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Research Article

PREDICTION OF SURFACE HARDNESS IN A BURNISHING PROCESS USING TAGUCHI METHOD, FUZZY LOGIC MODEL AND REGRESSION ANALYSIS

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ABSTRACT

The available work is aimed for comparison and estimation of surface hardness in ball burnishing process of aluminum alloy based upon the Taguchi technique, Fuzzy logic and regression models. The ball burnishing parameters like burnishing speed, force, feed rate and number of passes were designed using Taguchi L_{25} orthogonal design matrix. Taguchi's signal to noise ratio was used to optimize the surface hardness. The effect of burnishing parameters on surface hardness was established by analysis of variance. Fuzzy logic was conducted using Matlab Toolbox. Taguchi technique, second order regression model and variance analysis were developed using MINITAB 17. The predicted hardness values of performance parameters were operated to compare the distinct models. The results of predicted models indicated that the consistent predictive model is the fuzzy logic model. With high correlation coefficient (R^2= 97.52 %), the model was regarded adequately accurate.

Keywords: Ball burnishing, surface hardness, Taguchi method, fuzzy logic, regression model.

1. INTRODUCTION

Recently, substantial interest has been given to the post-machining metal finishing operations like the burnishing, shut pinning, water jet pinning and laser pinning processes in the manufacturing industry. Burnishing is a cold-working process in which the burnishing force is conducted to a workpiece surface by hard smooth ball and roller [1, 2]. Burnishing is regarded as a fast, simple and low-cost process with advantages like enhancing mechanical properties of the manufactured pieces [3], reducing surface roughness [4, 5], proposal of good finishing accuracy, improving hardness on the workpiece surface [6], enhances wear resistance [7], fatigue [8], corrosion resistance [9], and maximum residual stress in compression [10]. Most of the ball burnishing process parameters such as burnishing speed, ball material, ball size, lubrication, burnishing force, workpiece material, feed rate, number of passes affect mechanical properties [1-10].

In the literature, some statistical methods such as response surface methodology (RSM) [6], desirability function analysis [11], fuzzy logic [4], artificial neural network [5], grey relational

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analysis [2], and Taguchi method [12] have been performed for optimization and prediction of quality characteristics. Basak and Goktas [4] optimized the burnishing parameters using fuzzy logic. Kurkute and Chavan [13] modeled and optimized the surface roughness and microhardness roller burnished aluminum alloy using RSM. Kumar et al. [14] used Taguchi technique and fuzzy logic model in roller burnishing process for estimation of surface roughness and hardness of AA 2014 and AA 6063 aluminum alloy. These models were compared to each other to obtain minimum surface roughness and maximum hardness. El-Taweel and El-Axir [12] analyzed and optimized the ball burnishing process on surface roughness and micro-hardness of brass using Taguchi technique. Sarhan and El-Tayeb [15] performed the estimation of surface roughness in burnishing of brass C3605. The approach used the fuzzy rule-based approach. The results, which acquired from the fuzzy model, are immensely coherent with the experiments. Esme et al. [16] focused on the surface roughness and microhardness of AA 7075 aluminum alloy using grey-based fuzzy algorithm. Kahraman [6] developed an empirical model for the prediction surface hardness of AA 7075 aluminum alloy using RSM with central composite design. Sagbas and Kahraman [17] studied optimal burnishing parameters for surface hardness of AA 7178 aluminum alloy using Taguchi method. Dweiri et al. [18] optimized the surface roughness roller burnished nonfer rous component using fuzzy model.

In this paper, surface hardness was estimated as a function of four factors, namely, burnishing speed, feed rate, burnishing force and number of passes. ANOVA was conducted to analyze the effect of control factors on surface hardness. Additionally, obtained results from Taguchi method, regression analysis and fuzzy logic model for surface hardness in ball burnishing process were compared and analyzed to each other.

