Mathematical and Neural Network models for prediction of wear of mild steel coated with Inconel 718 – A Comparative Study

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Abstract- Many wear models can be found in the literature to predict the type and amount of wear but there is no general wear model which can be adopted for all wear problems due to the complex and dynamic nature of the phenomenon. In the present work, an attempt has been made to study the influence of wear parameters like applied load, speed and sliding distance on the dry sliding wear of mild steel coated with Inconel 718 using pin on disc apparatus and build Mathematical and Neural Network models. A plan of experiments based on Taguchi's orthogonal array was developed to acquire data in a controlled way for different sliding distances, under different loads, and different speeds. The experimental results were used to develop mathematical model using MINITAB 13 and ANN model using MATLAB7 successfully. The validity of the modeling approaches is demonstrated by comparing the predicted results with experimental results. The predictions of these models show a good agreement with experimental values.

Index Terms- Wear, INCONEL 718, Plasma spraying, Mathematical model, MINITAB13, ANN model, Matlab7

I. Introduction

When one surface is moving relatively over another, adhesive wear occurs. The adhesive wear is proportional directly to the load applied and the sliding distance and inversely with the hardness of the metal. It is found that the adhesive wear is 15% of the industrial wear. At the microscopic level, every surface is rough and contains microscopic irregularities. When two surfaces meet, the contact takes place at these projections called asperities. When load is applied on these surfaces, stresses induced at the asperities cross the elastic limit and they deform plastically and adhere to one another. When the surfaces slide against each other, the adhesion breaks. The contacting surface which is weaker breaks and gets deposited on the other surface. Since the wear occurs at the surface, applying wear resistant coatings on these surfaces offers a solution to this problem. In this direction, plasma spray coating technology has taken a prime position as it offers wide variety of substrates and coatings for thicknesses ranging from microns to a few millimeters. For predicting sliding wear of coatings, Design of Experiments (DOE) and Artificial Neural Networks (ANN) are useful tools. DOE is a powerful statistical technique for studying the effect of multiple variables simultaneously on the output. Generally, every system is influenced by two sets of process variables. They are controllable and uncontrollable variables. The objective of experiments is to determine the most influential controllable variables on the output response, to minimize the output variations and to minimize the effects of uncontrollable variables. The Neural Networks are found to be good function approximators in many applications. They are the data processors and the data is collected from experiments carefully designed. [Hani Aziz Ameen et al., (2011); Chandra Mouli K.V.V. et al., (2006)].

Recently, several researchers have applied Taguchi's technique and Neural Networks in their studies in engineering. Dinesh et al (2004) used a plan of experiments, based on the techniques of Taguchi to study the dry sliding wear studies on hybrid MMC's and found that sliding distance is the wear factor that has the highest physical as well as statistical influence on the wear of the composite Al2219 reinforced with SiC and graphite reinforcements. Abbas Khammas Hussein (2009), used Taguchi approach to optimize pack aluminization parameters in carbon Steel and found that the use of 4%wt. of NH_4Cl at diffusion temperature of 700^{o}C and diffusion time of 5hr to be the optimum condition. Chandra Mouli et al (2006) used Taguchi's method to predict the optimum process parameters for prediction of optimum output from a blast furnace under the influence of seven independent parameters. Khamlichi et al (2008) applied Taguchi's method to optimize friction behavior of clutch facings using pin on disk test and friction coefficient of clutch facing materials was found to be very sensitive to the interaction between the sliding speed and temperature. An experimental design based on the Taguchi method was applied by Pascal Deprez et al (2009) to optimize the use of a dynamic sealing element of water pump of automotive combustion engines. Basavarajappa et al (2009) used Taguchi approach and studied the effect of filler materials on dry sliding wear behavior of polymer matrix composites and developed a mathematical model using linear regression model. They studied the tribological behavior of glass epoxy polymer composites with SiC and Graphite particles as secondary fillers and investigated the influence of wear parameters like, applied load, sliding speed, sliding distance and percentage of secondary fillers, on the wear rate and concluded that the inclusion of SiC and Graphite as filler materials in glass epoxy composites will increase the wear resistance of the composite greatly. Thamizhmanii et al (2007) used Taguchi's method to show that the depth of cut has significant role to play in producing lower surface roughness followed by feed and the cutting speed has lesser role to play on surface roughness. Sujan Kumar Pal and Prasanta Sahoo (2007) applied Taguchi method in the optimization of coating parameters for surface roughness in electroless Ni-P coating of mild steel specimen and found that the optimal process parameter combination for resulting surface roughness is 80 ^oC of bath temperature, 17 gm/liter use of sodium hypophosphite and 30 gm/liter use of nickel chloride and nickel sulphate. Subramanian et al (2009) studied the plating parameters and developed a model using artificial neural network and also developed a mathematical model using regression model . Chandra Mouli K.V.V. et al., (2006) used Taguchi's method to predict the optimum process parameters and forecasts the outputs at these parameters using neural networks for prediction of optimum output from a blast furnace under the influence of seven independent parameters.

