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Optimization of Surface Roughness in Deep Hole Drilling using Moth-Flame Optimization

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Abstract: This study emphasizes on optimizing the value of machining parameters that will affect the value of surface roughness for the deep hole drilling process using moth-flame optimization algorithm. All experiments run on the basis of the design of experiment (DoE) which is two level factorial with four center point. Machining parameters involved are spindle speed, feed rate, depth of hole and minimum quantity lubricants (MQL) to obtain the minimum value for surface roughness. Results experiments are needed to go through the next process which is modeling to get objective function which will be inserted into the moth-flame optimization algorithm. The optimization results show that the moth-flame algorithm produced a minimum surface roughness value of 2.41µ compared to the experimental data. The value of machining parameters that lead to minimum value of surface roughness are 900 rpm of spindle speed, 50 mm/min of feed rate, 65 mm of depth of hole and 40 l/hr of MQL. The ANOVA has analysed that spindle speed, feed rate and MQL are significant parameters for surface roughness value with P-value <0.0001, 0.0219 and 0.0008 while depth of hole has P-value of 0.3522 which indicates that the parameter is not significant for surface roughness value. The analysis also shown that the machining parameter that has largest contribution to the surface roughness value is spindle speed with 65.54% while the smallest contribution is from depth of hole with 0.8%. As the conclusion, the application of artificial intelligence is very helpful in the industry for gaining good quality of products.

Keywords: Deep hole drilling, machining, minimum quantity lubricants (MQL), moth flame optimization (MFO) algorithm, multiple linear regression (MLR), surface roughness.

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1. INTRODUCTION

Deep hole drilling process is a process machining that is applied in the industry to produce boreholes with high length-to-diameter ratios bigger than 10 [1]. Deep hole drilling is widely used in large range of industrial sectors such as automotive industry [2], aerospace industry [3], medical technology [4] and engineering process [5]. Most machinists who run the deep hole drilling process are based on the handbook or experience of the machinists themselves. Technological development now demonstrates the application of artificial intelligence is able to obtain the minimum values of machining performances for every machining processes.

Typically machining parameters are selected based on expertise or handbooks are highly conservative and are less helpful to get optimum machining parameters hence lead to less productivity and accuracy. The predictive modeling and optimization has been proven to provide a cheaper and time efficient and an effective alternative compare experimental research that more costly and time consuming [6]. Modeling and optimization process is one of the processes that has been widely applied in the industry to facilitate manufacturers in producing more quality products while saving cost and time. Hence it is very important to apply the modeling process to develop a model that translates the ambiguity among each involved parameters that affect the value of machining performance while optimization process is the branch of intelligent methods used to find the optimal machining conditions [7].

There are various types of modeling and optimization techniques used to solve problems in the industry. The most frequently used modeling technique is linear regression because of the simplicity of the model structures, ease of use and has relatively high accuracy [8]. The optimization techniques such as genetic algorithm [9], particle swarm optimization [10] and simulated annealing [11] have been long established and are often used for optimizing the machining performances. The innovation of new optimization techniques concurrently has perform in giving the best results in optimization process such as moth flame optimization algorithm [12], gravitational search algorithm [13] and artificial fish swarm algorithm [14].

The moth flame optimization (MFO) algorithm is an algorithm based on the natural movement of the moth that is triggered by the moon and the movement is called transverse orientation where the moth will maintain the fixed angle with respect to the moon to travel at night. However the moths are more likely to be tricked by the artificial lights and encourages the moth to move according to spiral path [15]. The advantages of the MFO algorithm is to have good exploration of the search space and not easily trapped in local optima because each moth is assigned with a flame and the series of flames is updated in every iteration and the best position of flame is saved so that the moth will get the guidance to look for optimal value faster without escape too far [16].

The industry has realize the advantages of modeling and optimization process in producing high-quality products. One of the most important machining processes is drilling and it is used in most assembly processes [17]. Machining parameters such as spindle speed, feed rate, depth of cut, tool wear and cutting fluids are important machining parameters affecting surface roughness [18]. A slight changes also contribute to a significant effect on the surface roughness value.

Thus, this research has applied multiple linear regression (MLR) for modeling process and MFO algorithm for optimization process in obtaining optimal value of spindle speed, feed rate, deep of hole and minimum quantity lubricants for achieving minimum value of surface roughness in deep hole drilling.

