Adaptive Control Optimization of Cutting Parameters for High Quality Machining Operations based on Neural Networks and Search Algorithms

J. V. Abellan, F. Romero, H. R. Siller, A. Estruch and C. Vila
Department of Industrial Systems Engineering and Design
Castellon, 12071, Spain

1. Introduction

In traditional Computer Numerical Control (CNC) systems, machining parameters are usually selected prior to machining according to handbooks or user's experience. These practices tend to select conservative parameters in order to avoid machining failure and assure product quality specifications. Less conservative practices try to find optimal machining parameters off-line to increase process productivity after conducting experimentation (Chien & Chou, 2001). However, variations during the machining process due to tool wear, temperature changes, vibrations and other disturbances make inefficient any off-line optimization methodology, especially in high quality machining operations where product quality specifications are very restrictive. Therefore, to assure the quality of machining products, reduce costs and increase machining efficiency, cutting parameters must be optimised in real-time according to the actual state of the process. This optimization process in real-time is conducted through an adaptive control of the machining process.

The adaptive control applied in machining systems is classified as (Liang et al., 2004; Ulsoy & Koren, 1989): Adaptive Control with Constraints (ACC), Geometric Adaptive Control (GAC), and Adaptive Control with Optimization (ACO). In the ACC systems, process parameters are manipulated in real time to maintain a specific process variable, such as force or power, at a constraint value. Typically, ACC systems are utilized in roughing operations where material removal rate is maximized by maintaining the cutting forces at the highest possible cutting force such that the tool is not in danger of breaking (Zuperl et al., 2005). In the GAC systems, the economic process optimization problem is dominated by the need to maintain product quality such as dimensional accuracy and/or surface finish (Coker & Shin, 1996). GAC systems are typically used in finishing operations with the objective of maintaining a specific part quality despite structural deflections and tool wear. Sensor feedback is often employed to measure surface roughness and dimensional quality between parts and adjustments, so tool offsets and feed overrides can be adjusted for the next part. In the ACO systems, machine settings are selected to optimize a performance index such as production time, unit cost, etc. Traditionally, ACO systems have dealt with adjusting cutting parameters (feed-rate, spindle speed and depth of cut) to maximise

material removal rate subject to constraints such as surface roughness, power consumption, cutting forces, etc (Venu Gopal & Venkateswara Rao, 2003). Other ACO systems optimise a multi-objective function which are more practical in industrial applications (Zuperl & Cus, 2005). For example, it is quite often to search the optimal cutting parameters to minimize the cost of the operation, maximize the production rate and maximize the part quality. ACO systems are basically composed of several units which integrate the machine-tool system and the equipment required for acquiring real-time process measurements and adjusting the cutting parameters. Fig. (1) shows a simplified scheme of a basic ACO system presented in (Koren, 1983). Basically, the ACO system requires a sensor system which provides real-time data for tool wear diagnosis and part quality prediction. The real-time data are used by process models previously obtained from experimental data. Tool wear and part quality models are used in the multi-objective function together with cutting parameters. An optimizer unit is then applied for searching optimal cutting parameters, and the selected parameters are sent to the CNC system.
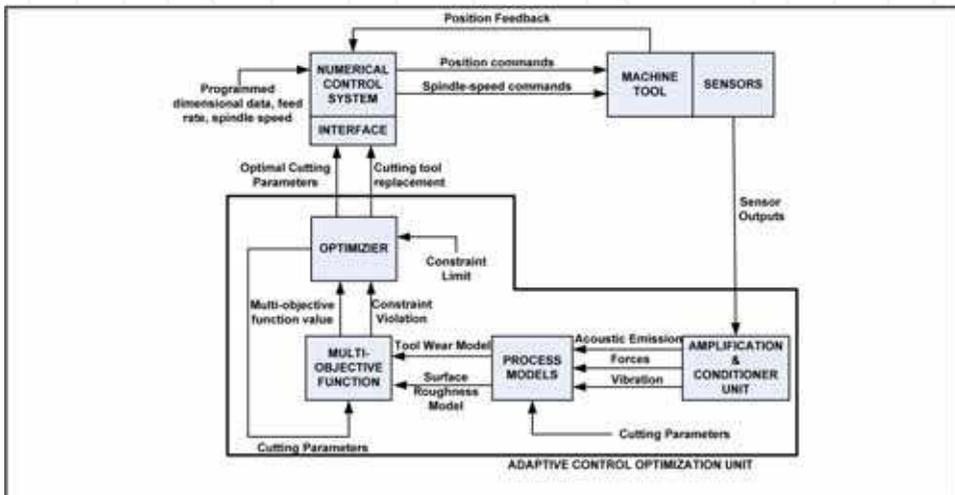

Fig. 1. Adaptive Control Optimization (ACO) scheme adapted from (Koren, 1983).

Interesting works related to ACO systems can be found in (Liu & Wang, 1999; Liu et al., 1999; Chiang et al., 1995). Liu (Liu & Wang, 1999) proposed an adaptive control system based on two neural network models, a Back-Propagation Neural Network (BP NN) and an Augmented Lagrange Multiplier Neural Network (ALM NN). The BP NN was used for modeling the state of the milling system, using as a single input the feed parameter and sensing the cutting forces on-line. The ALM NN was used for maximising the material removal rate which it was carried out adjusting the feed rate. Chiang (Chiang et al., 1995) presented a similar work for end-milling operations, but surface roughness was also considered as constraint. Both research works were based on theoretical formulas for training the neural networks, and both applied an ALM NN for optimization, which it is claimed to be an approach that can greatly reduce processing time in comparison to conventional optimal algorithms and make real-time control possible. Liu (Liu et al., 1999) also extended his previous work with a new optimization procedure based on a Genetic Algorithm (GA).

