National Journal of Multidisciplinary Research and Development
ISSN: 2455-9040
Impact Factor: RJIF 5.22
www.nationaljournals.com
Volume 3; Issue 1; January 2018; Page No 256-261

Optimization of a boring operation using Taguchi based grey relational analysis

[1] Vikas Kumar Sukhdeve, [2] Dr. SK Ganguly
[1] Head of Department, Mechanical Engineering, Government Polytechnic, Gariyaband, Chhattisgarh, India
[2] Professor and Head, Mechanical Engineering, Bhilai Institute of Technology, Durg, Chhattisgarh, India

Abstract
In the present work, optimization of process parameters have been done for a boring operation with few set of predefined operational parameters like 'Feed Rate (mm/rev)', 'Depth of Cut (mm), Cutting Speed (m/min) and 'Material Property (S_{yt} in MPa)' using Taguchi based Grey Relational analysis In this project, first boring operation has been performed on three type of materials like Aluminum (S_{yt} = 225 MPa), Steel (S_{yt} = 440 MPa) and Brass (S_{yt} = 217 MPa) Then values of few output parameters like Material Removing Rate (MRR)(gm/sec), Vertical Force (kg force) and Surface Finish (R_a value) have been noted down for different values of the above mentioned input process parameters for in three levels Then Taguchi based Grey Relational Analysis is implemented to optimize the operational parameters which are also input variables to achieve best result of the performance parameter or response parameters.

Taguchi based Grey Relational analysis is actually a Design of Experiment (DOE) approach to optimize a set of operational parameters of any process to obtain best possible values of few predefined performance parameters In the present work L9 Orthogonal Array has been created using the process parameters with their three level values and then experiments done with those set of input parameters to produce respective output values Then Grey analysis has been done to find out optimized combination of the input parameters to have best value of performance parameters.

Keywords: design of experiment (doe), Taguchi method, grey analysis

Introduction

Designed of any process or system largely depend on the fact that how it has been efficient and successful running Many experiments are conducted to develop any process or system and successfully designed process or system is gone through a fruitful experiment so developing any system or process Design of Experiment (DEO) has a very important roal.

Vikas and Ganguly [9] studied that for investigating any process or system a systematic approach of DOE is needed For any system or process, input variable are made to change in a planned way so that design of structured tests series are conducted Pre defined outputs are achieved while changes of planned input variable The importance of DOE is that while required minimizing resources can gain to maximizing information It has more to offer than 'one change at a time' experimental methods, because it allows a judgment on the significance to the output of input variables acting alone, as well input variables acting in combination with one another.

Risk occurs always in 'one change at a time' testing, the researcher may find a significant effect on the output (response) which is occurs by varying one input variable failing to discover that another variable change can alter the effect of the first (ie some kind of interaction or dependency) Finding first significant effect may lead the experimenter to stop the test In order to disclose dependency or interaction, the experimenter carrying the tests in the first place believing 'one change at a time' testing, and then make for exactly what data are needed to evaluate them ie whether input variables change the response on their own, when assorted, or not at all In terms of resource the exact length and size of the experiment are set by the design (ie before testing begins)

Paul G Mathews [10] can explain that DOE can be used to find answers in situations such as "what is the main contributing factor to a problem?", "in the presence of noise how well does the system/process executed?", "what is the best configuration of factor values to minimize variation in a response?" etc In general, these questions are arises as particular types of studies In the illustration given above, these are problem solving, parameter design and robustness studies In each case, DOE is used to find the answer; the only thing that makes them different is factors used in the experiment"

The order of tasks to using this tool starts with identifying the input variables and the response (output) that is to be measured For each input variable, a number of levels are defined that represent the range for which the effect of that variable is desired to be known An experiment plan is produced which tells the experimenter where to set test parameter for each run of the test The response is then measured for each run The method of analysis is to look for differences between response (output) readings for different groups of the input changes These differences are then attributed to the input variables acting alone (called a single effect) or in combination with another input variable (called an interaction) DOE is team oriented and a variety of backgrounds (eg design, manufacturing, statistics etc) should be involved when identifying factors and levels and developing the matrix as this is the most skilled part Moreover, as this tool is used to answer specific questions, the team should have a clear understanding of the difference between control and noise factors.

