Intelligent Control System for HSM

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Abstract:

Next-generation of High-Speed Machining (HSM) systems demand advanced features such as intelligent control under uncertainty. This requires, in turn, an efficient administration and optimization of all system's resources towards a previously identified objective. This work presents an optimization system based on Markov Decision Process (MDP), where an intelligent control guides the actions of the operator in peripheral milling processes. Early results suggest that MDP framework can cope with this application, yielding several benefits, which are discussed in detail. Future work will address the full integration of the developed optimization scheme within a commercial machining center.

Keywords: *Markov Decision Process, optimization, High-Speed Machining, milling process, neural network.*

1. Introduction

High-Speed Machining (*HSM*) requires high magnitudes of spindle speeds, feed rates, as well as acceleration and deceleration rates. Simultaneously, it is subjected to stringent restrictions such as low machining cost and time, as well as high precision and accuracy.

Intelligent machines have the potential to meet the strong competitiveness demanded by new businesses. For example, intelligent CNC machines convey advance features such as prediction of operations, reduction of setup time, detection of cutting tool condition, acquisition of knowledge and inferences from incomplete information [1]. However, process planners still have great difficulties for measuring on-line process data on machining processes such as cutting tool life and surface roughness [5].

This paper presents the design and implementation of a novel Intelligent Control System for HSM, exhibiting several desirable features such as: prediction of key variables (surface roughness and cutting tool condition), definition and adaptation of optimal cutting conditions and operation policy, and an objective function-based optimization. Special emphasis is given to the decision-making module of this system.

This paper is an extended version of that presented at "**IFAC Workshop on Intelligent Manufacturing Systems'08**", and is organized as follows: Section 2 describes the state of the art on HSM, where key areas for improvement are identified. Section 3 introduces the industrial HS-1000 Kondia machining center and the data acquisition system where the experiments took place. Section 4 briefly describes the optimization scheme

proposed. Section 5 illustrates the intelligent system, while Section 6 discusses results. Finally, section 7 closes with some concluding remarks.

2. State of the art

Several optimization methods have been developed around process planning systems for machining processes.

A procedure for tool selection in milling operations was proposed in [2]. First, several alternatives of cutting tools were considered by an iterative method. Then, cutting data were refined by a set of technological constraints including tool life, surface finishing, machine power, and available spindle speeds and feed rates. Three user-defined optimization strategies were available (minimum cost, maximum production rate or predefined tool life).

In [3], a Cutting Parameters Optimization System (CPOS), based on a two-stage methodology, was introduced. First, a tentative number of passes and depth of cuts were determined through the so-called Volume Sectioning method. Then, the cutting speed and feed rate for each pass were optimized by using Genetic Algorithms (GA). The cutting tools were selected from predefined libraries. Two optimization criteria were considered (minimum production time and minimum production cost), accounting for several technological constraints.

A second order mathematical model was developed for Ra prediction as a function of the cutting speed, feed rate, depth of cut, and nose radius of the cutting tool in turning operations [10]. The minimization of Ra was taken as objective function and it was optimized using GA. A combination of these cutting parameters was optimized based on a GA approach.

Based on previous work by [3], an algorithm for the selection of optimal cutting conditions was proposed in [8], allowing the calculation of number of cuts required and machining time. [20] presented a new hybrid optimization technique based on the maximum production rate criterion and ten technological constraints. A general algorithm, called OPTIS, was used in conjunction with Artificial Neural Networks (ANN) in order to solve the complex optimization problem. OPTIS selects the optimum cutting conditions (based on minimum machining costs) from commercial databases. ANN ensured efficient and fast selection of the optimum cutting conditions and processing of available technological data. Compared to the GA and Linear Programming (LP) approaches, this hybrid optimization technique improved the optimal cutting parameters selection by around 30.41% and 20%, respectively. Based on OPTIS, [21] proposed an adaptive

neural controller for on-line optimal control of a milling process. The milling state was estimated *via* the cutting force's measurement. The feed-rate was selected as the optimized variable.

A two-phase optimization strategy based on the Taguchi dynamic characteristic theory was proposed in [12]. Experimental results showed that the machining time could be reduced with low process variance and increased robustness of the CNC milling processes.

[19] presented a Taguchi method coupled with Principal Component Analysis (PCA) for the optimization of high-speed CNC milling processes. Optimal process conditions were selected for producing the best dimensional precision and accuracy, surface roughness, and tool wear. The selected control factors were: milling type, cutting speed, feed per tooth, film material, tool material, number of teeth, rake angle and helix angle. Based on the PCA technique, an index for the inter-correlated multiple performance features of a high speed CNC milling process was computed, obtaining optimized settings.

A Genetically Optimized Neural Network System (GONNS) that selects the optimal cutting conditions for milling processes was proposed by [11]. GA was used to maximize the rate of metal removal and minimize the surface roughness based on different ANN models. A mathematical model based on both material behavior and machine dynamics was described in [9], able to determine cutting forces for end-milling operations. A GA optimized the cutting parameters for minimizing machining time and maximizing tool life for a constant rate of material removal.

[7] reviewed different optimization techniques in metal cutting processes, discussing a general framework for process parameter optimization. Reviewed optimization methods currently applied are: Taguchi method, Response Surface Methodology, Mathematical Iterative Search Algorithm, Genetic Algorithms, and Simulated Annealing. Furthermore, typical objective functions include: minimum production cost, maximum production rate, increase tool life and maximum profit rate, as well as weighted combination of these. Cutting constraints that should be considered in machining economics include: tool-life, cutting force, power, chip-tool interface temperature, and surface finish.

