6

Process Monitoring and Control of Machining Operations

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6.1 Introduction

Machining operations (e.g., drilling, milling) are shape transformation processes in which metal is removed from a stock of material to produce a part. The objective of these operations is to produce parts with specified quality as productively as possible. Many phenomena that are detrimental to this objective occur naturally in machining operations. In this chapter, we present techniques for monitoring and controlling the process phenomena that arise due to the interaction of the cutting tool and the workpiece (e.g., force generation, chatter, tool failure, chip formation).

Process monitoring is the manipulation of sensor measurements (e.g., force, vision, temperature) to determine the state of the processes. The machine tool operator routinely performs monitoring tasks; for example, visually detecting missing and broken tools and detecting chatter from the characteristic sound it generates. Unmanned monitoring algorithms utilize filtered sensor measurements that, along with operator inputs, determine the process state (Figure 6.1). The state of complex processes is monitored by sophisticated signal processing of sensor measurements that typically involve thresholding or artificial intelligence (AI) techniques.[1] For more information on sensors for process monitoring, the reader is referred to References 2 and 3.

Process control is the manipulation of process variables (e.g., feed, speed, depth-of-cut) to regulate the processes. Machine tool operators perform on-line and off-line process control by adjusting feeds and speeds to suppress chatter, initiate an emergency stop in response to a tool breakage event, rewrite a part program to increase the depth-of-cut to minimize burr formation, etc. Off-line process control is performed at the process planning stage; typically by selecting

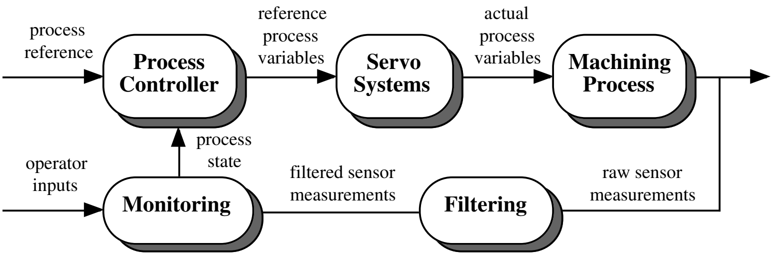


FIGURE 6.1 Process feedback control system.

process variables from a machining handbook or the operator's experience. Computer-aided process planning[4] is a more sophisticated technique which, in some cases, utilizes process models off-line to select process variables. The drawbacks of off-line planning are dependence on model accuracy and the inability to reject disturbances. Adaptive control techniques,[5] which include adaptive control with optimization, adaptive control with constraints, and geometric adaptive control, view processes as constraints and set process variables to meet productivity or quality requirements. A significant amount of research in AI techniques such as fuzzy logic, neural networks, knowledge base, etc. which require very little process information has also been conducted.[6]

This chapter concentrates on model-based process control techniques. A block diagram of a typical process feedback control system is shown in Figure 6.1. A process reference, set from productivity and quality considerations, and the process state are fed to the controller that adjusts the desired process variables. These references are input to the servo controllers that drive the servo systems (e.g., slides and spindles) that produce the actual process variables. Sensor measurements of the process are then filtered and input to the monitoring algorithms.

The trend toward making products with greater quality faster and cheaper has lead manufacturers to investigate innovative solutions such as process monitoring and control technology. Figure 6.2 shows the results of one study that clearly illustrates the benefits of process monitoring and control. A trend toward more frequent product changes has driven research in the area of reconfigurable machining systems.[7] Process monitoring technology will be critical to the cost-effective ramp-up of these systems, while process control will provide options to the designer who reconfigures the machining system. While process control has not made significant headway in industry, currently companies exist that specialize in developing process monitoring packages. Process monitoring and control technology will have a greater impact in future machining systems based on open-architecture systems[8] that provide the software platform necessary for the cost-effective integration of this technology.

The rest of the chapter is divided into six sections. The following three sections discuss force/torque/power generation, forced vibrations and regenerative chatter, and tool condition monitoring and control, respectively. The next section discusses burr and chip formation and cutting temperatures. These discussions focus on the development of models for, and the design of, process monitoring and control techniques. The last section provides future research directions. This chapter is not intended to provide an exhaustive overview of research in process monitoring and control; rather, relevant issues and major techniques are presented.

6.2 Force/Torque/Power Generation

The contact between the cutting tool and the workpiece generates significant forces. These forces create torques on the spindle and drive motors, and these torques generate power that is drawn from the motors. Excessive forces and torques cause tool failure, spindle stall (an event which is typically detected by monitoring the spindle speed), undesired structural deflections, etc. The cutting forces, torques, and power directly affect the other process phenomena; therefore, these quantities

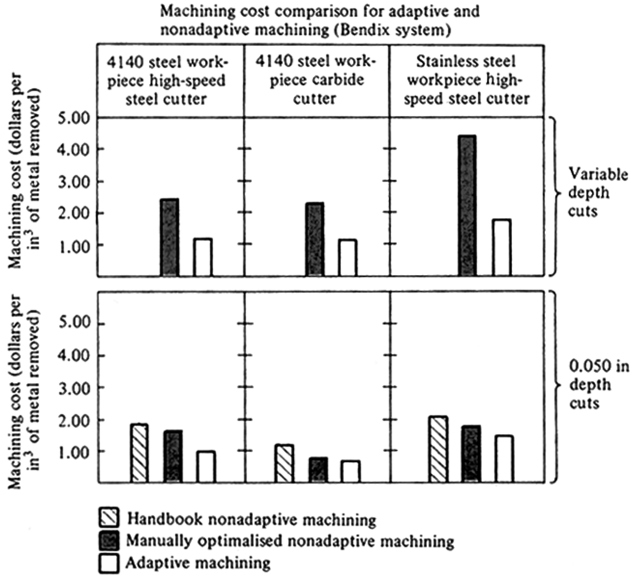


FIGURE 6.2 Machining cost comparison of adaptive and nonadaptive machining operations. (From Koren, Y. *Computer Control of Manufacturing Systems,* McGraw Hill, New York, 1983. With permission.)

are often monitored as an indirect measurement of other process phenomena and are regulated so that productivity is maximized while meeting machine tool and product quality constraints.

