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Productivity Improvement through Modeling: An Overview of Manufacturing Experience for the Food Industry

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ABSTRACT: Food production and manufacturing of durable goods share common needs for understanding, modeling, and controlling processing conditions in order to obtain desirable product characteristics. This article presents a review of research on manufacturing process modeling, with a focus on historical developments in the metrology and standards infrastructure to improve productivity and competitiveness of machining systems. To remain competitive, manufacturing requires accurate and reliable machines and processes whose characteristics are known and guaranteed for a wide variety of tasks and conditions. Productive, high-quality manufacturing will increasingly rely on a science-based understanding and monitoring of the available machining processes and equipment to produce the first part and every subsequent part on time and to specification with no significant time spent on process development or setup.

Introduction

Technological advancements over the past 100 y have led to dramatic improvements in production processes for food and for durable goods. Production rates for food and for durable goods have increased through a variety of significant changes, including improvements in the fundamental understanding of production processes to enable more effective large-scale operations and higher-speed processing technologies. While production of durable goods has employed computerized control, computer-based integration, and science-based modeling for a longer period of time than production of food products, progress in both fields has faced and will continue to face similar themes and barriers. This article presents a review of some significant developments in the science of durable goods production and an evolution of key modeling and measurement techniques as they apply to manufacturing of durable goods with comments on relevant analogs in the science of food production.

Manufacturing uses a diverse collection of processes in various combinations to transform raw materials into finished products. Most manufactured products consist of a collection of components produced separately and assembled to form final functional products. In general, processes for transforming raw

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materials into finished components ready for assembly fall within one of 3 classes: (1) *primary* processes to produce the general shape, (2) *secondary* processes to refine the product geometry, and (3) *tertiary* processes to modify the product surface and structural composition without substantially affecting the product's geometry.

Machining processes remove material by cutting material in the form of a chip away from a workpiece, as shown in Figure 1. These processes are often directly used as primary and secondary processes, but many other manufacturing processes, such as extrusion, forming, and stamping, rely on tools produced through machining. As such, machining processes play a pivotal role throughout manufacturing processes. Sawing, slicing, and other machining processes are commonly used in food production, but most food production processes rely indirectly on machining processes through the tools they use. For example, food products sold in particular shapes typically rely on a pan with the mating shape that was in turn shaped using a mold produced by machining. While this type of connection between a machined component and a shaped food product is indirect, the machining process can substantially affect the ability to engineer and control the food production process.

Machining processes such as milling and turning enable the manufacture of products ranging from consumer goods such as cell phones and sporting equipment to transportation equipment such as commercial and military airplanes. Thus machining processes have a highly leveraged impact on the economy and national security. Advanced machining processes and machine tools enhance productivity and product quality while allowing for the manufacture of ever more complex parts. These aspects make machining a pivotal process in manufacturing. Therefore, any advancement in the process can have a significant benefit to a variety of fields. However, despite its economic and technical importance, machining remains poorly understood due to the complex nature of physical and chemical interactions that occur during machining. Mallock (1881) provided one of the earliest publications providing insight into the nature of machining operations. Since that time, a large number of publications have attempted to capture machining-related knowledge to provide a basis for improving the efficiency and effectiveness of machining operations. While most of this knowledge might not directly translate into equivalent food production knowledge, the tools and techniques for expressing and modeling fundamentals of machining processes are applicable to food production processes. Examples of these techniques include statistical analysis of experimentally derived data, mathematical expressions derived from an understanding of the physical or chemical nature of the process, advanced numerical simulation, and artificial intelligence methods for managing knowledge and information.

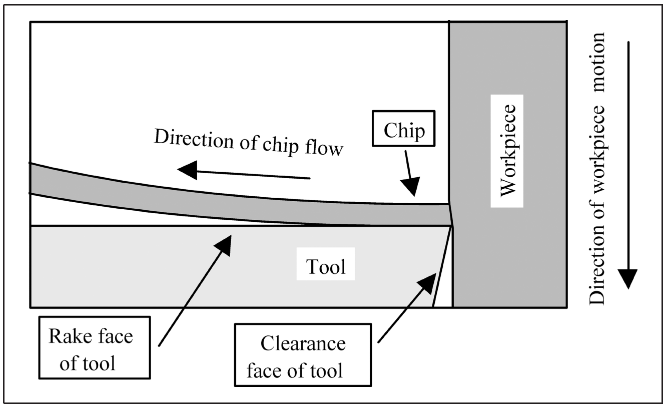

Figure 1 — Illustration of a machining process for removing material.

