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Procedia Engineering 38 (2012) 3900 – 3912

Procedia Engineering

www.elsevier.com/locate/procedia

International conference on modelling,optimisation and computing (ICMOC – 2012)

Application of regression and fuzzy logic method for prediction of tool life

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Abstract

This paper presents a model for predicting tool life when end milling IS2062 steel using P30 uncoated carbide tipped tool under various cutting conditions. A tool life model is developed from regression model obtained by using results of the experiments conducted based on Taguchi's approach . A second model is developed based on fuzzy logic method for predicting tool life. The results obtained from fuzzy method are compared with regression model. The results of the fuzzy model is found to be more closer to experimental values.

Keywords: Tool life; Taguchi method; regression model; fuzzy

1. Introduction

In a metal cutting process, the most significant aspect of tool life assessment is the measure of tool life [1]. It is clear from[2][3][4]that the factors that affect tool life are divided in to three categories :viz., the machine, the machining parameters, and the workpiece material. The variables included in the machining category are the cutting speed, the feed rate, the depth of cut and the cutting fluid. Tool life prediction is an important factor that has profound influence on productivity in industrial activities. High metal removal rate is intended to reduce the manufacturing cost and operation time[5]. The productivity in terms of machining cost , machining operation and quality of the work piece and its integrity strongly depend on tool wear and consequently it depends on the life of the tool. The maximum utilisation of cutting tool is one of the ways for an industry to reduce its manufacturing cost[6]. In order to maximise gains from a machining process an accurate process model must be constructed for an end milling process with speed, feed and depth of cut as input variables and tool life as the output variable.

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doi:10.1016/j.proeng.2012.06.448

Taguchi technique is a scientific approach of conducting experiments to generate, analyse and interpret data so that valid conclusions can be drawn efficiently. Here, experiments are conducted to measure tool life based on Taguchi approach for three level three factors. The experimental values are used in statistical package Minitab 15 to form the regression model to predict the tool life. The accuracy of the model is tested using the analysis of variance technique (ANOVA). The regression model values are compared with fuzzy model values .

2.Literature survey

In the literature, tool wear and tool life model have been extensively studied. Oraby and Hayhurst [7] developed models for wear and tool life using non linear regression analysis techniques in terms of the variation of a ratio of force components acting at the tool tip. Richetti et al [8] investigated the effect of the number of tools used in face milling operations and related it to the establishment of a tool life under specified cutting conditions. Choudhury et al [9] predicted the response variables like flank wear, surface finish and cutting zone temperature in turning operations using design of experiments and the neural net work technique and the values obtained from both methods were compared with the experimental values to determine the accuracy of the prediction. Yongjin and Fischer [10] developed tool wear index (TWI) and the tool life model for analysing wear surface areas and material loss from the tool using micro-optics and image processing/analysis algorithms. Huang et al [11] developed a multiple regression model in detecting the tool breakage based on the resultant cutting forces in end milling operations. Srinivas and Kotaiah [12] developed a neural network model to predict tool wear and cutting force in turning operations for cutting parameters : viz., cutting speed, feed and depth of cut. Chattopadhyay [13] used the feed forward back propagation artificial neural net work for evaluation of wear in turning operations using carbide inserts taking speed, feed and depth of cut as input parameters. Thomas et al [14] investigated the effect of cutting parameters on tool stiffness and damping, and obtained an empirical model for predicting the behaviour of the tool stiffness variation. Arsecularatne [15] developed a semi empirical method for predicting tool life in machining with restricted contact (RC) tools. Lin et al [16] investigated the effect of a cutting tool's geometrical shapes on tool wear, roughness of the machined surface and cutting noise produced and constructed a tool life prediction system. Jaharah A G Hani et al [17] described the tool life model when end milling tool steel using coated carbide tipped tool. Yao et al.[27] present a new method of tool wear detection with cutting conditions and detected signals which includes the model of wavelet fuzzy neural network with acoustic emission and the model of fuzzy classification with motor current. Puri et al. [26] present the use of fuzzy logic in the Taguchi method to optimize Electro Dischargre Machining (EDM) process with multiple quality characteristics. QunRen et al.[24] presents a tool wear monitoring method using Takagi-Sugeno-Kang fuzzy approach. Palanikumar et al. [25] employ the Taguchi method with fuzzy logic to optimize the multiple performance characteristics of a machining process.

