Project Summary

The research objective of this proposal is to use techniques from continuous-processing industries to create a model-based control method for the optimization of discrete-parts machining processes with multiple target objectives (*e.g.*, profit, quality, time), and to show that the developed methods can be scaled to effectively control systems of machining operations.

Though a large body of discrete manufacturing process models exists, few of these are put to practical use for closed-loop manufacturing control. Knowledge that the academic community has generated about process behavior is not used to impart intelligence to process control.

The work proposed herein has the potential to transform the way discrete part manufacturing equipment is controlled by directly incorporating models into the control scheme. For example, almost every CNC machining center controller lacks inherent physical process understanding. This work departs from all current approaches in discrete parts manufacturing, and will have a significant impact in the discrete-parts manufacturing sector by explicitly representing process physics in the control of machining processes. Furthermore, it is proposed to extend this idea of model-based manufacturing control to manufacturing systems by communicating individual process information and product quality measurements throughout the manufacturing network. This is a fundamentally new approach to systems-level control, requiring basic research in model abstraction, uncertainty and communication.

I will use the results of this research to make a difference in the education of young technical thinkers in my state. To integrate the proposed concepts with education, I propose to leverage this research and my facilities to develop a new instructor education structure for the Gateway to Technology (GTT) program, a nationwide a middle-school STEM program. The structure consists of an annual teacher workshop to communicate and demonstrate results, as well as semiannual visiting days for GTT students to interact with and understand the research. GTT encourages the involvement of women and minority students.

Intellectual merit. Model-based control (MBC) resides almost solely in the continuous process industry. This research will address barriers to the migration of MBC to the process level for machining of discrete parts, and will investigate scalability of the method to control machining networks. In this sense, the fundamental issues to be addressed are: types and forms of models for inclusion, how model abstraction and uncertainty increase with system complexity, and addressing how information is *created* and *communicated* among processes for application to system-level optimization.

Broader impacts. Broader impacts of the proposed work lie in transforming the way middle school STEM students are educated in the state, including underrepresented groups who have expressed explicit interest in engineering. A layered mentoring program will also be established, whereby sponsored students will mentor teams of undergraduates to prepare demonstrations of the concepts. Results of instructor and student experiences will be assessed on a continuing basis for educational validation and improvement. Research results will also be driven directly to machine tool manufacturers and partners through annual meetings at our equipment partner headquarters. The research results will be applicable to a wide range of processes, made available to equipment decision-makers, and will benefit society through higher-profit and better-quality US manufacturing.

Project Description

Objective. The research objective of this proposal is to use techniques from continuous-processing industries to create a model-based control method for the optimization of discrete-parts machining processes with multiple target objectives (e.g., profit, quality, time), and to show that the developed methods can be scaled to effectively control systems of machining operations.

Though physics-based models exist for most traditional manufacturing processes, as well as models currently being developed for aspects of complex manufacturing systems, these models are rarely incorporated into the closed-loop aspect of process control for *prediction*. Control is instead typically achieved by *reactionary* means; for example, using proportional-integral-derivative (PID) control on the residual error between measured and desired process states, an approach in which systems have to continually deviate from optimal in order to be corrected. This lack of modeling is also evident on the systems scale in quality feedback loops, where process output is measured, and manual adjustments made to the process to react to deviation. I conjecture that including physical process behavioral models within the closed-loop control will improve process performance. I also propose research to extend this idea to quality control of manufacturing systems. Specifically, I will model production process chain coupling and influence on product quality, and use it to feed back at the cellular or factory level with *predictive* methods in order to improve system output quality.

The **intellectual merit** of the proposed activity lies in addressing fundamental research barriers to migrating physical process intelligence to discrete parts manufacturing control. Additionally, barriers to scaling such an intelligent approach to manufacturing systems will be addressed to improve processes from a systems level. The **broader impacts** of this research lie in its integration with STEM education for accelerated middle school students; this benefit is for the students, and for me to become a better educator by understanding learning. This project is a vehicle to invest in the future human capital to lead the technical progression of national manufacturing. Additionally, the research will take input from and have direct benefit and accessibility to the machine tool industry through our existing industry partnership networks.

I will use the Model-Based Control (MBC) approach, which incorporates process and system prediction in a closed-loop control system. A specific procedure within this class, known as Model Predictive Control (MPC), has been used in continuous process industries (e.g., chemical manufacturing using reaction models). This method uses physical process models to predict system response to control action over a fixed time horizon, and to optimize that control action for best performance. However, the MPC method has only been superficially applied to discrete parts manufacturing processes, and rarely at the system level.

In Phase One of this research, I target the potential of model-based methods (specifically the MPC method because it addresses combinations of any chosen objectives) to improve machining control at the process level. I intend to explore fundamental concepts for use in physics-based and empirical machining process models such as tool wear, cutting force and power, flow stress, and machine dynamic deflection.

In Phase Two, I will identify and address barriers to applicability of model-based methods at the system level. As there is limited existing work in this area, the approach will depart from strict

MPC in order to supply information from upstream processes as input to model-based schemes in downstream processes, and conversely to communicate product quality information upstream. The focus application for this phase is a network of machining operations, where operations optimize themselves based on model input from upstream process and downstream quality signals. This phase of the work involves imparting intelligence for system-level optimization, and centers on concepts required to scale this approach, particularly determining the information necessary for modeling at larger scales, model representation, and for elucidating model uncertainty at different abstraction levels of control application.

