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Multi-Objective Optimization in CNC Turning of S45C Carbon Steel using Taguchi and Grey Relational Analysis Method

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Abstract – *The optimization of single performance characteristics has been successfully reported by many researchers. However, the multi-objective optimization is more difficult and challenging to be studied due to its complexity. This is because an improvement of one performance characteristic may lead to the degradation of other performance characteristic. In response to that, the study of multi-objective optimization in CNC turning of S45C carbon steel by using Taguchi and Grey Relational Analysis (GRA) method is reported in this paper. Based on grey relational analysis, a grey relational grade (GRG) is computed to optimize the CNC turning process with multiple performance characteristics which are surface roughness, material removal rate (MRR) and tool wear. In this study, two important parameters were selected, namely spindle speed and feed rate while the depth of cut was fixed. The experimental results show that machining parameter in CNC turning can be improved by using this approach.*

Keywords: Grey relational analysis, Grey relational grade, Material removal rate

1.0 INTRODUCTION

Turning operation is one of the most common methods used in metal removing process, especially to produce conical or cylindrical parts. Various types of parts can be produced by lathe machines such as flat surfaces, curved surfaces, grinding, and boring. Turning operation is defined as the removal of metal chips from workpiece in order to obtain a finished product with desired output characteristic. However, the current issue of turning process is to determine the optimal machining parameters in order to improve several performance characteristics such as surface roughness, Material Removal Rates (MRR) and tool wear simultaneously [1]. All these three outputs are the most critical responses in turning process that must be taken into consideration. Thus, the selection of machining parameters is very important because these parameters will directly influence the performance criteria. It is very difficult to select machining parameter setting that can provide good performance for all the responses simultaneously. Most of the current methods employed are only applicable for the optimization of single performance characteristic. Therefore, it is important to improve surface roughness, reduce tool wear and increase the MRR in turning process simultaneously by using an optimum machining parameter. The main machining parameters selected in this research are cutting speed and feed rate. It is to note here that the most common method used in machining research employs the Design of Experiment (DOE) technique, which is the Taguchi method [2-5].

Taguchi Method has been identified and proved as an effective design of experiment approach that aims to produce high quality products at relatively lower cost [6-7]. For example, a study was reported by Krishnamoorthy *et al.* in performing drilling of carbon fibre reinforced plastic (CFRP) composite plates to determine the quality of drilled holes [8]. In order to improve the quality of the holes drilled, the optimal combination of drilling parameters was determined using Grey Relational Analysis (GRA). Based on the GRA, they found that feed rate is the most influential factor in the drilling of CFRP composites that contribute to the quality of holes drilled [8]. Apart from that, the combination of Taguchi Method and GRA also has been successfully applied by other researchers to optimize the multiple performance characteristics in their studies [9-13].

However, the original design of Taguchi method is to optimize a single output characteristic only [14]. The improvement of multi-performance characteristic is not simple because each of the performance factors has its own characteristic. For example, MRR employs the "higher-the-better" performance characteristic, while surface roughness and tool wear use the "lower-the-better" [15]. Therefore, the improvement of one performance characteristic may lead to the degradation of another performance characteristic. Thus, for multi-performance characteristic, the GRA is used to convert the multi-performance characteristic value into a single Grey Relational Grade value. In other words, the complicated multi-performance characteristic is simplified into a single value to make the optimization process becomes easier. Therefore, this study will propose the near optimum machining parameter that can improve all three performance characteristics simultaneously by using the combination of Taguchi and GRA methods.

2.0 METHODOLOGY

2.1 Experimental Details

The experiment was conducted by using Chevalier FCL-608 turning machine. The machine is capable to deal with maximum spindle speed up to 6000 RPM, maximum cutting diameter of 260 mm and maximum cutting length of 290 mm. The material used is S45C carbon steel bar with dimension of 50 mm in diameter and 100 cm in length, which was machined by uncoated tungsten carbide insert. The experiment was performed under dry condition and straight cutting or turning. Two important machining parameters to be controlled were spindle speed and feed rate. Three levels of spindle speed and feed rate within acceptable operating range were selected as the input parameters while the depth of cut is fixed at 0.1 mm. By using Taguchi methods, an L9 orthogonal array which consists of nine experiments with different three-level input parameters was developed. In this study, the volume of materials to be removed from each of the experiments was fixed at 160000 mm^3 and this value was determined from the preliminary test. Table 1 shows the values of input parameters and their levels.

