

Project Summary - Dynamic Evaluation of Machine Tool Process Capability

Background: The process capability index (C_p) is an important quality measure of defect-free manufacturing operations. C_p for a machine tool is currently ill-defined, since machine tool builders only provide a static measure of accuracy and repeatability. C_p , which depends on the required part tolerances and the capabilities of the operation to make the part, must include dynamic effects such as changes in the process with cutting tools, machining strategies, age and environment. This lack of a reliable quality measure impacts large and small plant operations and decisions. For example, we show some real world examples where part quotations vary by an order of magnitude, due largely to an inability of small shop owners to know their process capability. This is a problem for the shop operator, losing a job (quote too high) or losing money (quote too low). The customer also suffers by having no independent guide in knowing when a batch of quotes are reasonable.

Research Goal: Our research will test the feasibility of dynamically measuring the process capability of a machine tool and relating this process capability to the generation of quotations for industry-specified parts. We will support the “Smart Machine Tool” initiative presented at a NIST workshop in Dec. 2002. A Smart Machine Tool should know both its static and dynamic process capability and report this information in a sensible fashion to the user. While there are many factors that determine the process capability of a machine tool, this study will focus on three parameters deemed to be amongst the most challenging and most significant: tool runout, tool deflection and tool wear.

Broader Impacts: If successful, this research would have the following broad impacts:

- Greatly improve the reliability of machine tools by giving them a self-knowledge of their process capabilities. According to the NIST MEL FY2002 report, annual expenditures on machining operations total more than \$200 Billion or about 2% of GDP.
- Self-knowledge of process capabilities will allow matching of specific machines with the requirements of a particular part such that the C_p yields “Six Sigma Quality”, i.e. 3.4 defects per million units.
- Machining strategies and cutting conditions (e.g. speeds and feeds) can be chosen to appropriately reflect the current capabilities of the machine tool.
- Part designers will be able to accurately estimate the cost of machined parts, and more importantly, receive accurate assessments of the cost of tolerance choices.

This research will produce valuable results that not only support the NIST Smart Machine Initiative, but are also consistent with the goals of The Integrated Manufacturing Initiative [www.imti21.org]. The project will act as leading edge focus to the international STEP-NC project, directing productive areas of research and development and providing requisite feasibility studies.

Intellectual Merit: Current machine tools are not self-aware of their process capabilities. Achievement of such a capability would be a major break-through, but presents a formidable challenge. Our unique approach is based on combining sensor data, mathematical models of both machine and process, and a new method for data representation of machine tools and process plans based on XML. The use of an Open Architecture Controller (OAC) allows us to run mathematical models of the process which can be continuously updated by sensor data input.

Research Team: The research team consists of the PI (Jerard) with expertise in the geometric modeling of machining and the XML database language, the Co-PI (Fussell) with expertise in mechanistic modeling and control of machining. Our external collaborative partners include MDSI, the maker of the Open Architecture Controller that we are using, VulcanCraft, a developer of machine tool simulation software, and Stone Machine Co., a machine shop located in Chester, NH.

Dynamic Evaluation of Machine Tool Process Capability

1.1 The Vision

Figure 1 is a conceptual model of our research plan for developing a machining process that is radically different from current technology. In the figure, green boxes (2,6,7,8) indicate areas where we have already made substantial progress and yellow boxes (1,3,5,9,10,11) are areas where we have some preliminary results. The focus of this research proposal is on determination of the Machine Process Capabilities, shown in red just above block 7 (paths A and B). In our model the Designer (1) supplies a part description (2) in NCML format. NCML is a language developed at UNH for representation of conceptual process plans [Jerard 02a,b] (more fully described in **Section 1.3.3**). The cost estimator (3) provides a bid which includes a breakdown of cost by machining features, thus enabling the designer to understand the relationship between design choices and costs. The Tool Path Planning (5) module compiles the macro conceptual process plan into individual toolpaths. The Machine Process Capabilities are also input to this module (**Path A**) to choose the proper strategies for the individual tool paths. The strategies include the choice of Unit Machining Operations (UMOs) [Choi 98] to make a given feature, tool choice, depth of cut, finish cutting allowance, etc. These strategies can be stored in Strategy Templates (4) (not a focus of this research proposal).

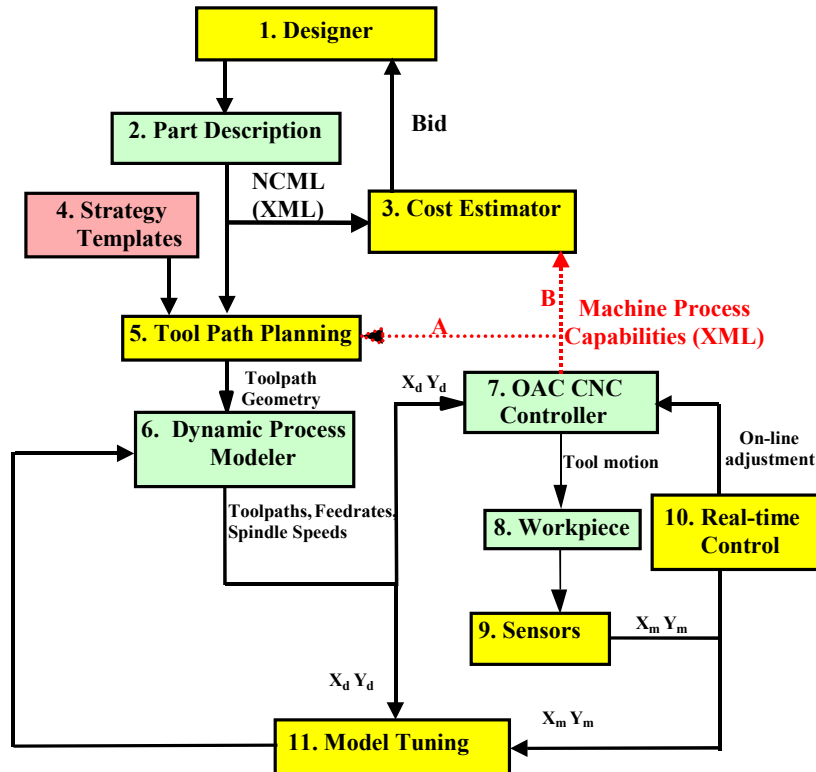


Figure 1 – Structure for a “smart” machine tool.

Speeds and feeds are set by the Dynamic Process Modeler (6) (see **Section 1.3.2**). The chosen feedrates for a given strategy depend on both the required accuracy (described by the tolerance information in the NCML file) and the Machine Process Capabilities. The Open Architecture Controller (OAC) (7) commands the cutting tool motion to remove material from the workpiece (8) and continuously collects cycle time data to calibrate the machining models and dynamically estimate the current process capabilities of the machine. Sensors (9) monitor the process and provide cutting force feedback to the Control module (10) which adjusts feedrates to compensate for process degradation such as tool wear. The sensor data is compared with process modeler data for Model Tuning (11). Vector data X_d , Y_d , from the process models, and X_m , Y_m , from the sensors, is stored during machining. The vectors represent the desired and measured process states of the machine that can be used in the control and optimization of the process. X_d is composed of the desired tool tip position, cut geometry, estimated process errors and cutting speeds, while Y_d contains the desired force vector.

In our previous research we have implemented a considerable portion of the vision embodied by **Figure 1** (See **Section 1.3**). In this proposal we will investigate methods for dynamic estimation of Machine Process Capabilities.

