets.

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