Process Monitoring and Control of Machining Operations

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1 INTRODUCTION

Machining operations (e.g., drilling, milling) are shape transformation processes where 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 naturally occur in machining operations which are detrimental to this objective. In this chapter, we present techniques for monitoring and controlling the process phenomena which 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 which, along with operator inputs, determine the process state (Figure 1). The state of complex processes are monitored by sophisticated signal processing of sensor measurements which typically involve thresholding or artificial intelligence (AI) techniques. [1] For more information on sensors for process monitoring, the reader is refereed to [2,3].

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, initiating an emergency stop in response to a tool breakage event, rewriting 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 process variables from a machining handbook or from the operator’s experience. Computer aided process planning (e.g., see [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 the dependence on model accuracy and the inability to reject disturbances. Adaptive control techniques (e.g., see [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. There has also been a significant amount of work in AI techniques such as fuzzy logic, neural networks, knowledge base, etc. which require very little process information (e.g., see [6]).

This chapter will concentrate on model-based process control techniques. A block diagram of a typical process feedback control system is shown in Figure 1. A process reference, set from productivity and quality considerations, and the process state are fed to the controller which adjusts the desired process variables. These references are input to the servo controllers which drive the servo systems (e.g., slides and spindles) which produce the actual process variables. Sensor measurements of the process are then filtered and input to the monitoring algorithms.

The trend towards making products with greater quality faster and cheaper has lead manufacturers to investigate innovative solutions such as process monitoring and control technology. Figure 2 shows the results of one study which clearly illustrates the benefits of process monitoring and control. There is also a trend towards more frequent product changes which 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, there are currently companies which 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 (e.g., see [8]) which 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 sections 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, the relevant issues and major techniques are provided.
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 which 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 effect the other process phenomena; therefore, these quantities are often monitored as an indirect measurement of other process phenomena and are regulated such that productivity may be maximized while meeting machine tool and product quality constraints.

2.1 Cutting Force Models

There has been a tremendous amount of effort 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 the parameters as 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 effect on the instantaneous feed, the effect of the cutting tool leaving the workpiece due to vibrations and intermittent cutting, tool geometry, etc. Two models which 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

\[ F = Kd^\beta V^\gamma f^\alpha \] (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 $\alpha$, $\beta$, and $\gamma$ are coefficients describing the nonlinear relationships between the force and the process variables. The model parameters in equation (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 force per spindle revolution such as a maximum or average force. 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 3).

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

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

(2)

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 since 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 which 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.

### 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. In [10], forces in milling operations were predicted from the current of the feed axis drive. 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.

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 (e.g., see [11]); however, model-based techniques have recently been gaining attention (e.g., see [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 (e.g., see [13]) have also gained recent attention. These techniques incorporate the cutting force model and require bounds on the model parameters. Regardless of the control approach, saturation limits must be set on the commanded feed. A lower saturation of zero is typical since a negative feed will disengage the cutting tool from the workpiece; however, a non-zero 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

\[ F = 0.76d^{0.65} \rho^{0.63} \]  \hspace{1cm} (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

\[ F(z) = \theta \frac{1}{z - 1} u(z) \]  \hspace{1cm} (4)

where \( \theta = 0.76d^{0.65} \) is the gain. Note 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

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

\[ f = \exp \left[ \frac{\ln(u)}{0.63} \right] \]  \hspace{1cm} (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 4.

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

\[ F(z) = \theta \frac{1}{z - 1} f(z) \]  \hspace{1cm} (7)

where \( \theta \) is the gain and is assumed to be unknown. The MRC approach is applied and the control law is

\[ f(z) = \frac{1}{z - 1} \frac{1 + b_0}{\hat{\theta}} [F_i(z) - F(z)] \]  \hspace{1cm} (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

\[ \hat{\theta}(i) = \hat{\theta}(i - 1) + K(i) \varepsilon(i) \]  \hspace{1cm} (9)

where

\[ K(i) = \frac{P(i - 1)f(i)}{[1 + f(i)P(i - 1)f(i)]} \]  \hspace{1cm} (10)

\[ P(i) = [1 - K(i)f(i)]P(i - 1) \]  \hspace{1cm} (11)

\[ \varepsilon(i) = F(i) - f(i)\hat{\theta}(i - 1) \]  \hspace{1cm} (12)
The parameter $P$ is known as the covariance and the parameter $\varepsilon$ 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 5 and 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.

