S.K. Shihab

Department of Materials Engineering, Collage of Engineering, University of Diyala, Diyala, Iraq
suhakarim_10@yahoo.com

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. Biermann and Heilmann [9] observed that use of coolant during face milling of aluminum alloys improves the surface roughness. Munoz-Escalonaa 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_a) and dimensional deviation (D_d) were measured. Surface roughness average values (R_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_d) was made with a digital vernier caliper (Mitutoyo, Japan).
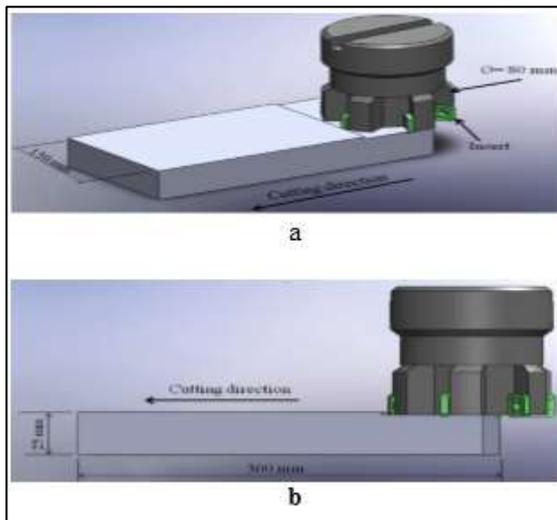
Figure 1: Schematic diagram of face milling (a) 3D view and (b) 2D view

Table 1: Wt% composition of EN 31

| C	Mn	Si	Cr	S	P	Mg
1.5	0.52	0.2 2	1. 3	0.0 5	0.0 5	46. 6
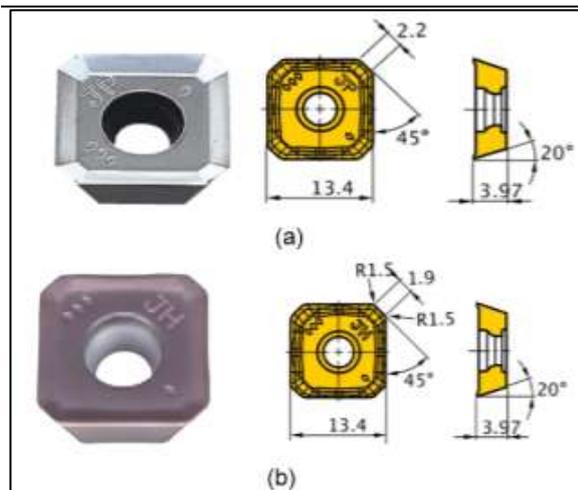
Figure 2: Tool inserts and their geometry: (a) SEG13T3AGFN-JP HTi10, (b) SEMT13T3AGSN-JH VP15TF

V. Taguchi design

Experiments were performed as per the Taguchi design L$_{18}$ mixed orthogonal array. Taguchi method is widely used for optimizing industrial/ production processes [21-23]. The Taguchi design comprises of the following steps: selection of a proper orthogonal array (OA) and conducting experiments as per the selected array; analysis of the collected data; identification of the optimum condition; confirmation of the result [21]. Many researchers have used the Taguchi method to optimize the various machining operations [10, 21-25].

Table 3 shows the L$_{18}$ 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).

$$S/N = -10\log\frac{1}{m}\sum_{i=1}^{m} y_i^2$$

(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 L_{18}

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:

Table 4 lists the values of R_a and D_d for all eighteen experiments and the corresponding S/N ratios that have been obtained from Eq. (1). The normal probability plot of the residuals for R_a and D_d are shown in Figure 3 and Figure 4 respectively, which depict that the errors are normally distributed as all the point either lie on the line or are close to it.

