Cycle-Time Reduction in Machining by Recursive Constraint Bounding

R. Ivester
Graduate Research Assistant.*
Mem. ASME

K. Danai
Associate Professor.
Mem. ASME

S. Malkin
Professor.
Fellow ASME

Department of Mechanical Engineering,
University of Massachusetts,
Amherst, MA 01003

Modeling uncertainty in machining, caused by modeling inaccuracy, noise and process time-variability due to tool wear, hinders application of traditional optimization to minimize cost or production time. Process time-variability can be overcome by adaptive control optimization (ACO) to improve machine settings in reference to process feedback so as to satisfy constraints associated with part quality and machine capability. However, ACO systems rely on process models to define the optimal conditions, so they are still affected by modeling inaccuracy and noise. This paper presents the method of Recursive Constraint Bounding (RCB_2) which is designed to cope with modeling uncertainty as well as process time-variability. RCB_2 uses a model, similar to other ACO methods. However, it considers confidence levels and noise buffers to account for degrees of inaccuracy and randomness associated with each modeled constraint. RCB_2 assesses optimality by measuring the slack in individual constraints after each part is completed (cycle), and then redefines the constraints to yield more aggressive machine settings for the next cycle. The application of RCB_2 is demonstrated here in reducing cycle-time for internal cylindrical plunge grinding.

1 Introduction

The advent of computer numerical control has enabled adaptation of machine settings for enhanced productivity. An important requirement when adapting machine settings is that the measurements of process and part quality remain within their specified limits so that part integrity is ensured. One adaptation approach in machining is Adaptive Control with Constraints (ACC), which regulates power or cutting force at a specified level (Daneshmend and Pak, 1986; Lauderbaugh and Ulsoy, 1988; Masory and Koren, 1985; Tomizuka and Zhang, 1988). Although ACC can avoid interruptions in the cut due to tool breakages in machining, or safeguard against thermal damage (burn) to the workpiece in grinding, it is not explicitly designed to improve process efficiency in terms of production cost or time.

The adaptation approach which explicitly addresses process efficiency is referred to as Adaptive Control Optimization (ACO) (Koren, 1983). In ACO, the machine settings are adapted so as to minimize production cost or cycle time in response to part and/or process feedback. This interactive approach to process optimization is adopted to enable the ACO systems to maintain constraint satisfaction despite modeling uncertainty, which is the primary factor hindering optimization of machining processes. Modeling uncertainty in machining arises from: (1) the diversity of machining conditions due to variations in material properties, tool/wheel type, and lubrication, (2) the stochastic nature of these processes caused by material inhomogeneity, workpiece misalignment, and measurement noise, and (3) process time-variability due to tool wear.

The first attempt at ACO was the Bendix System (Centner, 1964), where the machining removal rate was continually maximized through changes in the feedrate and spindle speed in response to feedback measurements of cutting torque, tool temperature, and machine vibration. However, the Bendix System was limited in applicability due to the need to estimate tool wear based on an accurate model. A subsequent advancement in ACO was the Optimal Locus Approach (Amitay et al., 1981; Koren, 1989), which made it possible to forego estimation of tool wear. In this approach, the locus of the optimal points associated with various levels of tool wear is computed, and the optimal point is sought where process and part quality constraints become tight. The Optimal Locus Approach can avoid estimation of tool wear by using the tightness of constraints as the measure for optimality. However, it still needs to rely on the accuracy of the process model for computing the optimal locus and determining *a priori* which constraints are tight at the optimum. Since the success of this approach depends on the premise that modeling uncertainty will have negligible effect on the accuracy of the optimal locus, it will produce sub-optimal results when this premise is invalid.

An ACO method which has been recently developed to overcome the difficulties posed by modeling uncertainty is Recursive Constraint Bounding (RCB_2) (Ivester and Danai, 1995). Like the Optimal Locus Approach, RCB_2 assesses optimality from the tightness in the constraints using measurements of process and part quality after each workpiece has been finished (cycle). It also uses the model of the process to find the optimal point. However, unlike the Optimal Locus Approach, RCB_2 assumes the model to be uncertain when determining which constraints are to be tight at the optimum and selecting the machine settings for each process cycle. It obtains the machine settings by solving a customized nonlinear programming (NLP) problem, and allows for uncertainty by incorporating conservatism into the NLP problem.

Under deterministic conditions (no modeling uncertainty), the NLP problem would yield the optimal machine settings for the process. In practice, however, the optimal point of the model would differ from that of the process, due to inherent modeling inaccuracies and randomness associated with constraints. As such, there is a strong possibility that the optimal point of the model will violate the process and part quality constraints. In order to avoid constraint violation, a recursive approach to constraint tightening (bounding) is adopted in RCB_2, where the distance from the constraint measurements of the cycle just completed to the absolute limit of the constraint is defined as the slack in each constraint. The NLP problem is then formulated so

* Presently a research associate at the National Institute of Standards and Technologies

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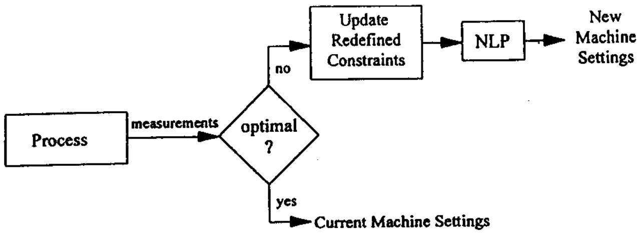

