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ROUGHNESS IMPROVEMENT IN MACHINING OPERATIONS THROUGH COUPLED METAMODEL AND GENETIC ALGORITHMS TECHNIQUE

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ABSTRACT: Due to the widespread use of highly automated machine tools, manufacturing requires reliable models and methods for the prediction of output performance of machining processes. The prediction of optimal machining conditions for good surface finish and dimensional accuracy plays a very important role in process planning. The present work deals with the study and development of a surface roughness prediction model for machining Al7075-T6, using Response Surface Methodology (RSM). Machining operations of work pieces made by Al7075-T6 covering a wide range of machining conditions have been carried out with by flat end mill with four teeth made by High Speed Steel. A RS model, in terms of machining parameters, was developed for surface roughness prediction using the Radial Basis Functions (RBF) technique. This model gives the process response sensitivity to the individual process parameters. An attempt has also been made to optimize the surface roughness prediction model using Genetic Algorithms (GA).

KEYWORDS: Milling; Cutting conditions; Surface Roughness; Response Surfaces Methodology; Genetic Algorithm

1 INTRODUCTION

Process modelling and optimization are two important issues in manufacturing. The manufacturing processes are characterized by a multiplicity of dynamically interacting process variables. A greater attention is given to accuracy and surface roughness of product by the industry these days. Surface finish has been one of the most important considerations in determining the machinability of materials. Surface roughness and dimensional accuracy are important factors to predict machining performances of any machining operation. Most surface roughness prediction models are empirical and are generally based on physical experiments. In addition, it is very difficult in practice, to keep all factors under control as required to obtain reproducible results. Generally, these models have a complex relationship between surface roughness and operational parameters, work materials and chip-breaker types. Optimization of machining parameters not only increases the utility for machining economics, but also the product quality to a great extent. In this context, an effort has been made to estimate the surface roughness using experimental data. In this study, a RS model based on RBF methodology for predicting surface roughness values in milling operation of work piece made of Aluminum (Al7075-T6) material has been developed. The accuracy of the RS model has been verified by experimental measurements. A Genetic Algorithm technique has been also used to optimize the surface roughness prediction model.

2 LITERATURE REVIEW

Theoretically, Ra is the arithmetic average value of the gap of the measured profile from the mean line throughout the sampling length [1]. Ra is also an important factor in controlling machining performance. Surface roughness is influenced by: tool geometry, feed, cutting conditions and the irregularities of machining operations such as tool wear, chatter, tool deflections, cutting fluid, and workpiece properties. The effect of cutting conditions (feed, cutting speed, radial engage, depth of cut) on surface roughness is discussed in this study. The Aluminium alloy Al 7075-T6 is usually employed in the aerospace industry to manufacture engine and structural components that demand: lighter, harder, stronger, tougher, stiffer, more corrosion- and erosion-resistant properties. A good understanding of the behaviour and of the relationship among: the work piece materials, the cutting tool materials, the cutting conditions and the process parameters is an essential requirement for the optimisation of the cutting process. A significant improvement in process efficiency may be obtained with a process parameters optimization that identifies and determines areas of critical process control factors and leads to the desired outputs or responses with acceptable variations ensuring a lower cost of manufacturing. The selection of optimal machining conditions is a key factor in achieving this condition. The first necessary step to process parameters optimization in any metal cutting operation is the ability

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to understand the principles governing the cutting processes developing an explicit mathematical model. The resulting model provides the basic mathematical input required for the formulation of the process objective function. The usage of an optimization algorithm provides an optimal or near-optimal solution to the overall optimization problem previously formulated. Taraman [2] used Response Surface Methodology (RSM) for predicting surface roughness. Boothroyd [3] investigated effect of speed, feed, depth of cut etc., on steel. Baradie [4] also emphasised the use of RSM in developing a surface roughness prediction model for turning grey cast iron of hardness 154 BHN. Tetsutaro and Naotake [5] applied Group Method Data Handling (GMDH) algorithm for the successful prediction and detection of cutting tool failure. Das et al, [6] applied an analytic hierarchy process (AHP) for on-line tool wear monitoring. Nowadays, artificial intelligence (AI) based modelling is a new trend in numerical modelling for machining operations [7]. It was found that usage of heuristic methods to model surface roughness prediction it was very limited, so emphasis was laid on the development of a surface roughness prediction model.

3 RS METHODOLOGY

The RSM is a dynamic and very important tool of design of experiment (DOE) in which the relationship among process responses and their input decision variables is mapped to achieve the objective of maximization or minimization of the response properties. The first necessary step in RSM is to map responses, i.e. Y as function of independent decision variables (X1,.,Xn).

3.1 PLAN OF EXPERIMENTS

An experimental testing activity made by 30 different conditions has been designed in order to model the true function of surface roughness response through RSM technique. The experimental testing conditions have been selected by a version of Latin Hypercube DOE, called *Optimal Latin Hypercube*. The ranges of definition for the analyzed variables are shown in Table 1.

