MULTI-OBJECTIVE OPTIMIZATION IN FRICTION DRILLING OF AISI1045 STEEL USING GREY RELATIONAL ANALYSIS

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Abstract: The friction drilling process has the great prospective to vitalize green manufacturing in hole-making process. The optimization of process performance in friction drilling can be realized through an appropriate selection on process parameters. However, some recognized techniques can successfully optimize only on a single-performance characteristic, and optimization on multi-performance characteristics can be difficult and challenging to investigate due to its complexity in the analysis. In this present work, a parametric optimization in friction drilling of medium carbon steel AISI 1045 using L25 orthogonal array design of experiments has been experimentally investigated. The grey relational analysis (GRA) has been utilized to determine optimum process parameters in friction drilling process by considering multi-performance characteristic, namely bush length and roundness error. The GRA results confirm that the best combination of process parameter is obtained as spindle speed 3000 rpm and feed rate 50 mm/min. It has been found that the spindle speed is the more significantly affected than feed rate to obtain a greater bush length and lower roundness error through response table. The confirmation test results show that the GRA succeeds in optimizing the process parameters in friction drilling process. The study revealed the multi-performance characteristic can be enhanced by selecting the proper process parameters.

Key words: Friction drilling, Optimization, Grey relational analysis, Bush length, Roundness error.

1. INTRODUCTION

The drilling process is widely employed in various industries with different workpiece thicknesses. As more than 40% of material removal process is carried out by drilling, it plays a vital role to be focused in machining process (Kaya et al., 2014). Friction drilling process is a non-conventional hole-making method, which the heat increases the ductility of the extruded material on to the front and backsides of the hole. Therefore, the boss and bush are formed on the topside and bottom of workpiece, respectively (Miller et al., 2005; Miller et al., 2006a; Boopathi et al., 2013). The friction drilling is not producing chip or wastage of material has caused all work-material from hole designates to generate the boss and bush. Hence, it is a propitious technology for chipless hole-making process with high efficiency, good surface quality and green drilling without environment impact (Miller et al., 2006b; Ku et al., 2011).

Figure 1 illustrates the basic five stages in friction drilling process. In first stage, the tip of the conical drilling tool reaches and interacts the workpiece (Figure 1(a)). The rotating drilling tool indents into the workpiece and guides friction drilling in both the axial and radial directions. Friction on the contacted surface that caused by axial force and the radial velocity between drilling tool and workpiece generates heat and softens the work-material. As the drilling tool is extruded into the workpiece (Figure 1(b)), at the beginning it forces the softened work-material flows sideward and upward. In third stage, with the workpiece heated and softened, the drilling tool is adequate to pierce through the workpiece (Figure 1(c)). After the conical part of drilling tool fully penetrates the workpiece (Figure 1(d)), the cylindrical part of drilling tool moves further downward to force aside more work-material and form a straight bush. As drilling process is accomplished, the shoulder part of the drilling tool contacts the top surface of workpiece. In final stage, the drilling tool retracts and leaves a hole with boss and bush on the workpiece (Figure 1(e)).

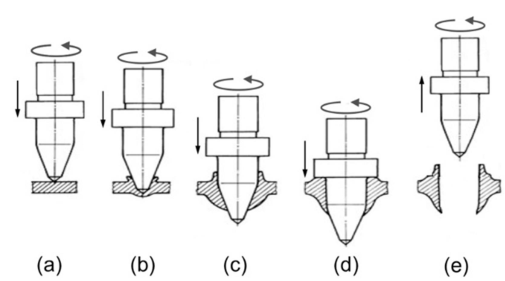

Fig. 1. Basic five stages in friction drilling process

Process parameters such as feed rate, spindle speed, geometry of drilling tool, material properties of workpiece and drilling tool, and workpiece thickness have influence on performance characteristics of the friction drilling, (Ku et al., 2010). Feed rate and spindle speed are the most basic and vital parameters in friction drilling process. Both parameters are very important to provide the highest yields of friction to be generated, which they can largely affect the value of axial thrust force and torque during the friction drilling process (Ku et al., 2011), and tool wear (Deghan et al., 2018). The drilled hole quality and bush length can indicate the efficiency of friction drilling process (Miller et al., 2006b). The bushes and holes generated by this process could be applied to increase the thickness of the workpiece for threading. Therefore, since many process parameters required for fabricating high quality of drilled hole, it is crucial to improve the process performance by determining the optimum process parameters of friction drilling process.