Research questions. I will pursue three initial questions to show the effectiveness of model based control when applied to individual machining processes (Phase One):

Q1. What elements of machining modeling should be included in a model-based control schema for machining, and how do they relate to optimization objectives?

Q2. Can physics-based or empirical models improve process-level control with respect to multiple objectives, which objectives can be effectively targeted, and how do the optimization objectives influence the model types and form?

Q3. What is the effect of model validity and uncertainty on model-based control performance, and how should uncertainty be incorporated to the control scheme?

I will then pursue two further questions to test scaling of the model-based approach for manufacturing system-level control (Phase Two):

Q4. What is the form of a model-based control scheme for manufacturing systems? That is, is model-predictive control applicable? How can it be embodied to make decisions?

Q5. How should model forms change as the scale and complexity of the controlled system increases? I anticipate a fundamental tradeoff between the scale of application (process, cell, enterprise), and corresponding model uncertainty (increasing with complexity) and controllability (decreasing with complexity).

Through the following final two questions I will address the role of model learning at all scales (Phases One and Two):

Q6. How is information created by and best shared among individual processes for system-level optimization?

Q7. Can process and system data from controlled systems be effectively fed back to the underlying models for updating to improve system performance, and for identification of changing system conditions?

This research is innovative in that MPC has traditionally been restricted to continuous process-level control. I expect to use it in a more uncertain and complex environment for <u>real-time optimizing of process profit and quality</u>. While this is a more challenging approach, I expect that it will yield a new set of research questions in the MPC domain, encompassing tradeoffs between model complexity, uncertainty, validity and controllability at the more complex systems-level. To address uncertainty, I will leverage information on uncertainty representation from Geographic Information Science (GIS), a field characterized by data uncertainty and ambiguity due to varying space/time conditions (e.g., wildfire, precipitation). Several treatments of formal representations of uncertainty exist[2-5]. I also expect to apply model-based methods to operational decision-making; a study of automation in this domain is warranted.

BACKGROUND

Machining Modeling. This section details several representative models suited for an MBC strategy. Each example represents an improvement domain affected by the research. Optimization over multiple objectives is possible when combined in the proposed control approach.

Cutting Tool Wear. There exist a multitude of tool wear models for different materials, tool geometries and machine architectures; over 20 such models were introduced in 2008 alone[6-19]. A major assessment of the validity and repeatability of these models was undertaken by Ivester et al. through the NIST Assessment of Machining Models (AMM) project[20, 21]. The motivation was to study the barriers to predictive modeling of machining introduced by unmodeled nonlinear or highly localized effects.

Cutting Force. The Merchant orthogonal cutting force model is a 2-D model for basic forces experienced in metal cutting[22]. There is a relationship between measurable forces in the thrust and tangential directions to derived forces along the idealized shear plane and tool rake face. This relationship serves as a seminal component of most analytic cutting models. Basic force relationships are also described for milling operations[23], and the directionality and magnitude of these forces are estimated on-machine through material definition in the path planning step. These basic force relationships add information to the control.

Multiphysics flow stress-Modeling based on constitutive laws. Flow stress approaches based on strain, strain rate and temperature allow quantification of required cutting energy. The classic Johnson-Cook (J-C) model of material flow stress accounts for these effects[24, 25]:

$$\sigma = \left(A + B\varepsilon^n\right)\left(1 + C\ln\frac{\dot{\varepsilon}}{\dot{\varepsilon}_0}\right)\left(1 - \left(\frac{T - T_r}{T_m - T_r}\right)^m\right) \tag{1}$$

where: σ is the equivalent flow stress, ε is the equivalent plastic strain, $\dot{\varepsilon}$ is the equivalent plastic strain rate, $\dot{\varepsilon}_0$ is the reference equivalent plastic strain, T is the workpiece temperature, T_m is the material melting temperature, T_r is the room temperature, and A, B, and C are material constants. Calamaz et al. improved this model by more accurately describing strain-rate dependence on temperature [26]. These and other models surveyed for accuracy[27] are amenable to inclusion in our model-based control scheme. The AMM project also involved Ford, Chrysler and GM, and concluded in a calibration data set for machining model validation[21], a good first step toward a usable generalized process model for machining. This research targets the model's direct migration to machine control to improve process performance and quality.

Model-Based Control (MBC). *MBC* is a term incorporating a number of approaches to introducing process models and simulation results (i.e., system response maps) to both real-time and user-level machine control. These methods are contrasted with traditional machine reference tracking control, where a desired path or state sequence is planned, and the control is actuated by actual deviation from plan; traditional methods can also incorporate feed-forward or look-ahead strategies to prepare for large changes in the reference, but this does not account for process physics. Model-based techniques extend this look-ahead strategy to predict how the system will respond to input changes, and control on the residual of the planned vs. *predicted* states.