It is very important to get the most information from each experiment performed Well – designed experiments can produce significantly more information and often require fewer runs than haphazard or unplanned experiments In addition, a well-designed experiment will ensure that the evaluation of the effects that had been identified as important For example, if there is an interaction between two input variables, both variables should be included in the design rather than doing a 'one factor at a time' experiment An interaction occurs when the effect of one input variable is influenced by the level of another input variable Designed experiments are carried out in four phases: planning, monitoring (also called process characterization or screening), optimization, and verification

Planning

Careful mapping helps to avoid problems that can occur during the perform of the experimental plan For example, personnel, equipment availability, funding, and the mechanical aspects of the system may affect the ability to complete the experiment The preparation required before beginning experimentation depends on the nature of the problem The following are some of the steps that may be necessary.

Problem Definition

variable which are correct are studied for developing a good problem At this step, identifying the questions that need to be answered

Object Definition

A distinguishable objective will ascertain that the experiment answers the right questions and produce practical, advantageous information At this step the objective of the experiment will be defined

Evolution of an experimental plan that will provide significant information

At this step review of relevant background information is, such as theoretical principles, and knowledge obtain through previous experimentation or observation For example, it is need to recognized which factors or process conditions impress process contribute and performance to process variability Or, if the process is already established and the effective factors have been identified, it may be necessary to determine the optimal process

Making certainly the process and measured systems are in control

Ideally, both the measurement and process should be in statistical control as measured by a functioning statistical process control (SPC) system Even if it does not have the process control thoroughly, it must be able to generate process settings Also, it is compulsory to determine the variability in the measurement system

Monitoring

In many process development and manufacturing applications, potentially influential variables are numerous monitoring decreases the number of variables by identifying the key variables that affect product quality This decrease allows process reformation efforts to be focused on the rally vital variables, or the "important few" monitoring may also suggest the "best" or optimal settings for these factors, and signalize whether or not curvature occur in the responses Then, it can use optimization methods to establish the best settings and define the character of the curvature Two – level full and fractional factorial designs are used large- scale in industry.

Plackett – Burman designs have low resolution, but their usefulness in some screening experimentation and robustness testing is widely recognized General full factorial designs (designs with more than two – levels) may also be useful for small screening experiments.

Optimization

Next step after identified the "vital/important few" by screening, the "best" or optimal values for these experimental factors needed to be determine Optimal factor values depend on the process objective For example, minimize the laser power and maximize the welding speed.

Verification

Verification involves performing a follow – up experiment at the predicted "best" processing conditions to ensure the optimization results.

Experiment with Taguchi

In the present work boring experiment has been done on plate specimen made of three different materials like Aluminum, Steel and Brass All the process parameters along with their three levels of values have been represented below

Table 1: Experimental Factors and Factor Levels

Factor	Parameter (Unit)	Level 1	Level 2	Level 3
1	Feed rate (mm/rev)	004	007	011
2	Depth of Cut (mm)	03	06	09
3	Cutting Speed (rpm)	200	800	2000
4	Material Property (S_{yt} in MPa)	Al (225)	Steel (440)	Brass (217)

After deciding on the input process parameters regarding the experiment and setting the values of those process parameters in three levels, L9 orthogonal array has been created using Taguchi method

The L9 orthogonal array represents nine combinations of levels of the input variables to do experiment with the specimen Following table represents all the nine combinations of the process parameters with respect to their different level values along with the mention of response parameters

Table 2: Orthogonal Array L9 of the Experimental Runs

Run	Factor1	Factor2	Factor3	Factor4	Response 1	Response 2	Response 3
	Feed Rate	Depth of cut	Speed	Material	MRR	Vertical Force	Surface finish
					gm/sec	Kg Force	Ra
1	2	1	2	3			
2	2	3	1	2			
3	3	2	1	3			
4	3	3	2	1			
5	2	2	3	1			
6	1	3	3	3			
7	1	2	2	2			
8	1	1	1	1			
9	3	1	3	2			

Next, experiments have been performed with the above mentioned values of process parameters with different combinations of levels to generate values of the response parameters as mentioned in the table The different process parameters and corresponding response parameter values have been mentioned below

Table 3: Experimental Runs and Results

Run	Feed Rate	Depth of Cut	Speed	Material	Force	Ra	MRR
1	007	03	800	217 (Brass)	25	0092	01725
2	007	09	200	440 (Steel)	17	0588	0119
3	011	06	200	217 (Brass)	55	0165	0109
4	011	09	800	225 (Aluminium)	2	1566	022
5	007	06	2000	225 (Aluminium)	6	1022	0163
6	004	09	2000	217 (Brass)	5	0165	0502
7	004	06	800	440 (Steel)	25	0721	0204
8	004	03	200	225 (Aluminium)	2	0942	0007
9	011	03	2000	440 (Steel)	3	0637	0495