Taguchi method has been widely recognized as a robust approach for design of experiment to examine the effect of process parameters and optimize their conditions at relatively a smaller number of experiment (Hasani et al., 2012; Kivak et al., 2012). Some researchers conducted the optimization study on process parameters using Taguchi method in friction drilling process (Patil & Bembrekar, 2016; Rao et al., 2017). However, these works established the optimum process parameters for only an individual process performance. Moreover, some studies noted that the Taguchi method was designed to optimize a single-performance characteristic (Vinayagamoorthy & Xavior, 2014; Shah et al., 2016). Hence, a practical method is needed to optimize any problem with multi-performance characteristics, since the identification of optimum process parameters is the main challenge in friction drilling process that can cover for several performance characteristics such as bush length, roundness error and surface roughness.

The grey relational analysis (GRA) has been proposed to engineering problem and has proven useful to address the incomplete and uncertain information (Pawadi & Joshi, 2011). GRA makes the optimization process becomes easier by altering the complicated multi-performance characteristics into a single value of grey relational grade. Some researches successfully utilized GRA to optimize the performance characteristics of AISI 304 in friction drilling (Ku et al., 2010; Ku et al., 2011). Both reports solved the multi-performance characteristics of bush length and surface roughness. El-Bahloul et al. (2015) uses hybrid Taguchi-fuzzy logic method to investigate the optimization in friction drilling of AISI 304 steel for five performance characteristics. The results show that the spindle speed and workpiece thickness are the most significant factors affecting the multi-performance characteristics. However, confirmation test shows a contradictory result that the bush length cannot be enhanced since many output responses have been examined. From the above reviews, the determination of optimum process parameters in friction drilling is needed for further investigation. The emphasize should be on the widely used medium carbon steel and multi-performance characteristics of bush length and roundness error. Bush length and roundness error are very important as it benefits to the connection length and clamping strength increases in friction drilling of thin-walled materials.

In this present work, an attempt has been made to develop a multi-objective optimization model based on GRA for determining the best combination of the process parameters, namely spindle speed and feed rate, to attain the optimum bush length and minimum roundness error on friction drilling of medium carbon steel AISI 1045 steel using a drilling tool of tungsten carbide WC. The paper is organized as follows: Section 1 covers the background and motivation of this work. In Section 2 and 3, the experimental procedure and multi-objective optimization using GRA are explained, respectively. Then, the optimization of the friction drilling based on orthogonal array with GRA is described in Section 4. Finally, the paper concludes with a summary of this study in Section 5.

2. EXPERIMENTAL WORK

Figure 2 shows a schematic diagram of experimental setup. In this study, a three-axis computer numerical controlled (CNC) vertical machining centre was used in drilling experiments to minimize the impact of external interference on the drilling quality. This machine has maximum spindle speed of 7000 rpm. The MasterCam CAD/CAM software has been employed to create CNC part program on a personal computer.

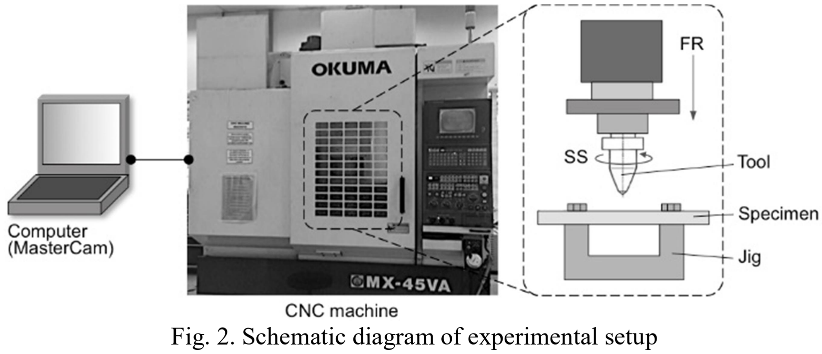

Fig. 2. Schematic diagram of experimental setup

In this study, the work-material was medium carbon steel of AISI 1045. The dimensions of each workpiece were 60 mm in length and width, and 3 mm in thickness. The chemical composition of the work-material is shown in Table 1. The drilling tool was fabricated by tungsten carbide (WC), which the chemical composition of WC and dimension of drilling tool are shown in Table 1 and Figure 3, respectively. The drilling tool was held by a standard collet tool holder. The shank length is 35 mm with the diameter of 8 mm. The tip angle of the drilling tool is 90° and followed by conical region with 37° to allow the contact area between the conical region and the workpiece for producing enough friction in the hole-making process. In addition, the length of cylindrical region is 10 mm to ensure a formation of straight bush at the end of the friction drilling process.

