Intelligent adaptive control of forces in milling processes.

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***Abstract*— Intelligent schedules has gained attention in manufacture environments due to increase competence. In this paper an intelligent adaptive discrete control is applied to a practical milling system in order to minimize process malfunctions. Two hierarchical supervisory levels compose the control: tuning and switching. The continuous unknown milling transfer function is discretized under a set of fractional order hold of correcting gains $\beta \in [-1,1]$ $(\beta - FROH)$ running in parallel. Each discrete plant parameter is tuned with a recursive least square algorithm. The correcting gain β of $(\beta - FROH)$ is switched within the given set in order to generate the optimal real control input to the plant through the minimization of a estimated error tracking performance index which evaluates the tracking error. The intelligent supervisory scheme chooses online the one with the smallest value has at each multiple of the residence time.**

I. INTRODUCTION

Milling is a cutting process widely used in the manufacturing of mechanical components. It is carried out by feeding a work-piece clamped on a table against a rotating multi-tooth cutter. In order to avoid machine malfunctions such as tool wear or breakage and to achieve a certain satisfactory degree of quality in the finishing of the working-piece, the peak cutting force on the working piece has to be maintained below a prescribed safety upper-bound. This fact implies that a control strategy has to be implemented in order to guarantee such safety and performance requirements.

Job-shops environments require adaptive techniques since tool-part combinations are different at each operation, batch and high volume environments are characterized by fixing or varying within a known range tool-part combinations [1]. *In this work, job-shop environments are taken into account to design the control scheme. It is supposed that the cutting parameters may be unknown or time-varying as a consequence of a complex milling geometry and the different operations to be performed. Thus, the control law should be able to attain the desired objectives even in the presence of uncertainties or variations in the system parameters. In this way, the nature of the system suggests to use an adaptive controller to address the milling force control problem.*

In the paper, the design of an intelligent adaptive control for milling processes is presented. It improves the behavior, specially the quality of the finishing process of the working piece through a more precise tool-work-piece interaction force control, in comparison with previous approaches. The milling system presented in [2] is considered to be approximately a linear plant with unknown time varying parameters which is a typical context in milling process.

The key point to achieve an improved behavior of the system is the use of sets of discretizations of the continuous plant running in parallel under different $\beta - FROH's$. Two hierarchical levels plan the algorithm. The first one tunes each parameter estimation vector through a suitable tuning algorithm (recursive least square, RLS), and, moreover, it can tune an optimal initial β-gain which let to better enhancement transient response behaviors [3]. The second one is related to implement switches through time to online select the correcting gain of the FROH and then the control input plant [8]. At this level, an identification performance index is defined and applied with the aim at finding the most appropriate value of β at each residence time in order to compare the various tracking errors. The framework chooses the identifier with the smaller index in order to parameterize the discrete control.

Hence, the intelligent control strategy is designed from the so obtained $\beta - FROH$-based discrete models, through the use of a correcting gain (not necessary with $\beta = 0$; i.e a ZOH) via a performance index.

The use of this kind of more complex control techniques is supported by the increasing competence in the manufacture field. Nowadays, machining processes are controlled on-line in contrast to the traditional CNC based systems, where the machining constant parameters are usually selected according to handbooks or operators´ experience leading to an 'ad-hoc' tuning of the control system. Furthermore, manufacturing environments are researching for more accurate controllers which lead to better surface finishing and/or higher production rates without damaging certain machine tool parts.

Previous works can be found in references [2,9-15]. In those papers, linear and time varying parameters models are widely used. Those models are dependent on the cutting parameters. Then, they will be time varying when complex parts are going to be milled. For this reason, adaptive control techniques are mainly employed to control the milling process. A successful application of the adaptive control to milling processes has potential machining-time savings, avoids tool wear and breakage, and enhances working piece finishing among other advantages.