Table 1 compares previous works in optimization of machining processes. Almost all of them are usable within narrow operating conditions only; some do not consider process variables, while others demand unavailable HSM handbooks. In this research, an intelligent control system, which includes a planning module, guides the operator in the decision-making process in order to minimize operating costs.

3. Experimental set-up

Experiments were carried out in an industrial HSM center HS-1000 Kondia, featuring a 25 KW drive motor, 3 axis, 24000 rpm maximum spindle speed and a Siemens open Sinumerik 840D controller (shown in Figure 1). Several sensors were installed as follows (Figure 2):

1. Three accelerometers and one Acoustic Emission (AE) sensor were installed on a ring. The ring was fixed to the spindle of the machining center (Figure 3).

2. Two accelerometers were fixed in the "x" and "y"-axis directions on the work-piece.

3. One AE sensor was fixed on the table.

4. A Kistler 3-component force dynamometer was fixed to the work-piece, in order to record force signals.

The signals were fed to two data acquisition boards with sample rates of 40,000 and 1,000,000, respectively (due to technical requirements of the AE sensors).

A milling process was carried out in a test piece of size 100 x 170 x 25 mm, with different Aluminium alloys (5083-H111, 6082-T6, 2024-T3, 7022-T6, 7075-T6), several cutting tools (25o helix angle, and 2-flute, Sandvik Coromant of 8, 10, 12, 16, and 20 mm) and several geometries (concave, convex or straight path), as shown in Figure 3. Table 2 lists the variables and their description.

Table 1. Comparison of previous works in optimization of machining processes (MMC = Minimum Machining Cost).

| Reference	Machining process [Optimization method]	Objective Function
Carpenter & Maropoulos, 2000	Milling [Iterative Method]	MMC, maximum production rate & tool life.
Dereli *et al.*, 2001	End Face milling [Volume Sectioning & GA]	Minimum machining time & MMC.
Suresh *et al.*, 2002	Turning [GA]	Minimum surface roughness.
Mursec & Cus, 2003	Turning, milling [Data from tool manufactures]	MMC.
Zuperl *et al.*, 2004	Turning [OPTIS algorithm & ANN]	Maximum production rate, & MMC.
Tzeng & Chen, 2005	Milling [Taguchi Dynamic Characteristic theory]	High machining efficiency & geometrical accuracy.
Yih-Fong, 2005	Milling [Taguchi and PCA]	Dimensional precision & accuracy, surface roughness, tool wear.
Zuperl *et al.*, 2006	Milling [Adaptive neural Controller]	Regulation the cutting force by adjusting the feed rate.
Tansel *et al.*, 2006	Milling [GONNs]	Maximum metal removal rate, & minimum surface roughness.
Palanisamy *et al.*, 2007	End Milling [Mathematical model & GA]	Minimum machining time & maximize tool life.
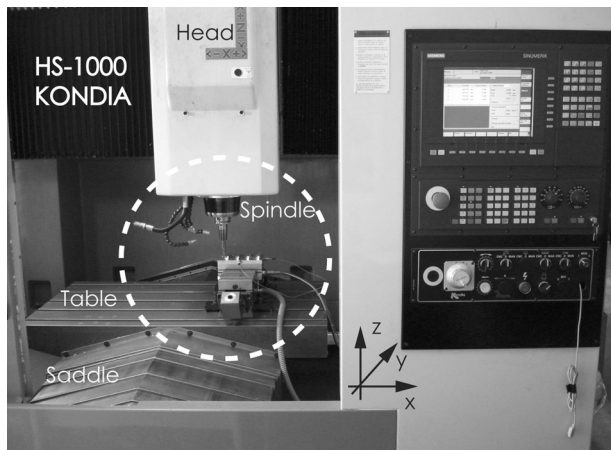
Fig. 1. HS-1000 Kondia machining center.
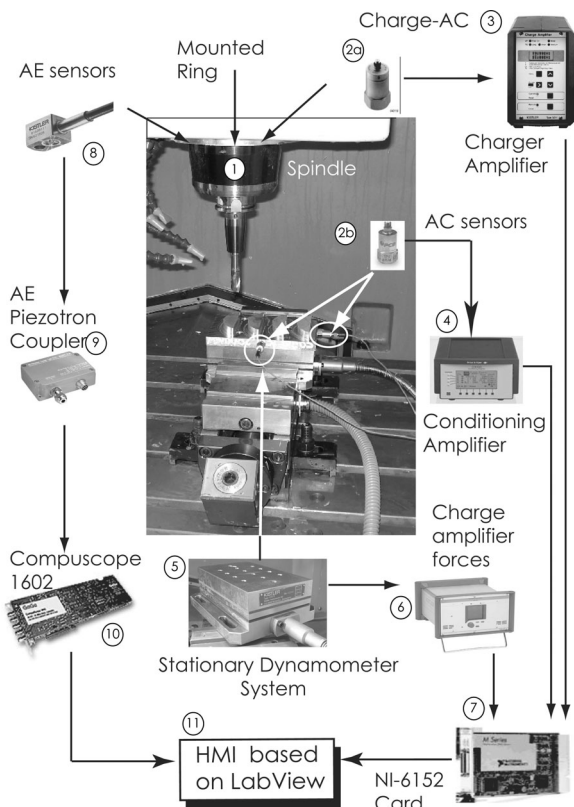
Fig. 2. Data acquisition system. The monitoring system is integrated by: (1) Supporting ring. (2a) Brüel and Kjaer accelerometers (charge sensitivity: 98 ± 2 pC/g, resonant frequency: 16 KHz & 42 KHz). (2b) PCB piezotronic accelerometers (x-axis & y-axis, sensitivity: 10 mV/g; range frequency: 0.35-20,000 Hz). (3) Charger amplifiers. (4) Conditioning amplifier. (5) Kistler 3-component forces Dynamometer (force range: -7.5 pC/N in x-axis and y-axis and -3.5 pC/N in z-axis, natural frequency: 3-5 KHz). (6) Kistler charger amplifier. (7) National Instruments data acquisition card. (8) Kistler Piezotron acoustic emissions (sensitivity: 700 V/m/s, freq. range: 50-400 KHz). (9) AE Piezotron coupler. (10) CompuScope card. Finally, (11) a HMI based on LabView for real time control and monitoring operations was developed.

