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.

Keywords: Box-behnken design, cutting forces, fuzzy logic, hard milling, sound, temperature
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 \((R_s\) and \(R_z\)) 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 arc welding (Singh et al., 2011), Abrasive water jet cutting (Chakravarthi 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 \((a_o)\) 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:

\[
x'_i = \frac{x_i - x_0}{\Delta x_i} , \quad i = 1, 2, 3
\]

where,

- \(X'_i\) = The coded value of input variable \(x_i\)
- \(x_i\) = The actual variable of input variable
- \(x_0\) = The real value of the input variable \(x_i\) at the center point of cube
- \(\Delta x_i\) = 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:
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
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:

$$\text{Triangle}(x; a, b, c) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & c \leq x \end{cases}$$

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. 2: Fuzzy logic architecture for hard milling process

Fig. 3: Membership functions for work piece hardness

Fig. 4: Membership functions for $F_x$ force
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 $B_3$ 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

$A_1, A_2, A_3, D_n, E_i$ and $F_i$ are fuzzy subsets defined by the corresponding membership functions of $\mu_{A_1}, \mu_{B_1}, \mu_{C_1}, \mu_{D_1}, \mu_{E_1}$ and $\mu_{F_1}$ 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:

$$\mu_{C}(y)=\left[\mu(x_1) \land \mu(x_2) \land \mu(x_3) \land \mu(x_4) \land \mu(y)\right] \forall$$

$$\mu_{C}(x_i) \land \mu(x_2) \land \mu(x_3) \land \mu(x_4) \land \mu(y)\forall$$

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

$$y_0 = \sum y\mu_{D_i}(y) / \sum \mu_{D_i}(y)$$

where, $y_0$ = Defuzzified output of each response variable $y$ = Output variable (i.e., center value of regions) $\mu_{D_i}(y)$ = 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., $\alpha = 0.05$). The reduced suitable regression models as follows in actual form as:

$$F_1 = 12040.51 - 338.200HRC - 747.19r_c - 23.342f_e - 6016.06a_e + 127.7a_p + 0.316966HRC \times f_e + 119.2HRC \times a_e + 1.516r \times f_e + 317.3r \times a_e + 7.50f_e \times a_e + 1.9f_e \times a_p + 2.4HRC^2 + 79.52r_c^2 + 1173.43a_e^2$$

$$R^2 = 0.9185$$

(6)

$$F_2 = 10651.86 - 471.21HRC + 25.9r_c - 3.054f_e + 1824.42a_e - 1427.2 a_p - 4.65HRC \times r_c - 36.16HRC \times a_e + 17.03HRC \times a_p - 257.70 r_c \times a_e + 251.4 r_c \times a_p + 0.698 f_e \times a_e + 1.40f_e \times a_p - 195.03 a_e \times a_p + 5.537HRC^2 + 40.02 r_c^2 + 0.017 f_e^2 + 824.35r_c + 79.48 a_e^2$$

$$R^2 = 0.9992$$

(7)

$$F_3 = 10706.28 - 534.4HRC + 698.6r_c - 0.84f_e + 1754.49 a_e + 33.7a_p - 16.0HRC \times r_c - 36.58HRC \times a_e - 13.47HRC \times a_p - 313.50r_c \times a_e + 70.69 r_c \times a_p + 6.68HRC^2 + 71.12 r_c^2 + 0.0149 f_e^2 + 879.054 a_e^2 + 352.64 a_p^2$$

$$R^2 = 0.9943$$

(8)

$$WST = 1194.23 + 18.44HRC - 46.38 r_c - 6.340f_e - 1043.70 a_e - 2106.6 a_p + 0.111HRC \times f_e + 19.954HRC \times a_e + 30.4HRC \times a_p + 48.71r_c \times a_e - 1.39f_e \times a_e - 0.628 HRC^2 + 18.32 r_c^2 + 0.009 f_e^2 + 278.468a_e^2 + 330.98a_p^2$$

$$R^2 = 0.9767$$

(9)

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<th>Approach</th>
<th>$F_1$</th>
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<th>$F_3$</th>
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<th>SPL</th>
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<td>0.02</td>
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<td>-0.15</td>
<td>-0.30</td>
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Table 3: Average error for each model
Table 4: Experimental settings for verification and results

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<tr>
<th>Trial No</th>
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<th>re</th>
<th>f</th>
<th>a</th>
<th>dp</th>
<th>Fx</th>
<th>Fy</th>
<th>Fz</th>
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<td>1</td>
<td>50</td>
<td>3.2</td>
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<td>0.7</td>
<td>1.2</td>
<td>942.87</td>
<td>1147.32</td>
<td>1145.65</td>
<td>701.32</td>
<td>95.22</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
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<td>1140.34</td>
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<td>700.42</td>
</tr>
<tr>
<td>2</td>
<td>50</td>
<td>2.0</td>
<td>0.20</td>
<td>0.4</td>
<td>1.0</td>
<td>436.26</td>
<td>952.46</td>
<td>934.23</td>
<td>570.43</td>
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</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>Fuzzy</td>
<td>435.34</td>
<td>958.08</td>
<td>935.35</td>
<td>573.34</td>
</tr>
<tr>
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<td>Model</td>
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<td>3</td>
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<td>0.16</td>
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<td>849.67</td>
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<td>Model</td>
<td>541.22</td>
<td>845.43</td>
<td>817.21</td>
<td>412.55</td>
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</table>

![Fig. 6: Fx force comparative graph for experimental, fuzzy and model](image1)

![Fig. 7: Fy force comparative graph for experimental, fuzzy and model](image2)

![Fig. 8: Fz force comparative graph for experimental, fuzzy and model](image3)

![Fig. 9: WST comparative graph for experimental, fuzzy and model](image4)

![Fig. 10: SPL comparative graph for experimental, fuzzy and model](image5)

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.

REFERENCES


