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Optimization of Wear Parameters in AISI 4340 Steel

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Abstract

This study investigated the optimization of wear behavior of AISI 4340 steel based on the Taguchi method under various testing conditions. In this paper, a neural network and the Taguchi design method have been implemented for minimizing the wear rate in 4340 steel. A back-propagation neural network (BPNN) was developed to predict the wear rate. In the development of a predictive model, wear parameters like sliding speed, applying load and sliding distance were considered as the input model variables of the AISI 4340 steel. An analysis of variance (ANOVA) was used to determine the significant parameter affecting the wear rate. Finally, the Taguchi approach was applied to determine the optimum levels of wear parameters. The results show that using the optimal parameter setting (load3, sliding speed1, and sliding distance2) a lower wear rate is achieved. The error between the predicted and experimental values is only 3.19%, so good agreement between the actual and predicted results is observed.

Keywords: *AISI 4340, wear, pin on disc, Taguchi method, neural network*.

1. Introduction

AISI 4340 steel have been used for a great number of applications, like aircraft landing gear, power transmission gear, and in the machine constructions industry with hardness between 28 and 38 Rockwell C (HRC). This kind of low alloyed steel is very cheap, compared with the expensive high alloyed tools steel, and it has an appropriated hardness combined with a very high toughness and tensile strength [1,2]. Moreover, the cutting tools used for hard turning are relatively costly as compared to grinding and hence there is a need to investigate the effect of wear parameters on tool life. It has also been reported that the properties and the composition of tool materials are critical to the behavior of machining forces which in turn affect the tool life. Therefore, it is necessary to study the influence of process parameters on tool wear in hard turning process. Several investigations have been carried out to study the tool wear and improve tool life as well as productivity. Luo et al studied wear behavior in turning of AISI 4340 hardened alloy steels using cubic boron nitride (CBN) and ceramic tools. Oliviera et al investigated the hard turning of AISI 4340 steel in continuous and interrupted cuts with whisker reinforced cutting tools [3, 4, 5, and 6].

In the present work, two of the techniques, namely, the neural network (NN) with a back-propagation network (BPN) and the Taguchi design method have been employed. MATLAB (2013) and MINITAB16 programs were used for the NN modelling and the Taguchi optimization technique, respectively. Sliding speed, applying load, and sliding distance were selected as the input factors, whereas wear rate was selected as the response. A BPN model was developed for the prediction of the wear rate. An analysis-of-variance (ANOVA) table was used to determine the significant wear parameters affecting the wear rate. An approach to determine the optimum wear parameter setting was proposed on the basis of the Taguchi design method.

2. Experimental Set-up and Test Procedure

In the present investigation, a pin on disc wear tests were performed on AISI 4340 steel which has been selected as work piece material. Table 1 shows the spectrochemical analysis (Measured Results) of this steel. All experiments were performed by using a pin on disc wear apparatus shown in Figure 1.

Table 1,
Chemical composition (wt%) of AISI 4340.

C	Al	Mn	S	P	Cu	Cr	Ni	Mo	Si
0.3534	0.0167	0.5913	0.0132	0.0221	0.0811	0.9112	1.6991	0.2892	0.2541

Fig.1. Pin on disc wear apparatus.

This machine facilitates study of wear characteristics in sliding contact under desired conditions. Sliding occurs between the stationary pin on a rotating disc. Normal load, sliding distance and sliding speed can be varied to suit the test conditions. The pin specimen was tested in pin on disc apparatus. To perform the test specimen was clamped in jaw. Pin weight losses were measured using an electronic balance having an accuracy of ±0.001 mg. Weight losses were converted to volume losses by dividing the weight to the density of steel (7.85 g/cm^3). Dry sliding wear tests were carried out using pin-on disk type wear tester at different parameters, where three levels of three parameters were selected as shown in Table 2. The tests were conducted at a constant time of 30 min.

Table 2,
Parameters with level values.

Parameters	Level 1	Level2	Level3
Load (N)	20	25	30
Sliding speed (r.p.m)	250	350	400
Sliding distance (cm)	6	8	10

In the present investigation an L_9 orthogonal array was chosen as shown in Table 3. The experiment consists of 9 tests (each raw in the L_9 orthogonal array) and the columns were assigned with parameters). The orthogonal array table in the Taguchi design method was applied to BPN as testing data. BPN was developed to predict the wear rate. The optimum wear-parameter combination was obtained by using an analysis of the signal-to-noise (S/N) ratio.