Prediction of tool life is an important study in metal cutting in order to maximize the utilisation of the tool and minimise the machining cost. The main goal of this work is to study the influence of cutting conditions such as cutting speed, feed and depth of cut on tool life in the end milling process. In this work , authors carry out experiments on mild steel using uncoated tungsten carbide insert. Here, experimental work is performed based on Taguchi approach . Then the regression model and fuzzy logic model are developed to predict tool life. This predicted values are compared with experimental values to determine prediction accuracy.

3 Tool life determination

Tool life can be defined as the length of cutting time that a tool can be used until catastrophic failure. The cutting tool should have a longer life. Conditions giving a very short tool life will be uneconomical because tool grinding and tool replacement cost will be high. There are a number of ways of expressing tool life such as (i) volume of metal removed (ii) number of work pieces machined and (iii) time units [18]. ISO standard 3685[19]dictates that the end of useful life is determined when a tool ceases to produce a desired part size and surface quality. In this work, allowable limit of flank wear is taken as the criteria for estimating tool life.

3.1.1 Tool life model

In this paper, Taguchi approach and regression method are applied to develop a mathematical model to predict the tool life for end milling of IS2062 steel. The relationship between the independent variables of process parameters (spindle speed, feed and depth of cut) and tool life can be represented by the following mathematical model

$$TL(\text{Tool life}) = C\,(v^{l} f^{m} d^{n}) \quad (1)$$

where , C is a model constant and l, m and n are model parameter. [16]

The above function (1) can be represented in linear mathematical form as follows

$$\ln TL = \ln C + l \ln v + m \ln f + n \ln d) \quad (2)$$

The equation (2) can be rewritten as under :

$$TL = \beta_0 + \beta_1 v + \beta_2 f + \beta_3 d \quad (3)$$

where TL is the measure of response (tool life), v, f ,d represent the values of the process parameter and $\beta_{0,}$ $\beta_{1,}$ β_2 ,β_3 represent the regression coefficients to be determined.

3.1.2 Development of the regression model

In this study, a multiple regression model is developed to predict tool life based on experimentally measured values. The coefficients for the regression model are determined using Minitab.

3.1.3 Steps in Taguchi approach

Taguchi approach is a systematic means of designing, conducting and analysing experiments which are of a great significance in quality planning. The steps in designing, conducting and analysing experiments are [20]as follows:

1. selection of factors for the study
2. selection of the number of levels for the factors
3. selection of appropriate orthogonal array
4. assignment of factors to columns
5. conduct of the test
6. analysis of the results

3.1.4 Selection of factors

Desired tool life may be achieved by properly selecting the independent process variable or factors which influence the surface quality. Specifications of the vertical milling machine,tool and the work piece used for the experiment are given in Table 1. In this work, spindle speed, feed and depth of cut are selected as factors to carry out the experimental work and the subsequent development of a mathematical model.

Table 1. Specification of vertical milling machine(Bharat Fritz Warner Ltd) , cutting tool and work piece

S.No	Parameter	value
1	Power of spindle motor	4 HP
2	Speed range of spindle motor	45- 2000 rpm
3	Power of feed motor	0.75 HP
4	Feed (X and Y direction)	16- 800 mm/ min
5	Cutting tool material	Uncoated tungsten carbide insert, (P 30 grade triangular shape)
6	Number of inserts	5
7	Diameter of insert holder	80mm
8	Work piece material	IS2062 steel
9	Hardness of work piece used	25HRC
10	Size of work piece	50 x 200 x 550 mm

3.1.5 Selection of the number of levels of the process variable

In order to develop the tool life prediction model , three factors at three levels each are selected. The selected process parameters for the experiment with their limits, units and notations are given in Table 2.