Much like the development of recipes for food processing and production based on experience derived from empirical testing, the parameters of machining process plans can be chosen through empirical testing and the experience of machine operators and programmers. Large empirical databases (Taylor 1907; Koenigsburger 1964) and industrial handbooks (Metcut Research Associates 1980) have been compiled to aid in process design, and play a role similar to cookbooks. Unfortunately, developing these databases and models is expensive and time-consuming, and these databases and models lose relevance as new tool materials, machines, and workpiece materials are developed. Similarly, cookbooks need to be updated with the introduction of new food production technologies and ingredients. Most models of machining operations rely on experimental data to define critical parameters of the models (Ivester and others 2000). For example, due to the development of high-speed machining centers and new tool materials over the past 10 y, speeds and feed rates have increased 10-fold, rendering previously existing databases, handbook tables, and models essentially useless. Rather than try to reproduce empirically derived databases in response to the introduction of new technologies, many manufacturers have embraced a more directed approach where they utilize a formalization of their understanding and knowledge of machining processes to construct appropriate process plans for production. Similarly, the food production industry increasingly relies on a fundamental understanding of physics and chemistry to guide the development of new processes and adapting established processes to new ingredients and equipment.

Manufacturers face challenging changes in the area of machining, such as improved dimensional accuracies, shorter lead times, smaller batch sizes, outsourcing, and intense global competition. This environment does not allow for the practice of costly and time-consuming trial runs, regular part inspections, and ongoing adjustments to achieve required part accuracies and process efficiencies. In order to successfully compete in this marketplace, manufacturers require flexible, adaptable, accurate, and reliable machining processes with known, optimized, verifiable behavior enabled through fundamental models. While some of the specific needs and challenges of industrial food production scientists and engineers differ, they share the need to make decisions based on fundamental models.

Machining process engineers must be able to predict and compensate for the many sources of error that change over time and are often task specific (Jurrens and others 2003). The following sections provide an overview of research activities aimed at developing the necessary infrastructure to realize this capability (Deshayes and others 2005; Ivester and others 2005). The research presented in this article focuses on work conducted at the Natl. Inst. of Standards and Technology (NIST) Manufacturing Engineering Laboratory (MEL), but also includes many references to related work. This overview is intended to provide food production scientists and engineers with insight into the strategies, experiences, and solutions developed for machining and how they might be relevant to the science of food production.

Computer-integrated manufacturing

Manufacturing requires the integration of diverse activities, including research and development, production processes, assembly and packaging operations, quality management, and customer service. The integration of these diverse activities through connections between computer systems is commonly referred to as computer-integrated manufacturing (CIM) (Merchant 1961; Rehg and Kraebber 2004). Quantitative models dramatically increase the effectiveness of linking these activities, enabling cost-effective selection of materials and processes to make high-quality products. This requires knowledge of materials and processes, as well as innovative approaches to product design, manufacturing, and assembly technologies. Product design must address ease of manufacturing, which involves reducing complexity, number of components, size, and material used. Accurate modeling of manufacturing process capabilities enables appropriate process selection, which in turn places requirements on material selection and product design. Models of production processing in CIM do not have to be science-based, but scientific approaches improve flexibility and adaptability. The adoption of computer integration for food production processes with other aspects of food production, including research and development, packaging, quality inspection, product delivery scheduling, and customer service, would yield similar substantial benefits as experienced for manufacturing of durable goods.

Manufacturing knowledge

Knowledge related to manufacturing encompasses an extremely broad spectrum of topics. This includes the mechanics and physics of the manufacturing processes, as captured through models of processing capabilities, and machine and tooling capabilities. Knowledge relevant to decision-making for manufacturing extends from the fundamental physics, mechanics, and chemistry of manufacturing processes to human ergonomics, product design requirements, customer needs, and market opportunities. Information from these and many other domains can have a dramatic impact on production decisions. As such, there is a confluence of information from many domains at numerous critical decisionmaking points in the production process.

Effective representation of critical information requires 2 fundamental elements: syntax and semantics. A standardized infrastructure provides syntax for expressing information. A well-defined dictionary can provide a common system of semantics, but dictionaries are typically constructed to support the needs of humans. Manufacturing operations involve communications between human beings, but also include communications between humans and computers and directly between computers. In order to effectively communicate critical process information, the communications infrastructure must support software-based automated processing of information and knowledge through fundamentally logical expressions of information that cannot be misinterpreted (Uschold and Gruninger 1996; Schlenoff and others 2000a, 2000b).

Software-based automated processing of information and knowledge critical for distributed manufacturing requires a standardized communications infrastructure that ensures effective representation of critical information (Ray 2002; Daconta and others 2003; Deshayes and others 2004). ISO 10303, Industrial automation systems and integration-product data representation and exchange, and its application protocols enable standardized expressions of product geometry and production requirements and constraints, so that design specifications can require a component be forged, machined, and then cleaned without ambiguity as to the order of operations or the relation of specific output requirements of each step to the overall product quality and profitability. Standardized definitions of terms provide a framework for ensuring that product specifications accurately portray designer intent and assist interpretation of product specifications in production (application protocols). Standardized cutting tool geometry specifications (ISO 5608; ISO 1832) ensure consistent expression of processing details that help ensure consistency in production regardless of location. Standardized instructions to machine tools (ISO 14649; ISO 10303:224) provide a common basis for defining machine instructions and the corresponding response of the machine to help ensure that the same operation will be executed the same way on different machines from different vendors. The current state of standards for providing a communications infrastructure continues to expand through enrichment of standardized details and application areas and has resulted in a remarkably substantial impact on industrial productivity (Gallaher and others 2002).

