Analysis, modeling and optimization of surface roughness in cylindrical traverse cut grinding using factorial design, RSM and simulated annealing algorithm

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Abstract. In the present investigation, a new hybrid technique response surface methodology (RSM) based simulated annealing (SA) algorithm approach is proposed to predict surface roughness for stainless steel material in traverse cut cylindrical grinding process. Experiments are designed as per full factorial design, wherein infeed, longitudinal feed and work speed have been considered as the important input parameters. Analysis of variance and graphical main and interaction plots have been plotted for analyzing the experimental data for identifying the relationships between grinding parameters and surface roughness. The variation of the performance parameter (surface roughness) with grinding parameters has been mathematically modeled by RSM. SA algorithm has been employed for solving the obtained mathematical model. Finally, the validation exercise is performed with optimum levels of grinding parameters. The results confirm the efficiency of the approach employed for prediction of surface roughness in this study.

1. Introduction

Nowadays, a lot research work is carried out in metal cutting industries for optimizing control parameters for improving accuracy and surface qualities of the machined surface. Cylindrical grinder is an efficient and effective machining / finishing operations used in the mechanical industries to create the cylindrical parts with high profile accuracy as well as better surface roughness [1]. The complex machining structure in the cylindrical grinding process i.e. simultaneous rotation of grinding wheel and work speed and traverse movement of the work table along with other interactive parameters such as grinding wheel properties, work-piece and machine parameters are limiting the ability of grinding process to produce accurate and fine finish jobs [2]. Selection of process parameters seeking better machining economics in cylindrical grinding is important task. Wrong selection of parametric setting
can have detrimental effects on quality of the ground surface and decreased efficiency grinding process.

To understand the significances of process conditions on output responses and developing relationships between the input and output parameters and optimize them is one of the important areas of research in traverse cut cylindrical grinding. Literature reveals that systematic optimization methodology based on design of experiments (DOE) could have ability to optimize the metal cutting operations (like grinding, turning, milling etc.) predictably, much research work is done so far in this respect. Full factorial design (FFD) is important methods of DOE, which was used by Baek et al. [3] for optimizing the grinding conditions and again, Thomas et al. [4] used same optimization methodology to analyze turning operation. Response surface methodology (RSM) is one of the widespread techniques of DOE. Kwak et al. [2] reported a study on RSM to optimize the surface finish and power spent during grinding in cylindrical external grinding operation. Lakshmi and Subbaiah [5] used integrated FFD along with RSM to optimize milling operations. Sahin and Riza [6] had been experimented and optimized the cutting conditions in turning using integrated factorial design and RSM approach. Rudrapati et al. [7] had made an experimental study to determine the factor effects and optimize the output responses by using RSM and genetic algorithm. Again, Rudrapati et al. [8] used RSM and TLBO to predict the performance characteristics in CNC turning operation. Adalarasan et al. [9] had been optimized the welding conditions in friction welding operation by Taguchi-SAA approach. Liao and Chen [10] utilized the applications of RSM along with SAA to analyze, model and optimize the process conditions in laser welding. Gohari et al. [11] had also optimized the milling process conditions to predict output responses by using RSM and SAA. Ganapathy [12] was analyzed turning operation to control turning parameters to predict output response by using regression analysis and SAA approach.

Present study is mainly focused to identify the effects of process settings and optimize them in traverse cut cylindrical grinding when machining of stainless steel. Experimental runs have been planned by factorial design and factor effects have been studied by analysis of variance (ANOVA) and graphical main and interaction plots. A new hybrid technique RSM based SA algorithm methodology is proposed and used in the present study to determine the global optimal conditions for traverse cut cylindrical grinding process.

2. Experimental planning and optimization techniques

Design of experiments (DOE): a procedure to attain a prognostic in formation of complex, multi-process conditions with minimum acceptable tests. Factorial design and RSM, which are two major approaches in DOE, those are used in the present study for examining and modelling the process parameters in cylindrical grinding operation.

A design in which each variable appears with every combination of every other variable is called full factorial design (FFD). In FFD, output performances are assessed at all settings of the input parameter levels. A three-factor three-level FFD has been employed to plan the experiments. Factorial design allows for studying effects of each variable on the response characteristic and combined influences of parameters on the response(s) through graphical main and interaction effect plots. Significances of grinding variables on responses can be examined by using analysis of variance (ANOVA) method and it is comparatively simple to estimation of major effects of a parameter.

