Design space investigation by Response Surface Model techniques in aeronautical metal cutting applications

A. Del Prete[1], A. A. De Vitis[1] & D. Mazzotta[2]
[1]*Department of Engineering Innovation, University of Salento, Italy*
[2]*AVIO S.p.A., Italy*

Abstract

A finite element model (FEM), which is able to predict the cutting interactions between the tool and the workpiece (cutting forces and cutting edge temperature) for a typical aeronautical engine Nickel-alloy Inconel 718, has been used to perform a reduced number of FEM calculations indicated by a DOE, in order to evaluate the design space for process parameters. These well-distributed results can be subsequently used to create and evaluate the quality in terms of correct response behaviour for the metamodels created through different approximation techniques (polynomial and neural network). The metamodels based on the best methodology (in terms of effectiveness of process behaviour prediction) have been used to optimize, through Adaptive Simulated Annealing (ASA) algorithms, the process parameters defined in a CAM part program block. The aim of the authors is to modify the Part Program operation parameters according to the constraints arising from the physical nature of the cutting process obtained by FEA.

Keywords: machining, FEM, optimization, RSM, ASA.

1 Introduction

The nickel-alloy Inconel 718 is usually well-used in the aerospace industry for the manufacture of components that require: lighter, harder, stronger, tougher, stiffer, more corrosion- and erosion-resistant materials capable of maintaining their mechanical properties at elevated temperatures, such as in jet engines. The unique and desirable heat-resistant characteristics of superalloys, on the other hand, impair their ability to be worked due to the extremely high temperature

www.witpress.com, ISSN 1743-3509 (on-line)
doi:10.2495/OP090171

generated at the cutting edge. These tough working conditions tend to deform the cutting tool, leading to accelerated wear during machining, particularly at higher speed conditions. The ability to be worked of aerospace alloys will continue to decline as new materials are developed to meet the increasing demand for higher temperature-resistant materials and for more efficient aero-engines (Ezugwu [1]). Considerable research and development efforts have been directed, worldwide, towards an improvement of the machining operations in order to ensure an efficient and cost effective machining of these superalloys and to understand their behaviour when they are machined at higher cutting conditions (Malinov *et al.* [2]). A good understanding of the behaviour and of the relationship among the workpiece 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 process parameters optimization that identify and determine areas of critical process control factors. The availability of such a methodology allows engineers to choose the desired outputs or responses with acceptable variations ensuring a lower cost of manufacturing (Montgomery [3]). The selection of optimal machining conditions is a key factor in achieving this condition (Tan and Creese [4]). The first necessary step for process parameters optimization in any metal cutting process is the ability to understand the principles governing the cutting processes by 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 formulated, which is subsequently implemented in the actual metal cutting process. One of the several optimization modelling techniques proposed and implemented is based on response surface design. Many researchers use Response Surface Models (RSM) to optimize problems in metal cutting process parameters. Taramen [5] uses a contour plot technique to simultaneously optimize tool wear, surface finish, and tool force for finished turning operation. Lee *at al.* [6] provide an interactive algorithm using both RSM and mathematical modelling to solve a parameters optimization problem in the turning operation.

2 Metamodels construction approach

The RSM is a dynamic and very important tool of design of experiment (DOE), in which the relationship between the responses of a process with their input decision variables are 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 a function of independent decision variables (X1,.,Xn). Normally RSM techniques are based on a series of experimentation, and may not be feasible or cost effective for manufacturers in many manufacturing situations. In this study, for the RSM construction the authors have used data drawn from the numerical simulations. In this way, if the simulation code has been previously validated through experimental-numerical correlation, it becomes possible to avoid costly experimental campaigns for data acquisition.

In order to model the true functions through metamodels based on data obtained with FEA, the authors have performed 40 simulations (with a version of Latin Hypercube DOE, called *Optimal Latin Hypercube*) based on design points selected within the two-dimensional design space, which has the following boundaries: feed for tooth (f) [0.04; 0.25 mm/rev]; cutting velocity (v_t) [100; 230 mm/sec.]. 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, *iSIGHT user's manual* [7].

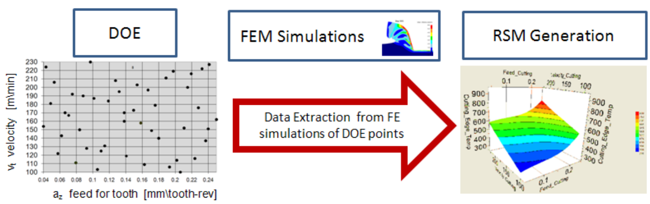

Figure 1: Metamodels construction procedure.