2. EXPERIMENTAL DETAILS

In this study, AA 7075 aluminum alloy was used as the workpiece material and its chemical composition given in Table 1. It was extensively used in defense and aerospace industry, rubber and plastic molds, rivet and nuclear applications. In experiments, the workpiece was taken in the shape of bars, diameter of 30 mm and length of 100 mm as a three part each having a length of 20 mm. The experimental set-up for the ball burnishing tests was shown in Figure 1. Distinct ball burnishing parameters were carried out on each part.

Table 1. Chemical composition of AA 7075 aluminum alloy

Chemical structure w/%	Al	Cu	Mg	Cr	Zn
	90.0	1.60	2.50	0.23	5.60

Stainless steel ball with hardness of 60 HRc and a diameter of Ø18 mm was used in the burnishing process. The experiments were carried out by using Doosan Puma 240 type industrial CNC lathe. The workpieces were assembled between the chuck and tailstock center on the lathe. Throughout burnishing process, there was no used coolant. Before burnishing process was conducted, the workpieces were cleaned with alcohol. To preserve any particles from ingress the surface of touch between the test apparatus and the workpiece, a ball cleaning process was conducted throughout the ball burnishing process.

Vickers hardness test was implemented using ZHVμ series Zwick micro hardness tester. These workpieces were tested and appraised for their microhardness. During the hardness test, a load of 5kgf was conducted with a loading duration 10 seconds. The indenter was performed the distinct places on the workpiece to avoid surface effects and overlap. Three reasonable measurements were acquired from overall workpieces.

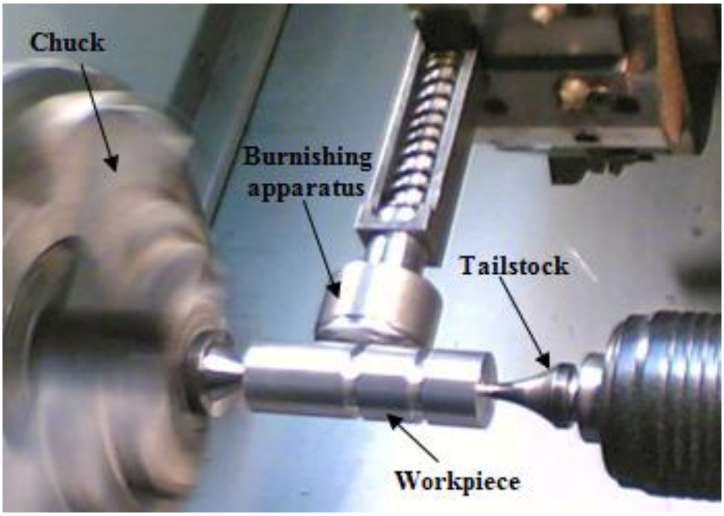


Figure 1. Expe rimental set up of the ball burnishing process

3. RESULTS AND DISCUSSION

3.1. Prediction of surface hardness using Taguchi Method

The Taguchi method developed by Genuchi Taguchi is a statistical method used to enhance the product quality. It is generally used in engineering analysis. This method drastically reduces the quantity of trials by using orthogonal arrays [19-21]. Moreover, it ensures a basic, fruitful and systematic approach to identifying the optimum ball burnishing parameters [22].

The Taguchi method utilizes a loss function to establish the quality characteristics. Loss function values are also transformed to a signal-to-noise (S/N) ratio [23]. In usually, there are three distinct quality characteristics in S/N ratio analysis, the lower-the-better, the nominal-the-best and the higher-the-better, respectively. For each level of control factors, S/N ratio is calculated based on S/N analysis. The aim of this work was to maximize hardness. Thus, the higher-the-better quality characteristic was used as indicated in Equation (1):

$$\eta = \frac{S}{N} = -10\log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y^2}\right) \tag{1}$$

where, n is the number of experiments and y is the experimental data [24].

Burnishing speed, burnishing force, feed rate and number of passes were used as control factors and surface hardness was regarded as output factor. Control factors and their levels were given in Table 2. The most proper orthogonal array L_{25} (4^5) was selected to define the optimal burnishing parameters and to analyze the effects of control factors.