Table 3,
L9 orthogonal array and a neural-network training set.

Load (N)	Speed (rpm)	Sliding Distance (cm)	Wear Rate (mm^3/m)	S/N Ratio
20	250	6	0.0046	46.74484337
20	350	8	0.0043	47.33063089
20	400	10	0.0039	48.17870786
25	250	8	0.0053	45.51448261
25	350	10	0.0044	47.13094647
25	400	6	0.0041	47.74432287
30	250	10	0.0058	44.73144013
30	350	6	0.0055	45.19274621
30	400	8	0.0052	45.67993313

The signal-to-noise (S/N) ratio is a measure of the magnitude of the data set relative to the standard deviation. If the S/N is large, the magnitude of the signal is large relative to the noise , as measured with the standard deviation [7,8] . There are several S/N ratios available depending on the types of characteristics. The nominal ratio is the best, higher is better and lower is better [8] . We would select the S/N if the system is optimized when the response is as small as possible. The S/N ratio for the LB (lower is better) characteristic is calculated by using the following equations [9]:

$$L_j = \frac{1}{n}\sum_{k=1}^{n} y_i^2 \qquad \text{... (1)}$$

$$\eta_j = -10 log L_j \qquad \text{... (2)}$$

Where y_i is the response value, L_j is the loss function and η_j is the S/N ratio.

3. Statistical Analysis

The results of the experiments were evaluated by the analysis of variance (ANOVA) . The main objective of the analysis was to determine the influence of every parameter on the variance of results, regarding the total variance of all the parameters. This is defined by the sum of squares. The calculation of ANOVA was made on the basis of the recommendations in [8]:

$$SS = \sum_{i=1}^{N}(y_i - \bar{y})^2 = \sum_{i=1}^{N} y_i^2 - CF \qquad \text{... (3)}$$

$$CF = \frac{T^2}{N} \qquad \text{... (4)}$$

To calculate the effect of an individual parameter on the variance a more useful equation is used:

$$SS_A = \frac{A_1^2}{N_{A1}} + \frac{A_2^2}{N_{A2}} + \cdots + \frac{A_n^2}{N_{An}} - \frac{T^2}{N} \qquad \text{... (5)}$$

The following equations are also needed for the calculations:

$$MSA = \frac{SS_A}{f_A} \qquad \text{... (6)}$$

$$F_A = \frac{MS}{E} \qquad \text{... (7)}$$

$$P_A = \frac{SS_A}{SS} \times 100 \qquad \text{... (8)}$$

Where:
SS: sum of squares.
y_i: Value of each results.
CF: correction factor.
T: the sum of all results.
N: the total number of results.
A_1 : The sum of results (y_i) where parameter (A_1) is present .
N_{A1}: number of experiments where parameter (A_1) is present .
MSA: mean square where parameter (A_1) is present.
f_A: degree of freedom of factor A .
F_A: F ratio.
P_A: Percentage of contribution for factor A .

The degree of freedom are an important part of the statistical analysis because they provide us with additional information about the process. The degree of freedom for the Taguchi array is defined as follows [9]:

DOF parameter = number of factor levels-1
DOF experiment= number of results-1
DOF error = number of all DOFs-number of DOFs of all parameters.

4. Experimental Results and Data Analysis

A neural network based on back propagation is a multilayered architecture made up of one or more hidden layers placed between the input and output layers [10] . The components of the input pattern consisted of the control variables of applied load, sliding speed and sliding distance whereas the output pattern component represented the wear rate. Table 3 shows a Taguchi L_9 orthogonal-array plan of the experiment and a training set for the neural-network application. The orthogonal-array table used in the Taguchi design method was applied to BPN as testing data .The network structure was selected to be the 3:4:1 type .The used BNP model is shown in Figure 2.