II. SYSTEM DESCRIPTION

A. Continuous-time Model

The milling system can be modeled as the series decomposition of a Computerized Numerical Control (CNC), which includes all the circuitry involved in the table movement (amplifiers, motor drives), and the tool-work-piece interaction model itself. A feed rate command f_c (which plays the role of the control signal) is sent to the CNC unit. This feed rate represents the desired velocity for the table movement. Then, the CNC unit manages to make the table move at an actual feed velocity of f_a according to the CNC dynamics. Even though the machine tool drive servos are typically modeled as high order transfer functions, they can usually be approximated as a second order transfer function within the range of working frequencies [6]. Besides, they are tuned to be over-damped (i.e without overshoot), so that they can be modeled as the first order system [2]:

$$G_s(s)=\frac{f_a(s)}{f_c(s)}=\frac{1}{\tau_s s+1} \quad (1)$$

where f_a and f_c are the actual and command velocity values of the table in (mm/s) respectively and τ_s is an average time constant, which depends on the type of the machine tool. In this study, τ_s is assumed to be 0.1 ms.

In addition, the chatter vibration and resonant free cutting process can be approximated as the first order system [2, 6]:

$$G_p(s)=\frac{F_p(s)}{f_a(s)}=\frac{K_c ba(\phi_{st},\phi_{ex},N)}{N\cdot n}\frac{1}{\tau_c s+1} \quad (2)$$

where K_c $\left(N/mm^2\right)$ is the cutting pressure constant, b (mm) is the axial depth of cut, $a(\phi_{st},\phi_{ex},N)$ is a non dimensional immersion function, ranging from 0 to N, depending on the immersion angle and the number of teeth in cut, N is the number of teeth on the milling cutter and $n(rev/s)$ is the spindle speed. The axial deep of cut function b in (2) may be time-varying leading to a potential time-varying system. In particular, the cutting process is assumed to be piecewise constant, while admitting sudden changes in the cutting parameters at certain time instants and while remaining time-invariant between changes. This assumption allows us to consider the cutting process to be described by the transfer function (2) with the time interval between changes.

The combined transfer function of the system, obtained from (1) and (2) is

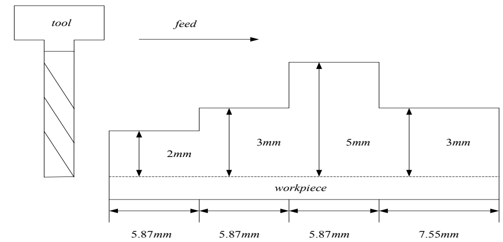

Figure 1: Work-piece profile to test control algorithms.

$$G_c(s)=\frac{F_p(s)}{f_c(s)}=\frac{B_c(s)}{A_c(s)}=\frac{1}{(\tau_m s+1)}\frac{K_c ab}{Nn(\tau_c s+1)}= \\ =\frac{K_p}{(\tau_m s+1)(\tau_c s+1)} \quad (3)$$

where the process gain is $K_p\ (N\cdot s/mm)=K_c ab/Nn$.

Figure 1 shows the sample work-piece depicting basic cutting geometry features with changes in the axial depth of cut used in the simulations. The spindle speed remains constant, $715rpm$; the work-piece is made of Aluminum 6067 whose specific cutting pressure is assumed to be $K_c=1200\,N/mm^2$. A 4-fluted carbide mill tool, full-immersed and rouging milling operation will be taken into consideration in the present paper.

Also, note that the desired final geometry of the piece to be milled involves changes in the axial depth of cut which implies suddenly changes of its value, according to the sudden changes assumption presented before. On the other hand, it has been taken into account that the control law computes new feed-rate command values at each sampling interval. Furthermore, it is worth to be mentioned that the CNC unit has its own digital position law executed at small time intervals in comparison with the sampled time of the control law, even though if high speed milling tool drives are used [2].

