Manufacturing Process Modeling and Application to Intelligent Control

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This paper reviews the major findings and intellectual contributions made over the past five years through research in the laboratory of Dr. Laine Mears at Clemson University. The focus of the laboratory's work is in modeling of traditional and novel manufacturing processes, and application of such models to process control through model-based control strategies. Introducing intelligence to the manufacturing process through physical descriptions of the phenomena being controlled allows for more precise control as compared with reactive systems or those with simple feed-forward control schemes. For traditional processes, new approaches to process characterization allow for more precise control. For novel processes and those developed in our lab, models are derived and successfully applied. The work outlined here has enabled not only a more accurate characterization of new and traditional processes, but also more effective and efficient strategies for their control.

Introduction

Discrete parts manufacturing processes such as machining, forming and joining have traditionally been controlled through reactive schemes; understanding and accurate modeling of the process physics allows for predictive control schemes to be employed. This type of approach models expected system behavior in response to inputs, and adjusts control action to maintain desired behavior.

An example of a reactive-type proportional-integral-derivative (PID) control system is shown in Figure 1. This type of system changes the control action based on the system output deviation (error) from a desired reference state. The system must depart from the ideal state to create a following error in order to impart corrective action.

However, this departure can be due to factors that are quantifiable and predictable through process modeling. This prediction of future system behavior is the basis for the model-based control approach.

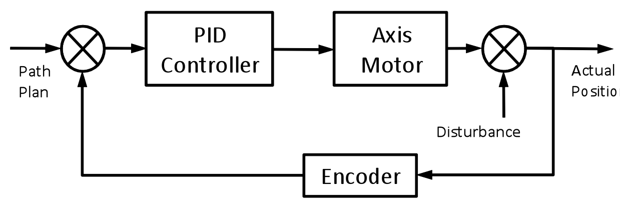

Figure 1: Reference Tracking Control. When the sensed path deviates from the path plan, the controller imparts a corrective action to the actuator.

Model-Based Control

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 typically not employed to impart intelligence to process control.

The work described here targets transformation of the control strategy for discrete part manufacturing by directly incorporating physical process models into the control scheme. For example, almost every CNC machining center controller lacks inherent physical process understanding, and operates purely by imparting corrective action when the position deviates from desired. The model-based control work in our lab departs from current approaches in discrete parts manufacturing, and intends to have a significant impact in the discrete-parts manufacturing sector by explicitly representing process physics in the control of manufacturing processes. Current efforts also focus on model-based control of 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, eliciting basic research findings in model abstraction, uncertainty and communication protocols.

Model Predictive Control

A specific focus strategy within the model-based class of control approaches is Model Predictive Control (MPC). Conceptually, MPC "looks ahead" to predict the response of the system and accordingly changing control actions, rather than waiting for system feedback to indicate departure from a desired state. Mathematically, 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 is actuated to drive toward the optimized state[1]. A block diagram of the general MPC approach is shown in Figure 2.

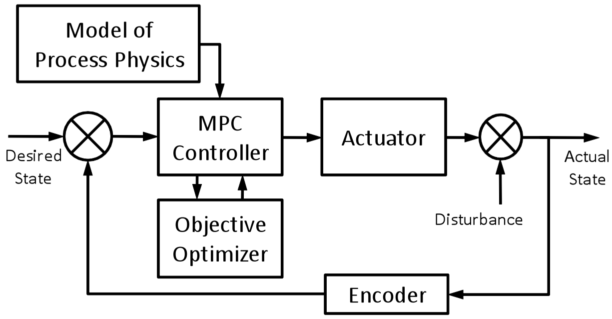

Figure 2: Model Predictive Control. The MPC controller uses a model of the process to predict behavior, then optimizes control action for the next time step.

In this approach, a process model is used to iteratively predict system behavior, and the prediction is used to optimize the process control. The controller then gives an input to the actuator and the process is repeated. This method also holds a potential benefit of verifying and updating the process models, improving our knowledge about system dynamics.

This method has two advantages over traditional control methods: *i*) it improves performance through a predictive understanding of the physics behind the system response rather than reactive compensation, and *ii*) it can be optimized with respect to any parameter(s) of interest even when the underlying model contains uncertainty.

