SMART MACHINING SYSTEMS: ROBUST OPTIMIZATION AND ADAPTIVE CONTROL OPTIMIZATION FOR TURNING OPERATIONS

Robert W. Ivester and Jarred C. Heigel
Manufacturing Engineering Laboratory
National Institute of Standards and Technology[1]
Gaithersburg, Maryland

KEYWORDS

Smart Machining Systems, Adaptive Control Optimization, Robust Optimization, Modeling Uncertainty

ABSTRACT

A critical aspect of smart machining systems is the appropriate management of knowledge and information to support effective decision-making. The uncertainty of model-based predictions of machining performance plays an important role in decision-making for machining optimization and adaptive control optimization. This paper presents a technique for managing modeling and measurement uncertainties for optimization and control. The resulting model provides a basis for predicting cutting performance to facilitate effective decision-making in a real-time control environment. The cutting performance is optimized when a balance of quality improvement versus cost reduction is obtained. The approach is demonstrated for an American Iron and Steel Institute (AISI) 1045 steel workpiece machined on a lathe under a range of controlled process conditions. Measurements of product quality resulting from the changes in process conditions form a basis for model-based robust optimization and adaptive control optimization that address uncertainties encountered in production environments.

INTRODUCTION

The goal of the Smart Machining Systems (SMS) program at the National Institute of Standards and Technology (NIST) is to develop, validate, and demonstrate the metrology, standards, and infrastructural tools that enable industry to characterize, monitor, and improve the accuracy, reliability, and productivity of machining operations, leading to the realization of autonomous machining systems. The characteristics of a Smart Machining System are: 1) self-recognition and communication of its capabilities to other parts of the manufacturing enterprise, 2) self-monitoring and optimization of its operations, 3) self-assessment of the quality of its work, and 4) self-learning and performance

[1] Commercial equipment and materials are identified in order to adequately specify certain procedures. In no case does such identification imply recommendation or endorsement by the National Institute of Standards and Technology, nor does it imply that the materials or equipment are necessarily the best available for the purpose. This paper is an official contribution of the National Institute of Standards and Technology and is not subject to copyright in the United States.

improvement over time (Deshayes et al. 2005; Jurrens et al. 2003). This paper reports progress in the development of capabilities for self-monitoring and optimization of operations by a Smart Machining System.

The selection of appropriate process parameters for machining operations plays a vital role in the cost of production and in the resulting part quality. In the effort to reduce the cost of production while maintaining adequate part quality, a variety of approaches to the selection of appropriate values for controllable process variables have been utilized, including handbook recommendations, process modeling (Armarego and Ostafiev 2001; Hong and Lian 2001; Ivester et al. 2006; Sun et al. 2005), virtual machining simulation (Karpat et al. 2005), and adaptive control optimization (Ivester et al. 1997; Jeong and Cho 2002; Liang et al. 2004; Lim and Story 2001; Masory and Koren 1985). One of the most difficult aspects of using any of these approaches stems from a lack of confidence that the resulting process behavior and part quality will be acceptable. Process behavior and part quality for machining processes vary under nominally identical conditions (Ivester et al. 2000) due to a variety of uncontrolled factors, such as the machine environment, homogeneity of the workpiece material, and performance consistency of the machine, tooling, and coolant.

This paper presents a technique for model-based hierarchical supervisory control of a turning operation that adaptively optimizes the production of a complex turned part. The supervisory level in the hierarchy uses a novel robust optimization technique to select process parameters that allows for variability of process behavior, part quality, and uncertainties associated with modeling and measurement. Process and product measurements from each fabricated part provide a means to update relevant models and repeat the robust optimization. The robust optimization provides updated values for the set points of the controllers for each of the process variables. This leads to an adaptive behavior that is similar to adaptive control optimization but relies on the inherent stability of existing individual controllers for each of the machining process variables.

