International Journal of Scientific Engineering and Technology (ISSN: 2277-1581)
Volume No.3 Issue No.11, pp: 1391-1396 01 Nov. 2014

Development of Fuzzy Logic Technique for Modeling Surface Roughness in Drilling of EN24 Steel with Coated Tools

G. Vijaya Kumar[1], K. Anand Babu[2], P. Venkataramaiah[3]
[1,2,3] Department of Mechanical Engineering, S. V. University, Tirupati, A. P, India

Email: [1]vijayluther2003@yahoo.co.in, [2]kumba.anand@gmail.com, [3]pvramaiah@gmail.com

Abstract – The present paper focused on the application of fuzzy logic for predicting the surface Roughness (R_a) in drilling of EN24 Steel using uncoated and coated tools. For conducting drilling experiments Taguchi L_{16} orthogonal array was used. The Taguchi method and Analysis of Variance (ANOVA) is employed to find out the influences of machining parameters on surface roughness for their optimization. The machining parameters used in the experiment were drilling speed, feed, tool type and coolant. The obtained experimental results were analyzed and the results revealed that coolant was the prevailing factor on the surface roughness followed by tool type, feed and speed. In addition, the fuzzy predicted values and experimental values of surface roughness are fairly close to each other. Therefore, the developed fuzzy logic model can be effectively used to predict the surface roughness in drilling of EN24 Steel.

Key words: Drilling, Surface Roughness, Taguchi, ANOVA, Fuzzy Logic Modeling Technique, EN24 Steel

I. Introduction

Drilling is one of the most widely used metal removal process in manufacturing industries like Aerospace, watch manufacturing, Automobile and medical industries, where quality is an essential factor in the production of slots, pockets, precision moulds and dies [1]. Among all metal removal process, 75% of material removed comes from drilling process only and this is most typically able by using a twist drill. In recent days the manufacturing industries shows a greater attention to dimensional accuracy and surface roughness of the products. Due to that, improper selection of cutting parameters and cutting tool leads to reduce the tool life, surface finish and dimensional accuracy of the product and this will leads to increase the total cost of the product [4]. In this research work, the optimal cutting parameters such as speed, feed, tool type and coolant for drilling operation is identified to maximize the surface quality.

In various engineering applications, the hardened steels such as EN24, EN8 and EN31 etc plays a significant role due its superior mechanical properties like hardness, strength and modulus. Therefore, these materials are gaining their importance in various manufacturing industries like aircrafts, aerospace, automotive, and die industries. In drilling of carbon steel materials EN24 many problems are raised include surface delamination, hole surface roughness, and higher tool wear. In order to minimize these machining problems, there is necessity to develop scientific methods to select machining parameters for damage-free drilling operation [5]. The cutting conditions which influence the surface quality and machining process are coolant, tool type, speed, feed, depth of cut. Among those, coolant is an important factor largely affects the machining process [10, 13]. The modern industries are therefore looking for a cooling system to provide dry (near dry), clean, neat and pollution free machining . Minimum Quantity Lubrication (MQL) refers to the use of cutting fluids of only a minute amount-typically of a flow rate of 50-500 ml/hour which is about three to four orders of magnitude lower than the amount commonly used in flood cooling, for example, up to 10 liters of fluid can be dispensed per minute. The concept of MQL, sometimes referred to as ‘near dry lubrication’ or ‘micro lubrication’ Machining under minimum quantity lubrication (MQL) condition is perceived to yield good machining performance over dry or flood cooling condition [10, 13]. Tools with TiN, TiCN, CrN, and TiAlN coating also play a significant role in drilling to improve multi performance [6, 18].

