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Edited by

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Preface

Nowadays, production systems have become more complex since they require adapting to the market challenges, to introduce more flexible mechanisms and control strategies in their structure to ensure the efficient use of system resources and to allow system layout reconfiguration.

The book presents an excellent overview of the recent developments in the different areas of Robotics, Automation and Control. Through its 24 chapters, this book presents topics related to control and robot design; it also introduces new mathematical tools and techniques devoted to improve the system modeling and control. An important point is the use of rational agents and heuristic techniques to cope with the computational complexity required for controlling complex systems. Through this book, we also find navigation and vision algorithms, automatic handwritten comprehension and speech recognition systems that will be included in the next generation of productive systems developed by man.

We would like to thank all the authors for their excellent contributions in the different areas of the control, robotics and automation. It is their knowledge and enthusiastic collaboration that lead to the creation of this book, which we are sure that will be very valuable to the readers.

October 2008

Editors

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Antonio Ramírez Treviño

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

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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.

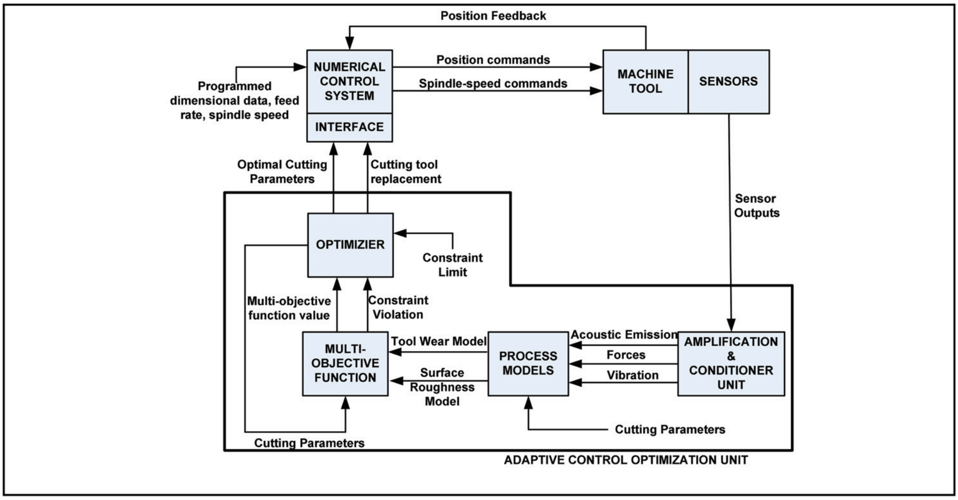

Fig. 1. Adaptive Control Optimization (ACO) scheme adapted from (Koren, 1983).

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.

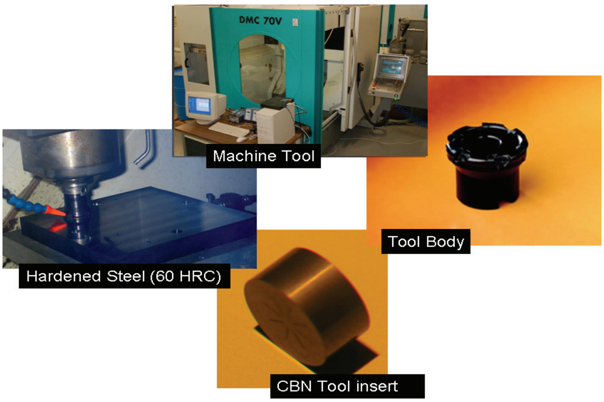

Fig. 2. Machining process analysed

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/1 = 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.