Fig. 1 Schematic of RCB_2

as to minimize the objective function (usually cycle-time or cost) while removing a portion of these slacks, thus yielding more aggressive machine settings for the next cycle. In RCB_2, the slack portions removed for each cycle are defined in terms of the confidence levels and noise buffers which account for the inaccuracy and randomness, respectively, of individual modeled constraints. The consideration of separate confidence levels and noise buffers for individual constraints in RCB_2 enables the convergence of individual constraints to be tailored according to the severity of modeling uncertainty associated with each constraint. The repeated minimization of the objective function with progressively smaller slacks leads to bound constraints and optimal machine settings. In this paper, the performance of RCB_2 is studied in simulation and its effectiveness is demonstrated in cycle-time reduction of cylindrical plunge grinding.

2 RCB_2 Method

Optimization of a machining process can be considered as a constrained nonlinear programming (NLP) problem where the machine settings correspond to the control variables, and the process and part quality measurements to the constraints. In general, a constrained NLP problem is defined as (Luenberger, 1989):

$$\text{minimize:} \quad f(\mathbf{x}) \tag{1}$$

$$\text{subject to:} \quad \mathbf{g}(\mathbf{x}) \le 0 \tag{2}$$

$$\mathbf{h}(\mathbf{x}) = 0 \tag{3}$$

$$\mathbf{x}_{LB} \le \mathbf{x} \le \mathbf{x}_{UB} \tag{4}$$

where $f(\mathbf{x})$ represents the objective function, $\mathbf{x} = [x_1, \ldots, x_n]^T$ denotes the vector of machine settings, $\mathbf{g}(\mathbf{x}) = [g_1(\mathbf{x}), \ldots, g_m(\mathbf{x})]^T$ and $\mathbf{h}(\mathbf{x}) = [h_1(\mathbf{x}), \ldots, h_p(\mathbf{x})]^T$ constitute the vectors of inequality and equality constraints, respectively, and $\mathbf{x}_{LB}$ and $\mathbf{x}_{UB}$ represent the lower and upper bounds of the machine settings, respectively. For machining processes, the objective function $f(\mathbf{x})$ usually represents cycle-time or cost, and the constraints are associated with part quality and/or machine limitations.

2.1 Methodology. RCB_2 relies on the premise that analytical models of machining processes are of the correct form, although they may be imprecise. As such, RCB_2 is designed to take advantage of the form of the relationships provided by these models, but compensates for their inaccuracies using measurements of process behavior and part quality as feedback. The basic role of RCB_2 is to assess the optimality of the process after each cycle from the measurements of process and part quality as the basis for changing the machine settings for the next cycle (see Fig. 1). RCB_2 obtains these machine settings by solving a NLP problem that has been customized for each cycle. The customized NLP problems are obtained by redefining the inequality constraints (Inequality (2)) as

$$\hat{\mathbf{g}}(\mathbf{x}(j)) \le \hat{\mathbf{g}}(\mathbf{x}(j-1)) - \mathbf{c}[\mathbf{g}(\mathbf{x}(j-1)) + \mathbf{n}] \tag{5}$$

to lead to a more aggressive set of machine settings when used as the basis of nonlinear optimization. Inequality (5) redefines the upper limit of the inequality constraints for the next cycle $\hat{\mathbf{g}}(\mathbf{x}(j))$ in terms of the modeled constraint values $\hat{\mathbf{g}}(\mathbf{x}(j-1))$ for the cycle just completed, the measured constraint values $\mathbf{g}(\mathbf{x}(j-1))$, the confidence levels $\mathbf{c}$ and the noise buffers $\mathbf{n}$, representing the allowable changes for individual modeled constraints. Assuming that the process is initiated with conservative machine settings that satisfy the process and part quality constraints, the confidence levels and noise buffers control how much the nonlinear program should tighten the constraints from one iteration to the next.

Constraint redefinition in RCB_2 is developed to account for the fact that the value of constraints cannot be accurately determined from the model due to modeling inaccuracies and process randomness (i.e., $\mathbf{g}(\mathbf{x}) \ne \hat{\mathbf{g}}(\mathbf{x})$). Therefore, machine settings that would minimize the objective function while satisfying $\hat{\mathbf{g}}(\mathbf{x}) \le 0$ do not necessarily ensure $\mathbf{g}(\mathbf{x}) \le 0$. In machining, it is generally possible to select conservative settings that satisfy the constraints. After the process is initiated with such settings, RCB_2 selects the machine settings such that the objective function will be reduced without violating the constraints. In order to ensure constraint satisfaction, the machine settings for the next cycle $\mathbf{x}(j)$ need to be selected such that $\mathbf{g}(\mathbf{x}(j)) \le 0$. However, the only information available to RCB_2 is in the form of the model and constraint measurements from the cycle just completed. Therefore, the redefined constraints that replace Inequality (2) need to be formulated in terms of $\hat{\mathbf{g}}(\mathbf{x}(j))$ as

$$\hat{\mathbf{g}}(\mathbf{x}(j)) \le \mathbf{U} \tag{6}$$

The main contribution of RCB_2 is its definition of this upper bound such that it is robust to modeling inaccuracy and randomness in the constraint values. As was stated earlier, RCB_2 relies on the premise that the model of the process correctly represents its form. Based on this premise, the assumption is made here that this model approximately represents the changes in the constraints due to changes in the machine settings, as

$$\mathbf{g}(\mathbf{x}(j)) - \mathbf{g}(\mathbf{x}(j-1)) \simeq \hat{\mathbf{g}}(\mathbf{x}(j)) - \hat{\mathbf{g}}(\mathbf{x}(j-1)) \tag{7}$$

