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Research Paper

Experimental Investigation and Optimizing Geometrical Characteristics and Surface Quality in Drilling of AISI H13 Steel

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Abstract. The aim of this paper is to investigate and optimize surface quality and geometrical characteristics in drilling process of AISI H13 steel, because they are critical items for precision manufacturing. After conducting the experiments, two regression models are developed to extensively evaluate the effect of drilling parameters on process outputs. After that, evolutionary multi-objective optimization algorithm is employed to find the optimal drilling conditions. Non-dominated Sorting Genetic Algorithm (NSGA-II) is developed and regression functions are taken into account as objective functions of algorithm to simultaneously optimize the surface roughness and deviation of circularity. The optimization results are successfully in agreement with experimental findings and finally the set of optimal drilling conditions is reported that can be selected by process engineer according to the priority and application. It is shown that, an increase in Cutting speed and liquid coolant intensity decreases the surface quality, while higher depth of cut, tool diameter and reed rate improve it. It is also found that tool diameter and depth of cut are the most effective input parameters on deviation of circularity. Finally, it can be concluded that, the implemented approach in this research provides an efficient method for other manufacturing processes to increase the performance and reduction of production costs.

Keywords: NSGA-II, Multi-Objective Optimization, Drilling Process, Hardened Steel.

1. Introduction

AISI H13 die steel is widely used in hot work components. Due to its excellent properties such as high toughness and fatigue resistance, the AISI H13 steel is used more than other materials in mold industry [1]. It is used at different industrial parts such as hot forging and pressing dies, extrusion dies, mandrels and punches, pressure pads, blanking and bending tools. Thanks to the industrial applications of hardened AISI H13 steel, manufacturing operations on this steel are really important [2]. Among manufacturing processes, traditional machining operations have unique advantages such as high production speed, surface quality and dimensional accuracy. Drilling process has great applications in different industries such as aerospace, oil and gas, and military industries [3]. Surface quality and geometrical accuracy are the most dominant challenges in drilling process required to be improved by optimal selection of process conditions [4]. To evaluate process conditions in drilling process, the experimental tests have been carried out by researchers [5-8]. Using the experimental tests, the relation between tool displacement and surface roughness was evaluated by Wojciechowski et al. [9]. In addition to experimental test, mathematical and intelligent methods have been also implemented for machining process to find the optimal process conditions. These techniques are able to find optimal process conditions for using at industrial applications [10]. In this regards, a hybrid method based on the Response Surface Method (RSM)

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and Genetic Algorithm (GA) was developed for optimizing surface roughness in drilling process [4]. Using Taguchi method, optimization of drilling conditions on surface roughness was performed by [10]. In this research, cutting speed and feed rate were studied to improve surface finish. The results showed that the cutting speed is more effective than feed rate on surface quality. The Taguchi method was used by Kıvak et al. [11] which led to optimize the drilling parameters. The effects of the cutting tool, feed rate and cutting speed were investigated. The results indicated that, increasing the cutting tool, feed rate and cutting speed increases the surface finish and reduces the axial force. Pereira et al employed the normalized normal constraint multi-objective optimization method to simultaneously optimize hole geometry and surface roughness was in helical milling of AISI h13 hardened steel [12]. Tyagi et al. [13] studied the Material Removal Rate (MRR) and surface roughness in drilling of low-carbon steel. The parameters of the cutting speed, the feed rate and the depth of the cut were arranged by Taguchi L9 orthogonal arrays. Dry drilling of AA2014 aluminum alloy at low cutting speeds was studied by [6]. To investigate the cutting speed and the feed rate, the Taguchi method was used. Balaji et al. [7] investigated the effects of parameters on the tool life in drilling AISI 304 stainless steel. Using the Grey-Taguchi integrated approach, the machining performance in terms of surface quality, specific energy consumption, and cutting forces was simultaneously optimized under cryogenic conditions by Mia et al. [14]. The intelligent systems were also used for optimization of process conditions in machining operations [8, 15]. Tool wear and cutting forces in milling process of aluminum alloy was evaluated by Adaptive Neuro-fuzzy Interface System (ANFIS) [16]. It has been shown that, these methods are very useful for optimizing the manufacturing processes compared to other mathematical methods. These methods become more efficient when optimization algorithms based on the intelligent approaches are used [17]. Artificial Neural Network (ANN) and GA were used to optimize tensile residual stress in machining process [15]. In addition, multi-objective optimization techniques are used to simultaneously optimize two or more testing conditions at manufacturing processes [18]. In this respect, tool wear and material removal rate were optimized simultaneously with integrated evolutionary strategy in CNC end milling process [19]. An experimental investigation was conducted to optimize tool life and surface roughness at turning of Inconel 718 alloy [20]. Non-Dominated Sorting Genetic Algorithm (NSGA-II) was used for multi-objective optimization of the process. As mentioned, intelligent techniques and evolutionary optimization algorithms have been successfully employed for optimizing manufacturing processes. In spite of several advantages of these strategies, unfortunately they have not been implemented sufficiently for drilling process. Therefore, these methods are deserved to be developed further for optimizing drilling process. This issue becomes more essential for drilling of AISI H13 steel, since this material is highly used in different industries for its excellent properties.