Food production faces a similar challenge in the effective representation of critical information driven by similar challenges in merging knowledge from diverse areas of expertise. The successful introduction of new products into the commercial food market requires utilization of research results on food development and production such as structured lipids (Osborne and Akoh 2002), expression of consumer reaction to the flavors of new products through flavor lexicons (Drake and Civille 2003), and assessment of what consumer markets these new products will succeed in (Mehrotra 2004). Rigorous definition of terminology and requirements for food production would help ensure effective communication among computers and humans across the globe. The development of a single monolithic standard for communication of food production information analogous to the role ISO 10303 for manufacturing could lead to similar major impacts on the productivity and efficiency of the food production industry.

Process planning

Process planning ranges from high-level conceptual planning decisions about what types of processes and facilities will be needed for production down to detailed planning decisions about the specifics of tool and fixture selection and processing parameters such as cutting speeds and depths. Conceptual planning addresses a broad range of concerns such as the balancing of activity loads at different locations within a facility, the ergonomics of assembly operations, the path of a part through a facility layout, and the sequence of assembly operations (Feng 2003). Detailed process planning addresses a collection of specific decisions for individual production steps, such as selection of a tool for a particular machining operation. Ideally, fundamental models of process behavior support these decisions, enabling more effective conceptual planning decisions. In the absence of reliable fundamental models, engineers must rely on experience-based understanding. As production circumstances change, the engineers must accept certain levels of risk that may lead to scrap, rework, product failure, or large-scale product recalls. Food production engineers can face similar problems leading to similarly undesirable consequences.

In the production of durable goods, the process planning stage represents a critical bridge between the development or design of new products and their subsequent production. Process planning activities must lead to feasible production plans that result in products that meet design requirements. Process planners must communicate with both product designers and production engineers to satisfy design requirements and respect limits of production capabilities. The effectiveness of modern process planning systems depends on rigorous representations of knowledge from design and production domains together with a computerized infrastructure for communications. In a similar manner, the planning of food production processes depends on clear communication of knowledge from product development and from production.

Process control

In order to produce products of acceptable quality, the production processes must be executed under the control guidelines specified in the process plan. Adjusting process parameters such as valve positions or pump voltages controls production process variables such as temperature or pressure. This is true for production of food and for production of durable goods. Mechanical or hydraulic control systems of the past typically adjusted a single parameter or input to control a single variable or output. A human operator typically performed adjustment of these parameters manually. With the advent of computerized control systems and electronic actuators, it became increasingly possible to automatically control single-input single-output (SISO) processes, and to simultaneously control multiple-input multiple-output (MIMO) processes. However, effective control systems depend on reliable and robust models of the relations between the process inputs and process outputs. This reliance is particularly acute for MIMO systems where the model must account for interdependencies between the inputs and outputs. It is important to note that automatic controls can only be applied to processes where the outputs are measurable in real time with adequate precision, accuracy, and where reliability, and adjustable inputs provide adequate influence on the outputs. Many problems of automatic control systems result from the reliability and robustness of the process model and the controllability and measurability of the outputs. When reliable and robust models are available for automatic control, efficiency of the production system is greatly enhanced. Additionally, these models contribute directly to reduced quality inspection and improved process planning, and indirectly to improved product design. Robust and reliable models for automatic process control could also help improve the efficiency and efficacy of food production systems. For example, given a robust and reliable model based on a scientific understanding of the relation between packaging atmosphere conditions and microbiological safety for different varieties of fresh produce (Farber and others 2003), it may be possible to customize the packaging atmosphere to improve safety without sacrificing product quality.

Machining Production Systems

Modern machining production systems strive to produce the first and every subsequent part on time and to specification through a science-based understanding, optimization, monitoring, and control of the available machining processes and equipment without significant time spent on process development, setup, or unexpected down-time. Ideally, a machining production system (1) knows its capabilities and condition and can be interviewed, (2) knows how to machine a part in an optimal manner, (3) monitors, diagnoses, and optimizes itself, (4) knows the quality of its work, and (5) learns (Jurrens and others 2003).

Machining is a complex activity based on a system of many diverse physical, electronic, and human elements with interacting and interdependent activities that are difficult to predict and control. Mathematical and physical models of machining systems aim to capture the interdependence of elements within the system to enable effective system analysis and optimization, as well as a predictive capability to compensate for effects of changes in the system (Deshayes and others 2005). The ability of the manufacturing system to accommodate unpredicted changes is an important factor determining robustness and longevity.

