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Parametric Optimization of Drilling Parameters in Aluminum 6061T6 Plate to Minimize the Burr

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Abstract: In the manufacturing, process a burr has been observed during the drilling through a hole in an aluminum bar. From the view of the life of a product, minimization of the burr should be significant. So in this research main aim is to identify how input parameters: drill diameter, point angle & spindle speed influenced output parameters burr height & thickness. To execute this operation a total of 27 examinations on an Aluminum 6061T6 plate is taken. Overall research performed into two stages. In first stage, Surface response methodology is used to design two objective functions for burr height & thickness with the help of input parameters and then these two objective functions combined to construct a single objective function. In next stage improved version of elephant swarm optimization (ESWSA) algorithm is applied to get the optimum input parameters. The predicted output variable after the optimization techniques (Test 2 & Test 3) further checked with experimental result to determine the accuracy of the proposed model. In a conclusion section it is seen that the average error of drill diameter, drill point angle & spindle speed are 1.72%, 3.84% & 3.89% respectively with average RMSE is 2.56 *10^-6. For further validation of effectiveness of proposed model is also compared with the state of art techniques in the field burr minimization.

IndexTerms: Drilling, Burr Minimization, Response Surface methodology, Optimization, ESWSA.

1. Introduction

Burr is an undesirable material raised beyond the work piece. In modern manufacturing industries, burrs are created in all machining process. Most of the machining process exit burr occurred more than entry burr. The nearness of burr creates numerous issues like obstruction, sticking, misalignment &short circuit. The breaking-off of burrs causes malfunctioning and thus shortens tools lifetime and jeopardizes worker's safe. Deburring is a solution to optimize the burr-related problem. The original deburring operation leads to a long machining time and increases the cost of production. Keeping this in mind, the best solution is to optimize the turning parameters to prevent or at least minimize the formation of burrs in the machining operation.

In modern research minimization of burr in a machining process is a huge challenge. Numerous analysis dealt with burr-related has been performed. Burr minimization can be depends upon mode & direction of cutting tools investigation in [1].An ANOVA based non linear model was proposed in a vertical milling process to obtain the minimum burr when exit beveling angle was kept at 15 degree [2]. Thakre [3] used empirical model: RSM to find out optimum drilling process parameters of an aluminum silicon carbide composite material, from the experimental result it has been seen that minimum burr could be obtained when feed rate is minimum & other two input constrain point angle and concentration of reinforcements are maximum. Gaitonde [4] investigated to minimize burr parameters by utilizing multiobjective Genetic algorithm RSM model. From the result analysis it has been seen that point angle & cutting speed of the drilling machine have a significant effect to get the optimum burr. Kim [5] Performed an experiment chart for three different materials: stainless steel, AISI 304L & AISI 4118 that how the burr production depends upon another new independent constrain, cutting condition by taking the influenced parameters like feed rate, spindle speed & several diameters are kept as constant. Lekkala [6] carried out the experiment on Taguchi-based FFD to minimize the burr parameters in aluminum alloy during the micro end milling operation. From the experimental result it has been concluded that tool diameter, depth of cut, and number of flutes were the potential input parameters. Error of this model was varied from 0.65% to 25 % due to complex geometry of the materials. Ko [7] proposed the different shapes of drill material to get the minimum burr formation. From the experimental result it was observed that step drill produced minimum burr due to minimum step angle & step size. Lee [8] observed the performance of Taguchi method & ANOVA for optimum production of burr corresponding to cutting conditions in a face milling operations. Outcome of this research was quite satisfactory. Narayanswami [9] has performed an experiment on CAD & optimization tool for the combine objective function of formation of burr height & thickness. From the result analysis it was seen that geometric structure, exit angle, centre position & radius of the cutter were the potential input attributes for minimization of burr formation. Gaitonde[10] has performed an experiment for optimization of burr dimensions: height & thickness using ANN PSO from full factorial design (FFD) based experimental data. From the experimental result it was seen that optimum burr was formed for maximum point angle. Gaitonde [11] observed that hole quality of a drilling parameters can be optimized with the proper selection of cutting elements. Gaitonde [12] performed an experiment on GA-RSM with experimental dataset designed by by Box- Behnken design. From the experimental result is concluded that the point angle is takes the significant role in optimum burr formation. Dey [13] observed the optimum burr (thickness & height) corresponding to potential input parameters point angle, spindle speed & drill diameter with the help of ANN model. From the experimental result it was seen that outcome of the proposed model fit with experimental result.