Now a day the application of optimization techniques is essential for the production of best quality product in less time and low cost. Taguchi’s method and analysis of variance (ANOVA) approach are the one of best methods to control the product quality and predicting the significance of machining parameters on output responses for optimization. [6] Stated that Taguchi method is a powerful tool to design optimization for quality and minimized the burr height and surface roughness in drilling of Al 7075 using Taguchi and response surface methodology. [8] Optimized the drilling parameter combination and determined the level of importance of the drilling parameters on Al/SiCp MMC through statistical analysis approach. [2] Stated that the Taguchi method is an efficient experimental method and optimized the machining performance of EN24 Steel using CNC Milling Machine which employed carbide End Mill cutting tool. And also determine the machining parameters significance on surface roughness using ANOVA, results revealed that feed rate was the prevailing factor affecting the milling of EN24. [9] Investigated the influence of wear parameters like sliding speed, applied load and sliding distance on the dry sliding wear of aluminium metal matrix composites. An orthogonal array, signal-to-noise ratio and analysis of variance are used to investigate the wear behavior of aluminium and its composite. [21] Optimized the testing parameters on wear behavior of MMC using Taguchi and determined the significance of testing parameters on wear behavior by analysis of variance. [3] Predicted and evaluated the thrust force and surface roughness in drilling of composite material using Taguchi and artificial neural network approach.

Most of the researchers was focused on minimization of surface roughness in machining and stated that minimizing the surface roughness was a serious task. In order to identify the surface quality and dimensional properties, it is necessary to use theoretical models for prediction purpose. The fuzzy logic modeling technique is used for prediction. Zadeh was first proposed the theory of fuzzy logics, has proven to be useful for dealing the uncertain and vague information. This theory has proved to be an effective means for dealing with objectives that are linguistically specified. Linguistic terms, such as 'low,' 'medium' and 'high' may be defined by fuzzy sets [11]. Since its introduction, fuzzy set theory has attracted the attention of researchers in mathematical and engineering fields [17].

In the present study, the fuzzy logic modeling technique is used as an efficient approach to predict the surface roughness values in drilling of EN24 Steel and the drilling experiments are conducted as per Taguchi L_{16} with uncoated and coated HSS tools under MQL environment.

II. Experimental Details

The main objective of this experiment is to determine the influence of machining parameters on drilling of EN24 Steel using radial drilling machine (fig.1) with HSS, TIN and TiAlN coated HSS tools (fig.2) under Dry and MQL environment by considering different speed, feed, cutting fluid and Tool type combinations. The chemical composition, mechanical properties of EN24 steel and Tool geometry of HSS drill bits is depicted in Table 1, 2 and 3 respectively.

Fig 1 Experimental setup of drilling experiments

Table I
Chemical composition of EN 24 Steel

Chemical composition	Percentage
Carbon, C	0.35 - 0.45
Manganese, Mn	0.45 - 0.70
Silicon, Si	0.10 - 0.35
Sulphur, S	0.040
Phosphorous, P	0.040
Chromium, Cr	0.90 - 1.40
Nickel, Ni	1.30 - 1.80
Molybdenum, Mo	0.20 - 0.40

Table II
Mechanical Properties for EN24

Tensile strength	850-1000
Yield strength	680 (MPa)
Elongation	13 (%)
Impact strength	54 (J)
Hardness	248 - 302 (HB)
Thermal conductivity	41.9 W/m-^{0}C
Density	7840kg/m^3
Elastic modulus	207x10^9 N/m^2
Melting point	1500^{0}C

The surface roughness is considered as an output response for analyzing the machining process, which is mostly used in industries. The surface roughness is measured using stylus type (Mitutoyo Corporation, japan) Taly-Surf (SJ-201P) surface roughness measuring instrument and drilled specimen of EN24 steel is shown in fig. 3 and fig. 4.

In this experiment four controllable parameters are considered and each parameter is set at four levels. The machining parameters and their levels are listed in Table 4. For full factorial design, the experimental runs required are (levels) $^{(factors)}$ equal to 4^4=256. To minimize the experimental cost, fractional factorial design is chosen, i.e., 4^{4-2}=16 runs. Therefore Taguchi experimental design L_{16} chosen for conducting experiments. Experiments are performed according to this design and the surface roughness values (R_a) are given in Table 5.

