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Research Article

Fuzzy and Regression Modelling of Hard Milling Process

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Abstract: The present study highlights the application of box-behnken design coupled with fuzzy and regression modeling approach for making expert system in hard milling process to improve the process performance with systematic reduction of production cost. The important input fields of work piece hardness, nose radius, feed per tooth, radial depth of cut and axial depth cut were considered. The cutting forces, work surface temperature and sound pressure level were identified as key index of machining outputs. The results indicate that the fuzzy logic and regression modeling technique can be effectively used for the prediction of desired responses with less average error variation. Predicted results were verified by experiments and shown the good potential characteristics of the developed system for automated machining environment.

Keywords: Box-behnken design, cutting forces, fuzzy logic, hard milling, sound, temperature

INTRODUCTION

In manufacturing process, hard milling recently paid great attention to produce engineering components in shortest route compared with EDM (Gopalsamy *et al*., 2010). The numerous benefits are large metal removal rate, less the thermal damage etc. Recent research work on hard milling studies have been carried out on mold and die steels (Ding *et al*., 2010; Cahskan *et al*., 2013). Machining of these materials in the hardness range between 45-60 HRC. During machining, the high hardness of work piece possibly to produce high heat generation in the cutting zone compared with conventional machining. This rapidly increase the cutting forces, tool wear etc., (Ozel *et al*., 2005; Dureja *et al*., 2009). Since, there are many variables involved and defining a single model is very difficult, due complexity and non-linearity of hard milling process. Nowadays, artificial intelligence approaches are used various manufacturing processes. Among many approaches, a fuzzy logic showed that to establish the model in easy way and less hardware and software resources. Many investigators modeled machining process using a fuzzy logic technique. Iqbal *et al*. (2007a) developed online and offline fuzzy models for hard milling process. The length of cut was considered as input for offline strategy and cutting force signals were in account for online strategy to determine a flank wear on both strategies. Ramesh *et al*. (2008) promised that, the adopted fuzzy expert system successfully predicting the three performance measures of tool wear, surface roughness and specific cutting pressure in machined titanium alloy. This ensures a guarantee for better output quality with least investment in production. A triangular membership function was chosen, each input variable was assigned three fuzzy sets and each output variable ranged in nine fuzzy sets for evaluation. Rajsekaran *et al*. (2011) modeled the surface roughness by fuzzy sets in turning of CFRP composite using CBN tool. An overall average percentage error obtained as low as 6.62%. Iqbal *et al*. (2007b) designed fuzzy expert system for optimizing and predicting the performance measures in hard milling of AISI D2 tool steel. The expert system supports to minimize the production cost and same time to improve the product quality. Kovac *et al*. (2013) conducted the dry face milling tests on AISI 1060 medium carbon steel using carbide inserts. A regression equation is developed and mamdani based fuzzy logic modeling has been done using Gaussian membership function. The fuzzy average error (i.e., 7.41%) produced lower than regression average error (i.e., 10.91%). Latha and Senthilkumar (2009) used triangular and trapezoidal membership functions for fuzzy rule based modeling in drilling of GFRP composites for surface roughness evaluation. They stated that trapezoidal membership functions achieved better validated output. Hanafi *et al*. (2012) used an integrated response surface method with fuzzy logic for machining of PEEK CF30 using TiN coated tools. Quadratic regression equations are developed for measured cutting force, cutting power and specific cutting pressure. The fuzzy logic models were predicted well with experimental results than regression model

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predicted values. For validation, nine experiments randomly conducted within the range and verified successfully with consistent error. Cabrera *et al*. (2011) studied the predictive fuzzy modeling of surface roughness parameters (R_a and R_t) in turning of reinforced Polyetheretherketone (PEEK) with carbon fibre 30% using TiN coated carbide tool. Triangular and trapezoidal membership functions effectively used to correlate with experimental results. The co-efficient of correlation obtained near one, which is the evident that the fuzzy rule based model effectively used to predict variables. Further, the fuzzy logic modeling widely applied and successfully modeled in surface grinding (Ali and Zhang, 2004), Submerged are welding (Singh *et al*., 2011), Abrasive water jet cutting (Chakravarthy and Babu, 2000; Vundavilli *et al*., 2012), Micro-hole EDM (Chun *et al*., 2008), Electro-chemical machining (Labib *et al*., 2011), Laser cutting (Pandey and Dubey, 2012), sludge dewatering process (Zhai *et al*., 2012) and plasma arc cutting (Özek *et al*., 2012) applications. In present study performs hard milling experiments in OHNS (Type O1) tool steel using coated (TiN+TiAlN) carbide inserts by the selected process variables. The performance measures are cutting forces, work piece surface temperature and sound pressure level. Further, build up an accurate hard milling information system using regression and fuzzy modeling techniques.