Table 2. Control factors and their levels

Symbol	Factors	Unit	Level 1	Level 2	Level 3	Level 4	Level 5
Bs	Burnishing speed	m/min	30	50	70	90	110
Fr	Feed rate	mm/rev	0.05	0.15	0.25	0.35	0.45
Bf	Burnishing force	N	50	100	150	200	250
Nop	Number of passes	-	1	2	3	4	5

Consequently, the higher-the-better was utilized as offered in the Equation (1). The average of the S/N ratio for each level of burnishing process parameters was computed and given in Table 3.

Table 3. S/N values for surface hardness

Levels	Control factors			
	Bs	Fr	Bf	Nop
Level 1	45.48	45.38	45.09	45.09
Level 2	**45.72***	45.60	45.30	45.27
Level 3	45.44	45.52	45.71	45.46
Level 4	45.54	45.52	**45.85***	45.80
Level 5	45.58	**45.73***	45.80	**45.88***

The highest S/N values indicated the optimal level of each process parameters. Therefore, it was shown that in Table 3 that the second level of Bs, the fifth level of Fr, the fourth level of Bf, and the fifth level of Nop were higher and thus the combination of parameters was $Bs_2Fr_5Bf_4Nop_5$. ANOVA was used to analyze the influences of burnishing process parameters on surface hardness. ANOVA which is a statistical method used for detecting individual interactions of all input parameters and their interactions. ANOVA was executed for a confidence grade of 95%. The ANOVA results for the surface hardness was displayed in Table 4. Burnishing force and number of passes were established as a significant factor since their p values are less than 0.05.

Table 4. Results of ANOVA for the surface hardness

Variance Source	Degree of freedom (DF)	Sum of squares (SS)	Mean square (MS)	F-Value	P-Value	Contribution (%)
Bs	4	108.2	27.06	0.69	0.622	4.60
Fr	4	148.2	37.06	0.94	0.488	6.30
Bf	4	1069.4	267.36	6.78	0.011	45.45
Nop	4	711.4	177.86	4.51	0.034	30.23
Error	8	315.7	39.46			13.42
Total	24	2353.0				100

According to Table 4, the percent contributions of the Bs, Fr, Bf and Nop factors on the surface hardness were found to be 4.60%, 6.30%, 45.45% and 30.23%, respectively. Therefore, the most significant factor on surface hardness was burnishing force (Bf, 45.45%). In the Taguchi method, Equation (2) was used for the prediction of surface hardness. $T_h$value displays the surface hardness value acquired from the experimental work (Table 5). As a result of the computations, the $T_h$value was found to be 189.72 HV.

$$Hardness_{predict} = (Bs_n - T_h) + (Fr_n - T_h) + (Bf_n - T_h) + (Nop_n - T_h) + T_h \quad (2)$$

where, n is the level value of the factors for the predict hardness value to be calculated.

Table 5. Mean values for surface hardness

Levels	Control factors			
	Bs	Fr	Bf	Nop
Level 1	188.6	186.2	179.8	185.6
Level 2	193.4	190.8	184.2	183.4
Level 3	187.2	189.0	193.0	187.6
Level 4	189.2	189.0	196.2	195.0
Level 5	190.2	193.6	195.4	197.0
T_h (surface hardness total mean value) = 189.72 HV				

3.2. Prediction of surface hardness using fuzzy logic model

In fuzzy inference system, model is in the shape of If-Then rules in place of a mathematical equation. A fuzzy inference system is consisted of a fuzzifier, an inference engine, a database, a rule base and a defuzzifier (Figure 2). To predict output data, the Mamdani fuzzy inference system was chosen. The burnishing speed (x_1), feed rate (x_2), burnishing force (x_3) and number of passes (x_4) were utilized as input parameters and surface hardness (y_1) was used as the output parameter. Fuzzy logic model was indicated in Figure 3.