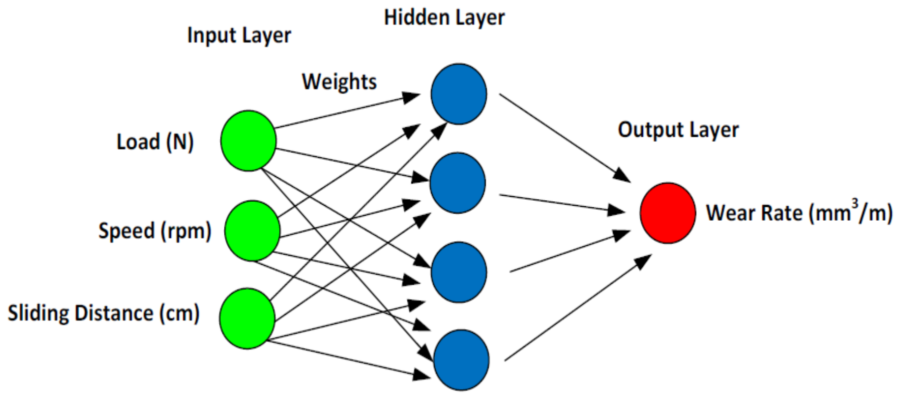

Fig. 2. 3:4:1 (3 inputs, 1 hidden layer with 4 neurons and 1 output) type of the BPN algorithm used for modeling.

The testing validity of the regression analysis and the neural network results was achieved by using the input parameters according to the design matrix given in Table 4 The performance of each BPN was calculated with the absolute error (%) of the tested subset using MATLAB ToolBox of neural network. The average absolute error (%) was calculated as 1.02 %. The wear rate can be predicted in a quick and accurate manner, the BPN results show that the predicted values were very close to the experimental values. The value of the multiple coefficients R^2 is 0.9441, which means that the explanatory variables explain 94.41% of the variability in the response variable. The predicted values of the wear rate were compared with experimental values as shown in Figure 3.

Table 4,
Test set for the validity of the constructed neural network.

Exp. No.	Load (N)	Sliding Speed (r.p.m)	Sliding Distance (cm)	wear rate (mm^3/mm)	
				Experimental	Predicted
1	20	250	10	0.0043	0.0041
2	25	250	6	0.0041	0.0039
3	30	400	10	0.0046	0.0044
4	25	350	8	0.0042	0.0043
5	30	400	6	0.0041	0.0041

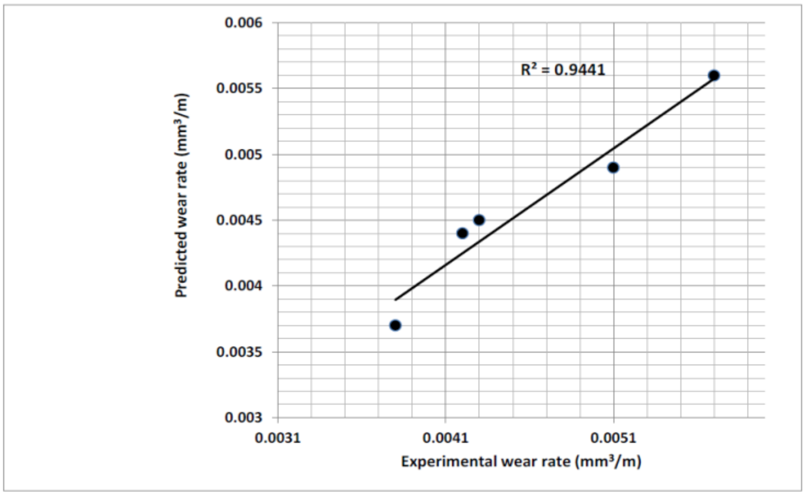

Fig.3. Comparison of experimental and predicted values (BPN Model).

The effect and optimization of wear settings for the minimum wear rate was investigated experimentally. The optimum wear-parameter combination was obtained by analyzing the S/N ratio . ANOVA was used to consider the effects of the input factors on the response and was performed on experimental data. The confidence level was selected as 0.95%. The results of ANOVA for the wear rate are shown in Table 5. The results of contribution percentage (%) are shown Table 6.

Table 5,
Results of ANOVA for the wear rate.

Analysis of Variance for Wear Rate (mm^3/m), using Adjusted SS for Tests

Source	DF	SS	MS	F
Load (N)	2	0.0000024	0.0000012	43.96
Speed (rpm)	2	0.0000011	0.0000005	19.00
Sliding Distance (cm)	2	0.0000001	0.0000000	1.72
Error	2	0.0000001	0.0000000	
Total	8	0.0000036		

Table 6,
Results of contribution percentage (%) of wear parameters.