2. METHODOLOGY

The experiments was conducted on CNC milling machine as the main machine to run the experiments for the deep hole drilling process to find the minimum value of surface roughness. The machining parameters involved are spindle speed, feed rate, depth of hole and MQL as shown in Table 1. There are other machines involved during these experiments as listed in Table 2. The material for the workpiece used is the cold mold steel 718 and the characteristics of the workpiece can be seen in Table 3. The type of tool chosen to run the experiments is HSS Co5 DH100 straight shank twist drills. These geometric features of tools are recommended in deep-hole drilling [19]. The characteristics of the tool is shown in Table 4. The MQL used in this experiment is palm oil and The capacity of high unsaturated fatty acids in palm oil enables high strength films responding well to the surface of the workpiece and work well as a good lubricant at the same time reduce tool wear and friction against the workpiece to ensure a good quality product [20]. The characteristic of palm oil used is indicated in Table 5.

Table 1. Machining parameters and constraints

Machining parameter	Level 1	Level 2	Level 3
Spindle speed, V (rpm)	700	800	900
Feed rate, f (mm/min)	50	60	70
Depth of hole, d (mm)	65	70	75
Minimum quantity lubricant, l (ml/hr)	20	30	40

Table 2. Machine and specifications

Machine	Specification	Application
Surface Grinding Machine	OKAMOTO Model 63DX ACC	Use for clean the workpiece
CNC Milling Machine	Maho Deckel Model MH500E Controller Philips	Use for deep hole drilling process
CNC Wire Cut machine	Sodick Model AQ537L Controller sodick LN1W	Use for cut the workpiece
Profilometer	Accretech Model Handysurf E-35B	Use for measure the surface roughness values

Table 3. The chemical composition of cold mold steel 718

Composition	Percentage (%)
Carbon	0.37
Silicon	0.3
Manganese	1.4
Chrome	2
Molybdenum	0.2
Nickel	1

Table 4. Characteristics of HSS drill used

Standard	DIN 1896/1
Tool material	Cobalts 5% HSS is used in the tool material
Helix angle	38°
Tolerance of the tool diameter	h8
Point angle	130°
Art. -Nr. EDP No.	DL600050
Drill diameter, d_1	5 mm
Overall length, l_1	195 mm
Flute length, l_2	135 mm

Table 5. Characteristics of palm oil

Density (g/cm^3)	0.91
Viscosity at 40ºc (mm^2/s)	40
Viscosity index	190

In the preliminary stage required to assign design of experiment (DoE) first before executing the experiments. The DoE is produced using Minitab 17 software and the experiments were designed based on two level full factorial with four center points. DoE is one of the powerful statistical analysis techniques which are being applied for modelling and analyzing statistical and engineering problems for developing, optimizing and improving various manufacturing process [21]. All experiments consist of twenty tests based on DoE as shown in Figure 1.

The next step is setting up the workpiece, tool and MQL system as depicted in Figure 2. All the experiments were done based on the DoE. Each experiment was performed using new DH100 CO5 HSS straight shank twist drills. Thus, this experiment involves twenty new twist drills are used. This is to ensure the identification of the effect of machining parameters on surface roughness while identifying the optimal machining parameters for a minimum surface roughness values. The output of this experiment is surface roughness measured by a profilometer.

The experimental results of deep hole drilling for surface roughness is shown in Table 6. The minimum value of roundness error is 2.49 µm. The optimal machining parameters are 900 rpm for spindle speed, 70 mm/min for feed rate, 65 mm for deep of hole and 40 l/hr for minimum quantity lubricant. It was found that minimum surface roughness obtained at hole 17.

Results for: Worksheet 2

Full Factorial Design

```
Factors:    4   Base Design:         4, 16
Runs:      20   Replicates:              1
Blocks:     1   Center pts (total):      4


All terms are free from aliasing.



Design Table (randomized)

Run  A  B  C  D
  1  -  -  -  -
  2  +  -  +  +
  3  +  -  -  -
  4  -  +  +  -
  5  +  +  +  -
  6  0  0  0  0
  7  -  +  -  +
  8  -  -  +  -
  9  0  0  0  0
 10  +  +  -  -
 11  +  -  +  -
 12  +  +  +  +
 13  +  +  -  +
 14  -  +  -  -
 15  +  -  -  +
 16  0  0  0  0
 17  -  +  +  +
 18  -  -  -  +
 19  -  -  +  +
 20  0  0  0  0
```

Figure 1. Design of Experiment

Figure 2. Experiment setup

ANOVA has been used for the analysis of results. ANOVA is a statistical analysis which purposely used to identify the factors which significantly affecting the performance measures [22]. Table 7 shows ANOVA results of surface roughness for deep hole drilling. Spindle speed, feed rate and MQL are significant parameters for surface roughness value with P-value <0.0001, 0.0219 and 0.0008 while depth of hole has P-value of 0.3522 which indicates that the parameter is not significant for surface roughness value. The spindle speed was found to have a large contribution of 65.54% while the smallest contribution was owned by the depth of hole with 0.8%.