Table 1: Input parameters and their levels used for orthogonal array

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Input Parameters	Levels		
	1	2	3
Spindle speed (RPM)	1000	2000	3000
Feed rate (mm/rev)	0.1	0.15	0.2

3.0 RESULTS AND DISCUSSION

In general, experimental results in Table 2 show that experiments 1, 6 and 7 gave the minimum value of material removal rate, surface roughness and tool wear. The values of these outputs are 17.8 mm^3/s, 0.77 µm and 0.118 mm for MRR, surface and tool wear respectively. Meanwhile, experiment 2, 3 and 9 produce the highest value of the same experimental output. As mentioned in the earlier section, multiple performance optimizations were carried out using the GRA, in which the optimization processes are explained below.

3.1 Grey Relational Analysis (GRA)

Prior to performing the GRA, there are several steps need to be followed. The first step is to normalize all of the experimental results. This step is also known as the grey relational generation. According to Taguchi methodology, surface roughness and tool wear are classified under the lower the better performance responses, whereas MRR is classified under the higher the better performance criteria. Table 2 shows the experimental results which were initially converted into Taguchi signal to noise (S/N) ratio. The linear data processing method for surface roughness and tool wear is the lower the better and is expressed as in Equation 1.

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{1}$$

Meanwhile, for MRR, 'the higher the better' is chosen and expressed as Equation 2 below:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{2}$$

where y_i is the ith experimental results in the kth experiment and $x_i(k)$= is the value after the grey relational generation. The normalized values are ranged between zero and one. Based on Taguchi methodology, the larger normalized values yield better performance and the ideal value should be equal to one.

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Table 2: Results of L_9 Orthogonal Array and Grey Relational Grade

No. of Experiment	Spindle speed (RPM)	Feed Rate (mm/rev)	MRR (mm^3/s)	Surface Roughness, Ra (µm)	Tool Wear (mm)	*S/N* Ratio for MRR	*S/N* Ratio for Ra	*S/N* Ratio for TW	GRG
L1	1000	0.10	17.8	4.17	0.169	25.01	-12.40	15.44	0.2718
L2	1000	0.15	26.7	4.44	0.179	28.53	-12.95	14.94	0.2617
L3	1000	0.20	35.6	4.81	0.163	31.03	-13.64	15.76	0.2840
L4	2000	0.10	35.6	0.97	0.124	31.03	0.26	18.13	0.6463
L5	2000	0.15	53.4	1.46	0.152	34.55	-3.29	16.36	0.4630
L6	2000	0.20	71.2	1.88	0.118	37.05	-5.48	18.56	0.6689
L7	3000	0.10	53.4	0.77	0.128	34.55	2.27	17.86	0.6763
L8	3000	0.15	80.1	0.88	0.130	38.07	1.11	17.72	0.6933
L9	3000	0.20	106.8	1.67	0.118	40.57	-4.45	18.56	0.8687

The second step is to calculate the grey relational coefficient (GRC) to express the relationship between the ideal and actual normalized experimental results. The formula for calculating the GRC is shown in Equation 3.

$$\varepsilon_i(k) = \frac{\Delta_{min} + \beth\Delta_{max}}{\Delta_{0i}(k) - \beth\Delta_{max}} \quad (3)$$

where $\Delta_{0i} = \|x_0(k) - x_i(k)\|$, is the difference of absolute value between $x_0(k)$ and $x_i(k)$. $\beth$ is the distinguished coefficient which is set between 0 to 1, which in this study was set to $\beth = 0.33$. Δ_{min} is the smallest value of Δ_{0i}; and Δ_{max} is the largest value of Δ_{0i}.

After that, the grey relational grades (GRG) were computed by averaging the GRCs for each performance characteristic and tabulated in the Table 2 last column. A higher value of GRG shows that the experimental result is closer to the optimum value. In this study, it can be clearly seen that experiment 9 out of L_9 orthogonal array has the highest value of GRG, which means it has the best multi response characteristics.