Although modeling inaccuracy and randomness prevent RCB_2 from directly using the above equation for redefining the constraints, it provides the basis for relating $\mathbf{g}(\mathbf{x}(j))$ to $\mathbf{g}(\mathbf{x}(j-1))$, as well as to $\hat{\mathbf{g}}(\mathbf{x}(j))$ and $\hat{\mathbf{g}}(\mathbf{x}(j-1))$ which are available to RCB_2 from the model.

In RCB_2, allowance for randomness is provided by noise buffers, $\mathbf{n} = [n_1, \ldots, n_m]$, which define the width of the noise distributions of $\mathbf{g}(\mathbf{x})$. If adequate constraint measurements are available, the noise buffer n_i can be obtained as

$$n_i = k_i s_i \tag{8}$$

where s_i represents the standard deviation of the i^{th} constraint measurements and k_i denotes a constant typically between 6 and 12. The noise buffer n_i can alternatively be estimated based on experience if adequate constraint measurements are unavailable. In order to explain how the noise buffers are utilized to establish upper bounds on the constraints, let us consider a case where the machine settings for the next cycle are very close to the settings for the cycle just completed, that is $\mathbf{x}(j) = \mathbf{x}(j-1) + \epsilon \simeq \mathbf{x}(j-1)$. For this case, the upper bounds on the actual constraint values can be defined as

$$\mathbf{g}(\mathbf{x}(j-1)+\epsilon) - \mathbf{g}(\mathbf{x}(j-1)) \le [\hat{\mathbf{g}}(\mathbf{x}(j-1)+\epsilon) - \hat{\mathbf{g}}(\mathbf{x}(j-1))] + \mathbf{n} \tag{9}$$

This inequality provides an upper bound on the change in the constraint measurements, but it is limited to infinitesimal changes in the machine settings. In cases where $\mathbf{x}(j) \ne \mathbf{x}(j-1) + \epsilon$, modeling inaccuracy could result in changes in the constraint measurements that are larger than $[\hat{\mathbf{g}}(\mathbf{x}(j)) - \hat{\mathbf{g}}(\mathbf{x}(j-1))] + \mathbf{n}$. In order to extend Inequality (9) so that larger changes in the machine settings can be accommodated, confidence levels $\mathbf{c} \in [0, 1]$ are introduced on the right hand side of inequality (9) as

$$\mathbf{g}(\mathbf{x}(j)) - \mathbf{g}(\mathbf{x}(j-1)) \le \frac{1}{\mathbf{c}} [\hat{\mathbf{g}}(\mathbf{x}(j)) - \hat{\mathbf{g}}(\mathbf{x}(j-1))] + \mathbf{n} \quad (10)$$

to account for the inaccuracy of individual modeled constraints. With the inclusion of the confidence levels, the upper bounds established in terms of the modeled values of constraints (right hand side of Inequality (10)) can be made sufficiently large so as to account for modeling inaccuracy associated with individual constraints. Accordingly, smaller confidence levels can be selected for constraints that are less accurately represented by the model so that a larger upper bound will be placed on the changes in the constraints.

While Inequality (10) defines the upper bound on the actual constraint changes, it does not provide the upper bound on $\hat{\mathbf{g}}(\mathbf{x}(j))$ ($\mathbf{U}$ in Inequality (6)) that is needed for the reformulation of the NLP problem. In order to develop this upper bound, we note that the absolute requirement in the NLP problem is $\mathbf{g}(\mathbf{x}(j)) \le 0$. This is equivalent to

$$\mathbf{g}(\mathbf{x}(j)) - \mathbf{g}(\mathbf{x}(j-1)) \le 0 - \mathbf{g}(\mathbf{x}(j-1)) \quad (11)$$

which defines the absolute limit on changes in the actual constraints. Satisfaction of this absolute limit in light of Inequality (10) is ensured when

$$\frac{1}{\mathbf{c}} [\hat{\mathbf{g}}(\mathbf{x}(j)) - \hat{\mathbf{g}}(\mathbf{x}(j-1))] + \mathbf{n} \le 0 - \mathbf{g}(\mathbf{x}(j-1)) \quad (12)$$

which states that the upper bound for Inequality (10) must be less than or equal to the upper bound for Inequality (11). Inequality (12) provides the basis for defining the upper limit on $\hat{\mathbf{g}}(\mathbf{x}(j))$ ($\mathbf{U}$ in Inequality (6)) so that constraint satisfaction is guaranteed. Rearranging inequality (12) yields