ANN based Taguchi method [14,15] was applied in a face milling to optimized burr formation. Several researchers utilized the hybrid computation-based predictive modelling in machining activity. Some of them are: A GA-RSM based model for obtaining the minimized burr height & thickness from experimental data consisting drilling parameters [11,16]. To predict & minimize the burr formation many researchers proposed genetic algorithm (GA)[4,12,17–19], artificial neural networks [20,21] fuzzy logic [22–24], ANFIS-SVR [20] etc making models. Huan [25]developed two models for prediction of forces: BPNN and hybrid GA-BPNN on a titanium composite material. From the experimental result it has been seen that that hybrid GA-BPNN model had better prediction accuracy than BPNN model.

Elephant Swarm Water Search Algorithm [26–28] has been proposed metaheuristic optimization technique which was motivated by the water asset search technique and social elephant swarm during dry season. As there were just a couple of parameters should have been set in ESWSA, the metaheuristic can be applied effectively and fewer fixations can be given to the parameters tuning. Up until now, ESWSA was applied to numerous issues in various teaches effectively, for example, displaying the fluid stream process[27], and demonstrating of the welding procedure [28].

The primary target of this work is to determine the optimum input parameters so that burr height & thikness will be minimum & for this proposes we used an empirical model: RSM which is optimized by improved renditions of ESWSA metaheuristic algorithms. The presentation of this paper is sorted out as follows. Section 2 portrays the issue plan of this examination work for demonstrating of the drilling process. In this section the test arrangement of a drill process illustratively depicted so as to get the trial datasets. Nonlinear numerical models for the process are likewise explained in section 3. In this section nonlinear model: RSM is explained here proposed methodology is explained in section 4. Improved ESWSA metaheuristic are also explained in the subsection of 4. Finally result analysis is followed by conclusion.

2. Experimental Set up

The objective of this research is to obtain the optimum burr height and thickness from different sets of the machining parameters. The ranges of the input parameters spindle speed, drill bit diameter, point angle are shown in Table 1.

Table.1. Experimental set up [24]

Machine tool	Drill material	Drill Diameter	Job material	Job dimension
Radial drilling machine	HSS (high speed steel) twist drills.	Diameters 8.65, 9.50 and 11.45mm	flat aluminum 6061T6 bar	length 150mm,width 40mm and thickness 12mm

2.1. Experiment Procedure

The flat aluminum 6061T6 bar work piece was firmly fixed in the vice (Pathak Industries Tools Pvt. Ltd.) shown in Figure 1. A pilot drill was used to pre-drilling of aluminum work piece for accurate drilling operation. Photographic view after the drill is shown in Figure 2. For these experiment three different sets of spindle speeds are chosen 626, 1262 and 2213 rpm which was measured in a digital tachometer. Now three drilling parameters (Drill point angle, drill diameter and spindle speed) with three different levels according to full factorial design has been chosen shown in Table 2. During the experiment, universal bevel protractor has been used to measure the point while Digital Vernier Caliper has been used to measure the process responses: average Burr height and thickness. Thus total (3*3*3) 27 number experimental data sheets are obtained. Cutting liquid is used to identify the depth of the bar.

Table .2. Input parameter level of a Drilling machine [20]

Parameters	Level 1	Level 2	Level 3
Drill diameter (mm)	8.65	9.50	11.45
Drill point angle (Degree)	86	104	118
Spindle speed (rpm)	626	1262	2213

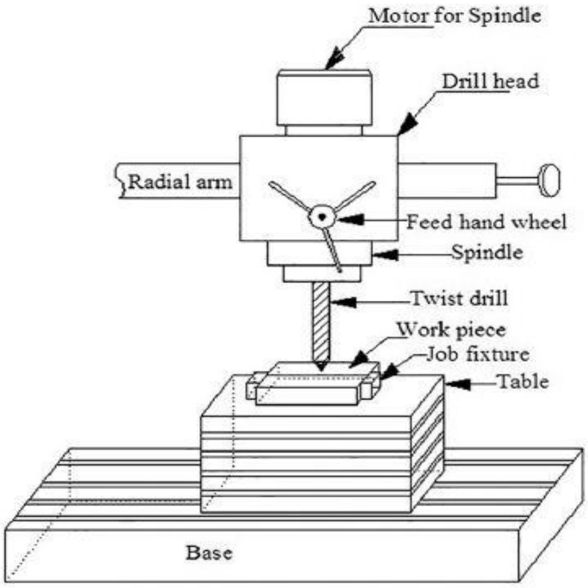

Fig .1. Schematic view of experimental setup[20]