Percentage contribution of each variable on wear rate

Variables	Percentage Contribution(%)
Load	66.66666667
Speed	30.55555556
Distance	2.777777778
Total	100

It was observed that the applying load and sliding speed have a great influence on the obtained wear rate after analyzing Table 4 and 5. The sliding distance do not effect significantly the obtained wear rate . The plot of the main-factor effects is shown in Figure 4. The S/N graph for the wear rate is shown in Figure 5. It is evident that the applying load (66.67%) and sliding speed (30.56%) have the most significant effect on the wear rate. Sliding distance (2.78%) has little effect on the wear rate.

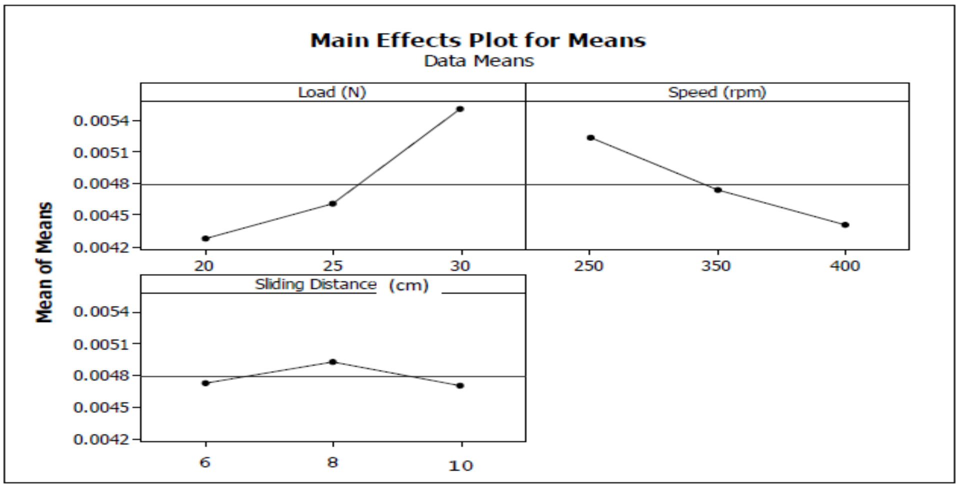

Fig.4. Main effect plot for wear rate vs. load, sliding speed and sliding distance.

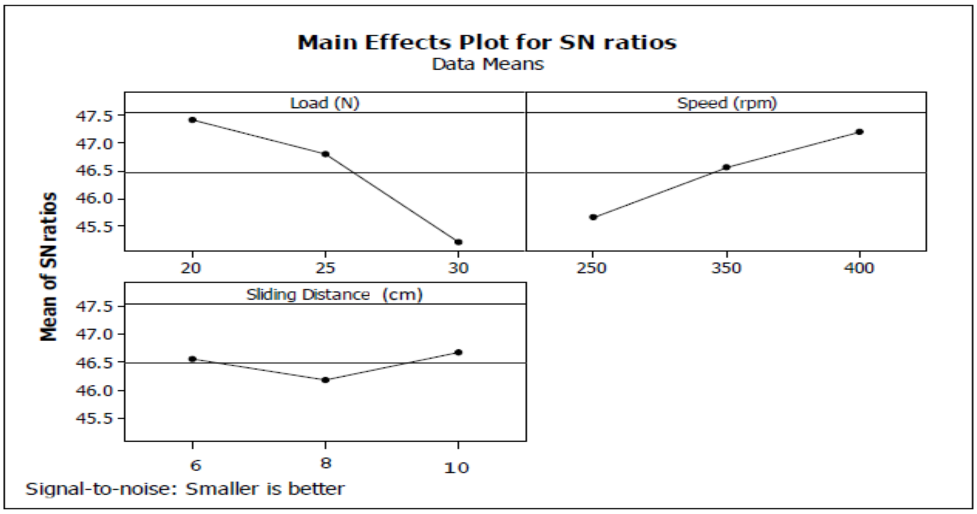

Fig.5. Main effect plot for SN ratios vs. load, sliding speed and sliding distance.

Optimum factor levels and S/N ratios obtained at the end of the Taguchi design technique are summarized in Table 7. Based on the S/N ratio plot in Figure 5, the optimum wear parameters for the AISI 4340 Steel are applying load at level 3, sliding speed at level1 , and sliding distance at level 2 . The applying load and sliding speed are two parameters affecting the wear rate compared to sliding distance.

Table 7,
Optimum factor levels and their S/N ratios.

