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Optimization of Roundness Error in Deep Hole Drilling using Cuckoo Search Algorithm

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Abstract: In the manufacturing industry, machining is a part of all manufacture in almost all metal products. Machining of holes is one of the most common processes in the manufacturing industries. Deep hole drilling, DHD is classified as a complex machining process .This study presents an optimization of machining parameters in DHD using Cuckoo Search algorithm, CS comprising feed rate (f), spindle speed (s), depth of hole (d) and Minimum Quantity Lubrication MQL, (m). The machining performance measured is roundness error, R_e. The real experimentation was designed based on Design of Experiment, DoE which is two levels full factorial with an added centre point. The experimental results were used to develop the mathematical model using regression analysis that used in the optimization process. Analysis of variance (ANOVA) and Fisher's statistical test (F-test) are used to check the significant of the model developed. According to the results obtained by experimental the minimum value of R_e is 0.0222µm and by CS is 0.0198µm. For the conclusion, it was found that CS is capable of giving the minimum value of R_e as it outperformed the result from the experimental.

Keywords: Deep hole drilling, roundness error, optimization, ANOVA, Cuckoo Search

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1. INTRODUCTION

Hole making process was recognized as one of the most important machining processes and plays a crucial role in product's quality. This process requires most of the machining time for a manufactured part [10]. Deep hole drilling, DHD is one of the most important processes for the production of a high-precision workpiece with high quality holes [3]. Generally, the term 'deep hole' refers to the ratio of hole depth to hole diameter exceeded 10:1[4]. DHD is differed significantly from conventional drilling processes, are relevant for a lot of different applications such as aerospace, automotive, wind energy and nuclear [15] where holes with high length to diameter ratios and very good qualities are necessary.

Roundness error, R_e is one of the main elements in DHD and also important in quality measurements and has a heavy effect on the performance of machines and instruments [20]. Accurate measurement and assessment of roundness error are one of the important processes in quality control and improvement. Kamaruzaman et al. [6] conducted a study in DHD and based on the results, the R_e in DHD is the necessity in a determination of product quality. In another work, Khan et al. [7] examined that hole quality aspects in DHD was influenced by R_e.

In today's competitive environment, modeling and optimization are considered as an important element for improving both aspect quality and productivity. Generally, modeling is the process of estimating the potential minimum value of the machining performance, while optimization is the process of estimating the potential minimum value of machining performance at the optimal point of machining parameters [18]. There are several literatures that related to modeling and optimization. Zainal et al. 2017 [19] employ regression analysis for modeling and Glowworm swarm optimization, GSO algorithm for minimize the surface roughness in EDM process. It was observed that GSO gives the minimum value compared to the experimental result. Deris et al. 2017 [5] proposed Harmony Search, HS algorithm in investigating the dimensional accuracy of die sinking EDM process and regression analysis for modeling. It is observed that HS gave better result by giving the minimum DA value compared with the experimental result. Then, Cuckoo Search, CS was introducing as one of the optimization algorithms. Based on the literature [9], CS applications is widely applied in engineering, pattern recognition, job scheduling, networking, Object-Oriented software (software testing) and data fusion in wireless sensor networks.

Thus, this study comes out with real experimentation in DHD process. Then, an effective mathematical model using regression analysis was developed and CS is used for optimization to determine the combinations of machining parameters that leading to the lower R_e.

2. METHODOLOGY

The methodology employed two parts involved tool and material and Design of Experiments, DoE for conducted the real experiment.

2.1 Tool and Material

For conducting the real experiment, a 3 Axis CNC Milling Machine was used, MAHO MH500E2 as illustrated in Figure 1. The tool and material used were 5mm High Speed Steel, HSS with twist drill bit and Cold Mold Steel 718. Twist drill is the common tools used with DHD and are designed to make round holes quickly and accurately in all materials. HSS was selected because of widespread use in the manufacturing and machining [17]. The chemical composition of Cold Mold Steel 718 includes 0.37% C, 0.3% Si, 2.0% Cr, 1.0% Ni, 1.4% Mn and 0.2% Mo. Cold Mold Steel was selected because of the several advantages based on the handbook of 718 SUPREME Edition 7 which no hardening risks, time saving, lower tool cost and easily carried out.