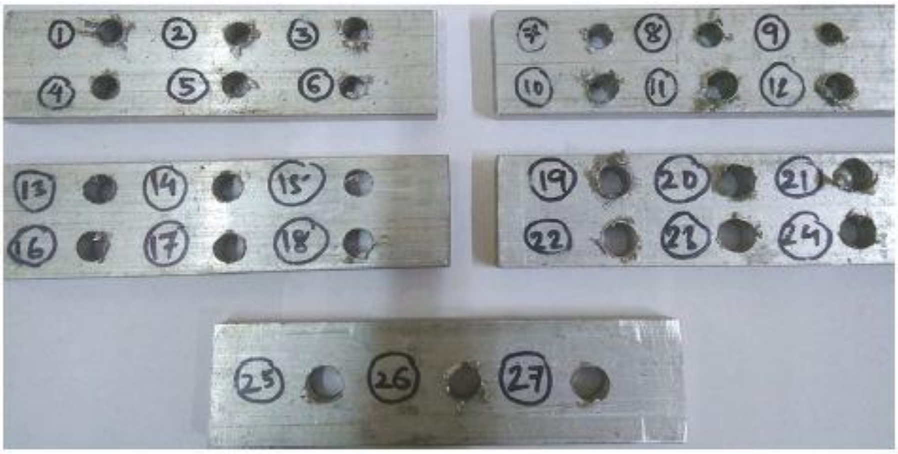

Fig.2. View of the work piece after drilling.[21]

To obtain the minimum burr height & thickness need to find out the optimum input constrain. For this purpose 27 number of combination of input constrain & average output parameters are tabulated in Table 3.

Table .3. Experimentally observed average burr height and thickness data [20]

Si NO	Drill diameter	Point angle	Spindle speed	Avg. height	Avg. thickness
	A	B	C	H	T
1	8.65	86	626	5.69	0.78
2	8.65	86	1262	3.44	0.48
3	8.65	86	2213	6.66	0.65
4	8.65	104	626	4.8	0.38

5	8.65	104	1262	3.91	0.68
6	8.65	104	2213	4.4	0.85
7	8.65	118	626	2.9	0.43
8	8.65	118	1262	4.57	0.39
9	8.65	118	2213	4.3	0.5
10	9.5	86	626	6.65	0.77
11	9.5	86	1262	6.84	0.95
12	9.5	86	2213	4.63	0.84
13	9.5	104	626	4.62	0.4
14	9.5	104	1262	3.36	0.44
15	9.5	104	2213	3.67	0.76
16	9.5	118	626	3.5	0.36
17	9.5	118	1262	6.1	0.44
18	9.5	118	2213	5.23	0.59
19	11.45	86	626	5.78	0.83
20	11.45	86	1262	6.98	0.69
21	11.45	86	2213	4.69	0.78
22	11.45	104	626	2.65	0.57
23	11.45	104	1262	4.43	0.48
24	11.45	104	2213	3.59	0.4
25	11.45	118	626	2.45	0.41
26	11.45	118	1262	6.36	0.7
27	11.45	118	2213	3.26	0.29

3. Mathematical Formulation

Due to nonlinear characteristics of the burr minimization i.e. average height & thickness of the burr has been observed with the change in drill diameter, point angle as well as spindle speed. Hence it is very difficult to find out the input parameter corresponding to the target value of burr height & thickness in conventional methods.

To overcome such situation a nonlinear mathematical models for process has been constructed with help of process input parameters & finally optimized it using computational intelligence. In this research nonlinear model needed to developed using computational intelligence method based on nonlinear relationship between input process parameters: drill diameter, point angle & spindle speed with output process parameters burr height & thickness. These models will assist with discovering the ideal working condition and to foresee the burr height & thickness (for example for various estimations of input dominant parameters) without recalibration. There various nonlinear scientific model to depict a procedure however the most well-known nonlinear models are ANN[29–32],RSM[33–35] and ANOVA [27,34–36].

In present research we utilized Response Surface Methodology (RSM) [28-30]as a factual model for constructing the objective function of burr height & thickness with the help of input constrain given in dataset of Table 3.The broadest utilizations of RSM are in the specific circumstances where a few information factors conceivably impact execution or reaction of the process. Therefore, in this present problem of RSM based modelling of burr height & thickness in drilling process can be expressed in term of drill diameter, point angle & spindle speed.Mathematical model was formulated from each response which correlates the response (Yield) to the process variables through first and second order as well as interactive terms according to Eq.(1).

$$Y = \beta_0 + \sum_{j=1}^{k} \beta_j X_j + \sum_{j=1}^{k} \beta_j X_j^2 + \sum_{j=1}^{k} \sum_{i=1}^{k} \beta_{ij} X_i X_i \tag{1}$$

Where, Y=Response (Drilling process output) & β_0, β_j and β_{ij} are the regression coefficient with $i, j = 1, 2\ldots k$ and X_i are the k input variables. For RSM based non linear model can be written as

$$f(A_i, B_i, C_i) = \beta_0 + \beta_1.A + \beta_2.B + \beta_3.C + \beta_{11}.A^2 + \beta_{22}.B^2 + \beta_{33}.C^2 + \beta_{12}.A.B + \beta_{23}.B.C + \beta_{13}.A.C \tag{2}$$

$$X = \{\beta_0, \beta_{1,}\beta_2, \beta_3\beta_{11}, \beta_{22}, \beta_{33}\beta_{12}, \beta_{23,}\beta_{13}\} \tag{3}$$

The fundamental target of this work is to build up a proficient metaheuristic with the end goal that we can foresee the burr height & thickness more precisely (by evaluating the ideal or best arrangement of qualities for the model parameters). In this exploration work, we have utilized fundamental Elephant Swarm Water Search Algorithm (ESWSA) advancement strategy [26,27] and for streamlining or demonstrating of machining control issue.