B. Discrete model under $\beta-FROH$

The problem of controlling a continuous plant is addressed by using a discrete-time controller. Such a discrete controller is obtained applying a model-reference pole-placement based control design to a discrete model of the plant (3) obtained by means of a FROH with a certain correcting gain β. The additional "degree of freedom" β provided by the FROH can be used with a broad variety of objectives such as to improve the transient response behavior, to avoid the existence of oscillations in the continuous time output during the inter-sample time intervals (i.e, ripple effects) of the system or to improve the stability properties of the zeros of the discretized system. Hence, the discretization of (3) under a FROH is formally calculated as :

$$H_\beta(z)=Z\left[h_\beta(s)\cdot G_c(s)\right] \quad (4)$$

where $h_\beta(s)=\left(1-\beta e^{-sT}+\frac{\beta\left(1-e^{-sT}\right)}{Ts}\right)\frac{1-e^{-sT}}{s}$ is the transfer function of a $\beta-FROH$, where z is the argument of the $Z-transform$, being formally equivalent to the discrete-time one-step ahead operator, q, used in the time domain representation of difference equations. This allows us to keep a simple unambiguous notation for the whole paper content. The sampling time T has been chosen to be inversely proportional to the spindle speed, *r*, as it is usual for this kind of systems [2,6, 10-12]. Note that when $\beta=1$, the $FROH$ hold becomes a first order hold (FOH) and the zero order hold (ZOH) is obtained for $\beta=0$, both being particular cases of the general FROH $\beta\in[-1,1]$. Furthermore, $H_\beta(z)$ may be calculated using just ZOH devices in the following way:

$$H_\beta(z)=\frac{B_\beta(z)}{z^{\delta_\beta}\cdot A(z)}=\frac{z-\beta}{z}Z[h_o(s)G_c(s)]+\frac{\beta(z-1)}{Tz}Z\left[h_o(s)\frac{G_c(s)}{s}\right]=$$

$$=\frac{B_\beta(z)}{z^{\delta_\beta}\cdot\left(z-e^{T/\tau_m}\right)\cdot\left(z-e^{T/\tau_c}\right)}\quad(5)$$

where $h_o(s)=\frac{1-e^{-sT}}{s}$ is the transfer function of a ZOH and $\delta_\beta=1$ if $\beta\neq 0$ and $\delta_\beta=0$ if $\beta=0$, which means that a fractional order hold with $\beta\neq 0$ always adds a pole at the origin.

C. Desired response: model reference

A second order stable system $G_m(s)=\frac{\omega_n^2}{s^2+2\xi\omega_n s+\omega_n^2}$ is selected as model reference exhibiting the suited closed-loop behavior. This system is characterized by a desired damping ratio, ξ and a natural frequency, ω_n. It is known that small value of ξ leads to a large overshoot and a large setting time. A general accepted range of values for ξ to attain a satisfactory performance is between 0.5 and 1, which corresponds to an under-damped system. Thus, a damping ratio of $\xi=0.75$ and a rise time, T_r, being equal to four spindle periods is usually selected for practical applications [2,13]. Furthermore, the natural frequency is that used for $\omega_n=2.5/T_r\ rad/s$. This continuous-time reference model is then discretized with the same FROH as the real system was in order to obtain the corresponding discrete-time reference model for the controller. *Then, a number of different discrete models obtained from a unique continuous reference model are considered depending on the value of β used to obtain the discretization. The overall parallel set is operated under supervisory switches*

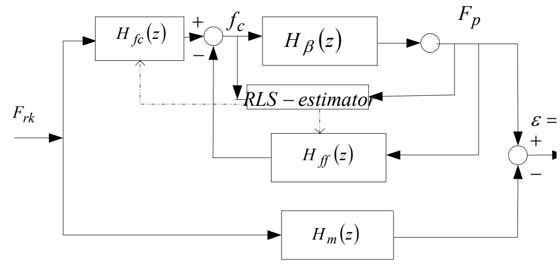

Figure 2: Basic adaptive model following control scheme.

through time to online select the active $\beta-FROH$ which parameterizes the adaptive controller.

III. CONTROL SCHEME

The intelligent control is based on adaptive model following control scheme. Then, firstly, it is explained to a better understanding of the intelligent framework.