According to the mentioned points and previous studies, optimizing surface roughness and geometrical characteristic in drilling process of AISI H13 has not been investigated yet. In addition, some of the process conditions, such as tool diameter and coolant flow rate, have not been studied. Therefore, it is necessary to take into account these parameters during the optimization procedure. Besides, simultaneous optimizing the drilling process of AISI H13 steel has not been conducted by intelligent methods such as Multi-Objective Optimization (MOO) algorithms. Based on this, at the present study, the effect of drilling parameters including tool diameter and coolant flow rate were experimentally evaluated on surface roughness and geometrical characteristic and the optimal process conditions were determined by using regression models and Non-Dominated Sorting Genetic algorithm (NSGA-II).

2. Design of Experiments

In traditional design of experiment, increasing the number of process parameters leads to a large number of experimental tests. At the present study, to reduce the number of tests, a special design of orthogonal arrays in the Taguchi method was used to study the entire parameters [21]. The tool diameter (D), cutting speed (R), feed rate (F), liquid coolant intensity (L) and the depth of cut at each step (A) were identified as effective factors on geometrical characteristics and surface finish. It should be noted that, laboratory conditions and feasibility of tests were reasons for selection of these parameters and their ranges. The range of each parameter is shown in Table 1. Since the number of factors at different levels is not the same, Taguchi mixed level design was used. To establish the design matrix, Minitab software was used as the statistical method. Taguchi L_{32} orthogonal array was designed. More detailed information about combinations of factor levels are reported in section 4. The surface roughness value (Ra) and out of circularity (mm) were considered as process outputs to be evaluated on testing conditions.

Table 1. The ranges of the parameters.

Levels	Diameters D (mm)	Feed Rate F ($mm.min^{-1}$)	Cutting Speed R (rpm)	Coolant intensity L ($cm^3.s^{-1}$)	Depth of cut A (mm)
1	18	100	100	70	0.2
2	21	200	200	52.5	0.1
3	24	250	300	35	
4	29	360	400	17.5	

3. Experimental Procedure

The AISI H13 tool steel was used for experimental drilling tests. The workpiece dimension was 320×200×35mm^3 and the chemical component of the workpiece material was analyzed and reported in Table 2.

Table 2. The Chemical composition of AISI H13 steel (wt. %).

	C	Si	Mn	P	S	Cr	Mo	V
%	0.38	0.8	0.43	0.03	0.002	4.96	1.28	0.1

All the experiments were carried out based on the design of experiments. The coordinates of the holes are shown in Fig 1. A fixture was used for the initial set and a CNC machine (VMC 1000-B model) as shown in Fig 2.a. The drilling process is shown in Fig 2.b. High Speed Steel (HSS) tools were used for all of the tests. The tool geometry is including point angle of $59°$, helix angle of $60°$, clearance angle of $8°$ and dead center edge angle of $120°$. According to the coordinates of the holes Fig 1, holes were marked by center drill bit. After drilling process, the surface roughness was measured by HOMMEL-ETAMIC T8000 RC needle roughness measurement device as shown in Fig 3.a. The data were obtained at four directions (With 90-degree rotation). The needle movement distance along each hole was 4.8 mm. The measurement of the surface roughness for a drilled hole is shown in Fig 3.b. Due to the material type and diameter size of the holes, the use of a digital caliper was sufficient for measuring deviation of circularity. The diameter of each hole was measured by a 500-173 MITUTOYO calibrated digital caliper at 3 different directions and each measurement was repeated 3 times. More in detail, the average of difference between measured hole size and nominal size at the 3 different directions were reported for measuring deviation of circularity. The process of circularity measurement is shown in Fig 4.

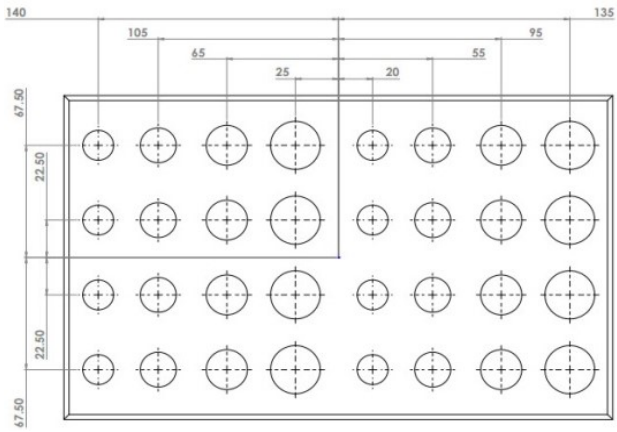

Fig. 1. Schematic of view and dimensions of drilling tests (all dimensions are in mm)