$$\hat{\mathbf{g}}(\mathbf{x}(j)) \le \hat{\mathbf{g}}(\mathbf{x}(j-1)) - \mathbf{c}[\mathbf{g}(\mathbf{x}(j-1)) + \mathbf{n}] \quad (13)$$

which defines the upper bound for $\hat{\mathbf{g}}(\mathbf{x}(j))$ in terms of the modeled constraints and their measured values from the cycle just completed. Inequality (13), which is identical to Inequality (5), represents the redefined constraints to be used in the customized NLP problem in place of Inequality (2). Note that under deterministic conditions (accurate model, without noise), the modeled constraint values $\hat{\mathbf{g}}(\mathbf{x})$ and their measured values $\mathbf{g}(\mathbf{x})$ would be identical, the confidence levels would be assigned the value of 1 (accurate model) and the noise buffers would have the value of 0 (noise-free conditions). Under these conditions, the right hand side of Inequality (13) would be reduced to zero, and Inequality (13) would be equivalent to Inequality (2).

The salient feature of RCB_2 is its robustness to modeling inaccuracy and noise. The conceptual basis of RCB_2's design is illustrated in Fig. 2. The dark and light data points in this figure represent measured and modeled values of a constraint for successive cycles, respectively, and the dotted arrows point to the upper limit of the constraint in successively reformulated NLP problems. The top of the gray area represents the allowable limit of a constraint, and the bottom of this area denotes the limit when noise is taken into consideration. (Note that the width of the gray area is the value of the noise buffer.) When the distance from a particular measurement to its limit is less than its noise buffer (data point within the gray area) the constraint cannot be safely tightened. In such cases, the value of $c_i[g_i(\mathbf{x}(j-1) + n_i]$ is set to zero (e.g., Cycle 6) signifying that the modeled constraint value should not be changed. When the distance from a particular measurement to its limit is greater than its noise buffer (data point outside the gray area) the constraint is tightened using Inequality (13). In such cases, the distance from each constraint measurement (dark data point)

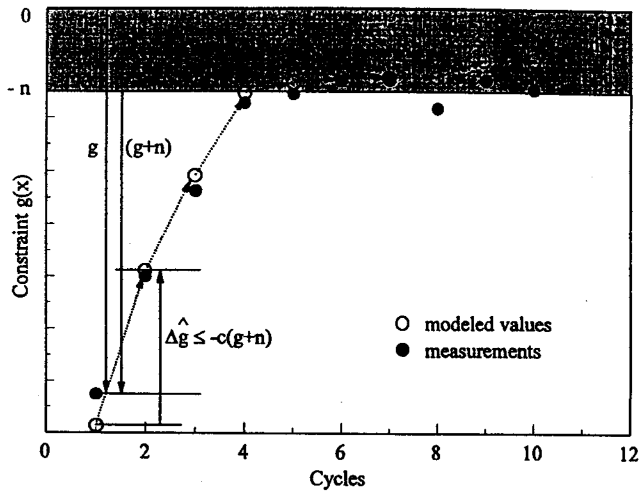

Fig. 2 Constraint tightening in RCB_2

to its upper limit represents the *slack* in the constraint ($0 - g_i(\mathbf{x}(j-1))$ in Inequality (12)), and the dotted arrows represent the portion of the slack ($-c_i[g_i(\mathbf{x}(j-1)) + n_i]$) that RCB_2 attempts to remove by reformulating the NLP problem. If the confidence level were assigned the value of 1 the actual constraint may fall above the gray area and result in constraint violation. Assigning a value less than one to the confidence level provides a safety margin to improve the likelihood of constraint satisfaction. This improvement, however, is provided at the cost of reducing the rate of convergence to the optimum, as will be discussed later in the simulation study.

As the NLP problem is repeatedly reformulated and solved, the machine settings approach their optimal values and the process and part quality measurements approach their respective limits. At the steady state, some slack may remain in the constraints due to the conservative estimates of the noise buffers, $\mathbf{n}$. After all of the constraint measurements have converged within these conservative noise buffers, the process can be repeated to obtain more constraint measurements for improving the estimates of the noise buffers using Eq. (8). In cases where the new noise buffer estimates are smaller than their original values, the NLP problem can be reformulated with the new noise buffers so as to further tighten the constraints and reduce the objective function.

2.2 Analysis in Simulation. The effectiveness of RCB_2 is first illustrated in simulation for single-pass turning, where two machine settings are adjusted so that the state-space can be depicted graphically. The cutting speed and feed were the machine settings for this problem, and power and surface roughness the constrained variables. The constraint measurements were simulated using a turning model (Ivester and Danai, 1995). In order to simulate noise, the values of power and surface roughness obtained for each cycle were multiplied by random numbers uniformly distributed between 0.9 and 1.1. Modeling inaccuracy was simulated by perturbing the coefficients and exponents of the simulation model within ten percent of their nominal values before each sequence of cycles. Only the nominal values of coefficients and exponents were used by RCB_2.