In spite of the potential application of ACO systems, their use in industry is limited due to the non-existence of reliable on-line monitoring systems for tool wear diagnosis and quality prediction (Azouzi & Guillot, 1997; Liang et al., 2004). Therefore, the optimal selection of cutting parameters is usually done off-line for the cutting-tool life-cycle (Ghani et al., 2004; Chien & Chou, 2001). The off-line parameters optimization is usually carried out through short cutting experiments which are later used to obtain an empirical model which could be optimized subjected to some constraints. Ghani (Ghani et al., 2004) optimized cutting parameters using a Taguchi's Design of Experiments in end milling operations. With a minimum number of trials compared with other approaches such as a full factorial design, the methodology presented reveals the most significant factors and interactions during cutting process which leads to choose optimal conditions. A similar methodology is described in (Zhang et al., 2007). However, both methodologies do not permit to evaluate quadratic or non-linear relations between factors, and the analysis is restricted to the levels analysed in each factor. A more generic approach although more costly in experiments is based on Response Surface Model (RSM) and Response Surface Model Optimization (RSMO). Suresh (Suresh et al., 2002) used RSM for modeling the surface roughness as a first and second-order mathematical model and the surface roughness optimization was carried out through GA. Cus (Cus & Balic, 2003) also applied GA for optimising a multi-objective function based on minimum time necessary for manufacturing, minimum unit cost and minimum surface roughness. All the process models applied in his research were empirical formulas from machining handbooks which were fitted through regressions. More complex models have also been applied for surface roughness and tool wear modeling to optimise off-line cutting parameters. Zuperl (Zuperl & Cus, 2003) also applied and compared feed-forward and radial basis neural networks for learning a multi-objective function similar to the one presented in (Cus & Balic, 2003). Choosing the radial basis networks due to their fast learning ability and reliability, he applied a large-scale optimization algorithm to obtain the optimal cutting parameters. Chien (Chien & Chou, 2001) applied neural networks for modeling surface roughness, cutting forces and cutting-tool life and applied a GA to find optimum cutting conditions for maximising the material removal rate under the constraints of the expected surface roughness and tool life.

These previous works are off-line optimization methodologies which can be efficient enough if tool wear effects have a minimal impact to surface roughness and/or a high surface roughness quality is not required. Otherwise, an on-line optimization methodology should be applied since optimal cutting conditions may vary during the cutting-tool life-cycle due to tool wear effects on surface roughness. In this chapter, an ACO system is presented for optimising a multi-objective function based on material removal rate, quality loss function related to surface roughness, and cutting-tool life subjected to surface roughness specifications constraint. The proposed system adjusts the cutting parameters during the cutting-tool life-cycle in order to maximise in real-time the multi-objective function. The core of the system is composed of three process models: a cutting-tool wear model for diagnosing the state of the cutting tool, a surface roughness deviation model for predicting the quality loss function and a cutting-tool life model. All models are developed using artificial neural networks to model the non-linear relationships in machining processes. Since the process models are black-box models, optimal cutting parameters are obtained applying genetic algorithms and mesh adaptive direct search algorithms. The proposed system is compared with 2 traditional methods for off-line cutting parameters selection: (1) selection based on suggested cutting parameters from handbooks, and (2) selection based on RSMO.

2. Experimental system

2.1 Machining process description

Machining hardened steels (hardness from 30 to 62 HRC) for moulds and dies with surface roughness specifications less than 0.3 microns are commonly applied in industry, and require costly and time-consuming traditional operations such as electro-discharge machining or grinding. Recently, some research studies have reported the use of high performance machining operations for these applications with important benefits as reducing lead times and costs (Siller et al., 2008). However, tool wear process impacts directly to surface roughness so optimal cutting parameters are difficult to obtain since they vary according to cutting-tool state. Therefore, although high performance machining can technically substitute grinding or electro-discharge machining, additional efforts should be conducted in order to tune cutting parameters for an optimal machining. For these applications, ACO techniques can improve the process significantly with respect to other non-adaptive optimization techniques.

The machining process studied in this paper is presented in Fig. 2, and it consists of a face-milling operation on workpieces of hardened AISI D3 steel (60 HRc) with dimensions 250x250 mm. The experiments were conducted on a CNC machining center suited for mould and die manufacturing, and the cutting tool used was a face milling tool with Cubic Boron Nitride (CBN) inserts. In order to generate a good surface finish and avoid run-out problems, a single insert was mounted on a tool body with an effective diameter of 6.35 mm.

Fig. 2. Machining process analysed

2.2 Monitoring system description

A monitoring system to estimate on-line tool wear and surface roughness is required to select the optimal cutting parameters according to the actual state of the machining process. In this chapter, the monitoring system implemented is a multi-component sensor system composed of a piezoelectric dynamometer, accelerometers and signal conditioners (Fig. 3). Two acquisition boards were used for data acquisition. The first board, an Iotech DaqBook 112, was used for acquiring cutting forces from the dynamometer and it was configured for a sample frequency of 3 kHz. A second board, an Iotech DaqBoard 3000, was used for vibration signal acquisition from accelerometers and it was configured for a sample

frequency of 100 kHz. Cutting forces were amplified and filtered by a Kistler 5405 amplifier configured with a low-pass filter of 300 Hz cut-off frequency. Vibration signals were amplified by a PCB 482A22 amplifier. Root-mean-square of forces and vibrations were calculated for each cutting pass at the cutting-location x = 175 mm for a 2 seconds data acquisition. Surface roughness (Ra) was measured by a Mitutoyo Surftest 301 profilometer at the cutting-tool locations x = 40 mm, x = 110 mm, x = 175 mm every cutting pass (sampling length λ = c/l = 0.8 mm and number of spans n = 5). Cutting tool wear (Vb) was measured by a stereo-microscope Nikon MZ12 after each face-milling pass every 250 mm length of cut. Fig. 4 describes the machining process with the Ra and Vb sampling procedure.

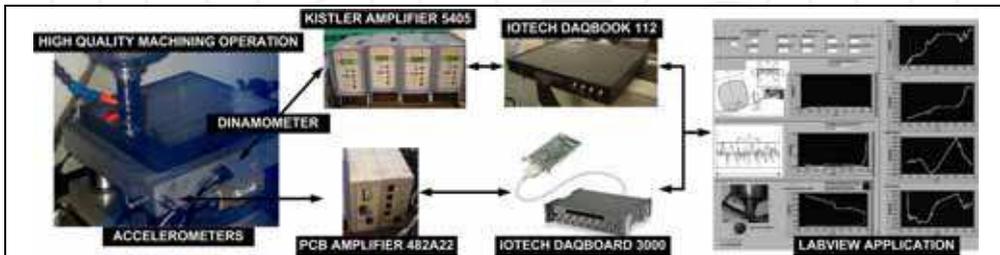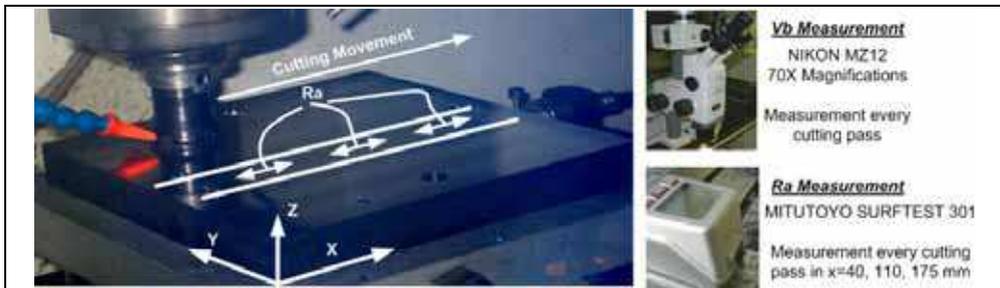
Fig. 3. Multi-component sensor system

Fig. 4. Machining process and surface roughness and tool-wear sampling.

