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Optimization of surface roughness and material removal rate in turning using gray-based Taguchi approach

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Abstract

This study investigated the multi-optimization of the turning process on AISI1045 steel material with CNMG cutting tool for an optimal parametric combination to yield the minimum surfaces roughness with the maximum MRR using a combination of a Grey relational analysis (GRA) and the Taguchi method. In view of the fact, that traditional Taguchi method can't solve a multi-objective optimization problem: To overcome this limitations Grey relation theory has been coupled with Taguchi method. Nine experimental runs based on an Orthogonal array of the Taguchi method were performed to drive objective functions to be optimized within the experimental domain the signification of the factors on the overall quality characteristics of the cutting process was also evaluated quantitatively using the Analysis of Variance ANOVA method. Optimal results verified through additional experiments.

Keywords: Turning parameters; Grey relational theory; Taguchi method; ANOVA; Material removal rate

1 Introduction

This study applied a Taguchi L9 orthogonal array to plan the experiments on the turning process [1]. The three controlling factors, including the cutting speed (V), the depth of cut (d) and feed rate (f), were selected [2],[3]. The Grey relational analysis is then applied to examine how the cutting factors influence the cutting force (F), the surface roughness (Ra) and the material removal rate (MRR)[4],[5]. An optimal parameter combination was then obtained. Through analyzing the Grey relational grade matrix, the most influential factors for individual quality targets of the turning process can be identified. Addition-ally, an analysis of variance (ANOVA) was also utilized to examine the most significant factors for the F, Ra and MRR in the turning process [6]-[10].

2 Material and method

2.1 Procedure adapted for optimization

The proposed optimization methodology combines Principal Component Analysis (PCA) [Antony (2000), Datta et al. (2009)], grey-Based Taguchi concept [Yigit Kazancoglu. (2011)] and Taguchi method [Datta et al. (2008)] based on selected Taguchi's Orthogonal Array (OA) Design of Experiment (DOE). The detailed methodology is described below. Assuming, the number of experimental runs in Taguchi's OA design is m, and the number of quality characteristics is n. The experimental results can be expressed by the following series: X1, X2, X3…………..Xi…………Xm

Here, Xi represents the i Th experimental results and is called the comparative sequence. Let, X0are the reference sequence:

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Let, X0={X_0 (1),X_0 (2)…………X_0 (k)………… X_0 (n) ⊦}⊣

The value of the elements in the reference sequence means the optimal value (ideal or desired value) of the corresponding quality characteristic. X0 and X0 both includes n elements and X0(k) and Xi(k)represent the numeric value of kth element in the reference sequence and the comparative sequence, respectively, k =1, 2... n. The following illustrates the proposed parameter optimization procedures in detail.

2.2 Step 1: Normalization of the responses (quality characteristics)

When the range of the series is too large or the optimal value of a quality characteristic is too enormous, it will cause the influence of some factors to be ignored. The original experimental data must be normalized to eliminate such effect. There are three different types of data normalization according to whether we require the LB (Lower-the-Better), the HB (Higher-the-Better) and NB (Nominal-the-Best).

2.3 Step 2: Checking for correlation between two quality characteristics

$$Q_i=\{X_0^*(i), X_1^*(i), X_2^*(i) \ldots\ldots\ldots\ldots\ X_m^*(i) \quad \} --(4)$$

Let

Where i= 1, 2…….. n.

It is the normalized series of the i th quality characteristic.

Step 3: Calculation of the principal component score

- Calculate the Eigenvalue λ_kand the corresponding eigenvector β_k (k=1, 2,......,n) from the correlation matrix formed by all quality characteristics.
- Calculate the principal component scores of the normalized reference sequence and comparative sequences using the equation shown below:

Here, Y_i (k) is the principal component score of the k *th*element in the *i^th^*series. X_i^*(j)Is the normalized value of the *j^th^*element in the *i^th^*sequence, and β_{kj} is the *j^th^*element of eigenvectorβ_k.

2.4 Step 4: Calculation of the individual grey relational grades

Calculation of the individual grey relational coefficients

Use the following equation to calculate the grey relational coefficient between X0 (k) and Xi(k).

Note that ξ is called the distinguishing coefficient, and its value is in between 0 to 1. In general it is set to 0.5, [Deng, 1989].

2.5 Step 5: Calculation of the overall grey relational grade

After the calculation of the grey relational coefficient and the weight of each quality characteristic, the grey relational grade is determined by:

$$\Gamma_{o,i} = \sum_{k=1}^{n} w_k r_{o,i}(k), i = 1.2.3 \ldots\ldots., m.$$

In this section, the multiple quality characteristics are combined into one grey relational grade, thus the traditional Taguchi method can be used to evaluate the optimal parameter combination. Finally the anticipated optimal process parameters are verified by carrying out the confirmatory experiments.