4. Optimization scheme proposed

[14-16] proposed an intelligent control system, illustrated in Figure 5. This control system integrates four main modules: data acquisition, cutting tool monitoring, sur-

face roughness monitoring and planning module. The first three are here briefly described, while the planning module will be presented in detail in the following section.

4.1. Data Acquisition Module

Based on the aforementioned data acquisition system, standard filtering was applied to the process variable signals. Some signals were pre-processed by the Mel Frequency Cepstrum Coefficients (MFCC), widely used in speech recognition systems [18], in order to find particular features.
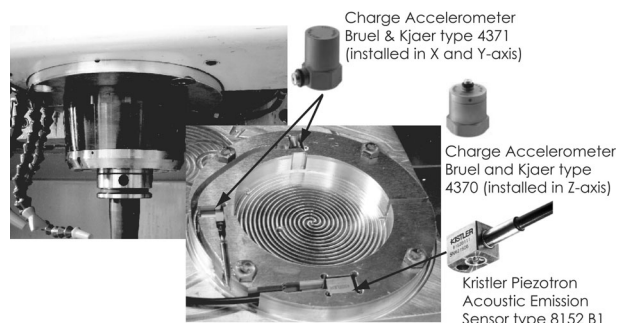

Fig. 3. Accelerometers and Acoustic Emission (AE) sensors installed on a ring fixed to the spindle of the CNC machining center.
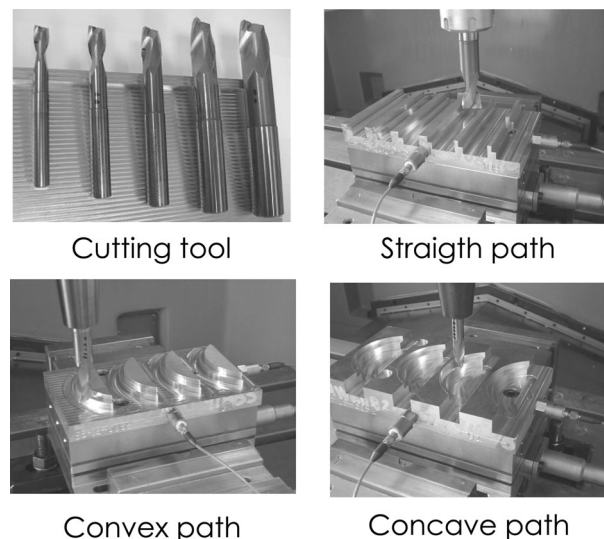

Fig. 4. Cutting tools (Sandvik Coromant 8,10,12,14,16 mm) and several Geometries (concave, convex, and straight path).
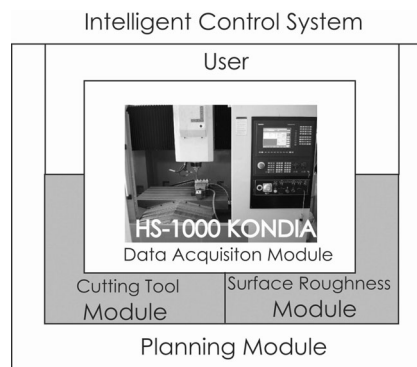

Fig. 5. Intelligent Control System. The system considers four integrated modules: data acquisition, cutting tool, surface roughness and planning module.

Table 2. Definition of Variables.

Variable	Description
V_f	Feed rate.
n	Spindle speed.
ap	Axial depth of cut.
ae	Radial depth of cut.
Curv	Curvature of the geometry.
D_{tool}	Cutting tool diameter.
f_z	Feed per tooth.
Fy	y-axis workpiece cutting force.
HB	Brinell Hardness.
Ra	Surface Roughness.
Ra^p	Predicted Ra.
Ra^d	Desired Ra.
V_B	Flank wear in cutting tools.
C_C	Cutting conditions: n, V_f, ap, ae.
P_C	Cutting parameters. Selection of the cutting tool, workpiece hardness, etc.
P_G	Geometric parameters. Geometry of the cutting tool and path of the cutting process.