3.1. Basic Elephant Swarm Water Search Algorithm (ESWSA)

Elephant Swarm Water Search Algorithm was first proposed by Mandal et al. [27]. This algorithm was mainly influence by the water search methodology of elephant swarm during dry spell with the assistance of various correspondence procedures. Let the optimization problem is d-dimensional & the elephant group are randomly placed. Now the position of i-th elephant group of a swarm after t-th iteration is given as $X_{i,d}^{t} = (x_{i1}, x_{i2}, \dots, x_{id})$& velocity is by$V_{i,d}^{t} = (v_{i1}, v_{i2}, \dots, v_{id}$. Locally best solution by i-th elephant group at current iteration $P_{best,i,d}^{t} = (P_{i1}, P_{i2}, \dots, P_{id})$ and Global best solution is denoted by $G_{best,d}^{t} = (G_1, G_2, \dots, G_d)$.These values are updated according to following equations depending on the switching probability (p) (Mandal,. 2019b)

$$V_{i,d}^{t+1} = V_{i,d}^{t} * \omega^{t} + \epsilon \odot \left(G_{best,d}^{t} - X_{i,d}^{t}\right) \quad \text{if } rand > p \ \text{[for global search]} \tag{4}$$

$$V_{i,d}^{t+1} = V_{i,d}^{t} * \omega^{t} + \epsilon \odot \left(P_{best,i,d}^{t} - X_{i,d}^{t}\right) \quad \text{if } rand \le p \ \text{[for local search]} \tag{5}$$

Where the range of ϵ within [0,1]. &ω^{t} are denotes element wise multiplication & inertia weight to balance between exploration and exploitation. It changes according to the following equation:

$$\omega^{t} = \omega_{max} - \left\{\frac{\omega_{max} - \omega_{min}}{t_{max}}\right\} \times t \tag{6}$$

Where, t_{max}, ω_{max}, $and\ \omega_{min}$ are the values of maximum iteration number, upper boundary (0.6) and lower boundary (0.4) of the inertia weight respectively. The updated position of an elephant group is expressed by following equation:

$$X_{i,d}^{t+1} = V_{i,d}^{t+1} + X_{i,d}^{t} \tag{7}$$

After finishing off all emphasis, the elephant bunches bit by bit update their position and will arrive at the best water asset position which is found by all multitude. The best position indicates the best answer for the improvement issue. It has been found from the writing [26] that p=0.6 gives unrivalled execution for ESWSA. In this way, we have additionally utilized this incentive for our current issue.

4. Methodology

To find out the suitable condition of the drilling what is optimum value of the input parameters or constrain to get minimum burr height & thickness. To get the minimum burr we construct two objective function on the basis of reference burr height & burr thickness using second order Response surface methodology with the help of three input constrain drill parameters, point angle & spindle speed. Finally these two objective functions combine to get a single objective function shown in Figure 3. To obtain the co efficient of the input parameters constrain corresponding to second order RSM model of burr height & burr thickness shown in Table 4. Minitab 16 used to model the second order equation of a RSM mode. Later on final objective function optimized by Elephant Swarm Water Search Algorithm tried against parameters or coefficients estimation issues for minimization of burr parameters. Here the trial dataset has been acquired from the examination as referenced in the prior section. The dataset comprises of 27 number of datasets comprise of drill diameter, point angle, spindle speed (as a dominant input parameters) & response parameters: Avg. height and thickness of the burr. This exploratory dataset has been utilized as a preparation dataset for the parametric improvement of RSM based model of the drill process. Target capacities for these cases are RMSE which is as of now examined in the previous section. After advancement, the best arrangement of coefficients can be acquired so that RMSE is limited.