MODEL DEVELOPMENT

Experiments have been performed for the development of empirical models to predict process behavior in terms of spindle torque, cutting forces, surface roughness, and tool wear. All experiments were performed on a 22 kW lathe. The workpiece material for all experiments was American and Iron and Steel Institute (AISI) 1045 steel cold rolled rod stock. Controller signals for spindle load and spindle speed were measured along with cutting, thrust, and axial forces from a 3-axis dynamometer. Analog filtering of the signals at 50 Hz before conversion to digital recordings by an oscilloscope avoided potential aliasing effects. Surface roughness measurements were made with a portable surface profilometer. Eight measurements were collected in a random pattern across the surface and averaged together. The average flank wear was measured using an optical microscope connected to a digital camera. Images of the inserts were compared to images of a calibrated length reference as a quantitative basis for converting dimensions in pixels to millimeters.

Several sets of experiments were performed under different experimental plans that focus on a combination of different machining and metrology aspects. Table 1 provides a list of inserts used and data collected for each. Simultaneous dynamometer and spindle load measurements for a range of forces, feeds, depths, and speeds establish a model to translate measured spindle load into estimated cutting forces. Experiments were performed for each of the four insert types to establish surface roughness models.

TABLE 1. KENNAMETAL INSERT DESIGNATIONS AND TESTS PERFORMED.

Insert Information	Data Collected				
ANSI Catalog #	3-Axis Forces	Spindle Load Signal	Diameter Accuracy	Surface Finish	Tool Wear
CNMG432RN	X	X	X	X	X
CPGM32505	X	X		X	
VCMR331		X		X	
VPGR3305				X	

Spindle Torque Model

It is necessary to avoid excessive cutting forces that can lead to tool breakage, spindle overload, and unacceptable workpiece deflection. However, traditional dynamometry for measuring cutting forces sacrifices stiffness and limits the machining setup to one cutting tool. In order to measure and control cutting forces while fabricating parts under practical conditions, a simple model has been developed and validated to relate cutting forces measured by dynamometry to the measured spindle load. Multiplying the measured cutting force by the working radius leads to the (zero-intercept) linear relationships shown in Figure 1 of measured torque versus net spindle load. The net spindle load is obtained by subtracting the "idle" load measured at the same spindle speed without cutting. The variation of the ratios (of torque to the measured values of net spindle load) with spindle speed, as shown in Figure 2, resembles the torque curve of the spindle motor. The combination of a constant ratio for speeds up to 70.2 rad/s and a ratio that is a power function of spindle speed above 70.2 rad/s as shown in Figure 2 provides a basis for modeling cutting force as a function of the spindle load. Equations 1, 2, and 3 capture this relationship as generated by curve fitting of the lathe's experimental data for the particular combination of motor and spindle, where *L* is the spindle load signal in volts, *D* is the working diameter in mm, and ϕ is the spindle speed in rad/s and *m* is the ratio between torque and spindle load.

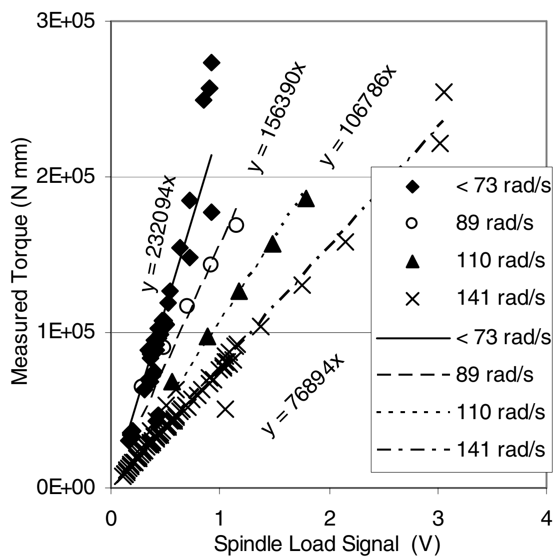


FIGURE 1. MEASURED TORQUE VERSUS SPINDLE LOAD AT DIFFERENT SPINDLE SPEEDS.