In the present work, a study of adhesive wear of mild steel coated with Inconel 718 and consequently, to develop Mathematical and Neural Network model is undertaken.

II. TAGUCHI'S METHOD AND ARTIFICIAL NEURAL NETWORKS

A. Taguchi's Method

Taguchi's method of experimental design is an efficient way to determine the optimum factor level combinations to achieve a minimum standard deviation (variation) while keeping the mean on the target. It is a most efficient problem-solving tool that can update or improve the performance of the product or process design and system with a sufficient experimental data. The Taguchi approach to experimentation provides an orderly way to collect, analyze, and interpret data to satisfy the objectives of the study. By using these methods, in the design of experiments, maximum amount of information for the amount of experimentation used can be obtained. Taguchi suggested the use of orthogonal arrays, which are the shortest possible matrix of permutations and combinations. The main aim of this method is that all parameters are varied, at the same time the effect on the performance and in the interactions can be studied simultaneously. The orthogonal array (OA) requires a set of well balanced (minimum experimental runs) experiments. In this method, main parameters, which are assumed to have an influence on process results, are located at different rows in a designed orthogonal array. With such an array, completely randomized experiments can be conducted. Taguchi's method uses the statistical measure of performance called signal–to-noise ratios (S/N), which is logarithmic function of desired output to serve as objective function for optimization. Three categories of S/N ratios are used: lower-the-better (LB), higher-the-better (HB) and nominal-the-best (NB). The parameter level combination that maximizes the appropriate S/N ratio is the optimal setting. The experimental results are analyzed using analysis of means and variance to study the influence of factors. Once the experiments are conducted, the results are then analyzed using analysis of variance (ANOVA). According to Taguchi method, the S/N ratio is the ratio of signal (desirable value, which is the mean for output characteristic) and the noise (undesirable value which is square deviation for output characteristic). The units of signal and noise are in decibel (dB). The S/N ratio is used to measure the quality characteristics. Mathematically it is computed using the following relationship

$$S/N = -10 \log_{10} [(1/n) \sum (1/ Y_i^{2})] \underset{i=1}{\overset{n}{\text{--------------------}}} \quad [2.1]$$

where n is the number of variables and y_i is the value of each variable. From the tabulated S/N ratios for each level in each parameter linear graphs are drawn. Based on the highest S/N ratio, the optimum level for each parameter is obtained [Dinesh et al.(2004); Chandra Mouli et al(2006); Thamizhmanii (2007)].

B. Artificial neural networks

The Neural Networks are data processors and are non-linear mapping systems that consist of simple processors, which are called neurons, linked by weighted connections. Each neuron receives inputs and generates an output that can be seen as the reflection of local information that is stored in connections. The output signal of a neuron is fed to other neurons as input signals via interconnections. Since the capability of a single neuron is limited, complex functions can be realized by connecting many neurons. It is widely reported that structure of neural network, representation of data, normalization of inputs-outputs and appropriate selection of activation functions have strong influence on the effectiveness and performance of the trained neural network. Number of neurons to be used in the hidden layer of a neural network is critical in order to avoid over fitting problems, which hinders the generalization capability of the neural network. Number of hidden layer neurons is usually found by using trial and error approach. A neural network usually consists of three layers i.e., input layers, hidden layers and output layer, where inputs are applied at the input layer and outputs are obtained at the output layer . Since a three layer neural network is universal in the sense that essentially any function can be implemented to any desired degree of accuracy with sufficient number of hidden neurons, the neural network in this study is limited to feed forward networks. Back propagation algorithm is well known for training neural networks. The feed forward back propagation network is a popular architecture among different types of neural networks and finds applications in several areas of Engineering. [Chandra Mouli et al (2006)]