6.2.1 Cutting Force Models

A tremendous amount of effort has occurred in the area of cutting-force modeling over the past several decades. However, these models tend to be quite complex and experimentation is required to calibrate their parameters because an analytical model based on first principles is still not available. The models used for controller design are typically simple; however, the models used for simulation purposes are more complex and incorporate effects such as tooth and spindle runout, structural vibrations and their impact on the instantaneous feed, the effect of the cutting tool leaving the workpiece due to vibrations, intermittent cutting, tool geometry, etc. Two models that relate the actual process variables to the cutting force and are suitable for force control design are given below.

The structure of the static cutting force is

$$F = Kd^{\beta}V^{\gamma}f^{\alpha} \tag{6.1}$$

where F is the cutting force, K is the gain, d is the depth-of-cut, V is the cutting speed, f is the feed, and α, β, and γ are coefficients describing the nonlinear relationships between the force and the process variables. The model parameters in Equation (6.1) depend on the workpiece and cutting tool materials, coolant, etc. and must be calibrated for each different operation. Static models are used when considering a maximum or average force *per spindle revolution.* Such models are suitable for interrupted operations (e.g., milling) where, in general, the chip load changes throughout the spindle revolution and the number of teeth engaged in the workpiece constantly changes during steady operation (see Figure 6.3).

The structure of the first-order cutting force, assuming a zero-order hold equivalent, is

$$F = Kd^{\beta}V^{\gamma}\frac{1+a}{z+a}f^{\alpha} \tag{6.2}$$

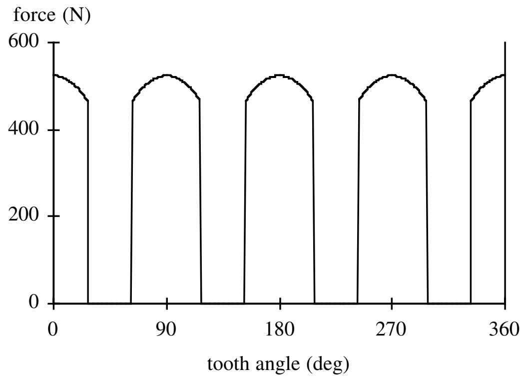


FIGURE 6.3 Simulated cutting force response for an interrupted face milling operation (four teeth, entry and exit angles of –/+ 27°). (From: Landers, R.G., Supervisory Machining Control: A Design Approach Plus Force Control and Chatter Analysis Components, Ph.D. dissertation, University of Michigan, Ann Arbor, 1997.)

where a is the discrete-time pole which depends upon the time constant and the sample period, and z is the discrete-time forward shift operator. The time constant, in turn, is sensitive to the spindle speed because a full chip load is developed in approximately one tool revolution.[9] In addition to the other model parameters, a must be calibrated for each different operation. First-order models are typically employed when considering an instantaneous force that is sampled several times per spindle revolution. Such models are suitable for uninterrupted operations (e.g., turning) where, typically, a single tool is continuously engaged with the workpiece and the chip load remains constant during steady operation.

6.2.2 Force/Torque/Power Monitoring

Load cells are often attached to the machine structure to measure cutting forces. Expensive dynamometers are often used in laboratory settings for precise measurements; however, they are impractical for industrial applications. Forces in milling operations were predicted from the current of the feed axis drive.[10] This technique is only applicable if the tooth-passing frequency is lower than the servo bandwidth and the friction forces are low or can be accounted for accurately. Torque is typically monitored on the spindle unit(s) with strain gauge devices. Again, expensive dynamometers may be used, but are cost prohibitive in industrial applications. Power from the spindle and axis motors is typically monitored using Hall-effect sensors. These sensors may be located in the electrical cabinet making them easy to install and guard from the process. Due to the large masses these motors drive, the signal typically has a small bandwidth.

6.2.3 Force/Torque/Power Control

Although the three major process variables (i.e., f, d, and V) affect the cutting forces, the feed is typically selected as the variable to adjust for regulation. Typically, the depth-of-cut is fixed from the part geometry and the force–speed relationship is weak (i.e., $\gamma \approx 0$); therefore, these variables are not actively adjusted for force control. References are set in roughing passes to maximize productivity, while references are set in finishing passes to maximize quality. References in roughing passes are due to such constraints as tool failure and maximum spindle power, and references in finishing passes are due to such constraints as surface finish and tool deflections (which lead to inaccuracies in the workpiece geometry).

Most force control technology is based on adaptive techniques;[11] however, model-based techniques have recently been gaining attention.[12] Adaptive techniques consider a linear relationship between the force and the feed and view changes in process variables and other process phenomena as changes in the cutting-force parameters. Model-based techniques directly incorporate the nonlinear model and the effects of other process phenomena must be estimated. Robust control techniques[13] have also gained recent attention. These techniques incorporate the cutting-force model and require bounds on the model's parameters. Regardless of the control approach, saturation limits must be set on the commanded feed. A lower saturation of zero is typical because a negative feed will disengage the cutting tool from the workpiece; however, a nonzero lower bound may be set due to process constraints. An upper bound is set due to process or machine tool servo constraints.

Two machining force controllers are designed and implemented next for the following static cutting force

$$F = 0.76 d^{0.65} f^{0.63} \tag{6.3}$$

where $\gamma = 0$ and F is a maximum force per spindle revolution in a face milling operation. For control design, the model is augmented with an integral state to ensure constant reference tracking and constant disturbance rejection.

A model-based design is now applied.[12] The control variable is $u = f^{0.63}$ and the design model (with an integral state) is

$$F(z) = \theta \frac{1}{z-1} u(z) \tag{6.4}$$

where $\theta = 0.76 d^{0.65}$ is the gain. Note that the nonlinear model-based controller utilizes process information (in this case, depth-of-cut) to directly account for known process changes. The model reference control (MRC) approach is applied and the control law is

$$u(z) = \frac{1}{z-1} \frac{1+b_0}{\theta} \left[F_r(z) - F(z) \right] \tag{6.5}$$

where F_r is the reference force and b_0 is calculated given a desired closed-loop time constant and sample period. The commanded feed is calculated from the control variable as

$$f = \exp\left[\frac{\ln(u)}{0.63} \right] \tag{6.6}$$

Therefore, the lower saturation on the control variable is chosen to have a small non-negative value. The experimental results for the nonlinear model-based controller are shown in Figure 6.4.