<u>*Model-Predictive Control (MPC)*</u>. The specific technique to be focused on in this research is the Model-Predictive Control approach applied to the machining process with multiple optimization objectives. In MPC, an objective function of weighted goals is defined, the system response to inputs is predicted over a finite time horizon, the behavior of the system is optimized with respect to the objective function, with design variables as the system inputs, and then the system actuated to drive toward the optimized state (see Figure 1). MPC is implemented through minimization of a penalty function across a finite time horizon. The objective incorporates three general areas: residual error of the new prediction $\hat{y}$ to previous predictions $\boldsymbol{r}$, cost of large changes to the control inputs $\boldsymbol{u}$, and error of the input to previous setpoints $\boldsymbol{s}$. These objectives are represented by the three terms of a single objective function with respective weighting parameters *Q*, *R*, and *N*, as shown in (2):

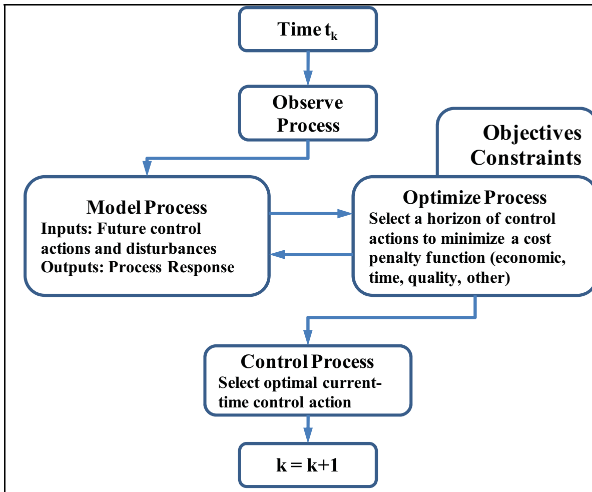


Figure 1 - Flowchart of Model-Predictive Control Approach. Process observations are fed to a model at each time step. The objective function is optimized over a finite time horizon to specify the next control actions.

$$J(k)=\sum_{i=N_w}^{N_p}[\hat{y}(k+i\,|\,k)-r(k+i\,|\,k)]^T\cdot Q\cdot[\hat{y}(k+i\,|\,k)-r(k+i\,|\,k)]+\sum_{i=0}^{N_c-1}[\Delta u^T\cdot(k+i\,|\,k)\cdot R\cdot\Delta u\cdot(k+i\,|\,k)]$$
$$+\sum_{i=N_w}^{N_p}[u(k+i\,|\,k)-s(k+i\,|\,k)]^T\cdot N\cdot[u(k+i\,|\,k)-s(k+i\,|\,k)] \qquad (2)$$

The objective *J* is optimized by varying inputs $\boldsymbol{u}$ over a time horizon beginning with N_w, containing N_p samples for the predictive term, and over a control horizon N_c for the input terms. Multiobjective methods will also be explored. Our method has two advantages over traditional control methods: it improves performance through a predictive understanding of the physics behind the system response rather than reactive compensation, and it can be optimized with respect to any parameter(s) $\boldsymbol{y}$ of interest even when the underlying model contains uncertainty.

Application of MPC to Discrete Part Process Control. MPC and other model-based methods have seen limited application to closed-loop control of processing equipment. Rather, they are employed in a limited sense as open-loop or non-real-time predictors of process condition and used to drive gross process intervention. An example is use of a tool wear predictor model to recommend a tool change frequency; this type of approach uses only limited process feedback such as accelerometer vibration data to assess departure from a "good" signature envelope.

Applying true model-predictive controllers to discrete parts manufacturing processes is extremely limited. Zirn et al. apply model-based control methods to machine tool axes to improve precision[28]. Itoh applies MBC to a form rolling machine to eliminate transient vibration[29]. Saffer and Doyle apply strict MPC to a paper making machine[30], and Tarău et al. apply models to the controller of a mail-sorting machine for throughput optimization[31]. Though these processes are somewhat continuous, the discrete product output highlights them as novel. An illustrative and simplified example of MPC use in the machining process is in the sidebar "How to Apply MPC to Machining?"

With regard to the MPC approach itself, Cano relaxes a fundamental assumption that the steady-state plant model is known[32]. He proposes a modified cost function that optimizes a more general family of plants, even when the underlying model is not originally known. This approach highlights an important aspect of the proposed research: inclusion of uncertainty in the model, and how uncertainty may affect a system as complexity grows. This effect is expected to become more appreciable at the systems level due to complexity and interactions of uncertainty from each system element source.

Manufacturing Systems Modeling. The second major phase of this proposed work is scaling of the model-based approach to control of manufacturing systems, particularly generation of knowledge within the processes and information sharing between processes for system-level optimization. Some treatments of manufacturing systems-level modeling include Zaletelj's framework for modeling manufacturing systems[33] using building blocks to represent multiple independent operations and their interactions. Thapa et al. propose an architecture to model Programmable Logic Controller (PLC)-based manufacturing systems[34] to facilitate integration between systems-level programming and programming at the device level. Graton proposes a modeling structure for quality data in distributed manufacturing systems, extending the basic one-product, one-station stochastic flow model to that of a multi- product,

How to Apply MPC to Machining?

A simplified illustrative problem of tool deflection's effect on control. Assume endmill deflection occurs solely in the tool (it doesn't). As shown in Figure 2, changing depth affects the thrust force, which deflects the cutting process.

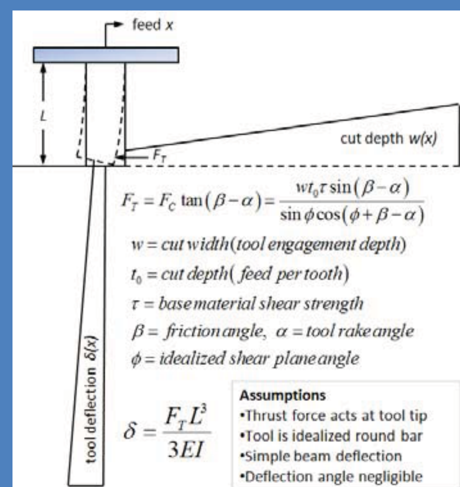


Figure 2 - Tool engagement depth effect on position error.