A. Basic model following adaptive controller

The aim of the model-following control strategy is to force the closed-loop system to behave as a prescribed reference model. Thus, the following control scheme of Figure 2 is taken into consideration, where $H_{ff}(z,k)=\frac{S(z,k)}{R(z,k)}$ is the feed forward filter from the reference signal, $H_{fb}(z,k)=\frac{T(z,k)}{R(z,k)}$ is the feedback controller, $H(z,k)$ is the discrete plant, $H_m(z,k)$ is the model reference and F_{rk} is the reference force, where recursive least square estimation algorithm is used.

The transfer function of the reference model is,

$$H_m(z)=\frac{B^-(z)B_m^{'}(z)A_o(z)}{A_m(z)A_o(z)}=\frac{B_m(z)A_o(z)}{A_m(z)A_o(z)}\qquad(7)$$

where $B_m^{'}(z)$ contains the free-design reference model zeros, $B^-(z)$ is formed by the unstable (assumed to be known) plant zeros, $B^+(z)$ is the monic polynomial of stable plant zeros and $A_o(z)$ is a stable monic polynomial including the eventual closed-loop stable pole-zero cancellations which are introduced when necessary so as to guarantee that the relative degree of the reference model is non less than that of the closed-loop system so that the synthesized controller is causal. $A_m(z)$ is also stable and monic. Then, the polynomials $R_k^{(l)}, S_k^{(l)}$ and T (T depend only on the reference model zeros polynomial which is of constant coefficients) have to be synthesized for each l^{th} controller where $T=B_m^{'}A_o$ and $R_k^{(l)}$ (monic), $S_k^{(l)}$ are unique solutions with degrees fulfilling

$\deg\left(R_k^{(l)}\right) = n, \deg\left(S_k^{(l)}\right) = n-1, \deg\left(A_m A_o\right) = 2n-1$,
$l = 1,2,..n$
of the polynomial Diophantine equations

$$\hat{A}_k^{(l)} R_k^{(l)} + \hat{B}_k^{(l)} S_k^{(l)} = \hat{B}_k^{(l)+} A_m A_o \Leftrightarrow \tag{8}$$
$$\hat{A}_k^{(l)} R_{1,k}^{(l)} + B^- S_k^{(l)} = A_m A_o$$

which have unique solutions for the above polynomial degree constraints provided that $\left(\hat{A}_k^{(l)}, \hat{B}_k^{(l)}\right)$ are all co-prime for $l = 1,2,..,n_l$ with $R_k^{(l)} = \hat{B}_k^{(l)+} \hat{R}_{1,k}^{(l)}$ and for all $1 \le l \le n_e$ at every sampling instant, being n_l the number of estimation schemes /adaptive controllers parameterizations. n=2 if a ZOH is used in view of the second order milling plant and reference model are not specifically continuous-time transfer function. For the cases when the FROH is used not being ZOH, n=3 since a new pole at the origin is automatically added to the discretized plant.
From (7)-(8), perfect matching is achieved through the control signal:

$$f_{c,k} = \frac{\hat{T}}{\hat{R}_k} F_{r,k} - \frac{\hat{S}_k}{\hat{R}_k} F_{p,k} \tag{9}$$

B. Multi-estimation scheme

The parallel multi-estimation scheme is composed of n_e different estimators. Each estimator is used to identify a different discretization of the continuous plant under an associate $\beta - FROH$. The main idea for the scheme implementation is that all the estimator/controller pairs are running in parallel at the same time while calculating each estimated control law, but only one of them, which is the active one for control purposes, actually generates the control law. In this way, each controller parameterization is updated for all time although only one is generating the control signal. The strategy is to use the controller

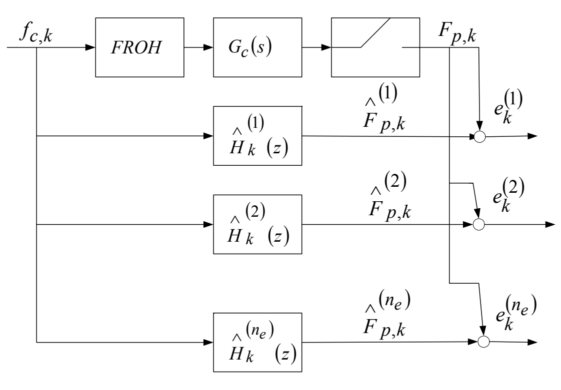

Fig. 3: Multi-estimation scheme

parameterization obtained from the best estimation model at each time interval according to the tracking error supervisory action. The closed-loop stability is guaranteed if the time interval between consecutive switchings is larger than an appropriate residence time [8]. The estimated output for each l^{th} identifier can be calculated as,