Fig 2 Drill bits (a) HSS (b) TiN coated HSS (c) HSS with 5% Cobalt (d) HSS with 8% Cobalt

Fig 3 Talysurf surface meter

Fig 4 Drilled specimen of EN24 Steel

Table III
HSS Drill Tool Geometry

Type of Drill tool	Tool Dia. (mm)	Point Angles (Deg.)	Flute Length (mm)	Helix Angle (Deg)	Total Length (mm)
TiN coated HSS	12	118^o	88	32^o	135
HSS	12	118^o	88	32^o	135
HSS with 5% Cobalt	12	118^o	88	32^o	135
HSS with 8% Cobalt	12	118^o	88	32^o	135

Table IV
Influential parameters and their levels

Sl. No	Influential parameters	Level 1	Level 2	Level 3	Level 4
1	Speed	90	125	315	450
2	Feed	0.15	0.2	0.3	0.36
3	Type of tool	HSS	Tin coated HSS	HSS with 5% cobalt	HSS with 8% cobalt
4	Coolant type	Dry	Veg. oil	Diesel	kerosene

III. Results and Analysis of Experiments

III.1. Taguchi Method

[7] Taguchi technique has been widely used in engineering analysis and consist of a plan of experiments with an objective of obtain the data in a controlled way, in order to determine the optimum solution in a manufacturing design, taguchi technique utilizes signal to noise ratio. The greatest advantage of this technique is to save the efforts in conducting experiments; saving experimental time, reducing the cost, and discovering significant factors quickly. [20] This method uses a special set of arrays called orthogonal array. This standard array gives a way of conducting the minimum number of experiments which could give the full information of all the factors that affect the response parameter instead of doing all experiments. The objective function in this work is to minimize the surface roughness, so that smaller the better S/N ratio is applicable and is defined according to taguchi technique as:

$$\frac{S}{N} = -10\log_{10}\left[\frac{\Sigma y^2}{n}\right] \quad \text{(Eq. 1)}$$

The S/N ratio values of surface roughness are calculated using Eq.1 from the obtained experimental results as per L_{16} orthogonal array and the vales are depicted in Table.4.

Table IV
Consolidated values obtained from experiments and their S/N ratios

Sl. No	Speed	Feed	Tool Type	Coolant Type	Surface roughness (R_a)	S/N ratios
1	90	0.15	1	1	1.29	-2.2118
2	90	0.2	2	2	0.52	5.6799
3	90	0.3	3	3	0.43	7.3306
4	90	0.36	4	4	0.65	3.7417
5	125	0.15	2	3	0.9	0.9151
6	125	0.2	1	4	0.54	5.3521
7	125	0.3	4	1	1.08	-0.6685
8	125	0.36	3	2	0.79	2.0475
9	315	0.15	3	4	0.28	11.0568
10	315	0.2	4	3	0.73	2.7335
11	315	0.3	1	2	1.3	-2.2789
12	315	0.36	2	1	1.67	-4.4543
13	450	0.15	4	2	0.52	5.6799
14	450	0.2	3	1	1.29	-2.2118
15	450	0.3	2	4	0.51	5.8486
16	450	0.36	1	3	0.95	0.4455

Note: 1-HSS, 2-HSS Coated with TIN, 3-HSS with 5% Cobalt, 4-HSS with 8% Cobalt
1-Dry, 2-Veg. Oil, 3-diesel, 4-kerosene

In general the larger value of S/N ratio is always considered for better performance apart from the type of the performance characteristics. The S/N Ratio is the difference between level 1 and level 4 indicates the significance of the influential parameters, greater the difference will be the most significant influential parameter. Table 4 shows that the input parameter coolant contributes most significantly towards the delta valve followed by tool type, feed and speed.

