Exploring the Effect of Dimensional Tolerance of the Inserts During Multi-Objective Optimization of Face Hard Milling Using Genetic Algorithm

Abstract- Surface roughness and dimensional deviation are critical quality dimensions of machined products and several machining parameters including tool insert dimensional tolerance affect them. Machining performance studies involving dimensional tolerance of the insert during machining, particularly hard face milling do not have considerable attention of the researchers. Therefore, the aim of the present work is to investigate the effect of the dimensional tolerance of the insert along with other machining parameters such as spindle speed, feed per tooth, and depth of cut on the roughness and dimensional deviation simultaneously. Experiments were conducted as per standard L18 mixed orthogonal array on a CNC vertical milling machine. Significance of machining parameters with respect to roughness and dimensional deviation was determined using Analysis of variance (ANOVA). Results revealed that among several machining parameters, feed per tooth greatly affects surface roughness and dimensional deviation. Optimum machining parameters that give minimum values of surface roughness and dimensional deviation simultaneously was obtained using Genetic Algorithm (GA).

Keywords- Face milling, Dimensional tolerance, Genetic Algorithm, Optimization

1. Introduction

Hard machining refers to machining of hard to machine materials by processes such as turning, milling, drilling, threading and broaching operations. Hard machining offers advantages over grinding in terms of high material removal rates (MRR), smaller machining times, flexible process design and almost no use of coolant. However, increased tool wear is a major disadvantage of hard machining. Hard milling is a process, which provides high accuracy, better surface finish, and overall quality improvement. In recent years, several authors have studied hard milling and considerable attention has been given to the understanding of the machinability of hardened steel [1-3]. In manufacturing industries, especially in die and mould manufacturing industries, machining of hardened steels is performed. Owing to the high strength of the hardened steels, their milling relatively poses difficulties during mould and die making [4]. Among several milling operations, the face milling is associated with relatively high metal removal rates and therefore, it is an operation of choice particularly for quick and precise machining of large, flat surfaces.

Product quality has always been a critical element in manufacturing operations. Machining processes are required to work with specific attention towards manufacturing specifications in order to produce high quality final products measured in terms of dimensional accuracy, surface roughness, etc. It has been reported that several mechanical properties including wear resistance and fatigue strength of machined parts depend largely on the surface roughness (R_a) [5-8]. In recent years, several researchers have studied the effect of milling parameters on the surface roughness. Bierzmann and Heilmann [9] observed that use of coolant during face milling of aluminum alloys improves the surface roughness. Munoz-Escalona and Maropoulos [5] developed a mathematical model for face milling of Al 7075-T7351 with square insert tools, which predicted the surface roughness with 98% accuracy. During dry milling of Hadfield steel with PVD TiAlN- and CVD TiCN/Al_{2}O_{3} coated carbide inserts, feed rate has been found to be the most influential factor for surface roughness [10]. Zhang et al. [11] found that the depth of cut is the main factor affecting the R_a during end face milling of C45E4 (ISO) steel [11]. An et al. [12] revealed that machining at high cutting speed...
minimizes the surface roughness but the feed rate and the depth of cut (DoC) affect it adversely. Accuracy and precision of mechanical design, manufacturing processes, and manufacturing systems are generally evaluated in terms of dimensional deviation emphasizing its importance in research pertaining to these fields. The tool wear itself is directly connected with a consecutive dimensional deviation of work piece from the nominal value. During machining, the magnitude of dimensional deviation gets affected by several factors such as work piece and cutting tool material, cutting conditions, etc. [13]. Researchers have performed studies about dimensional deviation of the work piece during machining [14-16]. Researchers [17-19] have reported methods for prediction of both roughness and dimensional deviation of the work piece. Dimensional tolerance of the inserts is an extremely important machining parameter specially, when it comes to machining of ultra-precise jobs such as production of machine tools, jigs and fixtures, measuring instruments and for that matter even the tool itself. Available literature pertaining to machining reveals that the effect of dimensional tolerance of the inserts on machining performance needs to be explored to understand and establish relationship between this important parameter with machining performance. Investigations of this nature shall be of great importance to the tasks, which require high precision and close dimensional tolerances. Keeping this in view, this paper investigates the effect of milling parameters i.e. dimensional tolerance of the inserts, cutting speed, feed rate, and depth of cut on the machining performance, including both dimensional deviation and surface roughness during face milling for EN 31 steel. Further, multi-response optimization of the face milling process has also been done using Genetic Algorithm (GA) to minimize the surface roughness and dimensional deviation simultaneously.

