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NEURAL NETWORK ANALYSIS FOR SLIDING WEAR OF 13%CR STEEL COATINGS BY ELECTRIC ARC SPRAYING

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ABSTRACT:- Artificial Neural Networks (ANNs) are a new type of information processing technique based on modeling the neural systems of human brain. The potential of using neural networks in prediction of wear rate quantities of 13%Cr steel coating produced by arc spraying, has been studied in the present work. The material is subjected to dry sliding wear test using pin-on-ring apparatus at room conditions. Effects of normal load, sliding speed and time on wear rate have been investigated by using artificial neural networks. The experimental results were used to train ANN model successfully with accepted mean square error (MSE) of 0.00077504. The ANN predictions shows very good agreement with experimental values with correlation coefficient of 0.99778, thus ANN can be considered excellent tool for modeling complex processes that have many variables.

***Keywords*:-** Artificial Neural Network; Wear; Coating.

1. INTRODUCTION

The application of coating to surfaces which subjected to wear is usually considered when difficulties arise in the fabrication of complete component from the coating material or where the cost of the operation prohibitive. It my also be appropriative to use coating where different properties (electrical, mechanical or tribological) are required for the surface of the component compared with those in the core[(1)].

Higher accuracy and longer life are required for various machines as a result of advances in industrial technology consequently, control of the wear which occurs between sliding surfaces has become an important target[(2)]. In recent years, the application of Artificial Neural Network (ANN) has attracted extensive interests in diverse fields.

Mishra et al.[3] used neural network model to predict the rate of erosion wear of Nickel-Aluminide coatings on steel by plasma spraying, the erosion studies were made at different velocities and impact angles. Velten et al.[4] used back propagation ANN with Levenberg-Marquardt algorithm to predict and analyze the wear behavior of short fiber reinforced polymer bearing materials. Sahu et al.[5] proposed neural networks for analysis and prediction of wear behavior of plasma sprayed alumna titania composite coatings. Wang et al.[6] designed a novel ANN-based optimal estimator for CBN tool wear modeling in hard turning, the estimator is designed based on a fully forward connected neural network and trained using the extended Kalman filter(EKF). Durmus et al.[7] used ANN to predict wear loss and surface roughness of AA 6351 aluminium alloy, experimental and ANN results have been compared and they showed coincidence to large extent.

Artificial neural network is inspired by the biological nerve system and is being used to solve a wide variety of complex scientific and engineering problems[8,9,10,11]. This computational technique is especially useful for simulations of any correlation that is difficult to describe with physical models because of the ability to learn by example and to recognize patterns in a series of input and output values from example cases. This remarkable capability of modeling is useful in the study of complicated problems, which usually cannot be solved by existing physical, theories or other mathematical approaches.

In the present work, feed forward neural network model with back propagation (BP) training algorithm is developed to predict the sliding wear rate of 13%Cr steel coating by electric arc spraying. Based on experimental databases, the neural network is trained to minimize the error and to generalize these experimental data. The well optimized and trained neural networks are used to predict the wear rate as a function of normal load, sliding speed and sliding time.

2. EXPERIMENTAL DETAILS

To enhance the adhesion strength of coating to the substrate a nickel-aluminum material system are used as bond coats for this application. Cylindrical shafts, having a dimension of 54mm diameter and 60cm in length, of nodular cast iron were coated with Ni-Al wire of 1.6mm diameter (bond coat) to a thickness approximately (0.05 to 0.1 mm), using the following operating parameter.