Figure 1. 3 Axis CNC Milling Machine

Before start the experimentation, the Cold Mold Steel 718 top and bottom faces should be cleaned with Surface Grinding Machine to give a good surface on workpiece and to reduce the inaccuracies while doing the experimentation. Then Table 1 lists the machine specifications used.

Table 1. Machine specification which are used

Machine	Specification
Surface Grinding machine (OKAMOTO Model 63DX ACC)	Clean the surface of workpiece
CNC 3 Axis Milling Machine (MAHO MH500E2)	Produce the holes
Coordinate Measuring Machine , CMM (ZEISS Model Contura G2)	Measure the roundness error

2.2 Design of Experiment (DoE)

Design of experiments, DoE involves a set of statistical techniques to process improvement and planning. Using DoE, the machining parameters level can be adjusted to achieve the best output levels and a robust process which is a process has minimum variability [8]. There are a lot of types methodologies of DoE such as factorial designs, Taguchi, Response Surface Methodology and etc and is always challenged to select the appropriate methodology depending on the objective of the experimental. In this study, the experimentation is based on the Full Factorial design. Full Factorial is the simplest and most common type of factorial design [2]. Minitab 16 statistical software was used to produce the DoE with four machining parameters, 2 levels (low and high) expressed as $2\times 2 \times 2 \times 2 = 2^4 = 16$ experimental trials. Additional 4 centre runs are needed for checking the repeatability of the model, giving the total 20 experimental trials. The machining parameters and levels are shown in Table 2. The levels of each machining parameters were selected based on the tool manufacturer's recommendation, machine manual and industrial practices and literature survey. The values of R_e measurements were measured via Coordinate Measuring Machine (CMM) in assistance with Calypso 4.10 software and the experimental results are shown in Table 3.

Table 2. Machining parameters and their levels

Machining parameters	Units	Level		
		-1	0	+1
f	mm/min	65	75	85
s	rpm	900	1000	1100
d	mm	50	55	60
m	ml/hour	20	30	40

Based on the Table 3, the minimum value of R_e was 0.0222 µm.

Table 3. Experiment results of R_e

Exp No	*f*	*s*	*d*	*m*	R_e (µm)
1	65	900	50	20	0.0382
2	65	1100	50	20	0.0222
3	85	900	50	20	0.0503
4	85	1100	50	20	0.0315
5	75	1000	55	30	0.0290
6	65	900	60	20	0.0605
7	65	1100	60	20	0.0239
8	85	900	60	20	0.0433
9	85	1100	60	20	0.0277
10	75	1000	55	30	0.0492
11	65	900	50	40	0.0467
12	65	1100	50	40	0.0511
13	85	900	50	40	0.1247
14	85	1100	50	40	0.0359
15	75	1000	55	30	0.0371
16	65	900	60	40	0.0313
17	65	1100	60	40	0.0295
18	85	900	60	40	0.0602
19	85	1100	60	40	0.0317
20	75	1000	55	30	0.0385

3. RESULTS AND DISCUSSION

In this section the detail procedures of modeling and optimization are discussed using regression analysis and CS.

3.1 Modeling

In this study, the mathematical model for R_e has been developed using regression analysis. Regression analysis is a statistical tool used for modeling and examining the relationship between two or more variables [1]. The mathematical model is generated using Minitab 16 software based on experimental results. The purpose of developing mathematical model relating to the machining parameters and machining performance is to facilitate the optimization of the machining process [14]. Then, the mathematical model was used as objective function for the optimization process. The mathematical model for R_e is represent in Equation 1 respectively.

$$Re = 0.164 + 0.000637f - 0.000126s - 0.00116d + 0.000709m \tag{1}$$

Where f = feed rate, s = spindle speed, d = depth of hole and m= MQL.