$$\hat{y}_k^{(l)} = \hat{\theta}_k^{(l)T} \varphi_k^{(l)} \text{ for } 1 \le l \le n_e \text{ and all } k \ge 0$$

where $\hat{\theta}_k^{(l)}$ and $\varphi_k^{(l)}$ are the parameter estimation vector and associate regressor, respectively. For each estimator, $\hat{\theta}_k^{(l)}$ possesses the discrete estimated parameters of each discretization of the continuous transfer function in the parallel multiestimation scheme and the regressor is composed by the plant input and output signals at different sampling times.

Figure 3 shows a multi-estimation scheme, where the estimated outputs are compared with the real plant output. $H^{(i)}(z)$ for $1 \le i \le n_e$ denotes the set of the plant discrete transfer function under the various discretizations with different values of the β correcting gains of the FROH, while $\hat{H}_k^{(i)}(z)$, $i = 1,..,n_e$ denote their corresponding estimated transfer functions at k^{th} sampling instant.

IV. Intelligent Framework

In this section, an intelligent framework is designed. The purpose of the framework is to organize the control steps. It is composed by two hierarchical supervisory levels, tuning and switching.

A. Hierarchical level 1: Tuning

At the same time, this hierarchical level is composed by two sub-levels: tuning the estimation vector parameters and tuning the initial β-value.

Sub-level 1: The estimation vector is tuned by the recursive least square estimation algorithm at each sampling instant,

$$\hat{\theta}_{k+1}^{(l)} = \hat{\theta}_k^{(l)} + \frac{P_k^{(l)} \varphi_k^{(l)} e_k^{(l)}}{1 + \varphi_k^{(l)} P_k^{(l)} \varphi_k^{(l)}} ; \hat{\theta}_o^{(l)} \ arbitrary,$$

provided that $tr\left(\hat{A}_o, \hat{B}_o\right)$ is a co-prime pair,

$$P_{k+1}^{(l)} = P_k^{(l)} - \frac{P_k^{(l)} \varphi_k^{(l)} \varphi_k^{(l)T} P_k^{(l)}}{1 + \varphi_k^{(l)} P_k^{(l)} \varphi_k^{(l)}} ; P_o^{(l)} = P_o^{(l)T} > 0$$

where $e_k^{(l)} = F_{p,k} - \hat{F}_{p,k}^{(l)}$ is the identification error for the k^{th} sample $\forall l \in N_e = \{1,2,..,n_e\}$.

Sub-level 2: The selection of the initial β-value, which the plant is first discretized for, plays an important role since the initial parameter vector is selected in a random way, and the choice of an adequate initial β gain parameter let the operator to enhance transient behavior [3]. There is not a rule of trump for tuning an appropriate initial β -value of the FROH. Machine tool operators´ experience can help for this purpose or the developed cost function in [3] can be used as alternative, as well.

B. Hierarchical level 2: Switching

The input to the plant $f_{c,k}$ is chosen by the switching rule. For this purpose, a supervisor is defined. The objective of the supervisor is to evaluate the performance of the possible controllers connected to the plant with the aim of choosing the current controller from the set of parallel controllers. The proposed estimated tracking error performance index, for switching supervisory purposes is,

$$J_k^{(l)} = \sum_{j=k-M}^{k} \lambda^{k-j} \left(F_{pm,k} - \hat{F}_{p,k}^{(l)} \right)^2$$

