Wear Studies on Incoloy-800 and Prediction of Wear by ANN Model

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ABSTRACT: **Wear is one of the predominant mechanisms responsible for machine component failures and resulting economic loss to the industry in form of loss of material, investments on large stocks of metal cutting tools and reduction in the operating life of machinery. Many methods and techniques like alloying, melt treating, heat treating, surface coatings, etc. have been tried for maximizing wear resistance of a range of super alloys. The present work is aim to modeling & prediction of parameters affecting mechanical wear of Incoloy-800 using Taguchi's methodology to design experiments and Artificial Neural Networking to model and predict the parameters. Wear has been defined as the progressive loss of substance from the operating surface of a body, occurring as a result of relative motion at the interface of a friction couple. Wear is quantified by volume loss per unit Newton meter. These preliminary experiments showed that the values of wear weight loss, height loss and wear rate are less at low sliding distance, low load and high speed. The final result shows that the contribution of sliding distance is 73.80%, 73.70% and 43.67% for weight loss, wear height loss and wear rate respectively.**

Keywords- *S/N ratio, ANOVA, Multiple Regression Model, ANN*

I. INTRODUCTION

As the technology is advancing every day challenges in the wear study, especially Aerospace industry is increasing exponentially. As Aerospace industry demands the components to perform on high temperature and stringent conditions the use of new and high strength super alloys are increasing day by day. With the introduction of new super alloys in aerospace industry it becomes a huge challenge to predict wear for such alloys. Wear is one of the predominant mechanisms responsible for machine component failures and resulting economic loss to the industry in form of loss of material, investments on large stocks of metal cutting tools and reduction in the operating life of machinery [3]. Many methods and techniques like alloying, melt treating (modification and grain refining), heat treating, surface coatings, etc. have been tried for maximizing wear resistance of a range of Nickel. Alloying has been the most popular among various methods used for improving and exploring the wear response of the materials against a counter-surface. Alloying alters the wear behavior due to solid solution strengthening and precipitation hardening. The present work is aim to modeling & prediction of parameters affecting mechanical wear of Inconel using response surface methodology to design experiments and Artificial Neural Networking to model and predict the parameters. Wear has been defined as the progressive loss of substance from the operating surface of a body, occurring as a result of relative motion at the interface of a friction couple. Wear is quantified by weight or volume loss per unit time or per unit sliding distance. Adhesive wear is generally considered to be the most prevalent form of wear; it exists whenever one solid material slides over the surface of another or is pressed against it.

Nickel-Iron based super alloys are the most complex and the most widely used in the high temperature applications. They currently comprise over 60% of the weight of advanced aircraft engines. Ni-Fe base super alloys are outstanding materials when it comes to usage in critical operating conditions due to their high stability of FCC structure right from room temperature up to melting point and high tolerance of Ni to other alloying additions which form phases which continuously react and interact with each other at high temperature without disturbing its phase stability. Nickel-based super alloys can be used for a higher fraction of melting temperature and are therefore more favorable than cobalt-based and iron-nickel-based super alloys at service temperatures close to the melting temperature of the materials. Hence these alloys can be used up to 0.7 to 0.9 Tm and up to 100,000 hours at fairly low temperatures. Nickel-Iron based alloy has been widely used in the aircraft and nuclear industry due to its exceptional thermal resistance and the ability to retain its mechanical properties at elevated temperatures over 700 °C. Nickel-Iron based super alloys are the one of the most difficult material to machine because of their hardness, high strength at high temperatures, affinity to react with tool materials and low thermal diffusivity. Of these nickel based alloys, Incoloy 800 can be used in the fabrication of critical components of turbine engines in aerospace applications. These alloys have excellent mechanical properties at elevated temperatures and good corrosion resistance. Incoloy 800 is a high-performance super alloy, which exhibits excellent mechanical strength, creep resistance at high temperatures, good surface stability, fatigue life, phase stability, and corrosion and oxidation resistance.

II. LITERATURE

Research on various work wear studies over the years have brought to describes adhesive wear is one of the predominant mechanisms responsible for mechanical component failures that result in a huge economic loss. Adhesive wear has been studied; the deterministic model formulated by Archard is frequently used. Investigation of the model involved an experiment consisting of a pin-on-bushing machine. Load & sliding-speed are used as variables while the geometry & material of the friction couple are constant. The generated data are analyzed using simple statistical methods. The median life characteristics are mathematically modeled. The application of these models in accelerated wear testing is highlighted; accelerating by increasing the speed of operation provides a better extrapolation as compared to using heavier loads [Farriikh S. Qureshi 1997].

TiNi alloy has been found to exhibit high resistance to wear, especially to erosion. The high wear resistance of the alloy may largely benefit from its pseudo-elasticity. Recent studies demonstrate that the wear resistance of TiNi alloy can be considerably enhanced when hard particles such as TiC are added as a reinforcing phase. It is expected that the wear resistance of such a composite could be further improved if the TiNi matrix can be strengthened with retained pseudoelasticity. Attempt is made to develop such a tribo composite, using nano-TiN powder to strengthen the matrix of the TiC/TiNi composite. The composite is made using a vacuum sintering process. Sliding wear behavior of this material is evaluated. It is demonstrated that the nano-TiN/TiC/TiNi composite exhibited excellent wear resistance, superior to those of the TiC/TiNi composite and WC/NiCrBSi hardfacing overlay. In order to understand the role of the nano-TiN powder, localized mechanical behavior and micro-scale wear of the TiNi matrix with and without nano-TiN powder are investigated using a triboscope. Worn surfaces are examined using SEM to better understand the wear mechanism and to find out clues for further development [LI 2001]. The presence of iron leads to different types of intermetallic in Al-Si alloys, among them needle shaped β-phase (Al5FeSi) can lead to variations in hardness of the Al-Si alloy which ultimately can affect the wear resistance of the alloy. In this paper, the effect of iron on wear behavior of cast Al-Si alloys has been reported. Sliding wear behavior of eutectic alloy Al-12Si-1Cu-0.1mg is investigated in dry sliding conditions by using pin-on-disk test configuration against heat treated EN31 steel counter-surface at room temperature. Hardness of the alloy increased with increase in iron addition primarily due to presence of needle shaped Fe-rich intermetallic but it leads to an increased wear rate [Mohit Dhiman 2008]. Wear mechanism of bush bearing at high temperature and anti-wear behavior of thin film of molybdenum trioxide (Mo03) that applied to the aluminium bronze alloy. High temperature wear is serious problem in many situations, such as a power generation, transport, and material processing etc., because of big influence of high temperature. The problems of high temperature wear are faster oxidation, loss of mechanical hardness and strength of the materials that form the contacting surfaces and changes in adhesion between these surfaces caused by the joint action of temperature and tribological parameters. Tribological behavior of high temperature wear is strongly depending condition of friction process. There are many ways to control friction and wear. But, most of these methods are not working in condition of high temperature because lubricating parts are easily lost their lubrication capability at high temperature. In case of solid lubrication, the solid is oxidized at high temperature, and behavior of solid materials is completely changed. We can reduce friction and wear with using molybdenum trioxide and its properties are available using for applications at temperatures up to 700°C [I.Bazarragchaa].