1.2 Motivation and Impact of Proposed Research

Annual U.S. expenditures on machining operations are estimated to be in excess of \$200 billion [NIST]. In December 2002, the National Institute of Standards and Technology (NIST) hosted a workshop on “Smart Machine Tools”. The workshop was organized by the Integrated Manufacturing Technology Initiative [IMTI] association to “assess the needs, opportunities, and requirements for increasing the intelligence of machine tools for material removal.” Although the workshop report had not been issued as of the writing of this proposal, the participants identified a number of research areas deemed to be of the highest priority. The top three priorities, as voted by the participants, were: 1. Develop standards for providing computer interpretable product specifications with robust data exchange, 2. Establish physics based process models for a smart machine tool testbed, 3. Capture and understand the information necessary to determine machine condition.

The vision embodied in **Figure 1** is differentiated from current technology in the following ways:

- Sensor data and process models are integrated together into an Open Architecture Controller
- Primary input to the CNC machine is NCML instead of G&M codes; individual toolpaths are compiled from the macro process plan based on the capabilities of the particular machine tool.
- The CNC machine is aware of its own process capabilities, information used by tool path generation algorithms to choose toolpath generation strategies (e.g. number of roughing and finishing paths), tool selection (e.g. diameter, length, material) and cutting conditions (axial and radial depth, speeds and feeds)
- Tolerance information in the NCML plan is used to match jobs with a machine tool whose current process capabilities can make the part to within the desired tolerance.
- Machining data (e.g. volumetric removal rates, cutting forces, etc) is continuously collected, providing a basis for generic cost estimation models [Jerard 02a,b] that allow designers to determine the cost implications of design decisions.

The last item in the list illustrates how the emergence of smarter machine tools affects not just the machining process, but the whole design and manufacturing process. As one scholar [Feng 00] put it, “..it is critical to be able to assess manufacturability and cost as early as possible in the design process. Errors made during the early stages of design tend to contribute as much as 70% to the cost of production.” Feng differentiates conceptual process planning from detailed process planning as an activity that permits consideration of manufacturability and its impact on product cost without actually generating G&M codes, fixturing and tooling plans. Our earlier research illustrated the feasibility of using NCML to represent conceptual process plans and to estimate machining costs (see **Section 1.3.3**). The calibration of the cost estimation models required many hours of observation and recording of machine cycle times. This data was then correlated with volumetric removal rates, tool and tolerance information. A machining center that collects this data continuously would be capable of calibrating the cost estimation models in a more automated fashion.

While current NC machines could certainly be programmed to collect machining cycle times, this data would be of very limited value without three other key elements: 1. geometric models of the process that correlate the cycle times with volumetric and surface area metrics, 2. a macro description of the process plan that relates the collected data to specific machining features and their associated tolerances, and 3. open-architecture controls that include customizable software libraries for data collection and toolpath generation.

Machine Tools in a “Six Sigma” World – A further motivation is provided by the adoption of the “Six Sigma” philosophy by much of industry. A full discussion of “Six Sigma” is beyond the scope of this proposal, but the concept is central to the motivation behind the proposed research. The use of statistical quality control (SQC) was pioneered by Dr. W. Edwards Deming when his teachings were embraced by Japanese industry after World War II. SQC relies on a commitment to continuously monitor the process and reduce its variability (i.e. the standard deviation – “sigma”). When “Six Sigma” levels of quality are achieved, there are only 3.4 defective parts per million. Achieving this level of quality requires attention to both the process and the allowable variability in the product. Ideally, minimum process variation is

combined with maximum allowable product variability to achieve both low cost and high quality. Jack Welch, GE's former CEO, reported that Six Sigma concepts saved GE more than \$2 billion [Pande 02].

Achieving Six Sigma in machining requires having a process with a level of precision commensurate with the tolerance requirements of the part. It is well known that precise tolerance requirements usually increases production costs. Of course there are many times when low tolerance variation is a requirement for acceptable product function. Unfortunately, there are many designers who specify unnecessarily tight tolerances, needlessly increasing manufacturing costs. Currently, there is no good way for designers to fully appreciate the cost ramifications of their tolerance choices. The popularity of outsourcing exacerbates the situation by separating the designer from the fabricator. In our NCML prototype system, the cost estimator gives a complete breakdown of the cost associated with materials, set-ups and individual machining features [Jerard 02b]. A breakdown of the part cost is communicated back to the designer.

The process capability index of a manufacturing operation is defined as [Dieter 00 p. 589]:

$$C_p = (USL - LSL)/(6 * \sigma)$$

where USL is the upper specification limit, LSL is the lower specification limit, and σ is the statistically measured standard deviation of the process. This index is very useful in that it establishes the relationship between the tolerances of the part and the standard deviation of the process. For example, a machine tool with a σ of 0.005mm achieves a "Six Sigma" level of quality when the $USL - LSL = .06mm$, corresponding to a $C_p = 2$. If σ changes to 0.01, then $C_p = 1$, (3σ quality) and the Defects Per Million (DPM) jump from 3.4 to 66,800! This huge difference is attributable to the statistical variation implicit in the normal distribution of a bell curve. While "getting it right" 93.32 percent of the time (3σ) would be great for a major league baseball hitter, a C_p of 2 (6σ) requires getting it correct 99.99966 percent of the time! Many Japanese firms and a few progressive U.S. firms are at 6σ . Many others are at 4σ levels (6,200 DPM).

Currently, CNC vendors typically only provide two indicators of precision, positioning accuracy (typically 0.005mm) and repeatability (typically 0.0025mm). It is not clear how these numbers relate to the σ of a machine tool. There are six different standards used worldwide: NMTBA (United States), ISO 230-2 (Europe), BSI BS 4656 Part 16 (British), VDI/DGQ 3441 (German), JIS B 6336-1986 (Japanese), and ASME B5.54-92 (USA). The numbers given for accuracy and repeatability vary depending on which standard is used.

A taxonomy of error sources for CNC machining is presented in [Choi & Jerard 98, pg. 252]. Examples include tool deflection, workpiece deflection, thermal expansion, tool runout, and tool wear. Many of the factors are dynamic in nature, changing with time, environmental conditions and usage. If machine tools are to become smart enough to know their own process capabilities, algorithms and data structures will need to be developed that enable continuous process characterization. The matching of jobs with machines must result in a C_p which reflects the current state of the machine, not the state corresponding to a brand new machine operating under ideal conditions. The strategies used to produce machining features will also be adjusted to reflect current machine capabilities. For example, inaccuracy related to servo control limitations can be compensated for by proper choice of feedrates. The Tool Path Planning Module (Block 5 in **Figure 1**) can make this adjustment if it knows both the required accuracy of the part and the current Machine Process Capability.

The complete process characterization of a CNC machine including its cutting tools, fixture characteristics and system dynamics is beyond the scope of this project. Fortunately, there are a number of other research efforts working on various aspects of the problem. Notably, NSF has sponsored the Virtual Machine Tool (VMT) consortium of six universities to develop models of CNC machines [VMT]. The emphasis of this group is on the development of models and compensation strategies for machine kinematics, thermal effects, workpiece error prediction, servo control and chatter avoidance. The specific tasks described in this proposal do not overlap those of the VMT, but are complementary to them.

We are motivated to propose this research for three reasons:

1. We have a unique facility and the research experience for testing the feasibility of a smart machine tool that can continually evaluate its own process capabilities,
2. Combining models with sensors, open architecture control, and an XML based information technology is a novel approach.
3. The research is complementary to, but does not overlap other NSF sponsored efforts.

1.3 Results from Recent NSF Support

In our previous NSF sponsored research we have investigated many of the components illustrated in **Figure 1**. We have created geometric and mechanistic models that accurately simulate the machining process. [Choi 98, Drysdale 89, Fussell 89ab, 92, 95, 00, Hemmett 99, 00, Jerard 89ab, 99, 00ab]. We have also developed a new language called NCML (Numerically Controlled Markup Language) that provides a conceptual description of process plans [Jerard 98, 01a, 02ab, Ryou 01].