Next, an adaptive force controller is designed. The control design model, including an integral state, is

$$F(z) = \theta \frac{1}{z-1} f(z) \tag{6.7}$$

where θ is the gain and is assumed to be unknown. The MRC approach is applied and the control law is

$$f(z) = \frac{1}{z-1} \frac{1+b_0}{\hat{\theta}} \left[F_r(z) - F(z) \right] \tag{6.8}$$

The term $\hat{\theta}$ is an estimate of the gain. In this example, the common recursive least squares technique is employed.[14] At the i^{th} time iteration, the estimate is calculated as

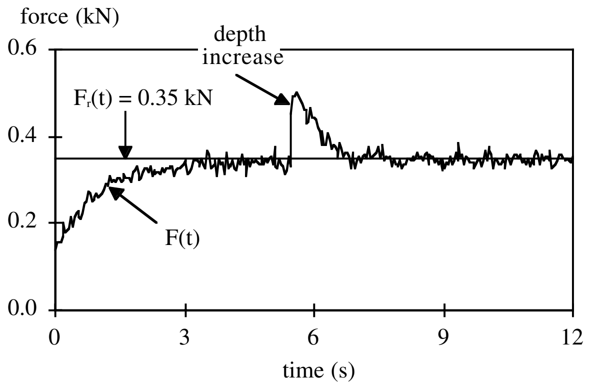


FIGURE 6.4 Force response, nonlinear model-based force controller. (From Landers, R.G., Supervisory Machining Control: A Design Approach Plus Force Control and Chatter Analysis Components, Ph.D. dissertation, University of Michigan, Ann Arbor, 1997.)

$$\hat{\theta}(i) = \hat{\theta}(i-1) + K(i)\varepsilon(i) \tag{6.9}$$

where

$$K(i) = \frac{P(i-1)f(i)}{\left[1 + f(i)P(i-1)f(i)\right]} \tag{6.10}$$

$$P(i) = \left[1 - K(i)f(i)\right]P(i-1) \tag{6.11}$$

$$\varepsilon(i) = F(i) - f(i)\hat{\theta}(i-1) \tag{6.12}$$

The parameter P is known as the covariance and the parameter ε is known as the residual. Estimating the model parameters on-line is a strong method of accounting for model inaccuracies; however, the overall system becomes much more complex, and chaotic behavior may result.

The experimental results for the adaptive controller are shown in Figures 6.5 and 6.6. Both approaches successfully regulate the cutting force while accounting for process changes in very different ways. The adaptive technique is useful when an accurate model is not available, but is more complex compared to the model-based approach.

6.3 Forced Vibrations and Regenerative Chatter

The forces generated when the tool and workpiece come into contact produce significant structural deflections. Regenerative chatter is the result of the unstable interaction between the cutting forces and the machine tool–workpiece structures, and may result in excessive forces and tool wear, tool failure, and scrap parts due to unacceptable surface finish.

The feed force for an orthogonal cutting process (e.g., turning thin-walled tubes) is typically described as

$$F(t) = Kd\left[f_n + x(t) - x(t-\tau)\right] \tag{6.13}$$

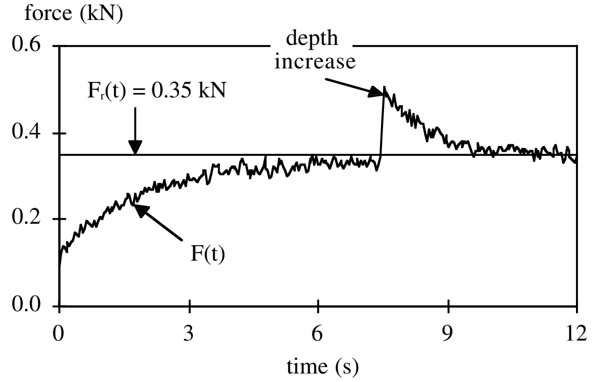


FIGURE 6.5 Force response, an adaptive force controller. (From Landers, R.G., Supervisory Machining Control: A Design Approach Plus Force Control and Chatter Analysis Components, Ph.D. dissertation, University of Michigan, Ann Arbor, 1997.)

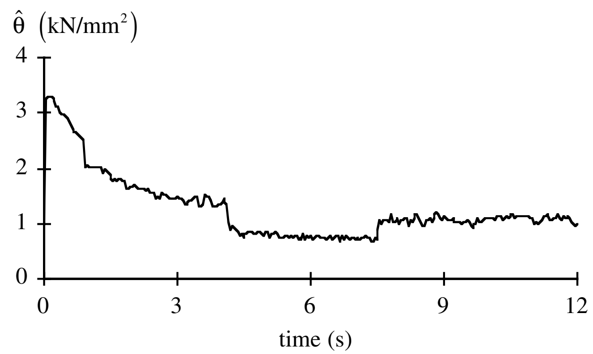


FIGURE 6.6 Force model gain estimate, an adaptive force controller. (From Landers, R.G., Supervisory Machining Control: A Design Approach Plus Force Control and Chatter Analysis Components, Ph.D. dissertation, University of Michigan, Ann Arbor, 1997.)

where f_n is the nominal feed, x is the displacement of the tool in the feed direction, and τ is the time for one tool revolution. The assumption is that the workpiece is much more rigid than the tool, and the force is proportional to the instantaneous feed and the depth-of-cut and does not explicitly depend upon the cutting speed. The instantaneous chip load is a function of the nominal feed, the current tool displacement, and the tool displacement at the previous tool revolution. Assuming a simple model, the vibration of the tool structure may be described by

$$m\ddot{x}(t) + c\dot{x}(t) + kx(t) = F(t) \tag{6.14}$$

where m, c, and k are the effective mass, damping, and stiffness, respectively, of the tool structure. The stability of the closed-loop system formed by equations combining (6.13) and (6.14) may be examined to generate the so-called stability lobe diagram (Figure 6.7) and select appropriate process variables.