The switching rule for the adaptive control re-parameterization is obtained from the performance index as follows, let switching sampling times sequence be denoted by $TS = \{t^{(1)}, t^{(2)}, \ldots, t^{(p)}\}$ where p is the number of switchings and $\left(t^{(i+1)} - t^{(i)}\right) \geq \tau_r = N_r T$, a known minimum residence time (or if it is unknown, then, it is replaced with some available upper-bound), for all $t^{(i)}, t^{(i+1)} \in TS$. Thus, the c_k – estimation scheme with $1 \leq c_k \leq n_e$, which parameterizes for all $k \geq 0$ the basic adaptive controller at any switching time in TS is updated as follows. Assume that the last switching time for the controller re-parameterization was $t^{(i)}$. Thus, for each current k^{th} sampling time, define the auxiliary integer variable:

$\overline{c_k} = \arg\left[i : J_k^{(i)} = \min\left(J_k^{(j)}\right), i, j \in n_e\right]$, for all integer $k \geq 1$

if $kT \geq t^{(i)} + \tau_r$ then $c_k \leftarrow \overline{c_k}$ end_if

if $c_k \neq c_{k-1}$ then $t^{(i+1)} \leftarrow kT$ and modify $TS \leftarrow \{TS, t^{(i+1)}\}$ end_if.

It is known that there is always a minimum residence time that ensures the closed loop stability provided that it is respected between consecutive estimation scheme switches. This value could be obtained from an ‘a priori’ knowledge or from experimental research.

V. SIMULATION RESULTS

Exhaustive worked out simulations have been developed for the milling system, applying to it the explained intelligent control building from a set of candidate correcting gains of $\beta - FROH$ devices with correcting gains, $\{-0.5, -0.3, 0, 0.3, 0.5, 0.8, 1\}$,and sampling time being inversely proportional to the spindle speed, $T = 1/r$, $r = 715/60\, s^{-1}$.

The transfer function of the milling system used in simulations is $G_c(s) = \dfrac{1}{(\tau_m s + 1)} \dfrac{K_c ab}{Nn(\tau_c s + 1)}$, with $K_c = 1200\, kN/mm$, $\tau_s = 0.1 ms$, $\tau_c = 1/Nn$, $N = 4$, $n = 715 rpm$ and a and b are variables with the milled part and milling operation.

The system introduces an unstable pole when $\beta < -0.6$, these cases have not been taken into consideration in this paper with the choice of the above set of correcting gains β .

The estimated vectors have been directly initialized from the corresponding discretization of the estimated continuous transfer function,

$$G(s) = \frac{-3s + 150}{s^2 + 20s + 550}$$

obtaining the set of parameter vectors $\theta^{(i)}$, $i = 1,2,..7$ corresponding to one gain β within the

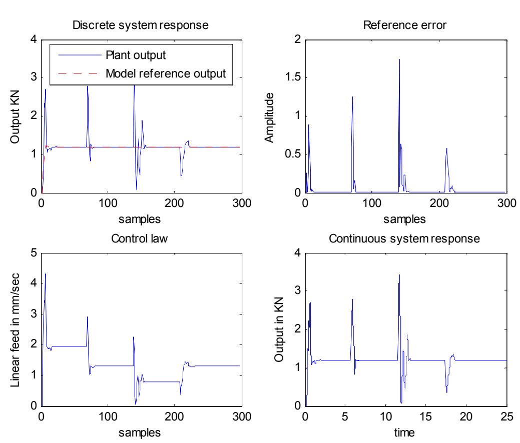

Figure 4: Output responses using the intelligent control.

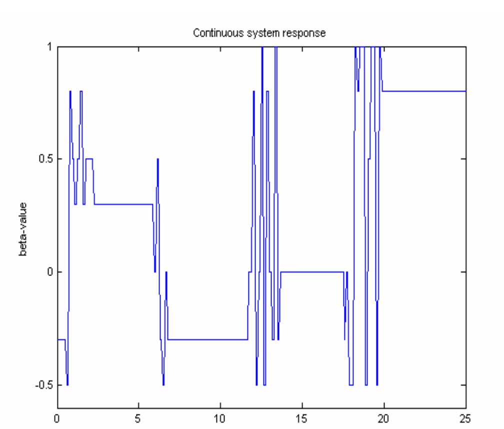

Figure 5: Active beta using the intelligent control.