Quantitative modeling of many elements of machining systems is an important and extremely challenging problem. Examples of elements of this problem include machine performance (ISO 230, ASME B5.54, ASME B5.57) material supply characteristics (Ivester and others 2000), process performance (Ivester and others 2005), and system control behavior. Modeling potentially enables more effective management and decision-making (Usui and Shirakashi 1982), but knowledge availability and measurement uncertainty (Taylor and Kuyatt 1994) limit the level of sophistication of models and simulations and increase uncertainty of predictions (Ivester and others 2006). Modeling uncertainty is challenging to quantify and depends on measurement uncertainty, model development and validation techniques, and the domain over which the model is applicable. Another source of uncertainty is the variation in production environment, workpiece material, and tooling. Characterization of these variations and their downstream effects are critical for decision making. As circumstances within the machining system change, modeling uncertainty increases and at some point the model is no longer useful for making decisions and needs to be reevaluated. Similarly, the ability to apply models of food production depends on the degree of conformance of the circumstances of model development to the circumstances of model application.

Modeling and simulation of machining processes

Machining processes play a pivotal role in manufacturing through direct participation in production by machining operations and through indirect participation by providing tooling for other production operations, such as casting, molding, or forging. Difficulties in realizing predictive models based on the fundamental physics of machining operations through numerical representations of analytical relationships arise from the extreme physical phenomena inherent in the system. Machining generates highly nonuniform plastic flow where severely localized stresses generate extreme plastic deformation (up to 40%) at high deformation rates (up to 10^6/s), which give rise to high thermal gradients (1000 °C/mm), high temperatures (400 °C), high heating rates (1000000 °C/s), and high pressures (10 MPa).

Early work on analytical modeling of machining provided approximate solutions to machining problems through 2-dimensional vector mechanics (Ernst 1938; Ernst and Merchant 1941; Martelloti 1941, 1945; Merchant 1945; Lee and Schaffer 1951; Subramani and others 1987) and through assumptions about deformation patterns around the cutting tool called "slip-lines" (Palmer and Oxley 1959; Oxley 1961; Oxley and Hatton 1963; Oxley and Welsh 1963; Usui and Hoshi 1963; Kudo 1965; Dewhurst and Collins 1973; Tay and others 1974; Dewhurst 1978, 1979; Rubenstein 1983; Fu and others 1984; Jawahir 1986). More recent work applied analytical techniques based on vibration and dynamics theory to model the stability of cutting tools (Moon 1988; Endres and others 1993; Davies and Burns 2001; Burns and Davies 2002). To improve the sophistication with which the complex interactions near the cutting tool can be represented, many researchers began modeling the cutting process using finite element-based simulation of metal cutting (Klamecki 1973; Shirakashi and Usui 1974; Lajczok 1980; Strenkowski and Carroll 1986; Carroll and Strenkowski 1988; Liu and others 1988; Hsu 1990; Strenkowski and Moon 1990; Chern 1991; Athavale 1994; Ceretti 1999; Maekawa 1999; Movahhedy and others 2000).

Unfortunately, the effects of complex plastic flow during machining are difficult to predict even with sophisticated finite element modeling software (Camacho and others 1993; Marusich and Ortiz 1995), and basic flow stress data for material behavior under such conditions (Hopkinson 1914; Childs 1997) are unavailable for most materials of practical interest (Shaw 1984; Trent and Wright 2000; Burns and others 2004). These difficulties have forced model development to rely on various levels of empirical input data taken from machining tests to model process variables of industrial interest (Koenigsberger and Sabberwal 1960; Lau and Rubenstein 1983; Nakayama and others 1983; Stevenson and others 1983; Carroll 1986). The limitations imposed on the range of applicability of machining models from their reliance on empirical input data have hindered their industrial use (Furness 1998), particularly for smaller businesses that are unable or unwilling to perform validation testing and for complex processes and materials (Chandrasekharan and others 1993).

The advantage of physics-based modeling is that predictions are made from the basic physical properties of the tool and workpiece materials together with the kinematics and dynamics of the process. Thus, after the appropriate physical data are determined, the effect of changes in tool geometry and cutting parameters on tool wear rate, geometric conformance, surface quality and other industrially relevant decision criteria can be predicted without the need for new experiments. If robust predictive models can be developed, this approach would substantially reduce the cost of gathering empirical data and would provide a platform for optimization of machining process parameters based upon the physics of the system during process planning.

Limitations on repeatability have hindered development of reliable machining models, even for a given combination of machine, tool, material, and environment. A variety of uncontrolled factors affect various measures of process and product quality, such as dimensional accuracy, surface quality, process reliability, and tool life. Examples of uncontrolled factors include material and tooling homogeneity, workpiece and tool holding repeatability (Medicus and Schmitz 2001), machine repeatability, environmental variability, and coolant effectiveness (Ivester and others 2000; Ivester and Kennedy 2002). Switching among different environments, tooling, or machines increases variation in process and product quality further.

The difficulty in precisely formulating machining models that are applicable to a wide range of environments, tooling, and machining platforms has limited the application of machining models to the improvement or optimization of machining processes. Adaptive control (Masory and Koren 1985) and recursive constraint bounding (Ivester and Danai 1996, 1998; Ivester and others 1997) techniques provide some means for coping with variability and repeatability issues (Liang and others 2004), but are not adequate for planning purposes. Effective planning, which is critical for agile manufacturing and modern machining production systems (Deshayes and others 2005), necessitates a methodical approach for addressing predictability of machining operations.

