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# EXPERIMENTAL DEVELOPMENT OF RSM TECHNIQUES FOR SURFACE QUALITY PREDICTION IN METAL CUTTING APPLICATIONS

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**ABSTRACT:** The aim of this work is to analyze the influence of cutting conditions on surface roughness with slot end milling on AL7075-T6. The considered parameters are: cutting speed, feed, depth of cutting and mill radial engage. Response surface models based on experimental data obtained with physical tests have been developed, the authors have performed a consistent set of experimental tests based on design points selected within the four-dimensional design space. Each test has been repeated 3 times to ensure the stability of the collected statistical data. These well-distributed results has been subsequently used to create RS models through approximation techniques based on polynomial and neural network methods and to verify their reliability in terms of correct responses behaviour. The obtained results show that the most significant factors affecting the surface roughness are feed and speed.

**KEYWORDS:** Milling; Cutting conditions; Surface Roughness; Response Surfaces Methodology;

## 1 INTRODUCTION

Surface quality is generally associated with surface roughness and can be determined by the roughness measurement. Surface roughness is determined by the material irregularities obtained from various machining operations. To quantify this process response average surface roughness definition, often represented with Ra, is commonly used. Theoretically, Ra is the arithmetic average value of the gap between the nominal profile and the measured one. Ra is also an important factor in controlling machining performances. Surface roughness is influenced by: tool geometry, feed, cutting conditions and other factors such as: tool wear, chatter, tool deflections, cutting fluid, and workpiece properties. The effect of cutting conditions on surface roughness is discussed in this study. Analytical models have been created to predict surface roughness as function of: cutting speed, feed and axial depth of cut. In this study, four different models for predicting surface roughness values in milling operation of workpiece made of Aluminum (Al7075-T6) material are developed. To generate the RS models statistical response surface, RSM and RBF methodology have been used. The accuracy of the RS models is verified by the experimental measurement.

## 2 STATE OF THE ART

The Aluminium alloy Al 7075-T6 is usually employed in the aerospace industry to manufacture 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. The application of this methodology allows to identifies the critical areas of the process having as result the manufacturing costs reduction [1]. The selection of optimal machining conditions is a key factor in achieving this condition [2]. For the process parameters optimization in any metal cutting operation the first necessary step is 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. An optimization technique provides an optimal or near-optimal solution to the overall optimization problem previously formulated. One of the several optimization modelling techniques proposed and implemented is based on response surface design. Many researchers use RSM to optimize problems in metal cutting process parameters. Taramen uses a contour plot technique to simultaneously optimize tool wear, surface finish, and tool force for finished turning operation [3]. Lee *et al* provide an interactive algorithm using both RSM and mathematical modelling to solve a parameter optimization problem in turning operation [4]. Fuh *et al* analyse the effect of change in workpiece material and each cutting parameter in various peripheral milling operations by a second order RSM [5].

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# 3 RS MODELS CONSTRUCTION APPROACH

The RSM is a dynamic and very important tool of design of experiment (DOE) in which the relationship among the 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). An experimental testing activity made by 30 different conditions has been designed in order to model the true function of surface roughness response through appropriate metamodels. 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 level of each considered variable [6]. Each test has been repeated 3 times to ensure stability of statistical data collected for a total of 90 experimental tests.

# 4 RS MODELS ALGORITHMS

## 4.1 GENERATION BASED ON POLYNOMIAL APPROXIMATIONS

The Response Surface Models used in this work are based on polynomials approximation used in model of: second, third and fourth order. The models based on approximation of third and fourth order do not have any mixed polynomial terms for terms up to the second order, but only pure cubic and quartic terms are included to reduce the amount of data required for model construction Equation (1).

$$\overset{\approx}{F}(x)=a_0+\sum_{i=1}^{N}b_i x_i+\sum_{i=1}^{N}c_{ii}x_i^2+\sum_{ij(i<j)}^{N}c_{ij}x_i x_j+\sum_{i=1}^{N}d_i x_i^3+\sum_{i=1}^{N}e_i x_i^4 \quad (1)$$

Where: N is the number of model inputs; $x_i$ is the set of model inputs; a, b, c, d, are the polynomial coefficients [6].