2. Experimental Details and Data Analysis
In the following sections, the details of experimental work and procedure for data analysis are presented.

I. Material
The experimentation was performed on a CNC vertical milling machine (model: Chandra; make: BFW, India). EN 31 steel plates with dimensions of 300 mm × 150 mm × 25 mm were used as work piece material and they were machined using a face milling cutter of 80 mm diameter. Figure 1 (a and b) shows the schematic of milling operation. EN 31 steel has high resistance to wear and it is widely used to manufacture such as brake roller, cylindrical roller, conical and needle rollers due to its poor thermal conductivity and its ability to maintain mechanical properties at high temperature [20]. Table 1 shows the chemical composition of the EN 31 steel.

II. Face milling Cutter
Face milling cutters with two types of solid carbide tool inserts i.e. SEG13T3AGFN-JP HTi10 and SEMT13T3AGSN-JH VP15TF, were used in the experiments. These two inserts having different dimensional tolerance. Figure 2 (a and b) shows a solid carbide tool inserts along with their geometry used in this study.

III. Machining conditions
The machining parameters selected in this study were the dimensional tolerance of the inserts (A), spindle speed (B), the feed per tooth (C), and the depth of cut (D). Two levels of dimensional tolerance and three levels each of the other machining parameters were selected. Table 2 shows the selected machining parameters and their levels.

IV. Measurement of the response variables
In this study, two response variables i.e. surface roughness average (R\text{a}) and dimensional deviation (D\text{d}) were measured. Surface roughness average values (R\text{a}) were measured immediately after the milling process using surface roughness test equipment (model: SURFTEST, SV-2100; make: Mitutoyo, Japan). The measurement of dimensional deviation (D\text{d}) was made with a digital vernier caliper (Mitutoyo, Japan).
Table 3 shows the L₁₈ mixed orthogonal array. This array has eighteen rows and four columns. The machining parameters are assigned to these columns as shown in Table 3. The goal of this study is to minimize both surface roughness and dimensional deviation and therefore, the lower-the-better quality characteristic was used for both the response variables. The signal-to-noise (S/N) ratio for lower-the-better quality characteristics is obtained from Eqn. (1).

\[
S/N = -10 \log \left( \frac{1}{m} \sum_{i=1}^{m} y_i^2 \right)
\]

(1)

Where S/N is the ratio of the mean (Signal) to the standard deviation (Noise), \(m\) is number of repetition of the measurement, \(y_i\) is the value of response variable for \(i^{th}\) experiment.

**VI. Multi-Objective Optimization Using Genetic Algorithm**

It has been reported that typically, the machining parameters exhibit a nonlinear relation with responses which causes difficulty in doing analytical optimization, especially in case of multi-objective optimization where more than one objective need to be optimized simultaneously [26]. Multi-objective optimization simultaneously optimizes two or more responses with conflicting objectives subject to certain constraints [27]. It has been observed that in multi-objective problems, such as the one considered in this study where the objective is to minimize both surface roughness and dimensional deviation, an attempt to improve an objective may further deteriorate the second objective. Thus, it may be difficult to obtain a single solution, which simultaneously optimizes each and every objective. In situations like this, a non-dominated, Pareto optimal solution is found as it improves an objective without worsening the other. Therefore, while solving a multi-objective optimization problem, the main objective is to find such non-dominated solutions. The genetic algorithm (GA) offers several advantages over other optimization methods and consequently, it has been used for solving multi-objective optimization problem considered in the present study. GA is very effective technique for solving multi-objective optimization problems as it computes an approximation of the entire Pareto front in a single algorithm run. Su and Hou [28] demonstrated the utility of multi-population intelligent genetic algorithm (MPIGA) in terms of its effectiveness in generating Pareto-optimal
solutions required to arrive at optimal solution. Liang and Leung [29] solved multimodal function optimization problems by integrating GA with adaptive elitist-population strategies (AEGA) and they reported that this technique is very efficient and effective for the multi-objective optimization of complicated real-world problems. Zio and Bazzo [30] applied a technique called clustering procedure to a multi-objective optimization problem i.e. redundancy allocation problem and found that this procedure considerably reduces number of representative solutions in the Pareto front which enables the decision maker to select the final solution based on the assumed preferences. Eiben and Smit [31] reported that application of evolutionary tuning algorithms provide superior values of the parameters involved in the multi-objective optimization problems. Moreover, GA was applied to optimize the machining parameters during turning and electro-discharge machining [32-36].