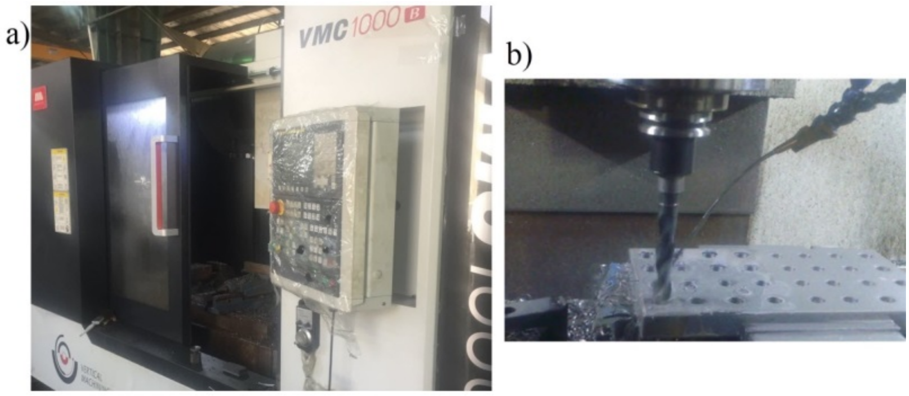

Fig. 1. (a) Drilling machine and (b) Drilling process

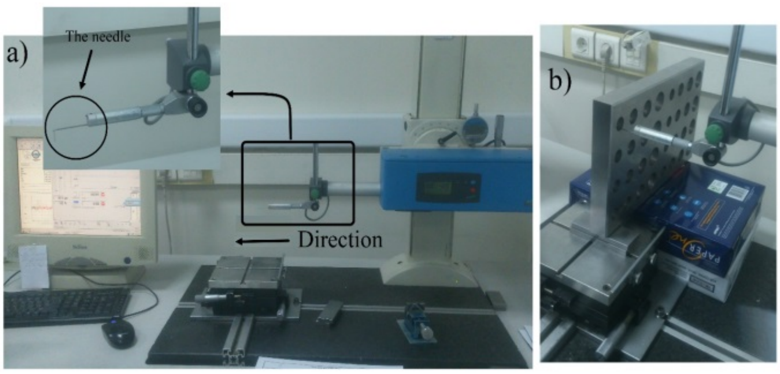

Fig. 3. (a) Measuring device and (b) Measuring the roughness of the holes

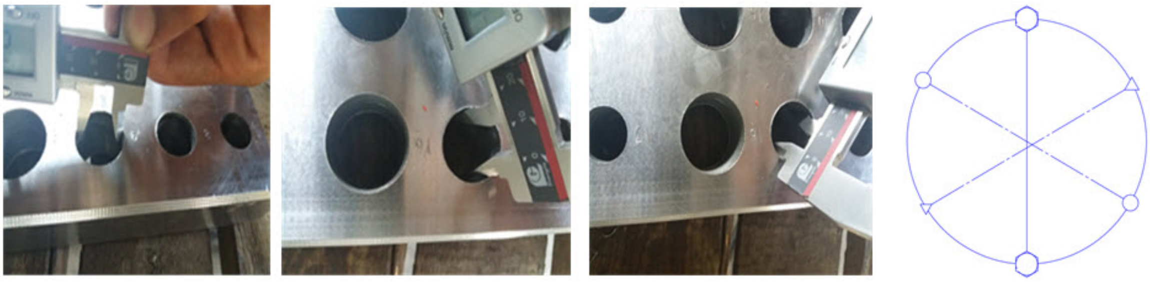

Fig. 4. The procedure and directions of circularity measurement of the holes

4. Evolutionary Optimization Algorithm

Evolutionary Optimization Algorithms (EOA) are widely utilized for optimization of the engineering problems. They have been developed based on the nature of evolutionary pattern to obtain the optimal conditions. It has been shown that results found by these algorithms are more efficient than other classical methods [22, 23]. For instance, genetic algorithm is one of the most common evolutionary optimization algorithms employed to solve single optimization problems. It has been extracted according to the evolution history of genetic in human's body. More information about EOA and GA are available in previous studies [24, 25].

4.1 Multi-Objective Optimization (MOO)

Many engineering problems are not limited to single objective optimization and two or more process outputs are required to be optimized simultaneously. For this purpose, MOO strategy is essential to be used. It should be underlined that, method of operating in MOO is completely different and more difficult than single objective optimization [26]. It is defined as the conflicting optimal solutions (optimal outputs) that dominate other solutions in input variables space (decision space). For example, Z is output space and X and Y are feasible solution in decision space. According to the definition of MOO in minimization problems, it is said that X dominate Y if and only if, $z_j(x) \leq z_j(y)$ for j=1, …, m (process outputs) and $z_j(x) < z_j(y)$ at least for one output (j). In this condition, X is dominated solution that is called Pareto optimal and the corresponding outputs in Z space is called Pareto front. While, all of the solutions in Pareto front are better than other possible solutions, they are not absolutely better than each other. In fact, each optimal solution is better than other Pareto members at least in one output and therefore, all of them are optimal solutions [27].

4.2 Non-dominated Sorting Genetic Algorithm

NSGA-II is one of the most efficient MOO algorithms employed in engineering processes. It is extended version of GA to find non-dominated sorting solutions (Pareto front). The basic procedure of the NSGA-II is shown in Fig 5. As illustrated in this figure, it is started with a random initial population (Pt). Using the genetic operators, population Qt is duplicated by population Pt and then, all of them (Pt and Qt) are taken into account as decision space (input solutions) to be evaluated by objective functions (F1, F2, F3). Using the definition of MOO and non-dominated procedure, all of the solutions classified and ranked based on the ascending order dominance. For the next step, the optimal Pareto fronts obtained at the top of the list are kept as parent population (Pt+1) and half of the solutions (at end of the list) are discarded. This procedure is called elitism strategy that leads to obtaining the optimal Pareto front. To obtain more diversity of the Pareto front and to find new optimal results, the crowding distance operator is used. In this method, the Pareto front's members that have more diversity than other members have priority to be remained at the next step. At the end, the population Pt+1 is used as the input solution of the next step (Pt) and this procedure is repeated to obtain optimal Pareto front. More information about (NSGA-II) and its operations are illustrated in detail in literature [20, 28].