III. EXPERIMENTAL DETAILS

A. Materials

In the present study, mild steel is used as the substrate and Inconel 718 powder is used for coating material. Table 1 and Table 2 give the Chemical properties of mild steel and Inconel 718.

Table 1: Chemical Properties of MS

C%	Mn%	Si%	S%	P%
0.20	0.51	0.19	0.011	0.010

Table 2: Chemical Properties of Inconel 718

Element	Carbon	Manganese	Silicon	Phosphorus
Max	0.08	0.35	0.35	0.015
Element	Cobalt	Aluminum	Boron	Titanium
Max	1.00	0.80	0.006	1.15
Nickel	Copper	Chromium	Sulfur	Molybdenum
55.0	0.15	21.0	0.015	3.30

B. Procedure of Coating

Atmospheric plasma spray coating was used for coating mild steel substrate with Inconel 718. To remove all dust particles, the substrate was cleaned with trichloroethylene. Before plasma spraying, it was grit blasted using 24 mesh Al_2O_3 grit blasting to create enough surface roughness to ensure a strong mechanical bond between coating and substrate. Inconel 718 powder is heated to about 10000^{o}k so that it is melted and ionized to plasma state. Then it is sprayed with a flow of 100 gm/ min using a plasma spray gun from a stand-off distance of about 5 inches with a voltage range of 40 volts, a current of 800 amps, Argon as primary inert gas with a flow of 40 lpm and hydrogen as secondary inert gas with a flow of 0.4 lpm to obtain a thickness of about 100 µm.

C. Procedure of Coating

DUCOM, Bangalore make computerized pin-on-disc wear testing machine with digital weighing balance was used for wear test of Inconel 718 coated mild steel. To investigate the dry sliding wear characteristics, the counter surface of high carbon EN31 steel having a hardness of HRC60 was used. Pins of diameter 10 mm and height 20 mm were machined and then coated. During the test, the pin was pressed against the counter surface by applying the load and rotated. After running through a fixed sliding distance, the specimens were removed, cleaned with acetone, dried and weighed to determine the mass loss due to wear. The difference in the mass measured before and after test gives the wear of the specimen. The wear of the specimen was studied as a function of the applied load, the sliding velocity and time.

D. Data Collection

DI.For Taguchi's Method

The experiments were conducted as per the standard orthogonal array. In the present work, with factors load and time at four levels and factor speed at two levels, from the standard orthogonal arrays tables, L16 is suitable. The table is as shown in Table 3.

The wear parameters chosen for the experiment are (i) load (ii) sliding distance (iii) speed. Table 3 indicates the factors and their levels. The experiment consists of 16 tests (each row in the L16 orthogonal array) and the columns were assigned with parameters. The first column was assigned to load, second column was assigned to sliding distance, and third column was assigned to speed. Wear was the response to be studied with the objective as smaller the better and was assigned fourth column. The experiments were conducted as per the orthogonal array with level of parameters given in each array row. The wear test results were subjected to the analysis of variance.

DII For Neural Network Model

In addition to the data collected for Taguchi's Orthogonal array, intermediate data was collected during the wear experiments. A total of 108 data was collected out of which 76 data is used to train the ANN model and the remaining was used as testing data.