3. Design of experiments

In order to compare cutting parameters optimization by RSMO and AI approaches, it is necessary to carry out a Design of Experiments (DoE) to be useful for both. RSMO requires classical designs of experiments such as Box-Wilson Central Composites Designs (CCD) or Box-Behnken designs (Nist, 2006), in case that it is only considered linear and quadratic effects. On the other hand, AI approaches require enough data for training and testing, varying the factors in all its domain, but it does not require any specific DoE design.

The factors considered in the experimentation were the feed per tooth (f_z) and the cutting speed (V_c). The radial depth of cut (a_e) was considered constant, with a value of 31.25 mm to maximize the material removal rate. The axial depth of cut (a_P) was defined as a constant (0.4 mm) since the machining operation studied was a finishing operation. The minimal experimentation required to apply RSMO with two factors is a face centered CCD with one center point which is equivalent to a 2^3 full factorial design. For each experiment, the face-

milling operation was carried out until the cutting tool edge was worn (Vb higher than 0.3 mm, usual value for finishing operations (ISO 8688-1, 1989)) or the surface roughness was outside specifications. Fig 5 shows the cutting conditions analysed and the order of the cutting experiments.
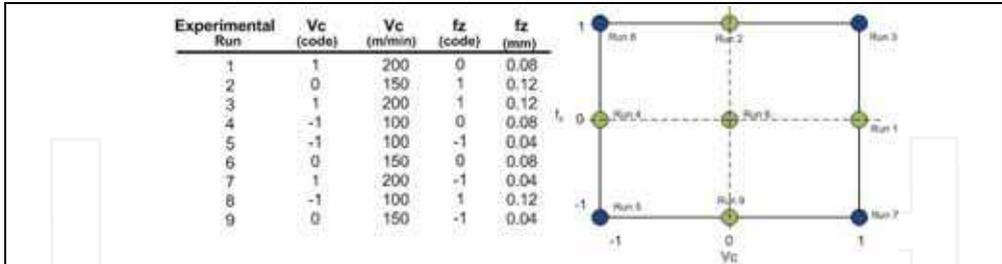

Fig. 5. Design of Experiments and run order. Face Centered Central Composite Design.

4. Definition of the optimization problem

The machining economics problem consists in determining the optimal cutting parameters in order to maximize/minimize an objective function. Typical objective functions to optimize cutting parameters are "minimize unit production cost", "maximize production rate", "maximize profit rate", etc. On the other hand, several cutting constraints have to be considered in machining economics, such as tool-life constraint, cutting force constraint, power, stable cutting region constraint, chip-tool interface temperature constraint and surface finish constraint (Cus & Balic, 2003).

4.1 Objective functions

Typically, three objective functions are considered in a cutting parameters optimization problem: (1) Material Removal Rate (MRR), (2) surface roughness and (3) cutting-tool life. MRR is a measurement of productivity, and it can be expressed by analytical derivation as the product of the width of cut (w), the feed velocity of the milling cutter (F) and the depth of cut (a_p) (Eq. (1)). Surface roughness is the most important criterion for the assessment of the surface quality, and it is usually calculated empirically through experiments. Some research works directly use the empirical relationship presented in Eq. (2), where Vc and f are the cutting speed and feed rate respectively and k, x_1, x_2, x_3 are empirical coefficients. Cutting-tool life is the other important criterion for cutting parameters selection, since several costs such as cutting-tool replacement cost and cutting-tool cost are directly related with tool life. The relation between the tool life and the parameters is usually expressed by the well-known Taylor's formula presented in Eq. (3), where K_T, α_1, α_2, α_3 are empirical coefficients.

$$MRR = w\, a_p\, F \tag{1}$$

$$Ra = k\ V_c^{x_1}\, f^{x_2}\, a_p^{x_3} \tag{2}$$

$$T = \frac{K_T}{V_c^{\alpha_1}\, f^{\alpha_2}\, a_p^{\alpha_3}} \tag{3}$$

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However, for high quality machining operations using CBN cutting tools, both traditional surface roughness and tool life equations may not provide a good estimation. Machining a very low feed speeds produce that additional mechanisms influence the surface roughness generation such as vibrations, engagement of the cutting tool, built up edge, etc. (Siller et al., 2008). On the other hand, CBN tools have a different wear process than traditional cutting-tools such as high speed steels, so Taylor's formula may not be directly applied (Trent & Wright, 2000). For both reasons, other empirical models based on experimental data must be applied instead of Eqs. (2,3).

For the case study presented in this chapter which is a high quality face milling operation based on CBN tools, two alternative objective functions were applied. Instead of Ra model, it is applied the quality loss function described by Eq. (4). Considering a desired Ra value, the quality loss function is usually applied to estimate the cost of manufacturing with a quality variation. The loss function is defined as:

$$W = A_{rework} \frac{V^2}{\Delta^2} \tag{4}$$

where Δ = Ra_{max} - Ra_{target} with Ra_{max} the maximum Ra defined by specifications and Ra_{target} the Ra desired; V^2 is the mean squared deviation as V^2 = $((Ra_{target} - y_1)^2 + \ldots + (Ra_{target} - y_n)^2)/n$, with n the number of samples; and A_{rework} is the part cost if the part is outside specifications. On the other hand, instead of the traditional Taylor's formula, it is applied an empirical model learnt from the experimentation which is defined by the Eq. (5), where f is the function learnt.