Arc voltage =28 v

Spray distance =8 cm

Wire feed rate =95 mm/s

Air pressure =6o psi(4.41par)

Rotation speed =30 rpm

Now the surface is completely prepared for coating by 13%Cr steel. Since the important factor for the successful bonding of sprayed metal is the time lag between preparations and spraying, this must be kept to minimum. After that the shaft is coated with 13%Cr steel by electric arc spray gun under the following condition:

Arc voltage =32 v

Spray distance =12 cm

Wire Feed rate = 100 mm/s

Air pressure =6o psi(4.41par)

Rotation speed =30 rpm

The spraying operations have been carried out using an arc spraying coating system (system smart Arc350 PPG, Sulzer Metco, Switzerlad). Commercial available wire of 13%Cr steel of 1.6 mm diameter was used in coating process. The shafts after coating are finishing to the required size by using wet grinding with medium hardness wheel type (vitrified 40-60 grit PEI). The surface speed is 180 m/min and work speed is 24 m/min insoluble oil is used as a coolant. The finished diameter leaves a coating thickness of 2 mm. A specimen of 26 mm length are cut from the coated shaft and prepared for testing as shown in Figure(1b). The stationary pin were cut from bearing .

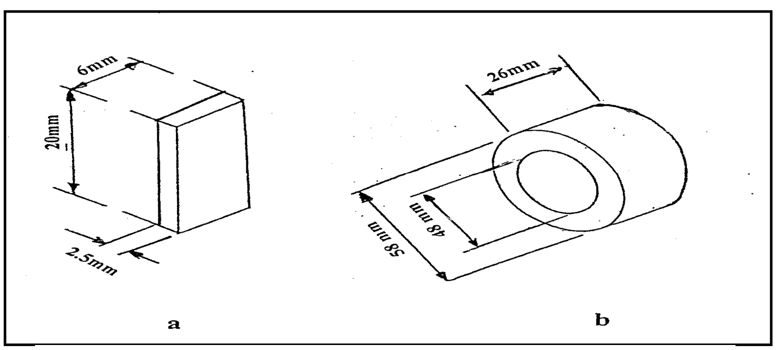

Fig.(1): A specimen a) Pin b) Tested ring shell and machined with dimension as shown in Figure(1a). Table(1) show the chemical composition of material used in this work. The wear test specimens were studied under dry (unlubricated) and under ambient conditions using pin-on-ring wear testing machine.

Table (1): Chemical composition of used materials.

Element / Sample	C	Si	Mn	P	S	Cr	Mo	Ni	Cu	V	Fe
shaft	3.9	2.08	1.13	0.035	0.32	0.21	0.36	0.105	0.198	0.006	Rem
Coating Wire	0.326	0.388	0.717	0.038	0.017	11	0.048	0.288	0.065	0.068	Rem
pin	0.072	0.002	0.38	0.003	0.017	-	0.008	-	-	0.002	Rem
Bond wire	Mn	Cu	Zn	Cr	Fe	Co	Mg	Al	Ni	-	-
	2.265	0.042	0.114	0.073	13.74	0.26	1.079	5	Rem	-	-

The test was carried out under varying loads, sliding speeds and time durations. Figure(2) Show the layout of wear testing machine. Tests were replicated at least three times for each experimental condition. The specimen should be cleaned by chemical solvent, to remove any forgone mater or wear debris before and after each test.

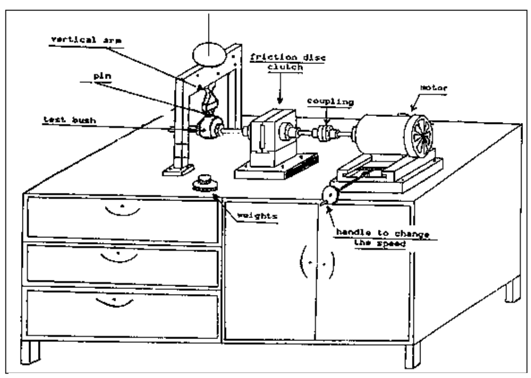

Fig.(2): Wear Test Machine **.**

After each test, the test machine was switched off, and the ring was taken out and the mass loss is measured using precision balance having 0.01 mg sensitivity. These mass losses of the tested rings were used to study the effect of load, sliding speed and time on the wear resistance of the coating under consideration.