III. EXPERIMENTATION

A. Experimental Design

Taguchi method and full factorial method explores the relationships between several process variables and responses. This is sufficient to determine which explanatory variables have an impact on the response variable of interest. Here, experimental design for wear studies and prediction categories into two sets- Taguchi's design and full factorial design. It is the most convenient way to estimate a first-degree polynomial model using factorial experiment designs and Taguchi's design. Order of 27 experiments and 60 experiments are generated for wear studies, prediction which is based on Taguchi and full factorial design respectively.

B. Work piece Material

Incoloy-800 is a 46/31 nickel-iron alloy with controlled additions of chromium and titanium. The work material used as the test specimen is Incoloy-800. Eight cylindrical pieces of 15mm long and 10mm diameter are used for the tests. It is now mostly used for reciprocating engines and wears resistance coupled with medium strength at high operating temperatures. It is still used in gas turbine engineering and also for industrial components and heat-treatment equipment. Table 1 gives the details of chemical

TABLE 1 Chemical composition of INCOLOY-800

Composition	% weight
Iron	46.461
Nickel	31.120
Chromium	20.090
Carbon	0.039
Manganese	1.020
Sulfur	0.011
Silicon	0.369
Copper	0.360
Aluminum	0.220
Titanium	0.310

C. Machine Tool

In the present investigation pin-on-disc (POD) wear testing machine by IEICOS is considered to perform wear studies. Typical and rigid system consists of a driven spindle and base plate for holding the revolving disk, a chuck to hold the pin, and attachments to allow the pin specimen to be forced against the revolving disk specimen with a controlled load. A variable speed motor, capable of maintaining constant speed under load is used. A load cell is used to convert force into electrical signal. Table2 and Table3 give the details of machine tool and chemical composition of disk on which specimen slides over it respectively.

TABLE 2 Details of Machine Tool

Model	IWFT - DD
Disk Rotation Ranging	100 – 1500 RPM
Maximum Normal Load	20 Kg
Frictional Force Range	0 – 20 Kg
Wear Measurement Range	0- 4 mm
Pin Size	10- mm
Disc Size	3 - 12 mm
Operating Voltage	230V AC 50Hz
Weight	Provided
Pins	One sample pin provided

TABLE 3 Chemical composition of Disk Material

Composition	Carbon	Chromium	Manganese	Silicon
% weight	1.20	0.35	0.75	1.60

D. Wearing Conditions

Using research paper related to wearing and hit and trial method have been done on this particular material INCOLOY-800. By seen the response of output, each parameter preliminary experiments are to be done. These preliminary experiments are performed to find the response of speed, load and sliding distance, as load and sliding distance are the most significant parameters while wearing.

TABLE 4 Process parameters with their levels for wear studies (Dataset-1)

Factor	Unit	Level 1	Level 2	Level 3
Speed	m/min	180	240	300
Load	Newton	60	80	100
Sliding Distance	meters	1000	2000	3000

TABLE 5 Process parameters with their levels for prediction by ANN (Dataset-2)

Factor	Unit	Level 1	Level 2	Level 3	Level 4	Level 5
Speed	m/min	180	240	300	-	-
Load	Newton	60	80	100	120	-
Sliding Distance	meters	1000	2000	3000	4000	5000

E. Weight Measurement

The measurements of average wear weight loss (WL) are made on weighing machine Table-6 show the specification of machine. Three measurements of surface roughness are taken at center and the average value is used in the analysis. It directly gives the value in digital format.

TABLE 6 Details of Weighing Machine

THE BOMBAYBURMAHTRADING CORP. Ltd.	
Model No.	E31207
CAP.	1203
Accuracy	0.0001 grams
Maximum capacity	120 grams
Input Supply	150-240 Volts

As the literature shows, the effect of speed on the wear is not much significant when compared with the other two wearing parameters (load and sliding distance), so the values of speed for the experiments were taken according to convenience. Based on those preliminary experiments, the feasible range of wearing parameters is selected as follows: Table 4, 5 shows the Process parameters with their levels for wear studies and prediction of wear of Incoloy-800 respectively which represents by dataset-1 and dataset-2 (levels of dataset-2 is made after analysis of datset-1).

IV. Results and Discussion

Wear Studies

A. *Effect of Process Variables on WL (wear weight loss)*

- S/N Ratio response

TABLE 7- S/N Ratio response table for wear weight loss

Level	Speed	Load	Sliding Distance
1	32.20	37.60	40.88
2	33.13	32.53	31.64
3	34.22	29.42	27.03
Delta	2.02	8.19	13.84
Rank	3	2	1

- ANOVA response

The value of P is less than 0.05 implies that all process parameters are responsible for wear weight loss, the interaction of load and sliding distance is also dominate. The contribution of sliding distance is maximum i.e. 73.80% whereas speed is least as 1.63%.

TABLE 8 ANOVA response table for wear weight loss

Source	DF	Seq SS	Adj MS	F test	P test	Contribution %
Speed (S)	2	0.00064712	0.00032356	2588.48	0.000	1.63
Load (L)	2	0.00908790	0.00454395	36351.6	0.000	22.9
Sliding Distance (D)	2	0.02928356	0.01464178	117134.24	0.000	73.80
S×L	4	0.000000048	0.000000012	0.096	0.270	Not Significant
S×D	4	0.000000088	0.000000022	0.176	0.105	Not Significant
L×D	4	0.0006	0.00	1365.7	0.000	1.63

		82859	0170 715	2		
Error	8	0.0000 01	0.00 0000 125			
Total	26	0.0397 02575				

- Regression Model

The regression of the first order equation for wear weight loss (WL) as a function of three input process variables are obtained by using the experimental data as shown given below:

$$WL = -0.013337 - 2.72222\times10^{-5}\times S + 0.000146111\times L + 5.47778\times10^{-6}\times d + 6.25\times10^{-8}\times S\times L - 5.41667\times10^{-9}\times S\times D + 1.66667\times10^{-7}\times L\times D \quad \ldots\ldots\ldots\ldots\text{Eq.1}$$

The accuracy of regression model of wear weight loss is ±5.707% as shown figure 1 which is less than ±10%. Hence the regression model is good and acceptable.

