INTELLIGENT CONTROL OF MACHINING UNDER MODELING UNCERTAINTY

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ABSTRACT

Optimization of machining operations is important for increased productivity. However, modeling inaccuracy in the form of bias and noise and the time-variability of machining processes due to tool/wheel wear precludes the application of traditional optimization methods. As a remedy, Adaptive Control Optimization (ACO) is proposed where the machine settings are adjusted according to feedback from the process so as to compensate for modeling inaccuracy. However, the present ACO systems still rely on models to represent various aspects of machining, and are therefore unsuitable for practical application. In this paper, the method of recursive constraint bounding (RCB2) is presented, which allows for inaccuracy in all components of the model by assigning confidence levels to estimates of individual constraints. RCB2 modifies the model based on measurements of part quality attributes. After each cycle, RCB2 determines the slack in part quality constraints. It then adapts the model for the next cycle so that it yields a more aggressive set of machine settings when optimized by nonlinear programming. The application of RCB2 is demonstrated in simulation for a turning operation, where it is shown to incrementally reduce cycle-time towards its minimum value despite inaccuracies in the model, the presence of noise in the simulated values of part quality, and time-variability of the process due to progression of tool wear.

1 INTRODUCTION

The advent of Computer Numerical Control (CNC) has made possible adaptation of machine settings on-line so as to improve the process. An important requirement in such adaptation is that the measurements of process and part quality remain within their specified limits (constraints), so that part integrity is ensured. One adaptation strategy in machining is Adaptive Control with Constraints (ACC), which aims to regulate the process by maintaining the magnitude of the power or cutting force at a prespecified level [3, 9, 11, 12]. Although, ACC is a promising strategy for avoiding interruptions in the cut due to tool breakages or safeguarding against workpiece burn, it does not explicitly improve process efficiency in terms of production cost or time.

The adaptation strategy that addresses process efficiency explicitly is referred to as Adaptive Control Optimization (ACO) [1]. In ACO, the machine settings are adapted in response to part and/or process feedback so as to minimize production cost or cycle-time. As such, ACO adopts an interactive approach to process optimization, as the mechanism to cope with modeling inaccuracies which preclude the use of analytical optimization. Modeling inaccuracy in machining arises from: 1. the diversity of machining conditions such as material properties, tool/wheel type, and lubricant on/off, 2. their stochastic nature due to material inhomogeneity, workpiece misalignment, and measurement noise, and 3. their time-variability due to tool/wheel wear.

The first attempt at ACO was the Bendix System [2], where measurements of cutting torque, tool temperature, and machine vibration were used as feedback to continually maximize the removal rate through changes in the feed-rate and spindle speed. The constraints of the problem were defined as the maximum and minimum spindle speed, maximum torque, maximum feed, maximum temperature, and maximum vibration amplitude. The main drawback which hindered the use of the Bendix System in production arose from its need for estimation of tool wear. Generally, accurate estimation of tool wear requires an accurate model which can only be obtained empirically through extensive experimentation. The cost associated with such experiments usually surpasses the potential savings expected through optimization.

A significant advancement to the Bendix System was the ACO strategy of Amitay et al. [1], where estimation of tool wear was bypassed. In this strategy, which was later generalized by Koren as the Optimal Locus Approach [7], the true optimum of the process is defined as the point where the

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update the model for the nonlinear program so that the cycle can be gradually moved towards its optimal point without violating constraints.

RCB_2 reduces cycle-time through removing the slack in constraints, characterized by the distance of part quality measurements from their allowable limits. Ideally, the whole constraint slack should be removed to achieve minimum cycle-time. However, the estimated slacks are generally inaccurate, corrupted by noise in the measurements of part quality and modeling bias. As such, only a portion of the slack is removed by *RCB_2* from cycle to cycle. The amount by which the slack is reduced is determined based on noise estimates and the level of confidence ascribed to each modeled constraint. In order to determine the machine settings that will remove the intended slack portions, the model is modified. This modification is performed by re-defining the constraint relationships for the next cycle as

$$g'_n(x(j+1)) \le 0 \tag{5}$$

where

$$\begin{aligned} g'_n(x(j+1)) &= \\ &= g_n(x(j+1)) - g_n(x(j)) - b(j+1) \end{aligned} \tag{6}$$

The above relationship defines $g'_n(x(j+1))$ in terms of the nominal modeled constraints g_n and a *buffer value* $b(j+1)$ representing the portion of the slack to be removed. By gradually reducing the *buffer values* after each iteration and re-applying the nonlinear program, *RCB_2* reduces the cycle-time while ensuring constraint satisfaction. The salient feature of *RCB_2* is its elaborate determination of the *buffer values* such that its performance in the presence of modeling bias and noise will be robust.