Table 2. Process variables and their levels

Process variable	units	notation	limits		
			1 (min)	2 (med)	3 (max)
Spindle speed	rpm	v	250	500	1000
feed	mm/min	f	50	80	125
Depth of cut	mm	d	0.1	0.15	0.2

3.1. 6 Selection of orthogonal array

The standard L18 orthogonal array[20] is shown in Table 3. From this standard table, column 2, 3 and 4 are selected for obtaining all combinations of three process parameters. This selected standard table in coded form and actual form are presented in a design matrix in Table 4. The experiments are conducted for all possible combinations of the parameter levels. These combinations are written in the form of a design matrix where the rows correspond to different trials and the columns to the levels of the parameter.

Table 3. L18 orthogonal array [20]

Trial no.	Factors							
	1	2	3	4	5	6	7	8
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

Table 4. Coded form and actual form

Trial No.	Coded form			Actual form		
	v	f	d	Speed rpm	Feed mm/min	Depth of cut mm
1	1	1	1	250	50	0.1
2	1	2	2	250	80	0.15
3	1	3	3	250	125	0.2
4	2	1	1	500	50	0.1
5	2	2	2	500	80	0.15
6	2	3	3	500	125	0.2
7	3	1	2	1000	50	0.15
8	3	2	3	1000	80	0.2
9	3	3	1	1000	125	0.1
10	1	1	3	250	50	0.2
11	1	2	1	250	80	0.1
12	1	3	2	250	125	0.15
13	2	1	2	500	50	0.15
14	2	2	3	500	80	0.2
15	2	3	1	500	125	0.1

16	3	1	3	1000	50	0.2
17	3	2	1	1000	80	0.1
18	3	3	2	1000	125	0.15

3.1.7 Conduct of the experiment as per the design matrix for the measurement of tool life

Machining experiments are conducted in a vertical milling machine as per the design matrix on IS2062 steel work piece material using an uncoated tungsten carbide tipped tool (P30 grade). The work piece(50 x 200 x 550mm) is placed with its longitudinal axis aligned with the direction of feed. The tests are carried out along the 550mm edge. The spectro analysis report of work piece material used is given in Table 5. Five inserts mounted on the tool holder are used in machining of workpiece in dry condition. Each experiment is started with a new cutting edge of an insert. The maximum flank wear of the tool for the use is 0.7mm [12]. In this work ,flank wear of tool upto 0.6 mm is considered as the limit. The cutting time is noted for different flank wear of 0.2mm, 0.4mm and 0.6mm.Flank wear is measured using ARCS Video measuring machine. Each experiment is continued until the flank wear limit (0.6mm) is reached. The tool life is obtained by summing up the cutting time of an insert for three stages of flank wear. The tool life values (response) and other values are presented in Table 6.

Table 5. Spectro analysis report of work piece

Material	Fe	C	Si	Mn	P	S	Cr	Mo	Ni	Al	Cu	Ti	V	W
Composition %	97.94	0.128	0.223	1.27	0.05	0.011	0.202	0.0272	0.0454	0.0503	0.0467	0.0092	0.0001	0.0009