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	$R_a(\mu m)$	$D_d(mm)$	S/N for R_a	S/N for D_d
1	0.025	500	500	0.4	0.356	0.05	8.971	26.021
2	0.025	500	2000	0.7	0.726	0.22	2.781	13.152
3	0.02	500	250	1.	0.852	0.32	1.391	9.897

	5		0	0			
4	0.025	1000	500	0.4	0.301	0.02	10.429	33.979
5	0.025	1000	2000	0.7	0.512	0.09	5.815	20.915
6	0.025	1000	2500	1.0	0.651	0.29	3.728	10.752
7	0.025	1500	500	0.7	0.387	0.05	8.246	26.021
8	0.025	1500	2000	1.0	0.872	0.26	1.190	11.701
9	0.025	1500	2500	0.4	0.990	0.09	0.087	20.915
10	0.13	500	500	1.0	0.312	0.08	10.117	21.938
11	0.13	500	2000	0.4	0.489	0.11	6.214	19.172
12	0.13	500	2500	0.7	0.385	0.1	8.291	20.000
13	0.13	1000	500	0.7	0.114	0.02	18.862	33.979
14	0.13	1000	2000	1.0	0.497	0.11	6.073	19.172
15	0.13	1000	2500	0.4	0.528	0.06	5.547	24.437
16	0.13	1500	500	1.0	0.218	0.03	13.231	30.458
17	0.13	1500	2000	0.4	0.618	0.04	4.180	27.959
18	0.13	1500	2500	0.7	0.705	0.06	3.036	24.437

Figure 3: Normal plot of residuals for surface roughness
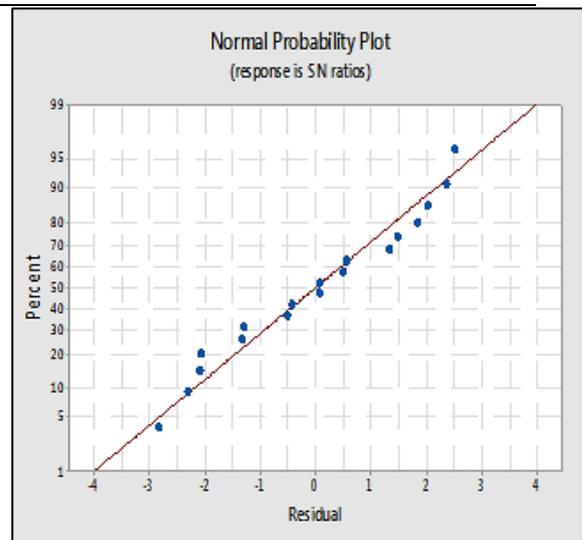
Figure 4: Normal plot of residuals for dimensional deviation

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

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.

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

(2)

Where β_0 *and* β_i are the constants called regression coefficients, k is the number of independent variables and ε 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:

$Ra = 0.194 - 1.885\ A + 0.000112\ B +$

$0.000207\ C + 0.033\ D$

(3)

$Dd = -0.0030 - 0.825\ A - 0.000058\ B +$

$0.000058\ C + 0.2000\ D$

(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	19.352	0.001	16.054
B	35.63	2	17.815	5.73	0.022	9.505
C	233.39	2	116.693	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	374.87	17				100.000

Table 6: ANOVA table for dimensional deviation

Factors	SS	DF	MS	F	P-Value	% Contribution
A	129.07	1	129.07	26.03	0.000	14.061
B	115.34	2	57.668	11.63	0.002	12.565
C	415.59	2	207.794	41.91	0.000	45.275
D	208.35	2	104.173	21.01	0.000	22.698
Error	49.58	10	4.958			5.401
Total	917.92	17				100.000

Table 7: Predicted values of R_a and D_d

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	0.02738
5	0.025	1000	2000	0.7	0.696	0.17438
6	0.025	1000	2500	1	0.809	0.26338
7	0.025	1500	500	0.7	0.441	0.05838
8	0.025	1500	2000	1	0.762	0.20538
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