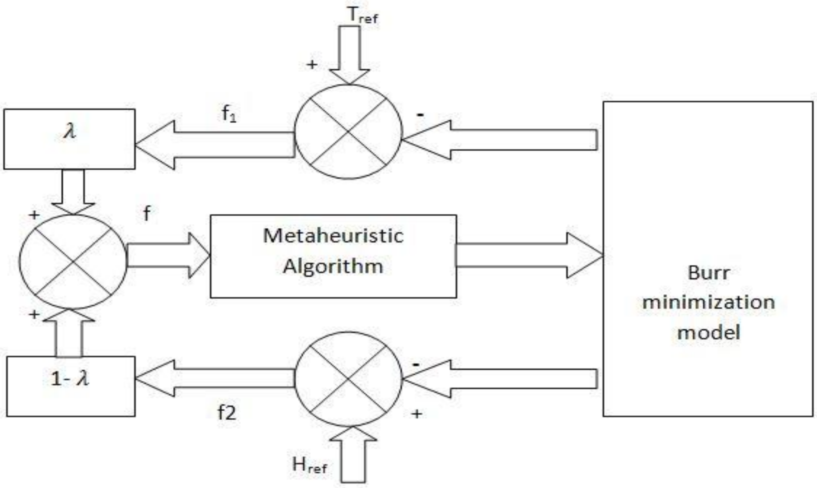

Fig .3. Flowchart of the optimization model

Table .4. Different Co-efficient of a RSM model from Minitab

Regression equation for avg. height		Regression equation for avg. Thickness	
Terms	Co efficient	Terms	Co efficient
Constant	15.8	Constant	-1.41
Diameter	6.36	Diameter	0.733
Angle	0.813	Angle	-0.0313
Speed	0.00125	Speed	0.000556
Diameter*Diameter	-0.273	Diameter*Diameter	-0.0273
Angle*Angle	0.0038	Angle*Angle	0.000138
Speed*speed	10^-6	Speed*speed	Nil
Diameter*angle	-0.0069	Diameter*angle	-0.00088
Diameter*Speed	0.00129	Diameter*Speed	0.000069
Speed*Angle	0.000034	Speed*Angle	2*10^-6

5. Result Analysis

In this study, the optimization problem model of the drill process shown in Fig.3. Table 4 represent the regression co efficient of burr height (H) & thickness (T) by using RSM model with the help of MINITAB 17 & to run the ESWSA code using Matlab 2013b. The specification of the computer is 2 GB RAM, Dual Core processor and Windows7 operating System. Due to stochastic nature of this algorithm is executed for 20 times for each case and the statistical analysis has been carried out. Equation 9 &Equation 10 are representing non linear regression equation for Thickness (T) & height (H) of the burr. Finally Eq. (11) is optimized by the novel elephant swarm water search algorithm.

*f1= (15.8 + 6.36 *x(1) - 0.813 *x(2) + 0.00125*x(3) - 0.273*x(1)^2 + 0.00388*x(2)^2 - 0.000001*x(3)^2 - 0.0069*x(1)*x(2)- 0.000129*x(1)*x(3) + 0.000034 *x(2)*x(3))* (8)

*f2 =(-1.41 + 0.733*x(1) - 0.0313*x(2) + 0.000556*x(3) - 0.0273*x(1)^2 + 0.000138*x(2)^2 - 0.00088*x(1)*x(2) - 0.000069*x(1)*x(3) + 0.000002*x(2)*x(3))* (9)

f = x(4)(4.17-(15.8 + 6.36 *x(1) - 0.813 *x(2) + 0.00125*x(3) - 0.273*x(1)^2 + 0.00388*x(2)^2 - 0.000001*x(3)^2 - 0.0069*x(1)*x(2)- 0.000129*x(1)*x(3) + 0.000034 *x(2)*x(3)))+(1-x(4))*(0.475-(-1.41 + 0.733*x(1) - 0.0313*x(2) + 0.000556*x(3) - 0.0273*x(1)^2 + 0.000138*x(2)^2 - 0.00088*x(1)*x(2) - 0.000069*x(1)*x(3) + 0.000002*x(2)*x(3)))* (10)

Where x(1) , x(2) & x(3) are represent the input variables drill diameters, drill point angle & spindle speed respectively .In Eq. (11) we take the reference thickness & height are 0.475 & 4.17 .

Table 5. Comparison study between the experimental & predictive model for validation

Test 1: Tref =0.475 & Href = 4.17			
	A	B	C
Experimental	9.3	108	1275
Result of this study	9.3564	112.394	1253.03
% Error	0.053%	3.7%	-1.72%

Test 2: Tref =0.64 & Href = 4.95			
	A	B	C
Experimental	10	96	1275
Result of this study	9.656261	93.6261	1322.90
% Error	-3.5%	-2.47%	3.68%

Test 3: Tref =0.57 & Href =5.11			
	A	B	C
Experimental	10.5	112	1275
Result of this study	10.328	118	1195.6
% Error	-1.63%	5.35%	-6.27%

