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Modeling and Optimization of Milling Process Output Characteristics Using Taguchi Method and Simulated Annealing Algorithm

Masoud Azadi Moghaddam [1], Hamid Dalir [2], , Farhad Kolahan [3]

[1] Department of Mechanical Engineering, Ferdowsi University of Mashhad, MAPNA, Operation and Maintenance (O&M) Company, Ferdowsi Combined Cycle Power Plant, Mashhad, Iran
[2] MAPNA, Operation and Maintenance (O&M) Company, Ferdowsi Combined Cycle Power Plant, Mashhad, Iran
[3] Department of Mechanical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran

Abstract
The proposed approach is based on statistical analysis on the experimental data gathered using Taguchi design matrix.Surface roughness (SR)is the most important performance characteristics of the face milling process. In this study the effect of input face milling process parameters on surface roughnessof AISI1045 steelmilled parts have been studied. The input parameters are cutting speed (v), feed rate (fz) and depth of cut (ap). The experimental data are gathered using Taguchi L_9 design matrix.In order to establish the relations between the input and the output parameters, various regression functions have been fitted on the data based on output characteristics. The significance of the process parameters on the quality characteristics of the process was also evaluated quantitatively using the analysis of variance (ANOVA) method. Then, statistical analysis and validation experiments have been carried out to compare and select the best and most fitted models. In the last section of this research,mathematical model has been developed for Surface roughness prediction using simulated annealing (SA) algorithm on the basis of experimental results. The model developed for optimization has been validated by confirmation experiments. It has been found that the predicted roughness using SA algorithm is in good agreement with the actual surface roughness.

Keywords:
Face milling process, Surface roughness, Optimization, simulated annealing (SA) algorithm, Analysis of variance (ANOVA), Orthogonal array technique.

Introduction

The surface quality is one of the most specified customer requirements and the major indicator of surface quality on machined parts is surface roughness.

The surface roughness is mainly a result of various controllable or uncontrollable process parameters and it is harder to attain and track than physical dimensions are. A considerable number of studies have researched the effects of the cutting speed, feed, depth of cut, and other factors on the surface roughness. In recent studies the effects of some factors on surface roughness has been evaluated and models has been developed. A central task in science and engineering practice is to develop models that give a satisfactory description of physical systems being observed [1-3]. The goal of this study is to obtain a mathematical model that relates the surface roughness to three cutting parameters in face milling, precisely to the cutting speed, feed rate and depth of cut[1].

There is various simple surface roughness amplitude parameters used in industry, such as roughness average (Ra), root-mean-square (RMS) roughness (Rq), and maximum peak-to-valley roughness (Ry or Rmax), etc. [2]. The parameter Ra is used in this study. The average roughness (Ra) is the area between the roughness profile and its mean line, or the integral of the absolute value of the roughness profile height over the evaluation. Therefore, the Ra is specified by the following equation [2]:

$$Ra = \frac{1}{L}\int_0^L |Y(x)| \, dx \tag{1}$$

Where Ra is the arithmetic average deviation from the mean line, L the sampling length, and Y is the ordinate of the profile curve. There are many methods of measuring surface roughness, such as image processing, microscopes, stylus type instruments, profile tracing instruments, etc[2].

Selection of appropriate machining parameters is an important step in the process planning of any machining operation. The present method of selection of machining parameters mainly depends either on previous work experience of the process planner or thumb rule or any machining data hand book. But it is a known fact that the machining parameters obtained from these resources are far from the optimal parameters and may be very much useful for theoretical investigations. The other possibility of selecting machining parameters is by conducting ‘trial and error’ experiments. But this act of experiments is purely non-technical and moreover time and cost is unnecessarily wasted for this purpose. The surface roughness of any manufacturing process has become critical because of increased quality demands.

Sometimes, even if the dimensions of the component are well within the dimensional tolerances, still there are possibilities of rejecting the component for the lack of required surface finish. Moreover surface roughness determines mechanical properties such as wear, corrosion, lubrication, electrical conductivity and fatigue behavior. Surface roughness is an important measure of the quality of a product and also greatly influences the production cost. Production of required surface finish on a component is mainly dependent on many parameters such as cutting speed, feed, depth of cut, tool nomenclature, cutting force, rigidity of the machine and so on. Among these parameters, cutting speed, feed and depth of cut are parameters which are easily controllable during the process of machining [3].

The main objectives of the present study are: 1) to establish the relationship between face milling process parameters and the process output characteristic (surface roughness), and 2) to determine the optimal parameter levels for minimum surface roughness by application of simulated anealing (SA) algorithm. The proposed procedure is based on statistical analysis of the experimental data. The article concludes with the verification of the proposed approach and a summary of the major findings.