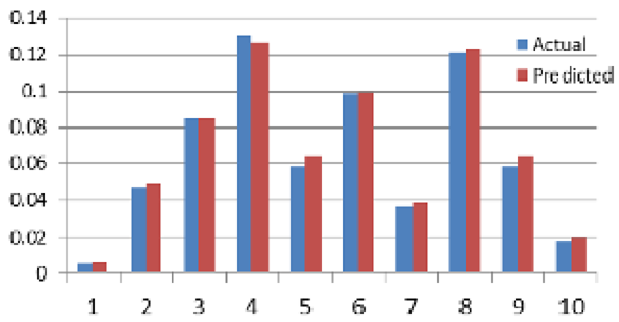

Figure 1 Comparison of actual vs. regression predicted values for wear weight loss

B. Effect of Process Variables on HL (Wear height loss)

- S/N Ratio response

TABLE 9 S/N Ratio response table for wear weight loss

Level	Speed	Load	Sliding Distance
1	-31.90	-26.50	-23.22
2	-30.97	-31.58	-32.46
3	-29.88	-34.68	-37.84
Delta	2.02	8.19	13.84
Rank	3	2	1

Statistical Inferences: The model delta value of 13.84 implies that the process parameter i.e., sliding distance is more evident factor and delta value of 2.02 indicates speed dominance is least.

- ANOVA response

The value of P is less than 0.05 implies that all process parameters are responsible for wear weight loss, the interaction of load and sliding distance is also dominate as shown in Table 10. The contribution of sliding distance is maximum i.e. 73.70% whereas speed is least as 0.944%.

TABLE 10 ANOVA response table for wear height loss

Source	DF	Seq SS	Adj MS	F test	P test	Contribution %
Speed (S)	2	182.1	91.05	280.1538	0.000	0.944
Load (L)	2	4528.9	2264.45	6967.538	0.000	23.49
Sliding Distance (D)	2	14207.9	7103.95	21858.31	0.000	73.70
S×L	4	2.1	0.525	1.615385	0.270	Not Significant
S×D	4	3.6	0.9	2.769231	0.105	Not Significant
L×D	4	349.5	87.375	268.8462	0.000	1.81
Error	8	2.6	0.325			
Total	26	19276.8				

- Regression Model

The regression of the first order equation for wear height loss (H_L) as a function of three input process variables are obtained by using the experimental data as shown in equation 2.

$$\boldsymbol{H_L = -21.387 - 0.0436531\times S + 0.234301\times L + 0.00878401\times D + 0.000100222\times S\times L - 8.68583\times10^{-6}\times S\times D + 0.000267263\times L\times D..Eq2}$$

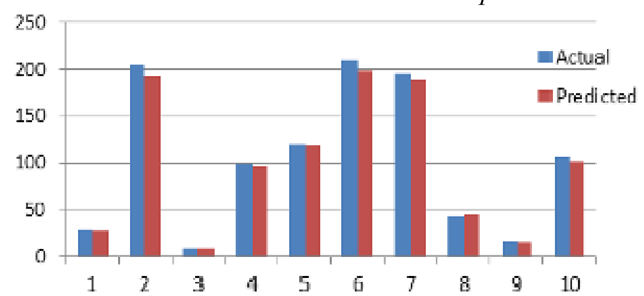

Figure 2 Comparison of actual vs. regression predicted values for wear height loss

The accuracy of regression model of wear weight loss is ±2.740% as shown figure 2 which is less than ±10%. Hence the regression model is good and acceptable.

C.Effect of Process Variables on WR (Wear rate)

- S/N Ratio response

TABLE 11: S/N Ratio response table for wear rate

Level	Speed	Load	Sliding Distance
1	-84.73	-81.24	-81.15
2	-83.80	-84.46	-84.29
3	-82.71	-85.54	-85.81

Delta	2.02	4.30	4.66
Rank	3	2	1

Statistical Inferences: The model delta value of 4.66 implies that the process parameter i.e., sliding distance is more evident factor and delta value of 2.02 indicates speed dominance is least.

- ANOVA response

The value of P is less than 0.05 implies that all process parameters are responsible for wear weight loss, the interaction of load and sliding distance is also dominate by 11.13 % shown in Table 12. The contribution of sliding distance is maximum i.e. 43.67% whereas speed is least as 9.78%.

TABLE 10: ANOVA response table for wear height loss

Source	DF	Seq SS	Adj MS	F	P	Contribution %
Speed (S)	2	96844311	48422157	757.55	0.000	9.78
Load (L)	2	344231153	81410384	3392.73	0.000	34.77
Sliding Distance (D)	2	432280723	133070181	4263.02	0.000	43.67
S×L	4	6045727	1007621	13.70	0.001	0.61
S×D	4	162660	2033259	38.25	0.000	0.016
L×D	4	110234454	25371181	591.64	0.000	11.13
Error	8	20697	2587			
Total	26	989819725				

- Regression Model

The regression of the first order equation for wear rate (WR) as a function of three input process variables are obtained by using the experimental data as shown given below (Eq.3)

WR = 7628.73 - 62.6681 × S + 227.767 × L + 6.0665 × D + 0.194576 ×S×L + 0640853×S×D - 0.0619411 × L × D ….Eq.3

The accuracy of regression model of wear weight loss is ±4.109% as shown figure3 which is less than ±10%. Hence the regression model is good and acceptable.

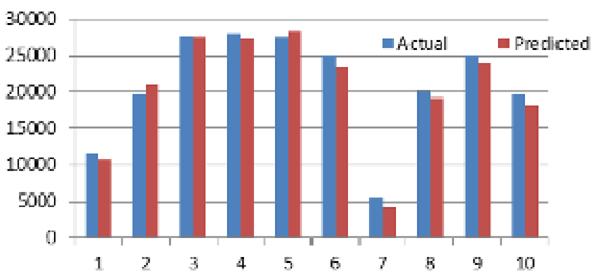

Figure 3: Comparison of actual vs. regression predicted values for Wear height loss

Prediction of Wear

D. Prediction of Wear Weight Loss

A. Two-layer Artificial Neural Network for wear weight loss the results obtained by training the network are presented in Table 13. From the Table 13, it is clear that the trial 3 i.e., a two layer feed forward neural network with 10 neurons in hidden layer has shown excellent performance (lower the BP value better is the prediction).