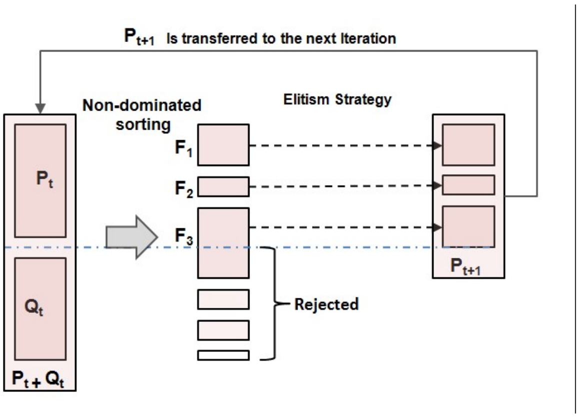

Fig. 5. Basic strategy of optimization in NSGA-II

5. Results and Discussion

The surface roughness and DoC were measured as outputs to investigate the effect of process parameters. In order to reduce idle time for changing the tool, the CNC machine was programmed so that, all of the possible tests were conducted for each drill bit at the suitable location and then, the tool was changed. Based on the order of performing the experiments, the results were reported in Table 3. The number of 8 testing experiments was conducted for each drill bit and the process was stopped (3 times for all 32 tests) to change the tool. In addition, the time for changing the tool and its reposition was more-or-less between 30 to 40 seconds. All the experimental results were summarized in Table 3. In this paper, statistical techniques were used to investigate the parameters. Signal to noise (S/N) ratio was utilized as a benchmark results for Taguchi methods. The best response between the levels of a parameter was determined by the largest S/N ratio, thus the optimal level of each parameter were detected [29]. The difference between the highest and the lowest S/N ratio of a parameter level identifies the amount of parameter's influence on process output [29]. For high product quality better results were established by the lowest value of surface roughness and DoC. Therefore, smaller-the-better characteristic was used to evaluate the results. The smaller-the-better characteristic is given by Eq. (1). In this equation, Yi are responses for the given factor level combination and N is number of responses in the factor level combination.

Table 3. Experiments results.

No.	Input drilling parameters					Measured data	
	A *(mm)*	D *(mm)*	F $(mm.min^{-1})$	R *(Rpm)*	L $(cm^3 s^{-1})$	DoC *(µm)*	Ra *(µm)*
1	0.2	18	100	100	70	0.03	3.76
2	0.2	18	200	200	52.5	0.04	4.18
3	0.2	18	250	300	35	0.06	5.2
4	0.2	18	360	400	17.5	0.05	5.53
5	0.1	18	100	400	70	0.2	2.4
6	0.1	18	200	300	52.5	0.15	4
7	0.1	18	250	200	35	0.18	3.55
8	0.1	18	360	100	17.5	0.15	4.6
9	0.2	21	100	100	52.5	0.02	4.61
10	0.2	21	200	200	70	0.02	4.42
11	0.2	21	250	300	17.5	0.05	5.55
12	0.2	21	360	400	35	0.02	4.66
13	0.1	21	100	400	52.5	0.18	3.1
14	0.1	21	200	300	70	0.23	3.8
15	0.1	21	250	200	17.5	0.2	3.77
16	0.1	21	360	100	35	0.26	3.2
17	0.2	24	100	200	35	0.02	3.98
18	0.2	24	200	100	17.5	0.01	4.8
19	0.2	24	250	400	70	0.09	3.57
20	0.2	24	360	300	52.5	0.08	3.76
21	0.1	24	100	300	35	0.19	3.88
22	0.1	24	200	400	17.5	0.21	4.03
23	0.1	24	250	100	70	0.22	3.72
24	0.1	24	360	200	52.5	0.23	4.25
25	0.2	29	100	200	17.5	0.13	4.82
26	0.2	29	200	100	35	0.14	4.8
27	0.2	29	250	400	52.5	0.2	3.8
28	0.2	29	360	300	70	0.25	4.1
29	0.1	29	100	300	17.5	0.28	4.14
30	0.1	29	200	400	35	0.32	3.53
31	0.1	29	250	100	52.5	0.37	3.13
32	0.1	29	360	200	70	0.39	3.11

$$S/N = -10 * Log\left(\frac{1}{n}\sum_{i=1}^{n} Y_i^2\right) \tag{1}$$

In general, it can be said that the increase of cutting speed (R) and liquid coolant intensity (L) decreases the Ra, while higher depth of cut (A), tool diameter (D) and feed Rate (F) leads to increasing the surface roughness. It was also found that (D) and (A) inputs are the most effective parameters on DoC. Among the experimental results, the optimum conditions were reported in test number 17 and 10 to obtain minimum Ra and DoC, respectively. More in detail, the results indicate that higher the amount of depth leads to increasing the surface roughness. Also, reduction in feed rate and an increase in liquid coolant intensity causes the surface quality is improved. Increasing the amount of the depth also increased chip thickness and cutting force that means high level in (A) factor increase the surface roughness. The obtained results indicate that, the minimum surface roughness was found 2.4 µm at amount of the depth 0.1 mm, tool diameter 18 mm, the cutting speed 400 rpm, the traverse speed 100 mm.min^{-1} and liquid coolant intensity 70 cm^{3}s^{-1}. It was also found that increasing the depth of cut leads to the reduction of deviation at the different cutting conditions. In addition, cutting speed approximately has no effect on DoC, while tool diameter is the most effective parameter so that higher tool diameters (from 18 to 29 mm) lead to the deterioration of DoC. In subsequent subsections, more detailed information is provided by analyzing the experimental results.