Machining temperature measurements

One of the most difficult aspects of machining process characterization is to accurately measure the distribution of temperatures in the area around the cutting tool, commonly referred to as the tool-chip-workpiece interaction zone. Machining temperatures in the tool-chip-workpiece interaction zone directly impact most process variables and measures of performance (Linn and others 1994), such as force, tool wear (Arsecularatne 2002), friction (Chien 1992; Tao and Lovell 2002), accuracy, residual stress (Okushima and Kakino 1971; Natarajan and Jeelani 1983; Hsu 1992), surface quality, subsurface damage, and burr formation (Komanduri 1993). Researchers and practitioners have developed and use a variety of techniques for direct and indirect measurement of these temperatures. Each of these techniques for thermal measurement of metal cutting provides insight from a different perspective while introducing unique difficulties and limitations.

Stephenson and Agapiou (1997) include a thorough review of the history of temperature measurement in metal cutting with intrinsic thermocouples and other techniques in their textbook. Starting in the 1920s, researchers investigated the use of the intrinsic work-tool thermocouple technique (Herbert 1926; Boston and Gilbert 1935; Trigger 1948; Grzesik 1990; Stephenson 1993). Infrared photography work started in the early 1950s but limitations in film sensitivity required substantial preheating of the workpiece (Boothroyd 1961). Later efforts directed at indirect temperature measurements focused on visible discoloration in HSS (high speed steel) tooling due to microstructural material transformations in the tool induced by temperatures reached during metal cutting (Trent and Wright 2000).

Recent improvements in commercially available infrared video technology (Aluwihare and others 2000; Yoon and others 2000; Davies and others 2003a, 2003b) enable effective measurement of cutting process temperatures based on the intensity of emitted infrared light (Sakuma and Kobayashi 1996). New InSb (indium antimonide) detector arrays capable of microsecond-level control of integration time and improved sensitivity to near-visible infrared light enable microscopic temperature measurements of metal cutting at substantially higher resolutions in both time and space (Ivester and others 2005), as shown in Figure 2. This enables comparisons of temperature measurements from high-speed infrared camera experiments together with force measurements obtained through a 3-axis piezoelectric dynamometer, as shown in Figure 3, to predictions of forces and temperatures through finite element model-based simulation, as shown in Figure 4. Comparisons of measurements and simulations, as shown in Figure 5, provide a basis for guiding research to improve measurements and simulations.

Empirical process models and optimization

In the absence of fundamental physics-based models of machining operations, empirical models can contribute to

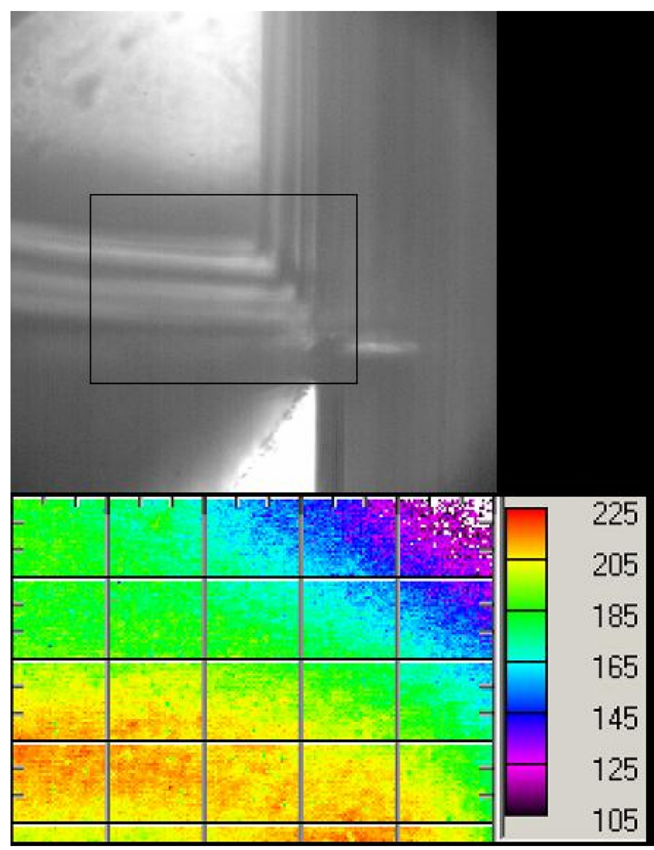

Figure 2—Example of microscopic visible (above) and infrared (below) high-speed videography of metal cutting processes (inset rectangle in visible spectrum image denotes approximately 0.3 mm horizontal infrared field of view). The units for the infrared video indicate radiation intensity as radiance temperature in °C, with a ±2 sigma expanded measurement uncertainty of 100 °C.

machining production systems within limited boundaries of process variations given access to adequate experimental data. The coupled work-tool (CWT) methodology (Deshayes 2003) defines a structured series of experiments for developing and calibrating an empirical model for machining with a minimal subset of varieties of cutting tools. The CWT method establishes cutting condition boundaries and a cutting force model for a wide variety of cutting tool geometries.