The weighting method is the simplest way of detecting wear rate. The specimen after cleaning is weighed before and after running and the weight loss during the experiment is used to calculate the wear rate. The following relation is used to investigate the wear rate(12).

Table(2): The results of wear rate from experimental data**.**

Exp. No.	Normal Load(N)	Sliding Speed(m/s)	Sliding Time(hr)	Wear rate (mm^3/mm)
1	5	1.5	2	5.52792E-09
2	5.5	1.5	2	6.90989E-09
3	6	1.5	2	8.29187E-09
4	6.5	1.5	2	9.67385E-09
5	7	1.5	2	1.24378E-08
6	7.5	1.5	2	1.79657E-08
7	8	1.5	2	2.21117E-08
8	8.5	1.5	2	2.62576E-08
9	9	1.5	2	4.14594E-08
10	9.5	1.5	2	8.98286E-08
11	10	1.5	2	1.31288E-07
12	10.5	1.5	2	2.07297E-07
13	11	1.5	2	2.69486E-07
14	11.5	1.5	2	3.15091E-07
15	12	1.5	2	3.67606E-07
16	7	0.5	2	1.24378E-08
17	7	0.7	2	1.48069E-08
18	7	0.9	2	1.61231E-08
19	7	1.1	2	1.31916E-08
20	7	1.3	2	1.27567E-08
21	7	1.5	2	1.24378E-08
22	7	1.7	2	2.31685E-08
23	7	1.9	2	2.72759E-08
24	7	2.1	2	3.45495E-08
25	7	2.3	2	3.51503E-08
26	7	2.5	2	4.06302E-08
27	7	2.7	2	4.52982E-08
28	7	2.9	2	5.28964E-08
29	7	3.1	2	7.28882E-08
30	7	3.3	2	1.25006E-07
31	7	2	1.2	1.20923E-08
32	7	2	1.4	1.33262E-08
33	7	2	1.6	1.42517E-08
34	7	2	1.8	1.72747E-08
35	7	2	2	3.4204E-08
36	7	2	2.2	3.67481E-08
37	7	2	2.4	3.88682E-08
38	7	2	2.6	3.90675E-08
39	7	2	2.8	4.36804E-08
40	7	2	3	4.76783E-08
41	7	2	3.2	4.85852E-08
42	7	2	3.4	5.30436E-08
43	7	2	3.6	5.70066E-08
44	7	2	3.8	7.63725E-08
45	7	2	4	9.32836E-08

$$K = \frac{V_r}{X} \qquad \ldots(1)$$

$$Vr = \frac{\Delta m}{\rho} \qquad \ldots(2)$$

$$X = Vs * T \qquad \ldots(3)$$

$$\therefore K = \frac{\Delta m}{\rho * Vs * T} = \frac{m_1 - m_2}{\rho * Vs * T} (mm^3 / mm) \qquad \ldots(4)$$

Where K=wear rate (mm^3/mm), Vr=volume removed (mm^3), X=sliding distance (m), Vs=sliding speed(m/s), T= sliding time(S), ρ =bulk density of coating(g/mm^3).

The experimental data is shown in Table(2) where the effect of load, sliding speed and time on the wear rate has been illustrated.

3. NEURAL NETWORK MODELING

Neural networks were originally inspired as being models of human nervous system. They have been shown to exhibit many abilities, such as learning, generalization, and abstraction[(13)] . Useful information about neural networks can also be found in[(13,14,15)]. These networks are used as models for processes that have input/output data available. The input/output data allows the neural network to be trained in a way that minimizes the error between the real output and the estimated (neural net) output. The model is then used for different purposes among which are prediction and identification.

The neural net structure that we will consider in this paper is shown in Figure(3). The inputs are linked to a hidden layer which in turn is linked to the output. The components of the hidden layer are called nodes or neurons. Each link is associated with a weight. These weights are determined from given input/output data about the process such that the least square error between the given output data and the model output is minimized. The optimization process for calculating the weights of the neural net is called training. If the data used for training is huge or the number of hidden nodes is large then the training may take a long time. Once the net is trained it can be tested on a different set of data than that used for training. It is a good approach to divide the given input/output data into three parts: one part is used for training whereas the others usually smaller parts are used for validation and testing the neural network model.