$$T = f(V_c, f, a_p) \tag{5}$$

4.2 Multi-objective function

The optimization problem for the case study is defined as the optimization of a multi-objective function which is composed of the objective functions defined by Eqs (1,4,5). Since these objective functions are conflicting and incomparable, the multi-objective function is defined using the desirability function approach. This function is based on the idea that the optimal performance of a process that has multiple performance characteristics is reached when the process operates under the most desirable performance values (Nist, 2006). For each objective function $Y_i(x)$, a desirability function $d_i(Y_i)$ assigns numbers between 0 and 1 to the possible values of Y_i, with $d_i(Y_i) = 0$ representing a completely undesirable value of Y_i and $d_i(Y_i) = 1$ representing a completely desirable or ideal objective value. Depending on whether a particular objective function Y_i is to be maximized or minimized, different desirability functions $d_i(Y_i)$ can be used. A useful class of desirability functions was proposed by (Derringer & Suich, 1980). Let L_i and U_i be the lower and upper values of the objective function respectively, with $L_i < U_i$, and let T_i be the desired value for the objective function. Then, if an objective function $Y_i(x)$ is to be maximized, the individual desirability function is defined as

$$d_i(Y_i) = \begin{cases} 0 & If\ Y_i(x) < L_i \\ \left(\dfrac{Y_i - L_i}{T_i - L_i}\right)^w & If\ L_i \leq Y_i(x) \leq T_i \\ 1 & If\ Y_i(x) > T_i \end{cases} \tag{6}$$

with the exponent w is a weighting factor which determines how important it is to hit the target value. For $w = 1$, the desirability function increases linearly towards T_i; for $w < 1$, the function is convex and there is less emphasis on the target; and for $w > 1$, the function is concave and there is more emphasis on the target. If one wants to minimize an objective function instead, the individual desirability function is defined as

$$d_i(Y_i) = \begin{cases} 1 & If\ Y_i(x) < T_i \\ \left(\dfrac{Y_i - U_i}{T_i - U_i}\right)^w & If\ T_i \le Y_i(x) \le U_i \\ 0 & If\ Y_i(x) > U_i \end{cases} \tag{7}$$

Fig. (6) shows the individual desirability functions according to different w values. The individual desirability functions are combined to define the multi-objective function, called the overall desirability of the multi-objective function. This measure of composite desirability is the weighted geometric mean of the individual desirability for the objective functions. The optimal solution (optimal operating conditions) can then be determined by maximizing the composite desirability. The individual desirability is weighted by importance factors I_i. Therefore, the multi-objective function or the overall desirability function to optimize is defined as:

$$D = (d_1(Y_1)^{I1} d_2(Y_2)^{I2} \dots d_k(Y_k)^{Ik})^{\frac{1}{(I1+I2+\dots+Ik)}} \tag{8}$$

with k denoting the number of objective functions and I_i is the importance for the objective function I, where $i = 1,2,\dots,k$.
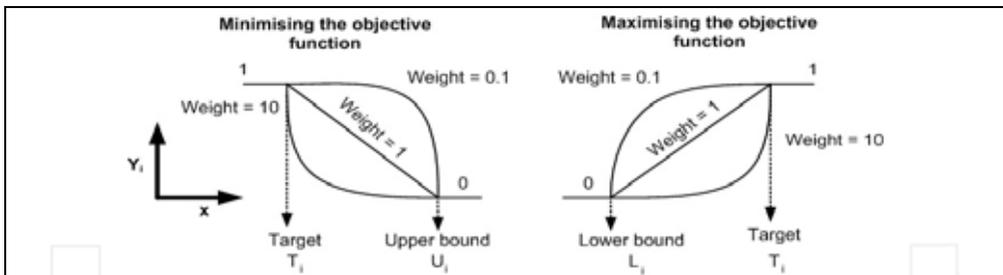

Fig. 6. Desirability functions according to the type of objective function

4.3 Constraints
Due to the limitations on the cutting process, manufacturers limit the range of the cutting parameters to avoid premature cutting-tool failures. Therefore, selected cutting parameters according to manufacturer specifications are constrained to:

$$V_{min} \le V_c \le V_{max} \tag{9}$$

$$f_{min} \le f_z \le f_{max} \tag{10}$$

$$a_p \le a_{max} \tag{11}$$

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Surface roughness specification is also considered a constraint that can be expressed as

$$R_a \leq R_{spec} \rightarrow V^2 \leq (Ra_{target} - Ra_{spec})^2 \tag{12}$$

In addition, cutting power and force limitations are usual constraints, but they are commonly applied only for roughing operations.

4.4 Summary of optimization problem and numerical coefficients

The weights and the individual desirability coefficients for each objective function were chosen according to each objective function in the machining process. First the weights were defined considering how the objective function increases/decreases as the ideal value is not matched. Secondly, a comparison among individual desirability coefficients was done to define how much more important is each objective function than the other one. For the case study presented, the objective functions were considered linear (w=1) and the coefficient of importance were chosen to prevail productivity and surface roughness quality than cutting-tool cost and cutting-tool cost replacements. Therefore, importance factors I_1 and I_2 which are related to material removal rate and surface quality loss function were chosen as 1, whereas importance factor I_3 which is related to cutting-tool life was chosen as 0.5.

Considering the maximum and minimum values of each objective function obtained analytically, the desirability functions were defined as follows.

- MRR desirability function

$$d_1(MRR) = \frac{MRR - 398}{2387 - 398} \tag{13}$$

MRR_{target} = 2387 mm³/min. $MRR_{minimum}$ = 398 mm³/min. Importance factor I_1=1.

- Desirability function of Ra deviation objective function

$$d_2(W) = d_2(V^2) = \frac{V^2 - 0.012}{0.0001 - 0.012} \tag{14}$$

V^2_{target} = 0.0001 μm². $V^2_{maximum}$ = 0.012 μm². Importance factor I_2=1. Note that the desirability function of quality loss W for surface roughness can be defined by the surface roughness deviation V^2 since Eq. (4) relates W with V^2 by a constant coefficient of A_{rework}/Δ^2.

- Cutting-tool life desirability function

$$d_3(T) = \frac{T - 7.43}{46.7 - 7.43} \tag{15}$$

T_{target} = 46.7 min. $T_{minimum}$ = 7.43 min. Importance factor I_3=0.5.

The multi-objective function or the overall desirability function to be optimized is:

$$D = (d_1(MRR)^1 d_2(V^2)^1 d_3(T)^{0.5})^{\frac{1}{(1+1+0.5)}} \tag{16}$$

constrained to:

$$100 \text{ m/min} \leq V_c \leq 200 \text{ m/min} \tag{17}$$

$$0.04 \text{ mm/rev} \leq f_z \leq 0.12 \text{ mm/rev} \tag{18}$$

$$a_p = 0.4 \text{ mm} \tag{19}$$

$$V^2 \le (0.1 - 0.2)^2 \ \mu m^2 \tag{20}$$

5. Parameter optimization based on handbooks

5.1 Description

Cutting tool parameters are traditionally chosen according to handbooks and cutting-tool data catalogs. For a given cutting-tool and workpiece material, a range of possible cutting-parameters are provided. The machinist chooses the parameters within the ranges using some well-known practices in shop-floor. Some of these practices are:

- Higher cutting speeds increase surface roughness quality but decrease cutting tool life.
- Higher cutting speeds decrease cutting tool life.
- Higher feed rates increase productivity as material removal rate is increased.
- Higher feed rates decrease surface roughness quality.
- Higher feed rates decrease cutting-tool life.
- Higher axial depth of cut increases productivity.
- Higher axial depth of cut decreases cutting-tool life.
- Very low axial depth of cut burns the workpiece surface and generates a low surface roughness quality and decreases cutting-tool life.