As a demonstration of machining the CWT methodology, a series of experiments provided a basis for producing an empirical model to optimize the machining of the part shown in Figure 6 according to the process plan shown in Figure 7, where the circled letters indicate surfaces produced by a sequential series of machining operations. The workpiece material, American Iron and Steel Inst. (AISI) 1045 steel, was turned in a 22 kW lathe using 4 different tool geometries with rake angles of $-6°$, $-1°$, $0°$, and $+9°$. Analysis of the experimental results provides upper and lower limits on process parameters such as cutting speed and feed through modeled relations to constrained process variables such as surface roughness, cutting force, and tool life.

The resulting models enable process planners to select appropriate process parameters allowing for anticipated levels of variability in process performance derived from scatter in the experimental data together with engineering estimations of potential disturbances to the process. The graph in Figure 8 shows an example representation of allowable ranges for controllable process parameters, feed and cutting speed, and limitations imposed by measured process variables, surface roughness, cutting force, and tool life. The variability and uncertainty in the modeled process parameters are reflected in a family of curves representing the extremes of the range of predicted behavior. As such, the most conservative (lower left) and least conservative (upper right) intersections of the families of curves represent the potential range of acceptable process parameters to achieve the desired process performance. During execution of the process, computerized-control of process parameters can utilize model-based optimization results to adaptively adjust process parameters in response to disturbances in order to maximize efficiency while regulating process variables within their respective limits.

NIST contributions to machining production systems

NIST researchers contribute to development of machining production systems through the development of measurements, techniques methods, and test beds, as well as through leadership and participation in industry forums and standards bodies. Measurements research addresses the development and provision of metrology expertise, traceability, and state-of-the-art

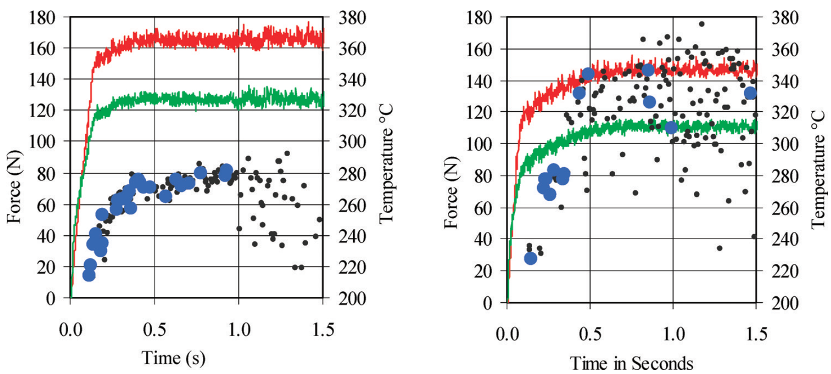

Figure 3 — Effect of increased surface speed on peak cutting temperature and cutting forces.

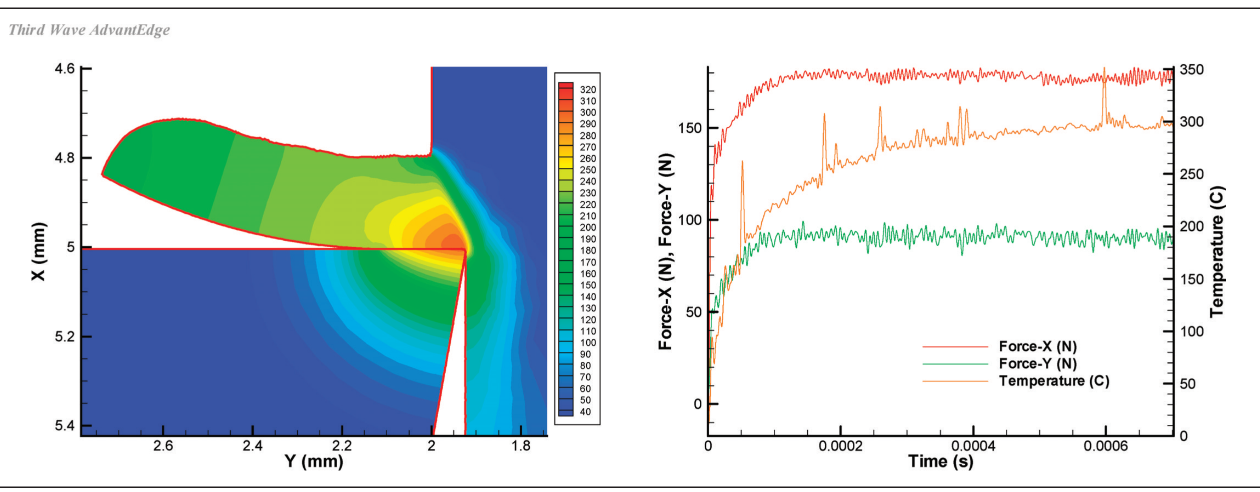

Figure 4 — Temperature profile and cutting forces of cutting process obtained through finite-element model simulations.