***Table 1**: Variables range of definition.*

Variable	Range
Feed (F) [mm/min]	(300 ; 1500)
Radial Engage (B) [mm]	(2 ; 12)
DOC [mm]	(0.2 ; 1.5)
Speed (S) [rpm]	(2500 ; 5000)

In this DOE technique an optimization process is then applied to this initial random Latin Hypercube design matrix. By swapping the order of two factor levels in a column of the matrix, a new matrix is generated and the new overall spacing of points is evaluated. This optimized process designs a matrix in which the points are spread as evenly as possible within the design space defined by the lower and upper levels [8]. Each test has been repeated 3 times to ensure stability of statistical data collected for a total of 90 experimental tests.

3.2 RBF TECHNIQUE

Radial Basis Functions (RBF) are a type of neural network used to approximate various types of behaviour. They adopt a hidden layer of radial units and an output layer of linear units, and they are characterized by reasonably fast training and reasonably compact networks. Weissinger was the first to use radial basis function to calculate the flow around wings [9]. This neural network uses the Gaussian curve to map values. The network has n inputs and k outputs. Radial basis network is a very efficient method when function approximation is needed because it has the ability to well represent nonlinear functions [8].

3.3 EXPERIMENTAL EQUIPMENTS

The tests were performed on a 3 axes CNC milling machine Benchman VMC-4000. The cutting tool used to perform the experimental tests is a flat end mill with four teeth, helix angle 40°, diameter dm = 16 mm, overhang length l1 = 92 mm, sharp length l2 = 32 mm and concavity angle ap = 2.5°. The tool is made by High Speed Steel with 8% of Cobalt. Machining experiments are performed on aluminum (7075-T6) block with dimensions of 200 mm × 100 mm × 100 mm. The chemical composition of the workpiece material is given in the following specification (wt.%): 1.6 Cu, 2.5 Mg, 0.23 Cr, 5.40 Zn. The work piece hardness is 150 BHN. Its mechanical properties are: tensile strength of 690 MPa, yield strength of 600 MPa, shear strength of 360 MPa and elongation of 11%. Every single block has been tested 8 times on each side for a total of 32 tests per block, [10]. The roughness on worked surfaces have been detected with Mahr's Perthometer Concept 6.5 profilometer. The measurements have been performed in the direction of the feed cutting along the centreline of the slot for a measurement length of 30 mm. The area of engagement (35mm) and disengagement (35 mm) of the cutter has been excluded from the data analysis measurement. For each analyzed working condition the experimental test has been repeated three times. The adopted Ra value in the RMS model has been obtained as the average of the measurements in the three tests. In this study the authors have used the arithmetical average roughness parameter Ra, whose equation is shown in Equation (1), in order to measure the roughness profile parallel to the feed which coincides with the cutter axis rotation:

$$R_a = \frac{1}{l_r} \int_0^{l_r} |z(x)| dx \tag{1}$$

4 RS MODEL EVALUATION

The approximation error analysis provides a visual representation of the quality of an approximation model for each response. The total error is calculated for each response using the % average error. The differences between the actual (workflow execution) and predicted (approximation model execution) values for all error samples are averaged and then normalized by the range of the actual values for each response, according to Equation (2).

$$I_{av,err} = \frac{\sum_{i=1}^{n} \sqrt{Y_{A,i}^2 - Y_{P,i}^2}}{n} \quad (2)$$

Where: $Y_{A;i}$ is a control response value; $Y_{P;i}$ is a predict response value on approximation surface and n is the number of sample control points. The normalized average error is the index used to evaluate the prediction capabilities of RS model. The check data sets include 16 experimental values of surface roughness. They are selected with a good distribution inside the cutting parameters design space and thereby to have a good check on the accuracy of the RS model. For the developed RS model adopting the RBF technique the calculated average error is equal to 13.8%.

5 SURFACE ROUGHNESS OPTIMIZATION

5.1 Experimental test

To evaluate the optimization results an experimental test has been designed through the definition of four sets of cutting configuration parameters. The geometrical dimensions of the raw material blocks are 100x60x50mm. The experimental layout is shown in Figure 1.

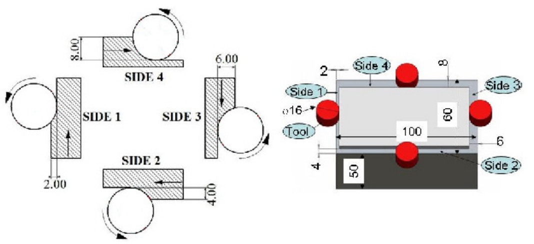

Figure 1: *Top view of the layout of the designed contour milling operation and tool radial engagements.*

The tool used is the same adopted in the experimental tests executed to develop the RS model. The measurements of Ra have been performed in the direction of the feed cutting along the centreline of the slot for a measurement length of 30 mm. The results are shown in Table 2:

Table 2: *Not optimized cutting parameters.*

Side	F [mm/min]	B [mm]	DOC [mm]	S [rpm]	$R_{a,exp}$ [µm]
1	1500	2	1	3500	10.8
2	1500	4	1.3	3500	9
3	1500	6	0.5	3500	10.6
4	1500	8	0.8	3500	11.3