TABLE 13: Performance of Two-layer NN for Weight loss prediction for Dataset2

Trail No.	Number of hidden neurons	Training Stop Criterion	No. of Iteration	Best performance (BP)	Regression Value R
1	6	Validation Stop	7	2.8264e-05 at 7th epoch	0.9912
2	8	Validation Stop	11	1.8981e-05 at 7th epoch	0.99494
3	10	Validation Stop	11	1.3148e-05 at 10th epoch	0.99736
4	12	Validation Stop	8	1.8828e-05 at 4th epoch	0.99688
5	14	Validation Stop	11	2.4121e-05 5th epoch	0.99218
6	16	Validation Stop	9	3.8322e-04 at 4th epoch	0.9901
7	18	Validation Stop	8	4.6275e-05 4th epoch	0.98242
8	20	Validation Stop	7	3.7448e-04 at 1st epoch	0.9163

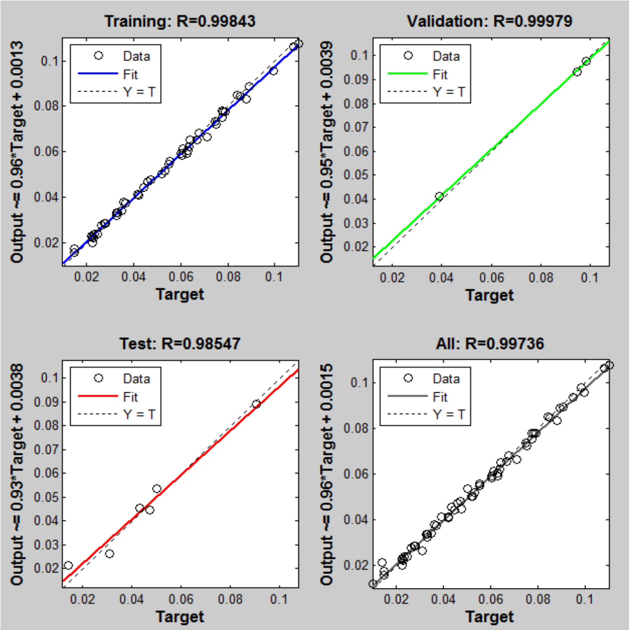

Figure 4: Regression plots of training, testing, validation and average of all sets of Two-layer Artificial Neural Network for wear weight loss

Figure 4 represents the results of regression plots of training, testing, validation and average of the three regression values. An average regression value of R=0.99736 i.e., close to 1 which means close relationship between the outputs and the targets as the data in the graphs lie on the line of fit. The same trend is observed and agreed for training, testing and validation individually. Once the neural network is successfully trained, it can be used to predict new results in the same knowledge domain. Figure 5 shows the difference between the experimental and the ANN predicted wear height loss values of the Incoloy-800 with the testing data for the best network selected. Based on the results obtained from the trained ANN model, predicted results were found to be in close agreement with the experimental results. The range of prediction error for the data tested is found to be ±2.93%.

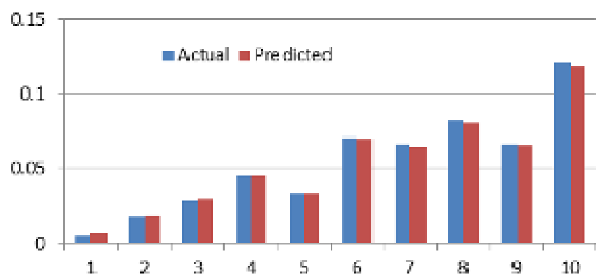

Figure 5: Comparison of actual and predicted wear weight loss for Incoloy-800

B. Three-layer Artificial Neural Network for Wear Weight Loss:

The results obtained by training the network are presented in Table 6.17. It follows from the Table 6.17, that the network corresponding to the three layer feed forward NN with 10 neurons in each of the two hidden layers performs the best with the regression value close to unity. The best performance is obtained at the 7th epoch, at which the MSE (mean square error) during training and validation is found to be 1.0275e-05.

Table 14: Performance of Three-layer NN for Weight loss prediction for Dataset2

Trail No.	Number of hidden neurons	Training Stop Criterion	No. of Iteration	Best performance	Regression Value R
1	3[2-2]-1	Validation Stop	7	281.0275e-05 at 1st epoch	0.037652
2	3[4-4]-1	Validation Stop	8	6.907e-05 at 5th epoch	0.82982
3	3[4-6]-1	Validation Stop	9	3.3649e-05 at 3rd epoch	0.84951
4	3[6-6]-1	Validation Stop	10	36.1959e-05 at 4th epoch	0.8752
5	3[6-8]-1	Validation Stop	9	5.7225 e-05 at 8th epoch	0.95194
6	3[8-6]-1	Validation Stop	12	1.6604 e-05 at 8th epoch	0.99211
7	3[8-8]-1	Validation Stop	12	5.6743 e-05 at 8th epoch	0.96007
8	3[8-10]-1	Validation Stop	9	1.6546 e-05 at 5th epoch	0.99596
9	3[10-8]-1	Validation Stop	6	1.8829e-05 at 8th epoch	0.99372
10	3[10-10]-1	Validation Stop	7	1.0275e-05 at 7th epoch	0.99897
11	3[10-15]-1	Validation Stop	4	32.4485e-04 at 1st epoch	0.86875
12	3[15-10]-1	Validation Stop	6	6.937e-05 at 3rd epoch	0.97646
13	3[15-15]-1	Validation Stop	5	7.8874e-05 at 4th epoch	0.95745
14	3[15-20]-1	Validation Stop	5	6.6256e-05 at 1st epoch	0.9921
15	3[20-15]-1	Validation Stop	4	2.2338e-04 at 3rd epoch	0.90656
16	3[20-20]-1	Validation Stop	5	30.2972e-04 at 3rd epoch	0.8817

Figure 6 shows results of regression plots of training, testing, validation and average of all sets. The regression values of training, validation, testing and average of all sets are 0.9999, 0.98822, 0.99249 and 0.99897 respectively. The average R value in three-layer is more than two-layer neural network. Therefore developed neural network can be used to predict new results.