Most of the machining algorithms we have developed in our research are based on discrete surface representations [Austin 97]. **Figure 2** shows the rendering of a 5-axis roughing pass on a turbine blade, using software developed at UNH. Modeling of cutting forces has added another dimension of realism to our simulations [Fussell 92, 95, 01ab].

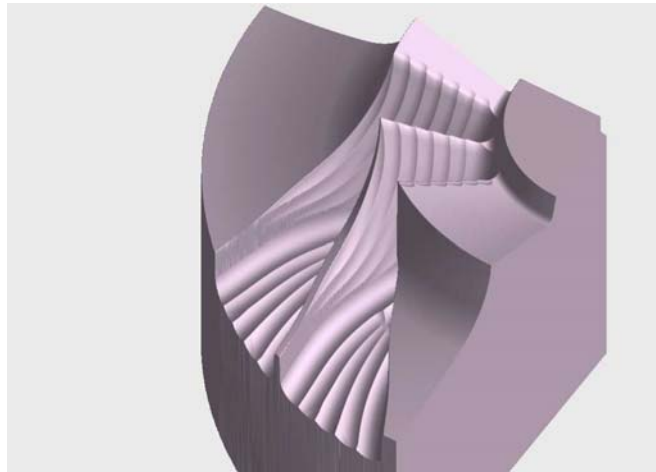


Figure2 Discrete model representation of a single turbine blade being roughed

1.3.1 Open Architecture Controller (OAC) (see Block 7 in Figure 1)

A primary focus of our current research is the integration of our machining models into a NC machine open architecture controller (OAC) [Altintas 94, Fussell 02, Koren 96, Park 95, Scofield 96, Wright 96, Yellowley 94]. The models can be used in conjunction with sensor data to perform on-line calibration. Under NSF Grant DMI-9872575 we retrofitted our FADAL VMC 4020 with an OAC supplied by MDSI [MDSI] of Ann Arbor, MI. The MDSI uses less than 5% of the processing cycles of the PC, leaving the rest for user programs [Jerard 00ab, 01b].

Unlike closed architecture controllers, the OAC allows the data collection program to access all of the process variables. The mechanism for doing this is shared memory access between the MDSI control software and our application software. Pointers provide access to the variables containing the x-y-z tool position, feedrate value and other sensor outputs such as force measured by an A/D board. The values of each of these variables can then be processed, analyzed and stored onto disk at a 1 KHz sampling rate. Short bursts of data can also be collected at 100 KHz.

1.3.2 Toolpath Planning and Optimization

The Toolpath Planning Module (Block 5 in **Figure 1**) must select a combination of spindle speed, feedrate, and cutting tool that machines the chosen material in a safe and efficient manner. To achieve this result a number of conditions must be met: 1) Is the peak force magnitude too large? If it is, the tool will deflect excessively causing poor surface tolerances or in the worst case tool breakage. 2) Is the stress on the cutting teeth less than the maximum allowable stress? 3) Does the spindle motor have enough power to cut the material? 4) Will the tool encounter chatter conditions? Our models are designed to answer the first three questions; chatter is an important issue that is being addressed by other researchers [Tian 01, Altintas 95]. The Dynamic Process Modeler models the cutting process and sets optimum feedrates.

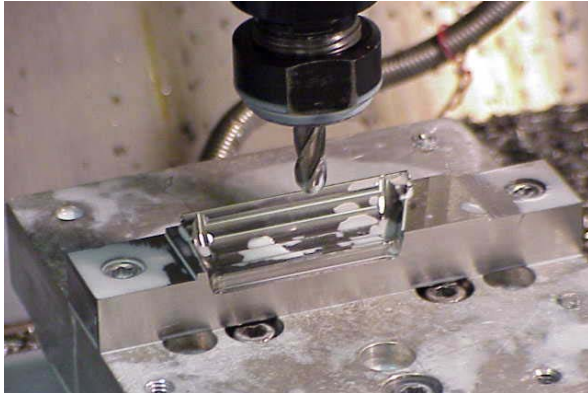


Figure 3a Turbine blade side 1 during semi-finishing, mounted on force dynamometer

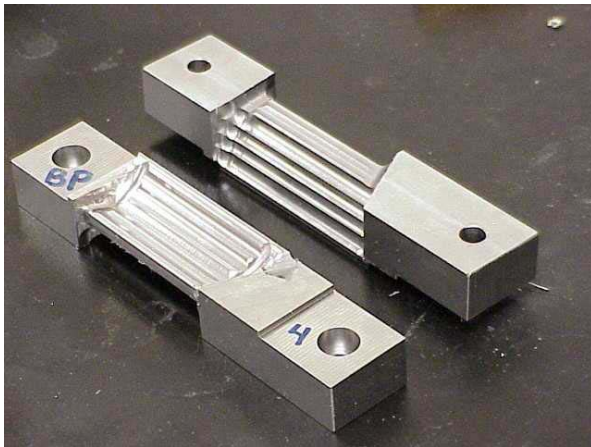


Figure 3b Turbine blade sides 1 and 2 after semi-finishing

In order to compare the cutting times and forces of an NC program prepared using the traditional methods with our feedrate optimizing program, we used an actual production part, the turbine blade shown in **Figures 3a and 3b**. Toolpaths were generated by programmers at our industrial partner, Turbocam, using their expertise to create a NC program that represents “best practice” in industry. The workpiece was machined in two phases; rough cutting with a 0.5” flat-end cutter and semi-finish machining with a 0.375” ball-end cutter. The semi-finish state required a set-up change since both sides of the part were cut.

The standard approach for setting cutting conditions is to use a table to choose proper spindle speeds and a constant feedrate based on anticipated worst case conditions [Metcut]. In actual practice, the geometry of the cut often varies widely, resulting in large cutting force variations for a constant feedrate. Our method for selecting optimum cutting conditions is quite different than the table based approach [Fussell 89ab, 92, 95, 01ab, Jerard 99, 00ab, 01b]. The user specifies a desired cutting force and maximum chip thickness. The algorithm calculates a feedrate that maintains a safe level of cutting force and tooth stress. In areas of large chip loads (e.g. large axial and radial depths of cut) the feedrate is determined by the cutting force; in other areas, the maximum chip thickness is the limiting factor. Maximum allowable cutting forces were set to 110 lb for the flat-end and 150 lb for the ball-end. The maximum chip thickness was 0.004” for the flat-end and 0.0015” for the ball-end.

The “best practice” and optimized programs were each used to cut four parts so that wear effects on the cutting force could be quantified. The part program of approximately 3000 lines took around 30 seconds to optimize, a rate of 100 lines/second (AMD Athlon 1800XP CPU, 256Mb Ram). One of the goals of our previous NSF research was to determine if our algorithms were fast enough to be applied in “real time” and these results confirm that they are. **Table 1** shows comparisons in cutting time and maximum cutting forces for the roughing and semi-finishing cases.

Stage	Cutting Conditions	Best Practice		Optimized		Difference	
		Time (min)	MAPF* (lb)	Time (min)	MAPF* (lb)	Δ Time	Δ Force
Roughing	0.5” carbide flat-end, 2000 rpm, 0.004” fpt, target force = 110 lb	6.89	66	4.10	99	-40%	50%
Semi-Finish	0.375” carbide ball-end, 2580 rpm, 0.0015” fpt, target force = 150 lb	9.94	105	8.65	115	-13%	9.5%

Table 1 Comparison of “best practice” and optimized programs. The overall improvement in cutting time was 24% with most of the improvement due to the roughing stage. *MAPF – Mean Average Peak Force – obtained by finding the mean of the average peak forces measured during all of the cutter passes. Peak forces are found by saving the maximum force measured during a time interval required for the cutter to rotate 10 revolutions (0.3 sec for 2000 rpm); these peak forces are averaged during one pass of cutter across the workpiece.