Table 6. Experimental design and results for surface roughness

No	Spindle speed	Feed rate	Depth of hole	MQL	Surface roughness
1	700	50	65	20	3.81
2	700	70	65	20	4.22
3	700	50	75	20	3.86
4	700	70	75	20	3.96
5	800	60	70	30	3.26
6	700	50	65	40	3.67
7	700	70	65	40	3.27
8	700	50	75	40	3.05
9	700	70	75	40	3.06
10	800	60	70	30	3.20
11	900	50	65	20	3.02
12	900	70	65	20	3.34
13	900	50	75	20	2.76
14	900	70	75	20	2.98
15	800	60	70	30	2.67
16	900	50	65	40	3.10
17	900	70	65	40	2.49
18	900	50	75	40	2.89
19	900	70	75	40	2.58
20	800	60	70	30	2.84

Table 7. ANOVA table of surface roughness

Source	Sum of square	df	Mean square	F-value	P-value
Model	3.85	4	0.96	25.38	< 0.0001
Spindle speed	2.88	1	2.88	75.90	< 0.0001
Feed rate	0.25	1	0.25	6.65	0.0219
Depth of hole	0.035	1	0.035	0.93	0.3522
MQL	0.68	1	0.68	18.04	0.0008
Residual	0.53	15	0.038		
Lack of fit	0.47	12	0.043	2.01	0.3085
Pure error	0.063	3	0.021		
Cor total	4.40	19			

Table 8. Contribution table of surface roughness

Source	Contribution (%)
Model	
Spindle speed	65.54
Feed rate	5.74
Depth of hole	0.80
MQL	15.58
Residual	39.81
Lack of fit	
Pure error	
Cor total	100

3. RESULTS AND DISCUSSION

The results obtained from experimental results have been applied for modeling process. Modeling process used is multiple linear regression. The objective function obtained from the modeling process is represent the relationship between each machining parameters involved which are spindle speed, feed rate, deep of hole and MQL to obtain the minimum value of surface roughness in deep hole drilling process. The objective function used to find the minimum surface roughness value is as described in Table 9.

Table 9**.** Objective function for surface roughness

Objective function
$Ra = 7.13125 - 0.00424375(S) + 0.0125625(f) - 0.00937500000000001(d) - 0.0206875(l)$

Where

Ra	Surface roughness
V	Spindle speed
f	Feed rate in
d	Depth of hole in mm
l	Minimum quantity lubricants (MQL)

The ANOVA and F-test were carried out to see the effectiveness of the mathematical model produced as well as the significance of the machining parameters. Table 10 shows the P-value for multiple linear regression model for surface roughness is significant with p-value of <0.0001. It can be seen that the MS value of the model is greater than MS value of residual which proves the model is significant. Table 11 shows F-calculated of the model is also greater than F-tabulated which indicates the model is significant.

Table 10. P-value for multiple linear regression model of surface roughness

Source	df	SS	MS	P-value
Regression	4	3.85	0.96	< 0.0001
Residual error	15	0.54	0.036	
Total	19	4.40		

Table 11. F-calculated and F-tabulated for multiple linear regression model of surface roughness

Source	df	SS	MS	F-value (calculated)	F-value (tabulated)
Regression	4	3.85	0.96	26.65	2.90
Residual error	15	0.54	0.036		
Total	19	4.40			

Table 12 presents the statistic summary of surface roughness which contains the value of R^2, Adj-R^2 and Pred-R^2. The model shows higher R^2 which indicates that the model explains variations in the surface roughness to the extent of 87.66%. The model also has higher Adj-R^2 value with 84.37% that defines the addition of interaction variables resulting in a better fit model. The value of Pred-R^2 also higher with 76.35% that specify the model enables to predict greatly.