The conceptual significance of *buffers* is illustrated in Figure 1 for a hypothetical constraint. In this figure, the top of the gray area represents the allowable limit of the constraint, and its bottom denotes this limit when noise is taken into consideration. When the constraint falls in the gray area, it is considered tight. The *bullets* in this figure mark the constraint values after each cycle, whereas the dotted arrows point to the buffered limits of the constraint in successively modified models. For each cycle, a nonlinear program is used to obtain the optimal settings, which tighten the modeled constraints up to their buffered limits. Since the modified models do not accurately represent the actual process due to the presence of noise and modeling bias, the optimal settings do not necessarily tighten the actual constraints precisely to their buffered limits. As shown in Figure 1, the actual constraint value may be below the buffered limit (cycle #3) or above it (cycle #4).

The main task of *RCB_2* is to determine the buffered constraints such that the actual constraints will not be violated. For this, *RCB_2* utilizes bounds of noise to estimate the maximum offset in measurements of various constraint values, and adopts confidence levels to represent the degree of uncertainty in individual constraints. In order to leave a safety margin for noise, a "worst-case" scenario is considered where each constraint measurement $g_a(x)$ is assumed to correspond to the lower level of its noise distribution. That is, it is assumed that the largest constraint measurement possible from the same set of control variables **x** would be at most equal to the current measurement value plus the width of the noise distribution n_R:

$$\max g_a(x(j)) = g_a(x(j)) + n_R \tag{7}$$

The $\max g_a(x(j))$ defined by Eq.(7) represents the maximum possible value of the constraint for the present cycle. However, in order to determine the machine settings for the next cycle such that the constraints will not be violated, the maximum constraint value for the next cycle ($\max g_a(x(j+1))$) needs to be estimated.

Let us first consider noise as the only source of uncertainty. In this case, $\max g_a(x(j+1))$ would be equal to the maximum possible constraints values for the present cycle ($\max g_a(x(j))$) plus the change in the *modeled* constraint value between the two cycles:

$$\Delta g_n = g_n(x(j+1)) - g_n(x(j)) \tag{8}$$

or

$$\max g_a(x(j+1)) = \max g_a(x(j)) + \Delta g_n \tag{9}$$

Now, for the measured constraints from the next cycle to satisfy Eq.(2), they have to abide by the relationship

$$\max g_a(x(j+1)) \le 0 \tag{10}$$

which when combined with Eq.(9), yields

$$\Delta g_n \le -\max g_a(x(j)) \tag{11}$$

The above equation when generalized according to Eq.(7), gives

$$\Delta g_n \le -[g_a(x(j)) + n_R] \tag{12}$$

which is significant in that it defines the maximum possible change in the modeled constraint value for the next cycle in terms of the present value of the constraint, when noise constitutes the only source of uncertainty.

The change in the modeled constraint value defined in Eq.(12) characterizes the amount that the constraint can be tightened when noise is considered alone. In order to account for modeling bias, *RCB_2* considers the degree of confidence, $c \in [0, 1]$, associated with the modeled value of each constraint to define the *buffer value* representing the portion of the Δg_n to be removed in the next cycle, as

$$b(j+1) = -c[g_a(x(j)) + n_R] \tag{13}$$

Substituting the above equation as the right hand side of Eq.(12) gives

$$\Delta g_n \le b(j+1) \tag{14}$$

which using Eq.(8) can be redefined as

One of the motivations for designing RCB_2 is to cope with modeling bias. Modeling bias was reflected in simulation by randomly selecting the value of each of the parameters k_1 - k_{10} from their corresponding range of values $[k'_i(1 - b_i), k'_i(1 + b_i)]$ before each run. The nominal value of each parameter, k'_i, was set as in Table 1, and its bias factor, b_i, was set at 0.1. Also, to simulate noise in measurements of surface roughness and power, n_1 and n_2 in Eqs.(17) and (18) were selected randomly for each cycle from a uniform distribution of [0.9, 1.1].