METHODOLOGY

Hard milling experiments:

Experimental planning: Response surface methodology based Box-Behnken Design (BBD) statistical technique is preferred to quantify the relationship between input variables and output variables. Box-behnken designs generally allowed each factor on three levels and fitting the second-order polynomial equations effectively (Montgomery, 2012). Based on preliminary trials and literature study, the five factors are namely work piece Hardness (HRC), nose radius (r_e), feed per tooth (f_z), radial depth of cut (a_e) and axial depth of cut (a_p) selected for the experimental work. The range of each factor as shown in Table 1. The coded values of each factor was found by the following equation:

$$X_i = \frac{x_i - x_0}{\Delta x_i}, \; i = 1, 2, 3 \tag{1}$$

where,

X_i = The coded value of input variable x_i

x_i = The actual variable of input variable

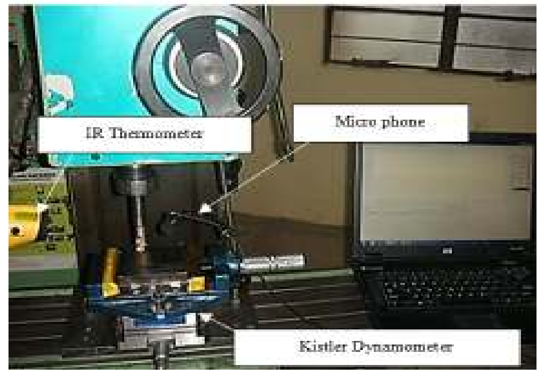

Fig. 1: Hard milling experimental setup

x_0 = The real value of the input variable x_i at the center point of cube

Δx_i = The step change within the experimental range

Experimental work: The work pieces were prepared as the required hardness levels with an accuracy of ±0.5 HRC and final dimensions obtained as 100×100×25 mm. A Heavy duty-milling (4HP power drive with maximum spindle speed of 3400 rpm) machine, suggested inserts and tool holder were employed. Each experiment done by three times and a fresh insert used to eliminate the statistical errors. The experiments carried out randomly and no coolant was preferred. A cutting force acquisition system consists of Kistler dynamometer (9257B type), charge amplifier (5070 type) and computer. An infrared thermometer (8839 type) captures a machined surface temperature near the chip obstruction at the underneath of the insert by pointing out a laser beam. A sound measurement unit consists of microphone connected to a computer. During machining, a detected cutting sound was stored in the computer and analyzed by "SEAWAVE" audio software. A machine idling sound gathered before the starting experiment. Further, an exact cutting sound was evaluated by subtracting the idle sound. The data's of forces in three directions, work piece surface temperature and cutting sound were collected using different acquisition systems from the hard milling experimental setup as shown in Fig. 1. The average of peak points considered to evaluate an each response variable. The evaluated values of all responses for each experiment as depicted in Table 2.

Modeling techniques:

Regression modeling: The BBD models the each response using the empirical second-order polynomial:

Table 1: Factors and levels

	Factors				
Level	Work piece Hardness (HRC)	Nose radius (r_e)	Feed per tooth (f_z)	Radial depth of cut (a_e)	Axial depth of cut (a_p)
Low (-1)	45	0.8	0.050	0.30	0.5
Medium (0)	50	2.0	0.125	0.55	1.0
High (+1)	55	3.2	0.200	0.80	1.5