Table 12. Statistics summary for multiple linear regression model

R^2	Adj-R^2	Pred-R^2
0.8766	0.8437	0.7635

In Figure 3 shows the normal probability plot of multiple linear regression model for surface roughness. The plot shows all the points are distributed on the straight line and scattered normally. There are no obvious pattern and all the results are within an acceptable range. It shows that the errors are small during performing the experiments. Therefore, it can be concluded that the model is adequate and valid.

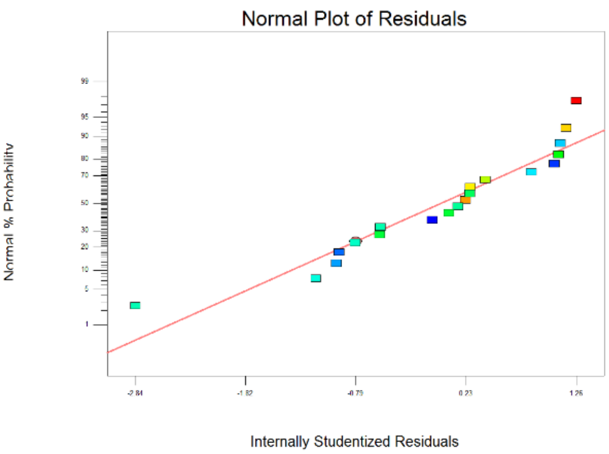

Figure 3. Normal probability plot for multiple linear model of surface roughness (by Design Expert)

Figure 4 shows the graph of experimental versus the multiple linear regression model fpr surface roughness values. It is observed that surface roughness values from multiple linear regression model show less variation from the experimental which indicate that the model can be used to predict the value of surface roughness accurately.

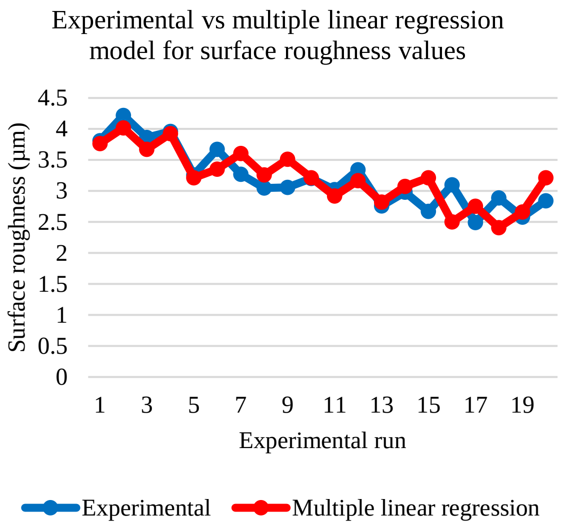

Figure 4. Experimental vs. multiple linear regression model for surface roughness values

The objective function obtained from the modeling process is very important for the next phase which is optimization process to obtain the optimal value for machining parameters which will affect the machining performance value. The month flame optimization (MFO) algorithm has been applied to obtain the optimal value for spindle speed, feed rate, depth of hole and minimum quantity lubricants that will give minimum value for surface roughness. Figure 5 below shows the flowchart of MFO algorithm.

The results of the MFO algorithm are compared with the experimental results as a benchmark. Table 13 shows the optimal solution for surface roughness generated by MFO algorithm with spindle speed is 900 rpm, feed rate is 50 mm/rev, depth of hole is 75 mm and MQL is 40ml/hr. The results have shown that MFO algorithm has minimum value of surface roughness which is 2.41 µm as stated in Table 14.

Table 13. Optimal solutions for surface roughness

Method	Optimal machining parameters			
	Spindle speed	Feed rate	Depth of hole	MQL
Experimental	900	50	65	40
MFOA	900	50	75	40

