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Parametric optimisation of multi response drilling process using Grey based Taguchi method

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Abstract: In the present work, optimization technique such as Grey based Taguchi methods have been used to predict surface roughness of drilled holes and drill flank wear into a single characteristic response. Experiments have been conducted in a radial drilling machine with five input parameters using L_{27} orthogonal array. Minimum flank wear and average surface roughness is the required objective parameter. It has been observed that combined response affected by almost all input parameters, but drill diameter is most significant and feed is least significant input parameter influencing the combined responses.

Keywords: Drilling, factorial setting, design of experiment, Grey Taguchi

1. Introduction

Manufacturing industries are trying to reduce the operation cost as well as better quality of product. Surface roughness has received serious attention for many years. In addition to tolerances, surface roughness imposes one of the most critical constraints for the selection of machines and cutting parameters in process planning. Drill wear is an important issue since wear on drill affect the hole quality and tool life of the drill. Direct visual inspection of cutting edge of tool and measurement of roughness of the drilled hole in a transfer line is not feasible and hence indirect methods using sensory feed back during drilling have been is use to assess the roughness of drilled hole and the wear of the drill. Design of Experiments (DOE) technique used to enhance the quality of products and processes and hence improve the quality of product at lowest cost. In this context, an effort has been made to minimize surface roughness and flank wear and combined responses from experimental data using Grey Taguchi method. It has also been decided to predict combined responses (flank wear and roughness) using same techniques.

It is hardly possible to find the surface roughness and flank wear prediction models in literature. Most prediction models are empirical and are generally based on experiments in the laboratory. Rehorn *et al.* [1] reported that drilling operation differs significantly from turning and face milling as drilling is a complex three dimensional material removal operations. Elanayar and Shin [2] suggested that crater wear prediction is seen to be poor in contrast with flank wear. Thangaraj and Wright [3] measured only the thrust force, and Braun *et al.* [4] used all drilling forces and spindle speed simultaneously for flank wear prediction. Azouzit and Guillot [5] reported that the sensor selection and fusion method assisted the experimenter in determining the average effect of each sensor on the performance of detecting surface finish in a turning operation. Choudhury and Bartarya [6] work focused on design of experiments for predicting tool wear. In their work flank wear, surface finish and cutting zone temperature were taken as response (output) variables and cutting speed, feed and depth of cut were taken as input parameters measured during turning operation. Chern and Liang [7] analyzed the effect of vibration in boring by investigating the surface roughness of workpiece with the help of Taguchi method and analysis of variance (ANOVA). Taraman [8] used Response Surface Methodology (RSM) for predicting surface roughness of different materials.

2. Experimental Design

Taguchi method uses a special design of orthogonal array to study the entire process parameters space with only small number of experiments. Taguchi method, a powerful tool for parameter design of the performance characteristics has been used to determine optimal machining parameters for minimization of surface roughness and drill flank wear in a drilling operation. Based on Taguchi's L27 Orthogonal Array design, control factors such as drill diameter, spindle speed, feed rate, cutting force and feed vibration signals are set at three different levels. The experiments have been performed based on Taguchi design, and the force signals and vibration signal are collected using Dynamometer and accelerometer and is stored in the computer through data acquisition system. Average Surface roughness and maximum flank wear were measured using surface roughness tester and optical microscope after conducting each set of experiment.

3. Parametric optimization

In this study, Grey Taguchi method has been used to determine optimal machining parameters for minimization of flank wear and surface roughness. The predicted data transformed into a signal-to-noise (S/N) ratio is given in equation 1for the case lower is better

S/N ratio for SF = -10log $_{10}$ ($\frac{1}{n}\sum_{i=1}^{n} y_{SF}^{2}$) (1)

Where y_{SF} is the simulated response

3.1 Grey relational analysis

In grey relational analysis, experimental data i.e. measured features of quality characteristics are first normalized ranging from zero to one using equation 2. Next, based on normalized experimental data, grey relational coefficient is calculated to represent the correlation between the desired and actual experimental data using equation 3. Then overall grey relational grade is determined by averaging the grey relational coefficient corresponding to selected responses using equation 4. This approach converts a multiple response process optimization problem into a single response optimization situation with the objective function is overall grey relational grade. The optimal factor setting for maximizing overall grey relational grade can be performed by Taguchi method.

In grey relational generation, the normalized data i.e. surface finish and flank wear corresponding to lower-the-better (LB) criterion can be expressed as:

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

Where $x_i(k)$ is the value after grey relational generation, max and min determine the maximum and minimum value of out put response y_i

$$\xi_i(k) = \frac{\Delta_{\min} + \psi\Delta_{\max}}{\Delta_{0i}(k) + \psi\Delta_{\max}} \qquad (3)$$

where $\xi_i(k)$ is the grey relational coefficient. $\Delta_{0i} = \left\| x_0(k) - x_i(k) \right\|$; ψ is the distinguishing coefficient $0 \le \psi \le 1$; $\Delta_{\min} = \forall j^{\min} \in i \forall k^{\min} \left\| x_0(k) - xj(k) \right\|$ is smallest value of Δ_{0i} and $\Delta_{\max} = \forall j^{\max} \in i \forall k^{\max} \left\| x_0(k) - xj(k) \right\|$ is largest value of Δ_{0i}.

Over all grey relational grade is given by $\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k)$ (4)

Where n is the number of process responses.