Another cause of unacceptable structural deflections, known as forced vibrations, arises when an input frequency (e.g., tooth-passing frequency) is close to a resonant structural frequency. The resulting large relative deflections between the cutting tool and workpiece lead to inaccuracies in

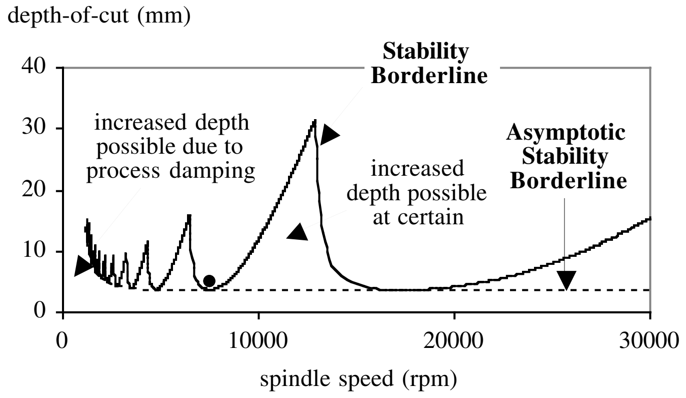


FIGURE 6.7 Stability lobe diagram. The tool structure's natural frequency is 12,633 Hz. Operating point (d = 5 mm, N_s = 7500 rpm) denoted by dark circle is used in the simulations in Figures 6.10 and 6.11.

the workpiece geometry. An example of forced vibrations may be found in Reference 15. When the tooth-passing frequency is close to a dominant structural frequency, productivity may be increased (see Figure 6.7); however, forced vibrations will occur. Therefore, the designer must make a trade-off between controlling regenerative chatter and inducing forced vibrations

In this section, common techniques for on-line chatter detection and suppression are presented.

6.3.1 Regenerative Chatter Detection

Regenerative chatter is easily detected by an operator because of the loud, high-pitched noise it produces and the distinctive "chatter marks" it leaves on the workpiece surface. However, automatic detection is much more complicated. The most common approach is to threshold the spectral density of a process signal such as sound,[16] force,[17] etc. An example in which the force signal is utilized for chatter detection (see Figure 6.8) demonstrates that chatter frequency occurs near a dominant structural frequency. Note that the tooth-passing frequency contains significant energy. In this application, the lower frequencies may be ignored by the chatter detection algorithm; however, if the operation is performed at a higher spindle speed, the force signal has to be filtered at the tooth-passing frequency. Also, the impact between the cutting tool and workpiece will cause structural vibrations that must not be allowed to falsely trigger the chatter detection algorithm.

These thresholding algorithms all suffer from the lack of an analytical method to select the threshold value. This value is typically selected empirically and will not be valid over a wide range of cutting conditions. A more general signal was proposed by Bailey et al.[18] An accelerometer signal mounted on the machine tool structure close to the cutting region was processed to calculate the so-called variance ratio

$$R = {\sigma_s^2}/{\sigma_n^2} \tag{6.15}$$

where σ_s and σ_n are the variances of the accelerometer signal in low and high frequency ranges, respectfully. A value of $R << 1$ indicates chatter.

6.3.2 Regenerative Chatter Suppression

Chatter is typically suppressed by adjusting the spindle speed to lie in one of the stability lobe pockets, as shown in Figure 6.7.[19] Feed has been shown to have a monotonic effect on the marginally stable depth-of-cut (see Figure 6.9) and is sometimes the variable of choice by machine tool

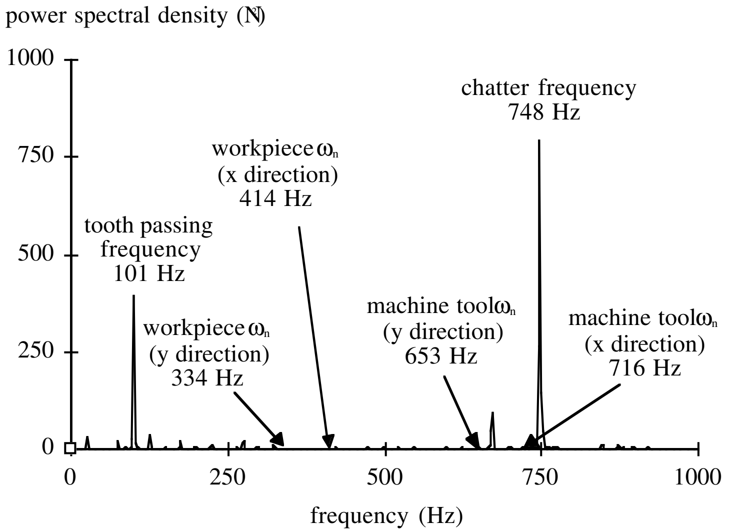


FIGURE 6.8 Power spectrum of force signal during chatter. (From Landers, R.G., Supervisory Machining Control: A Design Approach Plus Force Control and Chatter Analysis Components, Ph.D. dissertation, University of Michigan, Ann Arbor, 1997.)

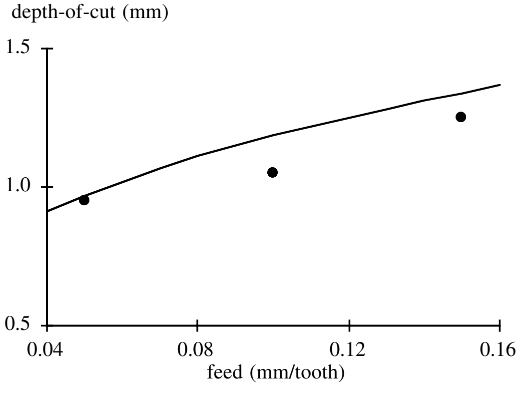


FIGURE 6.9 Theoretical prediction (solid line) vs. experimental data (circles) demonstrating the feed effect on chatter. (From Landers, R.G., Supervisory Machining Control: A Design Approach Plus Force Control and Chatter Analysis Components, Ph.D. dissertation, University of Michigan, Ann Arbor, 1997.)

operators.[20] The tool position may also be adjusted (e.g., depth-of-cut decreased) to suppress chatter, and while it is guaranteed to work (see Figure 6.7), this approach is typically not employed because the part program must be rewritten and productivity is drastically decreased.

Spindle speed variation (SSV) is another technique for chatter suppression.[15] The spindle speed is varied about some nominal value, typically in a sinusoidal manner. Figures 6.10 and 6.11 demonstrate how varying the spindle speed sinusoidally with an amplitude of 50% of the nominal value and at a frequency of 6.25 Hz will suppress chatter that occurs when a constant spindle speed at the nominal value is utilized (see Figure 6.7). Although SSV is a promising technique, little theory exists to guide the designer to the optimal variation and, in some cases, SSV may create chatter which will not occur when using a constant spindle speed. Further, it can be seen in Figure 6.11b that SSV will cause force fluctuations even though the chatter is suppressed.