Experimental set up

Test samples made of AISI1045 steel parts with dimensions 15×60×80 mm were prepared and used in experiments. The face milling experiments were performed by a tool for the face milling R245-12 T3 M-PM 4020 using inserts with 4 helical right-hand cutting edges, produced by Iscar. The experiments were conducted on MCV 400 CNC milling machine.The feasible range for cutting parameters is taken from the machine limitations. The surface roughness tester is used to measure the roughness of the milled work piece. The measured surface roughness was obtained by averaging the surface roughness values at a minimum of three locations on the milled surface. A cut-off value of 8 mm was used when measuring the surface roughness of the milled surface.

Process Parameter Setting

A challenging task in any process is the selection of optimum machining parameter combinations for obtaining higher accuracy due to process variables and complicated process mechanisms.

In design of experiments (DOE), the number of required experiments (and hence the experiment cost) increases as the number of parameters and/or their corresponding levels increase. That is why it is recommended that the parameters with less likely pronounced effects on the process outputs be evaluated at fewer levels. In addition, the limitations of test equipment may also dictate a certain number of levels for some of the process parameters. For this research a lot of experiments had been done to find the relatively appropriate machine tool parameters and their proper settings as shown in Table 1.

Table 1 Machining Parameters and their Levels

parameters	symbol	unit	Range	Level 1	Level 2	Level 3
cutting speed (v)	C	m/min	126-314	126	201	314
feed rate (f_z)	F	(mm/rev×tooth)	0.06-0.18	0.06	0.12	0.18
depth of cut (a_p)	D	(mm)	1-2	1	1.5	2

Taguchi Technique

Taguchi technique constructed a special set of general designs for factorial experiments that overcomes the drawbacks of partial factorial experiment. The method is popularly known as Taguchi’s method. The special set of designs consists of Orthogonal Arrays (OA). The OA is a method of setting up experiments that only requires a fraction of full factorial combinations. The treatment combinations are chosen to provide sufficient information to determine the factor effects using the analysis of means. Orthogonal refers to the balance of the various combinations of factors so that no one factor is given more or less weight in the experiment than the other factors. Orthogonal also refers to the fact that effect of each factor can be mathematically assessed independent of the effect of the other factors. Taguchi’s method, firstly, clearly defines orthogonal arrays, each of which can be used for many experimental situations. Secondly, Taguchi’s method provides a standard method for analysis of results. Taguchi’s method provides consistency and reproducibility that is generally not found in other statistical methods [4]. This study has been undertaken to investigate the effects of cutting speed (v), feed rate (fz) and depth of cut (ap) on surface roughness (SR). Therefore, L9 (33) design matrix has been used to carry out experiments (Table 2). Three process (input) parameters have been selected on the basis of literature survey and preliminary investigations. Preliminary experiments were conducted for the wide range of cutting speed, feed rate and depth of cut. Satisfactory results were obtained for 126-314 m/min, range of cutting speed. Similar observations were made for specified range of feed rate and depth of cut.

Table 2 The process characteristics an their output

No	V (m/min)	Fz (mm/(rev × tooth)	ap (mm)	SR (μm)
1	1	1	1	1.67
2	1	2	2	2.14
3	1	3	3	2.22
4	2	1	2	1.47
5	2	2	3	2.04
6	2	3	1	1.71
7	3	1	3	1.75
8	3	2	1	1.50
9	3	3	2	1.94

Mathematical modeling

Regression models can be used to predict the behavior of input variables (independent variables) and values associated with each test response results [5].

Linear Model

SR (Ra)= 1.23 - 0.00138 ×v + 2.72× fz + 0.377× ap (2)

Curvilinear Model

SR (Ra)= 2.02   0.0125×V + 13.5×fz + 0.000019×V2 42.2×fz2 + 0.00184×V×ap (3)

Logarithmic Model

SR (Ra) = 5.585×V-0.163×fz0.168×ap0.296 (4)

Adequacies of models were checked by analysis of variance (ANOVA) technique within the confidence limit of 95% [6-8]. Results are shown in Table 3. Given the required confidence limit (Pr), the correlation factor (R2) and the adjusted correlation factor (R2-adj) for these models, it is evidence that Curvilinear model is superior to other two, thus, these models are considered as the best representative of the authentic milling process throughout in this paper.