Table 2: BBD matrix with responses

	Factors					Responses				
Exp. No.	HRC	r_e	f_z	a_e	a_p	F_x	F_y	F_z	WST	SPL
1	45	0.8	0.125	0.55	1.0	541.34	402.05	366.77	266.44	71.08
2	55	0.8	0.125	0.55	1.0	794.33	1165.10	1255.07	417.13	71.87
3	45	3.2	0.125	0.55	1.0	593.35	605.39	790.05	513.80	83.54
4	55	3.2	0.125	0.55	1.0	610.79	1256.78	1293.70	590.11	84.58
5	50	2.0	0.050	0.30	1.0	312.57	526.44	470.18	367.20	60.72
6	50	2.0	0.200	0.30	1.0	352.90	959.16	968.76	560.65	90.98
7	50	2.0	0.050	0.80	1.0	204.46	644.38	635.10	480.35	67.09
8	50	2.0	0.200	0.80	1.0	807.46	1129.46	1097.47	569.35	96.77
9	50	0.8	0.125	0.55	0.5	542.58	749.46	701.98	413.98	67.76
10	50	3.2	0.125	0.55	0.5	311.23	600.13	786.24	491.04	70.85
11	50	0.8	0.125	0.55	1.5	833.55	588.85	799.53	530.05	79.69
12	50	3.2	0.125	0.55	1.5	675.11	1043.02	1053.46	724.03	100.85
13	45	2.0	0.050	0.55	1.0	550.23	335.64	361.05	358.51	60.08
14	55	2.0	0.050	0.55	1.0	472.90	1017.98	1015.48	388.51	68.96
15	45	2.0	0.200	0.55	1.0	456.34	756.32	763.89	470.12	86.88
16	55	2.0	0.200	0.55	1.0	854.46	1467.65	1429.41	678.51	97.03
17	50	2.0	0.125	0.30	0.5	183.68	547.68	591.28	429.66	63.23
18	50	2.0	0.125	0.80	0.5	249.47	762.24	769.87	459.89	64.96
19	50	2.0	0.125	0.30	1.5	609.68	752.90	872.34	618.42	95.55
20	50	2.0	0.125	0.80	1.5	747.57	869.94	966.84	660.87	107.76
21	50	0.8	0.050	0.55	1.0	787.35	519.13	498.69	339.64	54.65
22	50	3.2	0.050	0.55	1.0	295.68	667.01	744.19	501.27	70.88
23	50	0.8	0.200	0.55	1.0	743.57	980.88	994.77	478.51	87.04
24	50	3.2	0.200	0.55	1.0	797.68	1126.34	1158.71	696.34	90.78
25	45	2.0	0.125	0.30	1.0	527.68	391.26	409.27	381.20	83.04
26	55	2.0	0.125	0.30	1.0	301.35	1188.19	1214.51	441.51	83.54
27	45	2.0	0.125	0.80	1.0	302.88	621.47	627.69	362.66	88.37
28	55	2.0	0.125	0.80	1.0	672.68	1237.58	1250.01	522.74	89.01
29	50	2.0	0.050	0.55	0.5	234.24	523.62	528.87	419.43	58.98
30	50	2.0	0.200	0.55	0.5	383.68	863.45	891.24	555.12	79.76
31	50	2.0	0.050	0.55	1.5	430.57	585.16	718.69	529.66	83.76
32	50	2.0	0.200	0.55	1.5	878.77	1136.16	1147.52	740.58	104.56
33	45	2.0	0.125	0.55	0.5	186.46	438.47	442.86	398.20	68.02
34	55	2.0	0.125	0.55	0.5	569.80	1057.69	1197.31	379.51	68.98
35	45	2.0	0.125	0.55	1.5	656.46	508.95	691.84	434.89	98.77
36	55	2.0	0.125	0.55	1.5	843.24	1298.52	1311.51	720.97	95.84
37	50	0.8	0.125	0.30	1.0	623.57	536.83	563.56	347.82	80.92
38	50	3.2	0.125	0.30	1.0	287.89	851.03	915.95	542.19	81.56
39	50	0.8	0.125	0.80	1.0	538.68	841.26	871.84	395.28	86.41
40	50	3.2	0.125	0.80	1.0	583.79	846.22	848.03	582.42	90.66
41	50	2.0	0.125	0.55	1.0	424.79	655.22	644.18	437.12	86.56
42	50	2.0	0.125	0.55	1.0	380.66	660.61	670.04	439.12	85.01
43	50	2.0	0.125	0.55	1.0	464.90	657.35	636.71	421.12	83.71
44	50	2.0	0.125	0.55	1.0	453.08	671.79	656.86	410.12	86.89
45	50	2.0	0.125	0.55	1.0	494.35	679.44	640.69	434.12	90.28
46	50	2.0	0.125	0.55	1.0	433.74	663.42	661.06	432.12	87.67

$$Y=\beta_0+\sum_{i=1}^{k}\beta_i x_i+\sum_{i=1}^{k}\beta_{ii}x_i^2+\sum_i\sum_j\beta_{ij}x_i x_j+\varepsilon \quad (2)$$

where,

Y	= The process response
k	= The number of the patterns
i and j	= The index numbers for pattern
β_0	= The mean of each observed responses
$x_1, x_2, \cdots, x_k$	= The coded independent variables
β_i	= The main effect
β_{ii}	= The quadratic effect
β_{ij}	= The interaction effect
ε	= The random experimental error component

The goodness of fit for the developed equations was analyzed through co-efficient of determination (R^2).