Table 6. Measured values and responses

Trial No	Actual form			Measured cutting time up to flank wear of			Response
	Speed	Feed	Depth of cut	0.2 mm	0.4 mm	0.6 mm	Tool life (minutes)
1	250	50	0.1	25	27	28	80
2	250	80	0.15	24	26	24	74
3	250	125	0.2	21	20	21	62
4	500	50	0.1	18	16	17	51
5	500	80	0.15	14	15	14	43
6	500	125	0.2	12	11	10	33
7	1000	50	0.15	10	9	10	29
8	1000	80	0.2	6	5	7	18
9	1000	125	0.1	5	6	5	16
10	250	50	0.2	30	29	28	87
11	250	80	0.1	24	23	26	73
12	250	125	0.15	21	20	22	63
13	500	50	0.15	16	16	19	51
14	500	80	0.2	15	14	15	44
15	500	125	0.1	10	10	11	31
16	1000	50	0.2	9	10	8	27
17	1000	80	0.1	7	6	7	20
18	1000	125	0.15	5	5	5	15

3.2 Fuzzy model

Fuzzy logic has a lot of applications in the real world. Basically the system will accept the input or some inputs and then pass the inputs to a process called fuzzification. In the fuzzification process, input quantity (can be digital, precise/imprecise) will undergo some translation into linguistic quantity such as low, medium,high of physical properties. The translated data will be sent to an inference mechanism that will apply the predefined rules. The inference mechanism will generate the output in linguistic form. The linguistic output will go through defuzzification process to be in numerical form (the normal data form). Defuzzification is defined as the conversion of a fuzzy quantity represented by a membership function to precise or crisp quantity[22]. In this work , the Mamdani fuzzy inference system is selected and fuzzy model is depicted in Figure 1. Here, spindle speed, feed and depth of cut are used as input parameters and tool life is used as output parameter. For fuzzification of these parameters(factors) the linguistic variables low(L), medium (M) and high(H), are used for the inputs shown in Table 7 and the linguistic variables very low (VL), low(L), medium (M) , high(H) and very high(VH), are used for the output shown in Table 8. For the three inputs and one output, a fuzzy associated memory or decision(also called decision rule) is shown in Table. 7 .The inference mechanism is used for fuzzy reasoning on fuzzy rules to generate a fuzzy value. The concept of fuzzy reasoning for three-input-one output fuzzy logic unit is explained as follows. The fuzzy rule base consists of a group of IF-THEN statements with three inputs, x1, x2, and x3 and one output y, i.e.,

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

Rule 1 : if x1 is A2 and x2 is B2 and x3 is C2 then y is D2 else

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Rule 1 : if x1 is An and x2 is Bn and x3 is Cn then y is Dn.

Ai, Bi, Ci and Di are fuzzy subsets defined by the corresponding membership functions. In the present work, using MATLAB tool box three fuzzy subsets are assigned to the three inputs ,as shown in Fig 2-4. Five fuzzy subset are assigned to the output as shown in Fig 5. The relationship between input and out put variables is developed through fuzzy rules. Eighteen fuzzy rules are shown in Table 9. Triangular , Gaussian and trapezoidal membership functions are chosen to compare the results. Five defuzzification methods are selected in triangular membership functions. They are centroid, bisector, mean of maximum(mom) , largest of maximum (lom) and smallest of maximum (som).