Meanwhile, based on GRG plot shown in Figure 1, the optimal process parameter level can be identified based on the highest value of GRG. Thus, the best parameter setting that has been found in the current study is S3F3, in which the spindle speed is at 3000 RPM and feed rate of 0.2 mm/rev.

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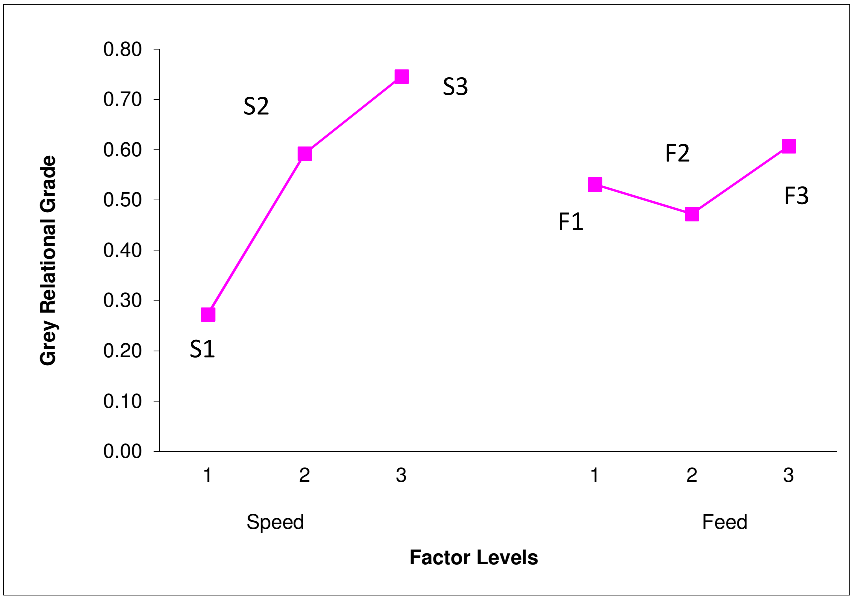

Figure 1: Grey relational grade plot.

3.2 Tool Wear

Tool wear is one of three performance characteristics investigated in this study. It is known that there are typically three types of tool wear on cutting tool namely; crater wear, flank wear and corner wear. However, in the current study only flank wear was observed. Flank wear occurs on the tool flank as a result of friction between the machined surface of the workpiece and the tool flank face. It can be clearly seen in Table 2 that the results of tool wear were decreasing as the input parameter is increasing. Surprisingly, this pattern of result is contradictory to the theory, in which higher input parameter will cause to higher damage on the tool. However, this scenario occurs due to the fixed value volume of material to be removed instead of fixed machining time. As mentioned earlier, the volume of material to be removed in each of the experiments was fixed to 16000 mm^3. Thus, different input parameter will exhibit different machining time or in other words, the higher input parameter will result to lower machining time. As a result, a higher damage to the tool will occur when the time of the tool being used is longer. Figure 2 shows the tool wear of different spindle speed which is (a) experiment 2 at 1000 RPM, (b) experiment 5 at 2000 RPM and (c) experiment 8 at 3000 RPM.

3.3 Analysis of Variance (ANOVA)

The main purpose of ANOVA is to statistically determine which machining parameter affects the performance evaluation the most. In other words, ANOVA is used to analyse the contribution of each factor on the multiple performance characteristics. The first step in determining ANOVA is by calculating the sum of the squared deviations from the total mean of the GRG. Next, the GRGs are separated according to the contributions and error of each machining parameters. Finally, any machining parameter that poses the highest mean square value is considered as the most significant machining parameter that affects the multiple performance characteristics. The result of ANOVA is shown in the Table 3. It is apparent that spindle speed is considered as the most significant factor as it represents 87.85% of the contribution to the combined outcomes of experiment. Meanwhile, feed rate is less significant as it only represents 6.84% of contribution towards the multiple experimental output. The error

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due to experiment determined from this ANOVA test is only 5.3%, which is statistically acceptable.