Fuzzy modeling: The performance measures of hard milling variables are largely probabilistic rather than deterministic. A fuzzy logic expert system provides to solve such a problem in simple and reliable manner. The theory of fuzzy set was introduced by Zadeh (1965), which deals uncertain and vague information. In any fuzzy set comprises of infinite number of membership functions that maps a universe of objects, say X is a set characterized, onto the unit interval (0, 1). Three main tasks performed in fuzzy modeling, namely as fuzzification, fuzzy inference and defuzzification. In fuzzification unit, crisp numerical input variables appropriately convert into fuzzy set based on defined membership functions. Next, the fuzzy inference engine workout on the basis defined 'IF-THEN' rules and membership functions that are applicable for any given input parameters and desired objective. The output

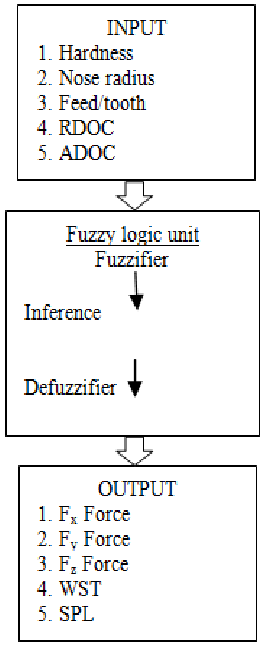

Fig. 2: Fuzzy logic architecture for hard milling process

obtained from an inference module is still fuzzy value. Further, a defuzzification unit converts fuzzy quantity into crisp value. The operation is opposite to the fuzzifier unit. A schematic fuzzy logic computing architecture of hard milling process as illustrated in Fig. 2. In fuzzy modeling, the input and output variables are treated as system variables. After deciding upon system variables, the next step was to define the all membership functions and universe of discourse for each variable. The memberships functions are defined by common shapes are triangle, trapezoidal, Gaussian and PI curve. Triangular membership function was chosen for defining a both input and output variables. Because, it needs only a three parameters comparatively with other membership functions (Rajasekaran *et al.*, 2011). A general equation described for triangle membership function as:

$$Triangle(x;a,b,c) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases} \tag{3}$$

where, a, b, c indicates for the triangular fuzzy triplet and x is a variable. The three fuzzy sets are assigned for each input variable as Low (L), Medium (M) and High (H). For example, defined membership function for work piece hardness was depicted in Fig. 3. Similarly, nine fuzzy sets were set as Extremely Low (EL), Lowest (LT), Lower (LR), Low (L), Medium (M), High (H), Higher (HR), Highest (HT), Extremely High (EH) for each output variable. The defined membership functions graphically illustrated for F_x force in Fig. 4. Based on the premise, the fuzzy rules were