$$m_{\phi \leq 70.2 \ rad/s} = 2.19 * 10^5 \qquad (1)$$

$$m_{\phi > 70.2 \ rad/s} = 1.39 * 10^8 * \phi^{-1.52} \qquad (2)$$

$$F = \frac{m * L}{D} \qquad (3)$$

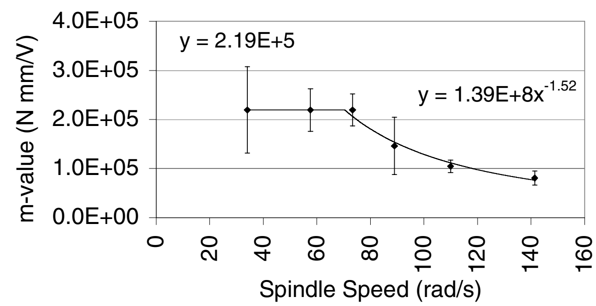


FIGURE 2. SLOPE VERSUS SPINDLE SPEED.

This model of cutting torque as a function of spindle load and speed has been tested and verified for various cutting tools across a range of practical cutting diameters. The uncertainty associated with this model was determined by comparing the calculated torque with the spindle load signal for each data point. Calculating the ±2s standard deviation of the differences produces the uncertainties of the ratios (slopes) in Figure 1 as Δm=±0.21 [Taylor and Kuyatt, 1994]. Force uncertainty is calculated using the propagation of errors in Equation 4.

$$\Delta F = F\sqrt{\left(\frac{\Delta D}{D}\right)^2 + \left(\frac{\Delta L}{L}\right)^2 + \left(\frac{\Delta m}{m}\right)^2} \qquad (4)$$

Cutting Force Models

The cutting force models used in this paper were developed by regression analysis of a linearized power-law relationship through logarithmic transformation. Cutting force (*Fc*) models for the four different insert types are of the form in Equation 5 as functions of the depth (*d*) in mm, feed (*f*) in mm, and surface speed (*v*) in m/min. The parameters *K, a, b,* and *c* for each insert are given in Table 2. Model uncertainties were determined as the range of *K* (±*ΔK*) that encompasses all of the points in the data set. Radial and axial force models were derived using the same techniques but are beyond the scope of this paper.

$$Fc = K * d^a * f^b * v^c \tag{5}$$

TABLE 2. CUTTING MODEL PARAMETERS AND ASSOCIATED UNCERTAINTIES

Insert	Cutting Force Model Variables				
	K (N)	***ΔK*** (N)	***a***	***b***	***c***
CNMG432RN	2130	150	0.888	0.783	-0.0395
CPGM32505	3855	380	0.976	0.779	-0.196
VCMR331	343	105	0.942	0.729	0.219
VPGR3305	343	105	0.942	0.729	0.219

CNMG432RN and CPGM32505 insert force models were derived from dynamometer force data, whereas the VCMR331 and VPGR3305 insert force model was derived using the spindle load signal and Equation 1. The same force model is used for the VCMR331 and VPGR3305 inserts since the only differences between the two are in relief angle, nose radius, and dimensional tolerances. The VCMR331 and VPGR3305 insert models have a greater uncertainty when compared to CNMG432RN and CPGM32505 models due to their dependency on the modeled relationship between force and spindle load. The role of this larger uncertainty in the context of robust optimization and adaptive control optimization will be discussed later in the paper.

Surface Roughness Models

As with the cutting force models used in this paper, the surface roughness models were developed by regression analysis of a linearized power-law relationship through logarithmic transformation. Surface roughness models for the four different insert types are of the form in Equation 6 as functions of the depth (*d*) in mm, feed (*f*) in mm, and surface speed (*v*) in m/min. Values for the parameters *K, a, b,* and *c* are given in Table 3.

$$Ra = K * d^a * f^b * v^c \tag{6}$$

This model does not explicitly account for the effects of tool wear on surface roughness, so roughness measurements were made for various levels of tool wear. Consequently, *ΔK* accounts for both process variation and insert wear. This uncertainty is associated with the *K* value where it can be inserted into the propagation of errors equation (Equation 7). Model uncertainties were determined as the range of K (ΔK) that encompasses all of the points in the data set.