Figure 1, demonstrates the interaction effect of cutting speed and feed rate (depth of cut remained constant). As illustrated, by increasing the feed rate within the range of 0.06-to-0.18 mm/rev×tooth, the SR increses. Similarly by increasing the cutting speed, within the range of 126-to-314 m/min, the SRdecreses.

Figure 2, demonstrates the interaction effect of cutting speed and depth of cut on SR. As illustrated, by increasing the depth of cut within the range of 1-to-2 mm, the SR increases, Similarly by increasing the cutting speed, within the range of 126-to-314 m/min, the SR decreses.

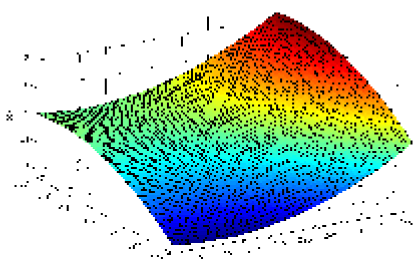

Figure 1. interaction of v and fz plot for SR

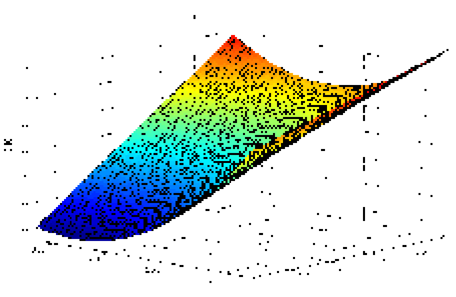

Figure 2. interaction of v and ap plot for SR

Figure 3, demonstrates the interaction effect of depth of cut and feed rate on SR. As illustrated, by increasing the depth of cut within the range of 1-to-2 mm, the SR increases, Similarly by increasing the feed rate, within the range of 0.06-to-0.18m/min, the SR increases.

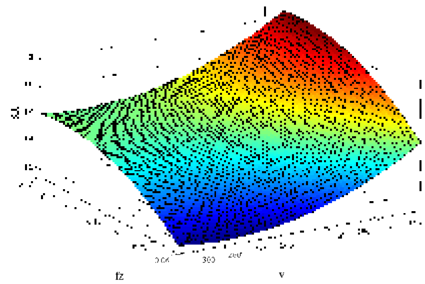

Figure 3. interaction of v and fz plot for SR

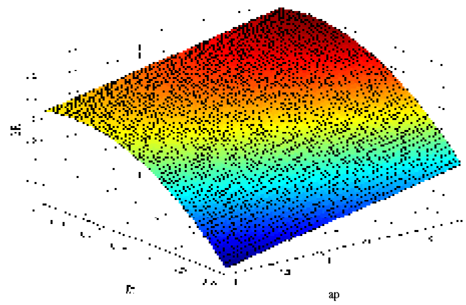

Figure 4. interaction of ap and fz plot for SR

Analysis of variance (ANOVA)

The ANOVA is used to investigate the most influential parameters to the process factor-level response. In this investigation, the experimental data are analyzed using the contribution rate. ANOVA has been performed on the above model to assess their adequacy, within the confidence limit of 95%. ANOVA results indicate that the model is adequate within the specified confidence limit. The calculated determination coefficient (R2) for this model is 98.1%. Result of ANOVA is shown in Table 3.

According to ANOVA procedure, large contribution rate indicates that the variation of the process parameter makes a big change on the performance characteristics (Table 3).

In this study, a confidence level of 95% is selected to evaluate parameters significances [2].

Table 3 Result of ANOVA for SR

Machining parameter	Degree of freedom (Dof)	Sum of square (SS_i)	P- value	Contribution Percentage (%)
V	2	0.151400	0.005	24
fz	2	0.180067	0.012	29
v × v	2	0.000000	0.019	1
fz × fz	2	0.000000	0.035	1
V × ap	4	0.257733	0.039	41
Error	3	0.000000	0.004	-
Total	15	0.58920	-	-

ANOVA results may provide the percent contributions of each parameter [11].

The percent contributions of the milling parameters on SR is shown in Figures 5. According to Figure 5, v × ap is the major factor affecting the SR with 41% contribution. It is followed by fz ,v , v ×v, fz × fz with

29% , 24%, 1% and 1% respectively. The remaining (4%) effects are due to noise factors or uncontrollable parameters.