Table IV
Response Table for Signal to Noise Ratios smaller is better

Level	Speed	Feed	Tool type	Coolant
1	3.63513	3.86003	0.32675	-2.38660
2	1.91156	2.88845	1.99734	2.78211
3	1.76430	2.55797	4.55578	2.85621
4	2.44057	0.44510	2.87168	6.49982
Delta	1.87083	3.41493	4.22904	8.88642
Rank	4	3	2	1

Figure 5 shows the main effect plot for S/N ratio for surface roughness. It is observed that greatest variation was due to coolant and the optimal cutting parameters for conducting drilling experiments on EN24 Steel for obtain a good surface quality is given below:
Speed at level 1: 90 rpm
Feed at level 1: 0.15 mm/rev
Tool type at level 3: HSS with 5% Cobalt
Coolant: kerosene

International Journal of Scientific Engineering and Technology (ISSN: 2277-1581)
Volume No.3 Issue No.11, pp: 1391-1396 01 Nov. 2014

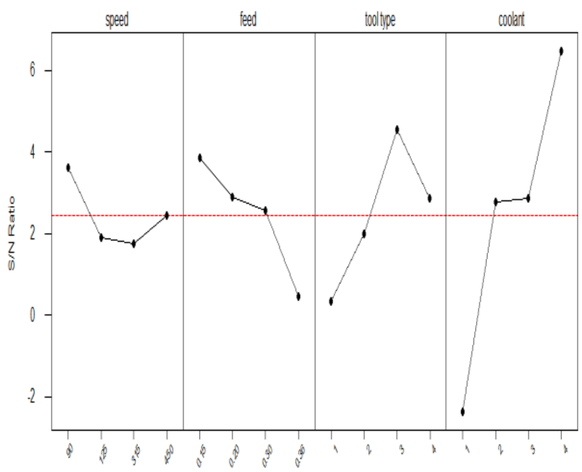

Fig 5 Effect of speed, feed, tool type and coolant on surface roughness

III.2. ANOVA

In addition to the S/N ratio, a statistical analysis of variance (ANOVA) can be employed to find out the percentage of contribution of influential parameters on surface roughness values. The statistical Analysis of variance approach was invented by Sir Ronald Fisher, who was a Statistician and Geneticist. Based on the ANOVA, the relative importance of the machining parameters with respect to surface roughness was investigated to determine more accurately the optimum combination of machining parameters. The analysis is carried out for the level of significance of 5% (the level of confidence is 95%). Table 5 shows the result of ANOVA analysis for the machining outputs of EN24 Steel. From the Table 5, it is observed that the coolant factor (Percentage contribution, P = 59.30%) has statistical and physical significance on the EN24 Steel followed by Tool Type (P = 13.80%), feed (P = 9.19%) and speed (P = 3.20%).

Table V

ANOVA results for S/N ratios of Surface Roughness

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% of cont.	Rank
Speed	3	8.66	8.66	2.89	0.22	0.877	3.20	4
Feed	3	24.84	24.84	8.28	0.63	0.641	9.19	3
Tool type	3	37.30	37.30	12.43	0.95	0.516	13.80	2
Coolant	3	160.27	160.27	53.42	4.09	0.139	59.30	1
Error	3	39.17	39.17	13.06			14.49	
Total	15	270.24					100	

IV. Fuzzy modeling

Lotfi Zadeh [12] was first introduced the Fuzzy logic technique based on fuzzy set theory in the year 1965. In the recent years, the applications of fuzzy set theory in engineering field have been developed significantly including the area of artificial intelligence (AI).

[19] The process of fuzzy inference is based on four basic concepts such as fuzzy sets, linguistic variables, possibility distributions, these three are fundamental concepts used in fuzzy logic and fuzzy IF–THEN rule is one of the important concepts used in most of the industrial applications. Generally construction of rule base is done by two types of fuzzy logic rules such as Mamdani type or Sugeno type rules.