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, the relationships between the machine settings and constraints were not affected by accumulated tool wear. The first cycle of each test was begun with conservative values for the machine settings, so that the constraints would be satisfied. Using simulated constraint values

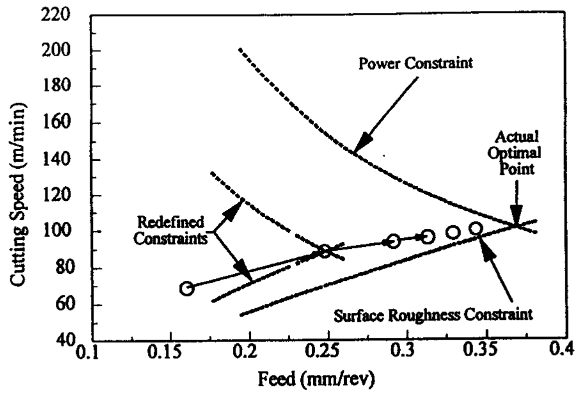

Fig. 3 Gradual tightening of constraints in the turning problem

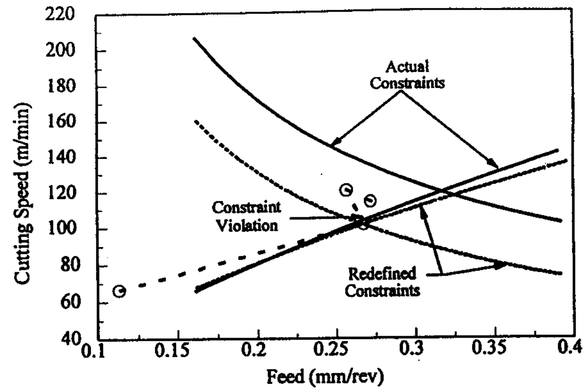

Fig. 5 Violation of constraints when confidence levels are set too high

and confidence levels of 0.5 for both the power and surface roughness constraints, the redefined constraints for the subsequent cycles were obtained by RCB_2 using Inequality (13). These redefined constraints were then used to determine the next set of machine settings using the Sequential Quadratic Programming (SQP) algorithm (Powell, 1978). A series of machine settings selected by RCB_2 is shown in Fig. 3 within the state-space of this problem. The results indicate that the machine settings move towards the optimal point from cycle to cycle without violating the constraints despite the approximate model used by RCB_2 and the presence of noise in the simulated values of the constraint measurements.

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 Fig. 4. 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 is not obtained without a price, since larger confidence levels correspond to greater risks for constraint violation. One case of constraint violation is shown in Fig. 5, where a confidence level of 0.9 was selected inappropriately given the degree of inaccuracy of the model.

Another important feature of RCB_2 is its adaptability to changing process conditions caused by progression of tool wear. In order to evaluate the performance of RCB_2 in such circumstances, a smaller depth-of-cut was used to eliminate the need for changing tools at the beginning of each cycle. This made it necessary to cope with process time-variability due to tool wear.

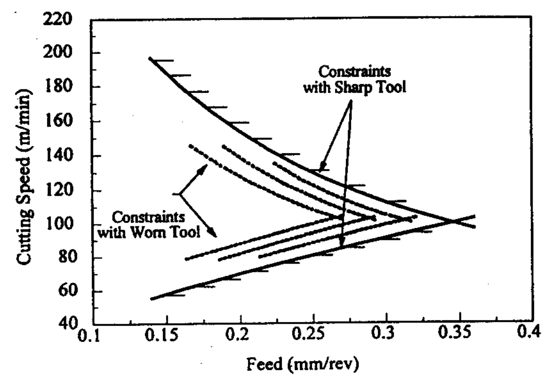

Fig. 6 Distortion of the turning feasible space due to tool wear

The conditions for the first few cycles of this run are very similar to those of the original run. However, as tool wear progresses the constraints become more difficult to satisfy (see Fig. 6). Therefore, in order to continue satisfying the constraints, it becomes necessary to select more conservative machine settings which is reflected in larger values of cycle-times (see Fig. 7). After the cycle-time reaches a certain threshold, it is more economical to change the tool than to continue with a worn tool.

3 Experimental Verification

The RCB_2 method was validated experimentally for internal cylindrical plunge grinding. In cylindrical grinding, material is removed from the internal cylindrical surface by feeding a grinding wheel that is rotating at a high speed into the workpiece