5.1 Surface quality analysis

Surface finish is an important indication of machinability, since it has significant effect on service life, assembly conditions, and performance of the machined component. Therefore, it is really necessary for customers in advanced industries to have a production with low surface roughness. Vibration in the machining, built-up edge formation and high feed rate and depth of cut are introduced as the major reasons for increasing the surface roughness that they need to be controlled during the process [30]. In the design of experiment, a main effect is the influence of an input variable on an output averaged across the levels of any other inputs. In fact, it can be used to evaluate the effect of each drilling parameter on process output. Based on this, the main effect plot on surface quality is shown in Fig 6. According to the results reported in Fig 6, the liquid coolant intensity and depth of cut are more effective than other process conditions. While increasing the coolant intensity improves surface quality, enhancement of depth of cut leads to the deterioration of surface roughness. The results also indicate that, drill bit diameter has the lowest influence on surface roughness and it is improved slightly when tool diameter is increased. The reason of this event can be related to the prevention of tool vibration when thicker drill bit is used.

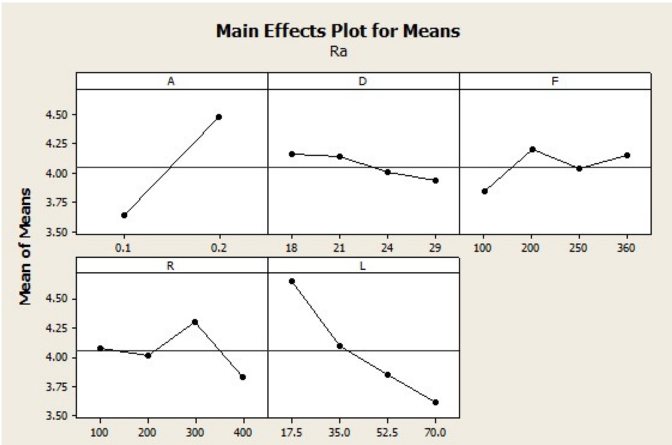

Fig. 6. The main effect plot for surface roughness (Ra)

To evaluate drilling conditions and provide correlation between drilling input parameters and process output (roughness), different regression models were examined and finally the linear model was employed. The regression model to predict surfaces roughness is shown in Eq. (2). To verify effectiveness of the model, the experimental results were compared with corresponding estimated data and it was reported in Fig 7. The Mean Absolute Error (MAE) for estimation of surface roughness was obtained 7.46%. As can be seen, there is a reasonable agreement between experimental and estimated results and therefore the regression model can be used efficiently for evaluation of the input parameters on surface roughness at the next step.

$$Ra = 4.04 + 8.33A - 0.0223D + 0.00104F - 0.000456R - 0.0193L \tag{2}$$

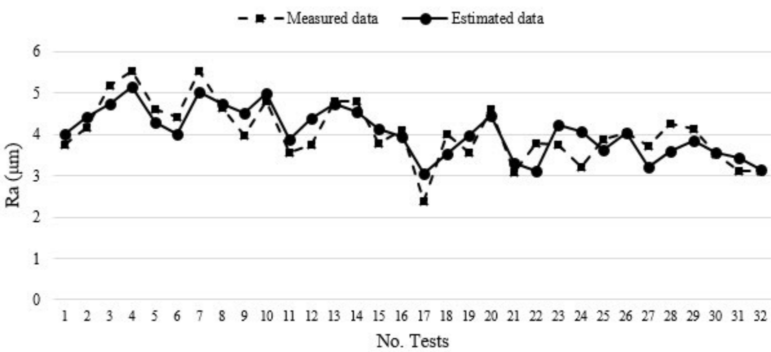

Fig. 7. The comparison between estimated and measured data on Ra

5.2 Analyzing Deviation of Circularity

It is clear that the diameter of hole is one of the major issues in drilling process. In this aspect, precise assembly of the components is directly influenced by geometrical characteristic of hole and it is considered as an important factor for engineers. The machine tool vibration and radial force are considered as critical indications for hole size accuracy. Therefore, the optimum conditions are obtained when the critical factors are reduced. The main effect plot on DoC is shown in Fig 8. The results indicate that the depth of cut and drill bit diameter are the most effective parameters on DoC compared with other inputs. More in detail, higher drill bit diameter increases the cutting forces and consequently more vibration are induced during the drilling process. As the result of this event, DoC is expected to enhance. Regarding the depth of cut, although higher tool diameter increases the torque and radial force, it also increases the contact between tool and workpiece that lead to the higher stiffness and consequently reduction of tool vibration during the drilling process. Increasing the feed rate also increases the tool vibration due to the more strain hardening induced into the workpiece material. Consequently, this event leads to the higher deviation of deviation of circularity.