RSM is a set of mathematical procedures, employed in the present work to investigate the relationship between performance variables and a set of quantifiable experimental factors. RSM is often utilized to build the mathematical relation between controllable factors and output response [13]. Furthermore, developed mathematical equation can be utilized to determine the operating condition that produces improved response, satisfies process requirements and identifies optimum parametric
condition which excepted produces enhanced component quality over the quality obtained [14]. Second order mathematical model developed by RSM is given as follows:

\[ Y = \beta_0 + \beta_1(A) + \beta_2(B) + \beta_3(C) + \beta_{11}(A^2) + \beta_{22}(B^2) + \beta_{33}(C^2) + \beta_{12}(A*B) + \beta_{13}(A*C) + \beta_{23}(B*C) \]  

(1)

where, all \( \beta \)'s are regression measurements; \( A, B, C \) are input process variables and \( Y \) is the performance characteristic which is needed to be enhanced.

2.1 Simulated annealing (SA) algorithm

In the present study, simulated annealing is proposed to solve the mathematical equation to optimize the surface finish. It was introduced in 1982 by Kirkpatrick et al [15]. It is a stochastic optimization technique that able to find global optima by using probability function. It works based on single point search method and then it resembles the coding procedure of molten metals by annealing process [16]. The atoms in the molten metal can move freely about to each other at higher temperature. If the temperature is slowly minimized and the passage of the atoms gets suppressed and starts to make well-ordered. And then crystals have been formed with least amount of energy levels. However, creation of crystal varies on cooling level(s). If the temperature is lowered drastically, the polycrystalline state has been formed, which may contains higher energy levels than crystalline state. So, in order to get the absolute lowest possible energy level / state, cooling has been done at slow rate. The method of slow cooling is termed as annealing. The simulated annealing process replicates this method of slow cooling of molten metal to obtain the minimum function value in optimization problems [17, 18]. While solving the second order response mathematical model by using SA in the present work, similar procedure is followed to optimize grinding conditions. In the present investigation, MATLAB software is utilized to optimize surface finish. SAA’s basic operations are taken care of by SA optimization toolbox of MATLAB and finally, it produces the optimal combination for the desired surface roughness (Rq).

3. Experimental details

As stated earlier that present investigation is intended to analyze and optimize the control parameters in traverse cut cylindrical grinding. Three levels of the process variables are selected in the present work and shown in Table 1. Experimental runs have been conducted on stainless steel material on cylindrical grinding machine as per full factorial design as given in Table 1. After finishing the experimental runs, surface finish (Rq) has been evaluated using stylus-type profilometer. Surface roughness has been measured in three different places and the averaged. Surface roughness parameter Rq has been chosen for present study, because, it is important roughness parameters which is used to define the condition of the machine parts. The observed data are discussed and analyzed in the next section.

4. Results and discussion

As mentioned earlier, FFD experiments have been done and the corresponding output response is observed by measuring surface roughness. The output results along with full factorial design matrix are shown in Table 1. The data shown in the Table 1 has been used to analyze and optimize the cylindrical grinding process to enhance / minimize the surface finish by using ANOVA and RSM based SAA.

4.1 Parametric influence on surface roughness

Analysis of variance (ANOVA) technique is employed to determine the relative magnitude of the effect of each variable on Rq and to approximate the error variation. The larger the variable influence relative to the error variance may be assessed from the F-column. Higher the F-value, the more factor
effect is compared to the error variance [19]. From Table 2, it is concluded that work speed is the variable which has greater influence on surface finish (Rq).

Table 1. FFD matrix and output response

| S. No | Infeed (A) | Longitudinal feed (B) | Work speed (C) | Surface roughness (Rq) |
|-------|------------|-----------------------|----------------|------------------------|
| 1     | 0.04       | 70                    | 160            | 0.995                  |
| 2     | 0.06       | 90                    | 80             | 0.744                  |
| 3     | 0.06       | 90                    | 160            | 0.874                  |
| 4     | 0.05       | 90                    | 80             | 0.961                  |
| 5     | 0.06       | 80                    | 112            | 1.246                  |
| 6     | 0.05       | 90                    | 112            | 1.503                  |
| 7     | 0.04       | 80                    | 112            | 1.33                   |
| 8     | 0.05       | 90                    | 160            | 1.077                  |
| 9     | 0.04       | 80                    | 80             | 1.39                   |
| 10    | 0.04       | 70                    | 112            | 1.077                  |
| 11    | 0.04       | 90                    | 80             | 0.858                  |
| 12    | 0.06       | 70                    | 80             | 1.08                   |
| 13    | 0.05       | 70                    | 112            | 1.253                  |
| 14    | 0.04       | 90                    | 160            | 0.995                  |
| 15    | 0.06       | 80                    | 80             | 0.979                  |
| 16    | 0.05       | 80                    | 80             | 0.968                  |
| 17    | 0.04       | 80                    | 160            | 1.11                   |
| 18    | 0.05       | 70                    | 80             | 0.924                  |
| 19    | 0.05       | 80                    | 160            | 1.003                  |
| 20    | 0.06       | 80                    | 160            | 1.41                   |
| 21    | 0.04       | 70                    | 80             | 1.22                   |
| 22    | 0.06       | 70                    | 112            | 1.193                  |
| 23    | 0.06       | 90                    | 112            | 1.313                  |
| 24    | 0.05       | 80                    | 112            | 1.147                  |
| 25    | 0.04       | 90                    | 112            | 0.818                  |
| 26    | 0.06       | 70                    | 160            | 1.123                  |
| 27    | 0.05       | 70                    | 160            | 0.984                  |