The procedure for computing the MFCC can be summarized as follows:

1. A small segment of the signal is selected for applying a Discrete Fourier Transform (DFT), in order to compute the magnitude of the energy spectrum in a logarithm scale.
2. The real frequency scale (f_{Hz}) is mapped to the perceived frequency scale (f_{Mel}) as:

$$f_{Mel} = 2595 \log\left(1 + \frac{f_{Hz}}{700}\right)$$

3. After a triangular band-pass filter is applied for smoothing the scaled spectrum, the MFCC are computed using the inverse DFT:

$$MFCC_c = \sum_{j=1}^{N_p} y(j) \cos\left(\frac{\pi}{N_p}\left(j - \frac{1}{2}\right)c\right)$$

where *y(j)* is the output of the triangular band-pass filter, N_p is the number of band-pass filters, *c* defines the Cepstrum coefficient number ($c = 1, 2,...,N_c$), and N_c defines the total number of Cepstrum coefficients.

4.2. Cutting tool Module

The cutting tool wear condition is defined as a gradual loss of tool material at contact zones with the workpiece. It has a direct impact on the final dimensions of the product, surface finishing and surface integrity. Direct monitoring is not easily implemented due to non-standard measuring methods.

An indirect monitoring approach based on vibration measurements was developed [13]. Vibration signals were characterized by MFCC and associated with the cutting tool condition. The cutting tool states were defined as: new ($0 < V_B < 75 \, \mu m$), half-new ($75 \, \mu m < V_B < 150 \, \mu m$), half-worn ($150 \, \mu m < V_B < 250 \, \mu m$), and worn ($250 \, \mu m < V_B$), where V_B is the flank wear according to ISO-8688-2 norm. A Hidden Markov Model

(HMM) framework was developed in order to identify V_B based only on the MFCC of the vibration signals in the work-piece (y-axis).

4.3. Surface Roughness Module

Several factors affect the surface roughness (Ra), such as: feed per tooth, cutting tool diameter, radial depth of cut, work-piece hardness, etc.

A Response Surface Methodology (a statistical and mathematical technique) was applied for modeling Ra. Applying an ANOVA, four models were obtained for computing the Ra:

$$Ra = f(f_z, D_{tool}, ae, HB, Curv)$$

Each model was developed for a single cutting tool condition (V_B). Verifying that the residuals followed a normal distribution statistically validated these models.

It is also possible to predict Ra during the machining process by applying an Artificial Neural Network (ANN) model. The ANN model was built based on cutting parameters (f_z, D_{tool}, ae, HB, Curv) and on-line measurement of process variables (MFCC of Fy, the y-axis workpiece cutting force), as follows:

$$Ra = ANN(f_z, D_{tool}, ae, HB, Curv, Fy, V_B)$$

An estimator based on multi-sensor and data fusion provides an improved and robust estimation. For details see [17].

5. Planning module

A CNC machining center could have three main intelligent areas: cutting tool monitoring, operation & machine tool modeling and adaptive control [6]. The planning module on the proposed system has two main tasks:

- Computation of the optimal cutting parameters that minimizes the surface roughness. There are two operating modes: pre-process and in process.
- Computation of the machining policy that minimizes the production cost.

5.1. Cutting parameters (off-line optimization)

One of the key tasks of the planning module is the computation of the optimal cutting parameters before the cutting operation (*off-line optimization*). Given a set of variables provided by the operator (C_C, P_C, P_G, Ra^d), the surface roughness (Ra^p) is estimated, and the cutting parameters are optimized with a Genetic Algorithm (GA). Figure 6 shows the detailed procedure.

5.2. Cutting parameters (on-line optimization)

The second key task of the planning module is the computation of the optimal cutting parameters during the machining process (*on-line optimization*).

Considering some process variables and the on-line estimated V_B, the actual surface roughness (Ra^p) is estimated. First, the difference between the Ra^p and the desired surface roughness (Ra^d) is computed:

$$\Delta Error = (Ra^p - Ra^d)/Ra^d$$

Based on this error and the previous feed per tooth $(f_{z,n-1})$, the new $f_{z,n}$ is re-computed:

$$f_{z,n} = f_{z,n-1} (1-\Delta Error)$$

Finally, the Ra^p is re-estimated on-line, based on current process variables and new cutting parameters. This iterative scheme can yield improved strategies for the next work-piece. Figure 7 shows the detailed procedure.

5.3. Machining Policy

The third key task of the planning module is the optimization of the machining policy, based on a minimization of the production costs. The policy, which generates guidelines for the operator, is limited to the available universe of variables of this problem (different Aluminum alloys, cutting tool diameters, and cutting tool wear condition).

A methodology based on the Markov Decision Process (MDP) [4] was here implemented. The key characteristic of a Markov model is a probability law in which the future behavior of the system is independent of the past behavior, given its current condition. Therefore, a MDP is a controlled stochastic process satisfying the Markov property with a cost assigned to state transitions. A solution to a MDP is a policy mapping states to actions, and that determines the state transitions to minimize the cost according to the performance criterion.
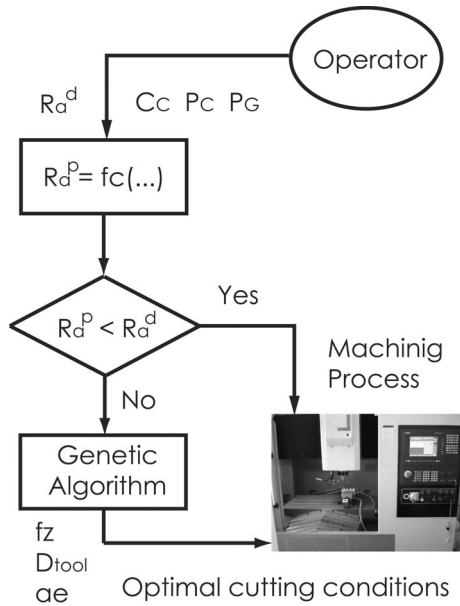

Fig. 6. Off-line optimization of cutting parameters.