Response Table for Signal to Noise Ratios
Smaller is better

Level	Load (N)	Speed (rpm)	Sliding Distance (cm)
1	47.42	45.66	46.56
2	46.80	46.55	46.18
3	45.20	47.20	46.68
Delta	2.22	1.54	0.51
Rank	1	2	3

According to Figure 6 (a), higher applying load at higher sliding speed gives a greater wear rate compared to the combination effect of applying load and sliding distance as shown in Figure 6 (b) and the combination effect of sliding speed and sliding distance as shown in Figure 6 (c) . Table 8 shows a multiple linear regression equation developed for wear rate. This developed model gives the relationship between independent/ predictor variable and a response variable. Figure 7 shows comparison of predictive performance when using the developed model with experimental data.

It can be see there is a better model fit. As these values are closely resembling the actual data with minimum error (R^2=0.9049), design of experiments by Taguchi method was successful for calculating wear rate from the regression equation.

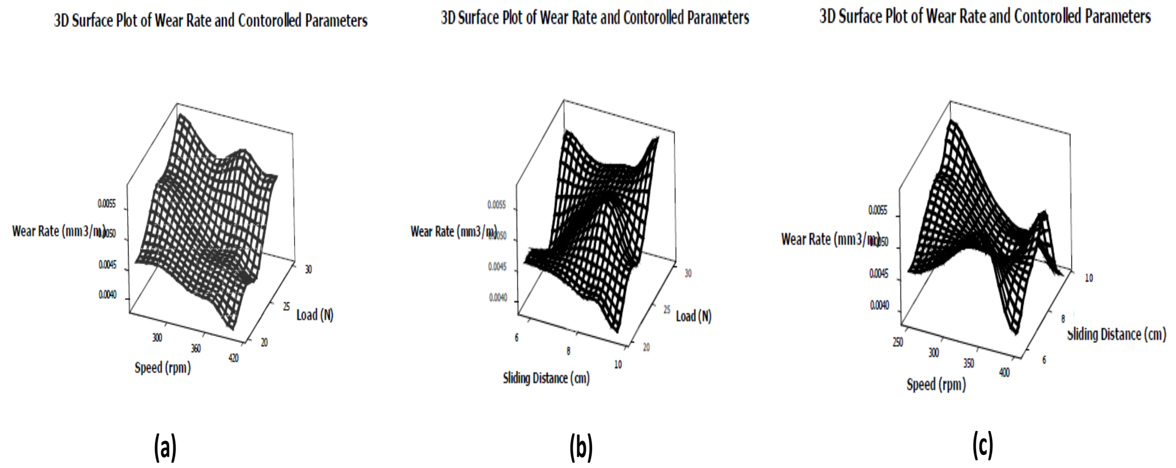

Fig. 6. 3D surface plot for wear rate vs. load, sliding speed and sliding distance.

Table 8,
Regression equation of wear rate.

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Regression Equation

Wear Rate (mm3/m)  =  0.00350873 + 0.000123333 Load (N) - 5.47619e-006 Speed
                      (rpm) + 9.52381e-009 Sliding Distance (cm)


Coefficients

Term                     Coef
Constant               0.0035087
Load (N)               0.0001233
Speed (rpm)           -0.0000055
Sliding Distance (cm)    0.0000000
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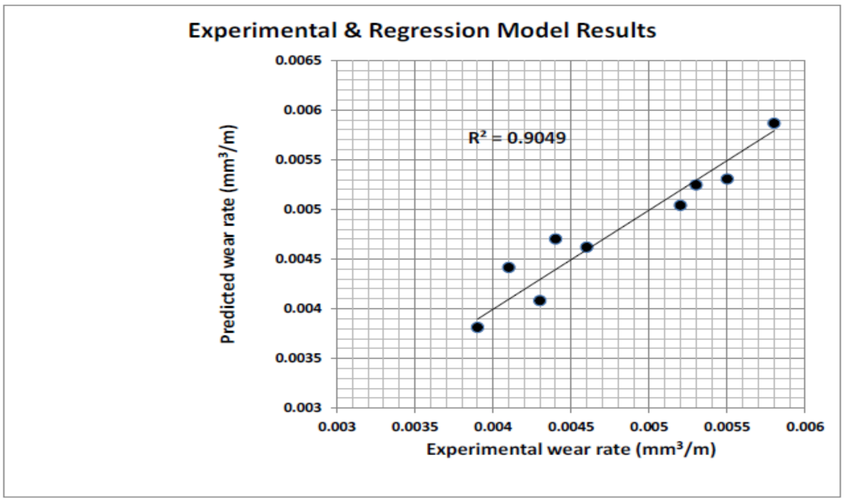

Fig.7. Comparison of experimental and predicted values (Regression Model).