E. Mathematical Model

Linear regression technique was used to study the dry sliding wear of mild steel coated with Inconel 718. The generalized linear regression equation can be written as,

$$Y = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_1 x_2 + a_5 x_2 x_3 + a_6 x_3 x_1 + a_7 x_1 x_2 x_3 \qquad [3.1]$$

Y is the wear height loss. The variables x_1, x_2, x_3 are the load, time and speed respectively. The a_1, a_2 and a_3 are the coefficients of the independent variables x_1, x_2 and x_3 respectively. The a_4, a_5, a_6, and a_7 are the interaction co-efficients between x_1x_2, x_2x_3, x_1x_3 and $x_1x_2x_3$ respectively. Since the experiments were designed for two speeds only, the main effects only are considered and interactions are neglected. After calculating each of the coefficients of equation, the final linear regression equation for the wear of mild steel coated with Inconel 718 when tested against a pin on disc set up can be expressed in the following form

$$Y = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 \qquad [3.2]$$

F. Neural Network Model

The architecture of ANN consisting of three layers is shown in Figure 1. The layer where the input patterns are applied is the input layer, the layer where the output is obtained is the output layer, and the layers between the input and output layers are the hidden layers. Hidden layers are so named because their outputs are not directly noticeable. The addition of hidden layers enables the network to extract higher-order statistics which are particularly valuable when the size of the input layer is large [Schalkoff , 1997]. Neurons in each layer are interconnected to preceding and subsequent layer neurons with each interconnection having associated connection strength. The input signal propagates through the network in a forward direction, on a layer-by-layer basis. The hidden layers add non-linearity to the system. There are many hidden layers, i.e., many levels of non-linearity and interactions. The selection of number of hidden layers and neurons in them is the most important factor to be considered while solving a problem [Aleksendric and Duboka, 2006].

In the present work, an ANN was modeled using MATLab® (MATLAB 7.7). A feed forward back propagation network was selected which uses LMBP (Levenberg–Marquardt algorithm Back propagation) algorithm with Mean Square Error (MSE) as the performance measuring parameter. The optimization process is obtained by using a TRAINLM function. TRAINLM is a network training function that updates weights and bias values in a back propagation algorithm according to Levenberg–Marquardt optimization. LMBP is a highly efficient method for solving non-

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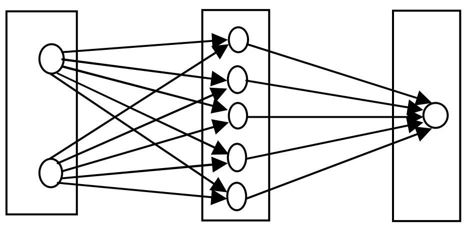
linear optimization problems [Hafizpour, Sanjari and Simchi, 2009]. The network is a three layer network with three neurons in input layer, one neuron in output layer and 9 neurons in the hidden layer. Speed, load and sliding distance are the parameters used as input and wear height loss as output. Since best neural network architecture was unknown in advance, trial and error method was used during training process to find out number of hidden neurons which optimized the network for matching a particular input/output function. Number of neurons in the hidden layer is varied and in the optimized structure of the network, this number is 9 and the number of cycles for optimizing the network for best performance is 14.



Input Layer (I) Hidden Layer (H) Output Layer (O)

Figure 1: Architecture of three layer neural network

IV. RESULTS AND DISCUSSIONS

A. Wear test results

The wear tests were conducted using Pin on Disc tribometer in accordance with ASTM G99 standard. The speed was varied in two levels ie 200 and 400 rpm, load was varied in four levels ie 20, 30 40, 50 N and sliding distance was varied in four levels ie 339.34, 603.26, 867.19and 1131.10 meters. To complete all the tests for all combinations, 16 tests were conducted as per the orthogonal array. The plan of tests was developed with the aim of relating the influence of load, sliding distance and speeds with the wear. On conducting the experiments, the wear results for various combinations of parameters were obtained and are as shown in Table 3.

Table 3: Wear Rate Results of All Combination of Parameters by Taguchi Approach

Load in	Sliding	Speed in	Wear in
20	339.34	200	2
20	603.26	200	4
20	867.19	400	6
20	1131.10	400	8
30	339.34	200	5
30	603.26	200	7
30	867.19	400	9
30	1131.10	400	10
40	339.34	400	9
40	603.26	400	10
40	867.19	200	13
40	1131.10	200	16
50	339.34	400	10
50	603.26	400	13
50	867.19	200	15
50	1131.10	200	18

B. Minitab Results

BI. Main Effects Plot

The main effect plot is shown in Figure 2. It is clear that the factor load has largest steep and hence has maximum effect on the wear. The optimum level for a factor is the level that gives the highest value of objective function. So the optimised parameters are at 20N, 263.93 and 200rpm where wear is minimum.