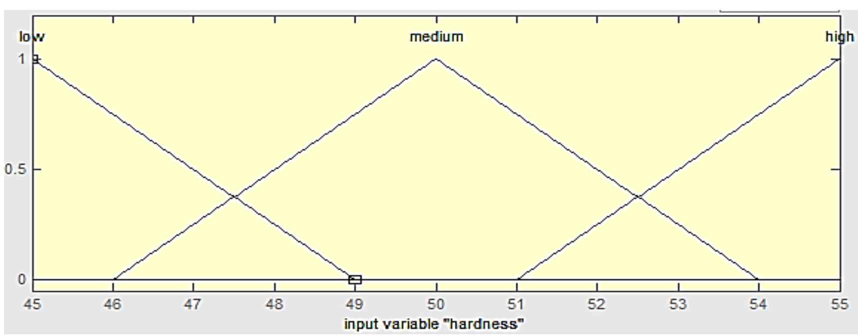

Fig. 3: Membership functions for work piece hardness

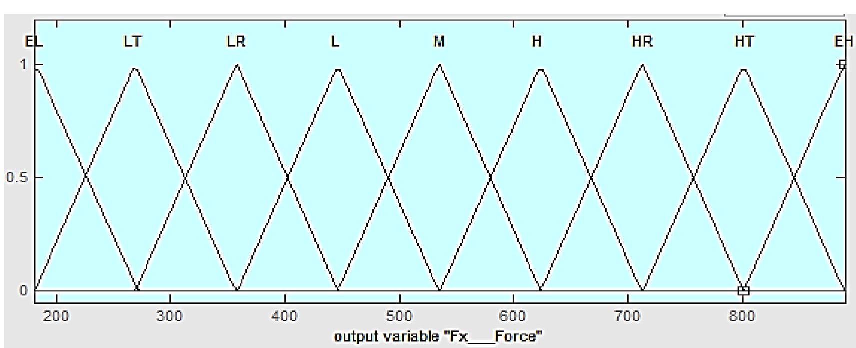

Fig. 4: Membership functions for F_x force

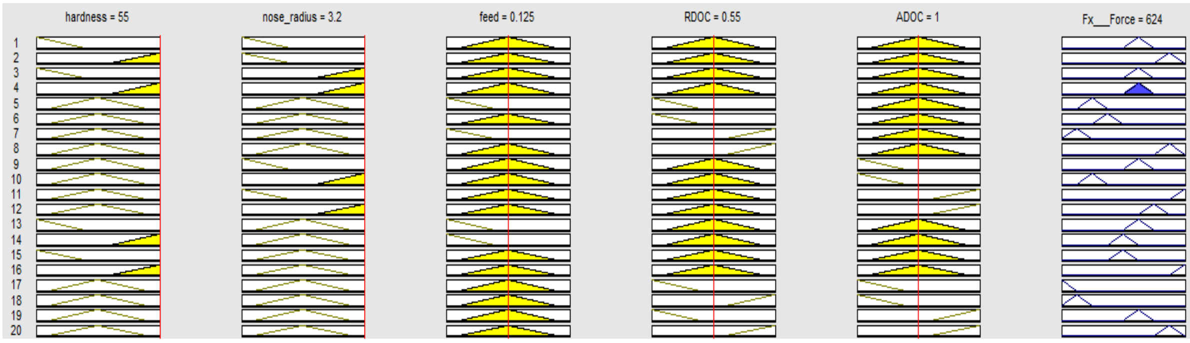

Fig. 5: Rule viewer

generated within the available system variables. The membership functions and rules were formulated based on human knowledge to get desired effect. Typically, forty-six set of 'IF-THEN' conditional rules were composed for five inputs and one output formulated 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 and x_5 is E_1, then y is F_1; else
Rule 2: If x_1 is A_2 and x_2 is B_2 and x_3 is C_2 and x_4 is D_2 and x_5 is E_2, then y is F_2; else
Rule 3: If x_1 is A_3 and x_2 is B3 and x_3 is C_3 and x_4 is D_3 and x_5 is E_3, then y is F_3; 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 and x_5 is E_n, then y is F_n; else

A_i, B_i, C_i, D_i, E_i and F_i are fuzzy subsets defined by the corresponding membership functions of μ_{Ai}, μ_{Bi}, μ_{Ci}, μ_{Di}, μ_{Ei} and μ_{Fi} respectively. x and y are input and output variables. Mamdani and sugeno fuzzy models are of two fuzzy inference systems are commonly adopted for fuzzy modelling work. However, many real world problems solved by Mamdani method (Latha and Senthilkumar, 2009; Hanafi *et al*., 2012; Ramesh *et al*., 2008). The reason is simple and ease to use comparatively with other membership functions. By adopting mamdani implication method (Max-min approach), the fuzzy reasoning of these rules evaluated to obtain a fuzzy output. The membership function of the output of fuzzy reasoning can be expressed as:

$$\mu_{F_0}(y) = [\mu_{A_1}(x_1)\wedge\mu_{B_1}(x_2)\wedge\mu_{C_1}(x_3)\wedge\mu_{D_1}(x_4)\wedge\mu_{E_1}(x_5)\wedge\mu_{F_1}(y_1)\vee\ldots\ldots \mu_{A_n}(x_1)\wedge\mu_{B_n}(x_2)\wedge\mu_{C_n}(x_3)\wedge\mu_{D_n}(x_4)\wedge\mu_{E_n}(x_5)\wedge\mu_{F_n}(y_1)\vee] \quad (4)$$

where, $\wedge$ is the minimum operation and $\vee$ is the maximum operation. At last, a centroid method is used to obtain non-fuzzy value by using the equation:

$$y_0 = \frac{\sum y\mu_{D_0}(y)}{\sum \mu_{D_0}(y)} \quad (5)$$

where,
y_0 = Defuzzified output of each response variable
y = Output variable (i.e., center value of regions)
$\mu_{D_0}(y)$ = Aggregated membership function