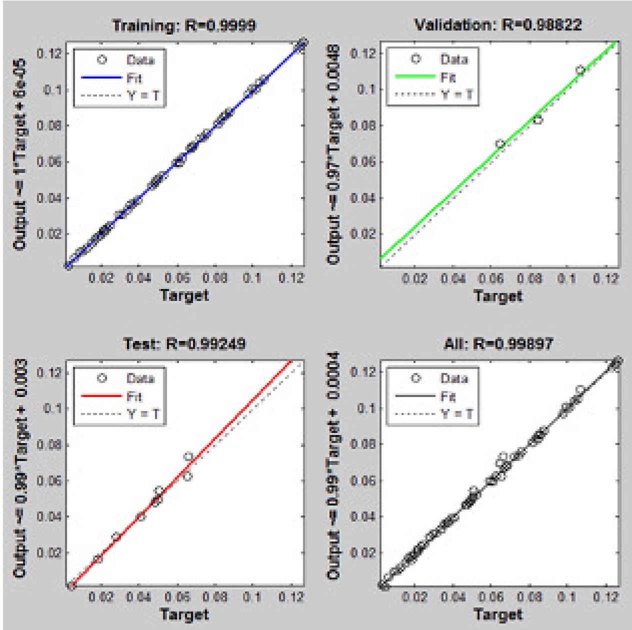

Figure 6: Regression plots of training, testing, validation and average of all sets of Three-layer Artificial Neural Network for wear weight loss

The difference of values between the experimental and ANN predicted are indicated in Figure 7 (graphical representation) for Incoloy-800.

It is clear that the difference values are significantly less, with an error range of ±0.98%.

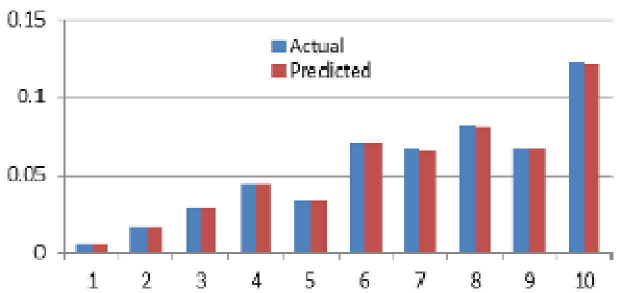

Figure 5: Comparison of actual and predicted wear weight loss for Incoloy-800

E. Prediction of Wear Height Loss:

- Two-layer Artificial Neural Network for wear height loss: The results obtained by training the network are presented in Table 15. It is clear that the trial 3 i.e., a two layer feed forward neural network with 8 neurons in hidden layer has shown excellent performance.

Table 15: Performance of Two-layer NN for Height loss prediction for Dataset2

Trail No.	Number of hidden neurons	Training Stop Criterion	No. of Iteration	Best performance	Regression Value R
1	4	Validation Stop	11	6.35437 at 5^{th} epoch	0.98719
2	6	Validation Stop	22	1.3309 at 7^{th} epoch	0.99879
3	8	Validation Stop	16	0.12449 at 9^{th} epoch	0.99908
4	10	Validation Stop	21	2.7505 at 15^{th} epoch	0.99651
5	12	Validation Stop	10	26.786 at 5^{th} epoch	0.96687
6	14	Validation Stop	6	203.2458 at 5^{th} epoch	0.94393
7	16	Validation Stop	11	447.2863 at 9^{th} epoch	0.82807
8	18	Validation Stop	8	18.7192 at 3^{rd} epoch	0.9612
9	20	Validation Stop	9	1.7538 at 3^{rd} epoch	0.96071

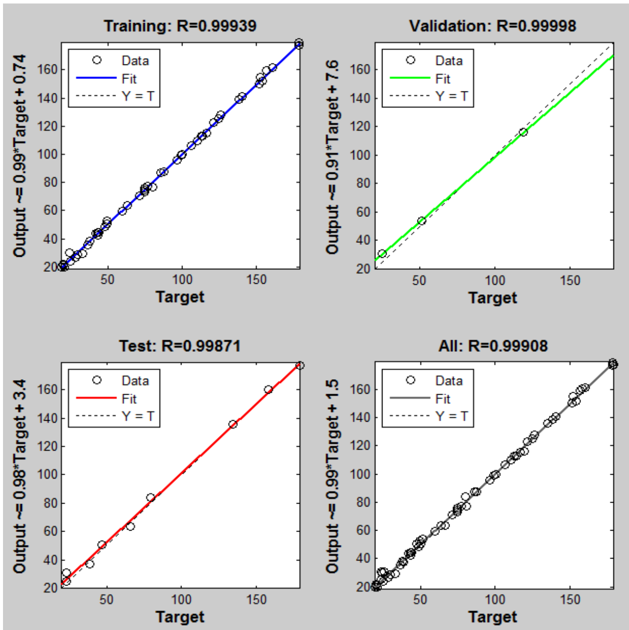

Figure 6: Regression plots of training, testing, validation and average of all sets of Two-layer Artificial Neural Network for wear height loss

Figure 6 represent the results of regression plots of training, testing, validation and average of the three regression values. The Figure shows an average regression value of R=0.99908 i.e., close to 1 which means close relationship between the outputs and the targets as the data in the graphs lie on the line of fit. The same trend is observed and agreed for training, testing and validation individually. The difference of values between the experimental and ANN predicted are indicated in the Figure 7 (graphical representation) for Incoloy-800. It is clear that the difference values are significantly less, with an error range of ±2.65 %.

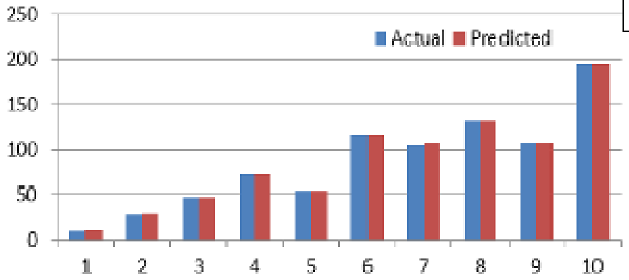

Figure 7: Comparison of actual and predicted wear height loss two-layer Artificial Neural Network

- Three-layer Artificial Neural Network for wear height loss: The results obtained by training the network are presented in Table 16.

It follows from the Table 16 that the network corresponding to the three layer feed forward NN with 6 neurons in each of the two hidden layers performs the best with the regression value close to unity. The best performance is obtained at the 24th epoch, at which the MSE during training and validation is found to be 0.016274.