In the present work, the surface roughness prediction model is developed using fuzzy logic technique for drilling of EN24 Steel. The Mamdani type Fuzzy Inference Systems (FIS) is used for modeling and [15] Mamdani's fuzzy inference method is the most commonly used fuzzy methodology. It was proposed in 1975 by Ebrahim Mamdani to control a steam engine and boiler combination by synthesizing a set of linguistic control rules obtained from experienced human operators. The fuzzy logic prediction model is developed using Fuzzy Logic toolbox available in MATLAB software.

IV.1. Fuzzification of input parameters

The fuzzifier uses triangular membership functions to fuzzify the input and output variables. Triangular membership functions are easy to use and require

$$\text{Triangle}(x;\, a,\, b,\, c) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases} \qquad (Eq.\ 2)$$

only three parameters to define. It is defined as a triangular shape which is a function of vector x that depends on three parameters a, b and c and is mathematically expressed as shown in Eq. (2) [14].

The input variables such as speed, feed, Tool type and Coolant are fuzzified into three fuzzy sets i.e. Low (L), Medium (M) and High (H) as shown in the Fig.6.

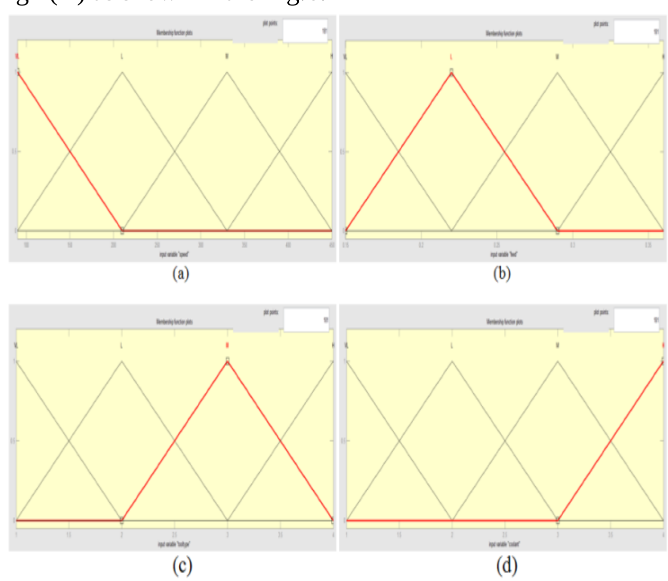

Fig 6 Fuzzification of input variables (a) speed (b) feed (c) tool type (d) Coolant

The output responses surface roughness is fuzzified into nine fuzzy sets i.e. very low (VL), low (L), medium low (ML), medium (M), medium high (MH), high (H) very high (VH), very very high (VVH) and very very very high (VVVH) and is depicted in fig. 7 to increase the accuracy of prediction.

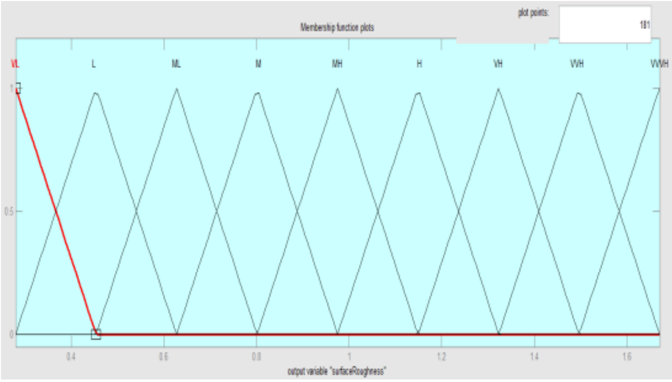

Fig 7 Fuzzification of output responses (surface Roughness)

IV.2. Fuzzy 'if –then' Rules

The fuzzy rules are generated based on experimental results and 16 fuzzy rules were developed for 16 experimental results by taking the max-min compositional operation. The fuzzy rule base consists of a group of IF- THEN statements with four inputs (x1, x2, x3, x4, and x5) and one output y.