According to the final goal of the machining process, the machinist selects the best cutting-tool parameters combination. For example, if the only important constraint is a high cutting tool life, the machinist will select a low cutting speed, low feed rate and low-medium axial depth. Fig. 7a describes the typical optimization process based on handbooks.
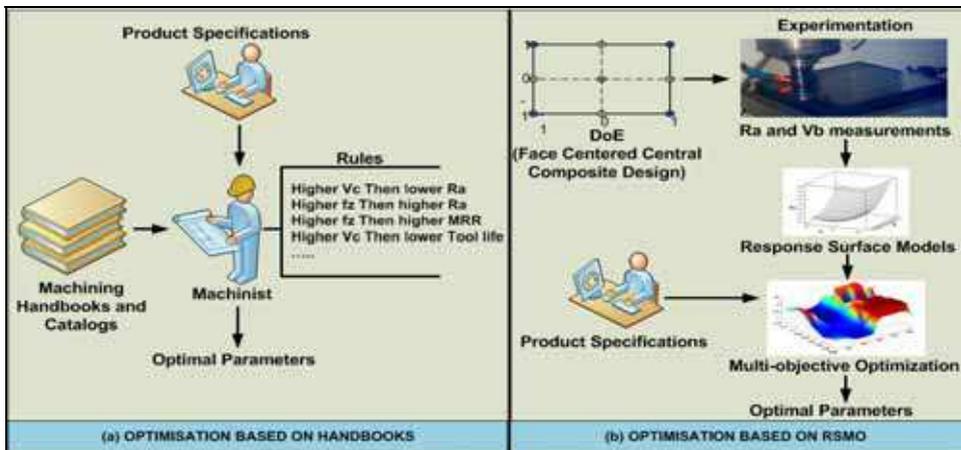

Fig. 7. Off-line cutting parameters optimization.

5.2 Optimization results

As it was explained above (section 4.4), the MRR is the most important objective function together with product quality whereas tool life is less important ($I_1=1$; $I_2=1$; $I_3=0.5$). A high feeding value increases MRR but decreases surface roughness, so it seems reasonably to fix the feeding value to an intermediate value. On the other hand, as V_c increases, both MRR

and part quality increase, but cutting tool life decreases considerably. As both MRR and part quality are much important than cutting tool life, it seems reasonably to fix V_c at its maximum value. Therefore, the optimal cutting parameters based on catalogs and handbooks can be defined as V_c=200 m/min and fz=0.08 mm. Experimentation was conducted in order to check the overall desirability function at these cutting conditions. The experimental results showed a cutting tool life T=10.8 min, an average surface roughness deviation of V^2=1.6 $\cdot 10^{-3}$ μm^2, and a MRR=1592 mm^3/min. The overall desirability was 0.472, and the evolution of the overall desirability function due to surface roughness variability along cutting tool life-cycle is shown in Fig (8).
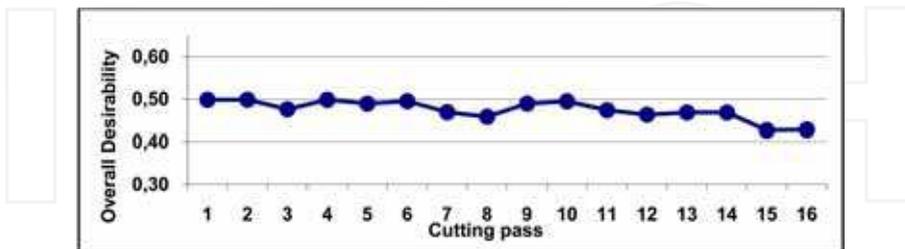

Fig. 8. Overall desirability function along cutting tool life-cycle. Parameter optimization based on handbooks. Vc=200m/min; fz=0.08mm; ap=0.4mm

6. Parameter optimization based on RSMO

6.1 Description

A less conservative method to optimize cutting parameters could be carried out through the Response Surface Model Optimisation methodology (RSMO). RSMO is a collection of mathematical and statistical techniques that are useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response (Montgomery, 2001). In most RSM problems, the form of the relationship between the variable to be optimized (the response) and the independent variables is unknown. Thus, the first step in RSM is to find a suitable approximation for the true functional relationship between the response and the set of independent variables. First and second-order models are commonly applied to approximate the function through least squares. Considering a response surface y defined by y=f(x_1,x_2…x_k) where x_1, x_2, …, x_k are independent variables, the optimal value of the response surface will be the set of x_1, x_2, …, x_k for which the partial derivatives $\frac{\partial \hat{y}}{\partial x_1} = \frac{\partial \hat{y}}{\partial x_2} = \cdots \frac{\partial \hat{y}}{\partial x_k} = 0$. This point is called the stationary point and it could represent a point of maximum response, a point of minimum response, or a saddle point. A general mathematical solution for the location of the stationary point can be obtained as follows. Given a second-order model in matrix notation as:

$$\hat{y} = \hat{\beta}_o + x'b + x'Bx \tag{21}$$

where

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_k \end{bmatrix} \quad x = \begin{bmatrix} \hat{\beta}_1 \\ \vdots \\ \hat{\beta}_k \end{bmatrix} \quad and \quad B = \begin{bmatrix} \hat{\beta}_{11} & \frac{\hat{\beta}_{12}}{2} & \cdots & \frac{\hat{\beta}_{1k}}{2} \\ & & \ddots & \frac{\hat{\beta}_{2k}}{2} \\ sym & & & \hat{\beta}_{kk} \end{bmatrix} \tag{22}$$

That is, b is a (k x 1) vector of the first-order regression coefficients and B is a (k x k) symmetric matrix whose main diagonal elements are the pure quadratic coefficients ($\hat{\beta}_{ii}$) and whose off-diagonal elements are one-half the mixed quadratic coefficients ($\hat{\beta}_{ij}$, $i \neq j$).