Processing of data

To find out optimized combination of values of the process parameters for the best values of response parameters it is needed to do the Grey analysis with the experimental values as mentioned in the table above

For the Grey analysis we have to first normalize the values of the experimental values as mentioned below

First step in GRA is to normalize all the experimental data in the range of zero to one Such normalization is necessary because the range and the unit in one response may vary from the others If the response is of ‘higher-the-better’ characteristics, equation for normalizing is as follows:

$$x_i^*(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i - \min x_i(k)}$$

If ‘lower-the-better’ criterion is to be followed, then the following equation is to be utilized for normalizing the corresponding data:

$$x_i^*(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i - \min x_i(k)}$$

Implementing the above mentioned inequalities or relations we have got the processed data which has been represented below

Table 4: Experimental Runs in Observe data and Normalized Data

Exp No	Force	Ra	MMR	N_Force	N_Ra	N_MRR
1	25	0092	01725	0967	1000	0334
2	17	0588	0119	0000	0664	0226
3	55	0165	0109	0767	0950	0206
4	2	1566	022	1000	0000	0430
5	6	1022	0163	0733	0369	0315
6	5	0165	0502	0800	0950	1000
7	25	0721	0204	0967	0573	0398
8	2	0942	0007	1000	0423	0000
9	3	0637	0495	0933	0630	0986

Here $x_i^*(k)$ and $x_i(k)$ are the normalized data and observed data respectively for ith experiment using kth response

Experimental Procedure

Here in this section a detailed procedure has been mentioned regarding experimental methodology by virtue of which experimental data have been generated

The field data was acquired in Bhilai Steel Plant, machine shop Machining was conducted on Jig boring machine where normal condition for machine operation temperature is 20^0C,Limit of Relative dampness of the atmosphere is 55% CERATIZIT make S40TI type of cutting tool inserts is used for boring operation

Fig 1

In this experiment work piece specimen size of steel, brass and aluminum plates are 400*70*25 mm

The following sequential procedure was used to carry out the experiment under dry condition

1. In order to properly control the depth of cut the internal diameter of the work pieces has been fixed to 25 mm via drilling operation up to plate thickness
2. Boring operations in different material is started with fresh cutting edge As per orthogonal array L^9 experiment run is conducted and accordingly vertical force is measured
3. After each pass removed metal chips is collected and weight is done and also surface roughness is measured on roughness meter SJ-201
4. In each trial, surface roughness, volume of metal removed, time and vertical force is identified

Optimization with grey

After normalizing the responses, the next step is to calculate the grey relation coefficient (GRC) GRC is denoted by for kth response It can be calculated by using equation below

$$\zeta_i(k) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_i(k) + \zeta\Delta_{\max}}$$

Where, $\Delta_i(k)$ is the absolute value of the difference between and $x^0{}_i(k)$ and $x^*{}_i(k)$ $\Delta_i(k) = |x^*{}_i(k) - x^0{}_i(k)|$ Δ_{max} and Δ_{min} are the global maximum and global minimum values in the different data series, respectively The distinguishing coefficient lies between 0 and 1, which is to expand or compress the range of GRC, general, ξ= 05 is taken

Table 5: After Data Processing Sequence

Exp No	Force	Ra	MMR	D_Force	D_Ra	D_MRR
1	25	0092	01725	0033	0000	0666
2	17	0588	0119	1000	0336	0774
3	55	0165	0109	0233	0050	0794
4	2	1566	022	0000	1000	0570
5	6	1022	0163	0267	0631	0685
6	5	0165	0502	0200	0050	0000
7	25	0721	0204	0033	0427	0602
8	2	0942	0007	0000	0577	1000
9	3	0637	0495	0067	0370	0014

Table 6: Calculated grey relation coefficient and grey relation grade

Exp No	Force	Ra	MRR	N_Force	GRC_ Force	GRC _Ra	GRC_MRR	GRG
1	25	0092	01725	0967	0938	1000	0429	0789
2	17	0588	0119	0000	0333	0598	0393	0441
3	55	0165	0109	0767	0682	0910	0386	0659
4	2	1566	022	1000	1000	0333	0467	0600
5	6	1022	0163	0733	0652	0442	0422	0505
6	5	0165	0502	0800	0714	0910	1000	0875
7	25	0721	0204	0967	0938	0540	0454	0644
8	2	0942	0007	1000	1000	0464	0333	0599
9	3	0637	0495	0933	0882	0575	0972	0810