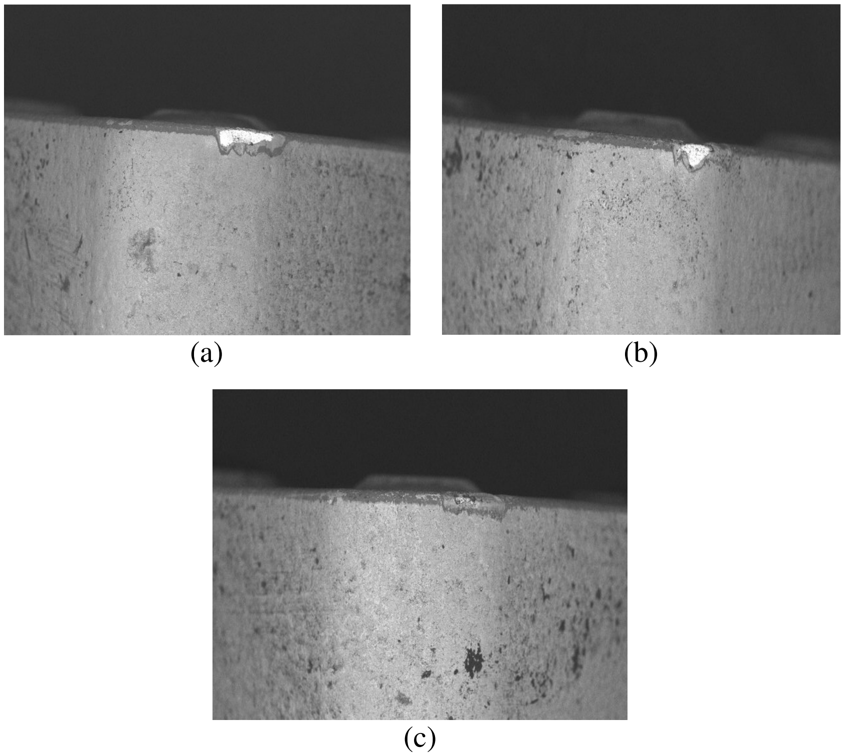

Figure 2: Photographs of the tool wear at different parameter inputs or number of experiments (a) Exp. 2 (b) Exp. 5 (c) Exp. 8.

Table 3: ANOVA results based on Grey Relational Grade

Control Factor	Degree of Freedom	Sum of Square	Mean of Square	F-test	F-ratio	% of Contribution
Speed	2	0.350	0.175	33.142	19	87.85
Feed	2	0.027	0.014	2.582	19	6.84
Error	4	0.021	0.005			5.30
TOTAL	8	0.3988				

3.4 Confirmation Test

Once the optimal machining parameters have been identified, validation test was conducted to predict and verify the improvement of the performance characteristic using the new optimal machining parameters. The formula for estimating the GRG, $\hat{\gamma}$ can be expressed as Equation 4 below.

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q}(\bar{\gamma}_i - \gamma_m) \quad (4)$$

where γ_m = total mean of GRG, $\bar{\gamma}_i$ = mean of GRG at optimal level, q = number of machining parameters that significantly affect the multiple performance characteristics. The comparison between predicted and actual machining performance for all three performances criteria using their optimal machining parameter is shown in Table 4. The predicted value of tool wear is closed to actual experiment which is 0.116 mm and 0.118 mm. Meanwhile, the value of surface roughness is also improved to 1.55 µm in prediction compared to 1.67 µm from experiment. However, the value of MRR is decreased from 106.8 mm^3/s in the actual experiment to 97.9 mm^3/s in prediction. The conformation test also shows that the percentage error between prediction and actual experiment is 1.72%, 7.43% and 9.09% for tool wear, surface roughness and MRR. Overall, all of these percentage errors are statistically acceptable as the values are less than 10%.

Table 4: Results of confirmation test

	Optimal Conditions S3F3		
	Prediction	Experiment	
Setting Level	S3F3	S3F3	%Error
TW (mm)	0.116	0.118	1.72
Ra (µm)	1.55	1.67	7.43
MRR (mm^3/s)	97.90	106.80	9.09
Grey Relational Grade	0.816	0.869	6.43

4.0 CONCLUSION

In general, the use of Taguchi and GRA to optimize the turning process of S45C carbon steel with multiple performances characteristic is successfully reported in this paper. Result from GRA shows that the optimum parameter setting found in the current study is S3F3, in which at spindle speed of 3000 RPM and feed rate of 0.2 mm/rev. Meanwhile, the result of confirmation test shows that the actual experimental value is close to the prediction value with percentage error less than 10%.

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