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.
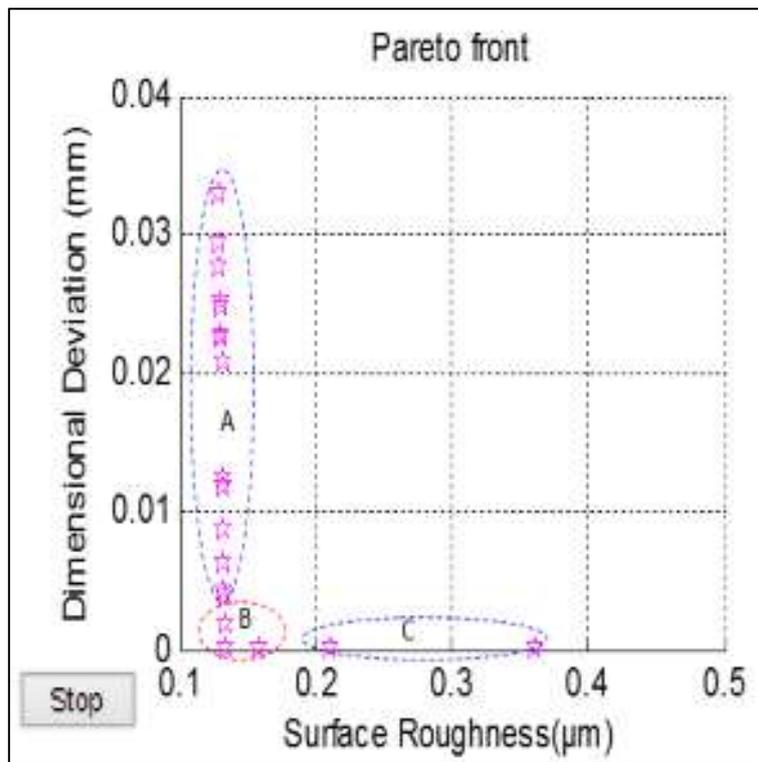
Figure.5: Pareto-optimal set of solutions

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)	R_a (μm)	D_d (mm)
1	0.1300	559.6164	500.0793	0.4041	0.128	0.032892471
2	0.1300	559.6164	500.0793	0.4042	0.128	0.032868044
3	0.1300	559.6162	500.0776	0.4218	0.130	0.029352517
4	0.1299	559.6208	500.1274	0.4302	0.130	0.027556396
5	0.1300	559.6162	500.0796	0.4427	0.130	0.025159905
6	0.1298	559.6209	500.1268	0.4441	0.130	0.024732436
7	0.1300	559.6164	500.0793	0.4552	0.130	0.022669577
8	0.1299	559.6164	500.1274	0.4552	0.130	0.022559954
9	0.1300	559.6162	506.9199	0.4630	0.131	0.020707559
10	0.1300	559.6164	500.0776	0.5067	0.131	0.012356552
11	0.1298	559.6164	500.0778	0.5085	0.132	0.011814312
12	0.1300	559.6164	500.0793	0.5246	0.132	0.008778283
13	0.1298	559.6208	500.1268	0.5246	0.133	0.008621463
14	0.1300	559.6164	500.0796	0.5370	0.133	0.006305333
15	0.1300	559.6167	500.0793	0.5468	0.133	0.00435243

	0					3
16	0.1299	559.6208	500.1274	0.5487	0.134	0.003847612
17	0.1300	559.6165	500.0777	0.5594	0.134	0.001777312
18	*0.1298*	*559.6164*	*500.0798*	*0.5675*	*0.134*	*6.63E-06*
19	0.1209	621.5995	506.4114	0.5472	0.159	6.27E-06
20	0.1208	621.5998	506.4160	0.5468	0.159	4.35E-06
21	0.1009	767.9522	506.8843	0.5070	0.211420	2.77E-06
22	0.1009	767.9523	506.8843	0.5070	0.211445	6.97E-08
23	0.0864	1145.73440	899.9535	0.4427	0.360340	1.06E-08
24	0.0864	1145.7344	899.9538	0.4427	0.360340	3.54E-09

In real life situations, the responses often conflict to fulfill the different objective simultaneously. Therefore, it is generally difficult to find a single solution for all the objectives considering the 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 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 Table 9 that optimization with GA provides not only a better solution but also optimizes the response variables simultaneously. In addition, confirmation test was performed at optimum levels of controlling parameters. The result of confirmation test is also presented in Table 9. Table 9 reveals that the results obtained from the confirmation test shows a good agreement with the optimized values of responses using GA. Therefore, the results obtained from the confirmation tests reflect successful optimization.