In this study, two process parameters are considered, i.e. spindle speed (SS) and feed rate (FR). Each parameter was set at five different levels as listed in Table 2. To achieve the aims of what the optimal friction drilling controlled parameters for obtaining larger bush length and lower roundness error, a basic L25 (2^5) orthogonal array (Nouira & Bourdet, 2014) was used to establish the experimental design. As performance characteristics or output responses, the bush length (BL) and roundness error (RE) has been considered. After the friction drilling process, the bush length (Figure 4) for each hole on the drilled workpiece was measured using an automatic height gauge. It was measured from the bottom surface of workpiece to the serrated edges of bush. A digital microscope that integrated with measurement system was used to measure the roundness error. For the measurement of roundness error, the minimum radial zone circle (MZC) technique (Kuram & Ozcelik, 2013; Beruvides et al., 2014) was employed as shown in Figure 5. Using this technique, after determining the centre and radius for average circle, the maximum and minimum radius are computed as the higher and lower distances from the centre to any boundary point to obtain roundness error.

Table 1. Chemical composition of workpiece and drilling tool

Workpiece: AISI1045				
C	Mn	P	S	Fe
0.42-0.50%	0.6-0.9%	0.04%	0.05%	Bal.%
Drilling tool: WC				
C	Ni	Cr	Fe	W
4.8-5.6%	8.5-11.5%	4.4-5.6%	<0.3%	Bal.%

Table 2. Process parameters and their levels

Level	Process parameter	
	Spindle speed (rpm)	Feed rate (mm/min)
1	1000	50
2	2000	100
3	3000	200
4	4000	300
5	5000	400

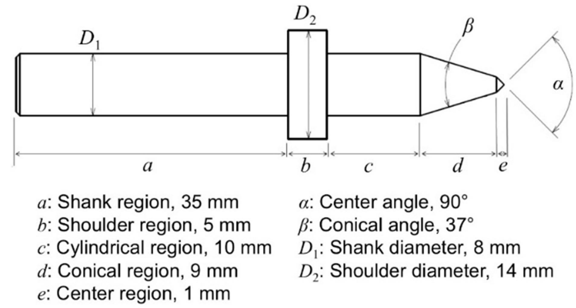

Fig. 3. Design and dimension of drilling tool

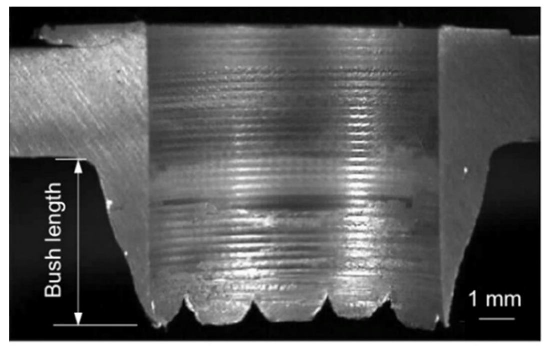

Fig. 4. Cross-sectional view of drilled hole

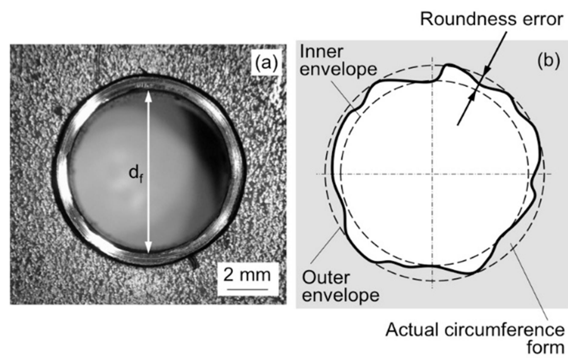

Fig. 5. (a) Top view of drilled hole, (b) roundness error definition

3. GREY RELATIONAL ANALYSIS

To transform the optimization problem from a multi-objective to a single-objective, grey relational grade can be employed. In this study, the optimization of process parameters has been identified that simultaneously to maximize the bush length and minimize the roundness error. Hence, the grey relational analysis (GRA) was used in the present study. The following procedure was executed to convert a multi-objective optimization problem into a single-objective problem.