Model accuracy is indicated by **Figure 4** comparing the actual and model predicted average peak forces of the thirty-four passes which comprise the semi-finishing program. The average percent error is 13.8%. A similar graph for the flat-end roughing had an error of 16.8%. While not perfect, these are well within the expected range of predictions for metal cutting force estimation when changing cutting

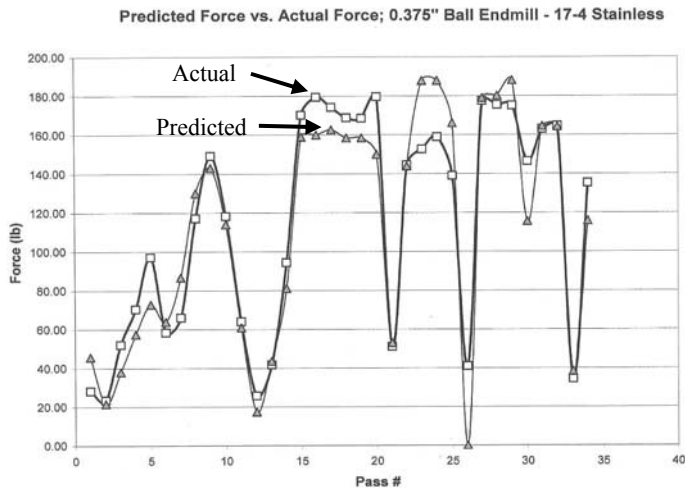


Figure 4 Predicted and actual mean avg. peak forces for ball endmilling of turbine blade sides 1 and 2

conditions are encountered.

Figure 5 shows the average peak forces for each pass for four turbine blades. A new tool was used at the beginning of the tests and was not replaced. Cutting forces grow larger as the tool begins to wear. The difference between the forces predicted by the model and the actual forces increased as the cutting progresses. Feedrate optimization based on the original characteristics of the tool would result in excessive forces. By decreasing the initial cutting force, as shown in **Figure 6**, the wear effects are decreased and tool life is extended. The Model Tuning block (11) of **Figure 1** uses the difference between model predicted and actual forces to perform on-line calibration of the Dynamic Process Modeler.

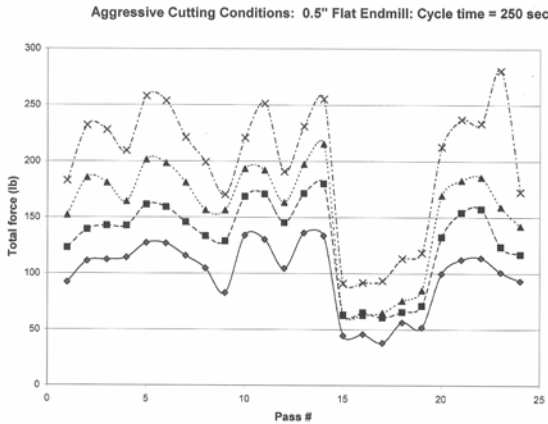


Figure 5 Force profiles resulting from aggressive cutting of 4 turbine blade parts with the same tool

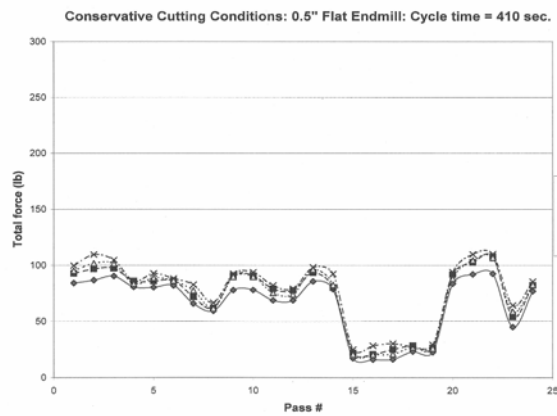


Figure 6 Force profiles resulting from conservative cutting

1.3.3 NCML: A New Language for Representation of Machining Process Plans

In another NSF research project (DMI-9713906) we worked on the development of a "clean interface" between design and manufacturing, analogous to the model successfully used in the electronics industry in the MOSIS project for the manufacturing of VLSI chips [Meade 80, MOSIS]. The research accomplishments are summarized: 1. Creation of a new format for representation of machining process plans, NCML (Numerically Controlled Markup Language). NCML uses XML, the standard for exchange of data on the web, to represent machining features. 2. Development of a prototype system to illustrate how NCML can be effectively used to represent process plans for prismatic machined parts, 3. Testing of the methodology with a number of parts obtained from three different sources: The Design Repository located at Drexel University, Manufacturing Quote Inc., a commercial company that is in the business of matching buyers and sellers of custom machined parts, and Stone Machine Co., a local machine shop that is typical of the type of fabrication facility which would use NCML.

Ten parts were chosen from the three different sources (three from the Stone Machine Company, three from Mfgquote.com and four from the National Design Repository). **Figure 7** graphically illustrates the transition of one of these parts as information is added in the NCML based process. Four different phases are shown. The first image shows the design schematic drawing from which the NCML is generated. The second image is the VRML model of the part, which is generated automatically from the NCML document.

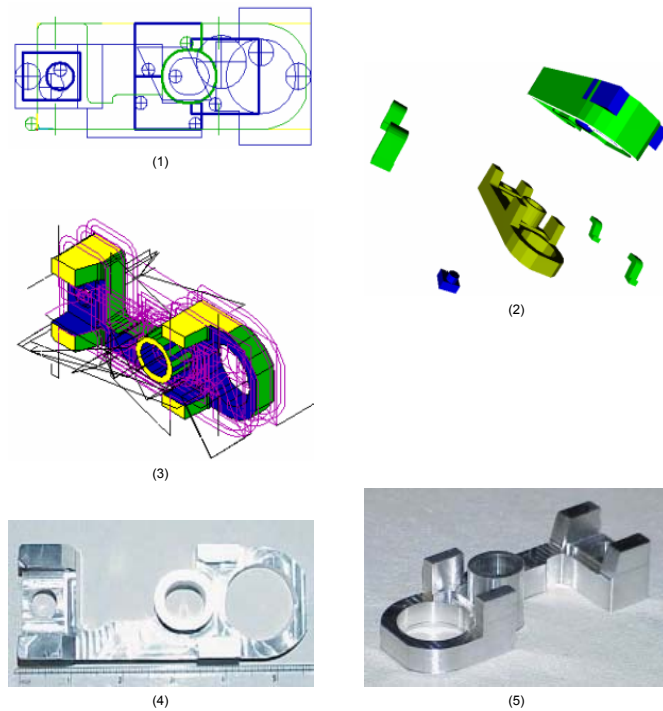


Fig. 7- Sample test part - gehause

Each NCML operation is shown as a machining volume. This VRML model is used as a graphical communication aid. The third image shows toolpaths generated by the process planning module (Block 5 of **Figure 1**) of the prototype system. The fourth and the fifth images show the actual machined part after executing toolpaths on the CNC machine.