Table 14. Minimum surface roughness value

Method	Minimum surface roughness
Experimental	2.49
MFOA	2.41

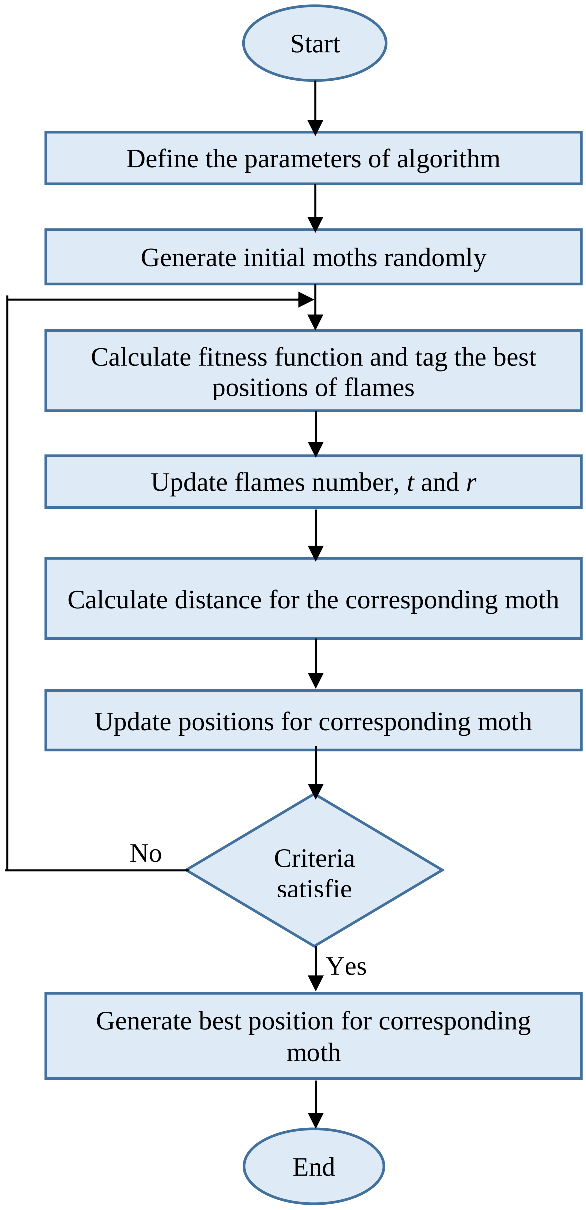

Figure 5. Flowchart of MFO algorithm

Figure 6 presents that the MFO algorithm reached the optimal solution at the 5th iteration. It is clearly stated that MFO algorithm has an improvement in searching the minimum value of surface roughness and the searching of minimum value of surface roughness only in 0.483s of CPU time as shown in Table 15.

The calculations of validating the optimization result are given in Table 14. The minimum value of surface roughness obtained from the calculation is 2.41 µm which is similar with the optimization result in Table 16. This can be taken as the indicator that the same result will obtained when this optimal solution are tested through the actual experiment process.

The percentage of improvement was measured based on the result from experiment and optimization process using MFO algorithm for the purpose to see the improvement done by the MFO algorithm. The result has proved that there is a 5% percentage improvement as a result of optimization process using MFO algorithm as shown in Table.

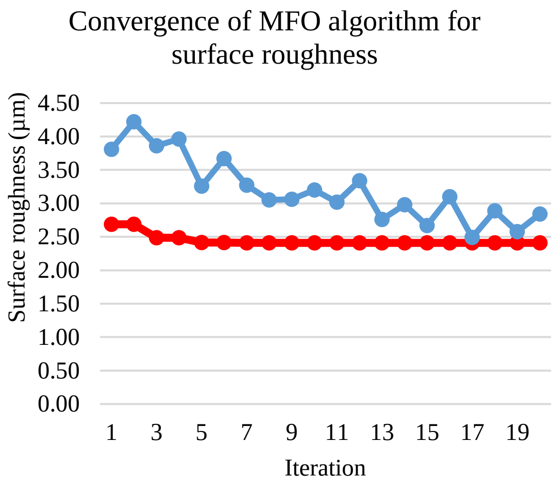

Figure 6. Experimental vs. multiple linear regression model for surface roughness values

Table 15. CPU Time

Iteration	CPU
5th iteration	0.483s

Table 16. Validation of surface roughness

Validation equation	Minimum surface roughness
Ra = 7.13125 - 0.00424375(S) + 0.0125625 (f) – 0.00937500000000001(d) – 0.0206875(l) Ra = 7.13125 - 0.00424375(900) + 0.0125625 (50) – 0.00937500000000001(75) – 0.0206875(40)	Ra = 2.41 µm

4. CONCLUSION

This research emphasizes the application of MLR and MFO algorithm to obtain optimal value for machining parameters involved such as spindle speed, feed rate, depth of hole and MQL and minimize the value of surface roughness. The result of research, analysis and validation shows that MLR and MFO algorithm is proven that both are significant for minimizing the value of surface roughness. The outcome of the research has helped optimizing machining parameters and minimize the value of the surface roughness in deep hole drilling which would have been a requirement in a determination of product quality. Hence the application of MLR and MFO algorithm are very suitable for all areas and not only focus on machining area only.

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