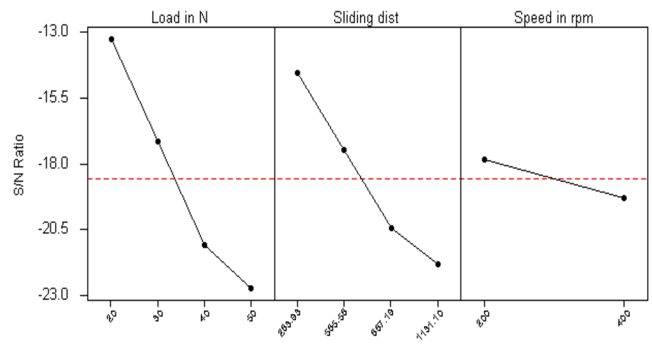


Figure 2: Main Effects Plot

BII. Analysis Of Variance

Table 4 shows the results of the ANOVA analysis. The purpose of conducting ANOVA is to determine the relative magnitude of the effect of each factor on the objective function and to estimate the error variance (F). The largeness of a factor effect relative to the error variance can be judged from the F column. The larger the F value, the larger is the factor effect. Referring to the F column of the ANOVA Table, the largest value of F is in the factor load row while the speed row has the least value of F. This means that the factor load has the greatest effect while the factor speed has the least effect on wear. The effect of sliding distance is in between the speed and load.

Table 4: Results of the ANOVA

Source	DF	Seq SS	Adj SS	Adj MS	F
Load in N	3	198.687	198.687	66.229	211.93
Sliding distance in m	3	94.688	94.688	1.563	101
Speed in rpm	1	1.563	1.563	1.563	5
Error	8	2.5	2.5	0.313	
Total	15	297.437			

BIII Mathematical model

Table 5 shows the results of Regression analysis. It helps to develop a mathematical model based on the main effects of speed, load and time. The Table 6 gives the values of coefficients of the factors in the mathematical model with R square value R-Sq = 97.7%. The general model considering the main effects is given by

$$\textit{Wear} = a_o + a_1 * \textit{Load in N} + a_2 * \textit{Sliding distance in m} + a_3 * \textit{Speed in rpm} \qquad [4.1]$$

Table 5: Regression Analysis

Predictor	Coefficients
Constant	- 6.3715
Load in N	+ 0.3125
Sliding distance in m	+ 0.0082411
Speed in rpm	- 0.003125

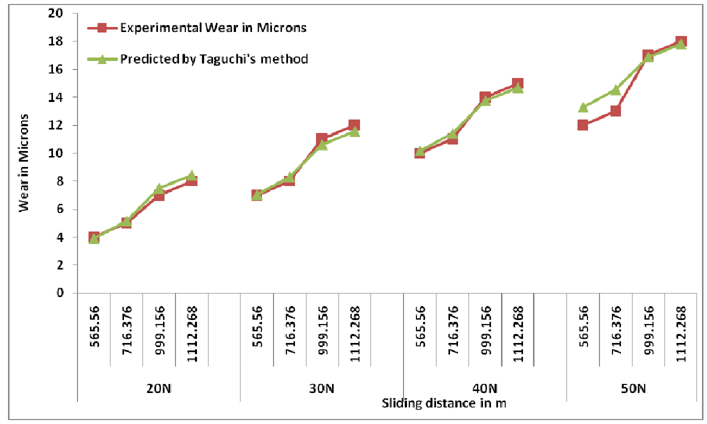
The mathematical model based on the results of regression results is given as

$$\textit{Wear in micro m} = -\,6.3715 + 0.3125 * \textit{Load in N} + 0.0082411 * \textit{Sliding distance in m} - 0.003125 * \textit{Speed in rpm} \qquad [4.2]$$