Current work in generalized model-based approaches for manufacturing includes identifying appropriate control schemes for different types of process approaches.

Model-Based Control Application to Manufacturing

Model-based methods have been used extensively in continuous process industries such as chemical manufacturing[2], however this approach is novel in discrete parts industries. Some of the barriers to its implementation are formulation of an effective strategy through selection of which models to include in control, balancing of model complexity (accuracy) vs. computational cost, and access to commercial equipment control architectures. With respect to the last point, open-architecture control is key to implementation. Some of the applications deployed in the manufacturing industry include model based controls to improve machining axes precision[3], eliminate transient vibrations in form rolling[4], and control a paper-making machine[5].

Application to Novel Positioning Control

A new approach to precision positioning has been investigated and designed in our lab which integrates vision feedback for precision motion control in a multiple-independent-axis system[6]. The intent is to use vision feedback to image a flat pixel array, and to use the array to command desired motion graphically. The system representation is shown in Figure 3.

A key benefit to this type of feedback control system is that the error mapping process is eliminated. In a typical precision multi-axis system, imperfections in axis straightness and squareness must be externally measured, then inverted and mapped to the controller. This error mapping process is tedious and expensive, and does not incorporate time-varying phenomena.

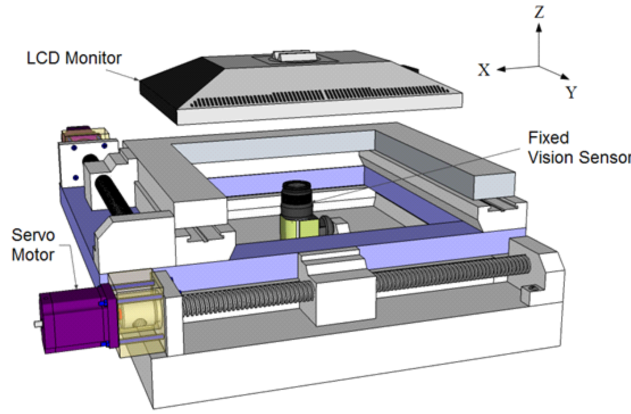

Figure 3: Novel Positioning System. A grounded camera images a pixel array carried by the stage. Commands are given graphically on the array, and control is achieved through model-based motion control.

The designed position controller overcomes these problems, and is specifically enabled by research findings in model-based control, particularly prediction of model error behavior. The image processing introduces a delay to the feedback, and the vision system updates at a much slower rate than the motion controller; therefore model-based control must be used in the interim to predict system behavior when feedback is unavailable. This nature restricts the use of an observer-based control as the actual feedback signal is not available at a high enough frequency for adequate estimation of the plant states. This importance of accurate system dynamic modeling for vision-based model-aided control applications has been documented. Unbounded deviations between the model output and the plant's output can even lead to system instability. Therefore, first- and second-order error extrapolation algorithms have been investigated to reduce the deviation between model prediction and actual plant output[7].

Key findings have been published in model-based control for time-delayed and intermittently-controlled systems[7-10], and a fully-functional prototype realized.

This system was designed and demonstrated for a 2-axis positioning stage. Work is continuing in this area to extend the findings to include a rotational degree of freedom for correcting degree errors.

Application to Machining and Tool Wear

The eventual objective of almost all machining tool wear related experiments/modeling is to obtain an "industrially-acceptable" final part. This translates to its surface roughness being within acceptable limits, besides other criteria. For this purpose, surface roughness control was methodically imparted by further developing the known dominance of feed on surface quality. Based on researching the effects of feed and speed on the surface roughness of milled 6061 aluminum, a recipe was consequently prescribed for maximizing

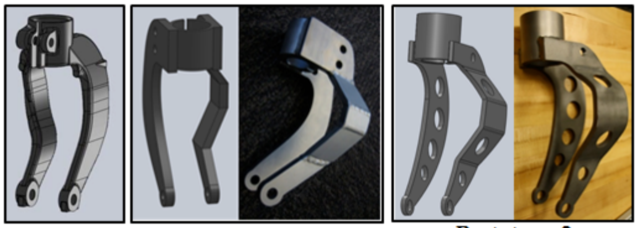

Figure 4: Solid Models and Fabricated Prototypes. Total life-cycle cost models justified these two prototype redesigns from functional and economical standpoints.