2.6 Experimental procedure and test results

2.6.1 Experimental setup

The cutting experiments were carried out on an experimental lathe setup wsing CNMG carbide inserts for the machining of the AISI 1045 (of diameter 32mm and 150mm length) required for conducting the experiment have been prepared first. Three numbers of samples of same material and same dimension have been made. After that, the diameter of each samples have been measured accurately with the help of a high a high digital vernier caliper. Then, using different levels of the process parameters three specimens at 9 different levels have been turned in lathe accordingly; machining time for each sample has been calculated accordingly. After machining, the diameter of each machined parts have been again measured precisely with the help of the digital vernier caliper. Then surface roughness and surface profile have been measured precisely with the help of a portable stylus-type profilometer, Talysurf (Taylor hobson, surtronic 3+, UK).

Four parameters design was performed as shown in table. Note that is not an obstacle for the methodology followed. The standard (L9(34)) orthogonal matrix experiment was used table

Table 1 Machining parameters for experimentation

Factors	Level 1	Level 2	Level 3
Cutting speed (rpm)	250	350	400
Feed (mm/rev)	0.034	0.051	0.069
Depth of cut (mm)	0.2	0.6	1
Tool nose radius(mm)	0.4	0.8	0.4

Table 2 L9 Orthogonal Array (OA)

Exp.No	Run order	A	B	C	D	Speed (rpm)	Feed (mm/rev)	Depth of cut(mm)	Tool nose radius
1	3	1	1	1	1	250	0.034	0.2	0.4
2	2	1	2	2	2	350	0.051	0.6	0.4
3	1	1	3	3	3	400	0.069	1	0.4
4	4	2	1	2	3	350	0.034	1	0.8
5	6	2	2	3	1	400	0.051	0.2	0.8
6	5	2	3	1	2	250	0.069	0.6	0.8
7	8	3	1	3	2	400	0.034	0.6	0.4
8	7	3	2	1	3	250	0.051	1	0.4
9	9	3	3	2	1	350	0.069	0.2	0.4

An average of three measurements of the surface roughness (Ra, Rq, Rz) was taken to use in the multi-criteria optimization. Also the MRR was calculated

3 Result and discussion

Table 3 Experimental data

Surface Roughness Ra in µm	Surface Roughness Rq in µm	Surface Roughness Rz in µm	MRR in (mm^3/min)	Time Taken in sec
3.613	4.5	22.8	129.41	268
5.43	6.78	33.79	446.336	124
6.98	8.74	43.86	1422.42	8505
4.94	6.01	27.49	635.63	187

4.14	5.16	26.13	296.858	112
4.69	5.86	29.3	550.098	132.5
4.3	5.49	27.8	466.392	170
5.68	7.11	35.5	735.176	180.5
4.69	5.85	29.13	339.988	93.5

Table 4 Normalized data

SI NO	Ra in µm	Rq in µm	Rz in µm	MRR (mm3/min)	Time Taken sec
Ideal sequence	1.000	1.000	1.000	1.000	1.000
1	1.000	1.000	1.000	1.000	0.319
2	0.665	0.663	0.674	0.289	0.689
3	0.517	0.515	0.519	0.090	1.000
4	0.730	0.748	0.829	0.203	0.457
5	0.872	0.872	0.872	0.435	0.763
6	0.769	0.768	0.777	0.235	0.645
7	0.839	0.819	0.820	0.277	0.502
8	0.635	0.632	0.642	0.176	0.473
9	0.769	0.768	0.782	0.380	0.214

Table 5 Check for correlation between the responses

SI NO	Correlation between responses	Pearson correlation coefficient	Comment on correlation on component
1	Ra and Rq	0.998	Both are correlated
2	Ra and Rz	0.963	Both are correlated
3	Ra and MRR	0.836	Both are correlated
4	Ra and time	-0.538	Both are correlated
5	Rq and Rz	0.974	Both are correlated
6	Rq and MRR	0.84	Both are correlated
7	Rq and time taken	-0.545	Both are correlated
8	Rz and MRR	0.77	Both are correlated
9	Rz and time	-0.575	Both are correlated
10	MRR and time	-0.459	Both are correlated

Table 6 Eigenvalues, eigenvectors, accountability proportion (AP) and Cumulative accountability proportion (CAP) computed for the responses