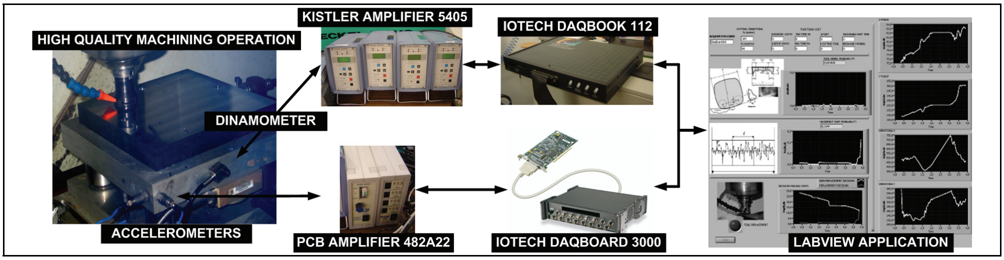

Fig. 3. Multi-component sensor system

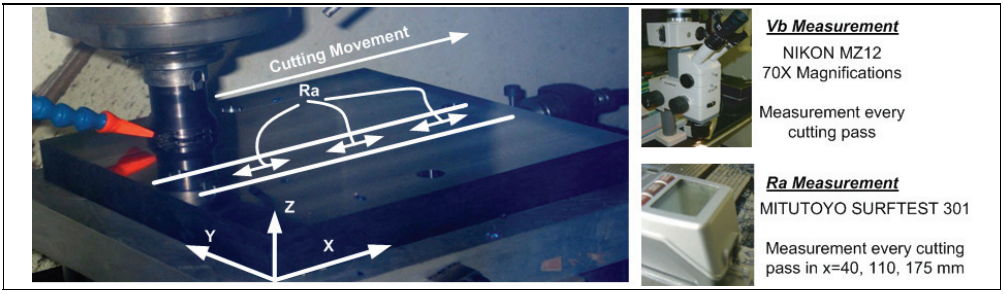

Fig. 4. Machining process and surface roughness and tool-wear sampling.

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.

Experimental Run	Vc (code)	Vc (m/min)	fz (code)	fz (mm)
1	1	200	0	0.08
2	0	150	1	0.12
3	1	200	1	0.12
4	-1	100	0	0.08
5	-1	100	-1	0.04
6	0	150	0	0.08
7	1	200	-1	0.04
8	-1	100	1	0.12
9	0	150	-1	0.04

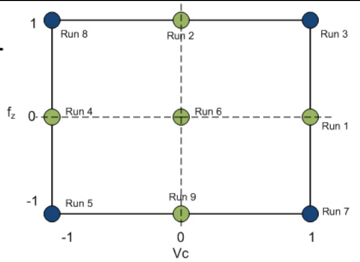

Fig. 5. Design of Experiments and run order. Face Centered Central Composite Design.

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.

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

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

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

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 $\Delta = Ra_{max} - Ra_{target}$ with Ra_{max} the maximum Ra defined by specifications and Ra_{target} the Ra desired; V^2 is the mean squared deviation as $V^2 = ((Ra_{target} - y_1)^2 + \dots + (Ra_{target} - y_n)^2)/n$, 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

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

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

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

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:

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

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

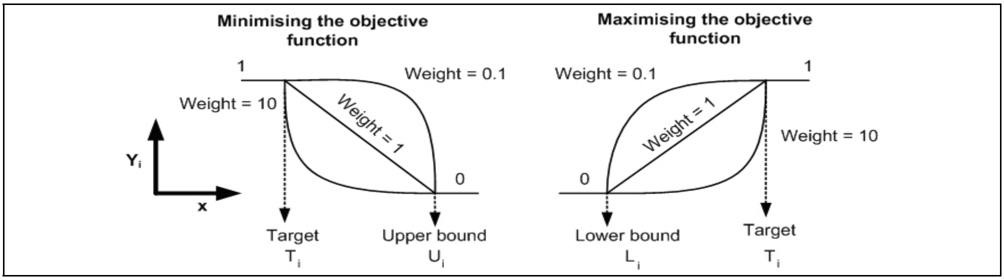

Fig. 6. Desirability functions according to the type of objective function

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:

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

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

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

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:

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

constrained to:

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

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