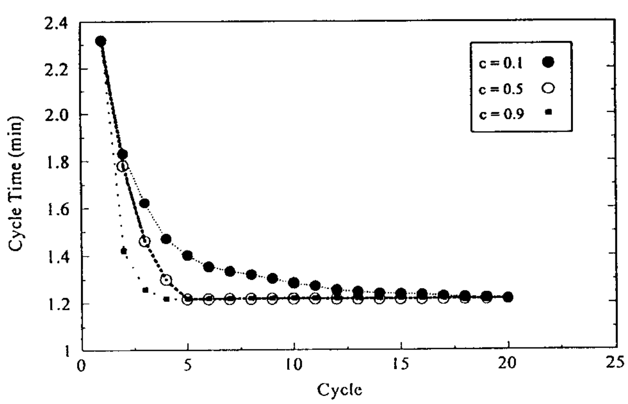

Fig. 4 Reduction in cycle-time by RCB_2 with different confidence levels

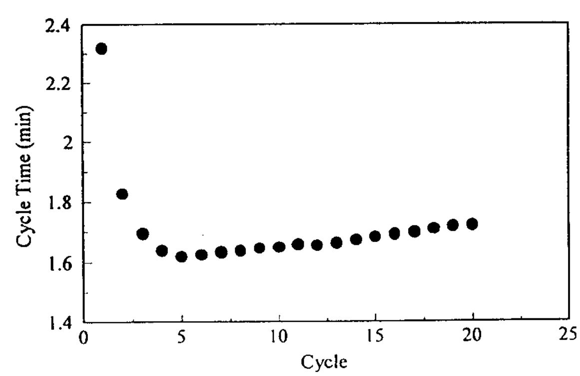

Fig. 7 Increasing cycle-times due to tool wear

which rotates at a much lower speed (see Fig. 8). The infeed control cycle $\mathbf{u} = [u_1, u_2, u_3]$ is typically characterized by three successive stages as illustrated in Fig. 9: (1) roughing with a relatively fast infeed velocity u_1, (2) finishing with a slower infeed velocity u_2, and (3) spark-out at zero infeed velocity ($u_3 = 0$). This is followed by rapid retraction to disengage the wheel from the workpiece.

In response to the controlled infeed, the radial size reduction of the workpiece follows the actual infeed curve as shown in Fig. 9. The transient in the actual infeed at the beginning of each stage is attributed mainly to the elastic deflection of the system and to the radial wear of the grinding wheel. This transient behavior can be approximated by a first order system characterized by a time constant (Malkin and Koren, 1984).

The nonlinear programming problem for this grinding operation can be defined as (Xiao et al., 1993)

$$\text{Minimize cycle-time:} \quad T = t_1 + t_2 + t_3$$

$$\text{with respect to:} \quad u_1, u_2, t_1, t_2, t_3, s_d \qquad (14)$$

subject to:

$$g_1 = z_1 - q_2 \leq 0 \quad \text{(burning constraint)} \qquad (15)$$

$$g_2 = R_m - R_{max} \leq 0 \quad \text{(surface finish constraint)} \qquad (16)$$

$$g_3 = r - r_{max} \leq 0 \quad \text{(out-of-roundness constraint)} \qquad (17)$$

$$h_1 = u_1 t_1 + u_2 t_2 - \Delta r = 0 \quad \text{(size constraint)} \qquad (18)$$

The objective function for this problem is the total cycle-time T, which is defined as the sum of the times for the three successive infeed stages, $[t_1, t_2, t_3]$. The machine settings are the stage times $[t_1, t_2, t_3]$, the programmed infeed rates for the first two stages $[u_1, u_2]$, and the dressing lead s_d. For these experiments, the wheel was dressed after each cycle using a single point diamond dresser. The dressing lead s_d, which specifies the crossfeed per revolution of the wheel, determines the initial sharpness of the wheel. Minimization of the total cycle-time requires that tradeoffs among the three stage times be balanced through an examination of their relationships with the various constraints using Eqs. (15)–(18). The burning constraint in Eq. (15) requires that the thermally damaged (burned) layer on the workpiece due to excessive grinding temperatures during the roughing stage be completely removed during the subsequent finishing stage. As such, a deeper layer of thermally damaged material caused by a more aggressive roughing infeed rate can be balanced by a longer time for the finishing stage. An alternative to this burning constraint is to completely avoid thermal damage during the roughing stage, which is more restrictive but may be desirable for grinding of critical components (Xiao et al., 1993). The inequality g_2 defines the surface finish constraint, where R_m denotes the measured surface roughness and R_{max} its maximum allowable value. The inequality g_3 defines the out-of-roundness constraint, where r represents the out-of-roundness value and r_{max} the maximum allowable out-of-roundness. The equality h_1 defines the size requirement, where Δr denotes the radial depth of material to be removed. The relationships among the constraints and machine settings are given in (Xiao et al., 1993).