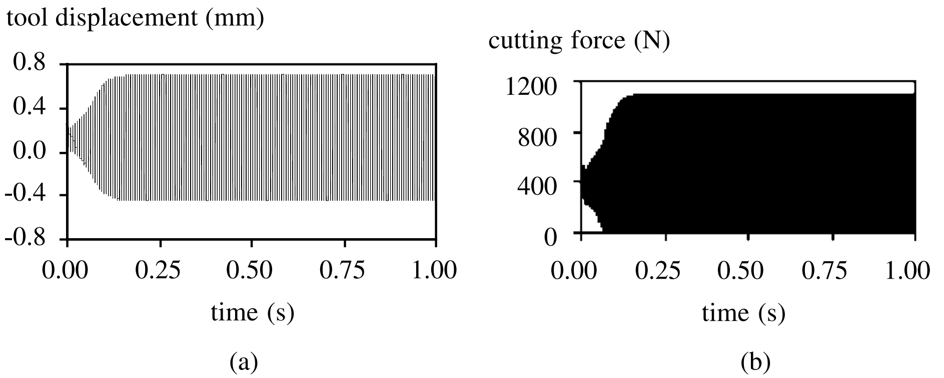


FIGURE 6.10 Simulated responses of force and structural displacements for constant speed machining. Cutting conditions given in Figure 6.7.

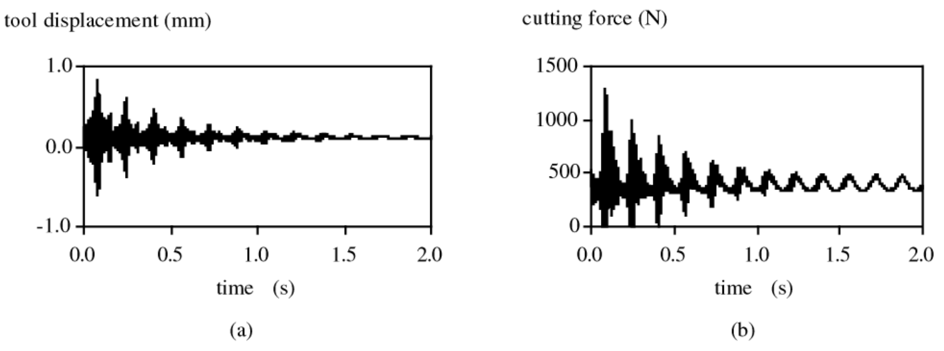


FIGURE 6.11 Simulated responses of force and structural displacements for variable speed machining. Cutting conditions given in Figure 6.7.

6.4 Tool Condition Monitoring and Control

Some of the most common monitoring techniques concentrate on tool condition monitoring. Vision sensors and probes are used to detect missing cutting tools in a tool magazine and to ensure the correct tool is being used. Vision and force sensors are also used to detect tool–workpiece collisions or tool–tool collisions in parallel machining operations. If a collision is detected, an emergency stop is typically initiated and the part program must be rewritten. The monitoring and control of the more complicated tool condition phenomena (i.e., tool failure and tool wear) are discussed next.

6.4.1 Tool Failure

A tool has failed when it can no longer perform its designated function. This event may occur when a significant portion of the tool breaks off, the tool shaft or cutting teeth severely fracture, or a significant portion of one or more teeth chip. Broken tools drastically decrease productivity by creating unnecessary tool changes, wasting tools, and creating scrap parts, and possibly injuring operators.

The simplest way to detect a failed tool is to use a probe or vision system to inspect the cutting tool. While this inspection is typically performed off-line, some techniques are being developed

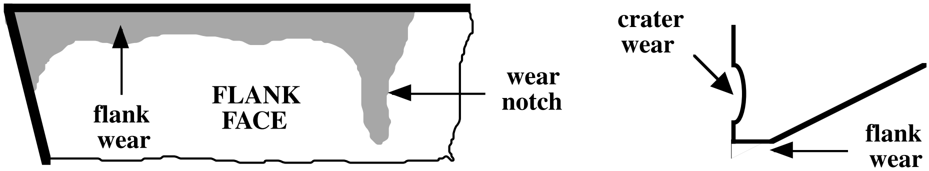


FIGURE 6.12 Illustration of different types of tool wear.

for on-line detection;[21] however, chip and coolant interference is still a major obstacle to overcome. Many sensors have been used to indirectly detect tool failure, including acoustic emission, force, sound, vibration, etc. In these indirect methods, the signal magnitude, root mean square value, or the magnitude of the power spectrum, among others, are inspected, typically via thresholding. One example is given in Altintas[10] where the residual of a first-order adaptive auto-regressive time series filter of the average (during a tooth pass) drive current was monitored to detect insert chippage. Creating a static threshold value is difficult to do in complex machining operations; therefore, dynamic limits are often set to account for entry and exit conditions, changes in process variables, etc. For operations where the feed rate is not adjusted, these limits may be correlated with time; however, in general, these limits should be correlated with position. Pattern recognition techniques may also be utilized. If a signal is compared to a stored pattern, then breakage may be determined independent of the signal magnitude. Comparison to teach-in signals (i.e., an average of several signals in similar operations where breakage did not occur) is another technique. Currently, little theory exists to guide the user in setting these limits.

When a tool failure event has been detected, an emergency stop is typically initiated. A significant amount of time is spent not only changing the cutting tool and workpiece, but also restarting the machine tool or machining line. This loss of productivity can be avoided by an intelligent reaction to the tool failure event. For example, the cutting tool may be moved to the tool change position and vision may be utilized to examine the workpiece surface to verify whether or not the workpiece must be scrapped. As another example, if a tooth chips in a milling cutter, optical techniques may be used to determine if the workpiece and tool are undamaged and, if so, the feed can be decreased and cutting may continue.

There have been some studies to detect the onset of tool failure. In Rice and Wu,[22] the energy release rate of an acoustic emission signal was monitored in interrupted cutting tests to determine the advancement of a fracture event. If a tool does fail, steps must be taken to ensure that failure does not happen again. Typically, a process parameter, i.e., the feed is adjusted; however, a reference force may also be adjusted if a force control scheme is being employed.