We also developed an application to estimate machining costs directly from the macro description of the process plan in NCML (Block 3 in **Figure 1**). This application was tested by applying the quotation helper to parts posted on MfgQuote.com. Since most of the parts are viewed and examined under a nondisclosure policy, only test results can be presented. Table 2 compares the cost estimates generated by our system with statistics obtained from the MfgQuote website. After each RFQ has been awarded, bidders are allowed to see the high, low, average and median quotes for the job. These values were compared to our estimates. The wide range

of bids is in itself quite interesting. The ratio of the high to the low bid of RFQ 884 is 13.8! What did the \$6300 bidder see that the \$455 bidder did not? Our automatically generated estimate of \$1319 was very close to the median bid of \$1357. The economic health of a job shop depends on the quality of its bidding process, but based on Table 2 it appears to be much more art than science.

Table 2 Quoting range test results

Part ID	Qty	Quoting Statistics (\$).				NCML Estimation (\$)		Comparison (%)	
		Max	Min	Ave (A)	Median (M)	Machining	Overall (E)	E/A	E/M
RFQ-884	250	6300	455	1736	1357	619	1319	75	97
RFQ-953	35	7599	654	2544	1795	1134	1458	57	81
RFQ-1081	25	2197	1050	1440	1351	653	959	67	71
RFQ-1113	2*10	1350	272	634	542	61	613	97	113
RFQ-1093	1	626	50	252	220	10	274	108	125
Average								81	97

The NCML cost estimator only takes a few minutes to generate a cost estimate. This estimation process starts with a Macro Simulation which calculates volume and surface areas. The parameters obtained from the calibration process can then be used to quickly estimate machining times. The fixed costs associated with the part are then added to the machining costs to obtain the estimate. Estimation values are as close as 81% of the average quotes and 97% of the median quote. The calibration of our models was done by meticulously measuring cutting times of machining jobs at Stone Machine Co., a job shop located in Chester, N.H. (see letter of cooperation in Appendix I). In our future vision (**Figure 1**), "Path B" from the OAC to the cost estimator is continuously providing process capability information for accurate calibration of the cost model.

For brevity, much of the detailed description of NCML and the methodology used to create the cost estimation have been omitted. A more complete description may be found in our publications [Jerard

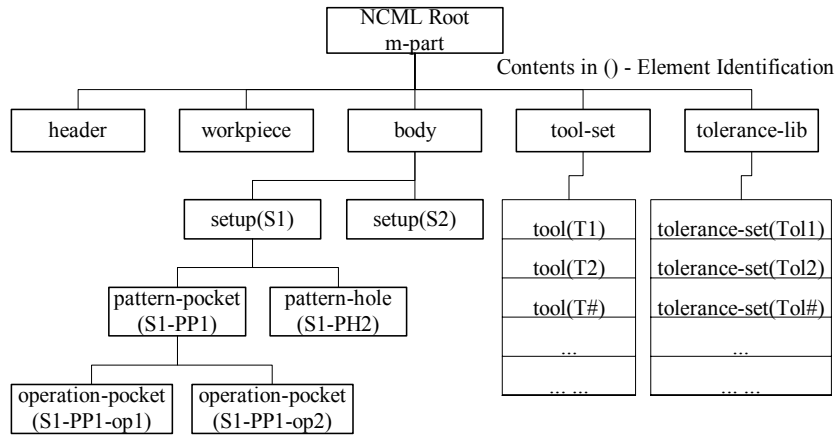


Figure 8 - Simplified NCML structure and components

02a,b] which are available on our website (www.unh.edu/dml). The key elements of the project which are applicable to this proposal are: 1. NCML is a “macro” description of machining process plans which include XML representations of the workpiece, machining features necessary to transform the workpiece into the desired finished part, required tolerances and tooling description, 2. NCML is a potential replacement for “G&M codes”, the traditional method for programming CNC machines, 3. Since NCML relies

on XML, it is “web friendly”, simple and compact. XML stands for eXtensible Markup Language and is a meta language that enables the creation of application specific languages. There are numerous sources of information about XML on the web. For example, see www.xml.org where users can register their DTD’s for others to share.

NCML is a relatively compact language, consisting of a mere 58 elements. A simplified schematic of the NCML structure is shown in **Figure 8**. Despite its simplicity, the power of the method is illustrated by the results shown in **Figure 7** and **Table 2**. With an NCML representation of the test parts, we can easily generate tool paths, VRML representations and cost estimates. One goal of this research proposal is to extend NCML to the representation of machine tools to unambiguously describe both its physical and process characteristics. NCML has the potential to unify the representation of process plans and machine tools into a single format. We believe that this is a powerful idea that will enable truly “smart” machine tools by intelligently matching the requirements of a given part with the capabilities of a given machine tool.

Our past research has also explored implementation of on-line calibration [Jerard 01b, Fussell 02] of models (Block 11 in **Figure 1**) and adaptive adjustment of feedrates [Richards 02] (Block 10 in **Figure 1**). The primary focus of this research proposal is on the information content and flow from Block 7 (OAC Controller) to Blocks 3 and 5 (Cost Estimator and Toolpath planning). **Section 2** of this proposal describes the specific research tasks. **Section 3** explains the significance and how the work fits into the overall vision embodied by **Figure 1**.

We are sometimes asked why we are not using STEP-NC [SNC_P01] since it shares some of the same goals as NCML and is in the process of becoming an accepted standard. While STEP-NC has great potential it has two characteristics that make it an inappropriate choice for our project: complexity and functionality. Despite being immensely more complex than NCML, it lacks the ability to represent process plans in a hierarchical fashion and its library of machining features is more limited than NCML. The automatic cost estimation capability that we have already demonstrated has yet to be realized in STEP-NC. We performed a fairly detailed comparison [Ryou 01] and determined that it was not a good choice for our development efforts. We believe that it is likely that STEP-NC will benefit by the demonstration of features embodied within NCML and eventually assimilate them.

2. Project Description

Our research will test the feasibility of dynamically measuring the process capability of a machine tool and relating this process capability to the generation of quotations for industry-specified parts. Part accuracy is affected by many different types of errors, e.g. machine axis squareness, encoder inaccuracy, cutting tool runout, tool deflection and tool wear [Choi 98, p. 252]. Some of these errors are static, e.g. machine squareness and encoder inaccuracy, while others are dynamic, e.g. tool deflection and wear. A Smart

Machine Tool should know both its static and dynamic process capability and report this information in a sensible fashion to the user. While there are many factors that determine the process capability of a machine tool, this study will focus on three parameters deemed to be amongst the most challenging and most significant: tool runout, tool deflection and tool wear. Process capability associated with these parameters will be investigated along with the information structure needed to capture important characteristics of the machining process.

2.1 Experimental Testbed

Integration of our OAC machining center with a variety of sensors is necessary to measure the machining process state in real-time. This includes sensors already available on the machine that provide slide positions and velocities. Additional sensors are needed to measure slide motor currents, cutting force, acoustic noise, and spindle radial acceleration [Altintas 92, Dolen 94, Smith 87, Stein 86]. The objective is to integrate all the sensor information into an XML database that synchronizes measured data with model data. Implementation concerns include sampling rates of sensors, signal conditioning, data synchronization, and handling the large arrays of data that must be accessible to the process modeler.

2.1.1 Sensor installation and interfacing to OAC

All sensors not resident on the NC machine are available in our lab. We will use a Kistler three-axis load cell to measure cutting forces. There are other less intrusive methods, such as strain gages in the spindle bearings [Promess], but for proof of concept, the load cell is adequate. Three other types of sensors, i.e. a shunt resistor, accelerometer and microphone, will be mounted on the machine and integrated with the OAC. Precision shunt resistors will be used to measure the feed drive currents for estimation of cutting forces, and eventually to predict tool wear and breakage [Altintas 88, 92, Smithey 01, Sutherland 89]. The acceleration of the spindle head during cuts is intended to help in the prediction of broken and worn tools, while the sound pressure from the cutting operation is intended for chatter prediction [Altintas 95, Smith 87, 91, Tian 01]. We will not be investigating chatter in this research, however we understand its importance and want to build our system to accommodate it in the future. The data from the sensors will be integrated into our XML data base to help determine the dynamic process characterization of the machine tool [Jerard 01b].