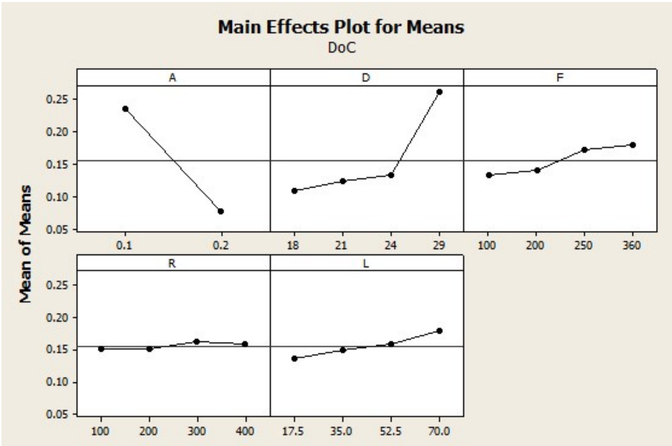

Fig. 8. The main effect plot for DoC

The minimum deviation measured was around 0.01 mm at tool diameter of 24mm, depth of cut of 0.1 mm, cutting speed of 100rpm, feed rate of 200 $mm.\min^{-1}$ and the liquid coolant intensity of 17.5 cm^3s^{-1} (test Number 10). In order to evaluate the effect of input drilling parameters on DoC the linear regression model was obtained and reported in Eq. (3). The comparison between experimental results of deviation of circularity and corresponding results of regression model is given in Fig 9. In addition, The Mean Absolute Error (MAE) for estimation of DoC was obtained by 8.73%. As shown in this figure, not only the linear regression model provides satisfactory agreement with experiments, but also the trend of the estimate results is reasonable compared with experiments at the different testing conditions. Therefore, this model can be used successfully at the next step of the paper.

$$DoC = -0.0018 - 1.59A + 0.0138D + 0.000198F + 0.000036R + 0.000807L \tag{3}$$

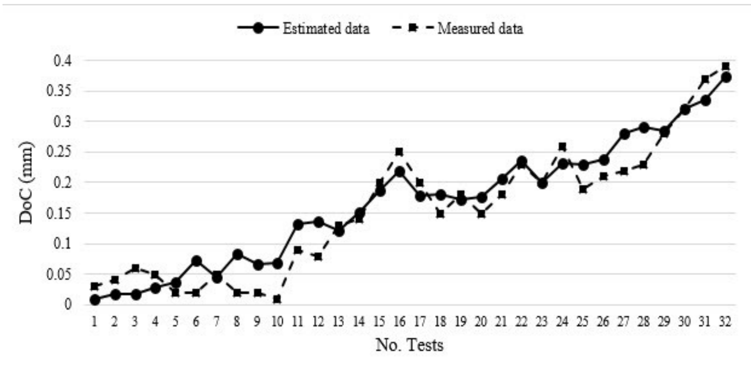

Fig. 9. Compare estimated and measured data on DoC

5.3 Optimization of the process

At previous step, the regression functions were used to evaluate the effect of each drilling parameters separately on surface roughness and DoC. However, it is not possible to take into account multi inputs at the same time and to find the optimal process conditions by only using these predictive models. Therefore, in this section, NSGA-II was used to simultaneously optimize surface roughness and DoC in drilling process of AISI H13 steel. The optimization toolbox in MATLAB software was employed and the genetic operators of NSGA-II were adjusted and calibrated before optimizing the process. In this respect, the regression functions were defined as objective functions of optimization algorithm and the input drilling conditions (including diameter of tool (D), feed rate (F), cutting speed (R), liquid coolant intensity (L), and amount of the depth (A)) were introduced as input variables. The basic procedure of the optimization is illustrated in Fig 10. As can be seen, in each step of optimization new input parameters were generated by algorithm (based on the genetic operators) and their corresponding surface roughness and DoC were evaluated by regression models. After that, the elitism strategy and crowding distance operator was used to select optimal individuals (for the next step) and to find the Pareto front. This procedure was repeated for several iterations. Finally, the number of 45 optimal solutions (Pareto front's members) was sorted according to the process outputs and was reported in Table 4. The evolution of Pareto front formation and optimal Pareto was also shown in Fig 11. In this figure objective1 and objective 2 are DoC and Ra, respectively.

Table 4. The optimal results of multi-objective optimization

NO.	Input drilling parameters					Estimated optimal data	
	A *(mm)*	D *(mm)*	F *(mm.min^{-1})*	R *(rpm)*	L *(cm^{3}s^{-1})*	DoC *(μm)*	Ra *(μm)*
1	0.20	18.00	100.01	100.00	17.50	0.016	4.62
2	0.19	18.01	100.13	131.65	19.66	0.019	4.56
3	0.19	18.03	100.06	100.11	24.87	0.023	4.47
4	0.19	18.10	100.00	102.55	27.84	0.026	4.42
5	0.19	18.01	100.18	115.21	33.36	0.029	4.31
6	0.19	18.05	100.29	110.61	38.28	0.034	4.21
7	0.19	18.00	100.03	119.06	42.43	0.037	4.13
8	0.19	18.00	100.14	130.17	44.58	0.039	4.08
9	0.19	18.01	100.13	137.10	46.12	0.041	4.05
10	0.19	18.03	100.30	124.13	46.17	0.043	4.04
11	0.19	18.01	100.22	122.35	54.09	0.048	3.89
12	0.19	18.02	100.35	130.52	59.31	0.053	3.79
13	0.19	18.12	100.20	182.50	57.62	0.054	3.80
14	0.19	18.10	100.42	249.07	49.40	0.055	3.90
15	0.19	18.12	100.04	189.85	58.03	0.061	3.75
16	0.19	18.02	100.38	122.64	69.36	0.061	3.60
17	0.19	18.05	100.10	134.12	59.85	0.063	3.73
18	0.19	18.07	100.36	220.57	69.26	0.070	3.53
19	0.18	18.06	100.12	328.28	69.33	0.084	3.43
20	0.17	18.16	100.21	289.31	68.35	0.100	3.37
21	0.16	18.13	100.36	171.10	64.02	0.114	3.39
22	0.16	18.29	100.58	293.67	69.16	0.120	3.26
23	0.17	19.37	100.33	298.75	69.84	0.127	3.26
24	0.15	18.15	100.47	327.69	69.40	0.135	3.16
25	0.15	19.24	100.26	166.49	69.39	0.146	3.20
26	0.13	18.27	100.47	298.95	69.40	0.166	3.01
27	0.14	19.76	100.13	248.60	67.90	0.172	3.09
28	0.13	18.18	100.59	291.17	69.30	0.178	2.95
29	0.12	18.30	100.44	310.04	69.32	0.185	2.91
30	0.11	18.39	100.53	344.90	69.84	0.201	2.81
31	0.12	19.43	100.47	348.23	69.31	0.213	2.81
32	0.14	22.42	100.27	335.56	69.88	0.222	2.91
33	0.12	20.53	100.34	308.28	69.93	0.227	2.79
34	0.10	18.63	100.51	360.47	69.98	0.232	2.66
35	0.10	19.75	100.22	354.59	69.77	0.247	2.64
36	0.10	20.93	100.43	358.76	69.73	0.263	2.61
37	0.10	23.17	100.27	329.28	68.40	0.280	2.66
38	0.10	23.36	100.29	360.99	69.51	0.299	2.55
39	0.10	24.20	100.25	360.95	69.92	0.309	2.53
40	0.10	24.70	100.13	360.29	69.58	0.317	2.52
41	0.10	25.57	100.26	361.93	69.98	0.330	2.49
42	0.10	26.98	100.09	360.04	69.88	0.337	2.53
43	0.10	26.90	100.11	358.91	69.71	0.348	2.47
44	0.10	28.11	100.12	362.11	69.64	0.363	2.45
45	0.10	28.99	100.11	362.38	69.99	0.378	2.41