6.4.2 Tool Wear

The contact between the cutting tool and the chips causes the shape of the tool to change (Figure 6.12). This phenomenon, known as tool wear, has a major influence in machining economics, affects the final workpiece dimensions, and will lead to eventual tool failure. A typical tool-wear curve is shown in Figure 6.13. The tool wears rapidly in the initial phase and then levels off to a constant rate during the steady phase. From an economic point of view, the designer would like to use the tool until just before it enters the accelerated wear phase during which the tool will eventually fail.

The three main tool-wear mechanisms include abrasion between the cutting tool and workpiece, which is always present; adhesion of the chips or workpiece to the cutting tool, which removes cutting tool material and is more active as the cutting temperature increases; and diffusion of the cutting tool atoms to the chips or workpiece, which is typically active during the accelerated tool-wear phase.

The most well-known equation describing tool wear was developed by F. W. Taylor early in the twentieth century.[23] This equation, known as Taylor's tool equation, is

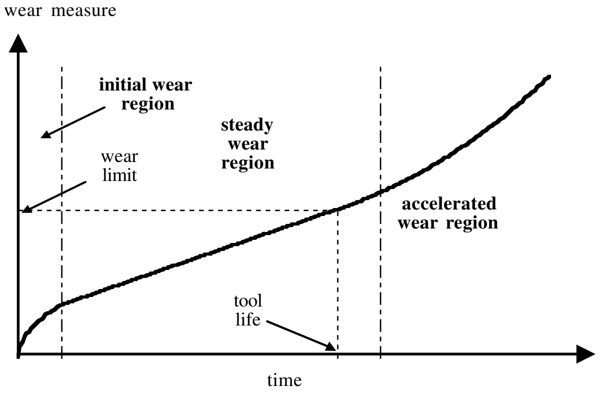


FIGURE 6.13 Typical tool wear history.

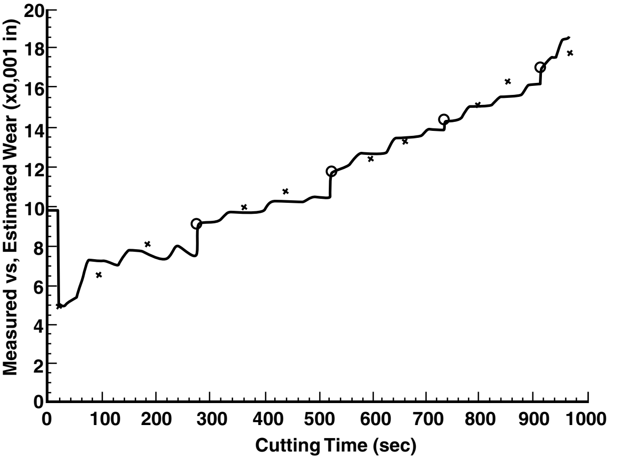
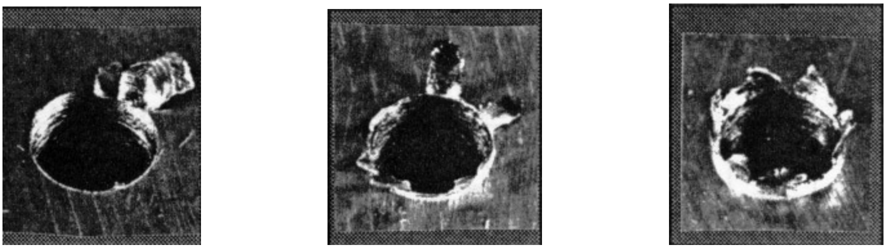


FIGURE 6.14 Estimated (solid line) vs. measured (crosses) flank wear. The circles are vision measurements used to recalibrate the adaptive observer. (From Park, J.J. and Ulsoy, A.G., *ASME Journal of Engineering for Industry*, 115, 37, 1993. With permission.)

$$Vt_l^n = C \tag{6.16}$$

where t_l is the tool lifetime and C and n are empirically determined constants. Modified Taylor equations include the effects of feed rate and depth-of-cut, as well as interaction effects between these variables. Increased testing is required to determine the extra model coefficients; however, these models are applicable over a wider range of cutting conditions. Models relating tool wear and cutting forces have also been developed.[24,25] See Kendall[26] for more information regarding cutting tool-wear mechanisms and modeling.

The most reliable way to monitor tool wear is by direct visual inspection. Indirect techniques utilizing such measurements as acoustic emission, force, temperature, vibration, etc. have also been developed, or the final part geometry may be measured. Similar to tool breakage monitoring, these indirect signals are typically processed to expose those characteristics that are highly correlated



(a) (b) (c)

FIGURE 6.15 Exit burrs in a through-hole drilling operation and their burr ratings: (a) 1, (b) 3, (c) 5. (From Furness, R.J., Ulsoy, A.G., and Wu, C.L., *ASME Journal of Engineering for Industry*, 118, 10, 1996. With permission.)

with tool wear. Again, cutting tests are required to determine this correlation. In Park and Ulsoy,[25] a hybrid tool-wear monitoring technique was investigated. An adaptive observer was applied to estimate wear on-line and a vision system was used intermittently (e.g., between parts) to recalibrate the observer (Figure 6.14). The reader is referred to Dan and Mathew[27] for an overview of tool-wear monitoring.

The two main issues in tool-wear regulation are to compensate for tool wear and to control the tool-wear rate. As the tool wears, the workpiece dimension may become out of tolerance; thus, the tool position must be adjusted (typically through the part program) to compensate for the tool wear. From an economic point of view, it is desirable to regulate the tool-wear rate so that the tool life corresponds to the scheduled tool change period in mass production, or to maximize tool life in job-shop situations.

6.5 Other Process Phenomena

6.5.1 Burr Formation

Small, undesirable metal fragments left on the workpiece after the machining operation is complete are known as burrs (Figure 6.15). Burrs cause improper part mating, accelerated device wear, and decreased device performance. Because it is typically impossible to avoid the formation of burrs, the designer should strive to reduce the complexity of subsequent deburring operations by minimizing the burr strength and ensuring the burrs form at easily accessible workpiece locations.