2.1.2 Algorithms for collection, storage and processing of machining workcell data

A data acquisition board has been integrated with the OAC for sensor data collection at a rate of 100khz. The OAC also allows direct real-time access of the tool position and speed at a rate of 1khz. The measured process state vector \mathbf{X}_m and process output vector \mathbf{Y}_m can be formed from the sensor measurements. When combining the data to form the process vectors we have to consider thinning and synchronization. Thinning is necessary to reduce the vast amount of data that results from sampling at 100khz. We have to decide what data to keep, e.g. peak force, and at what time to store it. Time and position should be synchronized with each sensor data sample that is stored so it can be correctly related to the process model outputs.

2.2 Information Technology for Machine Tool Representation

NCML is a conceptual process plan described with machining features. For this research, these capabilities must be expanded to incorporate the NC machine, cutting tool definitions, as well as a workpiece material data. The required information content can be divided into a number of subcategories:

- Physical/structural (footprint, axis travel, tool changer, table sizes, weight, stiffness, etc.)
- Motion (kinematic chain, axis travel, speeds, acceleration, damping, power, spindle speed, etc.)
- Control/sensors (control algorithms, tachometers, encoders, transfer functions, etc.)
- Process (cutting tool, workpiece material, coolant,

2.2.1 XML representation of CNC machines

The physical and process characteristics of the machine tool will be stored in XML format. The format will be general enough to represent any machine tool, but we will start by applying it to the specific

configuration in our lab which is a 3 axis FADAL VMC with a 2 axis rotary tilt table, retrofit with an MDSI OAC. Our research will focus on determining the required Document Type Definition (DTD) characteristics for an XML application of this type.

There has been very little work on the development of standard representations of machine tools and their error sources. We are aware of the work currently being done at NIST [Soons 00, Lee 01] on XML representation of machine tools, and it is our intention to take maximum advantage of that work. Their representation divides machine tool information into two categories: model specific (axis configuration, axis range, axis speeds, physical footprint, spindle speed, spindle power, table size, etc) and machine specific characteristics (thermal errors, contouring errors geometric errors, machine dynamics and stiffness).

2.2.2 Representation of cutting tools and workpiece materials

The XML representation must have a tool data base that includes the tool's physical characteristics (i.e. diameter, length, profile, number of flutes, helix angle, rake angle, material and coating) and also its process characteristics (i.e. cutting parameters that relate chip thickness to cutting forces, tool runout, tilt angle in the holder, wear characteristics, etc.). While physical characteristics can be assessed for a tool "on the shelf", process characteristics can only be determined once the tool is mounted in the machine.

Accurate prediction of cutting forces presents a formidable challenge. The Assessment of Machining Models (AMM) effort (<http://www.nist.gov/amm>) at NIST examined cutting data from four separate laboratories for the same material (1045 steel), same cutting conditions, tools and methods. The results indicate large variations in the force data for seemingly identical conditions. From our experience, tool runout is a likely source of these differences, since it is a factor that is difficult to replicate on different machines (see **Figure 9** for an example of the force variation caused by runout). It is therefore essential to develop a method in which calibration is done on a continuous basis. Other effects like wear (See **Figure 5**) are also capable of continuously changing the relationship between cutting conditions and the resulting forces. Accurate prediction of cutting forces is a key requirement for achieving high quality since it affects tool deflection, workpiece deflection and chatter.

2.3 Machining Models for Dynamic Process Characterization

The real-time sensor data that we collect will be used with process models to dynamically characterize the cutting process, maintain part quality and continuously track the process state of the machine. Specifically, our goal is characterization of tool runout, tool wear, and tool deflection. To accomplish this goal requires accurate cutting force and tool wear models.

The vector force cutting models we are now investigating are based on normal and friction tooth forces [Altintas 00, Ko 02, Yang 93, 94, Yucesan 96, Yun 01, Zhu 01] that are transformed from the local tooth coordinate system to the tool x, y, z coordinate system. As an example, the vector force equation for a flat end mill, using average chip thickness, can be written as a set of constants and cut/cutter geometry terms:

$$\begin{aligned}
 F_x &= K_n f_t A + K_f K_n f_t B & K_n &= K_{nc} (h_{avg})^{p_1} \\
 F_y &= K_n f_t C + K_f K_n f_t D & K_f &= K_{fc} (h_{avg})^{p_2} \\
 F_z &= K_n f_t E + K_f K_n F
 \end{aligned} \tag{1}$$

where F_y , F_x , and F_z are the cutter force components. A,B,C,D,E and F are summations of geometry terms that are constant for a given tool rotation angle. These terms are available from the vector \mathbf{X}_d . The terms p_1 and p_2 are needed because of the non-linear relationship between cutting force and chip thickness; K_{nc} and K_{fc} are specific cutting energies that depend on tool geometry and workpiece material. In our current research, we have been able to successfully determine these parameters by experimental calibration.

2.3.1 Off-line iterative solution of force model parameters

An iterative approach will be used to find the best model parameters from the cutting data stored in the XML data base. This is necessary because runout, runout locating angle, chip flow angle, and cutting coefficients are typically unknown. Several nested iteration loops are necessary. The outer loop will start with an assumed runout angle and work through loops for runout, chip flow angle and finally for cutting coefficients.

Our current work has demonstrated the feasibility of this approach in predicting the force for a four flute carbide end mill (flat) cutting aluminum, as shown in **Figure 9**. The calibration procedure is able to accurately estimate runout, and runout locating angle. Peak forces are greatly affected by runout. The maximum Y force on tooth 1 is much greater than tooth 3 (220N vs 75N).

Our proposed work will explore how this iterative approach can be modified to make the algorithms faster and more robust. The simplest approach is to assume that the chip flow angle is constant and equal

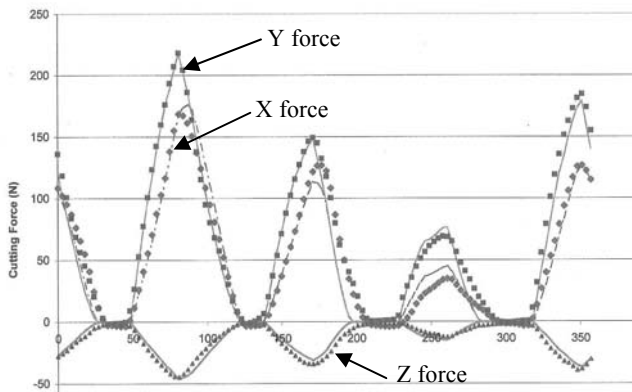


Figure 9 – Cutting force (N) vs tool rotation angle (deg). Measured X,Y & Z force components are compared to simulated force. Four fluted flat end mill has runout causing uneven chip thickness and different peak forces. Material Al 6061 T6. 12.7mm tool diameter, 750 rpm, .0508mm feed per tooth.

to the helix angle. The need to iterate for runout estimation can be eliminated if it is measured on the machine, but in many cases these values are not precisely known, particularly after a tool change. Finally, we will develop algorithms to automate the data processing required to average x,y,z forces for multiple tool rotations, and to align the angular position of the force data with the model simulation data.

We currently have a number of cutting test results that can be used to evaluate our parameter estimation methods. These include aluminum, steel, stainless steel, tool steel, Inconel, and titanium for the workpieces, and HSS and carbide for the tools. Accurate force, feedrate and spindle speed data are typically available for every three degrees of tool rotation.