## 4.2 GENERATION BASED ON ARTIFICIAL NEURAL NETWORK

*Radial Basis Functions* (RBF) are a type of neural network used to approximate various types of behaviour. They utilize a hidden layer of radial units and an output layer of linear units, and they are characterized by reasonable fast training and reasonable compact networks. Weissinger was the first to use radial basis function to calculate the flow around wings [7]. 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 [6].

# 5 EXPERIMENTAL EQUIPMENTS

The tests were performed on a 3 axes CNC milling machine Benchman VMC-4000. The cutting tool used in the experiments, shown in Figure 1, is a flat end mill with: four teeth, helix angle 40°, diameter $d_m$ = 16 mm, overhang length $l_1$ = 92 mm, sharp length $l_2$ = 32 mm and concavity angle $a_p$ = 2.5°. The tool is made by High Speed Steel with 8% of Cobalt.

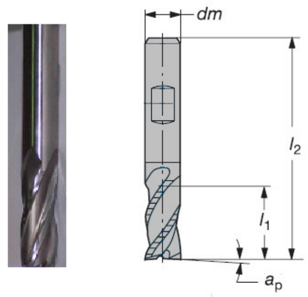


***Figure 1:*** *Flat end mill used in the experimental tests*

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 workpiece hardness is equal to 150 BHN. Its mechanical properties are: tensile strength 690 MPa, yield strength 600 MPa, shear strength 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, as shown in Figure2.

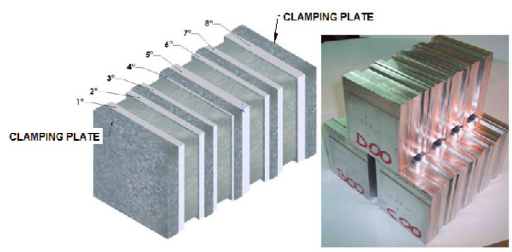


***Figure 2:*** *Aluminum sample block used in the experimental tests.*

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 examined working condition the experimental tests has been repeated for three times and the considered Ra is obtained as the average of the measured ones in each produced sample. Ra calculated values have been used to feed the RS models.

### 5.1 SURFACE ROUGHNESS

In this study the authors have used the arithmetical average roughness parameter Ra, whose equation is shown in Equation (2), in order to measure the roughness profile parallel to the feed which coincides with the cutter axis rotation:

$$R_a = \frac{1}{l_r}\int_0^{l_r} |z(x)| dx \qquad (2)$$

## 6 RS MODELS 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 (3).

$$I_{av,err} = \frac{\sum_{i=1}^{n} \sqrt{Y_{A,i}^2 - Y_{P,i}^2}}{n} \qquad (3)$$

Where: $Y_{A;i}$ is a control response value; $Y_{P;i}$ is a predicted response value on approximation surface and $n$ is the number of sample control points.
The error value normalization allows the error level of different responses with different magnitudes to be compared in respect to approximation model predictions. The error is calculated with 16 experimental tests, based on sample control points specifically allocated inside the design space previously defined to calculate approximation surfaces. From the average approximation error analysis, Table 2. It is possible to detect how the metamodels that give the best approximation of the real behaviour of the analyzed response are the ones created with the approximation technique based on the neural networks (RBF). The resulting data confirm that for the metamodels based on the polynomial approximation, the confidence of prediction of the analyzed responses behaviour is as much closer to reality as bigger is the grade of the polynomial used to create the RS model.

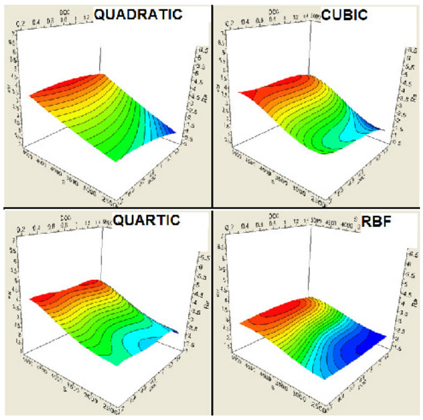


***Figure 3:*** *Comparison for the four adopted techniques to generate surface roughness RS models with F = 300 mm/min, radial engage B = 2mm and having as variables Depth Of Cut (DOC) and speed (S).*

As reported in Figure 3, it is possible to assert that the obtained RS, depending on the chosen technique, have different positions for their local maximum and minimum values.