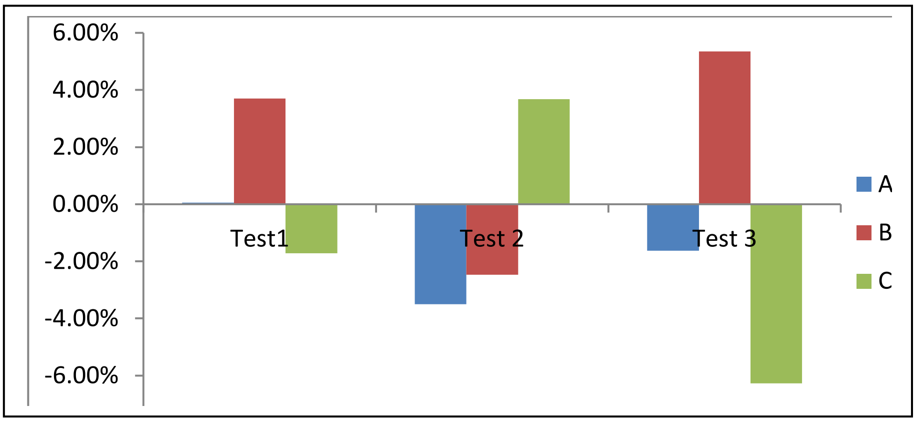

Fig.4. Error for three different sets of test data sets

Table .6. Comparison with other state of art technique

References	Methods	Outcomes
[37]	Second order mathematical with Taguchi optimization techniques	Maximum accuracy to predict the burr height is about to 90%
[38]	ANOVA based Taguchi optimization technique	Maximum accuracy of the Material removal rate(MRR) is 93.74%
[20]	Adaptive fuzzy inference system & Support vector regression analysis	Accuracy for burr height for ANFIS & SVR are 97.1% & 93.98% while the thickness accuracy are 96.7% & 92.9 % respectively.
Present model	RSM based improved ESWSA optimization technique	For given set of burr thickness & height average accuracy of drill parameter, point angle & spindle speeds are 98.28%, 96.14% & 96.11% respectively

From Table 6 it concludes that the proposed model performance effectiveness is much better than the previous state or arts techniques or algorithms by means of accuracy in burr minimization process.

6. Conclusion

Modeling of drilling process is an interesting task in modern era. Generally in drilling process unwanted burrs is depends on drill diameter, drill point angle and spindle speed. In this research 27 number of experimental data sets are taken which contained three different sets values of input parameters like drill diameter, drill point angle & spindle speed and corresponding to responses: burr height & thickness to design the non linear model. In this research in primary stage we have used an empirical model: Response Surface Methodology (RSM) to establish the relationship between the input & response variables of drilling process.

In next stage we consider the workable limit of burr height & thickness as a reference value to construct a single objective function (shown in a methodology section|) with the help of process independent constrain & finally an improved version of suitable metaheuristic optimization technique, Elephant Swarm Water Search Algorithm (ESWSA) is used to find out the optimal values of the input parameters for the safe sets of burr responses: burr height & thickness.

For testing purpose we have taken 3 different sets of data shown in Table 5, after applying the optimization techniques we get the average error of drill diameter, drill point angle & spindle speed are 1.72%, 3.84% & 3.89% respectively and average RMSE is 2.56 *10^-6. Computational time for optimizing the burr parameters is approximately 21.563 seconds on average. Fig. 4 shows percentage of error of drill diameter, drill point angle & spindle speed for the three different sets of testing datasets. Above all this the main disadvantage of this algorithm is the convergence speed is in inconsistent. However this algorithm can predict the burr height & thickness quite satisfactory accuracy. For the validation of proposed model it is further compared with the previous state of art techniques.

In future further tunings of the metaheuristics are necessary to achieve more efficiency, accuracy, convergence speed, stability and success rate.

Contour plot:

Burr height will be maximum during following conditions: drill angle maximum more than 114°&spindle speed moderate 1200-2000rad/m (shown in Fig.5) , during low drill angle(90°) but independent of drill diameter (shown Fig.6) & during maximum diameter (10.5 -11.5 mm) and spindle speed (1200-1600rad/m) shown in Fig.7.

Burr thickness will be maximum during following conditions: drill diameter 9-11 mm & very low drill angle less than 90(shown in Fig. 8) , during the drill diameter 9-10mm but very high spindle speed 2200rad/m (shown Fig.9) & during very low drill angle throughout wide range of spindle speed shown in Fig.10.