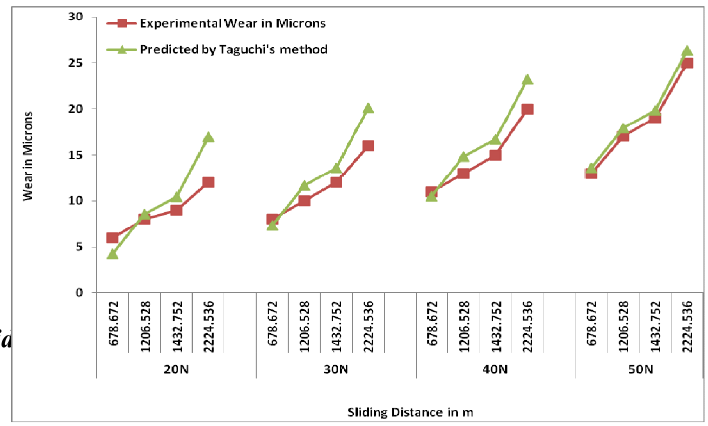
The average error on verification by comparing the experimental results with the values predicted by the above model was found to be -0.02397%.

BIV. Prediction

The prediction of mathematical model was tested with 8 data sets from the original process data. Each data set contained inputs such as speed, load, sliding distance. Predicted results were compared with experimental sets. Figure 3(a) and (b) present the comparison of predicted output values for sliding wear height loss by the mathematical model with those obtained experimentally at 200rpm and 400 rpm respectively at loads 20N, 30N, 40N and 50N. It is observed that the values of wear predicted by the mathematical model show good agreement with the experimental results.



(a) At 200rpm



(b) At 400rpm

Figure 3: Comparison graphs of experimental values of wear and values predicted by Mathematical Model

C. Artificial Neural Network

CI. Model Implementation

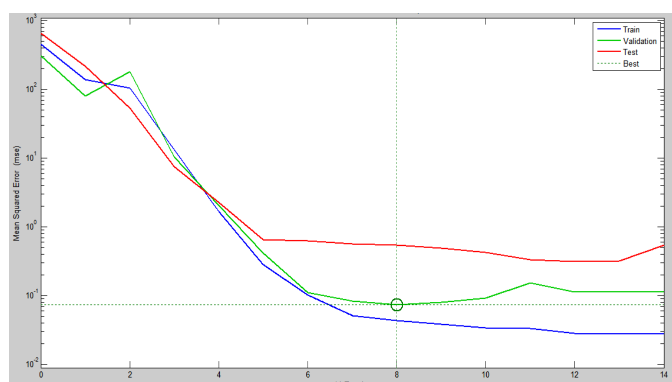
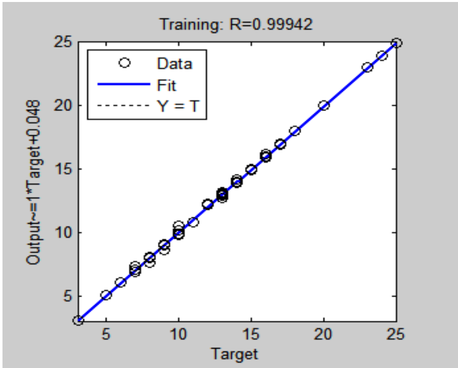
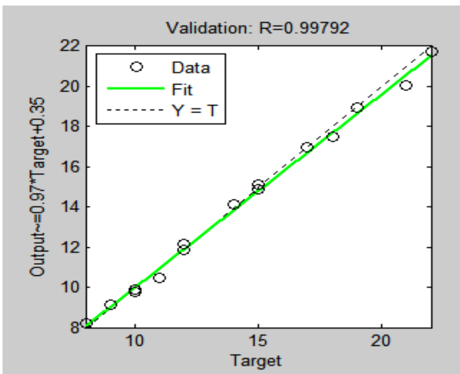