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.

Table 9: The predicted and optimized values of response variables

	A	*B* (rpm)	*C* (mm/tooth)	*D* (mm)	R_a (μm)	D_d (mm)
Predicted	0.13	500	500	1	0.141	0.08975
	0.13	1000	500	0.7	0.187	0.00075
Optimized	**0.13**	**559**	**500**	**0.57**	**0.134**	**6.63E-06**
Confirmation test	**0.13**	**559**	**500**	**0.57**	**0.136**	**4.24E-05**

Acknowledgements

References

[1] R. Bian, E. Ferraris, N. He, and D., "Reynaerts: Process Investigation on Meso-Scale Hard Milling of Zro2by Diamond Coated Tools," *Precision Engineering*, Vol. 38, pp. 82-91, 2014.

[2] A. Alrashdan, O. Bataineh, and M. Shboo, "Multi-Criteria End Milling Parameters Optimization of AISI D2 Steel Using Genetic Algorithm," *Int J Adv Manuf Technol.*, Vol. 73, pp. 1201-1212, 2014.

[3] H.A. Sonawane, and S.S. Joshi, "Modeling of Machined Surface Quality in High-Speed Ball-End Milling of Inconel-718 Thin Cantilevers," *Int J Adv Manuf Technol.*, Vol.78, pp. 1751-1768, 2015.

[4] B. Denkena, J. Kohler, and B. Bergmann, "Development of Cutting Edge Geometries for Hard Milling Operations," *CIRP Journal of Manufacturing Science and Technology*, Vol. 8, pp. 43-52, 2015.

[5] P. Munoz-Escalona, and P.G. Maropoulos, "A Geometrical Model for Surface Roughness Prediction When Face Milling Al 7075-T7351 with Square Insert Tools," *Journal of Manufacturing Systems*, doi:10.1016/j.jmsy.2014.06.011, 2014.

[6] G. Halevi, and R. Weill, "Principles of Process Planning: A Logical Approach. Springer" Berlin, ISBN 0-412-54360-5, 1995.

[7] S. Rawangwong, J. Chatthong, W. Boonchouytan, and R. Burapa, "Influence of Cutting Parameters in Face Milling Semi-Solid AA 7075 Using Carbide Tool Affected the Surface Roughness and Tool Wear," *Energy Procedia*, Vol. 56, pp. 448-457, 2014.

[8] S. Rawangwong, J. Chatthong, W. Boonchouytan, and R. Burapa, "An Investigation of Optimum Cutting Conditions in Face Milling Aluminum Semi Solid 2024 Using Carbide Tool," *Energy Procedia*, Vol. 34, pp. 854-862, 2013.

[9] D. Biermann, and M. Heilmann, "Improvement of Workpiece Quality in Face Milling Of Aluminum Alloys," *Journal of Materials Processing Technology*, Vol. 210, pp. 1968-1975, 2010.

[10] T. Kıvak, "Optimization of Surface Roughness and Flank Wear Using the Taguchi Method in Milling of Hadfield Steel with PVD and CVD Coated Inserts," *Measurement*, Vol. 50, pp. 19-28, 2014.

[11] G. Zhang, J. Li, Y. Chen, Y. Huang, X. Shao, and M. Li, "Prediction of Surface Roughness in End Face Milling Based on Gaussian Process Regression and Cause Analysis Considering Tool

Vibration," *Int J Adv Manuf Technol.*, Vol. 75, pp. 1357-1370, 2014.