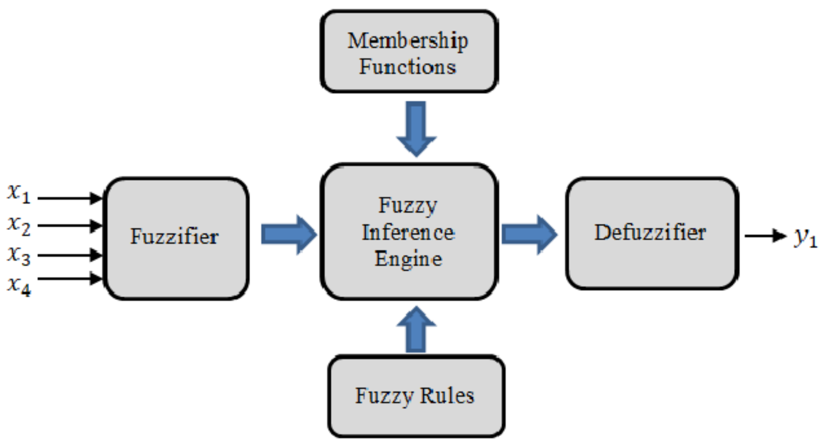


Figure 2. Structure of fuzzy logic system with four inputs and one output

In fuzzy logic, the range of input/output parameters are detected initially. Then, to acquire fuzzy sets, triangular membership function was used for fuzzification. In fuzzification, numerical input and output values are transformed into linguistic terms like lowest, low, medium, high, highest, etc. The range of input parameters and membership functions were shown in Figure 4, while the range of output parameter and membership function were shown in Figure 5. Eventually, triangular membership function was utilized to defuzzify it to acquire the outputs. Defuzzification is the process of transformation of fuzzy amount into exact amount. Centroid defuzzification method which computed the centroid of the area under the membership function was conducted in this work [25].

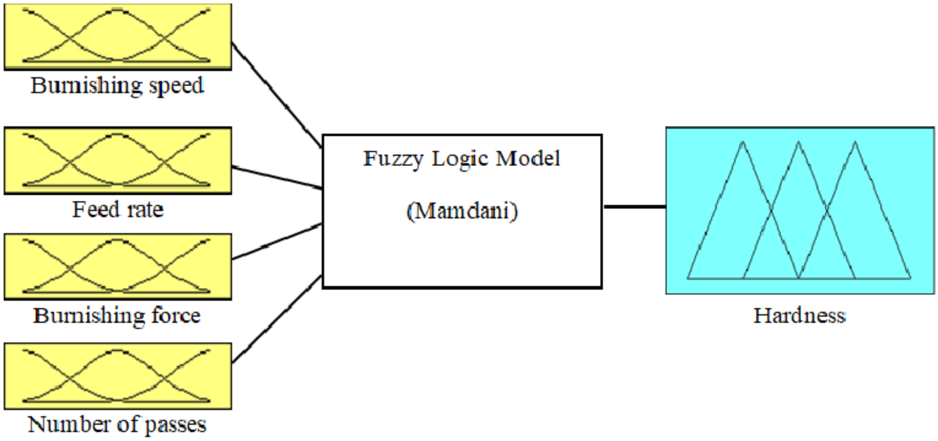


Figure 3. Fuzzy inference system

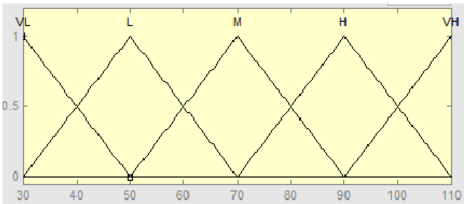
The equation (3) of the triangular membership function was offered below:

$$triangle(x; a, b, c) = \begin{Bmatrix} 0 & x \leq a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ \frac{c-x}{c-b} & b \leq x \leq c \\ 0 & c \leq x \end{Bmatrix} \quad (3)$$