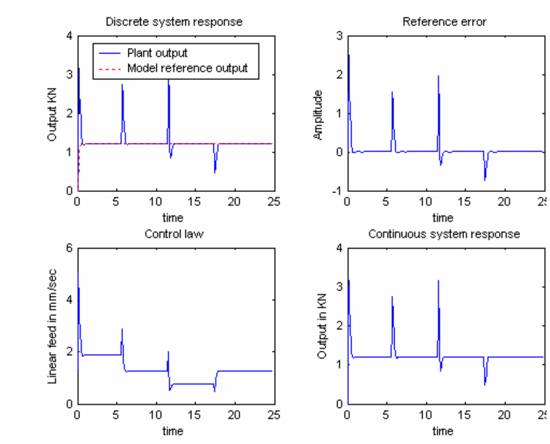

Figure 6: Output responses just using a ZOH.

set, $\{-0.5,-0.3,0,0.3,0.5,0.8,1\}$. The residence time is chosen to be two sampling periods. The sampling period is, $T = 0.0839s$, the reference signal is set to 1.2KN, and the reference continuous transfer function is $G_m(s) = \dfrac{98.62}{s^2 + 15.89s + 98.62}$.

For the each developed control, four output figures are plotted. The first one depicts the model reference and the plant output signals versus sample time; the second one shows the evolution of the tracking error signal, $\left(e = \hat{F}_p - F_{pm} \right)$; the third figure represents the controller response and, finally, the fourth graphic shows the continuous-time domain system response obtained using the $\beta - FROH$. The figures show that the steady-state force tracks the reference force which is set to $1.2\,KN$, except for the peaks appreciated when the axial depth of cut, and then the transfer function, is suddenly altered and in the transient response. The programmed feed rate is feasible and the transient response is normally oscillating with a great maximum overshoot and large setting time. In any case, the designed intelligent control can help to reduce large overshoots in the system´s response.

On the other hand, there are abruptly and oscillating overshoots in the output when the axial depth of cut changes suddenly. This characteristic is due to the intrinsic structure of the closed-loop output. The main purpose of this paper is not either reducing or avoiding these jumps. Some ‘a priori’ information about the work-piece geometry is required to design a successful control, as in [12], where a CAD model of the work-piece is used to modify the control command when the axial depth of cut changes in order to minimize the overshoots due to abrupt changes in the transfer function.

In this paper, the control scheme is handled to show that the system transient response can be enhanced with respect to the use of ZOH. This can lead to avoid overloading of the insert, because the maximum removed chip-thickness would not increase the principal tensile stress in the cutting wedge beyond the ultimate tensile strength of the tool material, this can also lead to prevent a fracture of the shank, and fulfill the machine tool requirements, such as power and torque availability [10]. Moreover, if the reference force is selected near the tool breakage limit, the large overshot lead to tool breakage [13,14]. Then, if the overshoot of the system response is reduced, the reference force can be increased, improving the time production requirements.

The maximum overshoot of the continuous-time system response is selected as index to compare the transient response when the intelligent framework is programmed and when only a unique ZOH device is used in the control scheme of figure 2. Simulation results predict a better peak transient response behavior when the intelligent control is used respect to the control scheme of figure 2 under ZOH discretization in a broad range of initial parameter vector. Figure 4 displays the outputs of the supervised intelligent control tuning the initial value of β to -0.3, [3]. The overshoot of the force is enhanced respect to use a ZOH device (figure 6). In this way, the developed intelligent adaptive control can lead to reduce the transient response overshoot in a broad range variety of the initial parameter vector. Moreover, the intelligent scheme possesses inherent attractive properties of the basic adaptive control scheme (i.e, without using switches) under ZOH discretization, which makes this control strategy more versatile since the basic scheme can be considered within the general framework of intelligent schemes. Figure 5 displays the switches of the active β value through time.