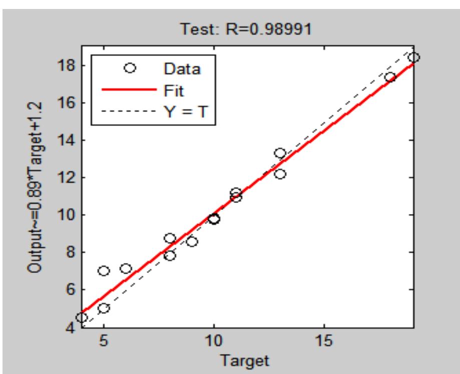
Figure 4: The Mean squared error (MSE) performance plot of ANN



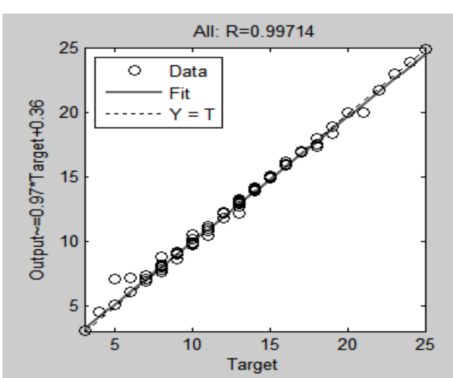
(a). Regression plot for training



(b). Regression plot for validation



c). Regression plot for testing



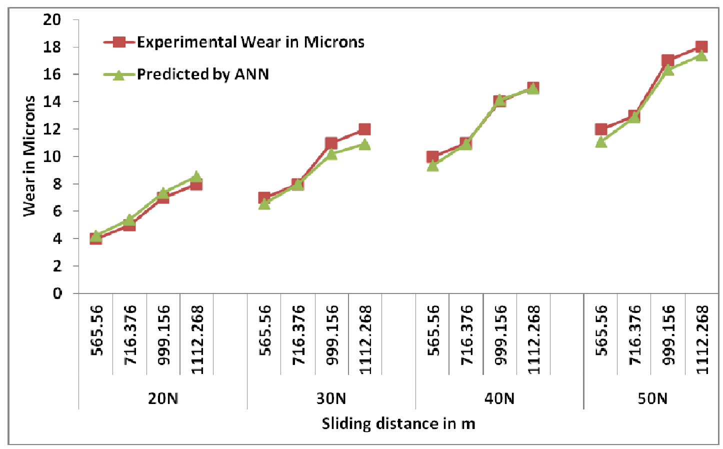
(d). Overall regression plot

Figure 5: The regression plots of training, testing, validation and average of all sets.

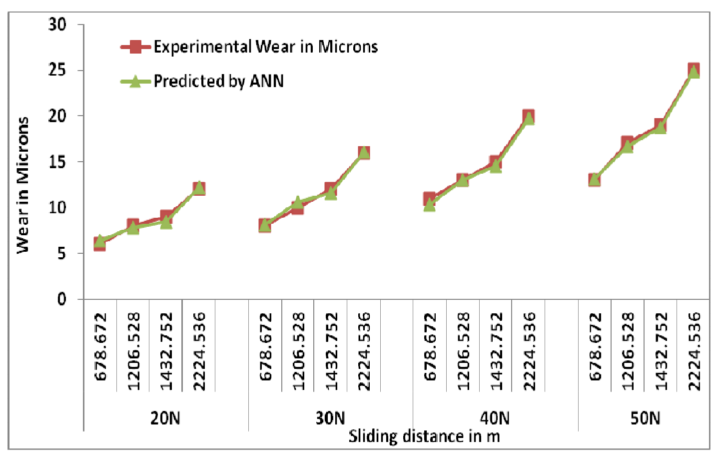
The performance of the network is shown in Figure 4. The performance is measured using MSE (Mean Square Error) over the epochs i.e., the number of iterations carried out by the network in order to achieve generalization. The ANN achieved stable state after 8 cycles of training. It is observed that the error decreases over the epochs or iterations carried out by the network during training, validation and testing. Generalization was stopped at the 14th epoch as there was no improvement. The best performance was obtained at the 8th epoch at which the MSE during training and validation was found to be 0.073437.