The first step is grey relational generation to normalize (in the range between one and zero) the experimental data according to the type of performance response. In this study, BL has been characterized as larger-is-better and the original sequence can be normalized using equation (1).

However, RE was to be minimized (smaller-is-better characteristic), the original sequence should be normalized as equation (2).

$$x_i^*(k) = \frac{x_i(k) - x_{i\,min}(k)}{x_{i\,max}(k) - x_{i\,min}(k)} \quad (1)$$

$$x_i^*(k) = \frac{x_{i\,max}(k) - x_i(k)}{x_{i\,max}(k) - x_{i\,min}(k)} \quad (2)$$

where $x_i^*(k)$ and $x_i(k)$ are original sequence after the data processing and observed data, respectively, for i^{th} experiment using k^{th} response. The smallest and largest values of $x_i(k)$ in the k^{th} response are $x_{i\,\min}(k)$ and $x_{i\,\max}(k)$, respectively.

Second step is the calculation of grey relational coefficient (GRC) from normalized data to express the relationship between the ideal and actual experimental data. The GRC, $\xi_i(k)$ can be calculated as equation (3).

$$\xi_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_i(k) + \zeta\Delta_{max}} \quad (3)$$

where $\Delta_i(k)$ is the deviation sequence of the reference sequence, $x_0^*(k)$ and the comparability sequence, $x_j^*(k)$. Δ_i is the difference in absolute value between $x_0^*(k)$ and $x_j^*(k)$ as shown in equation (4). $\Delta_{\min}$ of equation (5) and $\Delta_{\max}$ of equation (6) are the smallest and largest values of Δ_i, respectively.

$$\Delta_i = |x_0^*(k) - x_j^*(k)| \quad (4)$$

$$\Delta_{min} = \min_{(\forall j \in i)} \min_{(\forall k)} |x_0^*(k) - x_j^*(k)| \quad (5)$$

$$\Delta_{max} = \max_{(\forall j \in i)} \max_{(\forall k)} |x_0^*(k) - x_j^*(k)| \quad (6)$$

ζ is the distinguishing coefficient ($\zeta \in [0,1]$) and is used to adjust the different of the relational coefficient. In general, ζ is 0.5 (Kuram & Ozcelik, 2013; Nayak et al., 2014).

The third step is the computation of grey relational grade (GRG) by averaging the weight of GRC corresponding to each response. GRG shows the relationship among the series and is calculated as equation (7).

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \quad (7)$$

where n is the number of responses or number of performance characteristics (in this study n is 2, which are BL and RE). As the final step, the optimum parameter is determined by referring to the higher value of GRG. Higher value of GRG corresponds to the closer experimental value to the ideal normalized value. Thus, higher GRG indicates that the corresponding parameter combination is closer to the optimal

4. RESULTS AND DISCUSSION

Table 3 indicates the L25 experimental layout (column two and three), which levels 1 to 5 of each control factor referred by 1 to 5, respectively. It provides a total 25 experimental runs and each run has a combination of different factor levels. Moreover, each run was repeated three times. From the results of these three replications, the mean values of BL and RE are listed in column 4 and 5 of Table 3, respectively. Since it is difficult to identify the optimum process parameters for achieving larger BL and minimum RE, thus, the next step is by normalizing the experimental results using GRA. As the BL and RE respectively, have been characterized as larger-is-better and smaller-is-better characteristics to provide better quality of drilled hole, equation (1) was utilized to normalize the BL experimental data and equation (2) has been used for normalizing the experimental data of RE.