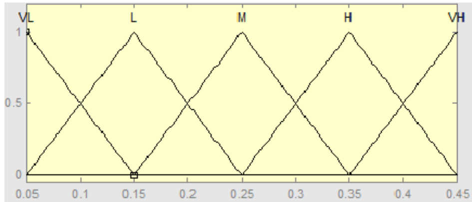
where a, b, c means the triangular fuzzy triplet which defines the x coordinates of the three corners of the underlying triangular membership function [26]. Linguistic expression used to describe the relation between the inputs and outputs were referred to fuzzy rules. These rules can be shown as:

Rule 1: if x_1 is A_1 and x_2 is B_1 and x_3 is C_1, and x_4 is D_1 then y_1 is E_1 else
Rule 2: if x_1 is A_1 and x_2 is B_2, and x_3 is C_2, and x_4 is D_2 then y_1 is E_2 else
.
.
Rule n: if x_1 is A_n and x_2 is B_n, and x_3 is C_n, and x_4 is D_n then y_1 is E_n else

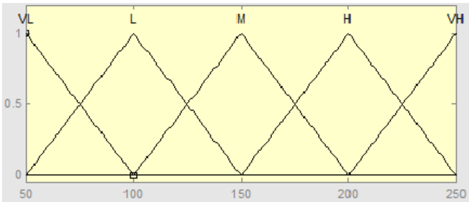
The fuzzy sets are symbolized by membership functions which were exemplified by Figure 4 and Figure 5. Five fuzzy sets were selected for the variables of inputs (VL, L, M, H, VH), and eleven fuzzy sets were utilized for the surface hardness (VVVVL, VVVL, VVL, VL, L, M, H, VH, VVH, VVVH, VVVVH). The number of fuzzy rules was adjusted according to the Taguchi L_{25} orthogonal array. Hence, numerical values were replaced with linguistic values.



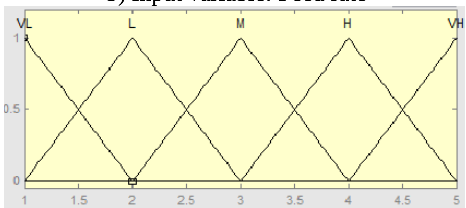
a) Input variable: Burnishing speed



b) Input variable: Feed rate

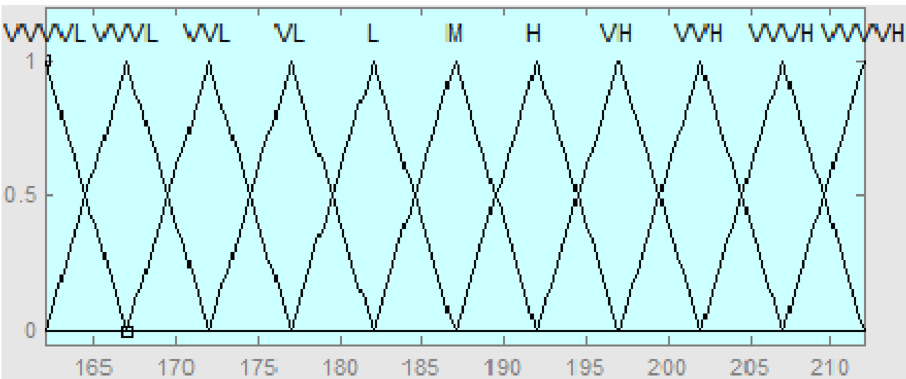


c) Input variable: Burnishing force



d) Input variable: Number of passes

Figure 4. Membership function of input parameters



Output variable: Surface hardness

Figure 5. Membership function of output parameter

The relation between input parameters and output parameter variables was improved by fuzzy rules. In overall 25 rules were shown in Figure 6. Figure 7 indicated the twenty-five rule and dispersion utilized in the suggested Taguchi based fuzzy logic modelling.