Table 2: Machining conditions

| Factors                  | Symbol | Unit | Level 1 | Level 2 | Level 3 |
|--------------------------|--------|------|---------|---------|---------|
| Dimensional tolerance of the insert | A      | mm   | 0.025   | 0.13    | -       |
| Spindle speed            | B      | rpm  | 500     | 1000    | 1500    |
| Feed per tooth           | C      | mm/tooth | 500   | 2000    | 2500    |
| Depth of cut             | D      | mm   | 0.4     | 0.7     | 1       |

Table 3: Experimental layout using an L₁₈

| Expt. No. | A | B | C | D |
|-----------|---|---|---|---|
| 1         | 1 | 1 | 1 | 1 |
| 2         | 1 | 1 | 2 | 2 |
| 3         | 1 | 1 | 3 | 3 |
| 4         | 1 | 2 | 1 | 1 |
| 5         | 1 | 2 | 2 | 2 |
| 6         | 1 | 2 | 3 | 3 |
| 7         | 1 | 3 | 1 | 2 |
| 8         | 1 | 3 | 2 | 3 |
| 9         | 1 | 3 | 3 | 1 |
| 10        | 2 | 1 | 1 | 3 |
| 11        | 2 | 1 | 2 | 1 |
| 12        | 2 | 1 | 3 | 2 |
| 13        | 2 | 2 | 1 | 2 |
| 14        | 2 | 2 | 2 | 3 |
| 15        | 2 | 2 | 3 | 1 |
| 16        | 2 | 3 | 1 | 3 |
| 17        | 2 | 3 | 2 | 1 |
| 18        | 2 | 3 | 3 | 2 |

3. Results and Discussion

The details of the data analysis and related technical discussions in light of the available literature are presented in the following sections:

I. Analysis of S/N ratio

Table 4: Experimental results and S/N ratio for surface roughness and dimensional deviation

| Expt. No. | A  | B   | C   | D   | Rₐ(µm) | Dₐ(mm) | S/N for Rₐ | S/N for Dₐ |
|-----------|----|-----|-----|-----|--------|--------|------------|------------|
| 1         | 0.02 | 500 | 500 | 0   | 0.356  | 0.05   | 8.971      | 26.021     |
| 2         | 0.02 | 500 | 200 | 0   | 0.726  | 0.22   | 2.781      | 13.152     |
| 3         | 0.02 | 500 | 250 | 1   | 0.852  | 0.32   | 1.391      | 9.897      |
Analysis of variance (ANOVA) was used to determine the statistically significant factors that influence the $R_a$ and $D_d$. The analysis was made for a level significance of 5%. The ANOVA results for surface roughness and dimensional deviation are presented in Table 5 and Table 6 respectively. Table 5 reveals that the dimensional