3 Theory of metamodels based on polynomial approximations

The RSMs used in this work are based on polynomials approximation used in models of the second, third and fourth order. The models based on the approximation of the third and fourth order do not have any mixed polynomials for terms of the upper second order (see table 1 the comparison), but only pure cubic and quartic terms are included to reduce the amount of data required for the model construction (eqn. (1)).

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

where: N is the number of model inputs; x_i is the set of model inputs; a, b, c, d, are the polynomial coefficients (*iSIGHT user's manual* [7]).

Table 1: Number of coefficients in polynomials involving two input parameters.

	Number of Coefficients	
Polynomial Degree	Complete Formulation	Reduced Formulation
2	6	6
3	10	8
4	15	10

4 Theory of metamodel based on artificial neural network

Radial Basis Functions (RBF) are a type of neural network used to approximate the behaviour of several types of systems. 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 [8] was the first to use radial basis functions to calculate the flow around wings. This neural network utilizes the Gaussian curve to map values. The network has n inputs and k outputs. The radial basis network is a very efficient network when function approximation is needed, because it has the ability to represent nonlinear functions.

5 Simplified finite element 2D model and data extraction methodology

The analyzed operation is a down cut mill operation. In the climb mode shown in fig. 2(A), the feed on each tooth is bigger at the point of initial contact with the workpiece and becomes very small at the end of the tooth-workpiece engagement.

The maximum force exchanged between the tool and the workpiece occurs when the tooth surface impacts on the workpiece. To detect components F_x and F_y, a simplified 2D model has been chosen (fig. 2(B)), where the real feed per tooth is the DOC on the finite element model ($a_{z,\ max}$) and the cutting speed is equal to the tangential velocity of the cutter (V_t). The values of the exchanged forces between the tool and the workpiece used in the study were detected when the value of the observed forces in the simulation post processing can be considered stable. Cutting temperature data utilized to create metamodels are an average of the temperature extracted in five fixed nodes detected on the cutting edge and meshed when the thermal steady state condition on the tool-workpiece interface was reached (after about 2 mm of cutting length).

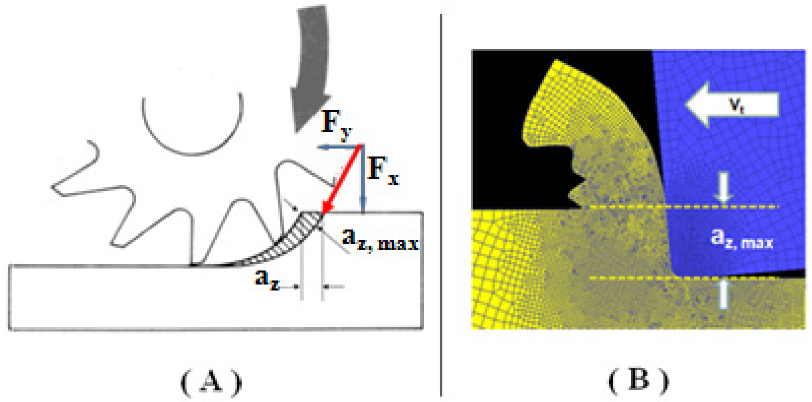

Figure 2: (A) Climb mill operation; (B) FE simplified 2D model.

6 Finite element model

Finite element (FE) analysis of the dry milling operations with the circular insert in WC and no wear have been carried out. A two-dimensional plane-strain thermo-mechanical analysis, based on the updated Lagrangian formulation, was performed using the implicit FE commercial code properly developed for machining FEA. For this purpose, the workpiece (dim 4x1.5 mm) was initially modelled with 6500 bilinear four-node quadrilateral elements, with dimensions respectively of 0.007 mm along the cutting edge, 0.01 mm on the first 0.3 mm on machined surface and 0.15 mm in the remaining area. The insert in tungsten carbide (WC) with 8% in Cobalt has been characterized using the software default material library. The tool orthogonal rake angle was $\gamma = -7°$, the cutting edge radius was r_ε=0.05 mm and it has been modelled as rigid. It has been meshed and subdivided into 1500 elements with the very small dimension of 0.004 mm, in the nose zone in order not to lose the small radius of curvature in this area. The material properties of the cutting insert have been characterized using the software default material library. A constant frictional stress law on the rake face is assumed equal to a fixed percentage of the shear flow stress of the machined material (eqn. (2)).