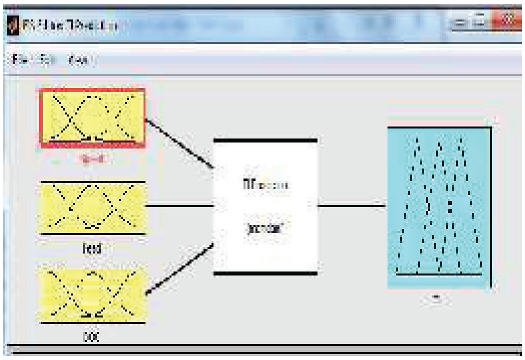

Figure 1. Fuzzy model

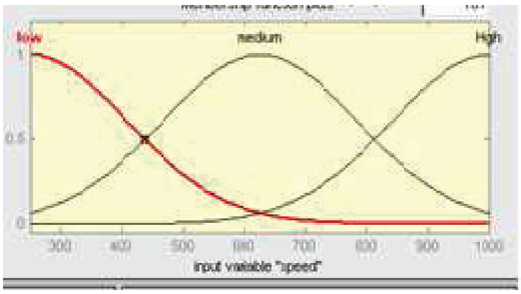

Figure 2. Gaussian Membership function-Speed

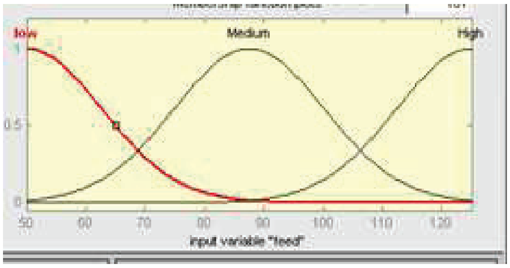

Figure 3. Gaussian Membership function-Feed

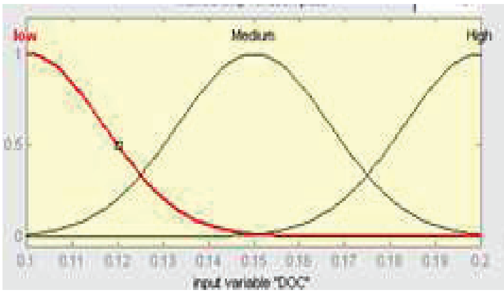

Figure 4. Gaussian Membership function-DOC

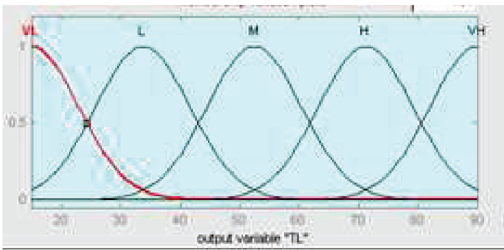

Figure 5. GaussianMembershipfunction-Tool life

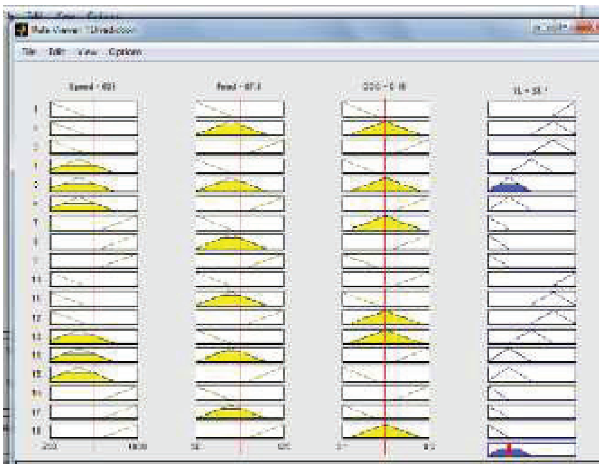

Figure 7. Rule viewer in Fuzzy

Table 7. Fuzzy input coded form

Process variable form			Linguistic variable form		
Spindle speed	feed	Depth of cut	Spindle speed	feed	Depth of cut
250	50	0.1	Low (L)	Low (L)	Low (L)
500	80	0.15	Medium (M)	Medium (M)	Medium(M)
1000	125	0.2	High (H)	High (H)	High (H)

Table 8. Fuzzy output coded form

Tool life	Linguistic form
15-30	Very low (VL)
31-45	Low (L)
46-60	Medium (M)
61-75	High (H)
76-90	Very High (VH)

Table 9. Fuzzy rules

Trial No.		Linguistic input variable				Linguistic output variable
		Spindle speed	feed	Depth of cut		Tool life
1		L	L	L		VH
2		L	M	M		H
3		L	H	H		H
4		M	L	L		M
5		M	M	M		L
6		M	H	H		L
7	IF	H	L	M	THEN	VL
8		H	M	H		VL
9		H	H	L		VL