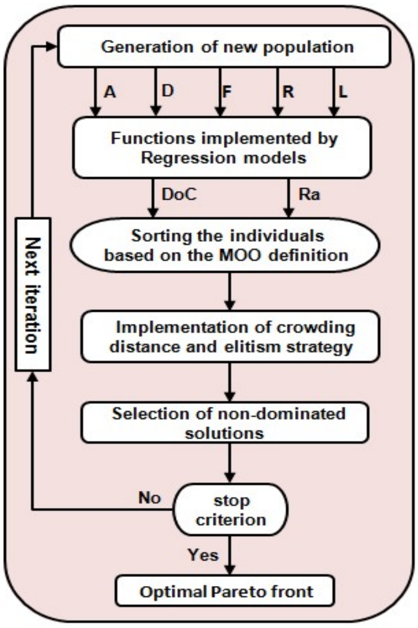

Fig. 10. Basic procedure of optimizing the surface roughness and DoC

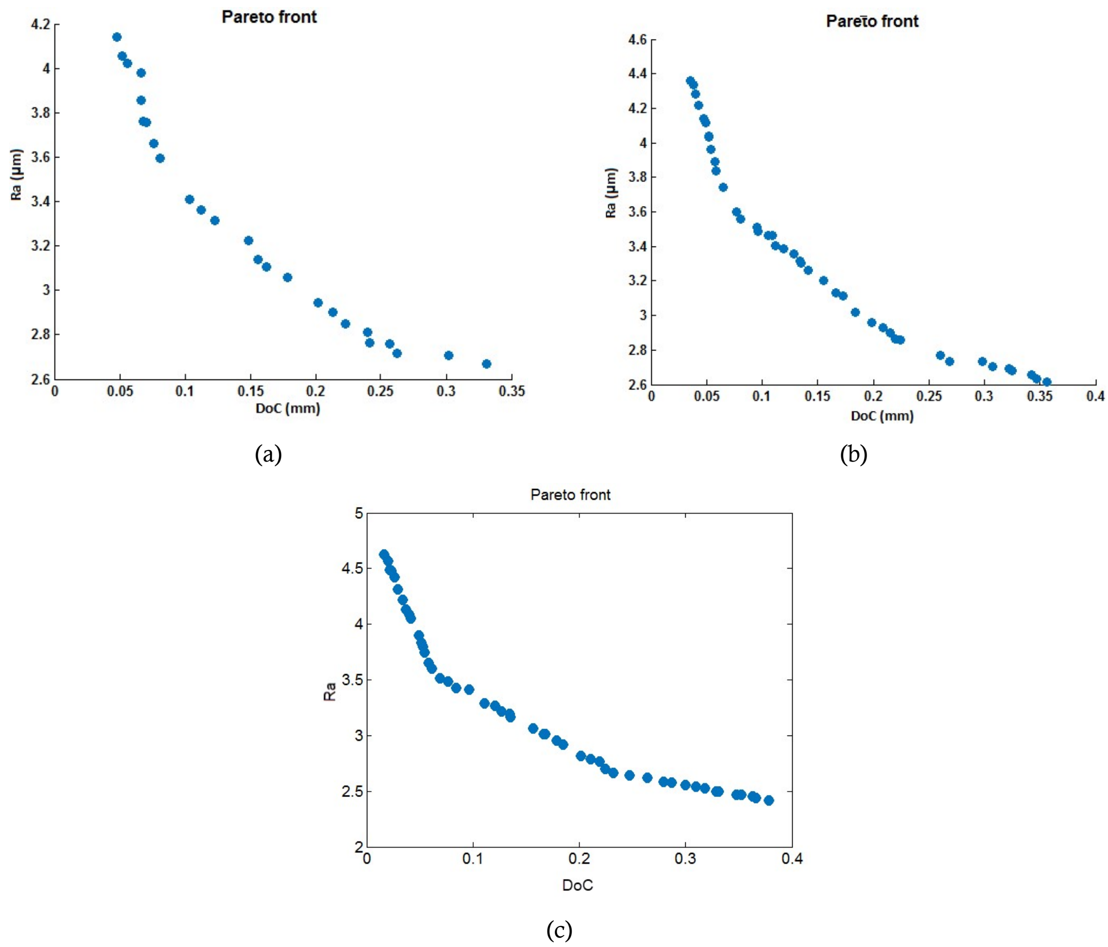

Fig. 11. The evolution of Pareto front formation at (a) 50 iteration, (b) 100 iteration, and (c) optimal Pareto front

It can be said that, all of the estimated results are optimal and they are not absolutely better than each other. In fact, any of them is more suitable than others for processing output of Ra or DoC and the optimal drilling conditions can be selected according to the engineer's requirement and priority. It should be noted that, during the multi-objective optimization with NSGA, continuous parameters are obtained based on the nature of the algorithm. Therefore, to apply these optimal parameters by process engineer, they should be rounded to the nearest parameters that can be selected in practice. It should be noted that, there is a very good agreement between estimated optimal results in Table 4 and experimental tests reported in Table 3. In more detail, not only the minimum and maximum process outputs (Ra and

DoC) for experimental and estimated results are similar, but also the corresponding input drilling parameters are in a same range. Therefore, it can be said that, the results of optimization is reliable and other results can be extracted from the optimization. The results indicate that, geometrical characteristics and surface quality in drilling process of AISI H13 steel are improved when feed rate is kept at the minimum level (100 mm.min^{-1}). Decreasing the amount of the depth and increasing the cutting speed, tool diameter, and liquid coolant intensity lead to deterioration of DoC and improvement of Ra. it seems the optimal results in top and end of the list are quite optimal only for one process output. Therefore, to make the balance between the process outputs at the same priority, the results of the middle of the list is appropriate. For instance, at test number 19 the DoC and Ra are less than 0.1 (mm) and 3.5 (μm), respectively. It should be reminded that, at the present study, optimizing the surface roughness and DOC were performed on the AISI H13 with moderate hardness due to the technical limitation of drilling process of this material at hardened state. As an evolution of this work, optimizing finishing process of hardened AISI H13 can be developed at future studies.

6. Conclusion

AISI-H13 tool steel is widely used in production of different types of dies (such as forging, cutting, and extrusion dies) because of its excellent properties. Therefore, selection of the optimal drilling conditions is an essential task for engineers. In this research, the surface quality and geometrical characterize in drilling process of AISI-H13 steel was studied, since they are critical items in precision manufacturing and assembly of components. For this purpose, several tests were conducted based on the design of experiment to take into account the influence of tool diameter, depth of cut, rotation speed, feed rate and liquid coolant intensity on surface roughness and deviation