$$\tau = m \cdot k \tag{2}$$

where k is the shear flow-stress of the workpiece material and m is a friction factor, assumed to be equal to 0.5. A value of 100 kW/m^2K has been adopted for the interface heat transfer coefficient, h. For the workpiece made of Inconel 718, proper values were defined for the following characteristics: Young's module; Poisson's ratio; thermal expansion; heat capacity; emissivity; thermal conductivity. Corresponding values are experimentally defined in the range of temperature [20°C; 1200°C] by the industrial partner AVIO S.p.A. For workpiece material characterization in the plastic field a Johnson Cook constitutive model it has been adopted, see eqn. (3) (Bil *et al.* [9]).

$$\sigma_{eq} = \left(A + B\varepsilon^n\right)\left[1 + C\ln\left(\frac{\dot{\varepsilon}}{\dot{\varepsilon}_0}\right)\right]\left[1 - \left(\frac{T - T_{room}}{T_{melt} - T_{Room}}\right)^m\right] \tag{3}$$

where ε is the plastic strain, $\dot{\varepsilon}$ is the strain rate (s^{-1}), $\dot{\varepsilon}_0$ is the reference plastic strain rate (s^{-1}), T is the temperature of the work material (°C), T_{melt} is the melting temperature of the work material (1400 °C) and T_{room} is the room temperature (20 °C). Coefficient A is the yield strength (MPa), B is the hardening modulus (MPa), C is the strain rate sensitivity coefficient, n is the hardening coefficient and m is the thermal softening coefficient. For the constants present in the J&C equation the authors have used the follow values: ε_0=1.001 [1/sec.], A = 450 [MPa], B = 1700 [MPa], C = 0.017, n = 0.65, m = 1.3 (Uhlmann *et al.* [10]).

7 Quality metamodels 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 the predicted (approximation model execution) values for all error samples are averaged and then normalized by the range of the actual values for each response. Normalizing the error value allows one to compare the error level of different responses with different magnitudes in respect to approximation model predictions. The error is calculated based on a number of sample points (19 in this case) specifically allocated for error analysis. From the average approximation error analysis (table 3) it is possible to evaluate how the metamodels that give the best approximation of the real behaviour of the three analyzed responses are the ones created with the approximation technique based on the neural networks (RFB). The resulting data confirm that for the metamodels based on the polynomial approximation, the confidence of prediction of the analyzed responses behaviour is much closer to reality as is the larger grade of polynomial used to create the metamodel itself.

Table 2: Comparison of % average error for analyzed responses for each examined approximation technique.

Response	2° Order	3° Order	4° Order	RBF
T_{max}	12.2%	11.6%	9.7%	0.9%
F_x	1.1%	1.0%	0.6%	0.04%
F_y	3.9%	3.8%	3.0%	0.1%

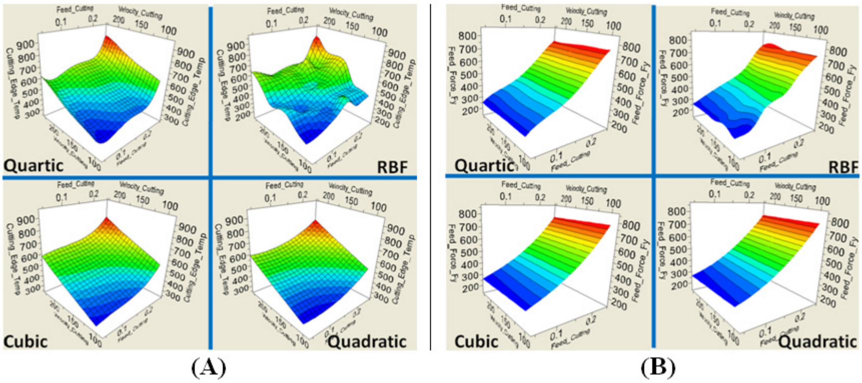

Figure 3: Metamodel shapes comparison for the four adopted techniques. (A) for T_{max} response; (B) for F_y response.

In fig. 3(A) for the response cutting edge temperature, it is possible to appreciate how the shape of the response surface varies a lot, ranging from the one created starting with second grade polynomials (quasi-linear) to the one created with the RBF technique that presents a much less regular surface where there are local maxima and minima. The metamodels of the thrust force F_y (fig. 3(B)), also show a more linear performance in the RS of the fourth grade or in the RBF. Similar behaviour has been found for the cutting force F_x. The highly non-regular behaviour of the cutting temperature has been highlighted by the detected average error. The latter is significant in the metamodels created with a low polynomial grade and cannot predict the real values for highly non-linear responses.