instrumentation for measurements relevant to manufacturing, including form and dimension, force, vibration, temperature, and material properties. Additionally, developments of methods provide enabling technology to apply metrology to improve the machining process, part accuracy, and machine reliability. Test beds provide a means to validate standards specifications and to benchmark proposed models and methods. Participation in and organization of industry forums assists in the identification of industry needs and fostering collaborations. Participation in standards bodies provides opportunities to contribute to the development of documentary standards for product performance and data interoperability, such as (1) sensor/actuator interfacing and networking—(IEEE 1451); (2) machine tool performance characterization (ISO 230, ANSI/ASME B5.54, ANSI/ASME B5.57) and data formats for machine tool properties (ASME B5.59-1, ASME B5.59-2); and (3) high-level machine tool programming languages (ISO 10303-238). Research on enabling metrology and standards for machining at NIST covers 4 broad areas of technical developments machining knowledge, process planning, predictive modeling, and optimization and control of machining.

Discussion

The advent of mass production of food products and durable goods stems from advancements in science and technology and has led to dramatic improvements in productivity. Early developments focused on enabling more effective large-scale operations

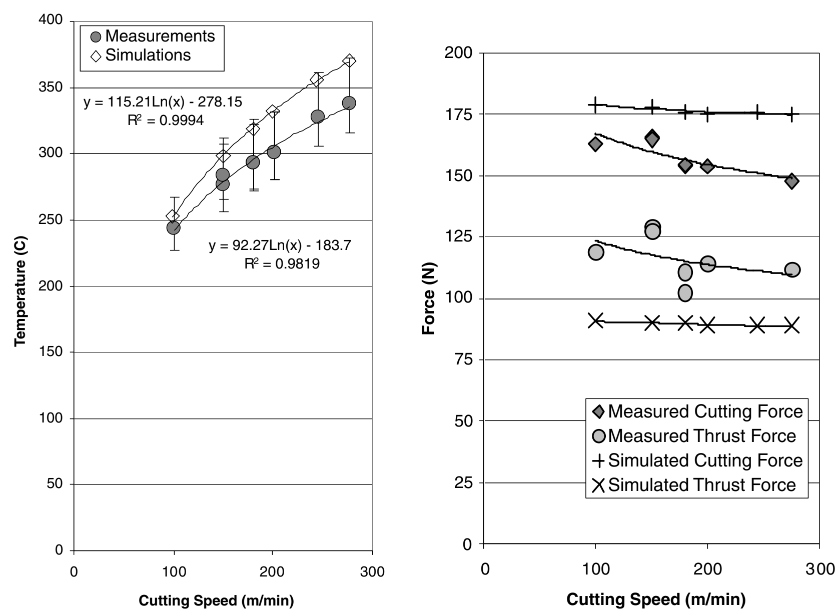

Figure 5—Comparison of measured and simulated dependencies of temperature and force on cutting speed, where the vertical bars in the chart on the left represent ±2 sigma expanded measurement uncertainty for maximum cutting temperature.

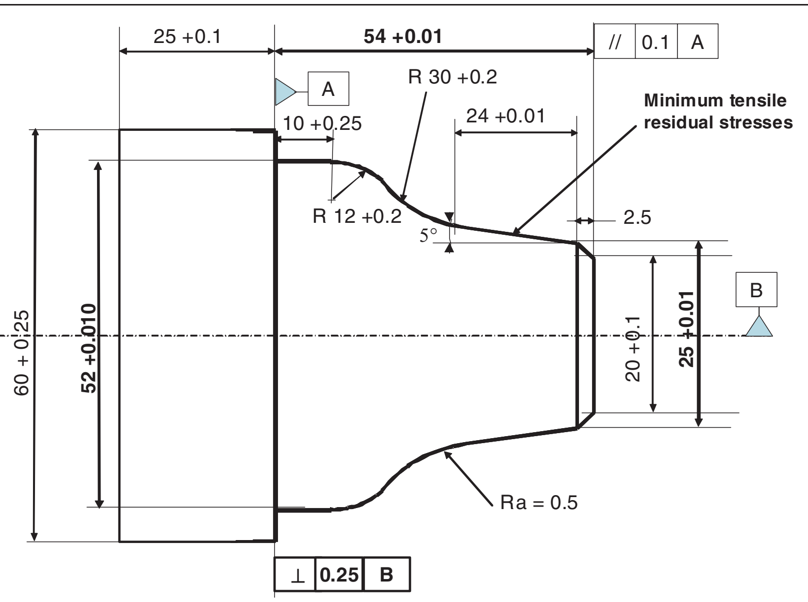

Figure 6—Design of example machined part, all dimensions in mm.

and higher-speed processing technologies. Later developments have improved the flexibility and adaptability of production systems to change in response to market developments. While most technological progressions in food and durable goods production have been independent, they have followed similar themes, faced similar barriers, and encountered similar enablers and drivers. This article presented a review of developments in the science of computerized integration of production activities, scientific representation of production knowledge, and scientific modeling of production processes and equipment for improved planning, control, and optimization. These developments have, to some degree, been paralleled by analogous developments in food production. However, the production of durable goods has been reliant on computer-based integration for longer than the food production industry, and so more research resources have been focused on science-based modeling in a computer-based environment. The goal of this article has been to present some of the key issues and lessons learned in the production of durable goods so as to benefit researchers in food science.