10	L	L	H	VH
11	L	M	L	H
12	L	H	M	H
13	M	L	M	M
14	M	M	H	L
15	M	H	L	L
16	H	L	H	VL
17	H	M	L	VL
18	H	H	M	VL

4 Results and analysis

4.1 Determination of coefficients for regression model

The process model relates the independent variables to the dependent variables of the process. The relationships between these independent variables and dependent variables are to be determined by developing a regression based mathematical model. The regression model is obtained using the experimental data. Here, the first order polynomial model is used to form mathematical model. The first order model for these selected factors is given in equation (3). Minitab is employed to determine the regression coefficients for developing mathematical model. The value of the regression coefficients gives an idea as to what extent the independent variables affect the response quantitatively. The less significant coefficients can be eliminated along with the responses they are associated with , without affecting much of the accuracy of the model. To achieve this, the students t test is used. After finding the significant coefficients obtained using Minitab , the final model is developed using only the significant coefficients. The regression model for tool life developed based on the coefficients determined using the statistical package is given in (4).

$$\ln TL = 11.7- 0.924 \ln v - 0.49 \ln f + 0.0679 \ln d \quad (4)$$

The above model finally can be reduced to :

$$TL = 12057\, v^{-0.924} f^{-0.49} d^{0.0678} \quad (5)$$

This model indicates that spindle speed would have a significant effect on tool life value followed by feed.

4.2 Checking the accuracy of the model

The accuracy of the model is tested using analysis of variance technique (ANOVA). As per this technique (i) the higher the value of R^2, the more successful is the simple linear regression model in the desired level of confidence (say 95%)[21] (ii) adjusted $R^2 < R^2$, (iii) model p values less than the p values in the desired level of confidence (say 95%) and (iv) variance should be minimal. Table 10 shows that the model is satisfactory. The results of the experimental value obtained by using Minitab are depicted in Figure 6.

Table 10. R^2, adjusted R^2 and P value and variance from Minitab

Predictor	coefficient	SE coefficient	t	p
Constant	11.6854	0.3466	33.72	0.000
Speed	-0.92367	0.03508	-26.33	0.000
Feed	-0.48979	0.05308	-9.23	0.000
Depth of cut	0.06795	0.06983	0.97	0.347
Variance S= 0.0842432		R^2 = 98.2 %	Adjusted R^2 = 97.9 %	

Analysis of variance (ANOVA)

source	DF	SS	MS	F	P
Regression	3	5.5299	1.8433	259.73	0.000
Residual error	14	0.0994	0.0071		
total	17	5.6293			