Block diagrams for two approaches are shown below. The first is traditional PID, the second MPC with the deflection model included.

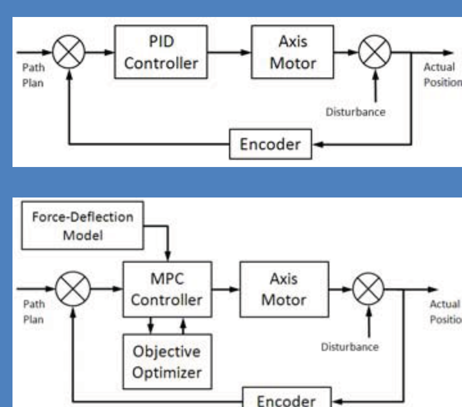


Figure 3 - Traditional Axis Control (top); MPC control (bottom)

multi-station manufacturing system[35]. Shuang and Xifan proposed a hybrid system model, incorporating continuous aspects of process control (e.g., positioning) with discrete systems-level models for stochastic simulation[36]. Papakostas investigates the complexity and the stability of manufacturing systems through a set of manufacturing models based in nonlinear dynamics[37]. Model interoperability concerns have been recently addressed for application to manufacturing systems through development of standards based in process specification language (PSL), a platform-neutral ISO standard for manufacturing model representation[38-42]. I will use elements of these works as a basis for scaling the approach to the systems level.

Applying MBC at the Systems Level. Closed-loop model-based control techniques have seen some limited research progression at the systems level[43-46]. Specifically, Sun investigates the interaction of raw material quality with upstream tool degradation with downstream product quality[47]. This model describes both propagation of the interaction, and information integration between tool reliability and product quality measures. Sun's approach is at the center of this proposal's described need for system-level control, and serves as pertinent background for the proposed research.

PI Experience. With ten years in industry and five years in academia involving manufacturing control research at the process and systems level, I have both hands-on and academic experience in problems caused by lack of process knowledge and incorporation of this knowledge to process control. My process design work involved process sensing and feedback control optimization for precision turning, grinding, and cold rolling processes. I observed the coupled effect of quality consistency throughout the manufacturing chain, specifically regarding rolling rather than turning of manufacturing rings. After installing a cold rolling process, I determined that this rolling caused residual stresses that affected the ability to complete the grinding process. Closing the information loop automatically as proposed here would have prevented grinding scrap and subsequent assembly quality problems that in one instance ended up costing well over $50,000.

How to Apply MPC to Machining Simulation Results

Simulated axis position output when cutting the variable-depth surface shown in Figure 2 (h_i=3mm, h_f=4mm) using traditional and model-based axis control is given in Figure 4.

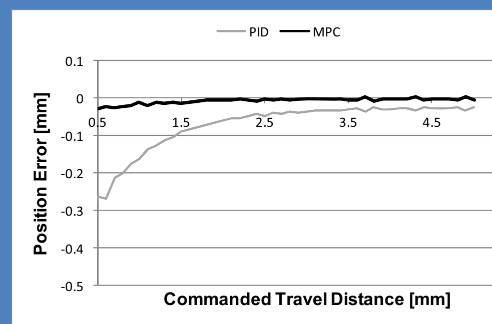


Figure 4 – PID and MPC Axis Control. Tool engagement varies uniformly from 3mm to 4mm along a 25-mm cutting length. Simulation is a 6mm HSS, 2-flute cutter with 100mm length in mild steel. Position disturbance is normally-distributed with 2µm standard deviation.

The PID-controlled system ***reacts*** to the encountered force, while the MPC system ***predicts*** and compensates, reducing average error by 90%. This is just a simple example; the methodology can be extended to vibration, tool wear, and other physical and empirical models of the machining process.

In my academic career, I have also researched adaptive process control, incorporating physical models, real-time communication between independent control systems, and integration of sensing sources for control. I developed an adaptive system to automatically position parts to 2.5μm accuracy by sliding on a plate[48]. The system control incorporated fundamental frictional modeling, and was able to identify changes to the system frictional state[49]. I also researched meta-modeling of quality and system performance data over distributed real-time networks, in the context of systems-level control[48].

Results from Prior NSF Support. The current NSF-sponsored work involves creating a new approach to machine stage positioning using Model-Predictive Control combined with model-based time delay process estimation. The work is framed in development of an alternative feedback approach consisting of a fixed camera, and pixel matrix screen attached to the moving stage (see Figure 5). A target image is generated on the screen, and a multi-input, multi-output controller used to command the servomotors to a fixed position in the camera field of view. In the first year, we have developed a new image processing algorithm that enables positioning resolution to 5μm (pixel size is 300μm, goal is <1μm). We have also tested a predictive MPC approach to compensate for disparity between control and imaging sample rates (controlling on prediction while waiting for new information). The work involves two graduate students, and has resulted in 2 publications[50, 51], and a technical paper at the CMMI conference. This current work represents a complete redesign of the approach for precision machine positioning control.