8 Example of CAE-CAM optimization procedure based on metamodels

Metamodels created with the most efficient methodology in predicting the three responses behaviour, namely the response surfaces created with RBF, constitute the basis for the optimization phase. This procedure has a considerable advantage; in the optimal solution research path, the optimization algorithm performs the iteration run using metamodels and it is for this reason preferable to the long calculation time typical of the calculation run of FEA (fig. 4).

In this study the authors have used, in order to optimize the process parameters, a modified version of the *Simulated Annealing* search algorithm (SA), called *Adaptive Simulated Annealing* (ASA). The distinct feature of this method is the temperature change mechanism, which is an important part of the transition probability equation. In conventional simulated annealing, the search begins with high temperature allowing a higher chance of transition to a worse solution. By doing so, the search is able to move off from local minima. However, as the search continues, the temperature continuously declines resulting in a reduced chance of uphill transition. Such an approach could be useful if the local minima are near the start point, but it might not lead to a near-optimal solution if some local minima are encountered at a relatively low temperature towards the end of the search. To overcome this difficulty, the adaptive simulated annealing method uses an adaptive cooling schedule, based on the profile of the search path, which adjusts the temperature dynamically. Such adjustments could be in any direction, including the possibility of reheating in order to push the search out of the local minima. This optimization activity aims to minimize the execution time through the maximization of the feed rate in compliance to physical micro-scale limits of the cutting process (max cutting temp., cutting forces). Figure 5 shows the optimization scheme adopted.

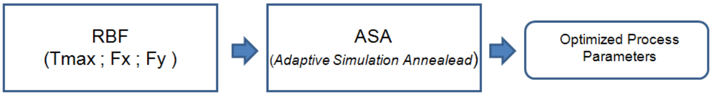

Figure 4: Flowchart of the adopted optimization procedure.

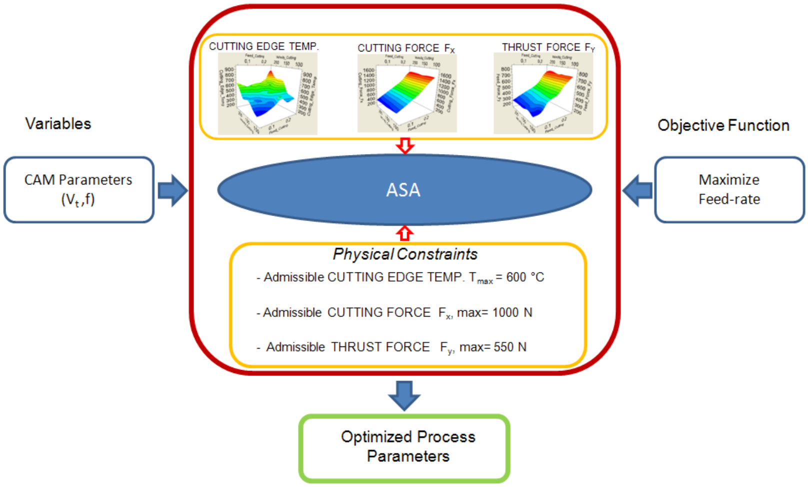

Figure 5: Scheme of optimization problem definition.

The problem can be stated as:

$$\begin{aligned}
&\textit{Variables:} && -V_t \in [100\,;\,230]\ mm/\text{sec.}\\
& && -f \in [0.04\,;\,0.25]\ mm/tooth-rev\\
&\textit{Constraints:} && -\textit{Max admissible Cutting Edge Temp. } T_{max} = 600^{\circ}\ C\\
& && -\textit{Max admissible Cutting Force } F_x = 1000\ N\\
& && -\textit{Max admissible Thrust Force } F_y = 550\ N\\
&\textit{Objective function:} && -\textit{Maximize feed rate } Va\ \ mm/min
\end{aligned}$$

The process parameters present in the analyzed block of the part program are feed and speed. They have been taken into consideration with these values: 1) feed (F) = 50 [mm / min]; 2) speed (S) = 96 [rpm]. Their respective values have been converted into the units of measurement used in the 2D finite element model and to define metamodel design space, f = 0.13 mm/tooth-rev and V_t = 209 mm/sec. After the optimization phase the new set of process parameters has been converted into the units of measurement used in the part program ($V_{t,opt}$= 225 mm/sec. to S = 107 rpm and f_{opt} = 0.18 mm/tooth-rev to F = 77 mm/min). Then, they have been incorporated into the analyzed part program block (fig. 6).