Result and Discussion

From the above analysis following response table can be created readily

Table 7: Response table for gray relation grade

Response Table				
Level	**A**	**B**	**C**	**D**
1	0705849	0732656	0566606	0568307
2	0578481	0602793	0677549	0631565
3	0689844	0638725	0730019	0774302
Delta	0127367	0129863	0163414	0205994
Rank	4	3	2	1

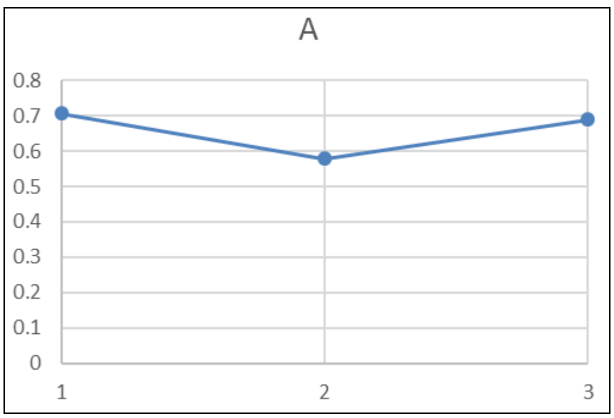
So as per ranking of the response the optimum combination of the process parameters are as follows

Table 8: Optimum Combination of Process Parameter

Parameter	Description with unit	Level
A	Feed rate (mm/rev)	1
B	Depth of Cut (mm)	1
C	Cutting Speed (rpm)	3
D	Material Property (S_{yt} in MPa)	3

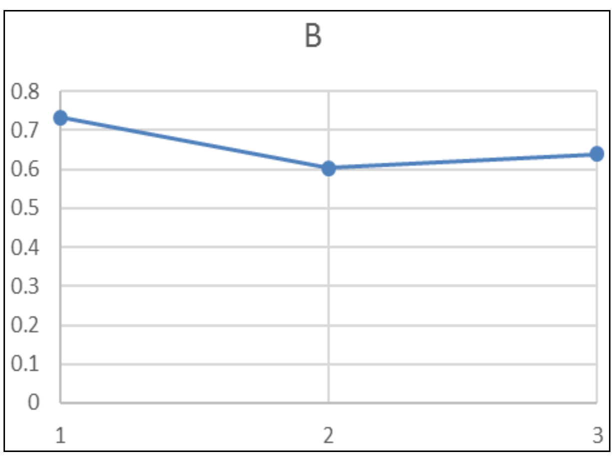
The mean of the grey relation grade for each level of boring parameters was calculated from Table 6 and summarized in Table 7, The larger the grey relation grade, the better the multiple performance characteristics, Therefore the optimal multiple performance characteristics for vertical force, surface roughness and material removing rate are as follows: feed rate of 004 mm/rev (Level 1), depth of cut of 03 mm (Level 1), cutting speed of 2000 rpm (Level 3) and material property of brass (S_{yt} in MPa) (Level 3) Figure 2 shows the boring parameter of feed rate in relation to grey relation grade where larger the better gray relation grade of 0705849 is for 004 mm/rev feed rate.