The main (Figure 1) and interaction (Figure 2) effect plots for process parameters Vs. surface roughness (Rq) are illustrated by taking the mean values of Rq. These plots are very useful to identify the factor effects, individually as well as combinedly. In a main / interaction plot, when the lines are parallel, main / interaction effects are zero. The slopes of the lines are more, the more influence the main / interaction effect has on the response. From Figure 1, it is noted that longitudinal feed (B) has larger effect on Rq and next is work speed (C). Infeed is insignificant as the line is almost parallel, as found from the Figure 1. From Figure 2, it is concluded that the non-parallelism of the lines in a plot...
reveals that considerable amount of the interaction exists between the two parameters, although interconnecting lines are strong symptom of interaction effect on $R_q$.

**Table 2. Analysis of variance for surface roughness ($R_q$)**

| Source | DF | Seq SS  | Adj SS  | Adj MS  | F     | P     |
|--------|----|---------|---------|---------|-------|-------|
| A      | 2  | 0.00183 | 0.00183 | 0.00092 | 0.05  | 0.955 |
| B      | 2  | 0.11521 | 0.11521 | 0.05761 | 2.92  | 0.111 |
| C      | 2  | 0.18507 | 0.18507 | 0.09253 | 4.7   | 0.045 |
| A*B    | 4  | 0.23062 | 0.23062 | 0.05765 | 2.93  | 0.092 |
| A*C    | 4  | 0.19776 | 0.19776 | 0.04944 | 2.51  | 0.125 |
| B*C    | 4  | 0.0674  | 0.0674  | 0.01685 | 0.86  | 0.529 |
| Residual Error | 8  | 0.15765 | 0.15765 | 0.01971 |       |       |
| Total  | 26 | 0.95555 |         |         |       |       |

4.2 Mathematical modeling and optimization

As already mentioned above, RSM comprises of combination of mathematical and statistical techniques which is applied on experimental data and the mathematical equation is developed and shown in Equation 2.

$$Y_{Rq} = -5.303 - 37.027A + 0.172B + 0.012C + 63.889A^2 - 0.001B^2 - 0.0001C^2 + 0.13AB + 0.18AC$$

where, $Y_{Rq}$ = output response, $A$ = infeed, $B$ = longitudinal feed and $C$ = work speed. Mathematical equation (Equation 2) can be used to predict the optimum conditions for obtaining the better $R_q$ value within the limits of process conditions. The simulated annealing algorithm is used in the present case, to solve the obtained mathematical model i.e. Equation 2. The steps are followed by using optimization toolbox in MATLAB software: 1. Select the objective function that is to be predicted, 2. Select the starting points of input parameters, 3. Fixing the lower and higher limits of input parameters, 4. Running the solver.

![Figure 1. Main effect plots for Rq](image-url)
At each iteration in the SA toolbox, a new combination of optimal parametric condition as well as output response variable is generated by the process. Optimum grinding condition is found from the SA toolbox is: infeed (A) = 0.06 mm/cycle, longitudinal feed (B) = 89.95 ≈90 mm/s and work speed (C) = 80.02 rpm and surface roughness (Rq) = 0.8599 μm. This setting is obtained in the range of the process variables selected in the work. Confirmatory experiment revels that the validity of the proposed hybrid optimization methodology for prediction of surface finish in stainless steel grinding.

5. Conclusion
Based on experimental results, optimal parametric setting for good surface roughness using RSM based SA algorithm using factorial design the following points can be concluded as listed below:

- From the ANOVA results, it is found that work speed is the factor that has more influence on surface roughness (Rq) than other factors as well as their interactions.
- From the main effect plots, it is noted that longitudinal feed and work speed are the significant factors for surface roughness
- Interaction effect plots revealed that all the interaction effects of input parameters have significant effect on output response (Rq).
- The second order mathematical equation is made by RSM to build relationships between input factors and output variable; this equation can be used for predicting Rq value for a given set of grinding parameters.
- The optimum grinding setting is obtained by using SAA is: infeed = 0.06 mm/cycle, longitudinal feed = 90 mm/s and work speed = 80 rpm. The optimum condition obtained from SA has been validated by confirmatory test.
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