The derivative of $\hat{y}$ with respect to the elements of the vector **x** equated to **0** is

$$\frac{\partial \hat{y}}{\partial x} = b + 2Bx = 0 \qquad (23)$$

The stationary point is the solution to Eq. (23), or

$$x_s = -\frac{1}{2}B^{-1}b \qquad (24)$$

To define whether the stationary point is a point of maximum or minimum response or saddle point, it is usually examined a contour plot of the fitted model. Refer to (Montgomery, 2001) for RSMO concepts.

In this section the RSMO methodology is applied to the high quality machining operation studied. The experimentation conducted through the DoE is used to obtained first and second order process models. The multi-objective function which is based on these models is optimized and the optimal cutting parameters are defined. Fig. 7b describes the optimization process based on RSMO in the machining process studied.

6.2 Machining process models based on first and second-order functions

RSM technique lets model the responses of interest W, T, and MRR as a first and second-order functions. After conducting the DoE shown in Fig. (5), a RSM was fitted for each response. The first and second order functions with its coefficient of determination were:

- Ra deviation (V^2) response:

$$V^2 = 0.0629 - 5 \cdot 10^{-4}V_c - 0.507f_z + 11.9 \cdot 10^{-6}V_c^2 + 1.49f_z^2 + 1.6 \cdot 10^{-3}V_c \ \ f_z \qquad (25)$$
$R^2_{adj}=89.1\%$

- T response:

$$T = 117.3 - 0.321V_c - 1372.3f_z + 5333.3f_z^2 + 2.037V_cf_z \qquad (26)$$
$R^2_{adj}=80.4\%$

- MRR response

$$MRR = 99.47 \ V_cf_z \qquad (27)$$

$R^2_{adj}=100\%$. Note that this is the exact analytical equation for MRR.
Fig. 9 shows the response surface models for each response analysed.

6.3 Optimization results

The optimum cutting parameters were obtained maximizing the overall desirability function, which depends on the previous first and second order models and the individual desirability and weights coefficients defined in section 4.4. The result of the optimization procedure showed the optimal cutting parameters V=165m/min and fz=0.12mm, with an overall desirability value of 0.61. To validate the RSMO result, experimentation was conducted with the expected optimal parameters. The experimental results showed a

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cutting tool life T=13.7 min, a surface roughness deviation function of V^2=5.5 $\cdot 10^{-3}$ μm^2, and a MRR=1967 mm³/min. The overall desirability of the experiment was 0.495, and the evolution of the overall desirability function due to surface roughness variability along cutting tool life-cycle is shown in Fig (10). Note that the expected overall desirability was 0.610 whereas the real value was 0.495. This error is due to the inaccuracy of the process models developed through this methodology.
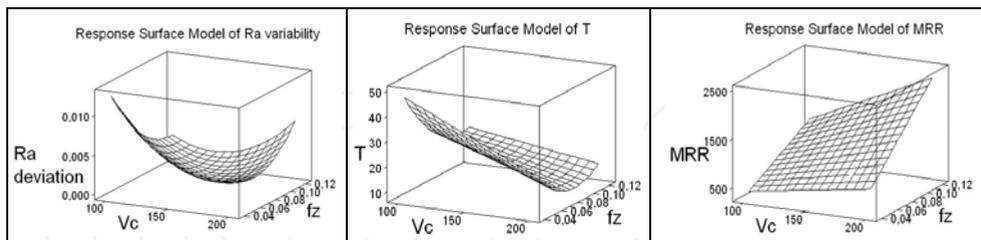

Fig. 9. Response Surface Models for deviation of Ra, T and MRR. Units: Vc (m/min); fz (mm); Ra deviation (μm^2); T (min); MRR (mm³/min).
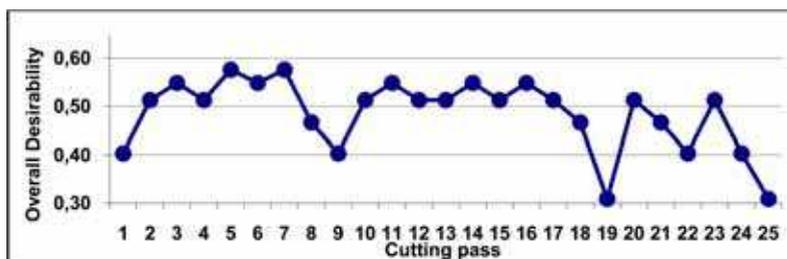

Fig. 10. Overall desirability function along cutting tool life-cycle. Parameter optimization based on RMSO. Vc=164m/min; fz=0.12mm; ap=0.4mm.

7. Parameter optimization based on AI

7.1 Description

Due to non-linearity, first and second order models from response surface methodology cannot be enough accurate to model tool-wear and surface roughness in machining processes. To overcome this limitation, AI techniques such as Artificial Neural Networks or Fuzzy Logic can be applied in order to deal with non-linearity. However, these AI models are called black-box models, and they cannot be optimized with conventional optimization methods. Due to this limitation, a cutting parameter optimization methodology based on AI models requires an advanced search methods for global optimization, such as Genetic Algorithms (GA) and Mesh Adaptive Direct Search (MADS) algorithms.

GAs are search algorithms based on the mechanics of natural selection and natural genetics, invented by (Holland, 1975), which can find the global optimal solution in complex multidimensional search spaces. A population of strings, representing solutions to a specified problem, is maintained by the GA. The GA then iteratively creates new populations from the old by ranking the strings and interbreeding the fittest to create new strings. So in each generation, the GA creates a set of strings from the previous ones, occasionally adding random new data to keep the population from stagnating. The end result is a search strategy that is tailored for vast, complex, multimodal search spaces. GAs

are a form of randomized search, in the way in which strings are chosen and combined is a stochastic process. This is a radically different approach to the problem solving methods used by more traditional algorithms, which tend to be more deterministic in nature, such as the gradient methods used to find minima in graph theory. However, although GA is an effective optimization algorithm, it usually takes a long time to find an optimal solution due to its slow convergence speed (Cus & Balic, 2003).

On the other hand, MADS algorithms are iterative search algorithms where the optimization is conducted through an adaptive mesh of points where the objective function is evaluated. At the first iteration, the mesh is built according to an initial point of the objective function. The algorithm computes the objective function at the mesh points until it finds one whose value is smaller than the objective function evaluated on the initial point. If a mesh point has a smaller value, the algorithm sets the next point in the sequence equal to this one and multiplies the current mesh size by a mesh expansion factor. The mesh is then expanded and the algorithm conducts a new iteration. In case none of the mesh points has a smaller objective function value than the value at the best current solution, the algorithm does not change the current point at the next iteration and the mesh size is contracted by a mesh contraction factor. After the re-size, a new iteration is conducted. The iterations are conducted until a stop condition is reached, typically when the mesh size reaches a minimum value. Refer to (Audet & Dennis, 2004) for concepts related to MADS.