A formal description of a MDP is as follows: $S = \{s_1, s_2, s_3, s_4, s_5\}$ is a finite set of states of the system. The possible states of the cutting tool wear condition are:

- s_1, new,
- s_2, half-new,
- s_3, half worn,
- s_4, worn, and
- s_5, tool fracture.

$A = \{a_1, a_2, a_3\}$ is a finite set of actions that the operator can take. The possible actions are:

- a_1, no action. This action represents an aggressive condition, because the operator uses the cutting tool until to reach the V_B maximum.
- a_2, change the cutting tool. It is a conservative condition, which implies to change the cutting tool when the Cutting Tool Module predicts the worn condition.
- a_3, stop the machine and inspect the cutting tool. It is an intermediate condition among the a_1 and a_2 conditions.
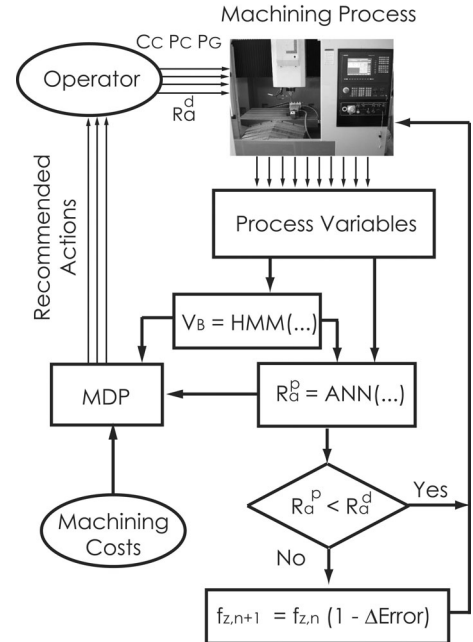

Fig. 7. On-line optimization of the cutting parameters and machining policy.

P: S x A is the state transition probability distribution function. For each action and state of the system, there is a probabilistic distribution over the states that can be reached after the actions. These transition matrices were defined to reach the tool fracture condition from any state of the cutting tool. The function $P(s|s',a)$ is defined as the probability of reaching state s starting in state s' and given action a. As shown in Figure 8, the transition matrices were computed by considering the evolution of the cutting tool life,

$$P_{a1} = \begin{pmatrix} 0.951 & 0.048 & 0 & 0 & 0.001 \\ 0.026 & 0.932 & 0.041 & 0 & 0.001 \\ 0.001 & 0.02 & 0.921 & 0.055 & 0.003 \\ 0 & 0.001 & 0.05 & 0.944 & 0.005 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

$$P_{a2} = \begin{pmatrix} 0.951 & 0.048 & 0 & 0 & 0.001 \\ 0.026 & 0.932 & 0.041 & 0 & 0.001 \\ 0.001 & 0.02 & 0.921 & 0.055 & 0.003 \\ 0.849 & 0.02 & 0.01 & 0.12 & 0.001 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

$$P_{a3} = \begin{pmatrix} 0.951 & 0.048 & 0 & 0 & 0.001 \\ 0.026 & 0.932 & 0.041 & 0 & 0.001 \\ 0.001 & 0.02 & 0.921 & 0.055 & 0.003 \\ 0 & 0.001 & 0.05 & 0.944 & 0.005 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

Additionally, the tool fracture was included to simulate a random failure of the cutting tool, which can happen at any time during the machining process.
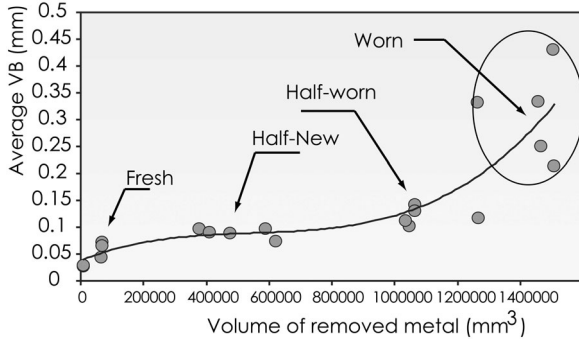

Fig. 8. Four states of the cutting tool condition can be identified. The measured V_B is a function of the removal metal v.

The instantaneous cost function f is defined for each action as:

- $fa_1 = \{44.15, 46.89, 49.28, 87.84\ 320.52\}$

- $fa_2 = \{44.15, 46.89, 49.28, 300.37\ 320.52\}$

- $fa_3 = \{49.2\ 51.94\ 54.32\ 52.59\ 320.52\}$

These cost functions were computed by considering: a) the decision cost for a right or wrong action (Decision Theory), b) operator costs, energy cost, and the operator labor, and c) the cost of the cutting tool. The cost function was defined for all the cutting tool wear conditions and for each action. For this demonstration, the cost functions were computed for 6082-T6 Aluminium alloy, cutting tool of 16 mm, and a machining time of 1.2 minutes.