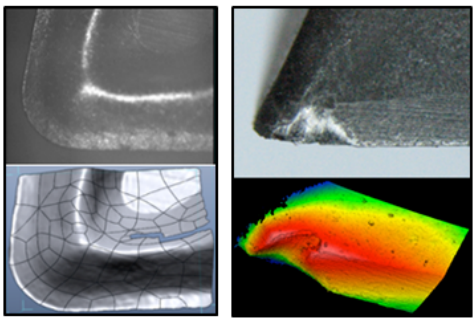

Figure 5: VTW Assessment of New/Worn Tools. This new wear characterization method/modeling captures the actual mechanics of wear from a 3D volumetric standpoint.

productivity (reducing cycle time), *i.e.,* increase table feed until the roughness limit, and then increase the surface speed within limits, to maximize material removal rate (MRR)[11].

Further, a systematic procedure was developed for integrating titanium alloys as a lightweight automotive material alternative for existing iron/steel components. The primary driving factors were the drive to reduce fuel consumption and emissions as well as to avail the unique beneficial material property combination of titanium alloys. The method was realized by the successful modeling/redesign (see Figure 4), process optimization, and validation of the front suspension fork of a current model BMW X5 sports activity vehicle for an eventual weight savings of 0.7kg (28%) for prototype 1 (P1) and 1.76kg (71%) for prototype 2 (P2), by replacing it with Ti-6Al-4V. Further, an elaborate life-cycle cost model was formulated whereby total costs were found to be closely comparable to that of the original component (OC), thus justifying the feasibility of replacement with Ti-6Al-4V from cost-sensitive and high-volume production standpoints[12].

Finally, a qualitative assessment of the inadequacies of the current manner of tool wear quantification led to the development of a comprehensive approach of volumetric tool wear (VTW) characterization (see Figure 5) and modeling. This enabled bridging the gap between traditional 1D wear assessment and the actual 3D nature of tool wear. It was then standardized, evaluated with a gauge repeatability and reproducibility study, and validated with controlled machining tests on Ti-6Al-4V. Further, a novel concept of the M-ratio and its derivatives were developed to quantify the efficiency

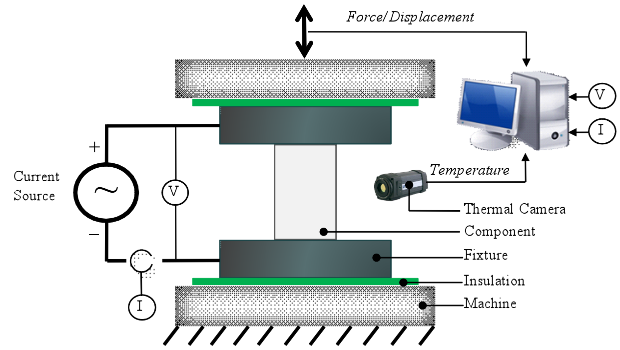

Figure 6: Electrically-Assisted Forming. Force is applied to a metallic component subject to an electric current field. Accurate modeling of the material response is essential for model-based control of the forming process.

of the cutting tool during each pass at a constant MRR[13].

Current work is in creating a generalized geometric model form for volumetric tool wear that can be characterized using a limited set of parameters. This model will be combined with underlying wear mechanisms to predict tool wear progression and feed back that information to a compensating control scheme.

Application to Electrically-Assisted Forming

Electrically-Assisted Forming (EAF) is a metal processing technique which applies a direct electrical current through the workpiece concurrently while the material is being formed. At present, this technique has only been studied on an experimental level in laboratory settings, and the heuristic results show increased fracture strain, reduced flow stress, and reduced springback; the enhanced process capability is beyond the range that would be expected from pure resistive heating effects[14]. A schematic of the EAF process for compression forming is shown in Figure 6.