VI. Conclusions

In this work, an intelligent adaptive discrete control to milling process has been presented. The proposed models to be estimated are obtained from the set of discretizations of a continuous transfer function under a $\beta - FROH$. The intelligent framework is designed to tuning the parameter vector at each sampling instant, as well as switching the value of the gain β which leads to the best tracking performance. The method selects the current value of the gain among a fixed set of possible values according to a online switching rule which is based on a supervisory estimated tracking error index. The proposed method has been applied to a practical milling process while improving transient response peak in a broad range of initial parameter vector.

On the other hand, the general FROH can be implemented by means of ZOH, which make this approach fairly feasible to be implemented in the manufacturing industry [16,17]. Then, an easily implemented device and the developed control strategy can lead to save machining time in the production process, avoid some process malfunctions or damage the tool less than if just a ZOH device is used.

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REFERENCES

[1] R.G. Landers, A.G. Ulsoy and Y.M. Ma, "A comparison of model-based machining force control approaches", International Journal of Machine Tools & Manufacture, 2004, vol. 44, pp.733-748.

[2] Y. Altintas, "Manufacturing Automation", Cambridge University Press, 2000.

[3] L. Rubio and M. De la Sen, "Discrete time model reference control of milling forces under fractional order holds. Part II: Extensions to Adaptive Control" In Proceedings of the ETFA 2006, pp.1005-1008.

[4] Y. Altintas, I. Yellowley and J. Tlusty, "The Detection of Tool Breakage in Milling Operations", Journal of Engineering for Industry, November 1988, Vol. 110.

[5] Y. Altintas, "Prediction of Cutting Forces and Tool Breakage in Milling from feed drive current measurements", Journal of Engineering for Industry, pp.386-392, November 1992, Vol. 114.

[6] K.S.Narendra and J. Balakrishnan, "Improving Transient Response of Adaptive Control Systems using Multiple Models and Switching", IEEE Transactions on Automatic Control, Vol. 39, nº9, pp. 1861-1866, 1994.

[7] K.S.Narendra and J. Balakrishnan, "Adaptive Control Using Multiple Models", IEEE Transaction on Automatic Control, Vol. 42,nº23,pp.171-187, 1997.

[8] A. Ibeas, M. De la Sen, and S. Alonso-Quesada, "A multiestimation scheme for discrete adaptive control which guarantees closed-loop stability", Proc. of the sixth WSEAS Multi-conference on Systems, pp.6301-6308, 2002.

[9] L.K. Lauderbaugh and A.G. Ulsoy, "Dynamic Modeling for Control of the Milling Process", Journal of Engineering for Industry, November 1988, Vol. 110.

[10] L.K. Lauderbaugh and A.G. Ulsoy, "Model Reference Adaptive Force Control in Milling", Journal of Engineering for Industry, February 1988, Vol. 111.

[11] A.Spence and Y. Altintas, "CAD Assisted Adaptive Control for Milling", Transaction of the ASME, September 1991, Vol. 113.

[12] Peng, Y.H., "On the performance enhancement of self-tuning adaptive control for time-varying machining processes", International Journal of Advanced Manufacturing Technology, pp. 395-403, 2004, 24.

[13] Y.Altintas, F. Sassani and F. Ordubadi, "Design and Analysis of Adaptive Controllers for Milling Process", Transaction of the CSME, pp.17-25, no.1/2, 1990, Vol. 14.

[14] Y.Altintas and C.C.H. Ma, "Direct Adaptive Control of Milling Force", IEEE International Workshop on Intelligent Motion Control, Istambul 20-22 August 1990.

[15] Y. Altintas, "Prediction of Cutting Forces and Tool Breakage in Milling from feed drive current measurements", Journal of Engineering for Industry, pp.386-392, November 1992, Vol. 114.

[16] R. Barcena, M. De la Sen and I. Sagastabeitia, " Improving the stability properties of the zeros of sampled systems with fractional order hold ", IEE Proceedings-Control Theory and Applications, 147(4); 456-464, Jul 2000.

[17] R. Barcena, M. De la Sen, I. Sagastabeitia and J.M. Collantes, " Discrete control for a computer hard disk by using a fractional order hold device ", IEE Proceedings-Control Theory and Applications, 148(2); 117-124, Mar 2001.