[12] Q. An, Ch. Wang, J. Xu, P. Liu, and M. Chen, "Experimental Investigation on Hard Milling of High Strength Steel Using PVD-AlTiN Coated Cemented Carbide Tool," *Int. Journal of Refractory Metals and Hard Materials*, Vol. 43, pp. 94-101, 2014.

[13] D. Mocnik, M. Paulic, S. Klancnik, and J. Balic, "Prediction of Dimensional Deviation of Workpiece using Regression, ANN and PSO Models in Turning Operation," *Technical Gazette*, Vol. 21, No.1, pp. 55-62, 2014.

[14] M. Gulpak, J. Solter, and E. Brinksmeier, "Prediction of Shape Deviations in Face Milling of Steel," *Procedia CIRP*, Vol. 8, pp.15-20, 2013.

[15] M. Gulpak, and J. Solter, "Development and Validation of a Hybrid Model for the Prediction of Shape Deviations in Dry Machining Processes," *Procedia CIRP*, Vol. 31, pp. 346- 351, 2015.

[16] E. Brinksmeier, and J. Solter, "Prediction of Shape Deviations in Machining," *CIRP Annals-Manufacturing Technology*, Vol. 58, No. 1, pp.507-510, 2009.

[17] H.H. Shahabi, and M.M. Ratnam, "Prediction of Surface Roughness and Dimensional Deviation of Workpiece in Turning: A Machine Vision Approach," *The International Journal of Advanced Manufacturing Technology*, Vol. 48, No. 1-4, pp. 213-226, 2010.

[18] K.A. Risbood, U.S. Dixit, and A.D. Sahasrabudhe, "Prediction of Surface Roughness and Dimensional Deviation by Measuring Cutting Forces and Vibrations in Turning Process," *Journal of Materials Processing Technology*, Vol. 132, No. 1–3, pp. 203-214, 2003.

[19] A.M. Ramos, C. Relvas, and J.A Simoes., "The Influence of Finishing Milling Strategies on Texture, Roughness and Dimensional Deviations on the Machining of Complex Surfaces," *Journal of Materials Processing Technology*, Vol. 136, No. 1–3, pp.209-216, 2003.

[20] L.B. Abhang, and M. Hameedullah, "Parametric Investigation of Turning Process on En-31 Steel," *Procedia Materials Science*, Vol. 6, pp.1516-1523, 2014.

[21] D. Philip Selvaraj, P. Chandramohan, and J.M. Mohanra, "Optimization of Surface Roughness, Cutting Force and Tool Wear of Nitrogen Alloyed Duplex Stainless Steel in a Dry Turning Process Using Taguchi Method," *Measurement*, Vol. 49, pp.205-215, 2014.

[22] H.L. Alwan, B.M.H Albaghdadi., M.M.H. AL-Khafaji, and A.A. Abbas, "Estimation of Cutting Tool Wear in Turning using Taguchi Method Depending on Weight of the Removed Tool Metal," *Engineering and Technology Journal*, Vol. 32, pp. 24-33, 2014.

[23] M.M. Hamadi, A.B. Abdulghafour, H.N. Ugla, "Optimizing Coating Process Parameters by Using Taguchi Experimental Design to Increasing Wear Resistance of Steel CK50," *Engineering and Technology Journal*, Vol. 32, pp. 2862- 2873, 2014.

[24] E. Kuram, and B. Ozcelik, "Multi-Objective Optimization Using Taguchi Based Grey Relational Analysis For Micro-Milling of Al 7075 Material with Ball Nose End Mill," *Measurement*, Vol. 46, pp. 1849-1864, 2013.

[25] N. Masmiati, and A.A.D. Sarhan, "Optimizing Cutting Parameters in Inclined End Milling for Minimum Surface Residual Stress-Taguchi Approach," *Measurement*, Vol. 60, pp. 267-275, 2015.