In practice, RCB_2 will be used to reduce cycle-time based on measurements of process and part quality at the end of each cycle. For this study, Eqs.(17)-(20) and the wear relationships in [6] were used to compute the measurements that would in practice be obtained from the process. The first cycle of each test was begun with conservative values for the control variables. Values for the power and surface roughness were then obtained through simulation. Based on these values, RCB_2 determined the control variables for the next cycle, with the objective of reducing the cycle-time while satisfying constraints.

The performance of RCB_2 was examined under various conditions. The first study was for a large depth of cut, where tool wear progressed so rapidly that it was necessary to change the tool after each cycle. As such, in the first study there was no distortion of the feasible region due to tool wear. For the first cycle, the control variables were selected conservatively as [v, f, d] = [70, 0.1, 2.54], which resulted in the constraint values

$$[g_{m1}, g_{m2}] = [-2.15, -2.13]$$

Using these simulated constrained values and confidence levels of 0.5 for both the power and surface roughness constraints, the buffer values for the next cycle were obtained by RCB_2 according to Eq.(13) as

$$b^T = [0.69, 0.59]$$

These buffer values were then incorporated into the nominal model (Eqs.(16)-(20)), to obtain a modified model (see Eq.(6)) that was used to determine the next set of control variables through nonlinear programming. The following cycles were simulated in a similar fashion, each using a new set of control variables determined by RCB_2. The progression of the control variables selected by RCB_2 within the feasible region is shown in Figure 4. The results indicate that the control variables move towards the optimal point from cycle to cycle without violating the constraints despite the approximate nature of the model and presence of noise in the measurements. The control variables, simulated constraint values, and cycle-times for ten cycles of this run are given in Table 2.

Next, the effect of confidence levels on the speed of convergence of RCB_2 was studied. For this, runs were performed with various confidence levels for the power and surface roughness constraints. The cycle-times from three runs with confidence levels 0.1, 0.5, and 0.9 are shown in Figure 5. The results indicate that although the convergence rate of RCB_2 was improved by increasing the magnitude of the confidence levels, the differences in cycles times were practically insignificant after the first few cycles. However, the rapid convergence rate associated with higher confidence levels does not come without a price, since larger confidence levels correspond to greater risks for constraint violation. One case of constraint violation is shown in Figure 6, where a

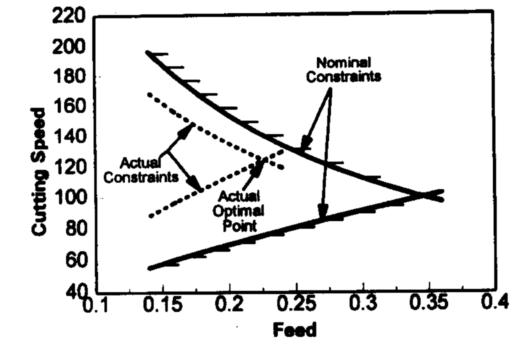

Figure 3 - Distortion of the turning problem space by modeling bias

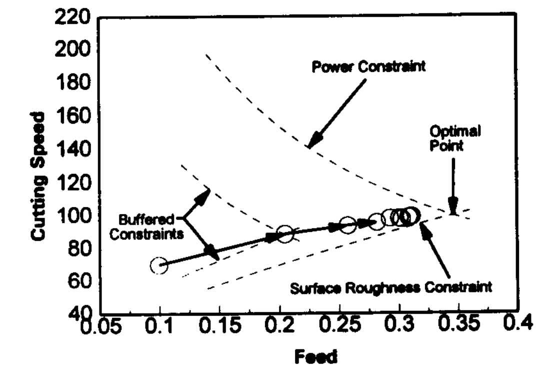

Figure 4 - Gradual reduction of cycle-time in the turning operation by RCB2

Table 2: Summary of RCB2 test results

Cycle	Cutting Speed, v	Feed, f	g_{m1}	g_{m2}	Time, t
1	70.00	0.100	3.85	1.87	138
2	88.64	0.205	5.28	2.84	108.8
3	93.85	0.258	5.15	3.17	102.2
4	95.78	0.280	4.70	3.37	98.5
5	98.11	0.290	4.95	3.01	96.4
6	98.18	0.301	5.38	3.75	95.6
7	97.61	0.303	5.72	3.37	95.6
8	98.83	0.309	4.85	3.52	95.6
9	99.12	0.310	4.90	3.53	95.6
10	99.35	0.311	5.65	3.43	95.6

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