TABLE 3. SURFACE ROUGHNESS MODEL PARAMETERS AND ASSOCIATED UNCERTAINTIES FOR THE K-VALUE.

Insert	Surface Finish Model Variables				
	K (μm)	***ΔK*** (μm)	***a***	***b***	***c***
CNMG432RN	54	14	-0.006	1.284	-0.261
CPGM32505	21	8	-0.086	1.123	-0.002
VCMR331	23	3.7	0.151	1.225	0.010
VPGR3305	40.5	14	0.033	1.095	-0.034

$$\Delta Ra = Ra\sqrt{\left(\frac{\Delta K}{K}\right)^2 + a\left(\frac{\Delta d}{d}\right)^2 + b\left(\frac{\Delta f}{f}\right)^2 + c\left(\frac{\Delta v}{v}\right)^2} \tag{7}$$

Tool Life Model

The wear patterns on the inserts were characterized in terms of nose wear, notch wear, peak flank wear, and average flank wear. For purposes of optimization and control, average flank wear was selected for modeling due to its impact on surface finish and dimensional accuracy. The volume of material that can be removed (*mr*) in mm^3 for a given level of allowable flank wear in mm, *w*, is expressed as a power-law relationship together with the depth (*d*) in mm, feed (*f*) in mm, and surface speed (*v*) in m/min. The tool life model for the CNMG432RN insert is given in Equation 8. Tool life model uncertainty (*Δmr*) is expressed in Equation 9 where $\Delta K = \pm 4.7 * 10^8$.

$$mr = 9*10^8 * d^{0.488} * f^{0.045} * v^{-0.821} * w^{1.241} \tag{8}$$

$$\Delta mr = mr\sqrt{\left(\frac{\Delta K}{K}\right)^2 + a\left(\frac{\Delta d}{d}\right)^2 + b\left(\frac{\Delta f}{f}\right)^2 + c\left(\frac{\Delta v}{v}\right)^2} \tag{9}$$

This model predicts the number of producible parts per insert for the roughing operation. The degree of tool wear per part for the remaining operations was deemed negligible for this application, but similar tool wear models could be developed for the other inserts if required.

ROBUST OPTIMIZATION

Robust optimization is a general term for optimization techniques that allow for uncertainty in controlled variables, constrained variables, their relationships, and the objective function. In this case, we have to determine the combination of feed, speed, and depth of cut that maximizes the material removal rate for each operation while constraining the allowable surface roughness and cutting torque. The robust optimization of the part shown in Figure 3 demonstrates this technique for optimization of the process plan prior to production. The design requirements for the grooves and contour of the part include tight tolerances for form, dimensions, and surface roughness. These design requirements translate into constraints in the optimization problem. The process plan for this part includes six operations on the outside diameter (OD), as given in Table 4. The optimization problem for each operation takes the following form:

Maximize: $v*f*d$ (10)

Such that: $F < F_{max} - \Delta F$ (11)

$R < R_{max} - \Delta R$ (12)

$mr < mr_{max} - \Delta mr$ (13)

with F, ΔF, R, ΔR, mr, and Δmr are defined as in Equations (1) - (9). The resulting optimization problem is then linearized through a logarithmic transformation and solved using the simplex algorithm. Conservative (large) estimates of the modeling uncertainties and the other uncertainties propagated through Equations 4, 7, and 9 lead to a somewhat conservative starting point for production, but this increases the probability that the first part will be of acceptable quality. Online measurements of process performance and part quality then provide a basis for adjusting the uncertainties and repeating the optimization problem for online Adaptive Control Optimization. Figure 4 shows the process parameters (feed and depth) and constrained process variables (cutting force and surface finish) for the first operation, roughing of the outer diameter (OD). The horizontal and vertical bars for the process variables are ± 2σ measurement uncertainties. The maximum allowable input values for the constrained process variables correspond to the edges of the graph in Figure 4a. Figures 4a and 4b illustrate the input values and corresponding output values for the control (C), robust (R) and adaptive control values AC1 and AC2.