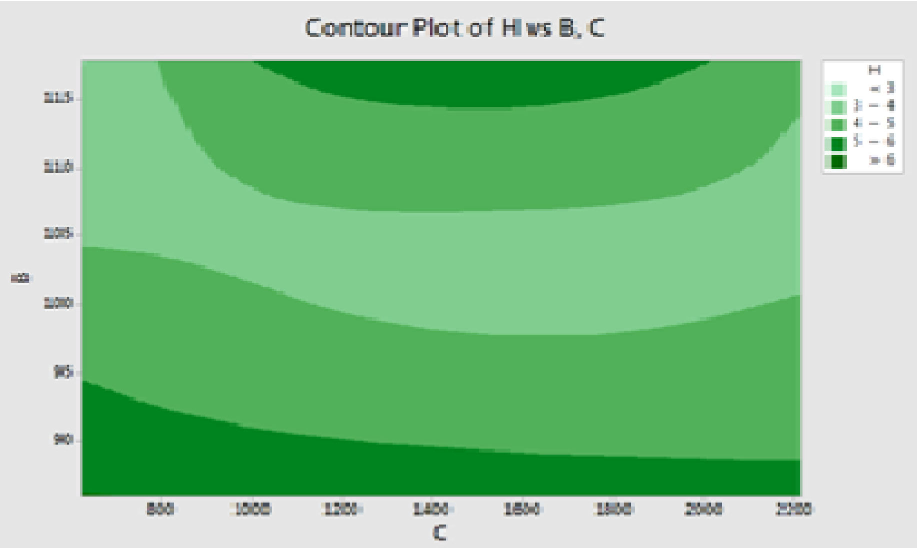

Fig. 5. Contour plot oh burr height with respect to drill angle & spindle speed

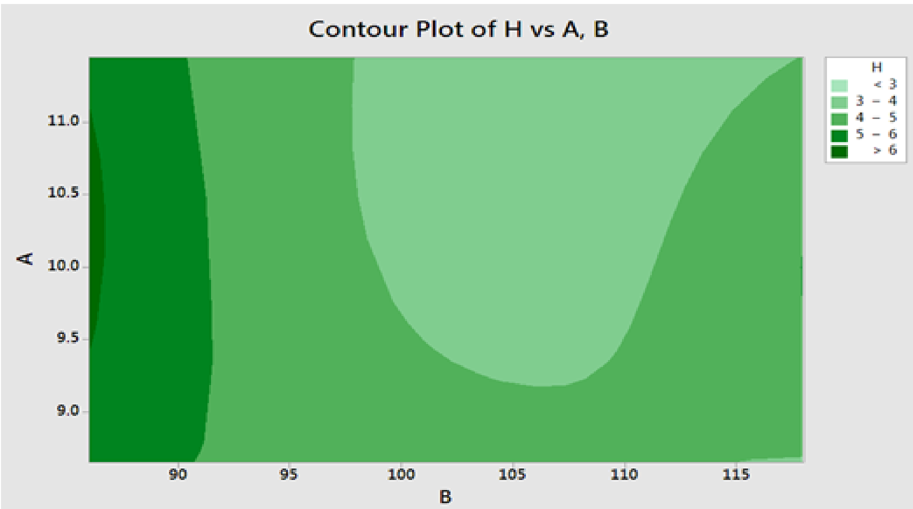

Fig. 6. Contour plot oh burr height with respect to drill angle & drill diameter

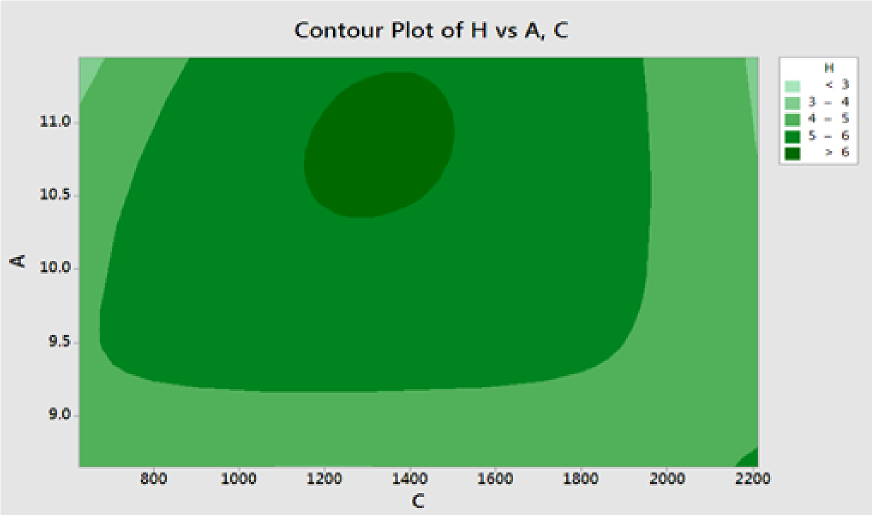

Fig. 7. Contour plot of burr height with respect to drill diameter & spindle speed