***Table 2:*** *Comparison of % average error for analyzed response for each examined approximation technique*

| RS Method | $R_a$ Average Error % |
|---|---|
| Polynomial 2°order | 15.6 |
| Polynomial 3°order | 14.8 |
| Polynomial 4°order | 14.6 |
| RBF | 13.8 |

## 7 RESULTS AND DISCUSSION

A Pareto chart was used to highlight the magnitude and the importance of each analyzed factor and their interactions on the process response (surface roughness). The chart reported in Figure 4 shows the absolute value of the effects reporting the reference line. Any effect that goes over this reference line is potentially important. In this case the reference line is placed at a significance level of 5%.

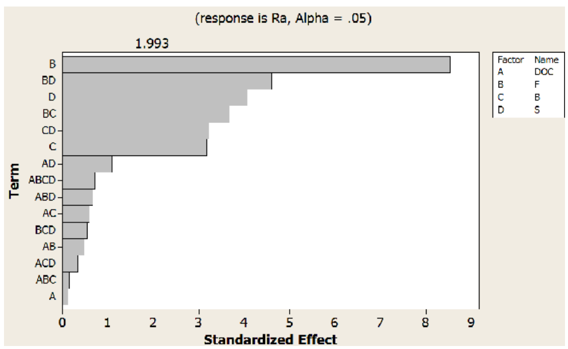


***Figure 4:*** *Pareto chart of the standardized effects*

It can be seen that the major effect for the studied case on surface roughness according to the theory is due to feed (B).This principal effect is followed by speed (D) and radial engage (C). The DOC effect (A) on surface roughness is negligible. Among the interactions, BD, BC, CD, have a significant influence on the analyzed response. Figure 5, Figure 6 and Figure 7 show the 3D surface graphs of the surface roughness related to most significant second-order interactions among indicated factors in the Pareto Chart (BD, BC, CD).

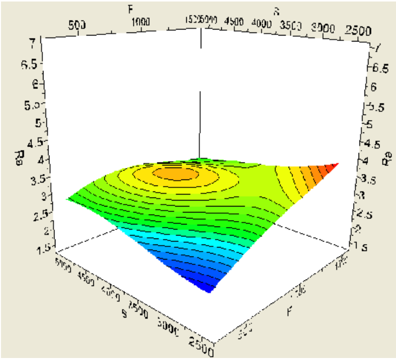

***Figure 5:*** *3D plot for RBF model of surface roughness, with B = 2mm, DOC = 0.2 mm and having as variables feed (F) speed (S).*

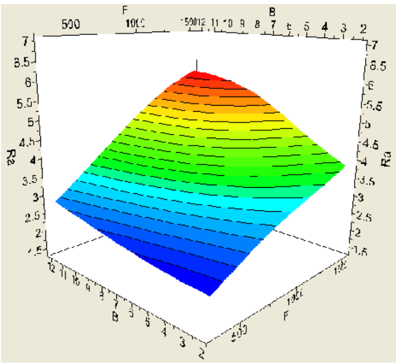

***Figure 6:*** *3D plot for RBF model of surface roughness, with DOC = 0.2 mm, S = 2500 rpm and having as variables feed (F) and radial engage (B).*

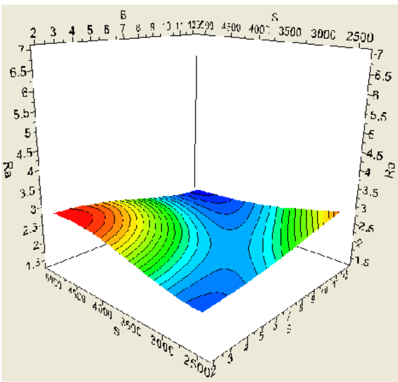

***Figure 7:*** *3D plot for RBF model of surface roughness, with F = 300 mm/min, DOC = 0.2 mm and having as variables speed (S) and radial engage (B).*

## 8 CONCLUSIONS

In this work the authors have evaluated the prediction capacity of four techniques for RSM generation. The study case concerns the analysis of the behaviour of surface roughness as a function of process parameters in an operation of end milling on AL7075-T6. The response surfaces have been created from data extracted from experimental tests performed on the basis of a DOE. The approximation method that has proved to be the most effective was the one based on neural networks (RBF). For this technique has been estimated an average error equal to 13.8%. In future work the authors will focus their efforts to improve the quality in terms of numerical-experimental correlation for the response surfaces created with this methodology and they will couple the developed RS model of the original problem with appropriate algorithms to perform the optimization of Part Program without executing any further experimental tests.

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