TABLE 4. TOOLING AND ALLOWABLE MAXIMUM SURFACE ROUGHNESS FOR OD OPERATIONS IN PRODUCTION OF DEMONSTRATION PART.

		Tooling		Finish
	Process Steps	Insert	Tool Holder	(µm)
1	Rough OD	CNMG432RN	MCLNR-164D	4.0
2	Rough Grooves	VCMR331	MCLNR-164D	2.0
3	Rough Contour	VCMR331	NVLCL-163D	3.0
4	Finish OD	CPGM32505	NVLCR-163D	2.5
5	Finish Grooves	VPGR3305	NVLCL-163D	2.0
6	Finish Contour	VPGR3305	NVLCR-163D	2.0

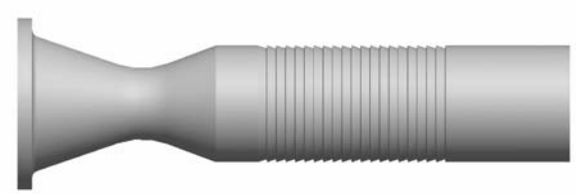


FIGURE 3. TEST PRODUCTION PART.

ADAPTIVE CONTROL OPTIMIZATION

The spindle load signal (Figure 5) provides an assessment of the current cutting conditions relative to the predetermined maximum conditions. Process-intermittent measurements of surface roughness and tool wear measurements after each lot of parts provide similar assessments.

Using the power/force conversion model developed earlier, the maximum cutting force and the associated uncertainty can be calculated after each pass of the cutting tool. If the measured maximum values plus the associated uncertainties for cutting force, surface roughness, and tool wear are below their respective allowable maximum values, then one or more of the uncertainty parameters is reduced by a fraction (0.25) of the difference. This allows the process input values to be changed, producing process output values closer to the maximum allowable values. As such, the Adaptive Control Optimization technique used here, Recursive Constraint Bounding (RCB) is loosely equivalent to a Proportional-Integral-Derivative (PID) control system wherein the P term is updated based on an analysis of the model, the measurement, and the uncertainty and the I and D terms are zero.

The advantage of RCB over a traditional PID control system is that the term is not static. Repeating the optimization problem with the reduced uncertainty parameter(s) then leads to more aggressive process parameters. After one or more parts are produced using the new process parameters, the adaptive control process can be repeated.

When all of the measurements of process behavior and product quality remain within their respective uncertainties, the process parameters remain the same. By setting the ratio for conservatively reducing the uncertainty parameters (0.25 in this case), the stability of the adaptive control system is high at the expense of responsiveness. The probability of overshooting the constraints is low provided the modeling uncertainties have been appropriately determined and the model is representative of the actual system behavior.

RESULTS

The results of this process for the test part in Figure 3 can be seen in Table 5. For purposes of comparison, parts were produced under conditions as recommended by the tooling vendor's catalog, labeled as "C" in the first column. Parts produced using the robust optimum process parameters as the initial and final settings for adaptive control are labeled as "R" and "AC", respectively. Across all inserts and process plan steps, the robust optimum from the process plan consistently met the maximum force and surface finish requirements. The surface roughness measurements and tool wear measurements were consistently within the ranges predicted by their respective models and associated ± 2σ uncertainties.

The differences between the process measurements and the maximums of their respective model prediction ranges enabled uncertainty reduction to enable more aggressive optimization. The final resulting process parameters are indicated by the rows labeled "AC" in the first column of Table 5. The spindle load signal for all six operations in the process plan for the initial and final adaptive control conditions in Figure 5 provides a graphic indication of the increase in spindle load and the more than 28 % decrease in cycle time. Overall, the approach successfully increased removal rate while meeting process behavior constraints.

CONCLUSION

Through integration of model-based process knowledge with modeling uncertainties, robust optimization, and adaptive control, this paper

TABLE 5. CONSERVATIVE CATALOG (C), ROBUST (R), AND FINAL (AC) CONDITIONS FOR EACH PROCESS STEP AND COMPARISON OF MODEL PREDICTIONS AND MEASUREMENTS.