5. Confirmation Tests

A confirmation experiment is the final step in first step iteration of designing an experiment process i.e., is the final step in Taguchi method and it is used to verify the optimal combination of the factor settings [9]. The purpose of the confirmation experiment is to validate the conclusions drawn during the analysis phase. The confirmation experiment is performed by conducting a test with a specific combinations of the factors and levels previously evaluated [9] . In this study, after determining the optimum conditions and predicting the response (wear rate) under these conditions , a new experiment was designed and conducted with the optimum levels of the wear rate parameters . The final step is to predict and verify the improvement of the performance characteristic. The predicted value of wear rate ($\hat{\eta}$) at the optimum levels is calculated by using the relation given as [8]:

$$\hat{\eta} = \eta_m + \sum_{i=1}^{n} (\bar{\eta}_i - \eta_m) \quad \text{... (9)}$$

Where η_m is the total mean of response, $\bar{\eta}_i$ is the mean of the response at the optimum level, and n is the number of the main wear parameters that that significantly affect the performance. The result of the experimental confirmation using the optimum wear rate parameters is shown in Table 9. It can be seen that the results are consistent, i.e. a good agreement between the predicted and actual wear rate being observed.

Table 9,
Predicted values and confirmation test results for wear rate.

Taguchi optimal parameters settings				
	Level	Prediction	Experiment	Error(%)
Load (N)	3			
Sliding Speed (r.p.m)	1	0.003789	0.00391	3.193454737
Sliding distance (cm)	2			

6. Conclusions

This study presents a prediction, optimization and modelling of the wear behavior of the AISI 4340 steel based on the Taguchi-based neural network with the back-propagation algorithm method . The following conclusions can be drawn from this study:

1. The main wear parameters that affect the wear rate of the AISI 4340 steel were determined as applying load (66.67%) and sliding speed (30.56%) among three controllable factors influencing the wear rate using ANOVA.

2. A neural network based on the back-propagation network (BPN) algorithm was constructed for predicting the wear rate. The predicted values were found to be very close to the experimental values.
3. The optimum parameter combination for the minimum wear rate was obtained by using the Taguchi design method with analysis of the S/N ratio.
4. The confirmation test supports the finding that the wear rate is greatly decreased by using the optimum design parameters. From confirmation test, the error (%) associated with wear rate is 3.193454737% resulting in the conclusions that the design of experiments by the Taguchi method was successful for calculating wear rate from the regression equation.
5. The obtained results indicate that the BPN model agreed with the Taguchi analysis.

7. References

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تحديد العوامل المثلى للبلى في الفولاذ نوع AISI4340

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الخلاصة

تتضمن هذه الدراسة تحديد العوامل المثلى لسلوك البلى في الفولاذ نوع- AISI 4340 على وفق طريقة تاكوجي تحت ظروف الإختبار المختلفة . و أُستخدمت في هذا البحث الشبكة العصبونية و طريقة تاكوجي لخفض معدل البلى في الفولاذ AISI 4340 . و تم إعتماد إسلوب الإنتشار العكسي للشبكة العصبونية للتنبأ بمعدل البلى . أما متغيرات الإدخال أي معاملات البلى التي تم إستخدامها للحصول على نموذج التنبأ فهي سرعة الإنزلاق و الحمل المسلط و مسافة الإنزلاق . كما أستخدم تحليل التباين لتحديد تأثير العوامل على معدل البلى . و أخيراً، تم تطبيق طريقة تاكوجي لتحديد المستويات المثلى لعوامل البلى . و أظهرت النتائج ، أن العوامل المثلى (الحمل 3 و سرعة الإنزلاق 1 ، و مسافة الإنزلاق 2) تؤدي الى خفض معدل البلى . كما أن قيمة الخطأ مابين القيم التي تم التنبأ بها و القيم التجريبية هي فقط 3.19% أي هناللك توافق جيد مابين النتائج التي تم التنبأ بها و النتائج التجريبية .