2.3.2 On-line estimation of force parameters

Accurate force model parameters are important to characterize the machine for the purpose of process planning. They are even more important during the cut, where tool wear and runout may greatly affect the tool force and subsequently part quality. These components of the smart machine tool shown in **Figure 1** will estimate the parameters on-line. We must investigate procedures for deciding when and where in the cut to calibrate the parameters. The geometry and speed of the cut should be constant for a period of time so data can be collected and reliably synchronized with the model based information.

The on-line data that is available in the state and output vectors, i.e. \mathbf{X}_m , \mathbf{Y}_m and the desired vector \mathbf{X}_d , provides the necessary information to estimate the model parameters. For example, the discrete vector force model constants K_{nc} , K_{fc} , p_1 , and p_2 , can be evaluated for each tool position θ , as described below. More accurate least squares estimations can be obtained by using a large number of these vectors.

The iterative estimation approach described in **Section 2.3.1** is first applied on-line to determine the runout magnitude and angle. Subsequently, runout is assumed constant as long as the tool remains in the spindle. The force relationships shown in **Eq 1** is then solved for K_n , K_f and θ_c as a function of tool position θ . A large data set is then developed containing $\ln(K_n)$, $\ln(K_f)$, θ_c and h_{avg} , the average chip thickness for that particular tool move. A least squares fit is now used to find the most accurate values for K_{nc} , K_{fc} , p_1 , p_2 , and θ_c in the form shown in **Eq. 1**.

2.3.3 Tool wear models

Tool wear can have a significant effect on cutting forces and cut geometry, and if left unchecked during machining can cause part and tool damage. **Figures 5** and **6** show the significant effect of tool wear

on cutting forces after four turbine blades are cut in stainless steel with the same tool. We propose to predict the tool wear during process simulation, and estimate the wear on-line during the cutting process.

Wear prediction: A standard wear equation can be employed in the simulation because the process modeler calculates the contact area and the feedrate for each tool movement. In our model, we slice the tool into a series of disks for calculation purposes. Wear on each discrete section of the tool, for each tool movement, can be easily summed to give the overall wear of the cutter. As an example, we can use the standard Taylor tool life equation to estimate tool wear [Barrow 71, Elbastawi 91 Ismail 93, Youn, 01]:

$$VT^n = C \quad (2)$$

where V is the cutting speed, T is the tool life, n is an exponential primarily dependent on tool material, and C is the Taylor constant. This formula can be applied to each discrete section of the tool, with the total wear based on a ratio between total time in contact with the workpiece, and the useful tool life T:

$$W(i, k) = \sum_{i=1}^{N_{\text{toolmoves}}} \frac{T_i}{C^{-n} V_i^n} \quad (3)$$

where W(i,k) is the tool wear parameter for disc i and flute k, $N_{\text{toolmoves}}$ is the number of tool moves made by the cutter, T_i is the time in the cut during that particular tool move, and V_i is cutting speed. Note that as the wear parameter W(i,k) approaches 1, the tool section and hence the tool is considered worn out. When a section of the tool shows significant wear in the simulation, the Real-time Control module (block 10 in **Figure 1**) will note the time into the cut, and initiate a request that on-line cutter wear be monitored and assessed on a continuous basis during the actual cut. The values of W(i,k) will be stored in the XML tool data base, and will be updated each time the cutter is used in a machining operation.

There are many other tool life equations that can be used to estimate wear, e.g. chip equivalent expressions, and probabilistic approaches. Taylor's equation is just one example of how we can use our modeling capability to provide wear estimates.

Validation and refinement of the tool wear model as well as development of empirical models relating force to wear, will be explored using force and wear data measured for a variety of simple test cuts. These include aluminum, steel, stainless steel, tool steel, and titanium for the workpieces, and HSS and carbide for the tools. Several radial depths, axial depths, and chip thicknesses will be used for each fixed cutting speed test. Wearland width VB and tool profile dimensions will be measured frequently during each cut. A multiple regression least squares fit will be used to correlate the tool wear to the cutting parameters.

On-line flank wear estimation: We propose to estimate the flank wear length VB of the tool using a combination of measurements and models. The models will be based on work by Smithey, Kapoor and DeVor [Smithey 01]. They combined a wear force model [Waldorf 96] with a slip-line field model to estimate the total force as a tool wears. The important feature of this work is that existing cutting coefficients, e.g. K_n and K_f , found from sharp tools, can be used to find the shear flow stress k and shear angle ϕ_s needed to predict the wear contribution to the total cutting force.

Our approach to on-line wear estimation will be as follows:

1. Use sharp tool/material cutting tests to find K_n and K_f (we already have a number of these coefficients)
2. Calculate k and ϕ_s from the slip-line field model (this will be a function of chip thickness)
3. Measure forces during a cut and subtract out sharp tool forces (sharp forces from our mechanistic model)
4. Use the resulting wear forces in a modified wear force model to estimate VB.

Several research issues must be addressed to make this a viable method. We first have to extend the wear relationships to include oblique cutting. We must also perform a series of wear tests to see how well these relationships apply to intermittent cutting. It will also require on-line force simulation (assuming a sharp tool) and synchronized comparison to the measured force. Finally, tests must be run to evaluate the accuracy of the wear land predictions.

2.3.4 Dynamic process characterization modeler

The dynamic accuracy of the cutting process will be determined by combining measured data with real-time simulation models of the process. Runout amplitude and locating angle, tool wear, and tool deflection, determined in real-time, will be combined to assess and characterize the cutting process.

Runout and tool wear can be estimated in real-time using the force and wear models described in Sections 2.3.2 and 2.3.4. Since they change very little over a short time interval, it is not necessary to estimate them during every tool move. Tool deflection, on the other hand, is dependent on the cutting geometry and can change with every tool movement. The total error experienced in the process for a particular tool move is a combination of these individual errors. Unfortunately, combining them is a complicated task, given the intermittent nature of end milling, and the complex cutting geometry.

We propose to run a geometric/mechanistic model in real-time to estimate the effect of all the errors on tool position. Input to the model will be supplied by the process data state vector \mathbf{X}_d and output vector \mathbf{Y}_m . The current runout and tool wear estimates will be included in the \mathbf{X}_d vector. The simulation will be run for each tool move. Tool deflections can be predicted with an accurate estimate of force and the tolerance deviation caused by this effect can be calculated. This is nontrivial and will require modifications of our simulation methods [Jerard 89ab].

2.4 Experimental Assessment

Extensive experimental assessment will be required to validate the proposed concepts and determine if the Machine Tool Process Capabilities can be characterized for a wide range of cutter types, workpiece materials and feedrates. Validation will require a comparison of three entities: 1. The geometric model of the part surfaces, i.e. the mathematically perfect surface, 2. The surface predicted by our simulation models and 3. The actual surface generated during cutting. In our previous research we developed simulation

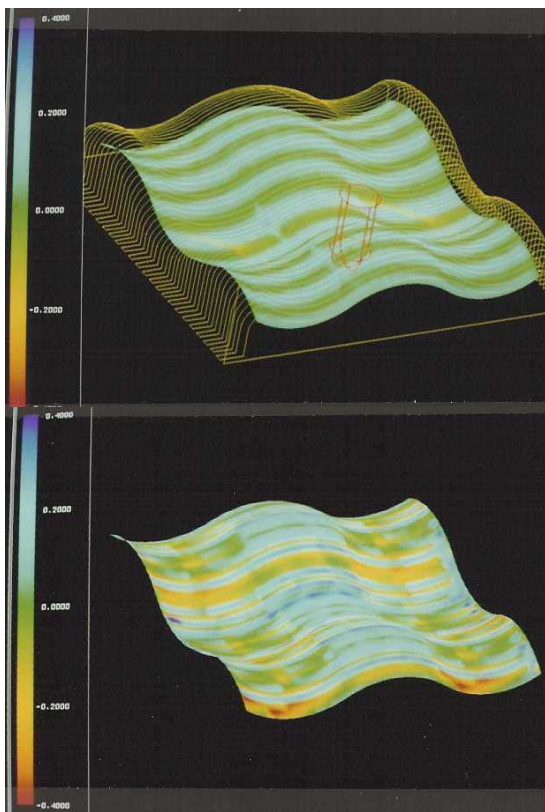


Figure 10 Simulation shows differences between mathematical surface and simulated surface; red = gouging, blue = excess, green is within tolerance. Bottom figure includes effect of tool deflection.