The three major burr types (poisson, roll-over, and tear) form due to workpiece plastic deformation. When the cutting-tool edge extends over a workpiece edge, material is compressed and may flow laterally forming a poisson burr. Roll-over burrs form when the cutting tool exits the workpiece and the chip bends over the edge instead of being cut. If a chip is torn from the workpiece, instead of being sheared off, some material from the chip will be left on the workpiece. The material is known as a tear burr. The reader is referred to Gillespie[28] for greater detail concerning burr models. Burr measurement is typically performed off-line by measuring the average height, base thickness, and toughness. Burr location and its accessibility are also important to note.

Process variables are known to have a strong effect on the physical characteristics of burrs. If the depth-of-cut in a face milling operation is too small, the cutting tool will push the material over the side of the workpiece and form a large, strong burr on the workpiece edge. In Furness, Ulsoy, and Wu,[29] a feed controller regulated the feed at 0.051 mm/rev as the tool exited the workpiece in a through-hole drilling operation to obtain an acceptable burr rating. The burr rating depended on burr thickness and peak height, percentage of the hole's circumference with an attached burr, and qualitative assessment of the relative ease of removal. Without adequate models, one is left to empirical techniques or AI methods to predict, and hence control, burr formation.

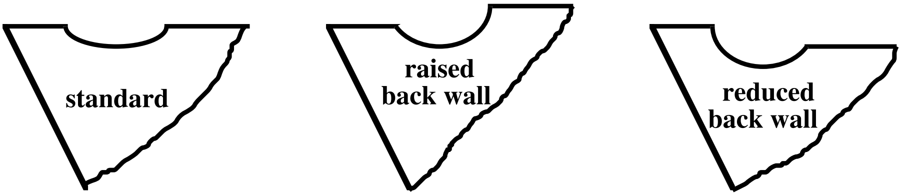


FIGURE 6.16 Illustration of common chip breakers.

6.5.2 Chip Formation

The three major chip formation types are discontinuous, continuous, and continuous with built-up edge (BUE).[30] Discontinuous chips arise when the operation continuously forms and fractures chips because of the workpiece's inability to undergo large amounts of plastic deformation, while continuous chips do not fracture but form continuous ribbons. Continuous chips with BUE form when part of the chip welds to the tool due to high cutting temperatures and pressures. Continuous chips (with and without BUE) will interfere with the normal interaction between the tool and workpiece and cause poor surface finish, as will discontinuous chips that do not clear the cutting zone. Therefore, chip control is the proper formation of chips that clear the cutting zone and are directed toward the chip conveyor system for efficient removal.

Research of the chip formation process goes back nearly a century, starting most notably with Taylor.[23] Theories have been developed to predict shear plane angle, chip velocity, etc. mainly for two-dimensional cases. More recently, chip curling and chip breaking models have been emphasized. These models, however, are not widely applicable. Currently, computational mechanics (i.e., finite element methods) and artificial intelligence (AI) methods have been applied. See van Luttervelt, et al.[31] for a comprehensive overview of the current status of machining modeling.

High-speed filming techniques have been used to directly monitor chip formation. Indirect methods include force, acoustic emission, and infrared emission measurements, and sensor fusion based on AI techniques.

Chip formation control is typically achieved through the design of chip breakers (Figure 6.16). The grooves cause an otherwise continuous chip to curl and fracture. Small amplitude, high-frequency variations in the feed are a relatively new technique for ensuring chip fracture. This variation is accomplished using a passive device attached to the cutting tool and may also be accomplished by varying the feed rate on-line; however, the variation frequency will be limited by the bandwidth of the servo system. The use of process parameters has also been investigated. While chip curling is typically independent of process variables, thicker chips formed from relatively large feeds break more easily than do thinner chips.[32] Due to the complexity and incomplete knowledge of chip formation, a database approach to selecting chip breakers and process variables is the most reliable method for chip control. See Jawahir and van Luttervelt[33] for a comprehensive overview of research in this area.

6.5.3 Cutting Temperature Generation

Friction between the cutting tool and workpiece generates significant temperature in the cutting zone. The cutting temperature affects the tool wear rate and workpiece surface integrity, and contributes to thermal deformation.

The most basic temperature models estimate steady-state cutting temperatures and typically have the following nonlinear relationship with the process variables[34]

$$T = aV^b f^c \tag{6.17}$$

where T is the workpiece temperature and a, b, and c are empirically determined constants. A comparison with experimental results shows most models are qualitatively correct, but quantitatively overestimate cutting temperatures and are unable to estimate cutting temperatures in operations with discontinuous chip formation.[35] The use of thermocouples and infrared data to measure cutting temperatures was investigated; however, cutting temperature measurements are rarely utilized in industrial settings.[35]

Similar to burr and chip formation, cutting temperature generation has received little attention from the control community. One investigation was performed by D'Errico, Calzavarini, and Settineri.[36] Using a simple static nonlinear relationship between cutting temperature and cutting velocity similar to Equation (6.17), with $c = 0$, a self-tuning regulator was developed to control the cutting temperature via adjustment of the cutting velocity.

6.6 Future Directions and Efforts

This chapter has presented the major techniques for monitoring and controlling the phenomena arising from the interaction of the cutting tool and the workpiece in machining operations. It can be readily seen that advances in the modeling of cutting mechanics are required; in particular, analytical models based on first principles applicable to a wide variety of cutting conditions must be developed. Currently, models are determined empirically and typically contain nonlinear terms that account for unmodeled effects. Further, the cost-effective design of process monitoring and control technology will require simulation tools that simulate not only cutting mechanics and monitoring and control modules, but also the machine tool structure and servo mechanisms. A comprehensive simulator will allow the designer to investigate process monitoring and control technology in a realistic environment (i.e., one with the appropriate complexities).

The biggest obstacles facing the implementation of process monitoring technology are low reliability, limited applicability, and the need for experimentation to determine threshold values, characteristic patterns, etc. Advances in models based on first principles and the increased use of sophisticated signal processing techniques will be required to overcome these obstacles. Other issues in process monitoring include the use of increasingly sophisticated sensors and the placement of these sensors in harsh machining environments. Advances in sensor technology to integrate the sensors with the machine tool or cutting tool and research into using computer numerical control (CNC)-integral sensors (e.g., drive current) will address these issues.