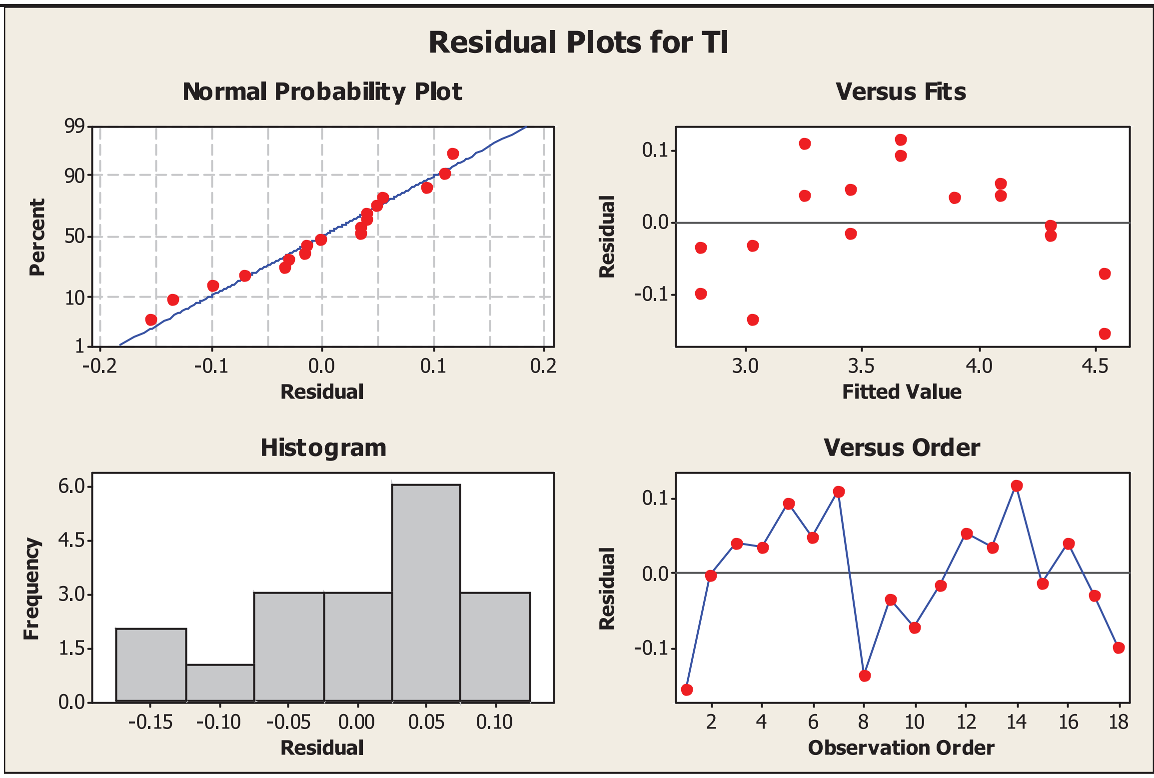

Figure 6. Normal probability plot, Histogram, residual vs fitted value and order

4.3 Fuzzy performance

The fuzzy model is validated by conducting prediction accuracy test using percentage error [23].

The percentage error of each prediction is used to determine the effectiveness of the fuzzy model. It is calculated based on the equation (1).

$$\text{Percentage error} = \frac{\text{predicted value} - \text{actual value}}{\text{actual value}} \times 100 \qquad (1)$$

The combination of Gaussian membership function and som gives less average error. Therefore, in Gaussian membership functions, som defuzzification method is considered .The fuzzy rule viewer of the established model is shown in Figure 7 . It indicates the behavior of the response over the change in values of all the significant machining parameters.

The surface models with two parameters showing two way interactions and relationships towards the desired response on tool life is shown Figures 8- 10.The plot is used to check the fuzzy rules and the membership functions on determining the effect of the input parameters on the output parameter such as tool life. Table 11 compares the predicted values of tool life by both models (i.e regression and fuzzy model) with the experimental values for the validation of experiments. The comparison is depicted in terms of % error in Figure 11. This shows that fuzzy logic model gives more accurate prediction on tool life.