Once the mathematical model has been developed, it is important to determine and check the validity of the mathematical model. ANOVA and F-test are used to analyze and evaluated the mathematical model. The ANOVA table includes Sum of Square (SS), Degrees of Freedom (DF), Mean Square (MS), F-value and P-value.

Table 4. The ANOVA result of Re

Source	**SS**	**df**	**MS**	**F value**	**P value**
Model	4.532E-03	4	1.133E-03	3.50	0.033
Residual	4.851E-03	15	3.234E-04		
Total	9.383E-03	19			

In this study, the ANOVA with 0.05 or 95% significant level, P coefficient <0.05 was used to identify the mathematical model. Based on the Table 4, it can be seen that the value of P is 0.033 which is less than 0.05 which indicates that the model is statistically significant [11]. Then, the F value = 3.50 is higher than F value $F_{0.05\ (4,\ 15)}$ = 3.06 (from F distribution Table) implied that the model is significant.

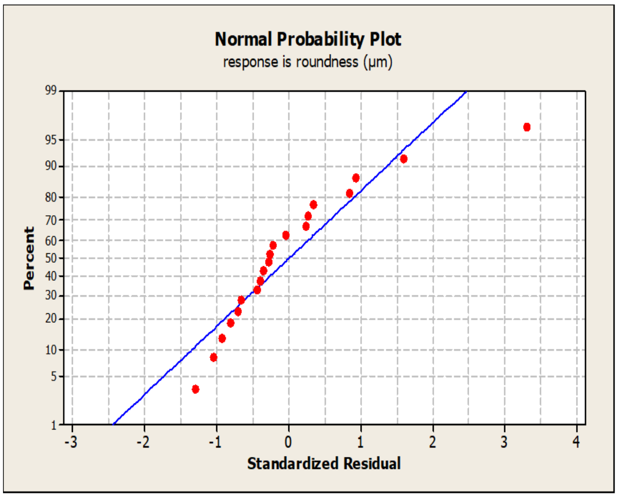

Figure 2. Normal probability plot for R_e

Graphical method also carried out to validate the model. The normal probability plot of the residuals for the R_e is shown in Figure 2. According to the plot, there are no obvious patterns even though some data points are far from the center line and it reveals that all the residual points are falling in a straight line which means, the errors are normally distributed. Distribution of data is good because all the points line up agreeably [13]. This indicates that the model is acceptable under given experimental range.

3.2 Optimization

The aim of the optimization process for any problem is to find a set of variables that will result in the best performance of a system. Nature inspired metaheuristic algorithms are becoming increasingly popular to solve optimization problems. In short, metaheuristic algorithms attend to find an optimal solution and obtain a good solution in a specific period of time. One of the newest optimization techniques is the Cuckoo Search, CS algorithm. This was established by Yang and Deb in 2009 [16]. CS in combination with levy flights [12] is one of the nature inspired metaheuristic algorithms which is based on the brood parasitism of some cuckoo species. The purpose of use of Lévy flight is to speed up the local search whereby CS can achieve optimal solutions rapidly. The basic idea of this algorithm is the specific egg laying and breeding of cuckoos itself. In this case if a host bird discovers the eggs are not its own, it will either throw these alien eggs away or simply abandon its nest and build a new nest elsewhere. The pseudocode of CS is shown in Figure 3.

Step 1: Initialize a population of host nests.
Step 2: Get a new cuckoo position randomly by Lévy fights.
Step 3: Evaluate the quality of the new cuckoo's position *Fi*.
Step 4: Choose *j*-th nest among n randomly.
Step 5: if *(Fi >Fj)* then Replace *j*-th nest by the new solution end if.
Step 6: A fraction of the worse nests (*pa*) are abandoned and new ones are built.
Step 7: Keep the best solutions.
Step 8: Rank the solutions and find the current best solution.
Step 9: if (stopping condition is met) then stop else go to 2 endif.