Currently, the largest research effort in process monitoring is the Intelligent Manufacturing Systems (IMS) project Sensor Fused Intelligent Monitoring System for Machining (SIMON) which is an international, industry-driven project with the goal of developing a practical monitoring system that can reliably identify actual cutting conditions according to information obtained from a sensor-fused system.[37] Another development in the field of process monitoring is a mapping theory to facilitate the cost-effective design of modular monitoring packages.[38] Given the machining operation, the so-called fault space (e.g., chippage, tool deformation) is generated. The characteristics of these faults are mapped to those of the required sensor and used to select the correct sensor package. The monitoring package will then be applied in the ramp-up phase of a machining system.

As process monitoring techniques become more reliable, process control will become more prevalent. During the ramp-up phase of a machining system, process controllers will provide an effective means of determining near-optimal process variables for complex operations. The part program can be modified to incorporate the new process variable time histories and then process controllers may be utilized in the production phase to reject disturbances. While process control is not widely implemented in industry today, a substantial amount of work has been done in research laboratories. This research has almost always been concerned with regulating a single process via a single process variable. Future research will be concerned with utilizing multiple process variables to control a single process and implementing multiple process controllers simultaneously in a single operation.

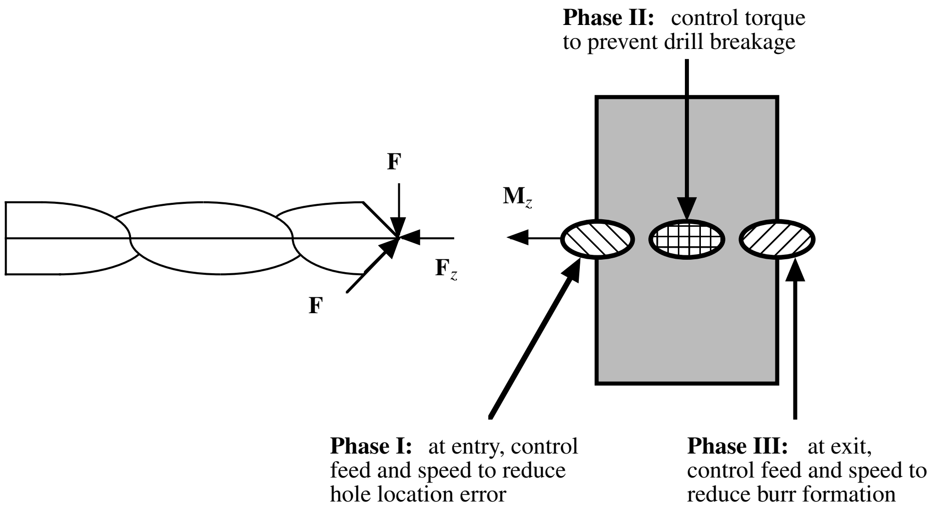


FIGURE 6.17 Illustration of an off-line supervisory control implementation in a through-hole drilling operation.

The concept of implementing multiple process controllers has lead to research in supervisory control.[29,39,40] The supervisory control of a through-hole drilling operation was investigated in Furness, Ulsoy, and Wu.[29] The objective was to maximize operation productivity subject to a set of machine, process, and quality constraints. Machine constraints included a maximum spindle speed and feed rate. Process constraints included a maximum torque to avoid drill breakage and cutting torque limitations, a maximum force to avoid buckling, and a minimum tool life to maintain a constant tool replacement period. Quality constraints included a maximum hole location error and minimum burr formation. The process controllers were supervised using an off-line optimization technique where the controller configuration depended on workpiece location (see Figure 6.17). The experimental results for the supervisory controller compared to other controller configurations are shown in Table 6.1.

A state-based, on-line supervisory controller was developed in Landers and Ulsoy.[40] A state supervisor monitored the operation including discrete events (e.g., tool–workpiece contact, chatter) and continuous signals (e.g., force model parameter estimates). Given the operation state, an operation supervisor configured the monitoring and control modules (i.e., turned them off and on, reset them, etc.). Experimental results for a face milling operation are shown in Figure 6.18. The force controller and chatter detector were turned on when the tool and workpiece came into contact. As the tool became fully engaged in the workpiece, chatter developed. The chatter suppressor rewrote the part program to add an additional tool pass and implemented a feed hold for five tool revolutions to allow the vibrations to die out. The force controller was then reset and machining continued. The force controller and chatter detector were turned off as the tool exited the workpiece and were again implemented as the second tool pass began.

TABLE 6.1 Comparison of Drilling Control Strategies[41]

	No Controller	Feed/Speed Controller	Torque/Speed Controller	Supervisory Controller
Machining time (s)	11.11	11.28	9.79	11.71
Burr rating	2.93	2.94	2.26	1.58
Hole location quality (in)	4.43 E-3	4.53 E-3	6.28 E-3	4.25 E-3
Event stoppages (%)	25	15	0	0

Source: Ulsoy, A.G. and Koren, Y., *ASME Journal of Dynamic Systems, Measurement, and Control,* 115, 301, 1993. With permission.

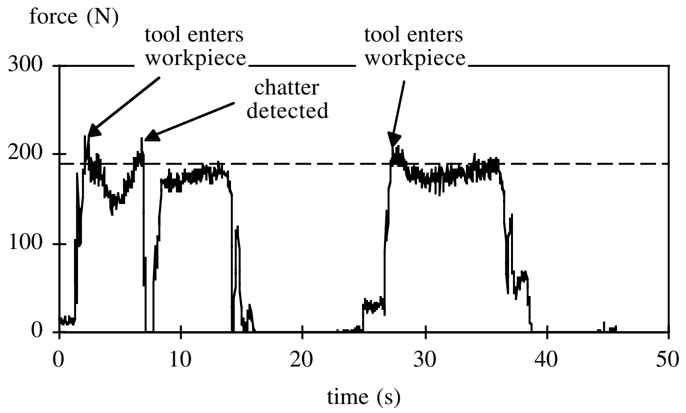


FIGURE 6.18 Force history results using a supervisory controller during a face milling operation. (From Landers, R.G., Supervisory Machining Control: A Design Approach Plus Force Control and Chatter Analysis Components, Ph.D. dissertation, University of Michigan, Ann Arbor, 1997.)

Acknowledgments

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