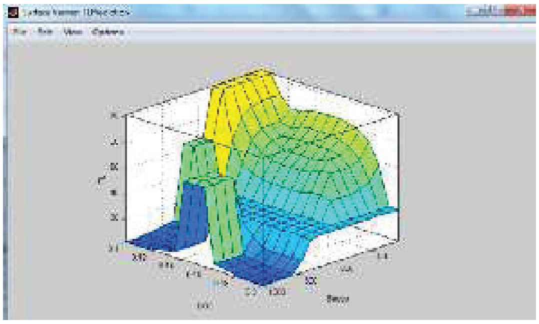

Figure 8. Tool life interaction with DOC and feed

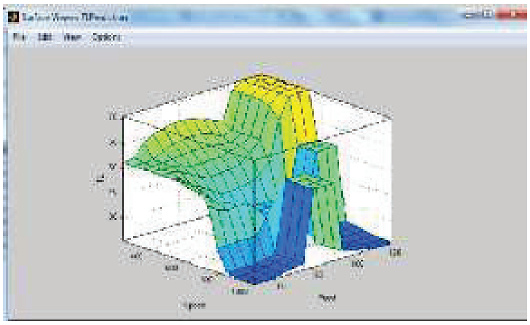

Figure 9. Tool life interaction with speed and feed

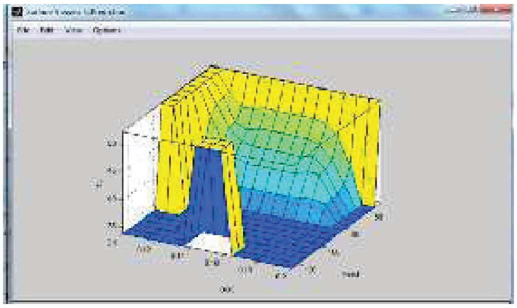

Figure 10.Tool life interaction with DOC and speed

Table 11. Predicted values and % error

Trial	Actual form	Response	Predicted values	% error

No				(Measured value)				
	speed	feed	Depth of cut	Tool life (minutes)	Using regression	Using fuzzy	Using regression	Using fuzzy
1	250	50	0.1	80	93.98	73	-17.48	8.75
2	250	80	0.15	74	76.49	72	-3.37	2.72
3	250	125	0.2	62	62.39	63	-0.62	-1.61
4	500	50	0.1	51	47.12	52	7.60	-1.96
5	500	80	0.15	43	38.51	42	10.44	2.33
6	500	125	0.2	33	31.41	32.2	4.82	2.42
7	1000	50	0.15	29	24.97	29.1	13.91	-0.34
8	1000	80	0.2	18	20.11	17.4	-11.69	3.33
9	1000	125	0.1	16	14.49	16	9.43	0
10	250	50	0.2	87	102.13	85	-17.39	2.29
11	250	80	0.1	73	72.68	72	0.44	1.37
12	250	125	0.15	63	60.16	62.9	4.51	0.16
13	500	50	0.15	51	49.59	51.5	2.76	-0.98
14	500	80	0.2	44	39.93	44.3	9.24	-0.68
15	500	125	0.1	31	28.78	31	7.15	0
16	1000	50	0.2	27	25.89	27.1	4.11	-0.37
17	1000	80	0.1	20	18.42	19.9	7.88	0.5
18	1000	125	0.15	15	15.25	15.1	-1.67	-0.67

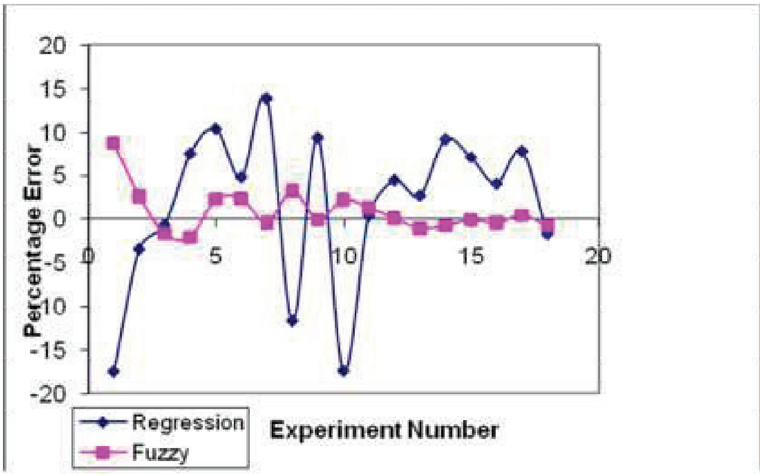

Figure 11 Comparison of errors in prediction of tool life

Conclusion

The paper highlights the use of Taguchi approach for conducting experiments. Two models(regression and fuzzy method) for predicting tool life in end milling are presented. The experimental values are used to develop the regression model and fuzzy logic model. The actual tool life values are compared with predicted values obtained from the regression model and fuzzy model. The fuzzy model is found to be capable of giving better prediction of tool life. The results of the fuzzy model also indicate that it is much more accurate in predicting the values of tool life when compared with the regression model.

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