### Table 5: ANOVA Results for Surface Roughness

| 5 | 0.02 | 100 | 500 | 0.301 | 0.02 | 10.429 | 33.979 |
|---|------|-----|-----|-------|------|--------|--------|
| 5 | 0.02 | 100 | 200 | 0.512 | 0.09 | 5.815  | 20.915 |
| 5 | 0.02 | 100 | 250 | 0.651 | 0.29 | 3.728  | 10.752 |
| 5 | 0.02 | 150 | 500 | 0.387 | 0.05 | 8.246  | 26.021 |
| 5 | 0.02 | 150 | 200 | 0.872 | 0.26 | 1.190  | 11.701 |
| 5 | 0.02 | 150 | 250 | 0.990 | 0.09 | 0.087  | 20.915 |
| 5 | 0.13 | 500 | 500 | 0.312 | 0.08 | 10.117 | 21.938 |
| 5 | 0.13 | 500 | 200 | 0.489 | 0.11 | 6.214  | 19.172 |
| 5 | 0.13 | 500 | 250 | 0.385 | 0.1  | 8.291  | 20.000 |
| 5 | 0.13 | 100 | 500 | 0.114 | 0.02 | 18.862 | 33.979 |
| 6 | 0.13 | 100 | 200 | 0.497 | 0.11 | 6.073  | 19.172 |
| 6 | 0.13 | 100 | 250 | 0.528 | 0.06 | 5.547  | 24.437 |
| 6 | 0.13 | 150 | 500 | 0.218 | 0.03 | 13.231 | 30.458 |
| 7 | 0.13 | 150 | 200 | 0.618 | 0.04 | 4.180  | 27.959 |
| 7 | 0.13 | 150 | 250 | 0.705 | 0.06 | 3.036  | 24.437 |

### Table 6: ANOVA Results for Dimensional Deviation

| 5 | 0.02 | 100 | 500 | 0.301 | 0.02 | 10.429 | 33.979 |
|---|------|-----|-----|-------|------|--------|--------|
| 5 | 0.02 | 100 | 200 | 0.512 | 0.09 | 5.815  | 20.915 |
| 5 | 0.02 | 100 | 250 | 0.651 | 0.29 | 3.728  | 10.752 |
| 5 | 0.02 | 150 | 500 | 0.387 | 0.05 | 8.246  | 26.021 |
| 5 | 0.02 | 150 | 200 | 0.872 | 0.26 | 1.190  | 11.701 |
| 5 | 0.02 | 150 | 250 | 0.990 | 0.09 | 0.087  | 20.915 |
| 5 | 0.13 | 500 | 500 | 0.312 | 0.08 | 10.117 | 21.938 |
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| 5 | 0.13 | 150 | 200 | 0.618 | 0.04 | 4.180  | 27.959 |
| 5 | 0.13 | 150 | 250 | 0.705 | 0.06 | 3.036  | 24.437 |

**Figure 3: Normal plot of residuals for surface roughness**

**Figure 4: Normal plot of residuals for dimensional deviation**
tolerance of the insert, spindle speed, and feed per tooth all have statistically significant on the surface roughness. However, depth of cut does not have statistically significant effect on the surface roughness. Further, from the analysis of the Table 6, it can be seen that all the machining parameters have statistically significant effect on the dimensional deviation. Furthermore, the analysis of the results showed that the feed per tooth is the dominant factor which affects both surface roughness and dimensional deviation with a percentage contribution of 62.257% and 45.275% respectively. The literature also reveals the same result i.e. surface roughness is mainly influenced by feed per tooth [24, 37-38].

II. Regression analysis
Regression analysis is used to establish relation between independent and dependent variables so as to predict dependent variable for a given set of independent variables. A first-order regression model is given in Eqn. 2.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \epsilon$$

(2)

Where $\beta_0$ and $\beta_i$ are the constants called regression coefficients, $k$ is the number of independent variables and $\epsilon$ is an error term. In the present study, $R_a$ and $D_d$ were chosen as output variables while dimensional tolerance of the inserts ($A$), spindle speed ($B$), feed per tooth ($C$), and DoC ($D$) were independent (input) variables. The first-order equations were as follows:

$$R_a = 0.194 - 1.885 A + 0.000112 B + 0.000207 C + 0.033 D$$

(3)

$$D_d = -0.0030 - 0.825 A - 0.000058 B + 0.000058 C + 0.2000 D$$

(4)

The predicted values obtained from first-order models (Eqn.3 and Eqn.4) for surface roughness and dimensional deviation respectively are shown in Table 7. On comparing the experimental values of response variables given in Table 4 with those of predicted values given in Table 7 a close agreement between experimental and predicted values is observed.