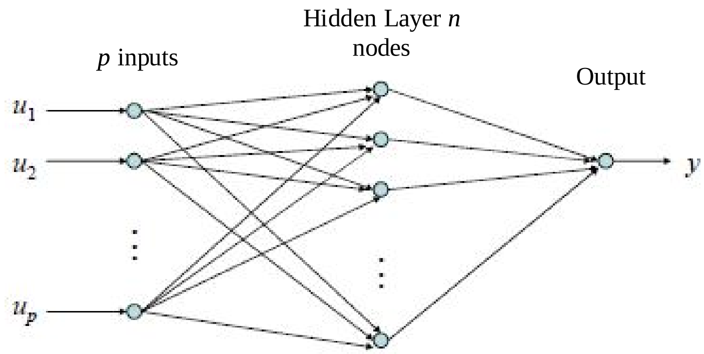

Fig.(3): Neural network**.**

Note that Figure(3) shows a neural net with one hidden layer. This is the case that we are going to consider since a number of results have been published showing that a feed-forward network with only a single hidden layer can well approximate a continuous function[14]. In practice, most processes are continuous. An artificial neural network mathematical model that represents the structure shown in Figure(3) is written as:

$$y= f(U) = W_o * \tanh(W_i * U+B_i)+b_o \qquad \ldots(5)$$

where,

y : is the output of the neural network model(in this work, y represent wear rate).

U : is a column vector of size p that contains the p inputs of the process(p equals three, normal load, sliding speed, and sliding time).

W_o : is a row vector of size n that contains the weights of the neural network model from the hidden layer to the output.

W_i : is a matrix that contains the weights of the neural network model from the inputs to the hidden layer. This matrix has n rows and p columns.

B_i : (not shown in Figure(3)) is a column vector of size n that contains the biases from the input to the hidden layer of the neural net model.

b_o : (not shown in Figure(3)) is the bias (scalar) from the hidden layer to the output of the neural net model.

tanh(Wi*U+Bi) : is a column vector that contains the hyperbolic tangent of the elements of the vector Wi*U+Bi.

Each input u_j, j=1,2,…p has lower and upper bounds, Lb_j and Ub_j, respectively. These bounds are calculated from the given input data. Lb_j is the minimum value of the jth input over the given data whereas Ub_j is the maximum value of the jth input over the given data. If all the inputs lie within their lower and upper bounds then the estimated output by the neural net should lie within the given output data range. In other words, the output bounds are dictated by the neural network and the input bounds.

The number of hidden neurons affects the performance of the neural net over the training and test sets of data. More neurons make the fitting of data more accurate over the training region. It is more important to check the performance of the model over the test set of data since it was not used to calculate the parameters of the model.

Over trained neural net may perform badly over the test set. The number of nodes is usually chosen by trying different values and selecting the one that performs best over both the training and test sets of data.

4. RESULTS AND DISCUSION

ANN model with three neurons in the input layer (normal load, sliding speed and sliding time); single hidden layer and one output neuron (wear rate) have been constructed at this work to predict the wear rate for various values of input parameters. The input variables are normalized so as to lie in the range of [-1,1], output values resulted from ANN model are within the same range and converted to their equivalent values based on reverse method of normalization. The determination of number of neurons in the hidden layer is done by trial and error approach to optimize the number of neurons in the hidden layer. Based on mean square error (mse) criterion, 3-2-1 architecture is selected to correlate the relationship between the inputs-output data. It was found that the network with single hidden layer having two neurons fits well in the proposed neural network model as shown in Figure(4). Nonlinear tangent sigmoid activation function has been used for hidden neurons and linear activation function for output neuron. Experimental database of 45 sets are used to develop the ANN in order to understand the input-output correlations. These databases are then divided into three subsets: a training subset, which is used for computing the gradient to construct the neural network model, exclusively used to adjust network weights and biases; a validation subset which is required to compute validation error.