In this section it is proposed an optimization methodology based on Artificial Neural Networks (ANN) models for modeling the machining process and GA-MADS algorithms to optimize the multi-objective function defined by Eq. (16) and the ANN models. The combination of GA and MADS algorithms lets reduce the computing time required for the optimization. Basically, GA is firstly applied in order to find the region where the multi-objective function is minimum. Then, the GA algorithm is interrupted and the MADS algorithm refines the search using the GA solution as the initial point of the mesh. The optimal cutting parameters are calculated when the MADS algorithm reaches the minimum mesh size. Fig. 11 describes the procedure of the optimization methodology proposed, based on process models using AI techniques and an initial Design of Experiments, and a GA-MADS optimization. Table (1,2) defines the main characteristics of the ANN models applied and the GA-MADS algorithms.
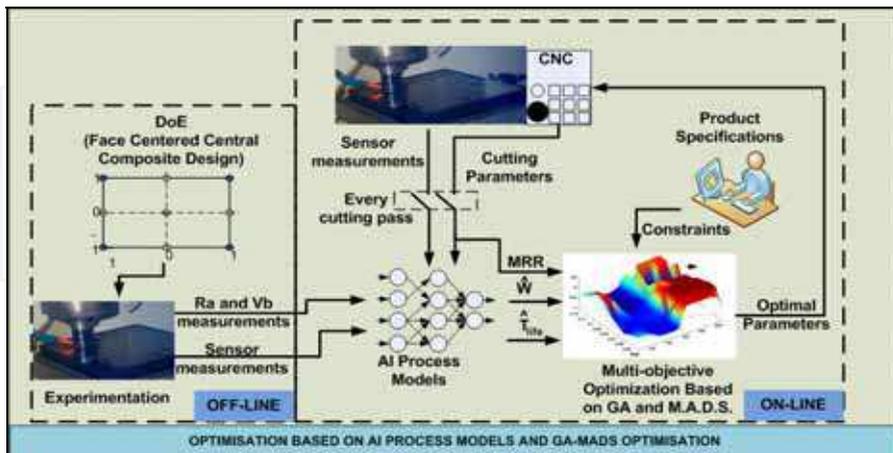

Fig. 11. On-line cutting parameters optimization based on AI

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7.2 Machining process models based on AI

After conducting the DoE, an experimental database composed of 188 samples of 9 different cutting conditions was generated. Each sample was defined by: surface roughness deviation (V^2), cutting tool wear state (% of use), root-mean-square of cutting forces in X, Y direction (RMS Fx, RMS Fy), root-mean-square of cutting forces in XY plane (RMS Fxy), root-mean-square of vibrations in X direction (RMS Ax), root-mean-square of vibrations in Y direction (RMS Ay), cutting time (Tc), cutting speed (Vc) and feed per tooth (fz). The experimental database was used to learn three ANN process models: (1) Ra deviation model, (2) Cutting-tool life model, (3) Cutting-tool wear state model. Before training the ANN, a statistical study was conducted for each model in order to discard those inputs variables that were not significant. The final inputs variables applied for each model and the main characteristics of the ANN models are shown in Table 1. Note that vibrations signals were discarded for all models since they were close related to the cutting-tool position, and they cannot provide any objective information about the state of the process. Fig 12 shows the response of each ANN model according to V_c and f_z values.

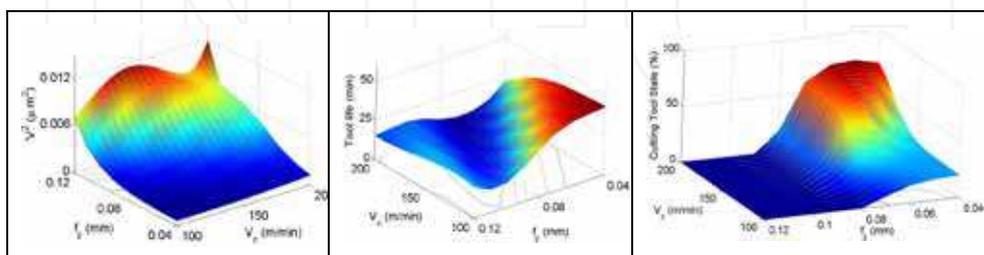| Ra deviation model		Cutting-tool life model		Cutting-tool wear state model	
Type	Backpropagation	Type	Backpropagation	Type	Backpropagation
Inputs	Vc, fz, State	Inputs	Vc, fz	Inputs	Vc, fz, RMS Fxy
Output	Ra_deviation	Output	T_life	Output	State
Hidden Layers	1	Hidden Layers	1	Hidden Layers	1
Neurons	3	Neurons	3	Neurons	2
Mapping functions	Logsig	Mapping functions	Logsig	Mapping functions	Logsig
Training Method	Lev-Marq.	Training Method	Lev-Marq.	Training Method	Lev-Marq.
Epochs	300	Epochs	300	Epochs	300
Learning Rate	0.05	Learning Rate	0.05	Learning Rate	0.05

Table 1. Characteristics of ANN models

Fig. 12. ANN models of : (1) surface roughness deviation -V^2- for a cutting tool wear of 50%; (2) cutting tool life –T-; (3) tool wear state for a RMS Fxy of 60N.

7.2 Optimization results

The optimum cutting parameters were obtained maximizing the overall desirability function every cutting pass of 250 mm length of cut. During the cutting pass, the cutting forces were acquired and the cutting-tool wear state was predicted by the cutting-tool wear state model. With the cutting-tool state prediction, the GA-MADS optimization procedure was conducted to maximize the overall desirability function, which is based on the MRR model, and the ANN models of Ra deviation and cutting-tool life. The optimal solution was obtained after an average processing time of 6 seconds, and the new cutting parameters were sent to the CNC controller for the next cutting pass. The process was repeated until the cutting tool was worn or the surface roughness was outside specifications. The result of the optimization procedure showed that the optimal cutting parameters vary considerably, from 200m/min to 130m/min and from 0.12mm to 0.07mm for cutting speed and feed rate respectively, with an expected overall desirability value of 0.545. The real overall desirability value after measure surface roughness deviation and tool-life was 0.520. The evolution of the overall desirability function and the variation of the optimal cutting conditions along the cutting tool life-cycle are shown in Fig (13).