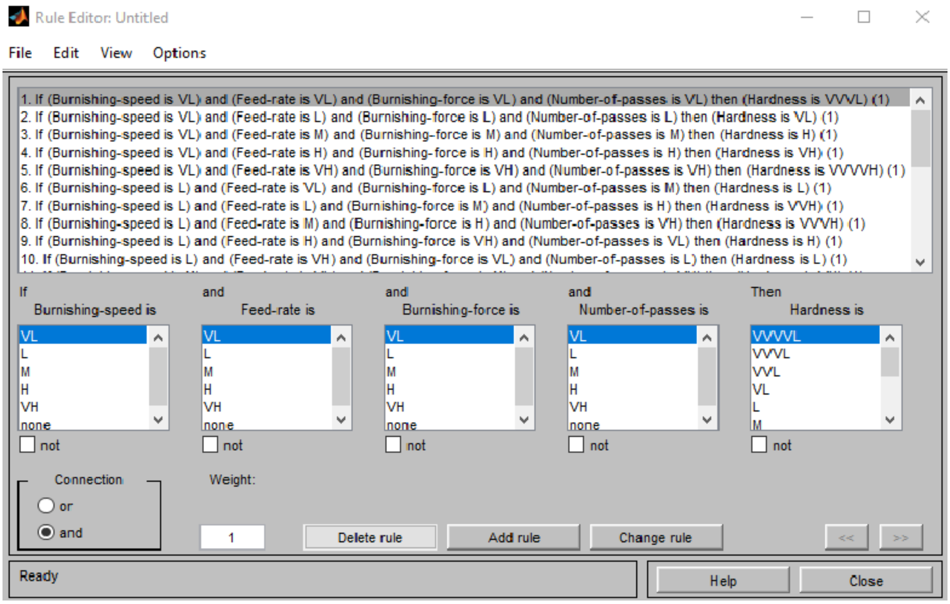


Figure 6. Rules conducted to mamdani fuzzy system

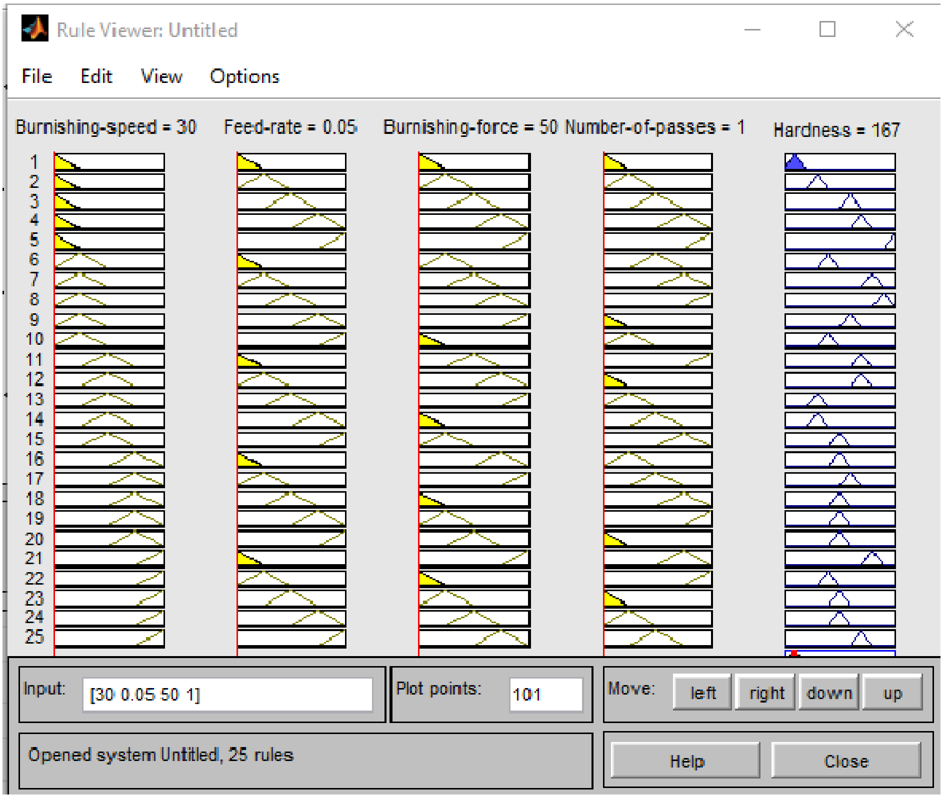


Figure 7. Taguchi based fuzzy logic rules

3.3. Prediction of surface hardness using regression analysis

Regression analysis is a statistical technique for predicting the relation among variables which have reason and result relationship. It establishes the correlation between a continuous dependent variable and continuous or discrete independent variables [27]. Mathematical models based on burnishing parameters were acquired from regression analysis to estimate surface hardness. Regression analysis was performed through Minitab 17 software. Hardness values were modeled as second order regression model. Equation (4) improved for surface hardness was as follow:

$$Hardness = 149.5 + 0.167Bs + 62.8Fr + 0.177Bf + 2.18Nop + 0.00037Bs^2 + 2Fr^2 - 0.000456Bf^2 + 0.928Nop^2 - 0.563BsFr + 0.00036BsBf - 0.0496BsNop - 4.87FrNop \quad (4)$$

3.4. Performance comparison of different predictive models

The experimental results and predicted distinct three models were shown in Table 6, which indicated that the Mean Absolute Percentage Error (MAPE) was 1.570 % for Taguchi method, 1.617 % for regression model, and 0.764 % for Fuzzy logic model.

Table 6. Experimental and predicted surface hardness values

Trial No	Experimental value	Taguchi Method	Regression Model	Fuzzy Logic Model
1	165	171.04	166.730	167
2	179	177.84	179.588	177
3	190	189.04	191.087	192
4	197	199.64	201.226	197
5	212	205.44	210.005	211
6	181	182.24	182.121	182
7	203	203.04	193.676	202
8	205	206.44	203.871	207