Rule 1: if x1 is A1 and x2 is B1 and x3 is C1 and x4 is D1 then y is F1

else

Rule 2: if x1 is A2 and x2 is B2 and x3 is C2 and x4 is D2 then y is F2

else

……………………………………………………………...…… ………

Rule n: if x1 is An and x2 is Bn and x3 is Cn and x4 is Dn then y is Dn.

Ai, Bi, Ci, Di and Ei are the fuzzy subsets defined by the corresponding membership functions, i.e. μ_{Ai} , μ_{Bi} ,μ_{Ci} μ_{Di} μ_{Ei} and μ_{Fi}. The 16 fuzzy rules are generated based on these rules and as shown in fig. 8.

1. If (speed is VL) and (feed is VL) and (tooltype is VL) and (coolant is VL) then (surfaceRoughness is VH) (1)
2. If (speed is VL) and (feed is L) and (tooltype is L) and (coolant is L) then (surfaceRoughness is L) (1)
3. If (speed is VL) and (feed is M) and (tooltype is M) and (coolant is M) then (surfaceRoughness is L) (1)
4. If (speed is VL) and (feed is H) and (tooltype is H) and (coolant is H) then (surfaceRoughness is ML) (1)
5. If (speed is L) and (feed is VL) and (tooltype is L) and (coolant is M) then (surfaceRoughness is MH) (1)
6. If (speed is L) and (feed is L) and (tooltype is VL) and (coolant is H) then (surfaceRoughness is L) (1)
7. If (speed is L) and (feed is M) and (tooltype is H) and (coolant is VL) then (surfaceRoughness is H) (1)
8. If (speed is L) and (feed is H) and (tooltype is M) and (coolant is L) then (surfaceRoughness is M) (1)
9. If (speed is M) and (feed is VL) and (tooltype is M) and (coolant is H) then (surfaceRoughness is VL) (1)
10. If (speed is M) and (feed is L) and (tooltype is H) and (coolant is M) then (surfaceRoughness is M) (1)
11. If (speed is M) and (feed is M) and (tooltype is VL) and (coolant is L) then (surfaceRoughness is VH) (1)
12. If (speed is M) and (feed is H) and (tooltype is L) and (coolant is VL) then (surfaceRoughness is VVVH) (1)
13. If (speed is H) and (feed is VL) and (tooltype is H) and (coolant is L) then (surfaceRoughness is L) (1)
14. If (speed is H) and (feed is L) and (tooltype is M) and (coolant is VL) then (surfaceRoughness is VH) (1)
15. If (speed is H) and (feed is M) and (tooltype is L) and (coolant is H) then (surfaceRoughness is L) (1)
16. If (speed is H) and (feed is H) and (tooltype is VL) and (coolant is M) then (surfaceRoughness is MH) (1)

Fig 8 Fuzzy rules for input and output responses

IV.3. Defuzzification

Finally the fuzzy output is transformed into a non-fuzzy value y_0 using defuzzification method because the output response of the fuzzy process is available only in fuzzy values. For this purpose, the centroid defuzzification method is used as it is the most popular method used in most of the fuzzy logic applications [16].

$$y_0 = \frac{\sum y \mu_{D_0}(y)}{\sum \mu_{D_0}(y)} \qquad \text{(Eq. 3)}$$

The non fuzzy value gives the output response (surface Roughness) value in numerical form and the fuzzy predicted values are tabulated in Table 6.