Research pertaining to the modeling and prediction of workpiece thermal profiles[15], material flow stress[16], and tribological aspects during EAF[17] has been performed. Specifically, a predictive algorithm based off of energy methods was developed which used classical metal forming equations with newly developed coefficients and equations to predict thermal and stress outputs[18]. These methods have been experimentally verified for both forging and bending operations thus far, but are applicable to other metal deformation processes. Along with these energy-based models, data-driven empirical models have been created to characterize material flow stress during forging operations[19].

Ongoing work is being performed in the areas of the incorporation of new and significant process parameters into Model-Predictive Control of this novel process. This control development work will identify diffrenent architectures for achieving different end objectives (*e.g.*, constant-force forming, constant-stress forming, or constant-energy forming); realization of these is enabled by the derivation of multiphysics process models in the authors' laboratory.

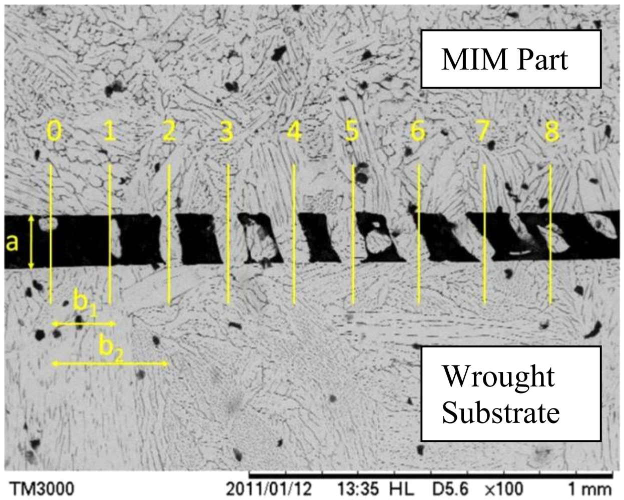

Figure 7: Sinter Bonding using Microfeatures. Microfeatures are injection molded into the MIM part (upper half). During sintering, the features bond to the substrate (lower half), and deform as the MIM part shrinks.

Novel Process Development and Modeling

In addition to development of new control approaches for traditional and emerging-technology processes, results have also been realized in development of entirely new manufacturing processes. The strategic approach is to identify cost-driven needs of industry, and to address the underlying research barriers to realization. Processes are physically prototyped for feasibility analysis.

Rapid Prototyping of Molds for Polyurethane Casting

A process for manufacture of polyurethane casting molds using fused deposition modeling (FDM) has been investigated[20]. This approach allows for rapid physical testing of prototype designs without costly machining of metal permanent molds. Key considerations of the process and tooling were quantified and used to drive process selection, tooling and materials.

A number of fundamental research barriers were addressed, including: the effect of FDM process parameters on the molding performance, development of tools to plan the FDM build path for maximum molding life, and an extensize investigation on material compatibility, mechanical and chemical finishing of the tooling.

Sinter Bonding of Powdered Metal Compactions to Solid Substrate

A new process for bonding of metal injection-molded (MIM) parts to a wrought metallic substrate has been designed and modeled in the authors' laboratory[21]. Figure 7 shows a micrograph of the bonded zone, where microfeatures were injection molded, bonded to the wrought material surface, and deform plastically to allow for shrinkage of the MIM compact during sintering.

Fundamental research findings were reported in: modeling of the sintering process between metal particles and a flat plate, particle size effects, and achievable functional

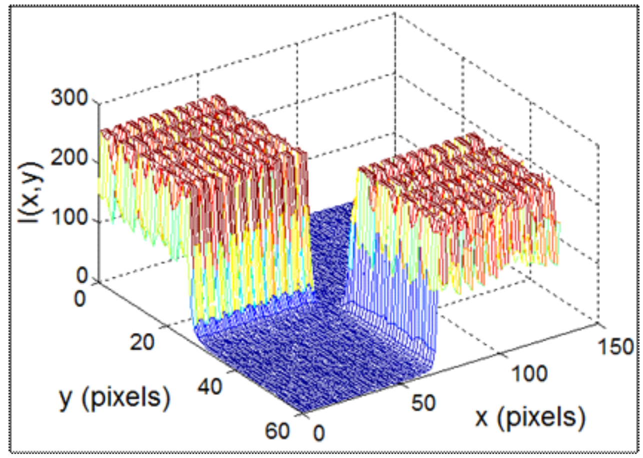

Figure 8: Position Sensing by Pixel Measurement. Image processing is used to quantify pixel intensity. Sub-pixel position control is achieved by intensity modulation.

performance for designs enabled by this technology. Additionally, an efficient FEM method for predicting sintering and deformation behavior was developed.