Table 3. Design of experiment and experimental results of bush length and roundness error

Exp. no.	Process Parameter		Output Response (Mean)	
	Spindle speed	Feed Rate	Bush Length (mm)	Roundness Error (mm)
1	1	1	5.692	0.100
2	1	2	5.469	0.085
3	1	3	3.949	0.157
4	1	4	4.417	0.123
5	1	5	4.124	0.142
6	2	1	5.468	0.112
7	2	2	5.867	0.080
8	2	3	5.472	0.120
9	2	4	5.330	0.121
10	2	5	4.803	0.104
11	3	1	5.813	0.061
12	3	2	5.637	0.111
13	3	3	5.513	0.130
14	3	4	5.354	0.074
15	3	5	5.289	0.106
16	4	1	5.559	0.148
17	4	2	5.223	0.094
18	4	3	5.380	0.101
19	4	4	5.568	0.059
20	4	5	4.967	0.145
21	5	1	5.516	0.124
22	5	2	5.363	0.128
23	5	3	5.337	0.128
24	5	4	5.010	0.085
25	5	5	5.246	0.091

The column two and three of Table 4 lists the processed experimental data after grey relational generation (i.e. normalization). It can be seen that the normalized values are ranged between zero to one. After normalization, all the sequences are denoted as $x_0^*(k)$ and $x_j^*(k)$ for reference sequence and comparability sequence, respectively. The best normalized result should be equal to one and larger normalized results mean to better performance. Next, the absolute value of deviation sequence of $\Delta_i(k)$ is governed using equation (4). In this study, the BL and RE are influence equally by all the process parameters. To calculate the GRC as given in column four and five of Table 4, the distinguishing coefficient ζ=0.5 was replaced in equation (3) by considering all process parameters have equal weightage.

Table 4. Normalized data, calculated GRC and GRG with its rank

Exp. no.	Normalized		GRC		GRG	Rank
	BL	RE	BL	RE		
1	0.909	0.582	0.845	0.544	0.695	5
2	0.792	0.735	0.707	0.653	0.680	6
3	0.000	0.000	0.333	0.333	0.333	25
4	0.244	0.344	0.398	0.432	0.415	23
5	0.091	0.157	0.355	0.372	0.364	24
6	0.792	0.459	0.706	0.480	0.593	10
7	1.000	0.789	1.000	0.703	0.852	3
8	0.794	0.381	0.708	0.447	0.578	14
9	0.720	0.367	0.641	0.441	0.541	18
10	0.445	0.544	0.474	0.523	0.499	21
11	0.972	0.980	0.946	0.961	0.954	1
12	0.880	0.466	0.806	0.484	0.645	7
13	0.815	0.276	0.730	0.408	0.569	15
14	0.732	0.844	0.651	0.762	0.706	4
15	0.699	0.520	0.624	0.510	0.567	16
16	0.839	0.095	0.757	0.356	0.556	17
17	0.664	0.639	0.584	0.581	0.583	12
18	0.746	0.568	0.663	0.536	0.600	9
19	0.844	1.000	0.762	1.000	0.881	2
20	0.531	0.119	0.516	0.362	0.439	22
21	0.817	0.340	0.732	0.431	0.582	13
22	0.737	0.296	0.655	0.415	0.535	19
23	0.724	0.296	0.644	0.415	0.530	20
24	0.553	0.731	0.528	0.650	0.589	11
25	0.676	0.673	0.607	0.605	0.606	7

Then, equation (7) was used to determine the GRG. The experiments order according to GRG values are listed in column six of Table 4. The higher GRG value has been found to be 0.954, indicating that the corresponding experimental data is closer to the ideally normalized experimental data. It is worth noting that the experiment number 11 has the highest GRG and therefore can be regarded as a best experimental sequence for multi-performance characteristics of the friction drilling process. Furthermore, Figure 6 shows GRG from Table 4 for all 25 experiments run as per L25 orthogonal array. The changes in the response when factors go from one level to other also can be observed in Figure 6, and it is very clear that the experiment number 11 has the highest GRG value. Therefore, it is demonstrated that all 25 runs have an optimal combination of process parameters setting for best multi-performance characteristics.

The multiple responses of performance characteristics of friction drilling can be evaluated using a response table using GRG as shown in Table 5. It can be seen that each level of process parameter has an average response characteristic as presented in the response table. By calculating the difference between the highest and lowest value for each characteristic response, the delta value indicates the effect size for each process parameter. Furthermore, the delta value can assist to estimate which factors have the greatest effect on the responses. It confirms that the spindle speed is more influence compared to feed rate on the bush length and roundness error and shown as first rank in Table 5. From Table 5 and Figure 7, it is also confirmed that the SS3 (3000 rpm) and FR1 (50 mm/min) characterize the highest value of GRG for spindle speed and feed rate, respectively. Hence, the combination of SS3-FR1 is the optimal combination of process parameter in friction drilling to obtain largest bush length with lowest roundness error.