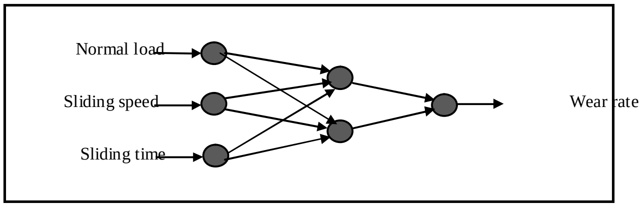

Fig.(4): ANN model**.**

This error is monitored during the training process. The validation error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set typically begins to rise. When the validation error increases for a specified number of iterations (after 25 iteration as shown in Figure(5)), the training is stopped, and the weights and biases at the minimum of the validation error are returned.

Finally, a test subset, the test set error is not used during training, but it is used to compare different models. It is also useful to plot the test set error during the training process as illustrated in Figure(5). 60% of the experimental data have been used for training the neural network model and 20% for validation and testing.

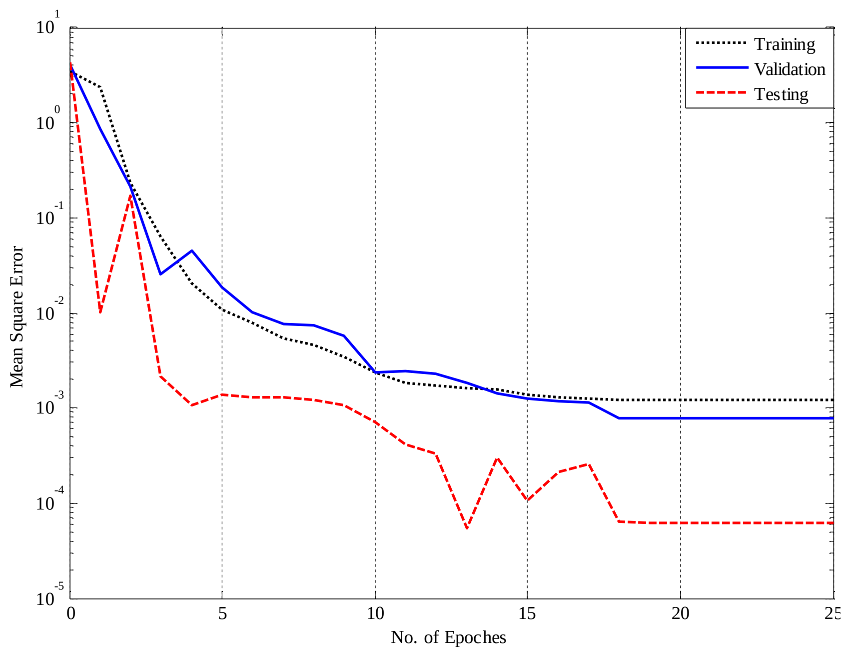

Fig.(5): Training Progress.

In this training session, validation is stopped after nineteen iterations at mse 0.00077504 with correlation coefficient 0.99778 as shown in Figure(6) which indicate excellent matching between the experimental data and prediction of the neural network model .

After training and testing processes were finished, the ANN can be recalled to do prediction effectively. To test the prediction performance of the trained network in training and testing processes, the experimental values were compared to the predicted values resulted from ANN as shown in Figure(7 ,8, and 9).