The measured specific bonding strength using this method is comparable with resistance welding, and allows for cost-efficient joining of complex MIM geometry to large-scale planar parts[22]. The sintering process has been modeled to allow for input to a model-based control strategy for the injection and sintering processes.

Work is continuing in this area on efficient forming of microfeatures, and shape and size effects of microfeature geometry.

Manufacturing Process Feedback

Sensing is a critical element of the total control system, particularly quantification of uncertainty in the signal. Accurate feedback improves system control as well as enabling improved estimation for parameters of the underlying models. This is true for direct feedback to control a single manufacturing process, as well as wider-range feedback of quality information within a manufacturing system.

Manufacturing Process Sensing

For specific process sensing, a new class of position sensor was developed that uses a vision system to provide precision feedback for simultaneous multi-axis positioning[23]. New image processing algorithms were developed that used a field of 300-µm pixels to provide positioning information with less than 2µm uncertainty as shown in Figure 8. The precision positioning is achieved by varying intensity levels and calculating a "centroid" of intensity.

This work is continuing with refinement of the image processing algorithms to provide more accurate information at a higher rate, both of which benefit control. Additionally, new approaches to image processing are being explored to provide comparison with the methods developed.

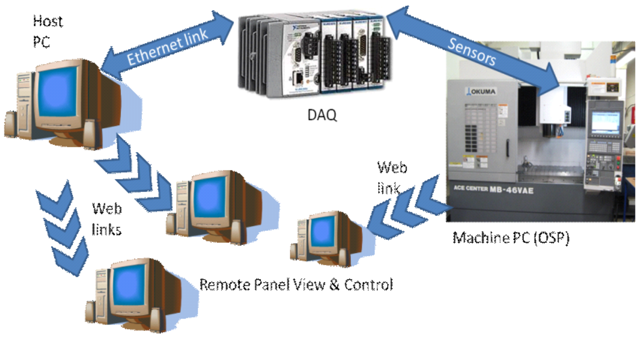

Figure 9: Communication System for Maintenance Monitoring. Sensor signals from individual machines are analyzed and communicated over local and wide-area networks.

Additionally for specific process sensing, a new class of force sensor has been characterized. The sensor studied consists of carbon nanoparticles embedded in a high molecular weight polymer; the composite exhibits a quantifiable relationship between applied force and contact resistance. This relationship was described under static loading[24]. Results were extended to dynamic load characterization, with applicability limits and uncertainty characteristics identified[25]. Additionally with respect to process monitoring, a state-of-the-art survey paper was generated that described the latest findings in tool wear monitoring and characterization[28].

Manufacturing System Feedback

Regarding quality feedback in a manufacturing system, research is performed in identification of critical architectures and communication issues within a plantwide condition-based monitoring system[27]. Of particular importance is definition of metrics for identifying what parameters to monitor and the corresponding sensing systems required, where to process the signals, and how to effectively communicate the resultant information over a wide-area network. An example of a communication architecture for a Condition-Based Monitoring system is shown in Figure 9.

Additionally, a state-of-the-art review paper describing latest research in integration of measurement process to the machine tool was produced[28]. In this work, the authors identified key issues to migration of the precision measurement process in machining from the quality lab directly to the machine tool. Primary barriers to this implementation parallel those of model-based process control, primarily a need for open-architecture control for effective system integration.

Conclusions

This paper has presented a review of primary results in modeling and model-based control of discrete parts manufacturing processes. A basic system of model-based strategies is presented, and challenges associated with application of such strategies to traditional and novel manufacturing processes is given. The new process of sinter bonding using microfeatures developed in our lab, and the extension of previous work in electrically-assisted deformation to fundamental modeling and control aspects present particular challenges which are currently being addressed in the lab. Overall, a system of model-based strategies has been outlined and effectively demonstrated across a variety of manufacturing domains.

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Notes and References

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