The graphical representation of grey analysis



Feed rate mm/rev

Fig 2: Grey relation grade v/s feed rate graph

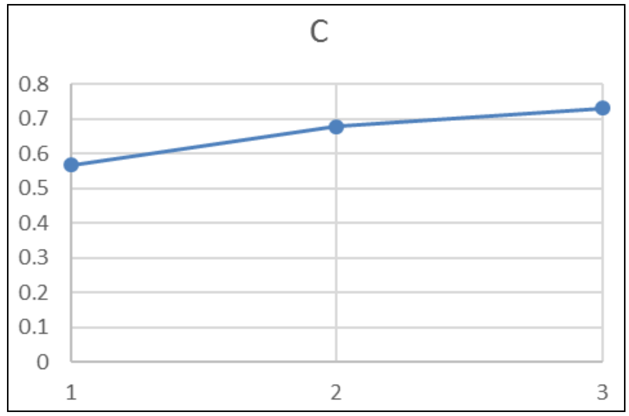


Depth of cut mm

Fig 3: Grey relation grade v/s depth of cut

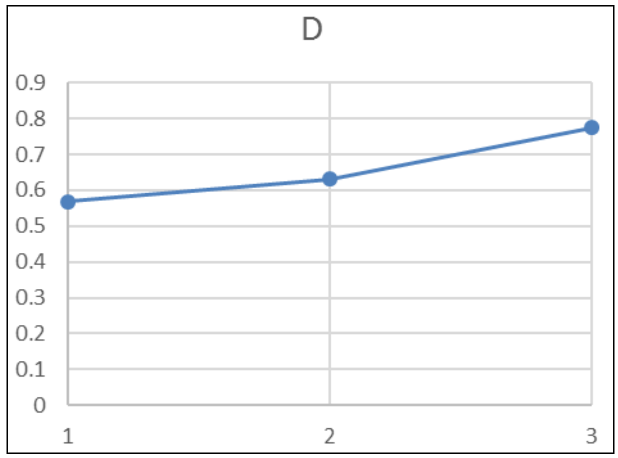
Figure 3 shows the boring parameter of depth of cut in relation to grey relation grade where larger the better gray relation grade of 0732656 for 03 mm of depth of cut

Figure 4 shows the boring parameter of cutting speedt in relation to grey relation grade where larger the better gray relation grade of 0730019 for 2000 rpm of cutting speed



Cutting speed m/min

Fig 4: Grey relation grade v/s cutting speed



Material property (S_{yt} in MPa)

Fig 5: Grey relation grade v/s material property

Figure 5 shows the boring parameter of material property in relation to grey relation grade where larger the better gray relation grade of 0774302 for brass 217 MPa of material property

Conformation Test

Once the optimal levels of the boring parameters are selected, the final step is to predict and verify the improvement of the performance characteristic by using optimum combination of boring parameters

The A1B1C3D3 was an optimal combination of boring parameters by the grey relational analysis Therefore, the A1B1C3D3 optimal combination parameters were regarded as the confirmation test The estimated grey relational grade can be obtained by using the optimal boring parameters The result of the conformation test is match with optimal combination of boring parameters

References

1. Muthuramalingama T, Mohanb B. Application of

Taguchi-grey multi responses optimization on process parameters in electro erosion. 2014; 58:495-502.
2. Mihir Patel, Vivek Deshpande. Application of Taguchi Approach for Optimization Roughness for Boring operation of E 250 B0 for Standard IS: 2062 on CNC TC, IJEDR. Volume 2, Issue 2 | ISSN: 2321-9939.
3. Kaining Shi, Dinghua Zhang, Junxue Ren, Changfeng Yao, Yuan Yuan. Multiobjective Optimization of Surface Integrity in Milling TB6 Alloy Based on Taguchi-Grey Relational Analysis, Advances in Mechanical Engineering, Volume 2014, Article ID 280313, 7 pages.
4. Raghuraman S, Thiruppathi K, Panneerselvam T, Santosh S. Optimization Of Edm Parameters Using Taguchi Method And Grey Relational Analysis For Mild Steel Is 2026, International Journal of Innovative Research in Science, Engineering and Technology. 2013, Vol 2, Issue 7.
5. Ajeet Kumar Rai, Shalini Yadav, Richa Dubey, Vivek Sachan. Application of Taguchi Method in the Optimization of Boring Parameters, International Journal of Advanced Research in Engineering and Technology. 2013; 4(4):191-199.
6. Shivapragash B, Chandrasekaran K, Parthasarathy C, Samuel M. Multiple Response Optimizations in Drilling Using Taguchi and Grey Relational Analysis, International Journal of Modern Engineering Research (IJMER). 2013; 3(2):765-768.
7. Reddy Sreenivasulu, Dr. Ch Srinivas Rao. Application of Grey Relational Analysis for Surface Roughness and Roughness Error in Driling of Al 6061 Alloy, International Journal of Lean Thinking, Volume 3, Issue 2.
8. Hartaj Singh. Taguchi optimization of process parameters: A review and case study, International Journal of Advanced Engineering Research and Studies E-ISSN2249–8974.
9. Vikas Sukhdeve, Dr. SK Ganguly. Utility of taguchi based grey relational analysis to optimize any process or system, Int J Adv Engg Res Studies/IV/II/Jan-March,2015/242-250, E-IS SN2249–8974
10. Paul Mathews G. Design of Experiments with Minitab book published. 2003-2005.