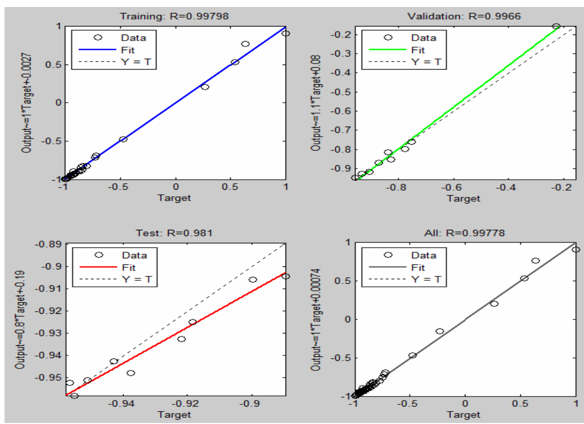

Fig.(6): Regression Analysis.

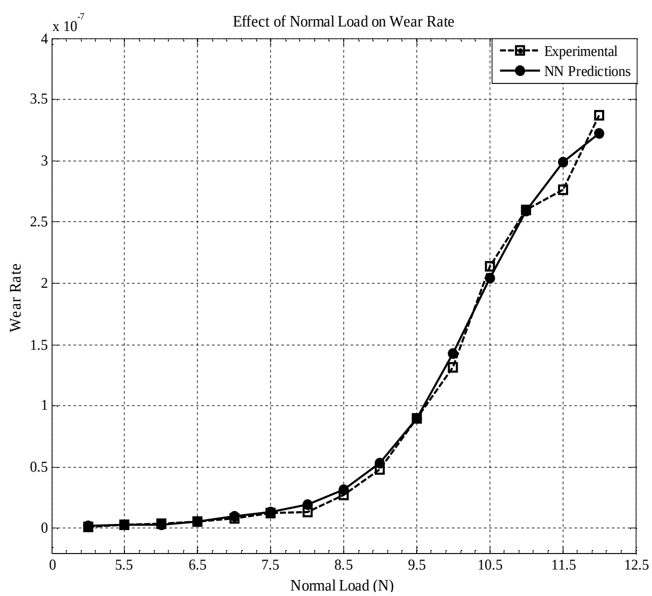

Fig.(7): Comparison plot for predicted and experimental values at constant Speed (1.5m/s) and Time (2hr).

5. CONCLUSIONS

In the present study, a feed-forward back propagation neural network was used to predict wear rate of electric arc spray coating. The experimental values of wear rate of the worn specimens were used for the training and testing neural network model. Satisfactory agreement between the experimental and neural network model results was obtained from using this type of neural network. Hence it can be said that artificial neural networks can be used efficiently as prediction technique in the area of coating test, wear and material characterization and the simulation can be extended to a parameter space larger than the domain of experimentation.

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استخدام الشبكات العصبية في تخمين السوفان ألانزلاقي لطلاء 13% كروم ستيل منتج بواسطة الرش بالقوس الكهربائي

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الخلاصة

الشبكات العصبية الاصطناعية نوع حديث من تقنية معالجة المعلومات مرتكزة على نمذجة النظام العصبي للعقل البشري. أن فاعلية أستخدام الشبكات العصبية في تخمين قيم معدل السوفان لطلاء 13% كروم ستيل منتج بواسطة الرشّ بالقوس الكهربائي تم دراستها في هذا البحث. تم اجراء فحص السوفان الجاف بأستخدام جهاز المسمارعلى الحلقة في ظروف الغرفة. تأثير الحمل العمودي, سرعة الانزلاق والوقت على معدل السوفان تمت دراستها بأستخدام الشبكات العصبية الاصطناعية. تم استخدام النتائج المختبرية لتدريب نموذج الشبكة العصبية بنجاح وبمعدل خطاء مقبول (معدل مربع الاخطاء) 0,00077504. تخمينات الشبكة العصبية اضهرت توافق جيد جدا مع القيم المختبرية وبمعامل ارتباط 0.99778 وبهذا تعتبر الشبكات العصبية اداة ممتازة لنمذجة العمليات المعقدة التي تمتلك العديد من المتغيرات.

الكلمات الدالة: الشبكة العصبية الاصطناعية, السوفان, الطلاء.