1. Computer-integrated manufacturing (CIM) systems improve the effectiveness of the overall system by reducing inefficiency and miscommunications, and ensuring the timely communication of critical information. Furthermore, when CIM systems are supported by science-based models, flexibility and adaptability improve dramatically.
2. The introduction of standardized structures for representing knowledge and information facilitates the effective flow of information in a CIM system.
3. Process planning, control, measurement, and optimization all depend on the reliability and robustness of models in a CIM system, and the systematic efficiency improves dramatically with increased rigor in the scientific basis for models.

Conclusions

Food production and traditional manufacturing of durable goods share common needs for understanding, modeling, and controlling processing conditions in order to obtain desirable

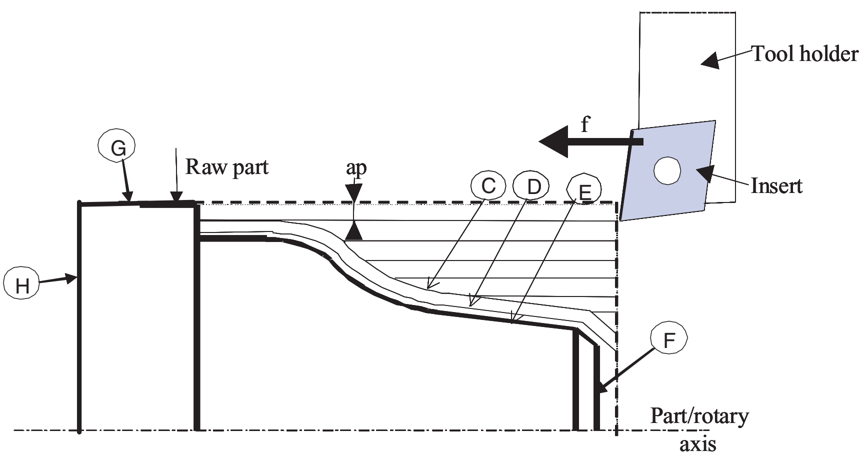

Figure 7 — Process plan for example machined part.

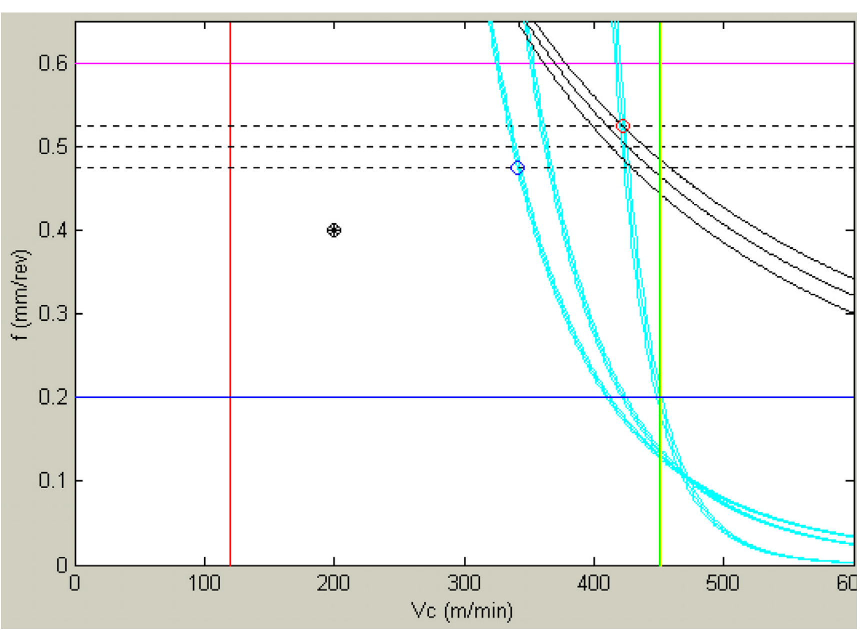

Figure 8 — Model-based prediction of dependence of process variables on process parameters, where V_c and f represent controllable process parameters and the curves represent constant values of process variables. The 3 circles represent a progression of changes in process parameters to optimize the process, where increasing either process parameter improves process efficiency.

product characteristics. This article is a review of research on manufacturing systems and models, with a focus on historical developments to enable machining systems to improve manufacturing productivity and competitiveness. The article presents several key findings in manufacturing research relevant to production of food and food science research. The integration of design, planning, and control of production processes through computer systems improves efficiency and adaptability. Standards to support the communication of knowledge and information improve system effectivity. Reliable and robust science-based models of production processes improve agility and efficiency.

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