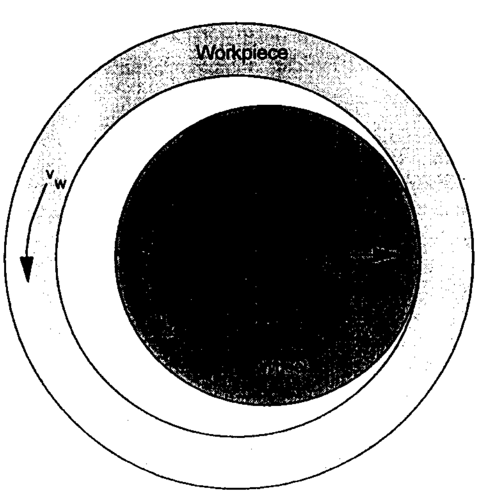

Fig. 8 Diagram of an internal cylindrical plunge grinding operation

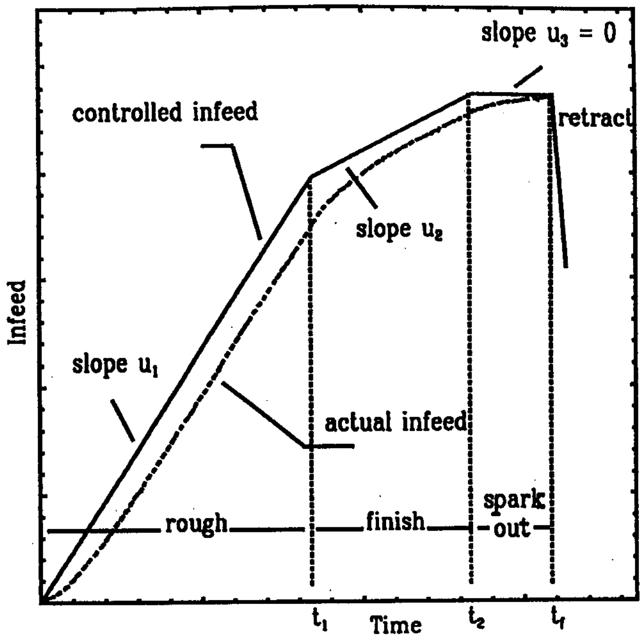

Fig. 9 Illustration of a grinding cycle consisting of roughing, finishing and spark-out stages

It has been suggested that the only in-process sensors which can be reliably utilized in the harsh environment of grinding are a power monitor which measures the wheel spindle power and a size gage which measures the workpiece diameter (Rao and Malkin, 1990). The output from the power monitor together with a thermal analysis is used to estimate the depth of the damaged (burned) layer z_1 on the workpiece. The output from the size gage, which directly indicates the remaining radial depth to be removed, is used to estimate the elastic deflection of the system and the radial wheel wear (or grinding ratio G). The information derived from these two in-process sensors, together with post-process measurement (inspection) of part quality (e.g., surface roughness and roundness), were used to satisfy the constraints while reducing the cycle-time.

The internal cylindrical plunge grinding system is shown in Fig. 10. The system consists of a Bryant Model 1116 internal grinder modified by the addition of a stepper motor infeed drive, an electrical workpiece drive for computer control in place of the original hydraulic motor, a wheel spindle power monitor (A. F. Green TT2), a diametral size gage (Marposs Micromar 5 and E9 amplifier), a Taylor-Hobson Surtronic 3P surface roughness gage, and a personal computer for data acquisition and control (Rao and Malkin, 1990). Out-of-roundness measurements were not available, so values for the out-of-roundness constraint were simulated based on the model equation. The arithmetic average surface roughness constraint and out-of-roundness constraint were selected as 0.7 μm and 0.6 μm, respectively. In these experiments, AISI52100 hardened steel bearing workpieces with an internal diameter d_w of 70 mm and width b of 9 mm were machined using a 32A80M6VBE grinding wheel with an external diameter d_s of 50 mm. The peripheral

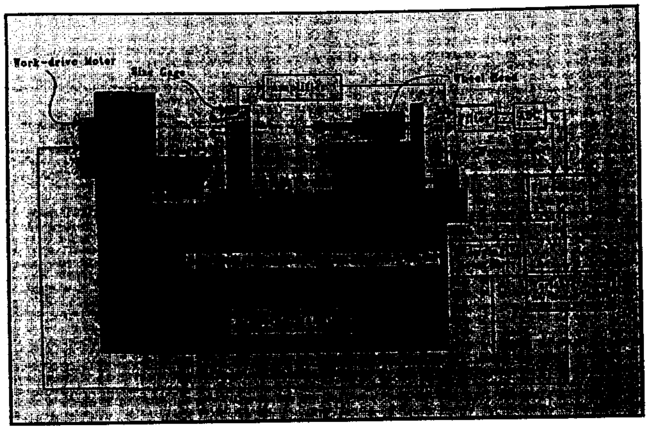

Fig. 10 Implementation of RCB_2 for cycle-time reduction of internal cylindrical plunge grinding

speeds of the wheel v_s and the workpiece v_w were 37 m/s and 0.55 m/s, respectively.

Of the four constraint relationships (Eqs. (15)–(18)) considered in this problem, the first three are inequalities, and the fourth is an equality. The first constraint, depth-of-burn, is not readily measurable, so it was estimated based on the measured value of power. Accordingly, the confidence level and noise buffer for the first constraint were set at 1.0 and 0, respectively. The confidence level and noise buffer for the second constraint (surface roughness) were set at 0.25 and 0.03, respectively. For the third constraint (out-of-roundness), the confidence level and noise buffer were considered as 0.25 and 0.04. Since the fourth constraint is an equality, no confidence level or noise buffer was associated with it.

4 Results

The initial machine settings for these experiments were selected as

$$[t_1, t_2, t_3, u_1, u_2, s_d] = [13.9, 6.7, 6.6, 16, 4, 110].$$

with units as given in Table 1. The constraints were then evaluated according to the measurements resulting from these settings as

$$[g_1, g_2, g_3] = [-0.038, -0.06, -0.45].$$

The negative constraint values obtained for the first cycle indicate that the constraints are not violated, and that they contain significant slack which can be removed to lead to reduced cycle-times. Using these machine settings in the constraint relationships yielded

$$[\hat{g}_1, \hat{g}_2, \hat{g}_3] = [-0.038, -0.08, -0.31].$$

The large negative value for the third constraint indicates that it can be tightened significantly, while the first two constraints have less slack.