| Table 5: ANOVA table for surface roughness |
| Factors | SS | DF | MS | F  | P-Value | % Contribution |
|---------|----|----|----|----|---------|----------------|
| $A$     | 60.18 | 1  | 60.182 | 19.35 | 0.001 | 16.054 |
| $B$     | 35.63 | 2  | 17.815 | 5.73 | 0.022 | 9.505 |
| $C$     | 233.3 | 2  | 116.69 | 37.52 | 0.000 | 62.257 |
| $D$     | 14.58 | 2  | 7.289  | 2.34 | 0.146 | 3.889 |
| Error   | 31.10 | 10 | 3.110  |  |  | 8.296 |
| Total   | 374.8 | 17 | 17 | 100.000 |

| Table 6: ANOVA table for dimensional deviation |
| Factors | SS | DF | MS | F  | P-Value | % Contribution |
|---------|----|----|----|----|---------|----------------|
| $A$     | 129.0 | 1  | 129.07 | 26.0 | 0.000 | 14.061 |
| $B$     | 115.3 | 2  | 57.668 | 11.6 | 0.002 | 12.565 |
| $C$     | 415.5 | 2  | 207.79 | 41.9 | 0.000 | 45.275 |
| $D$     | 208.3 | 2  | 104.17 | 21.0 | 0.000 | 22.698 |
| Error   | 49.58 | 10 | 4.958 |  |  | 5.401 |
| Total   | 917.9 | 17 | 17 | 100.000 |

| Table 7: Predicted values of $R_a$ and $D_d$ |
III. GA Optimization Solution

GA tool of MATLAB was used to generate Pareto optimal solution points for multi objective optimization (minimization) of surface roughness and dimensional deviations simultaneously. The controlled elitist genetic algorithm (NSGA-II) is a variant of GA and it was used to solve multi-objective optimization problem considered in the present study. This variant of GA retains the diversity of population and also generates an optimal pareto front with convergence to favor individuals with better fitness value. Objective function equations (fitness function) for minimization of both the response variables were written in the standard format in the “Mfile” extension and saved in the MATLAB directory. The objective functions are given below:

Objective I = min \[ R_a \]

Objective I = min \[ D_d \]

This file was run in the “gatool” using the “gamultiobj” solver. For solving the fitness function to generate the results, the bound constraints for all the four input variables were placed at the required constraint section. For implementation of “gamultiobj” solver following options were used: Population type: Double Vector/Bit Strong/Custom; Population size: 75; Creation Function: Constraint dependent; Selection function: Tournament (size 2); Crossover function: Scattered; Mutation function: Adaptive feasible; Direction of migration: Forward (migration function 0.2); Distance measure function: distance crowding and Stopping Criteria: 150 generations.

The Pareto front of optimization objective after first 50 iterations is shown in Figure 5. In Figure 5 the two response variables i.e. \( R_a \) and dimensional deviation are shown along x-axis and y-axis respectively and the individual non-dominated solution points are shown as the star marks between both the axes among the Pareto optimal set of all the star points which form the Pareto front. It can be seen from Figure 5 that in region A, the dimensional deviation decreases rapidly along with very little increase in the surface roughness. Meanwhile, the value of the dimensional deviation comes close to zero in region C. Thus, the region B is satisfying region to optimize i.e. minimize both the surface roughness and dimensional deviation simultaneously and it is regarded as an optimal region. This is also evident from the results listed in Table 8.