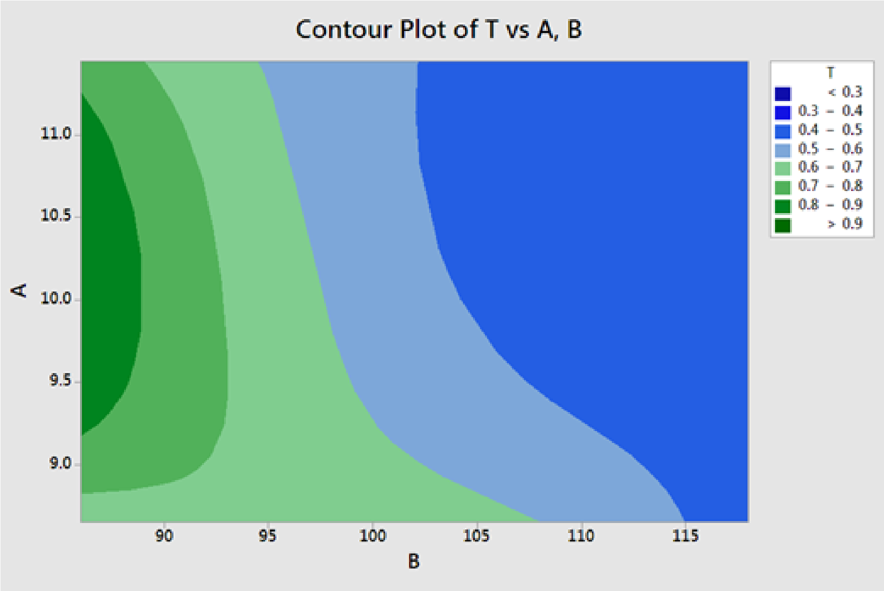

Fig. 8. Contour plot of burr thickness with respect to drill angle & drill diameter

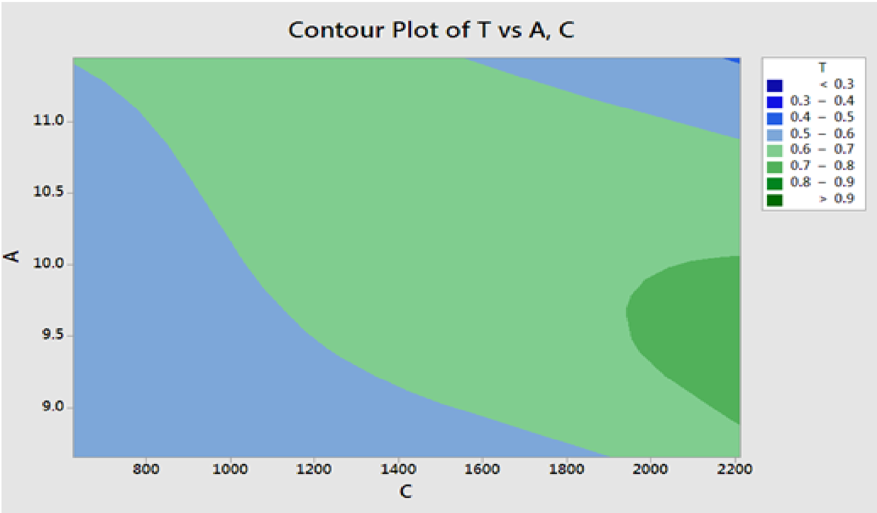

Fig. 9. Contour plot of burr thickness with respect to drill diameter & spindle speed

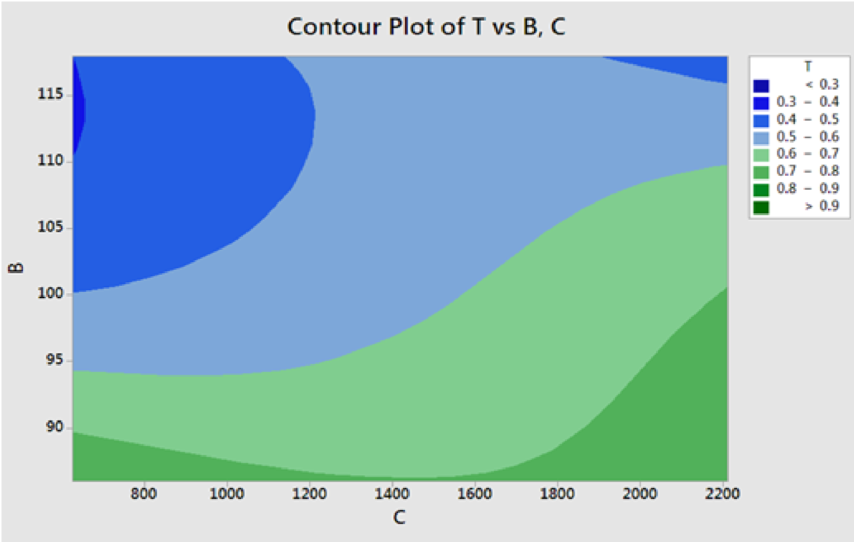

Fig. 10. Contour plot of burr thickness with respect to drill angle & spindle speed

Conflict of Interest

No conflict of interest was declared by the authors.

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