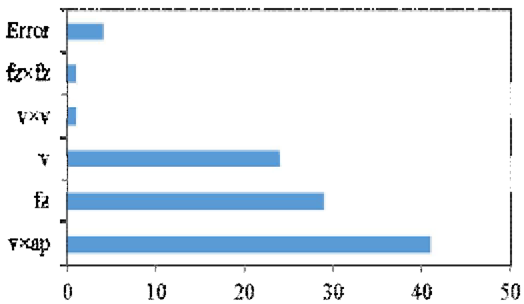

Figure 5. The effect of machining parameters on the SR

Proposed methodology

Simulated annealing (SA) algorithm is an optimization process whose operation is strongly reminiscent of the physical annealing of crystalline compounds such as metals and metallic alloys [18]. In condensed matter physics, annealing is a physical process that is used to reconstruct the crystal structure of a solid with a low energy state. A solid in a state bath is first heated up to a temperature above the melting point of the solid. At this temperature, all particles of the solid are in violent random motion. The temperature of the heat bath is then slowly cooled down. All particles of the solid rearrange themselves and tend toward a low energy state. As the cooling of the particle is carried out sufficiently slowly, lower and lower energy states are obtained until the lowest energy state is reached. Similarly, in face milling an energy function is created which is minimized. While minimizing efforts are made to avoid local minima and to achieve global minima. The lowest energy level gives the optimized value of face milling parameters.

A standard SA procedure begins by generating an initial solution at random. At initial stages, a small random change is made in the current solution. Then the objective function value of new solution is calculated and compared with that of current solution. A move is made to the new solution if it has better value or if the probability function implemented in SA has a higher value than a randomly generated number. The probability of accepting a new solution is given as follows:

$$p = \begin{cases} 1 & \text{if} \quad \Delta < 0 \\ e^{-\Delta/t} & \text{if} \quad \Delta \geq 0 \end{cases} \tag{5}$$

The calculation of this probability relies on a temperature parameter, T, which is referred to as temperature, since it plays a similar role as the temperature in the physical annealing process. To avoid getting trapped at a local minimum point, the rate of reduction should be slow [9]. In our problem the following method to reduce the temperature has been used:

$$T_{i+1} = cT_i \quad i = 0, 1, \ldots \quad \text{and} \quad 0.9 \leq c < 1 \tag{6}$$

Thus, at the start of SA most worsening moves may be accepted, but at the end only improving ones are likely to be allowed. This can help the procedure jump out of a local minimum. The algorithm may be terminated after a certain volume fraction for the structure has been reached or after a pre-specified run time.

Simulated annealing algorithm has diverse applications including improving the performance of other artificial intelligence techniques and determining the optimal set of process parameter [9, 10]. In this research, SA has been used. Results indicate that the proposed optimization procedure is quite efficient in optimization of face milling process parameters.

Optimization based on SA was executed using MATLAB software in less than 30 iterations (Figure 6) with 50 populations were used to run the program. The program is executed to get optimized machining parameters for minimizing SR.

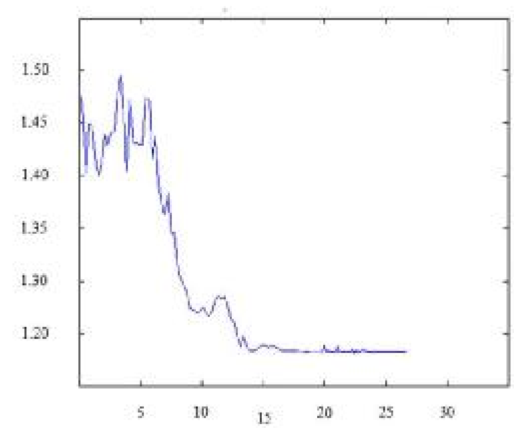

Figure 6. SA convergence curve for SR

Validation of Machining Parameters

The optimum machining parameters found using SA was validated by conducting experiments on the same specification of AISI1045 material. Table 4 shows the results of the confirmation experiments

Table 4 Experimental results of surface roughness for the optimized machining parameters

Machining characteristic	V	fz	ap	Predicted value	Experimental value	Error
SR	280	0.06	1	1.18	1.21	2.5%

Results and discussion

The effect of machining parameters on the surface roughness was considered. 9 experiments were conducted on AISI1045 and their corresponding surface roughness values measured. Then optimization based on SA was executed using MATLAB software in which 30 iterations with 50 populations were used to run the program. The computational time for execution of single run in a Core 2 Duo processor computer is observed to be 15 s in an average. Then once again experiments were conducted based on the recommended machining parameters of SA. It is observed from the conducted experiments, the surface roughness decreases with an increase in cutting speed and surface roughness decreases with a decrease in feed. The predicted surface roughness largely agrees with the experimental results. The difference (2.5%) between the results of proposed technique and the experiments may be attributed to the effects of vibration, spindle run-out, and work piece material property in actual machining.

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