Figure 3. CS pseudocode

In this study, the mathematical model would be optimized using a real coded of CS and run using MATLAB (R2010b) software. CS will optimize the machining parameters to produce the best possible R_e value with the assumed of lower bound (Lb) and upper bound (Ub). The Lb and Ub for four machining parameters are $65 \leq f \leq 85$, $900 \leq s \leq 1100$, $50 \leq d \leq 60$, and $20 \leq m \leq 40$. According to [17], the sufficient control parameters in CS are number of nests, n=25 and mutation probability value pa = 0.25. Other parameter settings include scale factor (β) = 1.5, step (s) = 1 .Then, the best set of optimal machining parameters by CS which give the minimum value of R_e can be found. Table 5 shows the optimum machining parameters and minimum R_e .

Table 5. Optimum machining parameters and minimum R_e

Method	**Optimal machining parameters [f, s, d, m]**	**Minimum R_e (μm)**
Experiment	65, 1100, 50, 20	0.0222
CS	73.3046,1100,58.138, 21.3873	0.0198

According to Table 5, the minimum value of R_e by experimental is 0.0222μm at the combination of machining parameters of 65 mm/min for feed rate, 1100 rpm for spindle speed, 50 mm for depth of hole and 20 ml/hour for MQL. Then by the CS optimization the minimum value of R_e is 0.0198μm at the combination of 73.3046 mm/min for feed rate, 1100 rpm for spindle speed, 58.138 mm for depth of hole and 21.3873 ml/hour for MQL. It is clear that CS has outperformed the minimum R_e value of the experiment.

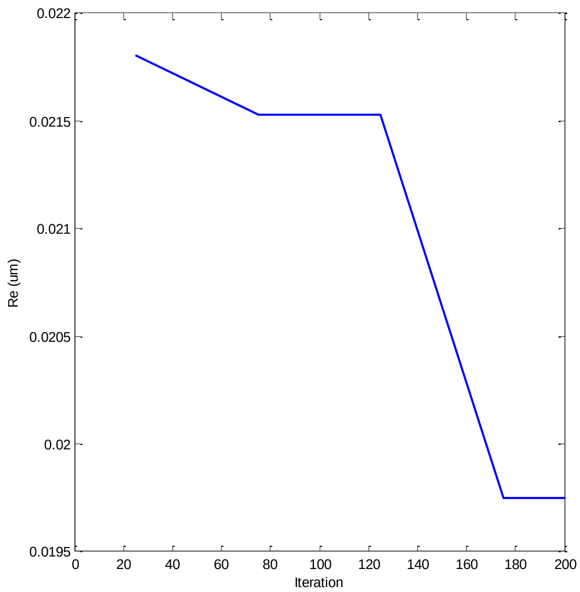

Figure 4. Convergence of CS algorithm for R_e

Then, Figure 4 show the convergence of CS for R_e. From the graph, it is indicated that the optimal machining parameters are obtained at the 175th generation iteration. After that, the validation of the model is shown in Table 6.

Table 6. Validation model of CS optimization for R_e

Equation	**Minimum R_e**
1	0.164+0.000637(73.3046) - 0.000126(1100) – 0.00116(58.138) + 0.000709(21.3873) = 0.0198μm

This validation as the indicators that the same results will obtain when this optimal machining parameters are tested through the actual experiment process. By transferring the optimal machining parameters values of CS into the model in Equation 1, the result is similar which 0.0198 μm. This shows that the same might be obtained when this set of optimal machining parameters are used in the real experiment process.

4. CONCLUSION

In this study, the real experimentation of DHD was done using full factorial design of DoE. Regression analysis is used for modeling to develop the objective function for optimization process. CS algorithm is used in optimization process in order to find the minimum value of R_e for DHD process. Based on the analysis from ANOVA and F –test, the results show that the model is statistically significant. After that, from the CS, the result indicated that CS gave the minimum R_e value compared to the experimental results. In pursuit of this, the optimization principles have to be adopted in the industrial environment especially for manufacturing system for giving more benefits and improvement for industry.

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