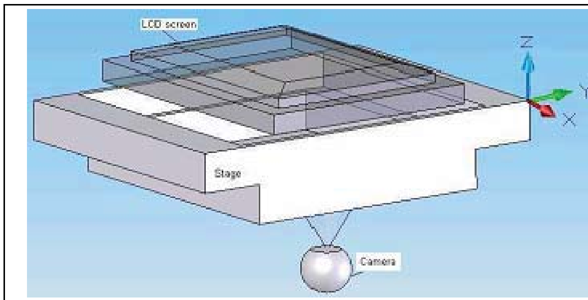


Figure 5 - Model-based positioner. A ground-based camera views an LCD screen image carried by an X-Y stage. Model-based control of the servomotors is employed between image acquisitions (NSF CMMI grant #0800507).

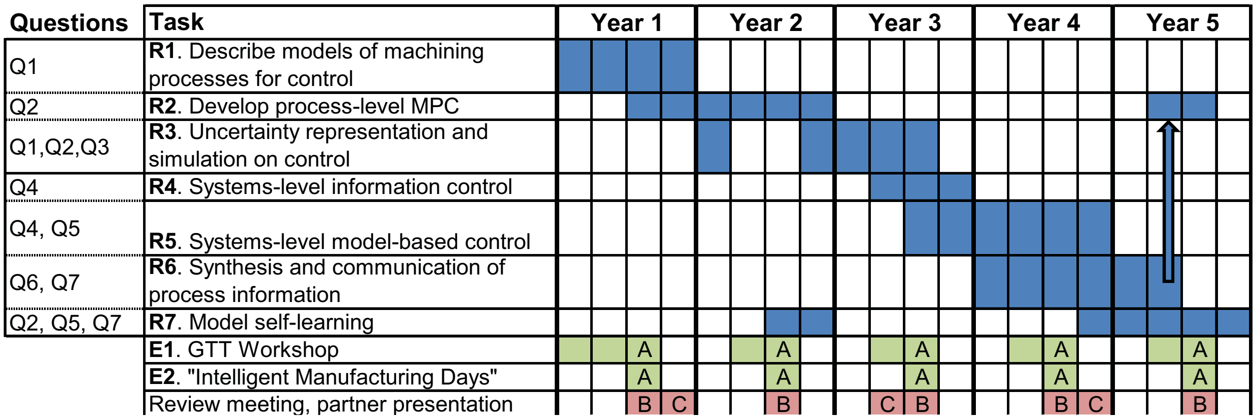
RESEARCH TASKS

This section details the major research tasks (denoted by 'R') to address the stated research questions over the next five years. The results are expected to provide a foundation for the PI's future research in model-based process control for manufacturing intelligence.

Approach. PARTNERS: We will keep constant lines of communication with our machine tool partner and the hardware manufacturer's network for input to research and education activities, and to make them aware of all current results.

STUDENTS: One graduate student will work on modeling and MPC approach development; the second graduate student (sponsored by the department) will focus on uncertainty representation in modeling. Both students will lead an undergraduate team for educational workshop activities and student days, as described in the Education section. In Year 4, the new student transitioning in will focus on systems-level MBC, and will also work with our industrial network on proposals to transition concepts to other areas.

The timeline of research and education tasks is given below.



Each task's approach, methodology, expected outcomes and potential risks are given below.

R1. Process model forms (from Q1): Describe the machining process models to be included in a model-based process control scheme. This task is coupled with R2.

METHODS (YEAR 1):

a. Survey and classify existing physics-based and empirical machining process models.
b. Codify models for control and establish model representation database.
c. Develop control-specific model variants.

EXPECTED RESULTS. The output from this task will be a set of physics-based and empirical models relevant to model-based control of the machining process. Initial areas to target for control are: tool wear, cutting forces and vibration, and material flow analysis.

RISK (*CONTINGENCY*). Models deemed required may not be available in literature (*develop models targeted for control*), models may not be amenable to process control (*combine simpler model forms with uncertainty - see R3*).

ASSESSMENT. Models in the database will be assessed for computational complexity, validity using FEM simulation, experimentation where appropriate.

R2. Optimization objectives and process control (from Q2): Develop the implementation of the Model-Predictive Control approach for discrete parts manufacture, particularly defining optimization objectives, related constraints and models to be used. Tied to R1.

METHODS (YEAR 2):

a. Formulate continuous MPC approach adaptation to discrete parts. Investigate transient influence by comparison of control in time-varying conditions vs. steady-state.
b. Define optimization objectives for different machining scenarios, and relate to model forms and information available. Quantify constraints.
c. Define multiobjective optimization methods as an alternative to traditional MPC optimization. Initial approach using Genetic and Evolutionary algorithms on PC or external hardware such as industrial Field-Programmable Gate Array (FPGA).
d. Develop virtual testbed for simulating different representations of model-based control.
e. Create physical testbed for control testing. This will be carried out using the open-architecture controller, which incorporates a PC for machine-embedded optimization. Additional hardware can be easily networked.

EXPECTED RESULTS: Task output is a Model-Based Control approach for machining, with different objective scenarios and information inputs. The implementation will be evaluated with respect to traditional and contemporary machining control approaches.

RISK (*CONTINGENCY*): Models or methods may be too complex for per-cycle optimization (*use dedicated hardware such as FPGA or graphical processing unit board*).

ASSESSMENT. MPC approach will be simulated and compared with validated simulations of traditional PID approaches. Physical prototyping will be evaluated directly with our machine tool partner to exchange knowledge.