| Expt. No. | A  | B  | C  | D  | \( R_a \) | \( D_d \) |
|-----------|----|----|----|----|---------|---------|
| 1         | 0.025 | 500 | 500 | 0.4  | 0.320   | 0.05638 |
| 2         | 0.025 | 500 | 2000 | 0.7  | 0.640   | 0.20338 |
| 3         | 0.025 | 500 | 2500 | 1     | 0.753   | 0.29238 |
| 4         | 0.025 | 1000 | 500  | 0.4  | 0.376   | 0.17438 |
| 5         | 0.025 | 1000 | 2000 | 0.7  | 0.696   | 0.14575 |
| 6         | 0.025 | 1000 | 2500 | 1     | 0.809   | 0.26338 |
| 7         | 0.025 | 1500 | 500  | 0.7  | 0.441   | 0.08775 |
| 8         | 0.025 | 1500 | 2000 | 1     | 0.762   | 0.10538 |
| 9         | 0.025 | 1500 | 2500 | 0.4  | 0.846   | 0.11438 |
| 10        | 0.13  | 500  | 500  | 1     | 0.141   | 0.08975 |
| 11        | 0.13  | 500  | 2000 | 0.4  | 0.432   | 0.05675 |
| 12        | 0.13  | 500  | 2500 | 0.7  | 0.545   | 0.14575 |
| 13        | 0.13  | 1000 | 500  | 0.7  | 0.187   | 0.00075 |
| 14        | 0.13  | 1000 | 2000 | 1     | 0.508   | 0.14775 |
| 15        | 0.13  | 1000 | 2500 | 0.4  | 0.592   | 0.05675 |
| 16        | 0.13  | 1500 | 500  | 1     | 0.253   | 0.03175 |
| 17        | 0.13  | 1500 | 2000 | 0.4  | 0.544   | 0.00125 |
| 18        | 0.13  | 1500 | 2500 | 0.7  | 0.657   | 0.08775 |
Table 8: Pareto optimal solution point and corresponding values of the response variables

| S.No. | Machining Parameters | Responses |
|-------|----------------------|-----------|
|       | A  | B (rpm) | C (mm/tooth) | D (mm) | Rₚ (µm) | Dₓ (mm) |
| 1     | 0.130 | 0     | 559.6164 | 500.0793 | 0.4041 | 0.128 | 0.03289247 |
| 2     | 0.130 | 0     | 559.6164 | 500.0793 | 0.4042 | 0.128 | 0.03286804 |
| 3     | 0.130 | 0     | 559.6162 | 500.0776 | 0.4218 | 0.130 | 0.02935251 |
| 4     | 0.129 | 9     | 559.6208 | 500.1274 | 0.4302 | 0.130 | 0.02755639 |
| 5     | 0.130 | 0     | 559.6162 | 500.0796 | 0.4427 | 0.130 | 0.02515990 |
| 6     | 0.129 | 8     | 559.6209 | 500.1268 | 0.4441 | 0.130 | 0.02473243 |
| 7     | 0.130 | 0     | 559.6164 | 500.0793 | 0.4552 | 0.130 | 0.02266957 |
| 8     | 0.129 | 9     | 559.6164 | 500.1274 | 0.4552 | 0.130 | 0.02255954 |
| 9     | 0.130 | 0     | 559.6162 | 506.9199 | 0.4630 | 0.131 | 0.02070755 |
| 10    | 0.130 | 0     | 559.6164 | 500.0776 | 0.5067 | 0.131 | 0.01235655 |
| 11    | 0.129 | 8     | 559.6164 | 500.0778 | 0.5085 | 0.132 | 0.01181431 |
| 12    | 0.130 | 0     | 559.6164 | 500.0793 | 0.5246 | 0.132 | 0.00877828 |
| 13    | 0.129 | 8     | 559.6208 | 500.1268 | 0.5246 | 0.133 | 0.00862146 |
| 14    | 0.130 | 0     | 559.6164 | 500.0796 | 0.5370 | 0.133 | 0.00630533 |
| 15    | 0.130 | 0     | 559.6167 | 500.0793 | 0.5468 | 0.133 | 0.00435243 |
In real life situations, the responses often conflict to fulfill the different objectives simultaneously. Therefore, it is generally difficult to find a single solution for all the objectives considering all responses together. In the present study, input control parameters of the Pareto optimal set of solutions along with the corresponding value of responses at each set of parameters using GA (multi-objective) are tabulated in Table 8. Table 8 reveals that an attempt to minimize the surface roughness leads to increase in the dimensional deviation and vice versa. Table 8 also reveals that each solution point provided by GA is a unique (none dominated) solution point. Therefore, a set of solution points is a better option to be determined instead of a single solution point for optimizing both the responses simultaneously. In addition, change in any of the control parameters further improves a response on the cost of others. Thus, it may be concluded that GA is a novel approach for solving such problems as it generates the Pareto optimal set of solutions rather than a single unique solution, which enables the decision maker to obtain a wide range of optimal setting of controlling parameters for simultaneous optimization of the response variables under investigation. Hence, operational flexibility is achieved as different parametric combinations may be used for desired responses within range. From the results of the predicted values of surface roughness and dimensional deviation obtained from Eqn. (3) and Eqn. (4) respectively and presented in Table 7, it can be seen that input parameters listed in the experiment number 10 leads to minimum value of surface roughness i.e. 0.141 µm while the input parameters listed in the experiment number 13 results in minimum value of dimensional deviation 0.00075 mm. From the optimization results obtained using GA (Table 8), it can be seen that run 18 result in minimum values of both surface roughness and dimensional deviation. Table 9 presents the minimum predicted values of surface roughness and dimensional deviation and the values of these responses obtained using multi-optimization by GA. It can be seen from reveals that an attempt to minimize the surface roughness leads to increase in the dimensional deviation and vice versa. Table 8 also reveals that each solution point provided by GA is a unique (none dominated) solution point. Therefore, a set of solution points is a better option to be determined instead of a single solution point for optimizing both the responses simultaneously. In addition, change in any of the control parameters further improves a response on the cost of others. 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Thus, it may be concluded that GA is a novel approach for solving such problems as it generates the Pareto optimal set of solutions rather than a single unique solution, which enables the decision maker to obtain a wide range of optimal setting of controlling parameters for simultaneous optimization of the response variables under investigation. Hence, operational flexibility is achieved as different parametric combinations may be used for desired responses within range. From the results of the predicted values of surface roughness and dimensional deviation obtained from Eqn. (3) and Eqn. (4) respectively and presented in Table 7, it can be seen that input parameters listed in the experiment number 10 leads to minimum value of surface roughness i.e. 0.141 µm while the input parameters listed in the experiment number 13 results in minimum value of dimensional deviation 0.00075 mm. From the optimization results obtained using GA (Table 8), it can be seen that run 18 result in minimum values of both surface roughness and dimensional deviation. Table 9 presents the minimum predicted values of surface roughness and dimensional deviation and the values of these responses obtained using multi-optimization by GA. It can be seen from