9	194	194.24	190.263	192
10	184	181.04	182.088	182
11	196	194.24	199.696	197
12	195	190.64	187.591	197
13	178	185.84	189.644	177
14	179	174.44	179.731	177
15	188	190.84	190.466	187
16	189	185.84	190.347	187
17	193	193.84	192.456	192
18	187	183.84	180.806	187
19	188	190.24	191.597	187
20	189	192.24	190.940	187
21	200	197.64	198.700	202
22	184	188.64	185.313	182
23	185	179.84	186.158	187
24	187	186.44	188.807	187
25	195	198.44	190.095	197
(%) MAPE		1.570	1.617	0.764

Distinct performance parameters can be utilized to appraise the convergence of experimental values to estimated values. The Mean Absolute Deviation (MAD), Mean Square Error (MSE), the Root Mean Square Error (RMSE), MAPE and correlation coefficient (R^2) were used to search the convergence between the target values and the output values [28].

In this paper, equation (5-9) were used as performance parameter to compare three distinct models:

$$MAD = \frac{\sum_{i=1}^{n} |o_i - t_i|}{n} \tag{5}$$

$$MSE = \frac{\sum_{i=1}^{n} (o_i - t_i)^2}{n} \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (o_i - t_i)^2}{n}} \tag{7}$$

$$MAPE = \frac{\sum_{i=1}^{n} |o_i - t_i|}{n} \times 100 \tag{8}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (o_i - t_i)^2}{\sum_{i=1}^{n} o_i^2} \right) \tag{9}$$

where t is target value, o is output value and n is total number of data. Performance values of three different models were given in Table 7. According to results of the MAD, MSE, RMSE and MAPE, the fuzzy logic model produced the best estimation for surface hardness, followed by Taguchi method and then the second order regression model.