					Removal	Model		Measured	
		d	f	v	Rate	Force	Finish	Force	Finish
		(mm)	(mm/rev)	(m/min)	(cm^3/min)	(N)	(μm)	(N)	(μm)
Step 1	C	1.3	0.25	187	59.37	758 ± 22	2.34 ± 0.61	742 ± 5	2.07 ± 0.04
	R	3.0	0.32	200	190.72	1867 ± 131	3.12 ± 0.81	1565 ± 12	3.06 ± 0.09
	AC1	2.6	0.38	200	195.32	1874 ± 132	3.91 ± 1.01	1535 ± 14	3.78 ± 0.08
	AC2	2.1	0.48	200	201.60	1778 ± 125	4.24 ± 1.10	1504 ± 15	4.15 ± 0.04
Step 2	C	0.5	0.20	256	25.60	186 ± 57	3.05 ± 0.49	204 ± 4	3.47 ± 0.02
	R	3.0	0.10	200	60.00	574 ± 176	1.71 ± 0.27	581 ± 8	1.82 ± 0.07
	AC1	3.0	0.13	200	78.00	695 ± 213	2.35 ± 0.38	675 ± 4	2.15 ± 0.02
Step 3	C	0.5	0.20	130	13.00	160 ± 49	3.03 ± 0.49	221 ± 3	3.63 ± 0.06
	R	3.0	0.14	130	54.60	667 ± 204	2.57 ± 0.41	753 ± 3	2.48 ± 0.06
	AC1	3.0	0.18	130	70.20	802 ± 245	3.49 ± 0.56	916 ± 3	3.40 ± 0.09
Step 4	C	0.2	0.10	190	3.80	55 ± 5	1.80 ± 0.68	36 ± 2	2.23 ± 0.04
	R	1.0	0.08	190	15.20	222 ± 22	1.61 ± 0.65	141 ± 3	1.81 ± 0.03
	AC1	1.0	0.10	190	19.00	264 ± 26	1.98 ± 0.80	118 ± 80	2.69 ± 0.03
Step 5	C	0.3	0.10	200	6.00	66 ± 20	2.61 ± 0.90	74 ± 2	1.97 ± 0.05
	R	2.0	0.05	190	19.00	234 ± 72	1.30 ± 0.45	226 ± 2	1.00 ± 0.06
	AC1	2.0	0.08	190	30.40	333 ± 102	2.18 ± 0.75	296 ± 2	1.54 ± 0.05
Step 6	C	0.3	0.10	110	3.30	58 ± 18	2.67 ± 0.92	76 ± 2	2.20 ± 0.06
	R	2.0	0.05	110	11.00	207 ± 63	1.33 ± 0.46	240 ± 2	1.16 ± 0.07
	AC1	2.0	0.08	110	17.60	292 ± 89	2.22 ± 0.77	301 ± 2	1.88 ± 0.04

demonstrates the potential for optimal achievement of first part correct production. The adaptive control optimization technique presented in this paper can sufficiently model process behavior while allowing for uncertainties and fluctuations encountered in real-world production. By monitoring process performance and product quality at the machine, Smart Machining Systems can vary cutting conditions to operate at maximum efficiency and enable better understanding of processes and their respective sources of uncertainty.

REFERENCES

Armarego, E.J.A. and D. Ostafiev (2001). "Multi-Constraint Optimization Analysis and Simulation of Single Pass Turning with Modern Chip Breaker Tools." *Transactions of NAMRI/SME*, Vol. 29, pp. 335-342.

Deshayes, L., L. Welsch, A. Donmez, R. Ivester, D. Gilsinn, R. Rhorer, and E. Whitenton (2005). "Smart Machining Systems: Issues and Research Trends." 12th CIRP Life-Cycle Engineering Seminar, Grenoble, France, April 3-5.