[26] T. Thepsonthi, and T. Ozel, "Multi-Objective Process Optimization for Micro-End Milling of Ti-6Al-4V Titanium Alloy," *Int J Adv Manuf Technol*, Vol. 63, pp. 903-914, 2012.

[27] T. Friedrich, C. Horoba, and F. Neumann, "Illustration of Fairness in Evolutionary Multi-Objective Optimization," *Theoretical Computer Science*, Vol. 412, pp. 1546-1556, 2011.

[28] C.H. Su, and T.H. Hou, "Using Multi-Population Intelligent Genetic Algorithm to Find the Pareto-Optimal Parameters for A Nano-Particle Milling Process Expert Systems With Applications," Vol. 34, pp. 2502-2510, 2008.

[29] Y. Liang, and K.S. Leung, "Genetic Algorithm with Adaptive Elitist-Population Strategies for Multimodal Function Optimization," *Applied Soft Computing*, Vol. 11, pp. 2017-2034, 2011.

[30] E. Zio, and R. Bazzo, "A Clustering Procedure for Reducing the Number of Representative Solutions in the Pareto Front of Multiobjective Optimization Problems," *European Journal of Operational Research*, Vol. 210, pp. 624-634, 2011.

[31] A.E. Eiben, and S.K. Smit, "Parameter Tuning for Configuring and Analyzing Evolutionary Algorithms," Swarm and Evolutionary Computation, Vol. 1, pp. 19-31, 2011.

[32] R.V. Rao and V.D. Kalyankar, "Parameter Optimization of Modern Machining Processes Using Teaching-Learning-Based Optimization Algorithm," *Engineering Applications of Artificial Intelligence*, Vol. 26, pp. 524-531, 2013.

[33] R. Dhabale, V.K.S. Jatti, and T.P. Singh, "Multi-Objective Optimization of Turning Process during Machining of AlMg1SiCu Using Non-Dominated Sorted Genetic Algorithm," *Procedia Materials Science*, Vol. 6, pp. 961- 966, 2014.

[34] C.J. Tzeng, and R.Y. Chen, "Optimization of Electric Discharge Machining Process Using the Response Surface Methodology and Genetic Algorithm Approach," *International Journal of Precision Engineering and Manufacturing*, Vol. 14, No. 5, pp. 709-717, 2013.

[35] R. Rajesh, and M. Dev Anand, "The Optimization of the Electro-Discharge Machining Process Using Response Surface Methodology and Genetic

Algorithms," *Procedia Engineering*, Vol. 38, pp. 3941-3950, 2012.

[36] R. Mukherjee, S. Chakraborty, and S. Samanta, "Selection of Wire Electrical Discharge Machining Process Parameters Using Non-Traditional Optimization Algorithms," *Applied Soft Computing*, Vol. 12, pp. 2506-2516, 2012.

[37] E. Vazquez, C. A. Rodríguez, A. Elias-Zuniga, and J. Ciurana, "An Experimental Analysis of Process Parameters to Manufacture Metallic Micro-Channels by Micro-Milling," *Int J Adv Manuf Technol*, Vol. 51, pp. 945-955, 2010.

[38] D. Huo, and K. Cheng, "Experimental Investigation on Micromilling of Oxygen-Free, High-Conductivity Copper Using Tungsten Carbide, Chemistry Vapour Deposition, and Single-Crystal Diamond Micro Tools," *Proc. IMechE Part B: J. Engineering Manufacture*, Vol .224, pp. 995-1003, 2009.

Author(s) biography

Suha K. Shihab is a Lecturer College of Engineering, University of Diyala, Diyala, Iraq. Her major research interest includes production engineering, manufacturing science, optimization of design of experiment in products and processes, and simulation. She received B. Sc. and M. Sc. in Production Engineering and Metallurgy from University of Technology, Baghdad, Iraq. She also received her Ph.D. in Production Engineering from Jamia Millia Islamia in New Delhi, India.