5.2 Optimization problem formulation

As already said, the roughness value on a machined component is an indication of its quality so it is desirable to have its value as lower as possible. Low Ra values can be achieved efficiently by adjusting cutting conditions with the help of an appropriate numerical optimization method. For this reason, minimization of surface roughness problem must be formulated in the mathematical format as below:

B=cost *and DOC*=cost
Find: *F,S,*
that Minimize: *Ra(F,S)*
Subjected to constraints:
$Ra \leq 7\ \mu m$
Within the following ranges of the defined design variables:
$300 \leq F \leq 1500$ *mm/min*
$2500 \leq S \leq 5000$ *rpm*

In the optimization problem definition above, a better solution is also forced through the constraint definition. In this study this formulation has been used to optimized all four considered working conditions (side1 to side 4 in Figure 1).

5.3 Coupled GA with RSM Optimization procedure

The proposed optimization problem is solved by coupling the developed RS model with the developed genetic algorithm as shown in Figure 2.

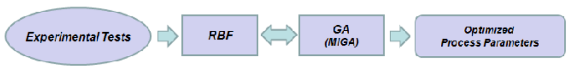

Figure 2: *Interaction of experimental measurements, RS model and GA during surface roughness optimization.*

The genetic algorithm solves the optimization problem iteratively based on biological evolution process in nature (Darwin's theory of survival of the fittest). In the solution procedure, a set of parameters values is randomly selected. Best combination of parameters leading to imposed target surface roughness is determined. New combination of parameters is generated from the best combination by simulating biological mechanisms of offspring, crossover and mutation. This process is repeated until surface roughness value with new combination of parameters cannot be further reduced anymore. The final combination of parameters is considered as the optimum solution. In this study the authors have used a *Multi-Island Genetic Algorithm* (MIGA). The main feature of Multi-Island Genetic Algorithm that distinguishes it from traditional genetic algorithms is the fact that each population of individuals is divided into several sub-populations called "islands". All traditional genetic operations are performed separately on each sub-population. Some individuals are then selected from each island and migrated to different islands periodically. Two parameters control the migration process: migration interval which is the number of generations between each migration, and migration rate which is the percentage of individuals migrated from each island at the time of migration. The critical parameters in GAs are: the size of the population, mutation rate, number of iterations etc. and their considered values are given in Table 3 for the studied case.

Table 3: *MIGA main parameters configuration.*

Option	Value
Sub population size	10
Number of island	10
Number of generations	10
Rate of crossover	1.0
Rate of mutation	0.01
Rate of migration	0.01
Interval of migration	5
Elite size	1

5.4 RESULTS ANALYSIS

The optimum cutting conditions leading to the minimum surface roughness are reported in Table 4.

Table 4: *Comparison of non-optimized and optimized cutting parameters: F [mm/min] and S [rpm]; for the given B [mm] and DOC [mm].*

Side	B	DOC	F	F_{opt}	S	S_{opt}
1	2	1	1500	1300	3500	2950
2	4	1.3	1500	900	3500	3600
3	6	0.5	1500	1200	3500	3800
4	8	0.8	1500	800	3500	2700

The predicted optimum cutting conditions by GA have been further validated with a physical measurement. Predicted surface roughness value is compared with the measurement in Table 5, where:

$R_{a,Nom}$: experimental Ra
$R_{a,Opt\text{-}Id}$: numerical optimized Ra
$R_{a,Opt}$: experimental optimized Ra
Er_% = $(R_{a,Opt}\text{-}R_{a,Opt\text{-}Id}/R_{a,Opt\text{-}Id})$x100:prediction error %
Im_% = $(R_{a,Nom}\text{-}R_{a,Opt}/R_{a,Nom})$x100: Ra reduction %

Table 5: *Ra Indexes evaluation; Ra, measure unit is [µm].*

Side	$R_{a,Nom}$	$R_{a,Opt\text{-}Id}$	$R_{a,Opt}$	Er_%	Im_%
1	10.8	7	8.2	17	24
2	9	7	7.9	12	13
3	10.6	7	8.1	14	24
4	11.3	7	8.2	15	27

Conclusions

In this study, a fourth order RS model for predicting surface roughness values in milling work piece surfaces made of Aluminum (7075-T6) material was developed. To generate the RS model was utilized a RBF technique. The accuracy of the RS model was verified with the experimental measurements. The accuracy error was found to be equal to 13.8 %. The developed RS model was further coupled with a developed GA to find the optimum cutting condition leading to the minimum surface roughness value. The predicted optimum cutting conditions was validated with an experimental measurements showing that GA improved the surface roughness respect to non-optimized experimental tests from 13% to 27% depending on the different examined cutting conditions. The differences between target surface roughness ($R_{a,opt\text{-}Id}$) and experimental values found with the validation tests ($R_{a,opt}$) are similar at % average error calculated for the RS model (about 14%). This indicates that the optimization methodology proposed in this study by coupling the developed RS model and the developed GA is effective and can be utilized if the RS model development is accurate, therefore in future work the authors will focus their efforts to improve the quality in terms of numerical-experimental correlation for the response surfaces.

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