### 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

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

where $f_n$ is the nominal feed, $x$ is the displacement of the tool in the feed direction, and $\tau$ 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 as well as 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
\[ m\ddot{x}(t) + c\dot{x}(t) + kx(t) = F(t) \]  \hspace{1cm} (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 (13) and (14) may be examined to generate the so-called stability lobe diagram (Figure 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 the workpiece geometry. An example of forced vibrations may be found in [15]. When the tooth passing frequency is close to a dominant structural frequency, productivity may be increased (see Figure 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.

### 3.1 Regenerative Chatter Detection

Regenerative chatter is easily detected by an operator due to 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 (e.g., see [16]), force (e.g., see [17]), etc. An example where the force signal is utilized for chatter detection (see Figure 8) demonstrates the 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 was performed at a higher spindle speed, the force signal would have to be filtered at the tooth passing frequency. Also, the impact between
the cutting tool and workpiece will cause structural vibrations which must not be allowed to falsely trigger the chatter detection algorithm.

These thresholding algorithms all suffer from the lack of an analytical method of selecting 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 [18]. An accelerometer signal mounted on the machine tool structure close to the cutting region was processed to calculate the so-called variance ratio

\[ R = \frac{\sigma^2}{\sigma_n^2} \]  

(15)

where \( \sigma \) and \( \sigma_n \) are the variances of the accelerometer signal in low and high frequency ranges, respectively. A value of \( R \ll 1 \) indicates chatter.

### 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 7 (e.g., see [19]). Feed has been shown to have a monotonic affect on the marginally stable depth-of-cut (see Figure 9) and is sometimes the variable of choice by machine tool 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 7), this approach is typically not employed since the part program must be rewritten and productivity is drastically decreased.

Spindle speed variation (SSV) is another technique for chatter suppression (e.g., see [15]). The spindle speed is varied about some nominal value, typically in a sinusoidal manner. Figures 10 and 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 7). Although SSV is a promising
technique, there is little theory to guide the designer as 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 11b that SSV will cause force fluctuations even though the chatter is suppressed.

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.

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 may injure operators.

The most simple 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 for on-line detection (e.g., see [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 magnitude of the power spectrum, among others, are inspected, typically via thresholding. One example is given in [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 feedrate 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, there is little theory 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 scraped. 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 [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 such as the feed is adjusted; however, a reference force may also be adjusted if a force control scheme is being employed.

4.2 Tool Wear

The contact between the cutting tool and the chips causes the shape of the tool to change (Figure 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 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 where 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

\[ V t_i^n = C \]  \hspace{1cm} (16)

where \( t_i \) is the tool lifetime and \( C \) and \( n \) are empirically determined constants. Modified Taylor equations include the effects of feedrate 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 [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 the characteristics which are highly correlated with tool wear. Again, cutting tests are required to determine this correlation. In [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 14). The reader is refereed to [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 such that the tool life corresponds to the scheduled tool change period in mass production, or to maximize the tool life in job shop situations.

5 OTHER PROCESS PHENOMENA

5.1 Burr Formation

Small, undesirable metal fragments left on the workpiece after the machining operation is complete are known as burrs (Figure 15). Burrs cause improper part mating, accelerated device wear, and decreased device performance. Since it is typically impossible to avoid the formation of burrs, the designer should strive to reduce the complexity of the subsequent deburring operation by minimizing the burr strength and ensuring the burrs form at workpiece locations that are easy to access.

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 refereed to [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 [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 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.

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 due to the inability of the workpiece to undergo large amounts of plastic deformation, while continuous chips do not fracture but rather 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 which do not clear the cutting zone. Therefore, chip control is the proper formation of chips which clear the cutting zone and are directed towards the chip conveyor system for efficient removal.

Research of the chip formation process extends nearly a century, starting most notably with [23]. Theory has been developed to predict shear plane angle, chip velocity, etc., mainly for two dimensional cases. More recently, there has been an emphasis on chip curling and chip breaking models. These models, however, are not widely applicable. Currently, computational mechanics (i.e., finite element methods) and AI methods have been applied. See [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 via the design of chip breakers (Figure 16). The grooves cause an otherwise continuous chip to curl and fracture. Small amplitude, high frequency variations in the feed is a relatively new technique for ensuring chip fracture. This variation is accomplished via a passive device attached to the cutting tool. This variation may also be accomplished by varying the feedrate 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 [33] for a comprehensive overview of research in this area.