Table 5. Response table for grey relational grade

Level	Spindle speed (SS)	Feed rate (FR)
1	0.49740	0.67591
2	0.61241	0.65887
3	0.68824	0.52191
4	0.61174	0.62663
5	0.56837	0.49485
Delta	0.19084	0.18106
Rank	1	2

After the optimum parameter is attained, the optimal combination of process parameter needs to be predicted and a confirmation test should be carried out to verify the improvement of quality characteristics. The estimation or prediction GRG ($\hat{\gamma}$) at optimum level of process parameter can be calculated using equation (8).

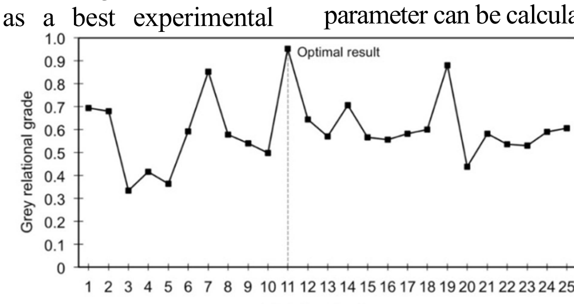

Fig. 6. Grey relational grade for multi-response

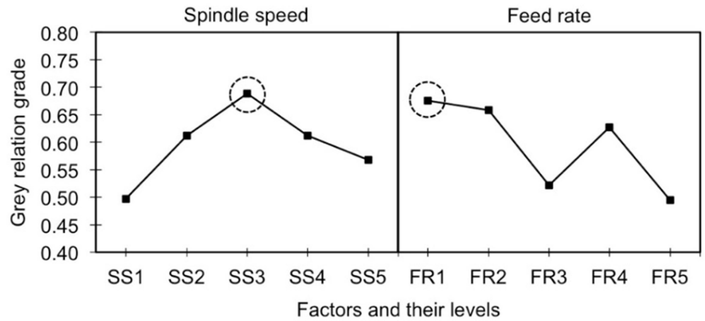

Fig. 7. Effect of friction drilling parameter levels on multi-response

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q}(\bar{\gamma}_i - \gamma_m) \tag{8}$$

where γ_m is the total mean of GRG, $\bar{\gamma}_i$ is the mean of the GRG at the optimum level and q is the number of the process parameter that affects the performance characteristics.

The results of confirmation test are shown in Table 6 and it can be verified that the value of bush length increased from 5.812 mm to 5.863 mm and value of roundness error has been improved from 0.061 mm to 0.054 mm. Furthermore, it is also indicating that the optimization process has improved the GRG value in confirmation experiment compared with predicted value from 0.954 to 0.998. From the results of confirmation test, it confirms that the results are acceptable in optimizing the process parameters of friction drilling process using GRA for multi-performance characteristics.

Table 6. Results of confirmation experiment

	Predicted experiment	Confirmation experiment
Level combination	SS3-FR1	SS3-FR1
BL (mm)	5.813	5.863
RE (mm)	0.061	0.054
GRG	0.954	0.998

5. CONCLUSIONS

The optimization of process performance in friction drilling can be accomplished through an appropriate selection on process parameters. In the present work, a parametric optimization in friction drilling of medium carbon steel AISI 1045 has been experimentally investigated on multi-performance characteristics to achieve a greater bush length with minimum roundness error. The L25 orthogonal array was used as experimental design and the process parameters of spindle speed and feed rate were optimized using grey relational analysis (GRA). The optimum processing parameters are found to be the combination of spindle speed 3000 rpm and feed rate 50 min/mm to obtain larger bush length and lower roundness error. It reveals that the spindle speed was more significantly affected to bush length and roundness error compared with feed rate. Based on the confirmation test, it validates an excellent improvement in the performance of friction drilling process using optimum process parameters. Analysis of different material thicknesses and tool dimensions would be taken into account and focused on future work.

6. ACKNOWLEDGEMENTS

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