Table VI
Comparison of fuzzy predicted Ra value with experimental result

Sl. No	Speed	Feed	Tool Type	Coolant Type	Surface roughness (R_a)	Fuzzy predicted R_a
1	90	0.15	1	1	1.29	1.3227
2	90	0.2	2	2	0.52	0.4537
3	90	0.3	3	3	0.43	0.4537
4	90	0.36	4	4	0.65	0.6275
5	125	0.15	2	3	0.9	0.9751
6	125	0.2	1	4	0.54	0.4537
7	125	0.3	4	1	1.08	1.149
8	125	0.36	3	2	0.79	0.8013
9	315	0.15	3	4	0.28	0.3347
10	315	0.2	4	3	0.73	0.8013
11	315	0.3	1	2	1.3	1.3227
12	315	0.36	2	1	1.67	1.6152
13	450	0.15	4	2	0.52	0.4537
14	450	0.2	3	1	1.29	1.3226
15	450	0.3	2	4	0.51	0.4537
16	450	0.36	1	3	0.95	0.9751

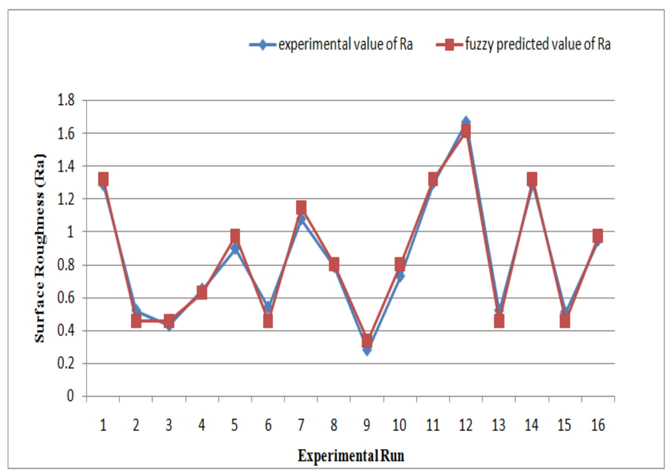

Fig 9 correlation between fuzzy predicted and experimental values of surface roughness (R_a)

From fig. 9 it is verified that the correlation exists between the surface roughness values obtained from experimental results and fuzzy modeling is highly satisfactory.

V. Conclusions

This paper has presented an application of Fuzzy logic modeling technique and ANOVA, Taguchi method for predicting and selecting the optimum parameter combination values of drilling parameters affecting the surface roughness in drilling of EN24 steel. The conclusions of the present work have been as follows:

1. Taguchi method has been found as the most efficient technique to analysis the surface roughness with respect to various drilling parameters combinations.
2. The level of most significant influential parameter on surface roughness is determined using ANOVA and the results revealed that coolant is most prevailing factor on the surface roughness of EN24 steel.
3. With proposed optimum conditions using Taguchi and ANOVA methods, a better surface roughness was obtained. The optimum levels were speed at 90 rpm, feed at 0.15 mm/rev, tool type is HSS with 5% cobalt and coolant is Kerosene.
4. Fuzzy logic modeling technique has been developed and used to predict the surface roughness and the results reveal that the predicted fuzzy values and experimental values of surface roughness are quite close to each other, which indicate that the surface roughness values can be predicated efficiently by fuzzy logic modeling technique in drilling of EN24 Steel.
5. The prediction accuracy of fuzzy logic modeling technique can be further improved by increasing the number of membership functions, number of variables and wider range of cutting conditions.

Acknowledgment

This research work has been conducted in the department of Mechanical Engineering in Sri Venkateswara University college of Engineering. The authors would like to acknowledge SVUCE for providing the research facilities and express their sincere gratitude to the authority of SVUCE.

References

i. *B. P. Patel, P. M. George, V. J. Patel, Experimental Studies on Perpendicularity of Drilling Operation using DOE, International Journal of Advance Engineering and Research Development, Volume 1,Issue 3, April 2014.*

ii. *Balinder Singh, Rajesh Khanna, Kapil Goyal, Pawan Kumar, Optimization of Input Process Parameters in CNC Milling Machine of EN24 Steel International Journal of Research in Mechanical Engineering & Technology, Vol. 4, Issue 1, Nov 2013 - April 2014.*

iii. *C. C. Tsao, H. Hocheng, Evaluation of thrust force and surface roughness in drilling composite material using Taguchi analysis and neural network, Journal of Materials Processing Technology 203, 342-348, 2008.*