R3. Model uncertainty (from Q1, Q2, Q3): No models are perfect; the uncertainty contained in prediction will be explicitly incorporated to model representations. This task targets evaluating uncertainty in prediction, defining limits of its applicability, and providing for real-time feedback to the model database. Tied to R7.

> "How can we figure out properties of the (infinite) unknown based on the (finite) known?...What can a (Thanksgiving) turkey learn about what is in store for it tomorrow from the events of yesterday?"
>
> - N.N. Taleb, describing Hume's induction problem[1]

METHODS (YEARS 2 and 3):

a. Survey representation of unmodeled effects, focus on control applicability.
b. Simulate the effect of uncertainty on controllability of process MPC.
c. Modify MPC approach to include uncertainty, identification and mitigation of catastrophic events.

EXPECTED RESULTS: An augmented model-based machining control approach that explicitly accounts for uncertainty, and knows its own limitations with respect to prediction.

RISK (*CONTINGENCY*): Uncertainty forms cannot be effectively modeled, "Black Swan" unexpected events occur (*Catastrophe is not always instantaneous; look to model prediction vs. reality to identify underlying trends at different time scales- ties with R7*).

ASSESSMENT. Uncertainty representation will be assessed through selected experimental designs, then on an ongoing basis through MPC prototype experiments.

R4. Systems-level control approach (from Q4): In the second major phase of this project, the model-based approach developed for discrete-parts processes will be scaled to control manufacturing systems. In the idea of system-level control, the "feedback" takes the form of information propagating through a network of processes, giving each process more information with which to make decisions. This task focuses on development of the larger control system using knowledge sharing (see sidebar on the next page).

METHODS (YEAR 3):

a. Formulate system-level control architecture, with process information feeding forward and quality information feeding back.
b. Integrate individual process controllers; define additional data streams and inputs.
c. Simulate the systems approach using defined data streams.
d. Create a networked testbed of individual MPC-controlled machine tools (directly involving our machine tool partner).

EXPECTED RESULTS: Definition of an architecture for systems-level feedforward and feedback control. Quality and throughput objectives will be targeted for optimization.

RISK (*CONTINGENCY*): Network speed not capable for real-time information transfer (*use real-time protocols, reduce data packet size*).

ASSESSMENT. Measurement of throughput and quality will be made with and without systems-level information availability. I will directly involve our machine tool partner.

R5. Systems-level modeling (from Q4 and Q5): To augment the individual control enhancements afforded by information sharing among processes, a multistage quality model will be developed and incorporated to the control approach.

METHODS (YEARS 3 and 4):

a. Formulate overall quality representation for multistage manufacturing.
b. Refine systems-level architecture developed in R4 to include this model for global optimization (define this approach as Systems Model-Based Control, SMBC).
c. Simulate SMBC, prototype on machining network with our machine tool partner.

EXPECTED RESULTS: A systems-level model-based control approach for optimizing the output of a machining system with focus on optimization of its output quality.

RISK (*CONTINGENCY*): Global model may adversely affect individual process control (*assess for this condition, apply weighted approach between system and individual controllers*).

ASSESSMENT. Validate quality model by experiment with metrology measurement. Measure networked prototype against independent multistage process.

How can Model-Based Control be Applied at the Systems Level?

Consider a two-stage (OP10, OP20) manufacturing system for machining parts. MPC control is used at OP10 with a nominal material machining model. During processing, data are collected and information derived from torque, temperature, vibration sensing and control actions.

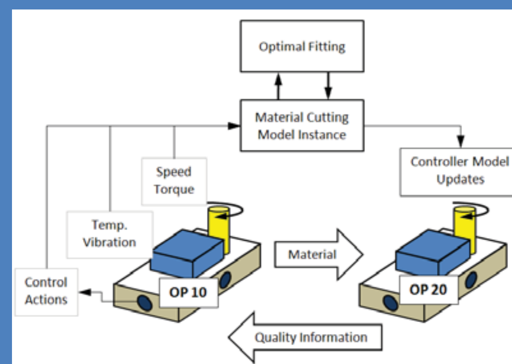


Figure 6 - System-level MBC

The data are input to a specific instantiation of the cutting model whose parameters are fit to represent the specific material lot and part being cut. This information is then communicated to the downstream operation, whose MPC controller is able to optimize an objective function that represents reality rather than an uncertain prediction. Conversely, output quality information is fed back to models of upstream operations.

R6. Sensing, synthesis, communication of process information (from Q6 and Q7): For system-level control to be effective, information will be taken from individual processes and passed both downstream (individual part information) and upstream (quality feedback). This task focuses on the synthesis and communication of that information.

METHODS (YEARS 4 and 5):

a. Quantify information quality at the machining process.
b. Develop data derivation methods such as process observer models for immeasurable process outputs.
c. Survey available protocols, fuse best practices, targeting interoperability, use existing open architecture representation standards such as PSL-derived standards[42].

EXPECTED RESULTS: A sensing and data communication protocol that communicates process-level part information in real time with per-piece tracking, and fuses current interoperability standards with network systems.

RISK (*CONTINGENCY*): Inability to measure needed information (*use process observers where observable quantities are used to model necessary information, e.g., force and position used to model frictional behavior*); Information cannot be directly passed from process to process (*follow data interoperability standards; use of gateway hardware*).