Table 16: Performance of Three-layer NN for wear height loss prediction for Dataset2

Trail No.	Number of hidden neurons	Training Stop Criterion	No. of Iteration	Best performance	Regression Value R
1	3[2-2]-1	Validation Stop	16	158.9102 at 7th epoch	0.86669
2	3[4-4]-1	Validation Stop	14	0.23815 at 14th epoch	0.99889
3	3[4-6]-1	Validation Stop	11	1.2012 at 15th epoch	0.9995
4	3[6-6]-1	Validation Stop	13	0.016274 at 7th epoch	0.99942
5	3[6-8]-1	Validation Stop	12	2.2381 at 6th epoch	0.99568
6	3[8-8]-1	Validation Stop	6	1.7791 at 13th epoch	0.99638
7	3[8-10]-1	Validation Stop	7	11.7712 at 3th epoch	0.95837
8	3[10-8]-1	Validation Stop	9	10.099 at 6st epoch	0.97211
9	3[10-10]-1	Validation Stop	11	3.5049 at 6th epoch	0.99006
10	3[10-15]-1	Validation Stop	8	13.0571 at 4th epoch	0.94205
11	3[15-10]-1	Validation Stop	8	47.4757 at 5th epoch	0.9366
12	3[15-15]-1	Validation Stop	7	35.3134 at1st epoch	0.92997
13	3[15-20]-1	Validation Stop	6	41.291 at 2nd epoch	0.92707
14	3[20-15]-1	Validation Stop	5	7.7841 at 3rd epoch	0.96534
15	3[20-20]-1	Validation Stop	8	106.2605 at2nd epoch	0.78864

Figure 8 shows results of regression plots of training, testing, validation and average of all sets. The regression values of training, validation, testing and average of all sets are 0.99952, 0.99984, 0.99877 and 0.99942 respectively. The average R value in three-layer is more than two-layer neural network. Therefore developed neural network can be used to predict new results.

Once the neural network is successfully trained, it can be used to predict new results in the same knowledge domain. Figure 9 shows the difference between the experimental and the ANN predicted wear height loss values of the Incoloy-800 with the testing data for the best network selected.

Based on the results obtained from the trained ANN model, predicted results were found to be in close agreement with the experimental result. The range of prediction error for the data tested is found to be ±0.75%.

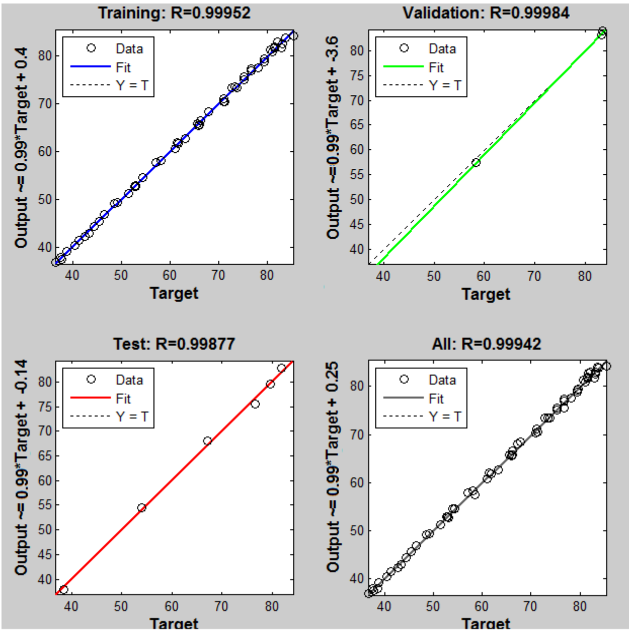

Figure 8: Regression plots of training, testing, validation and average of all sets of Three-layer Artificial Neural Network for wear height loss

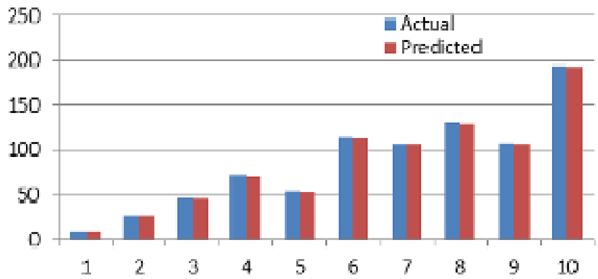

Figure 8: Comparison of actual and predicted wear height loss three-layer Artificial Neural Network

F. Prediction of Wear Rate:

- Two-layer Artificial Neural Network for wear rate: The results obtained by training the network are presented in Table 19. It is clear that the trial 4 i.e., a two layer feed forward neural network with 10 neurons in hidden layer has shown excellent performance.

TABLE 19: Performance of Two-layer NN for Wear rate prediction for Dataset2

Trail No.	Number of hidden neurons	Training Stop Criterion	No. of Iteration	Best performance	Regression Value R
1	4	Validation Stop	6	4982550639.4855 at 1^{st} epoch	0.49591
2	6	Validation Stop	15	56216590.023 at 23^{rd} epoch	0.99816
3	8	Validation Stop	9	158546516.0525 at7th epoch	0.98689
4	10	Validation Stop	16	2464335.9119 at 10^{th} epoch	0.99763
5	12	Validation Stop	12	243050786.1502 at 6^{th} epoch	0.8391
6	14	Validation Stop	10	437263529.6972 at 7^{th} epoch	0.97518
7	16	Validation Stop	10	122428302.2045 at 19^{th} epoch	0.9866
8	18	Validation Stop	7	882998682.849 at 5^{th} epoch	0.97254
9	20	Validation Stop	16	90928004.4131 at 10^{th} epoch	0.98963

Figure 9 presents the results of regression plots of training, testing, validation and average of the three regression values. It shows an average regression value of R=0.99763 i.e., close to 1 which means close relationship between the outputs and the targets as the data in the graphs lie on the line of fit.

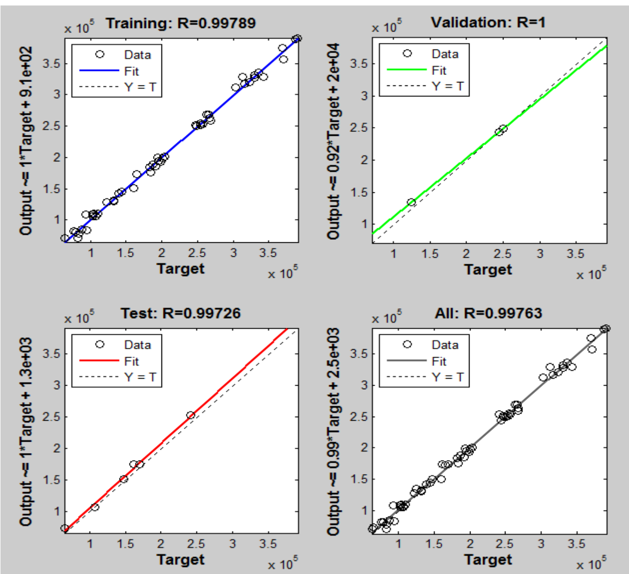

Figure 9: Regression plots of training, testing, validation and average of all sets of two-layer Artificial Neural Network for wear rate

The same trend is observed and agreed for training, testing and validation individually. The difference of values between the experimental and ANN predicted are indicated in the Figure 10 (graphical representation) for Incoloy-800. It is clear that the difference values are significantly less, with an error range of 6.538%.