R : S x A is a reward function for executing action a in the state s, assigning a real number for each action in each state of the system.

β defines a vector that maps the state space into the action space, that is, an action function, which assigns an action to each state. These are evaluated by the MDP algorithm to compute the optimal policy.

A stationary policy (π) is a policy that can be defined by an action function. The stationary policy is defined by the function β taking action $a(i)$ at time n, if $S_n = i$, independent of previous states, actions and time-steps. The set of all (decisions) policies is denoted by υ.

The Expected Discount Cumulative Cost will be used to compute the optimal minimum cost. The total discount factor problem is equivalent to using a present worth calculation on the basis of decision-making.

Let $\chi = \{x_n; n=0,1,...\}$ be a Markov Chain with Markov Matrix P. Let f be cost function and let α be a discount factor ($\alpha = 0.925$ is recommended). Then the expected total discounted cost is given by

$$E\left[\sum_{n=0}^{\infty} \alpha^n f(x_n)\Big| x_0 = i\right] = \left[(I - \alpha P)^{-1} f\right](i)$$

Therefore, the total expected discounted cost, under the probability law specified by the policy (π), is given by

$$v_\pi^\alpha = \left[(I - \alpha P_\pi)^{-1} f_\pi\right]$$

Thus, the discounted cost optimization problem can be stated as follows [4]:

Find π^α in ϑ such that $v_{\pi^\alpha}^\alpha(i) = v^\alpha(i)$ where the vector v^α is defined by

$$v^\alpha(i) = \min_{\pi \in \vartheta} v_\pi^\alpha(i)$$

The expected discounted cumulative cost with respect to a state i for a particular policy π and fixed discount factor α is defined by (for all i in S):

$$v_\pi^\alpha(i) = f_i^{\pi(i)} + \alpha \sum_{j \in S} P_{ij}^{\pi(i)} v_\pi(\textstyle\sum_\alpha |j)$$

The optimal total-cost function is defined as

$$v^*(\textstyle\sum_\alpha |i) = \min_\pi v_\pi(\textstyle\sum_\alpha |i)$$

which can be shown to satisfy the following optimality equations (for all i in S):

$$v^*(i) = \min_{k \in A}\left[f_i^k + \alpha \sum_{j \in S} P_{ij}^k v^*(\textstyle\sum_\alpha |j)\right]$$

The optimal policy can be found from the total-cost function as follows (for all i in S):

$$\pi^*(i) = \arg\min_{k \in A}\left[f_i^k + \alpha \sum_{j \in S} P_{ij}^k v^*(\textstyle\sum_\alpha |j)\right]$$

6. Experimental results

A further set of experiments was defined for different cutting conditions (see Table 3), in order to evaluate the system performance. The test pieces were designed to represent three typical geometries used in the molding industry (see Figures 9-11). The cutting conditions were defined to include central points, limit points, and external points into the domain. Also, the different workpiece materials were defined for these validation tests.
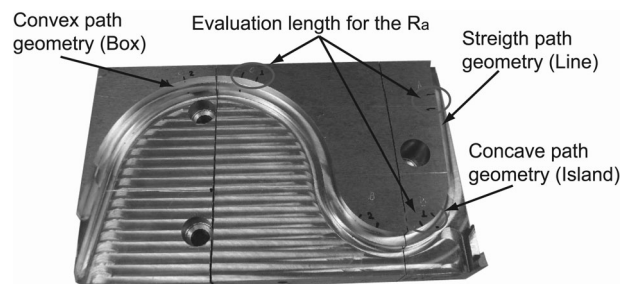

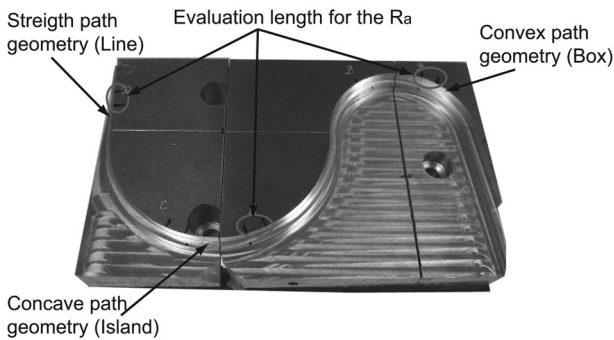Fig. 9. Test piece number 01 with the three machining geometries: straight, concave and convex paths.

Fig. 10. Test piece number 02 with the three machining geometries: convex, concave and straight paths.
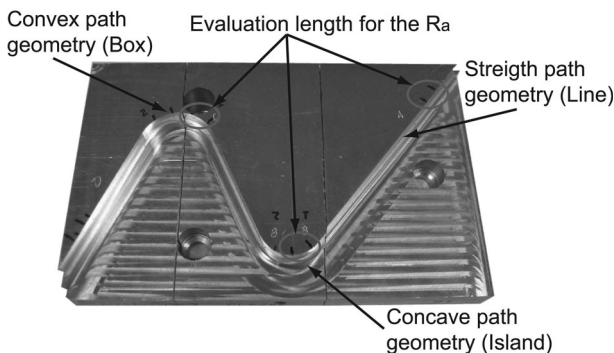

Fig. 11: Test piece number 03 with the three machining geometries: straight, concave and convex paths.

6.1. Off-line Optimization

The optimization step was validated with several tests.