of circularity. To provide more evaluation, the results of experiments were used for implementing a predictive model of drilling process. In this regard, linear regression models were developed and after that, the evolutionary optimization algorithm of Non-dominated Sorting Genetic Algorithm (NSGA-II) was used to simultaneously optimize the process. To do this, the regression functions were introduced as objective functions of optimization and the optimal Pareto front was obtained after some iterations. The results of experiments, regression models, and multi-objective optimization are summarized as follows:

- Since the influence of coolant flow rate and tool diameter has not been evaluated in drilling process of AISI H13, their variations were also taken into account as input parameters of drilling process. The results of experiments indicated that, increase in Cutting speed (R) and Liquid coolant intensity (L) decreases the Ra, while higher depth of cut (A), tool Diameter (D) and Feed Rate (F) leads to increasing the Ra. It was also found that (D) and (A) inputs are the most effective parameters on DoC. Among the experimental results, the optimum conditions were reported in test number 17 and 10 to obtain minimum Ra and DoC, respectively. Regarding the DoC, It was found that, cutting speed approximately is not effective, while tool diameter is the most important parameter so that higher tool diameters (from 18 to 29 mm) lead to the deterioration of DoC. It was also reported that, increasing coolant intensity (from 17.5 to70 cm^3s^{-1}) and feed rate (from 100 to 360 $mm.\min^{-1}$), increases the DoC and their effects are more visible at the lower depths of cuts.
- The results of the predictive models indicate that, liquid coolant intensity and depth of cut are more effective than other process conditions on surface roughness and drill bit diameter has the lowest influence on surface roughness and it is improved slightly when tool diameter is increased. It was also shown that, depth of cut and drill bit diameter is the most effective parameters on DoC.
- It should be noted that, simultaneous optimizing the drilling process of AISI H13 steel has not been conducted by intelligent methods such as Multi-Objective Optimization (MOO) algorithms. Therefore, the NSGA-II was implemented to simultaneously optimize the surface quality and deviation of circularity. The results of NSGA-II were successfully compared with experimental results (at similar testing conditions) and number of 45 optimal drilling conditions were sorted and reported in Table 4. All of them are optimal testing conditions that can be used according to the priority and application. The results in top and end of the list are quite optimal only for one process output, while the results at middle of the list are in an optimal range for both outputs. For example, at test number 19 the Doc and Ra are less than 0.1(mm) and 3.5(μm), respectively.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship and publication of this article.

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