RESULTS AND VERIFICATION

Table 2 Represents, the functional relationship between the input and output variables. The experimental results are used to get the mathematical models. The regression equations were obtained and analyzed by Design expert statistical software. The insignificant model terms were removed at 95% confidence interval (i.e., α = 0.05). The reduced suitable regression models as follows in actual form as:

$$F_x = 12040.51 - 338.200HRC - 747.19r_e - 23.342f_z - 6016.06a_e + 127.7a_p + 0.316966HRC \times f_z + 119.2HRC \times a_e + 1.516r_e \times f_z + 317.3r_e \times a_e + 7.50f_z \times a_e + 1.9f_z \times a_p + 2.4HRC^2 + 79.52r_e^2 - 1173.43a_e^2 \; (R^2 = 0.9185) \quad (6)$$

$$F_y = 10651.86 - 471.21HRC + 25.9r_e - 3.054f_z + 1824.42a_e - 1427.2\,a_p - 4.65HRC \times r_e - 36.16HRC \times a_e + 17.03HRC \times a_p - 257.70\,r_e \times a_e + 251.4\,r_e \times a_p + 0.698\,f_z \times a_e + 1.40f_z \times a_p - 195.03\,a_e \times a_p + 5.537HRC^2 + 40.02\,r_e^2 + 0.017\,f_z^2 + 824.35_e^2 + 79.48\,a_p^2 \; (R^2 = 0.9992) \quad (7)$$

$$F_z = 10706.28 - 534.4HRC + 698.6r_e - 0.84f_z + 1754.49\,a_e + 33.7a_p - 16.0HRC \times r_e - 36.58HRC \times a_e - 13.47HRC \times a_p - 313.50r_e \times a_e + 70.69\,r_e \times a_p + 6.68HRC^2 + 71.12\,r_e^2 + 0.0149\,f_z^2 + 879.054\,a_e^2 + 352.64\,a_p^2 \; (R^2 = 0.9943) \quad (8)$$

$$WST = 1194.23 + 18.44HRC - 46.38\,r_e - 6.340\,f_z - 1043.70\,a_e - 2106.6\,a_p + 0.11HRC \times f_z + 19.954HRC \times a_e + 30.4HRC \times a_p + 48.71r_e \times a_p - 1.39f_z \times a_e - 0.628\,HRC^2 + 18.32\,r_e^2 + 0.009\,f_z^2 + 278.468a_e^2 + 330.98a_p^2 \; (R^2 = 0.9767) \quad (9)$$

Table 3: Average error for each model

Approach	F_x	F_y	F_z	WST	SPL
Fuzzy	0.810	0.77	-0.3	0.26	0.34
Model	-1.660	0.02	-0.1	-0.15	-0.30

Table 4: Experimental settings for verification and results

Trial No.	HRC	r_e	f_z	a_e	a_p		F_x	F_y	F_z	WST	SPL
1	50	3.2	0.18	0.7	1.2	Exp	942.87	1147.32	1145.65	701.32	95.22
						Fuzzy	940.49	1140.34	1139.43	710.98	97.40
						Model	937.22	1141.71	1130.43	700.42	99.64
2	50	2.0	0.20	0.4	1.0	Exp	436.26	952.46	934.23	570.43	91.24
						Fuzzy	435.34	958.08	935.35	573.34	92.84
						Model	431.11	951.29	933.27	574.94	90.78
3	50	0.8	0.16	0.6	0.7	Exp	544.85	852.45	812.67	422.65	71.44
						Fuzzy	548.32	849.67	818.32	427.78	75.85
						Model	541.22	845.43	817.21	412.55	76.12