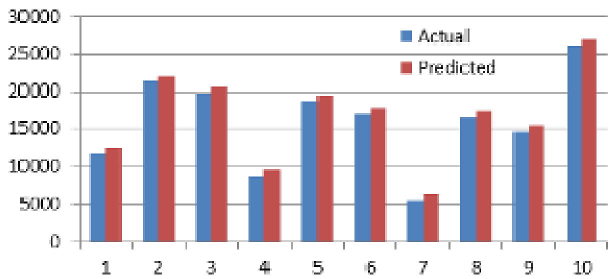

Figure 10: Comparison of actual and predicted wear weight loss two-layer Artificial Neural Network

- Three-layer Artificial Neural Network for Wear Rate: The results obtained by training the network are presented in Table 18. The network corresponding to the three layer feed forward NN with 10 neurons in each of the two hidden layers performs the best with the regression value close to unity. The best performance is obtained at the 11th epoch, at which the MSE during training and validation is found to be 968661.1499.

Table 18: Performance of Three-layer NN for Weight loss prediction for Dataset2

Trail No.	Number of hidden neurons	Training Stop Criterion	No. of Iteration	Best performance	Regression Value R
1	3[2-2]-1	Validation Stop	3	882272014.28 at 5^{th} epoch	0.95857
2	3[4-4]-1	Validation Stop	11	4880794.7462 at 9^{th} epoch	0.91003
3	3[4-6]-1	Validation Stop	14	358351.3792 at 59^{th} epoch	0.98491
4	3[6-6]-1	Validation Stop	12	339362.1911 at 10^{th} epoch	0.99729
5	3[6-8]-1	Validation Stop	11	180149814.60 at 4^{th} epoch	0.97669
6	3[8-8]-1	Validation Stop	9	1951270.4323 at 4^{th} epoch	0.99472
7	3[8-10]-1	Validation Stop	10	297797622.06 at 8^{th} epoch	0.86837
8	3[10-8]-1	Validation Stop	14	12763694.099 at 1^{st} epoch	0.99821
9	3[10-10]-1	Validation	15	968661.1499 at11^{th} epoch	0.99978

		Stop			
10	3[10-15]-1	Validation Stop	11	80186837.5583 at 4th epoch	0.96496
11	3[15-10]-1	Validation Stop	8	60262304.5494 at 5th epoch	0.98317
12	3[15-15]-1	Validation Stop	7	694095058.0142 at 1st epoch	0.55183
13	3[15-20]-1	Validation Stop	8	100698288.8522 at 1st epoch	0.9059
14	3[20-15]-1	Validation Stop	7	89618199.9827 at 5th epoch	0.95045
15	3[20-20]-1	Validation Stop	6	274887297.8097 at 1st epoch	0.51817

Figure 11 shows results of regression plots of training, testing, validation and average of all sets. The regression values of training, validation, testing and average of all sets are 0.9998, 0.99865, 0.99898 and 0.99978 respectively. The developed neural network can be used to predict new results.

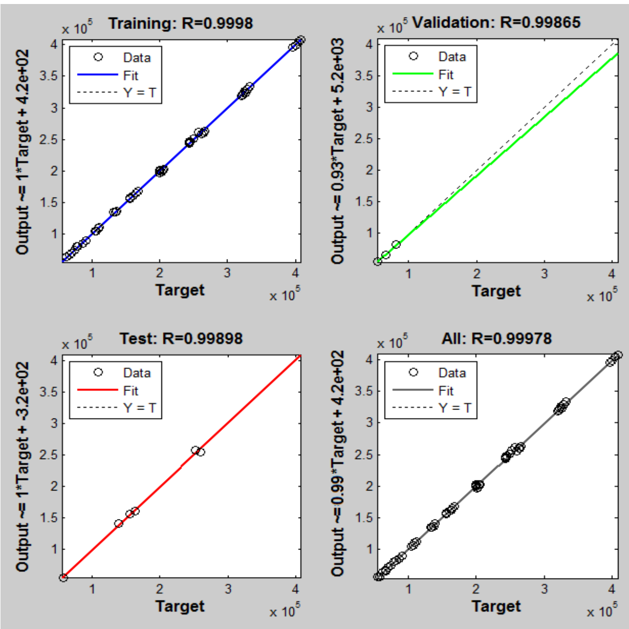

Figure 11: Regression plots of training, testing, validation and average of all sets of three-layer Artificial Neural Network for wear rate

Figure 12 shows the difference between the experimental and the ANN predicted wear height loss values of the Incoloy-800 with the testing data for the best network selected. Based on the results obtained from the trained ANN model, predicted results were found to be in close agreement with the experimental results. The range of prediction error for the data tested is found to be +2.196%.

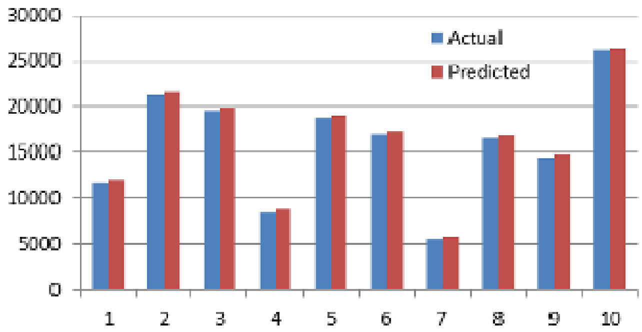

Figure 12: Comparison of actual and predicted wear rate three-layer Artificial Neural Network

G. Graphical representation

X, Y represent the load (in Newton), sliding distance (in meters) and Z for figure 13, 14, 15 represent wear weight loss in grams, wear height loss in microns and wear rate in cubic microns per Newton meter.