Hong, M. and Z. Lian (2001). "The Optimal Selection of Cutting Parameters in Turning Operations." *Transactions of NAMRI/SME*, Vol. 29, pp. 319-325.

Ivester, R., K. Danai, and S. Malkin (1997). "Cycle-Time Reduction in Machining by Recursive Constraint Bounding." *ASME Journal of Manufacturing Science and Engineering*, Vol. 119, No. 2, pp. 201-207.

Ivester, R., M. Kennedy, M. Davies, R. Stevenson, J. Thiele, R. Furness, and S. Athavale (2000). "Assessment of Machining Models: Progress Report." *Journal of Machining Science and Technology*, Vol. 4, No. 3, pp. 511-538.

Ivester, R., L. Deshayes, and M. McGlauflin (2006). "Determination of Parametric Uncertainties for Regression-Based Modeling of Turning Operations." *Transactions of NAMRI/SME*, Vol. 34, pp. 1-8.

Jeong, Young-Hun and Dong-Woo Cho (2002). "Control of the Cutting Force Normal to a Machined Surface using the Current of a Stationary Feed Motor." *Transactions of NAMRI/SME*, Vol. 30, pp. 517-523.

Jurrens, K., J. Soons, and R. Ivester (2003). "Smart Machining Research at the National Institute of Standards and Technology." DOE NNSA Small Lot Intelligent Manufacturing Workshop, Santa Fe, New Mexico, September 2-3 2003, proceedings number LA-14093, Los Alamos National Laboratory.

Karpat, Yiğit, Erol Zeren, and Tuğrul Özel (2005). "Workpiece Material Model Based Predictions for Machining Processes." *Transactions of NAMRI/SME*, Vol. 29, pp. 413-420.

Liang, S., R. Hecker, and R. Landers (2004). "Machining Process Monitoring and Control: The State-of-the-Art." *ASME Journal of Manufacturing Science and Engineering*, Vol. 126, pp. 297-310.

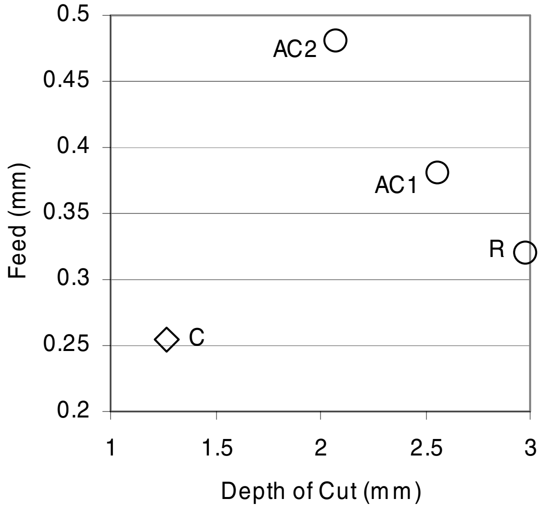
Lim, J. and J. Stori (2001). "Optimization of the Process Parameters in Drilling Using a Power Sensor for On-Line Estimation of Tool Wear." *Transactions of NAMRI/SME*, Vol. 29, pp. 287-294.

Masory, O. and Y. Koren (1985). "Stability Analysis of a Constant Force Adaptive Control System for Turning." *ASME Journal of Engineering for Industry*, Vol. 107, No. 1, pp. 295-300.

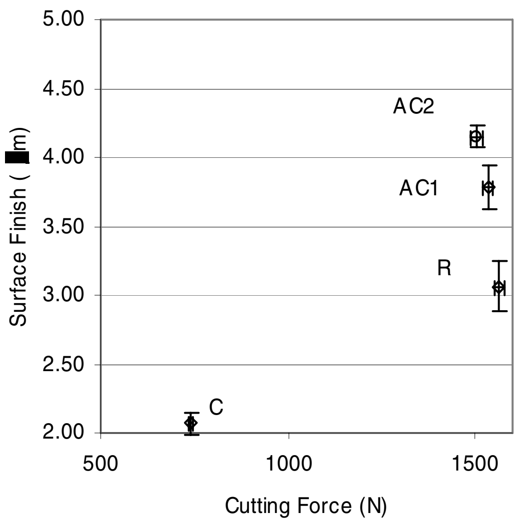
Matsumura, T. and E. Usui (2001). "Self-Adaptive Tool Wear Monitoring System in Milling Process." *Transactions of NAMRI/SME*, Vol. 29, pp. 375-382.