Table 1 Grinding machine settings and cycle-times obtained from RCB_2

Iteration Number	Cycle Stage Times (sec)			Infeed Rates (μm/s)		Dressing Lead, s_d (μm)	Cycle Time, T (sec)
	t_1	t_2	t_3	u_1	u_2		
1	13.9	6.7	6.6	16	4	110	27.2
2	9.3	4.1	6.1	25	4	72	19.5
3	9.5	4.5	4.6	24	4	73	18.6
4	9.5	3.7	4.6	25	3.3	80	17.8
5	9.5	3.7	4.4	25	3.2	82	17.6

Table 2 Constraint values obtained after each grinding cycle

Iteration Number	Constraints g_i		
	g_1	g_2	g_3
1	-0.038	-0.06	-0.45
2	-0.002	-0.03	-0.49
3	-0.003	-0.11	-0.21
4	-0.001	-0.06	-0.23
5	-0.003	-0.03	-0.01

For the second cycle, RCB_2 calculated the limits of the redefined constraints based on these constraint values (see Eq. (13)) which were then used to redefine the corresponding constraints for the next cycle as:

$$\hat{g}_1(\mathbf{x}(2)) \le \hat{g}_1(\mathbf{x}(1)) - c_1[g_1(\mathbf{x}(1) + n_1] = -0.038 + 0.038$$

$$\hat{g}_2(\mathbf{x}(2)) \le \hat{g}_2(\mathbf{x}(1)) - c_2[g_2(\mathbf{x}(1) + n_2] = -0.08 + 0.0075$$

$$\hat{g}_3(\mathbf{x}(2)) \le \hat{g}_3(\mathbf{x}(1)) + c_3[g_3(\mathbf{x}(1) + n_3] = -0.31 + 0.1025$$

Using a nonlinear program (Sequential Quadratic Programming (SQP) (Powell, 1978)), the machine settings for the second cycle were obtained as

$$[t_1, t_2, t_3, u_1, u_2, s_d] = [9.3, 4.1, 6.1, 25, 4, 72].$$

which represented the optimal point for the redefined optimization problem, such that $[\hat{g}_1, \hat{g}_2, \hat{g}_3] = [0, 0, 0]$. However, when the experiment was run with the above machine settings the constraint values were obtained as

$$[g_1, g_2, g_3] = [-0.002, -0.03, -0.49].$$

which were again less than zero, with considerable slack in the third constraint.

The above procedure was continued for three more cycles until the cycle-time was approximately minimized. The machine settings and cycle-times for the five cycles are listed in Table 1, with the corresponding measured constraint values listed in Table 2. The cycle-times are plotted in Fig. 11, and the surface roughness and out-of-roundness values are plotted in Fig. 12 against their allowable limits. The results in these figures indicate that the machine settings selected by RCB_2 corresponded to progressively tightened constraints (see Fig. 12). For the fifth cycle, both the surface roughness and out-of-roundness

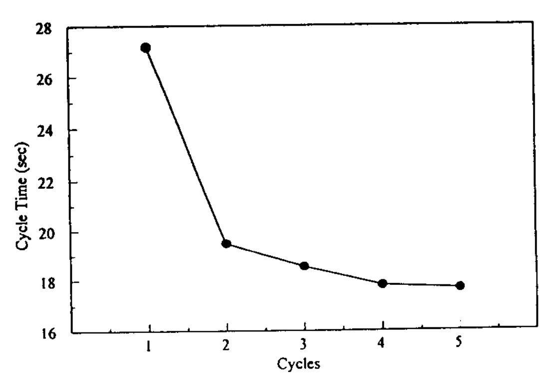

Fig. 11 Gradually reduced cycle-times by RCB_2 for grinding

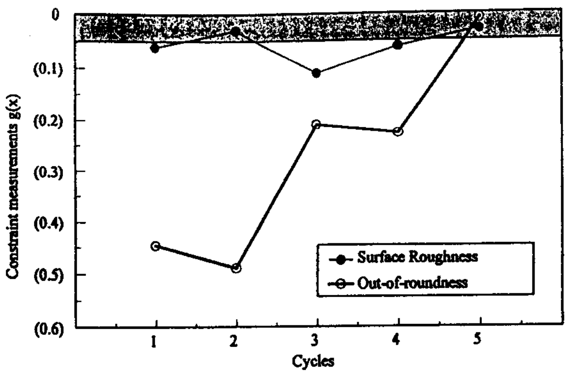

Fig. 12 Tightened constraints by RCB_2 for grinding

constraints were within their respective noise buffers, so the cycle-time could not be reduced further.

5 Conclusion

It has been demonstrated in this paper that RCB_2 can be used to adjust the machine settings from cycle to cycle in order to reduce cycle-time. For this, a model of the process is required that adequately represents the general form of the relationships between the machine inputs and part quality attributes. RCB_2 is designed to cope with modeling uncertainty and process time-variability due to tool wear. It can be used either as a selection guide to the machine operator, or as the basis of a supervisory module for production control. Since RCB_2 uses separate confidence levels and noise buffers for each constraint, incorporating additional machine inputs or constraints does not result in a combinatorial increase in computation time or convergence iterations.

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