Table 7. Performance values of predictive models

	Taguchi Method	Regression Model	Fuzzy Logic Model
MAD	2.938	3.076	1.440
MSE	12.627	17.338	2.560
RMSE	3.553	4.164	1.600
MAPE	1.570	1.617	0.764
R^2	86.58 %	81.58 %	97.52 %

Scatter plots for the experimental and estimated values with Taguchi method, regression analysis and fuzzy logic model were shown in Figure 8. The efficiency of the developed models was appraised by R^2 values. In Taguchi method, regression analysis and fuzzy logic model, R^2 values for the surface hardness were found as 86.58 %, 81.58 % and 97.52 %, respectively. The estimated values acquired with Taguchi method, regression analysis and fuzzy logic modelling were compared with experimental values and results were plotted as demonstrated in Figure 8. It was monitored from Figure 8 that the diversities between experimental and estimated values were low. It was accomplished that Taguchi method, regression analysis and fuzzy logic model could be used for forecasting the surface hardness in ball burnishing of AA 7075 aluminum alloy.

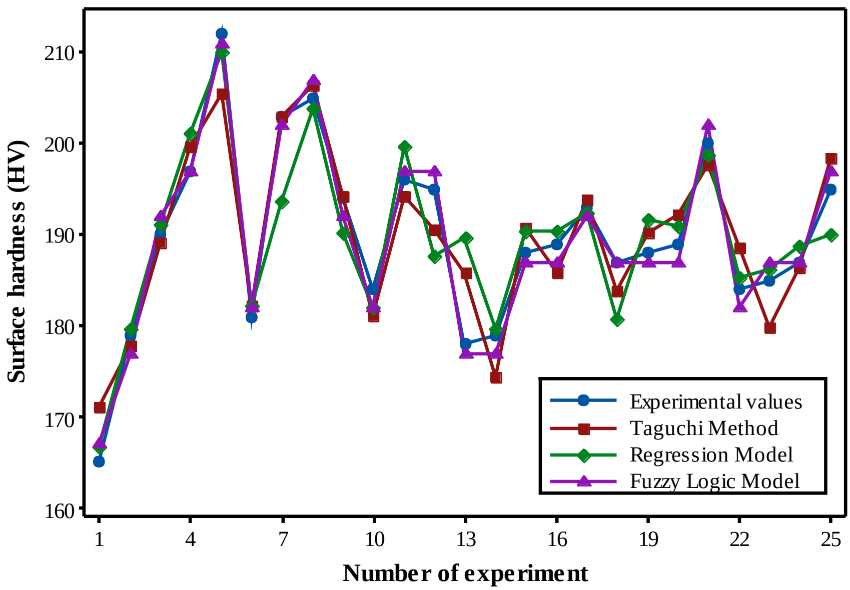


Figure 8. Comparison of experimental and predicted values for surface hardness

4. CONCLUSION

In this survey, surface hardness values obtained in ball burnishing process of AA 7075 aluminum alloy were modeled using multiple approach, including, Taguchi method, regression and fuzzy logic. The main results were as follows:

- The optimal level of the control factors to acquire better surface hardness were (level 2) 50 m/min burnishing speed, (level 5) 0.45 mm/rev feed rate, (level 4) 200 N burnishing force and (level 5) 5 number of passes.
- According to ANOVA results, the most important factor on surface hardness was burnishing force with contribution of 45.45 %, following number of passes with contribution of 30.23 %.
- Based upon the acquired values of performance parameters (MAD, MSE, RMSE, MAPE), the fuzzy logic model performed the best estimation of surface hardness, followed by the predict Taguchi method, and then the second order regression model.
- Fuzzy logic model is the best proper for estimating surface hardness. This model can produce an accurate relation between burnishing process parameters and surface hardness. Thus, fuzzy logic can be used to estimate surface hardness even before the ball burnishing process, which will be very much near to values and has acquired after burnishing process.
- Correlation coefficient (R^2) was obtained 86.58 %, 81.58 % and 97.52 % for Taguchi method, the second order regression model and fuzzy logic model, respectively. This means that the predicted results of fuzzy logic model are very near to actual experimental results.

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