3.2 Grey-Taguchi technique for analyzing multi-objective responses

Output responses such as Surface Roughness ($R_{a,}$) and flank wear is first normalized and over all grey relational grade is then calculated using equation 3 and 4. Equal weight age has been given to all the responses (0.5). Grey Taguchi has predicted output responses for 3 testing sample as well as at optimal setting as given in table 1. Now in order to check the conformity, experiment is conducted at this optimal setting and reported the variation caused as shown in table 1. The optimal parameter setting has been evaluated from the figure 1 which is given as 3-2-2-1-1. Grey Taguchi has predicted output responses for 3 testing sample as well as at optimal setting is given in table 1. Now in order to check the conformity, experiment is conducted at this optimal setting and reported the variation caused as shown in table 1.

4. Conclusion

Results of this study illustrate that Grey Relational Analysis procedure is simple and straight forward. It is a linear predictor model. The purposed method could able to predict four different testing sample within an error of $\pm 12\%$ error band line. This method is reliable and could able to implement that have more than two responses.

Reference

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Table 1 Error analysis of testing sample

Diameter (mm)	Speed (rpm)	feed rate (mm/rev)	Thrust force (N)	Feed Vibration (m/s^2)	Actual grey relational grade	S/N ratio of actual grey relational grade	Predicted S/N ratio grey relational grade	percentage of error
1	1	1	1	1	0.73536	-2.67		
1	1	1	1	2	0.540772	-5.33972		
1	1	1	1	3	0.494006	-6.12536		
1	2	2	2	1	0.80934	-1.83738		
1	2	2	2	2	0.603225	-4.39041		
1	2	2	2	3	0.446444	-7.00466		
1	3	3	3	1	0.464368	-6.66275		
1	3	3	3	2	0.358988	-8.8984		
1	3	3	3	3	0.950897	-0.43733		
2	1	2	3	1	0.663007	-3.56964		
2	1	2	3	2	0.504946	-5.9351		
2	1	2	3	3	0.485954	-6.2681		
2	2	3	1	1	0.773502	-2.23077		
2	2	3	1	2	0.60349	-4.3866		
2	2	3	1	3	0.437695	-7.17657		

2	3	1	2	1	0.466946	-6.61467		
2	3	1	2	2	0.363209	-8.79687		
2	3	1	2	3	0.81233	-1.80535		
3	1	3	2	1	0.603013	-4.39347		
3	1	3	2	2	0.701269	-3.08231		
3	1	3	2	3	0.773742	-2.22808		
3	2	1	3	1	0.768159	-2.29098		
3	2	1	3	2	0.838256	-1.53247		
3	2	1	3	3	0.670497	-3.47206		
3	3	2	1	1	0.897528	-0.93904	-1.05288	-12.123
3	3	2	1	2	0.732012	-2.70964	-2.59319	4.297619
3	3	2	1	3	0.832228	-1.59515	-1.59776	-0.16362
3	2	2	1	1		-0.5525	-0.59317	-7.36

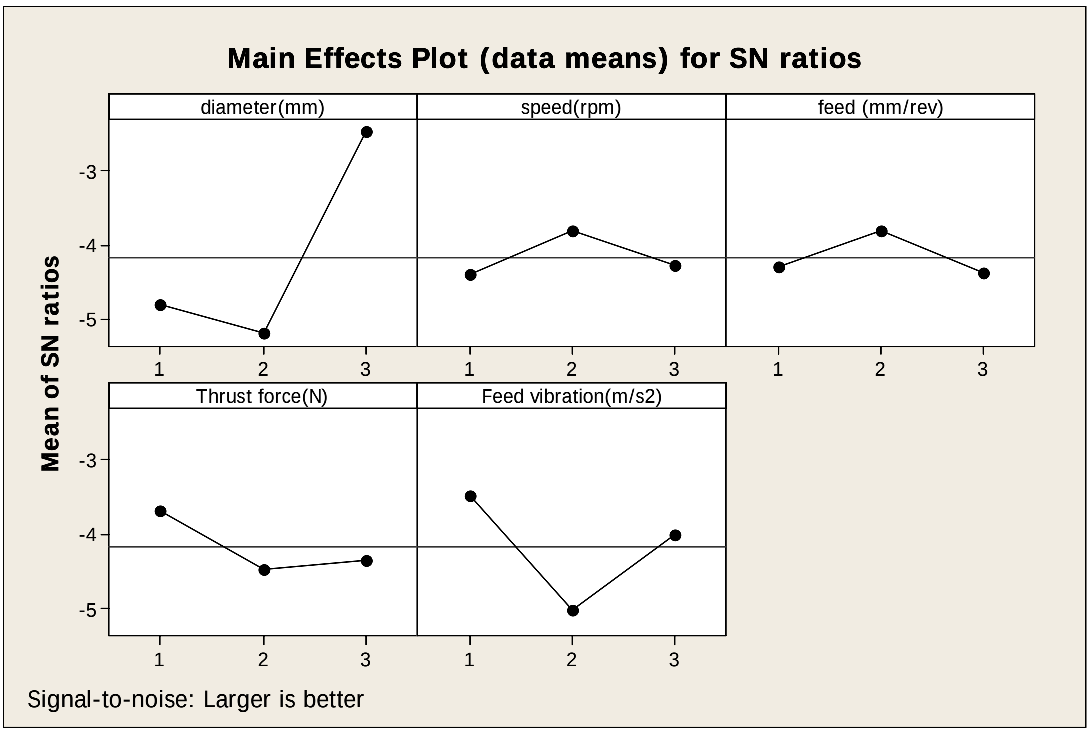

Figure 1 Evaluation of optimal parameter setting