iv. *C. Manikandan, B. Rajeswari, Study of Cutting Parameters On Drilling EN24 Using Taguchi Method, International Journal of Engineering Research & Technology, Vol. 2 Issue 7, July – 2013.*

v. *D.C. Montgomery, Design And Analysis Of Experiments, 5th Edn, John Wiley & Sons, Pp. 218-456, 2005.*

vi. *Erol Kilickap, Modeling and optimization of burr height in drilling of Al-7075 using Taguchi method and response surface methodology, Int J Adv Manuf Technol, 49:911–923, 2010.*

vii. *G Taguchi, Introduction to quality engineering, Asian Productivity Organization, Tokyo, 1990.*

viii. *Gul Tosun, Statistical analysis of process parameters in drilling of Al/SiCp Metal Matrix Composite, Int J Adv Manuf Technol, 55: 477-485, 2011.*

ix. *H. B. Bhaskar, Abdul Sharief, Dry Sliding Wear Behavior of Aluminium/Be3Al2 (SiO3)6 Composite Using Taguchi Method, Journal of Minerals and Materials Characterization and Engineering, 11, 679-684 2012.*

x. *J F Kelly, M G Cotterell, Minimal lubrication machining of aluminium alloys. J Mater Process Technol 120:327–334, 2002.*

xi. *K Raghukandan, K Hokamoto, P Manikandan, Optimization of process parameters in explosive cladding of mild steel and aluminum. Met Mater Int 10(2):193–197, 2004.*

xii. *L. Zadeh, Fuzzy sets, Information and Control 8, 338-353, 1965.*

xiii. *M Nouari, G List, F Girot, D Coupard, Experimental analysis and optimization of tool wear in dry machining of aluminium alloys. Wear 255:1359–1368, 2003.*

xiv. *M. Chandrasekaran, D. Devarasiddappa, Development of Predictive Model for Surface Roughness in End Milling of Al-SiCp Metal Matrix Composites using Fuzzy Logic, World Academy of Science, Engineering and Technology Vol:6, No. 7, 930-935, 2012.*

xv. *Rajesh Kumar Verma, Kumar Abhishek, Saurav Datta, Siba Sankar Mahapatra, "Fuzzy rule based optimization in machining of FRP composites" Turkish Journal of Fuzzy Systems, Vol.2, No.2, pp. 99-121, 2011.*

xvi. *S. A. Hussain, V. Pandurangadu, K. P. Kumar and V. V. Bharathi, A Predictive Model for Surface Roughness in Turning Glass Fiber Reinforced Plastics by Carbide Tool (K-20) Using Soft Computing, Jordan Journal of Mechanical and Industrial Engineering, Volume 5, Number 5, pp. 432 – 438, Oct. 2011.*

xvii. *T J Ross, Fuzzy logic with engineering applications, Int edn Mc-Graw Hill, New York, 1992.*

xviii. *T R Lin, R F Shyu, Improvement of tool life and exit burr using variable feeds when drilling stainless steel with coated drills. Int J Adv Manuf Technol 16:308–313, 2000.*

xix. *T. Rajasekaran, K. Palanikumar, B. K. Vinayagam, Application of fuzzy logic for modeling surface roughness in turning CFRP composites using CBN tool, Prod. Eng. Res. Devel., 5:191–199, 2011.*

xx. *Vishal Francis, S Ravi Singh, Nikita Singh, R Ali Rizvi, Santosh Kumar, Application of Taguchi method and ANOVA in Optimization of cutting parameters for material Removal rate and surface roughness in turning operation, International Journal of Mechanical Engineering and Technology, Volume 4, Issue 3, May – June, 2013.*

xxi. *Y. Shain, Optimization of Testing Parameters on the Wear Behavior of Metal Matrix Composites based on the Taguchi Method, Materials Science and Engineering A 408, 1-8, 2005.*