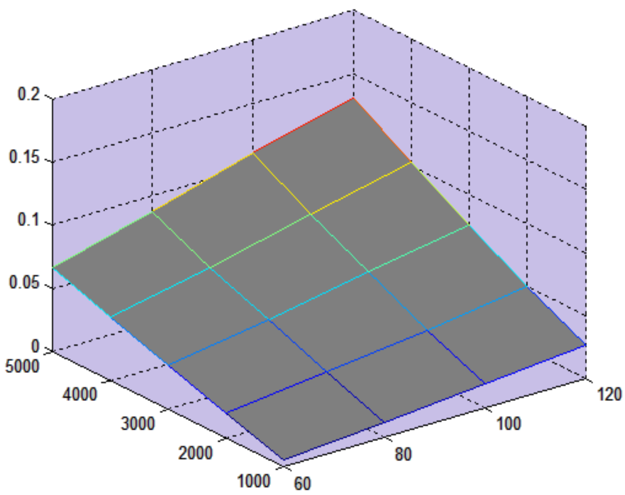

Figure 13: Predicted weight loss as a function of Sliding distance and Load at constant Sliding speed (180 m/min) for Incoloy-800

From the Figure 13 and 14 as load increases from 60N to 120N the change in wear weight loss is slightly increases as compare to sliding distance from 1000m to 5000m.

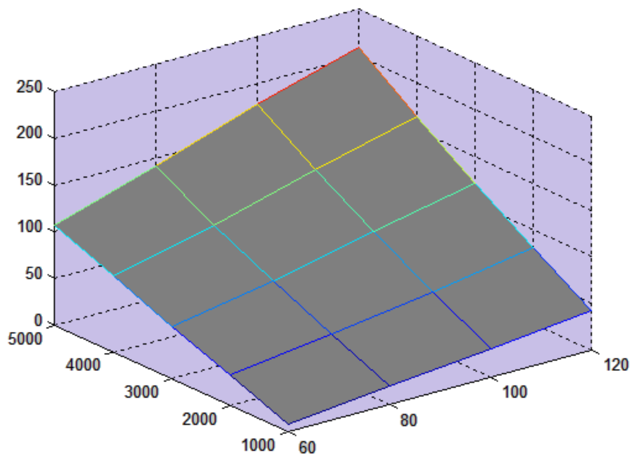

Figure 14: Predicted Height loss as a function of Sliding distance and Load at constant Sliding speed (180 m/min) for Incoloy-800

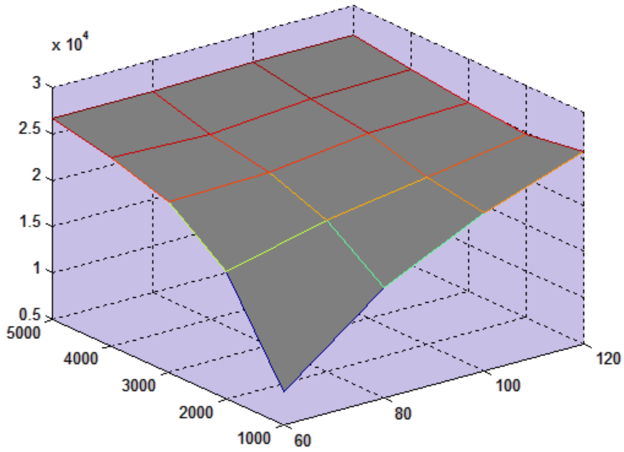

Figure 15: Predicted wear rate as a function of Sliding distance and Load at constant Sliding speed (180 m/min) for Incoloy-800

Figure 15 shows load from 60N to 80N and sliding distance from 1000m to 2500m, the response of wear rate is rapidly increases and then gradually increase. But the interaction of these two factors at maximum condition is constant.

H. Compression of two and three hidden layer of Artificial Neural Network

As per the analysis, the number of iteration for predicted the output response using two-layer neural network is more as compared to three-layer neural network as shown in Figure 16 (graphical representation).

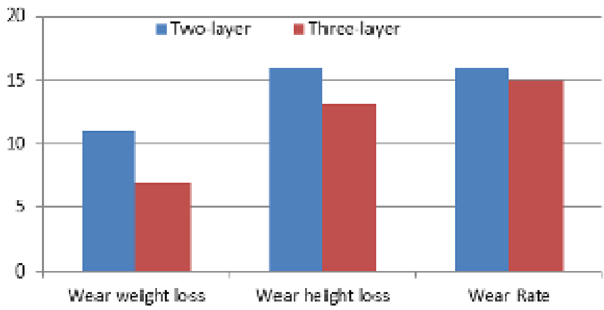

Figure 16 Comparison of iteration under two and three layer of ANN

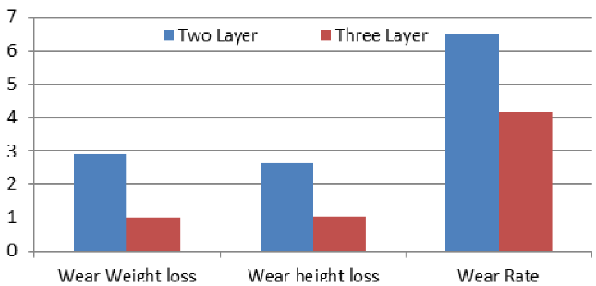

Figure 17 Comparison of %age error between two and three layer of ANN

The accuracy for predicted the output response shown in figure 17 using two-layer neural network is lesser as compared to three-layer neural network.

V. Conclusions

First, sliding distance is more evident factor for wear weight loss and height loss and wear rate and dominance of speed is least for all.

Second, at low sliding distance, low load and high speed gives minimum wear weight loss, height loss and wear rate.

Third, analysis shows that sliding distances and load contributes 73.80%, 78.70% and 22.90%, 23.49% whereas interaction between distance and load contributes 1.63%, 1.81% for wear weight loss and wear height loss respectively. In case of wear rate, sliding distance and load contributes 43.67%, 34.77% respectively and interaction between distance and load contributes 11.13%.

Fourth, the models generated for wear weight loss, height loss and wear rate by multiple regression method is acceptable.

Fifth, prediction of wear characteristics using ANN topologies clears that the three layer feed-forward network gives better performance value over the two-layer feed forward network as is evident from the best performance value (BPV) obtained after training the network. Al so on an average, the number of iteration taken by the network to reach the generalization is more in two-layer feed forward network than the three-layer feed-forward network.

In three-layer feed forward network, more number of neurons in first hidden layer and less number of neurons in second hidden layer is given better regression values with less BPV (best performance value) mostly.

Predicted error for different models is less than 10% hence generalized model is good and acceptable.

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