methods for quick comparison of the first two entities [Jerard 89a,b, Choi 98 p.305-308]. **Figure 10** shows a color map of a sculptured surface in which the colors represent the deviation between the mathematically defined surface and the surfaces generated by a simulation of the cutting of a sculptured surface with a ball-end cutter. In the top figure, the tool is considered to be perfectly rigid; tool deflection is included in the bottom figure. In the proposed research we plan to extend the results by measuring the actual cut surface with a Renishaw probe and making a similar comparison between the mathematically defined surface and the actual cut surface. If our simulated surface and our actual cut surface are very close to each other then we can be confident that we have a good characterization of the process capability of the CNC.

The simulation shown in **Figure 10** needs to be extended by including the effect of cutter runout and tool wear. Once these model enhancements have been implemented, their validity will be checked by cutting no fewer than six different materials: Al 6061 T6, Al 7075 T6, 1018 low carbon steel, A2 Tool steel, 64 Titanium and 718 Inconel. Our current research indicates that it is important to test the models with variable tool stiffness which can be achieved by using two different tool lengths. A variety of tool materials, helix angles and rake angles will also be tested. Axial and radial depth of cut will be varied along with feedrate to test our ability to predict tool deflection under a wide variety of chip loading conditions.

Note that the results shown in **Figure 10** were obtained

by intersecting the swept envelope of the tool with vectors perpendicular to the mathematically defined surface. Tool deflections only affect the accuracy of the final part if they are in the same direction as these perpendicular vectors. For example, the bottom of a flat end cutter will create a machined surface whose dimensional accuracy is hardly affected by the tool deflection whereas surfaces on the side of the tool are greatly affected. This is an important consideration when trying to determine if the finished part is going to be within the specified tolerances.

Tool wear affects not only surface finish, but also tool deflections. As shown in Figure 5, the cutting forces can increase as the tool wears. Increased forces cause larger tool deflections that adversely affect the process accuracy. Cutting forces will be measured using our three axis load cell. We will also use our Renishaw probe to measure the cut surfaces. Tool wear will also be measured after each cut.

Part quality is determined by dimensional accuracy and surface finish. The Renishaw probe measurements enable us to compare the surface accuracy with the model predicted accuracy and the desired surface tolerances. Surface finish will be measured with a profilometer. We will also investigate the force variations during each cut, and how they may contribute to dimensional problems.

Finally, the methods must be verified by cutting real parts and determining the accuracy of a cost estimation module that uses the process capability information. Real test cases will be provided by Stone Machine Co (see letter in Appendix I). The results shown in Table 2 will be augmented by many additional test parts from the ManufacturingQuote on-line bidding service.

3. Significance of the Research

This research, if successful, would demonstrate the key technology required for implementation of Six Sigma quality in the machining operation industry. Annual U.S. expenditures on machining operations are estimated to be in excess of \$200 billion [NIST]. We believe that our research team is unique in our ability to combine models, sensors, open architecture control and information technology. We envision that our efforts will be split about 50-50 between theory and experimentation.

These are the fundamental research questions that will be answered by the proposed research.

1. Can Machine Tool Process Capability characteristics be used to accurately estimate machining costs, thereby providing valuable feedback to designers about the cost implications of their design choices?
2. Can models and sensor data be used to accurately estimate the cutting process errors associated with tool deflection, runout and wear on a continuous dynamic basis?
3. What XML elements are needed to extend NCML to the representation of machine tools?
4. Is it possible to quantify the effect of cutting process errors on the tolerance variation of the workpiece?
5. Are the cutting force models general enough to work over a large range of cutting tools, feedrates, cutting durations and workpiece materials?
6. What sensors should be employed to monitor the machining process on a continuous basis?
7. How often does the data need to be collected?
8. How can the data be stored in an information technology framework?

If successful, this research would enable the calculation of a meaningful Process Capability Index for CNC machine tools. This is a significant result that will enable a host of other advances, including:

- Intelligent matching of CNC process capabilities with part tolerance requirements
- Adjustment of cutting strategies and process parameters to achieve desired process accuracy
- Feedback to the designer on the cost implications of design choices.

Education and Dissemination - This research project will support two graduate students and two undergraduate students for three years. Also, it is our plan to involve one or two graduate students who will be supported by teaching assistant positions at UNH. This gives us the potential of impacting six

students directly with our proposed research activities. Also, we intend to use the results of our work in undergraduate classes through demonstrations and active participation. We plan to employ UNH undergraduate heavily in the testing process. We have had good success in employing undergraduates to both prepare NC programs for testing and running the experiments.

Our previous research has been disseminated to our industrial partner Turbocam, and is currently being used to set feedrates for five-axis cutting of turbine and impeller blades. We intend to continue this approach with our new research. New and promising research results will be applied in an industrial setting. This will provide us with very useful feedback in terms of strengths and weaknesses of the methods.

Turbocam has recently created a subsidiary to commercialize our feedrate optimization algorithms through a legal agreement with the University of New Hampshire. This agreement allows us to freely publish our NSF sponsored research results. Turbocam will license CAM vendors and end users to use their commercial version of the software. In addition, our laboratory at UNH will have complete access to the program with limited access to the source code. This will allow us to concentrate more on the development of algorithms and testing while relying on the software engineers at Turbocam for a stable and robust software platform.

Support Letters (See Section I) - The letter of support from VulcanCraft, the developer of the N-See verification software expresses interest in the commercial development of our research results. The letter of support (see Section I) from Bob McGinnis, expresses interest in our proposed research by MDSI, the company which sells the OAC used in our research. Their agreement to cooperate with us gives us access to the expertise of the MDSI development team and also ensures that our results will be broadly disseminated to OAC users. Stone Machine Co. is a local job shop, typical of the many thousands of machine shops around the world. Stone is willing to work with us by providing test cases and acting as a real world reality check on our methods.

4. Research Plan

The research tasks of the previous sections are summarized below along with the time for completion and the responsible investigator. (F = Fussell, J = Jerard, M = months)

1. Experimental Testbed for Characterizing Process Capability

- 1.1 Sensor installation and interfacing to the OAC (F,4M)
- 1.2 Algorithms for collection, storage and processing of machining workcell data (J,4M)
- 1.3 Integration of XML and models into the OAC (J, 2M)

2. Information Technology for Machine Tool Representation

- 2.1 XML representation of machine tools (J,8M)
- 2.2 XML representation of cutting tools (J, 8M)
- 2.3 XML representation of workpiece materials (J,8M)

3. Machining Model for Dynamic Process Characterization

- 3.1 Iterative solution of force model parameters (F, 4M)
- 3.2 On-line estimation of force parameters (F, 6M)
- 3.3 Tool wear prediction models (F, 4M)
- 3.4 Dynamic process characterization modeler (F, 6M)

4. Experimental Assessment

- 4.1 Tests and procedures (F, 2M)
- 4.2 Calibration and assessment of the dynamic process characterization modeler (J,F, 10M)
- 4.3 Cost estimation based on dynamic machine tool process capability (J, 6M)