1. An operator defines the cutting conditions, cutting and geometric parameters, and the desired Ra value.
2. The planning module computes the Ra^p under these conditions.
3. The GA computes the new cutting conditions (f_z) based on the difference between the Ra^p and Ra^d, Figure 13.
4. If the $Ra^p > Ra^d$, GA re-computes new cutting conditions based on f_z and D_{tool}, Figure 14.
5. If the $Ra^p > Ra^d$, GA re-computes the new cutting conditions now based on f_z and ae, Figure 15.
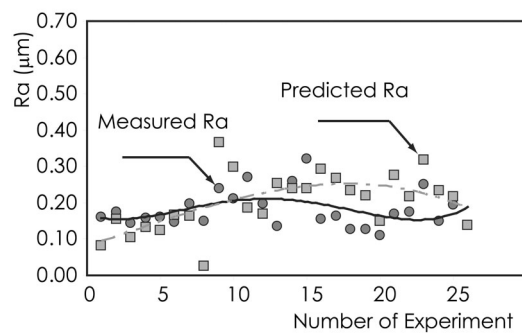

Fig. 12. Comparison between the measured and predicted Ra.

The GA was configured by 100 generations, 20 population sizes, 0.8 crossover probabilities, and 0.2 mutation probabilities. The feed per tooth ranged between 0.025-0.13 mm/foot, the radial depth of cut ranged between 1-5 mm and the cutting tool diameter 8-20 mm.

Table 3. Different cutting conditions, and geometric parameters defined for the new experiments(N: New, HN= Half-New, HW = Half-Worn, W: Worn, L: Line, I: Island, B: Box).

V_B	Experiment	f_z	ae	D_{tool}	HB	Curv
N	P_1-2024-L	0.075	3	12	109	0
	P_1-2024-I					0.037
	P_1-2024-B					-0.019
HN	P_3-2024-L	0.075	3	12	110	0
	P_3-2024-I					0.083
	P_3-2024-B					-0.556
N	P_4-2024-I	0.075	3	12	110	0.025
N	P_5-2024-B	0.075	3	12	109	-0.025
HN	P_1-5083-I	0.047	2	8	71	0.077
HN	P_1-7075-L	0.115	4.5	20	158	0
HW	P_1-6082-I	0.04	4	12	89	0.038
	P_1-6082-B					-0.0185
HW	P_2-6082-L	0.04	4	12	94	0
	P_2-6082-I					0.0385
W	P_2-7075-B	0.08	5	16	151	-0.0286
	P_2-7075-L					0
HW	P_3-7075-B	0.08	5	16	151	-0.0286
	P_3-7075-I					0.0222
	P_3-7075-L					0
W	P_1-CERTAL-B	0.04	4	16	144	-0.0185
W	P_9-2024-B	0.05	2	20	110	-0.0313
	P_9-2024-I					0.0208
HW	P_3-5083-L	0.05	2	16	67	0
	P_3-5083-I					0.0357
	P_3-5083-B					-0.0192

6.2. Machining Policy

The Markov Decision Process (MDP) was validated in the industrial HS-1000 Kondia machining center.
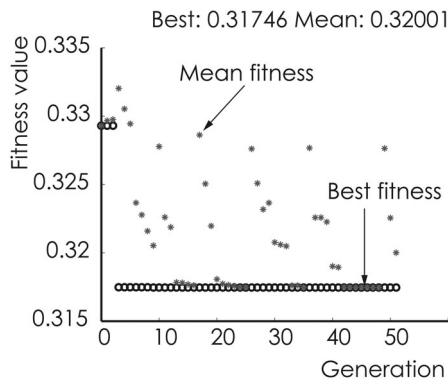

Fig. 13. Ra optimization based on f_z. GA computes the optimum cutting parameters.
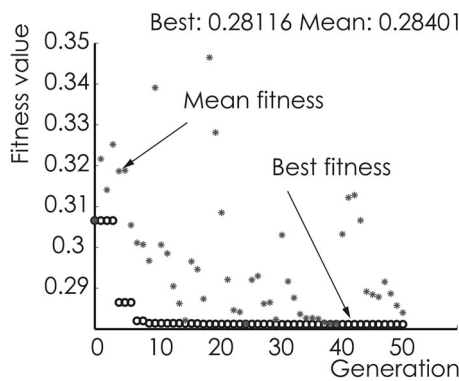

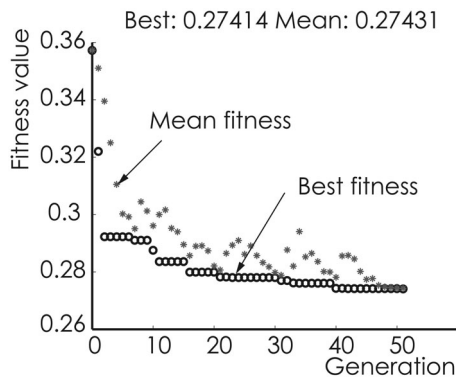*Fig. 14. Optimization based on f_z and D_{tool}.*

Fig. 15. Optimization based on f_z and ae.

The MDP can be solved using different algorithms: Police iteration and value iteration. The optimal total-cost function was computed based on the defined MDP and the information presented in section 5.3. The optimal total-cost function computed with the Policy iteration algorithm is given by

$$\upsilon^* = \{659.56, 704.04, 803.51, 868.92, 4273.6\}$$

The optimal policy (π) can be obtained by an iterating step that defines the actions of the operator that minimize the cost:

$$\pi = \{a_1, a_2, a_1, a_3, a_1\}$$

Based on this result, the recommendations are:

- For s_1 (new cutting tool condition) the action a_1 should be applied.
- For s_2, a_2 should be applied.
- For s_3, a_1 should be applied.
- For s_4, a_3 should be applied.
- For s_5, a_1 should be applied.