5.3 Cutting Temperature Generation

The friction between the cutting tool and workpiece generates significant temperature in the cutting zone. The cutting temperature affects the tool wear rate and the 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 (e.g., see [34])

$$ T = aV^b f^c $$

where $T$ is the workpiece temperature and $a$, $b$, and $c$ are empirically determined constants. A comparison with experimental results shows most models to be qualitatively correct, but to 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 [36]. Using a simple static nonlinear relationship between cutting temperature and cutting velocity similar to equation (17), with $c = 0$, a self-tuning regulator was developed to control the cutting temperature via adjustment of the cutting velocity.

6 FUTURE DIRECTION 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 is required; in particular, analytical models based on first principles which may be applied to a wide variety of cutting conditions must be developed. Currently, models are determined empirically and typically contain nonlinear terms which account for unmodeled effects. Further, the cost-effective design of process monitoring and control technology will require simulation tools which simulate not only the cutting mechanics and the 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 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 the 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 the required sensor characteristics which are 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.

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 [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 feedrate. 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 changing 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 17). The experimental results for the supervisory controller as compared to other controller configurations are shown in Table 1.

A state-based, on-line supervisory controller was developed in [40]. A state supervisor monitored the state of 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 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 suppresser 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.

7 ACKNOWLEDGMENTS

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8 REFERENCES


Table 1: Comparison of Drilling Control Strategies. [41]

<table>
<thead>
<tr>
<th></th>
<th>No Controller</th>
<th>Feed/Speed Controller</th>
<th>Torque/Speed Controller</th>
<th>Supervisory Controller</th>
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<tr>
<td>Machining Time (s)</td>
<td>11.11</td>
<td>11.28</td>
<td>9.79</td>
<td>11.71</td>
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<td>Burr Rating</td>
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<td>2.94</td>
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<td>Hole Location Quality (in)</td>
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<td>4.53E-3</td>
<td>6.28E-3</td>
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<td>Event Stoppages (%)</td>
<td>25</td>
<td>15</td>
<td>0</td>
<td>0</td>
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Figure 1: Process feedback control system.

Figure 2: Machining cost comparison of adaptive and nonadaptive machining operations. [42]

Figure 3: Simulated cutting force response for an interrupted face milling operation (four teeth, entry and exit angles of -/+ 27°). [17]

Figure 4: Force response - nonlinear model-based force controller. [17]

Figure 5: Force response - adaptive force controller. [17]

Figure 6: Force model gain estimate - adaptive force controller. [17]

Figure 7: Stability lobe diagram. Tool structure natural frequency is 12,633 Hz. Operating point (d=5 mm, N = 7500 rpm) denoted by dark circle is used in simulations below.

Figure 8: Power spectrum of force signal during chatter. [17]

Figure 9: Theoretical prediction (solid line) versus experimental data (circles) demonstrating the feed effect on chatter. [17]

Figure 10: Simulated responses of force and structural displacements for constant speed machining. Cutting conditions given in figure 7.

Figure 11: Simulated responses of force and structural displacements for variable speed machining. Cutting conditions given in figure 7.

Figure 12: Illustration of different types of tool wear.

Figure 13: Typical tool wear history.

Figure 14: Estimated (solid line) versus measured (crosses) flank wear. [25] The circled crosses are vision measurements used to recalibrate the adaptive observer.

Figure 15: Exit burrs in a through hole drilling operation and their burr ratings: (a) 1, (b) 3, (c) 5. [29]

Figure 16: Illustration of common chip breakers.

Figure 17: Illustration of an off-line supervisory control implementation in a through hole drilling operation.

Figure 18: Force history results using a supervisory controller during a face milling operation. [17]
Figure 1

Figure 2
Figure 3

Figure 4
Figure 5

$F_r(t) = 0.35 \text{ kN}$

Figure 6

$\theta (\text{kN/mm}^2)$
increased depth possible due to process damping
increased depth possible at certain

Figure 7

Figure 8
Figure 11

Figure 12
Figure 13

Figure 14
Phase I: at entry, control feed and speed to reduce hole location error

Phase II: control torque to prevent drill breakage

Phase III: at exit, control feed and speed to reduce burr formation
Figure 18