ASSESSMENT. Data representations will be evaluated for usability in the prototype network. Assessment is used to drive additional sensing and observer design.

R7. Model self-learning (from Q2, Q5, Q7): The described process-level and systems-level model-based control approaches are based in physical models of the machine, tooling, process and material. However, these predictive models have limited applicability and interpolation/extrapolation capability beyond the specific processes used to create them. For this purpose, a formalized method of automated model learning is motivated.

METHODS (YEAR 5):

a. Create feedback mechanism for model updating using real-time process data.
b. Establish rules for switching *between* model forms through validation measures.
c. Create database storage and communication mechanism for distributing model and control system updates.
d. Establish quantification of observed model changes and use to define the departure from *model updating* activity to *fault identification* activity.

EXPECTED RESULTS: Output of this task will be an automated machining model evaluation scheme that uses real-time feedback of process data and knowledge to "fine tune" the models used in specific MPC instances, and to identify system faults.

RISK (*CONTINGENCY*): Models may degenerate/confound with new information (*approach model updating from a historically-weighted perspective where large changes to model are penalized or flagged as faults rather than natural system changes*). Poor quality or incorrect data is encountered (*periodic manual validation of updates in first iterations*).

ASSESSMENT. Model update progression from prototype testing will be independently validated using Design of Experiments (old vs. modified models to assess improvement). Process quality output will also be evaluated to quantify benefit of model learning.

EDUCATION: Integrating Intelligent Manufacturing Research with Middle School Technical Curricula

Progression and results of this research will make a difference in the education and STEM career choices of young technical thinkers in my state. The activities of this research will be used to excite the technical spirit of 6th, 7th and 8th graders, including a large portion of female and minority students, in the Gateway to Technology (GTT) accelerated learning program[52] through supporting teacher education in current manufacturing issues in the automotive field and how advanced technology is addressing them. The goals of the education integration activities are to:

1. Increase middle-school students' awareness of challenges in manufacturing, of how synthesis of information and control can address these, and of the research and career opportunities available to participate in solving these problems.
2. Educate instructors of accelerated technology programs at the middle school level on current technology developments and research in automated manufacturing, and how manufacturing supports larger socioeconomic issues such as energy use.
3. Provide a continually-updated stream of instruction materials for local, regional, state and national instructors to access at different levels of involvement.

Gateway to Technology (GTT). The GTT program is a middle-school precursor to Project Lead the Way, a national high-school technology program. The program is based on fundamental principles of success for future technical careers, notably: working as team member, leading a team, listening to others' ideas, going beyond the classroom for answers, and understanding the societal impact of their ideas and products. The program actively encourages participation from minority and women students[52]. The PI has been working with a local middle school GTT program for two years through NSF RET grants, leading activities to improve the curriculum activities for 60 students per year. The activities outlined below broaden the GTT instructor involvement across the state (currently 78 middle schools) on a face-to-face level, and makes content available to GTT instructors nationwide.

EDUCATION INTEGRATION TASKS

E1. Train-the-Teacher Workshop: A summer workshop at our research lab will educate instructors in the GTT program on the most recent manufacturing-related issues critical to the U.S. economy, with the automotive industry as a rolling case study. Discussions will center on economic performance data, current events and trends in the automotive industry, and current research underway supporting near-term goals in automotive manufacturing. Students supported by the project will lead undergraduate teams[53] to develop illustrative examples of research issues deployable to the GTT classroom.

WORKSHOP FORMAT: The plenary information session of this workshop will present and discuss current findings and ideas in intelligent automotive manufacturing. The subsequent plenary instruction session involves presentation of a particular technical aspect of vehicle or manufacturing technology related to an area of GTT instruction. Five afternoon breakout sessions, one for each GTT instruction area will involve graduate students presenting and demonstrating instruction modules developed in conjunction with graduate classes and undergraduate teams. Table 1 lists the current modules of GTT and how the focus on intelligent automobile manufacturing supports this development.

I will demonstrate selected modules with physical equipment. In addition to the research activities, sponsored graduate students will also develop and make available open-source simulation modules to demonstrate concepts. These physical demonstrations will serve as examples for those given to students during class visits (see task E2). The day will close with an open discussion session, findings, conclusions, and plans for the following year, with an emphasis on improving and expanding the workshop.

Table 1 – Support of GTT Instruction Modules (adapted from [52])

GTT Area	Description	Curriculum Development Topics in Intelligent Manufacturing
Design and Modeling™ (DM)	Students use geometry, teamwork to design and develop product prototypes.	• Vehicle design process • Design for Manufacturing, Prototyping • Prototype Testing
The Magic of Electrons™ (ME):	Engaged in relevant hands-on projects, students unravel the mysteries of digital circuitry.	• Signal Acquisition • Signal Processing • Vehicular Electronics
The Science of Technology™:	Concepts of simple machines and energy applied to solve real-world problems.	• Manufacturing Energy Analysis • Hybrid Vehicle Systems
Automation and Robotics™ (AR)	Design and build automated systems that incorporate electrons, physics, and robotics	• CNC Machine Tools • CNC Programming • Industrial Robotic Programming
Flight and Space™ (FS)	Developed with NASA, this unit explores the technology of aeronautics and propulsion.	• Vehicle Aerodynamic Simulation • Vehicle physics and dynamics testing

The workshop approach will be phased over the 5-year project period. In the first year, I will pilot it with instructors from two local counties; in the initial implementation, the GTT instructors will actively contribute to development of the workshop format. In the second year, invitation will be expanded to a 10-county region that economically targets the automotive manufacturing and advanced materials industries. In years 3 and 4, the workshop concept will be expanded to the state level; instructors will be invited to attend personally or through virtual videoconferencing from remote sites. I have access to remote videoconferencing equipment, so even lab demonstrations can be shared virtually. I will also interface with the campus IT group for conference recording and distribution; I am currently piloting a recording technology for video feed. In year 5, I plan to expand the videoconference participation to the national level through invitations to each state leader and interaction with the national organization.