Genetic Algorithm		Mesh Adaptive Direct Search Algorthm	
Variables to optimise	Vc, fz	Variables to optimise	Vc, fz
Population Size	10	Initial Mesh Size	0.05
Generations	15	Max. Mesh Size	Inf
Crossover Frac.	0.8	Max. Func. Eval	Inf
Elite Count	2	Expansion	2
Mutation function	Gaussian	Contraction	0.5
Selection function	Stochastic	Poll Method	Positive Basis 2N
Initial ranges	Vc=[100,200] Fz=[0.04,0.12]	Polling order	Consecutive
Stop criterium	Stall Time: 6s Stall Generations: 7	Stop criterium	Tolerance Mesh: $5 \cdot 10^{-4}$

Table 2. Characteristics of search algorithms

8. Results and discussion

The results reported in the optimization methodology based on handbooks and catalogs show the most conservative cutting parameters as it was expected, where the overall desirability function has a value of 0.472. A simple RSMO through a 9 experimental runs provide enough information to improve cutting parameter selection and increase the overall desirability function to 0.495 which is an improvement of 5% in the desirability. The surface response models show that high cutting speeds increase surface roughness variability which were not taken into account by the machinist in the first optimization methodology. Although RSMO increases the overall desirability, the RSMO prediction is quite inaccurate as it is shown in the experimental validation. The predicted overall desirability by RSMO was 0.610 whereas the overall desirability function after the experimental validation was 0.495. The inaccuracy of the prediction is due to the inaccuracy of the process models, where

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surface roughness deviation and cutting-tool life models have been fitted by least squares with a low coefficient of determination, 89% and 80.4% respectively.

The methodology proposed in this chapter, based on AI techniques for modeling the machining process and the use of search algorithms to optimize the overall desirability function on-line, shows an overall desirability function of 0.520. This methodology compared with handbook optimization and RSMO increases the overall desirability in 10% and 5% respectively. The main benefits reported by this methodology are due to two factors. A first factor, the ANN process models let deal with non-linearity so this models are more accurate than response surface models for modelling high quality machining operations. Unlike RSMO where the error between the predicted overall desirability value and the experimental one was 19% (0.61 versus 0.495), the proposed methodology presents an error of 5% (0.545 versus 0.520). As a second factor, the on-line nature of the methodology lets adapt the cutting parameters every cutting pass so the system is more flexible to adapt any change in the objective function during the cutting-tool life. However, the ANN model for cutting tool state prediction based on cutting forces seemed to be low accurate due to the high variability of the cutting forces during machining. This variation produces that the cutting tool parameters selected each cutting tool pass were quite irregular. This effect is reflected in Fig. 13b, where cutting speed often varies from 195 to 150-130 m/min. The replacement of the direct measurement of cutting forces by indirect methods which are not so sensitive to cutting mechanisms such as current or power sensors might increase the overall desirability function and select optimal parameters with a more regular variation.
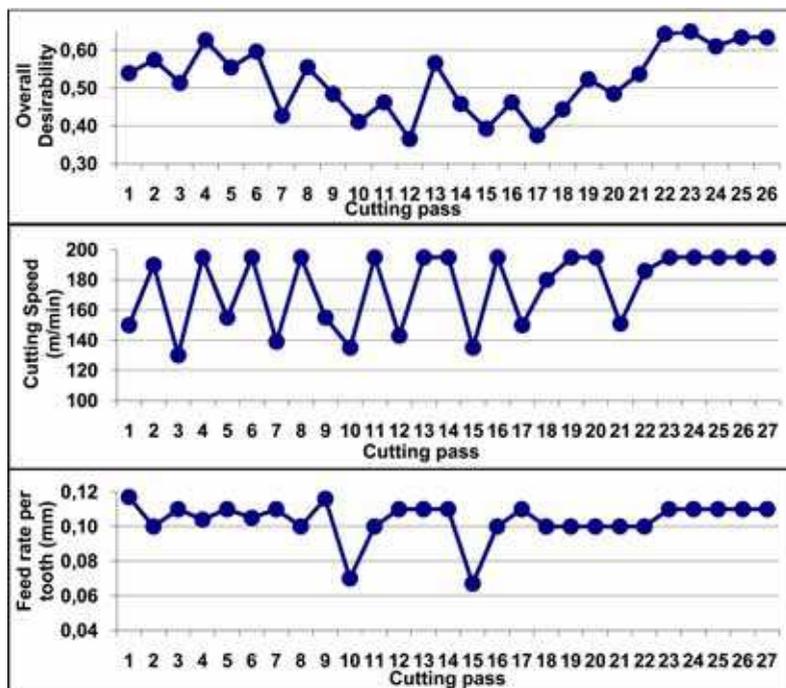

Fig. 13. (a) Overall desirability function along cutting tool life-cycle. Parameter optimization based on AI. (b) Adaptive cutting speed. (c) Adaptive feed per tooth

9. Conclusions

In this chapter, an Adaptive Control Optimization (ACO) system was presented for optimising a multi-objective function based on material removal rate, quality loss function related to surface roughness, and cutting-tool life subjected to surface roughness specification constraints. Unlike traditional optimization techniques, this methodology lets adapt the cutting parameters during the cutting-tool life-cycle in order to maximise in real-time the multi-objective function according to cutting-tool state. The core of the system is composed of three process models: a cutting-tool wear model for diagnosing the state of the cutting tool, a surface roughness deviation model for predicting the quality loss function and a cutting-tool life model. All models were developed using Artificial Neural Networks (ANN) to model the non-linear relationships in machining processes. The cutting parameter optimization is obtained applying genetic algorithms and mesh adaptive direct search algorithms. The system proposed was compared with 2 traditional methods for off-line cutting parameter selection: (1) selection based on suggested cutting parameters from handbooks, and (2) selection based on RSMO.

The results showed how conservative are the cutting parameters selected by off-line methodologies. A cutting parameter optimization based on handbooks provided an overall desirability function of 0.472, whereas cutting optimization through RSMO gave an overall desirability value of 0.495. The main inconvenient of RSMO is that this methodology is based on mathematical first and second order models which are not enough accurate for high quality machining operations. The new methodology proposed based on AI techniques increases the overall desirability function up to 0.520. The improvement is due to two effects: (1) the ANN process models deal with non-linearity so these models are more accurate than response surface models for modelling high quality machining operations; (2) the on-line nature of the methodology lets adapt the cutting parameters every cutting pass so the system is more flexible to adapt any change in the objective function during the cutting-tool life-cycle.

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