The process parameters indicated by the optimized block present an increase in the cutting speed of 11.5% and an increase in the feed rate of 38.4%. In fig. 8, the diagrams show the iterations carried out by the ASA searching the optimal solution.

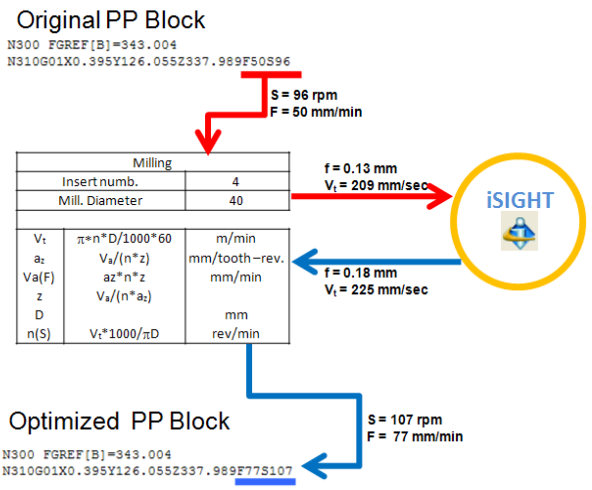

Figure 6: Flowchart of the input-output process parameters optimization.

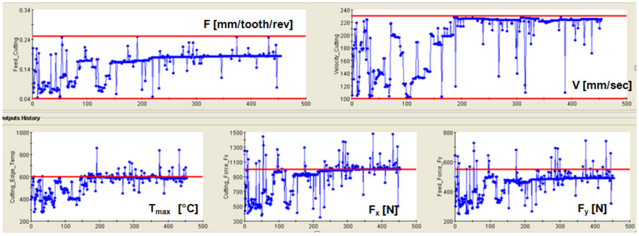

Figure 7: ASA iterations history.

9 Conclusions and further developments

In this article the authors have analysed the potentiality of four methods for the creation of response surfaces in order to thoroughly predict the behaviour of some of the typical responses of the physical phenomena of metal cutting processes.

The response surfaces have been created from data extracted from FEM simulations 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). The response surfaces created with this methodology have been later used as a basis for the optimization through an ASA algorithm of the process parameters of a part program block. In the future, the authors will focus on the search for numerical-experimental correlation of the FEM model in order to improve the accuracy of metamodels. Another research area will focus on the adjustment of CAE-CAM integration procedures in order to obtain automated process parameters optimization compliant to the physical limitations of the process and their replacement in the part program that has to be optimized.

References

[1] Ezugwu, E. O., Advances in the machining of nickel and titanium base superalloy. *Japan Society for Precision Engineering Conference*, pp. 1-40, 2004.
[2] Malinov, S. Sha, W. McKeown, J.J., Modelling the correlation between processing parameters and properties in titanium alloys using artificial neural network. *Computational Materials Science*, **21(3)**, pp. 375-394, 2001.
[3] Montgomery, D. C., *Introduction to statistical quality control* (2end ed.), Wiley, New York, pp. 86-87, 1990.
[4] Tan, F. P., & Creese, R. C. A generalized multi-pass machining model for machining parameter selection in turning. *International Journal of Production Research*, **33(5)**, pp. 1467–1487, 1995.
[5] Taramen, K., Multi-machining output-multi independent variable turning research by response surface methodology. *International Journal of Production Research*, **12(2)**, pp. 233–245, 1974.
[6] Lee, Y. H., Shin, H. M., & Yang, B. H., An approach for multi-criteria simulation optimization with application to turning operation. *Computers and Industrial Engineering*, **30(3)**, pp. 375–386, 1996.
[7] Engineous Software - *iSIGHT Version 3.0 User's Guide* - 2008.
[8] Weissinger, J. *Lift distribution of swept-back wings*. NACA pp.1120, 1947.
[9] Bil, H., Kilic, E., Tekkaya, A. E., A comparison of orthogonal cutting data from experiments with three different finite element models. *International journal of Machine Tools & Manufacture*. **44(9),** pp. 933-944, 2004.
[10] Uhlmann, E., Von Der Schulenburg, M.G., Zettier, R., Finite Element Modelling and Cutting Simulation of Inconel 718. *CIRP Annals - Manufacturing Technology,* **56(1),** pp. 61-64, 2007.