The results of regression plots of training, testing, validation and average of all are shown in Figures 5 (a) – (d). The plots show an average regression value of R = 0.99714 (a regression value close to 1) which means that the predicted values are in close relationship with the output as the data in the graphs lie on the best fit. The same can be attributed to training, testing and validation individually

CII Prediction



(a) At 200rpm



(b) At 400rpm

Figure 6: Comparison graphs of experimental values of wear and values predicted by ANN Model

The Neural network can be used to predict new results in the same knowledge domain after it is successfully trained. New input data in accordance with the experimental results are provided to the network for the prediction of wear height loss.

The entire domain knowledge obtained from the existing samples is stored as weights associated with each connection between neurons in digital form. By making use of the stored domain knowledge in the neural network which shows the relationship between the different parameters namely speed, applied load and sliding distance with output (wear height loss), the network makes the prediction.

The prediction of neural network was tested with 32 data sets from the original process data. Each data set contained inputs such as speed, load, sliding distance and the output values that were not considered in the training. Results were compared with experimental sets. Figure 6(a) and (b) present the comparison of predicted output values for sliding wear height loss with those obtained experimentally at 200 rpm and 400 rpm respectively for loads 20 N to 50 N in steps of 10N. It is observed that the values of wear predicted by the ANN show good agreement with the experimental results.

D. Comparison of Mathematical and Neural Network Predictions

Since both the Mathematical and Neural Network models are capable of predicting wear within the domain knowledge, the outputs of both the models can be compared by giving same testing data as input to both the models. Figure 7 presents the comparison graph of prediction of wear by both the models given the testing data consisting of 32 data which were not used for training the models.

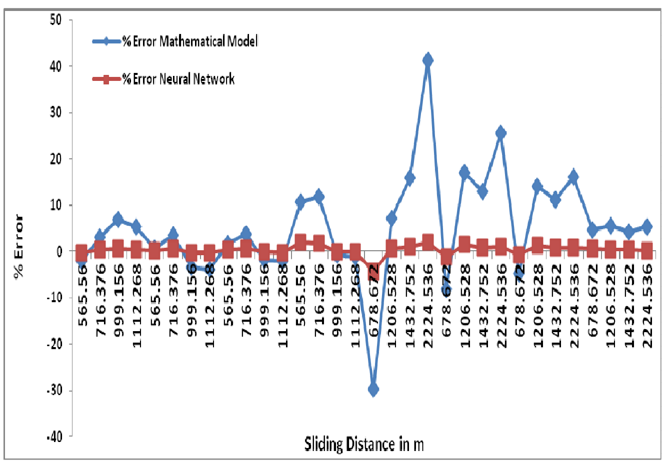


Figure 7: Comparison graph of % Error of wear prediction of Mathematical model and Neural network model

It is observed that 62.5% of prediction of wear of the testing data predicted by Neural Network model falls within ± 5 % error and the remaining 37.5% of data lies within ± 9 % error while about 47% of prediction of wear of the testing data predicted by Mathematical model falls within ± 5% error, about 19 % of data lies within ± 10 % error, 25% of data within ±20% error and the remaining 9% of data lies within ± 40% error. Thus Neural Network model developed is superior to the Mathematical model for wear prediction of Mild Steel coated with INCONEL 718 using plasma spray.

V. CONCLUSIONS

The following conclusions are drawn from the study on prediction of wear of mild steel coated with Inconel 718 using Neural Networks

1. Taguchi's robust design method can be used to analyse the wear problem of the coatings as described in this paper.
2. Load is the wear factor that has the highest physical as well as statistical influence on the wear of the coatings.
3. The R square value obtained for regression model was 97.9% which shows that satisfactory correlation was obtained.
4. The mathematical model developed by regression for prediction of wear of mild steel coated with Inconel 718 gives a prediction near to the actual value.
5. A three layer Neural Network model was successfully developed for prediction of wear of mild steel coated with Inconel 718 using MATLAB 7 and the correlation obtained was satisfactory as indicated by the best performance value of 0.073437 and the average regression value of 0.99714 .
6. The results obtained from the trained ANN model were found to be in close agreement with that of the experimental results.
7. The Neural Network model developed is superior to the Mathematical model for wear prediction of Mild Steel coated with INCONEL 718 using plasma spray.

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