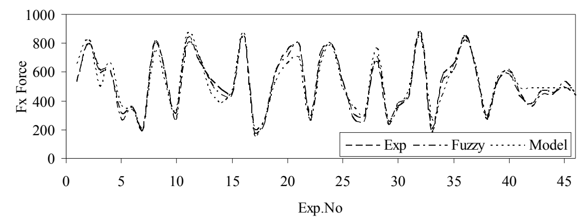

Fig. 6: F_x force comparative graph for experimental, fuzzy and model

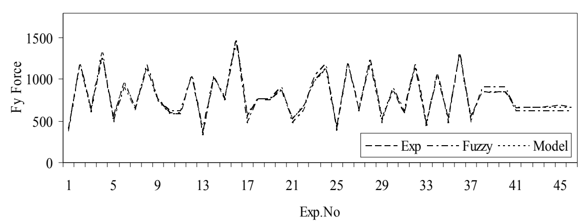

Fig. 7: F_y force comparative graph for experimental, fuzzy and model

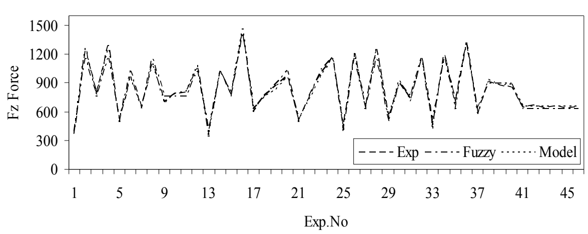

Fig. 8: F_z force comparative graph for experimental, fuzzy and model

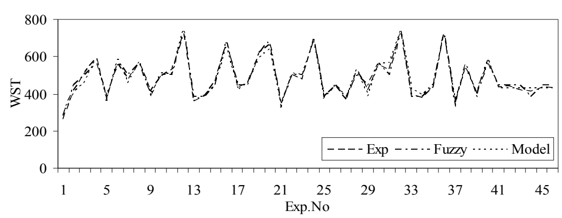

Fig. 9: WST comparative graph for experimental, fuzzy and model

$$SPL = 10.00 + 7.34\, r_e + 0.402\, f_z + 12.8\, a_e + 12.97\, a_p + 7.52\, r_e \times a_p - 2.750\, r_e^2 - 0.00091 f_z^2 \quad (R^2 = 0.9132) \tag{10}$$

All equations contain linear, interaction and quadratic terms. A measure of overall performance of

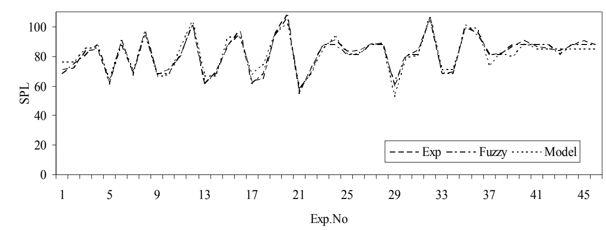

Fig. 10: SPL comparative graph for experimental, fuzzy and model

the models referred to R^2 value. The response variables for each experiment can be calculated within the range of the factors investigated in this study by substituting values of the input process parameters in Eq. (6)-(10). The values of R^2 were obtained as 0.9185 for F_x, 0.9992 for F_y, 0.9943 for F_z, 0.9767 for WST and 0.9132 for SPL. When R^2 approaches near unity, the better the response model fits the actual data and the difference between the predicted and actual values was less. For example, R^2 is obtained to 91.85%, which indicates that the hard milling process parameters explain in 91.05% of variance for F_x-Force. The fuzzy models were developed and computed using Fuzzy tool box in MATLAB 2010b. Through the fuzzy modeling, the F_x force of 624 N was obtained for the inputs of work piece hardness of 55 HRC, nose radius of 3.2 mm, feed per tooth of 0.125 mm, radial depth of cut of 0.55 mm and axial depth of cut of 1 mm (Experiment no 4) as illustrated in Fig. 5. The accuracy of the predicted values were checked with experimental values within the BBD experimental domain. It has been observed from Fig. 6 to 10, that the performance of both regression and fuzzy models were exhibited a better robustness to match its experimental value well. The average error variations for each model as depicted in Table 3. In order to validate the developed models, the verification experiments were randomly carried out and compared with the predicted values of all response values as illustrated in Table 4. The tabulated results were confirming the reliability of developed systems.

CONCLUSION

This study summarizes on innovative implementation of expert systems for hard milling of tool steel (Type O1) using coated carbide inserts. A box-behnken design effectively utilized for experimental work. The predictions of machining outputs were achieved through regression and fuzzy modeling. The promising results were obtained with very consistent average error variations (±1.5%). The great improved results were shown from the results of verification test for both developed models.

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