4. Conclusion

Based on the Taguchi L_{18} mixed orthogonal array, the face milling experiments on EN 31 with two types of solid carbide tool inserts steel were performed using a CNC vertical milling machine. Effect of four milling parameters including dimensional tolerance of the insert on two response variables i.e. surface roughness and dimensional deviation was investigated. The empirical relations between milling parameters and surface roughness as well as dimensional deviation were obtained. Multi-objective optimization problem was solved using GA and a set of GA Pareto-optimal solutions was obtained. It has been observed that Pareto frontier graphics provide several different situations which
facilitate the choice of right parameters for any condition and consequently, it helps the decision-making process. Conclusions that can be drawn on the basis of the present study are given below:
- Feed per tooth is the dominant factor affecting both surface roughness and dimensional deviation as their percentage contribution for these response variables obtained through ANOVA is 62.257% and 45.275% respectively.
- The dimensional tolerance of the inserts significantly affects both surface roughness and dimensional deviation. In addition, the best value of dimensional tolerance of the inserts that yields minimum value of surface roughness as well as dimensional deviation is found to be 0.13 mm.
- Multi-objective optimization using GA enables decision maker to select optimal milling parameters to optimize the surface quality in face milling.
- Multi-objective optimization using GA suggests that the optimum machining parameters i.e. dimensional tolerance of the inserts (A), spindle speed (B), the feed per tooth (C), and the depth of cut (D) are 0.13 mm, 559 rpm, 500 mm/tooth, 0.57 mm respectively, which result in best optimum values of the surface roughness at 0.134 μm and dimensional deviation at 6.63E-06 mm simultaneously.

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