E2. "Intelligent Manufacturing Days": To get students excited about manufacturing concepts, in which they take away "profound knowledge" of the importance ("profound" indicating knowledge acquired by doing instead of listening), they must see, touch and interact with the concepts. I will bring students who have demonstrated STEM interest, through their involvement with the GTT program, to the research laboratory on a semi-annual basis for hands-on education in intelligent manufacturing, automation, metrology, and vehicle technology. I will also engage in understanding of student learning to further my instructor development.

ASSESSMENT: Based on the previous NSF RET projects, I have established qualitative and quantitative baseline measures of student performance with respect to course learning objectives[54]. For the long-term activities proposed here, I will develop an evaluation rubric based on the existing course learning goals for GTT. Evaluation will incorporate pre-, mid- and post-course student assessments with respect to course learning objectives, with respect to attitudes toward manufacturing and intelligence integration, and with respect to future plans for education and career. To capture the future objectives of preparing students for technical research, the criteria design will reference data-driven evaluation research in classroom and workplace[55 56]. I will solicit involvement here from the Dept. of Engineering Education.

EXPECTED RESULTS: The proposed instructor support and student involvement link education to research in an industrially-practical environment. Instructors will gain a greater understanding of automotive manufacturing and technology issues, reflected in their instruction. Relevance will be ensured through input from industrial partners. The GTT course modules will be driven from the proposed research, with demonstration applications to be passed directly through to the students. I will perform additional aligned research as to how students view manufacturing and engineering, and its influence upon their choices of study path and career; this is an essential part of the program evaluation. Students benefit from the improved instruction in the classroom, but will also receive personal insight into critical issues affecting the U.S. economy, and how an ultramodern automotive research facility is addressing them.

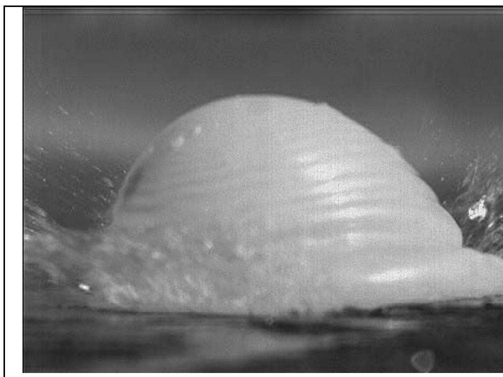


Figure 7 – What Happens to a Water Balloon? Balloon breaks at 3000 frames per second; students learn the role of high-speed videography analysis in automotive manufacturing research.

Results from Prior NSF Support.: I and an IE professor have worked with the GTT instructor at a local middle school to develop curricular enhancements. Through this NSF-sponsored work, we created two teams of undergraduates that have brought real-world pertinent manufacturing issues to his classroom. Results showed a quantitative statistical improvement in student learning, and a qualitative improvement in student experience (students were more excited about and more aware of real-world engineering)[54]. I have also brought students of the Gateway Academy robotic summer camps to our research lab, where I present overviews of automotive industry factors and research, and demonstrations of research techniques (e.g., “Robots Aren’t Perfect”, “Can you Touch a Micron?”, “What Happens to a Water Balloon?”; see Figure 7,8). These activities will serve as a basis for the proposed educational activities and expansion of student days.

VISION

Figure 8 – GTT students touring the Graduate Engineering Center. These are the future researchers and manufacturing leaders that I am working to inspire.

Student Responsibilities. One student will work on modeling and process MPC approach development; the second student will focus on uncertainty representation in the model forms. In Year 4, the new student transitioning in will focus on systems-level MBC, and will also work on proposals to transition this idea to other areas. All graduate students will lead a team for workshop activities and student days. This layered mentoring has an educational impact not only on the middle school students, but also on the graduate students involved.

Dissemination. Research results will be disseminated in archival journals, and a website will be created to communicate the current status, with links to appropriate presentations and interactive simulations. Results from the educational activities, in addition to passing through instructors to the GTT program, will be reported in educational journals and conferences.

Collaboration. The program has extensive partnership with industry. Results of this research will be important to a number of our partners, and will be made available through the industrial network afforded by our partnership with machine tool makers, who can assist in bringing results to a wider industry group. These industrial partners will also be advisors to the educational content.

Conclusion. As part of my long term career goal, I intend that my contributions over the next twenty years will play a substantial role in reviving US manufacturing capabilities through the development of intelligent manufacturing methods. Moving knowledge of model-based manufacturing process and system control from the laboratory into actual value-added manufacturing operations is critical to the national purpose of restoring our economic dynamism. This project will further industrial relationships to use the results, and will develop the human capital necessary to maintain it. Through a combination of compelling and engaging activities, school children interested in careers in STEM disciplines will learn why this nation must create a strong manufacturing industry, and why it is important for their future, as well as for our own.