Sun, W.P., Z.J. Pei, E.S. Lee, and G.R. Fisher (2005). "Optimization of Process Parameters in Manufacturing: an Approach of Multiple Attribute Decision Making." *Transactions of NAMRI/SME*, Vol. 33, pp. 187-194.

Taylor, B.N. and C.C. Kuyatt (1994). "Guidelines for Evaluating and Expressing the Uncertainty of NIST Measurement Results." NIST Technical Note 1297.

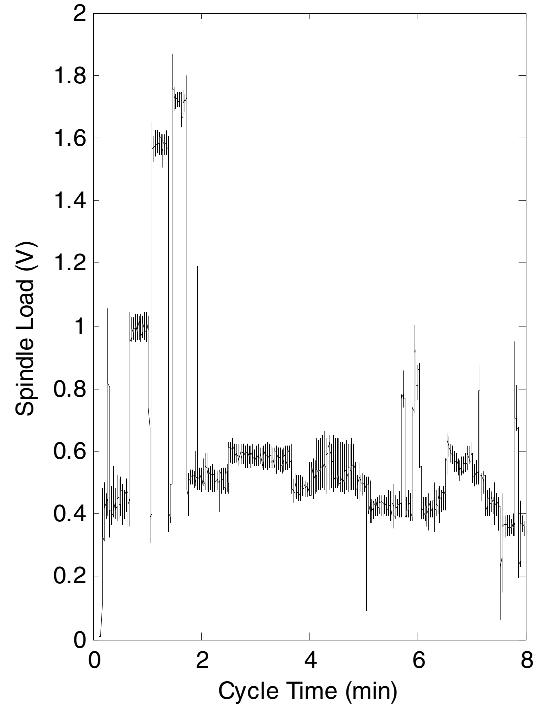


(A)

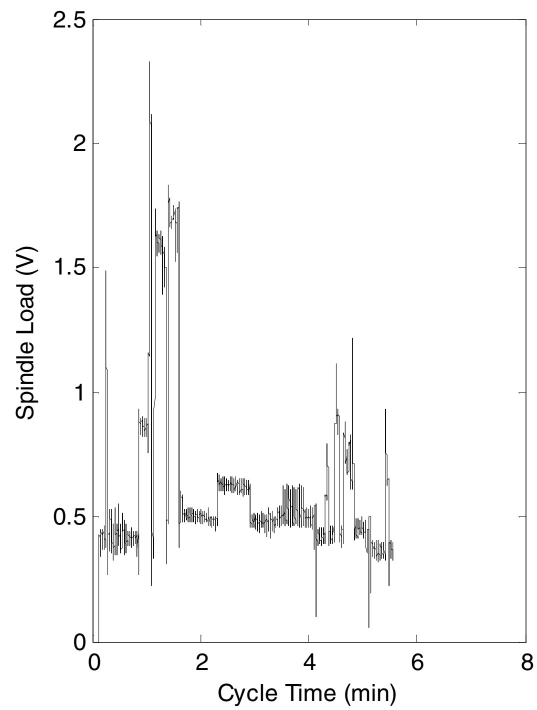


(B)

FIGURE 4: INPUT PARAMETERS (A) AND OUTPUT PARAMETERS (B) FOR SUPERVISORY ADAPTIVE CONTROL OF PROCESS PERFORMANCE THROUGH ADJUSTMENT OF INPUT PROCESS PARAMETERS.



(A)



(B)

FIGURE 5. TEST PART SPINDLE LOAD SIGNAL. INITIAL ROBUST CUTTING CONDITIONS (A), FINAL ADAPTIVE CONTROL CONDITIONS (B).