	ψ1	ψ2	ψ3	ψ4	ψ5
Eigen value	4.0637	0.6389	0.264	0.0325	0.0008
eigenvector	0.486	0.171	0.21	0.575	-0.600
	0.488	0.164	0.212	0.278	0.783
	0.479	0.081	0.419	-0.750	-0.162
	0.436	0.241	-0.851	-0.164	-0.034
	-0.327	0.938	0.107	-0.047	-0.005
AP	0.813	0.128	0.053	0.007	0.000
CAP	0.813	0.941	0.993	1.000	1.000

Table 7 Principal components in all L9 OA experimental observations

SI NO	ψ1	ψ2	ψ3
Ideal Sequence	1.562	1.595	0.097
1	1.7847	0.9562	0.0241
2	0.8424	0.989	0.365
3	0.4644	1.175	0.4653
4	1.0571	0.7929	0.5355
5	1.208	1.1839	0.4444
6	1.0131	0.9825	0.5193
7	1.1574	0.883	0.5114
8	0.8472	0.7511	0.4376
9	0.9909	1.2705	0.4264

Table 8 Quality loss estimates Δ0i (k) (for principal components)

Si No	ψ1	ψ2	ψ3
1	0.2227	0.6388	0.0729
2	0.7196	0.606	0.268
3	1.0976	0.42	0.3683
4	0.5049	0.8021	0.4385
5	0.354	0.4111	0.3474
6	0.5489	0.6125	0.4223
7	0.4046	0.712	0.4144
8	0.7148	0.8439	0.3406
9	0.5711	0.3245	0.3294

Table 9 Individual grey relational coefficients for the principal components

S. NO	ψ_1	ψ_2	ψ_3
1	1	0.7036	1
2	0.6082	0.7261	0.5995
3	0.4685	0.8865	0.4971
4	0.7321	0.6098	0.4441
5	0.8545	0.896	0.5155
6	0.7028	0.7215	0.4553
7	0.8092	0.6582	0.461
8	0.6105	0.5896	0.5217
9	0.6889	1	0.5324

Table 10 Calculation of overall grey relational grade

SI NO	$\Gamma_{0,}$	S/N Ratio
1	2.7036	8.6388
2	1.9338	5.7282
3	1.8521	5.3532
4	1.786	5.0376
5	2.266	7.1052
6	1.8796	5.4813
7	1.9284	5.7039
8	1.7218	4.7196
9	2.2218	6.9341

3.1 Conformation test

After evaluating the optimal parameter settings the next step is to predict and verify the enhancement of the quality characteristics using the optimal parametric conditions by the conformity test. Again experiment was conducted for optimal parameter setting and S/N ratio were found and the Table 5.1 reflects the satisfactory results of conformity test.

The estimated grey relation grade γ̂using the optimal level of the design parameters can be calculated as:(γ)̂=γ_m+∑_(i=1)^0▒(γ̂_j-γ_m)

Where γ_m is the total mean Grey relation grade , (γ_i)̂is the mean Grey relational grade at the optimal level, and o is the number of the main design parameters that affect the quality characteristics. Good agreement between actual and the predicted results has been observed.

Table 11 Conformity test

	Optimal process condition	
	Prediction	**Experiment**
Factor level	$A_1B_1C_1D_1$	$A_1B_1C_1D_1$
R_a in µm	----	3.998
R_q in µm	----	5.23
R_z in µm	---	24.78
MRRR in mm^3/min	---	205.3
Time taken	----	240
S/N ratio of overall utility index	8.245	9.738
Mean of overall utility index	2.60	4.88

The results show that using the optimal parameter setting (A1B1C1D1) cause a lower surface roughness and time taken and higher MRR were obtained.

4 Conclusion

In this study, the Grey-based Taguchi method was applied for the multiple performance characteristics of turning operations. A grey relational analysis of the material-removal rate, the cutting force and the surface roughness obtained from the Taguchi method reduced from the multiple performance characteristics to a single performance characteristic which is called the grey relational grade. Therefore, the optimization of the complicated multiple performance characteristics of the processes can be greatly simplified using the Grey-based Taguchi method. It is also shown that the performance characteristics of the turning operations, such as the material removal rate, the cutting time and the surface roughness are greatly enhanced by using this method. The aforesaid extended Taguchi method can be applied for continuous quality improvement of the product/process and off-line quality control.

According to this analysis, the most effective parameters with respect to the material-removal rate, the cutting force and the surface roughness are the feed rate, the depth of cut and the cutting speed and tool nose radius. The percentage contribution indicates the relative power of a factor to reduce the variation. For a factor with a high percentage contribution, there is a great influence on the performance. The percent contributions of the cutting parameters on the material-removal rate, the cutting force and the surface roughness are shown in Table 9.2 The depth of cut has high influence (57.69%) on Grey relation grade and feed has (28.37%) of influence on Grey relation grade. the cutting speed were found to be the second- and third-ranking factors respectively.

Compliance with ethical standards

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