Given that MDP is a stochastic model defined by a Markov system, the transition matrixes and an initial distribution of the states (i.e., $\{s_1, 0, 0, 0, 0\}$) were simulated several times to illustrate the variability of the results.

Figure 16 shows two simulations given the Pa_1 (aggressive condition) and Pa_2 (conservative condition) matrixes. Figure 16 (top plot) shows a normal evolution of the V_B in the cutting tool, where the operator does not take actions and waits for a possible tool fracture when the cutting tool reaches the maximum worn condition. Figure 16 (bottom plot) depicts the conservative condition, where the operator decides to change the cutting tool if the worn cutting tool condition is detected during the machining process.

Figure 17 illustrates the results of the variability of the Markov system for 30 evaluations. The "box and whisker" plot shows the comparative costs between the different actions and the optimal policy determined by the MDP. The boxes have lines at the lower quartile, median, and upper quartile values. The whiskers are lines extending from each end of a box to show the extent of the rest of the data. The boxes are notched to represent a robust estimate of the uncertainty about the medians for box-to-box comparison. These results demonstrate that the optimal policy presents the lower costs when compared with the aggressive, intermediate, and conservative actions.
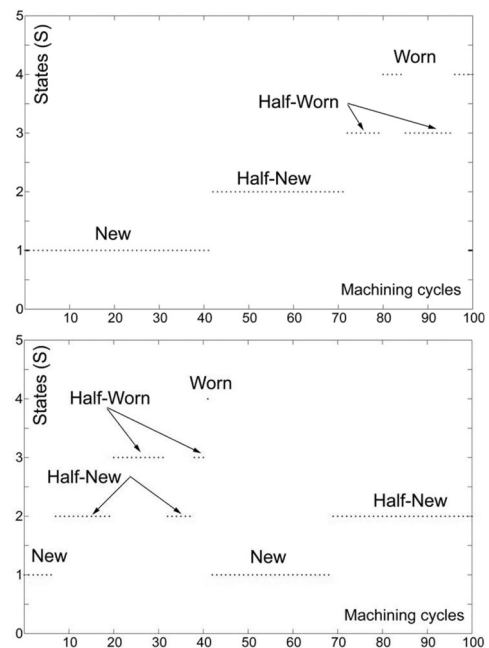

Fig. 16. Simulation of the Markov system with the two transition matrixes. Top plot presents an aggressive condition for the action a_1, and bottom plot a conservative condition for the action a_2.

It can be also observed that the machining policy based only on a_1, a_2 or a_2 have greater accumulated cost than the one yielded by the MDP for the 100 machining cycles. In Figure 17 (upper plot), the average accumulative cost for the 100 machining cycles is USD $4973.79, $4755.87, and $4385.18 for actions a_1, a_3, and optimal policy, respectively. Therefore, the potential savings are USD $588.6 and $370.7 for the a_1-optimal policy and a_3-optimal policy, respectively.
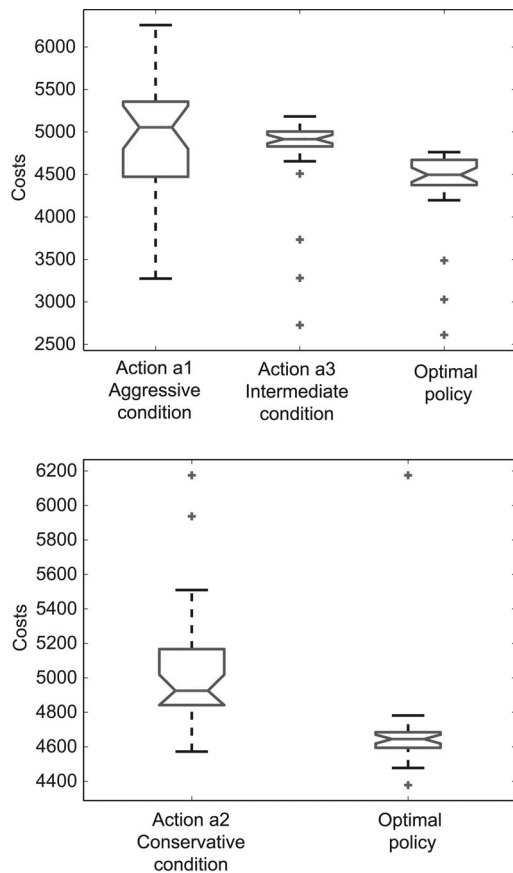

Fig. 17. Comparison of costs for the different actions and optimal policy by using the box a whisker plot. Results with Pa_1 (up plot) and Pa_2 (low plot) transition matrixes.

7. Conclusions

In this work, a planning module for High Speed Machining was designed and incorporated within an intelligent control system. This module is based on the Markov Decision Process (MDP) framework, yielding novel features in an optimization process. In particular, the MDP framework allows modeling decision-making under uncertainty where the actions of the operator are partly under control. Although early results are promising, the full integration of an MDP framework will require more research into the cross relationship between key variables. This will be investigated in future works.

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