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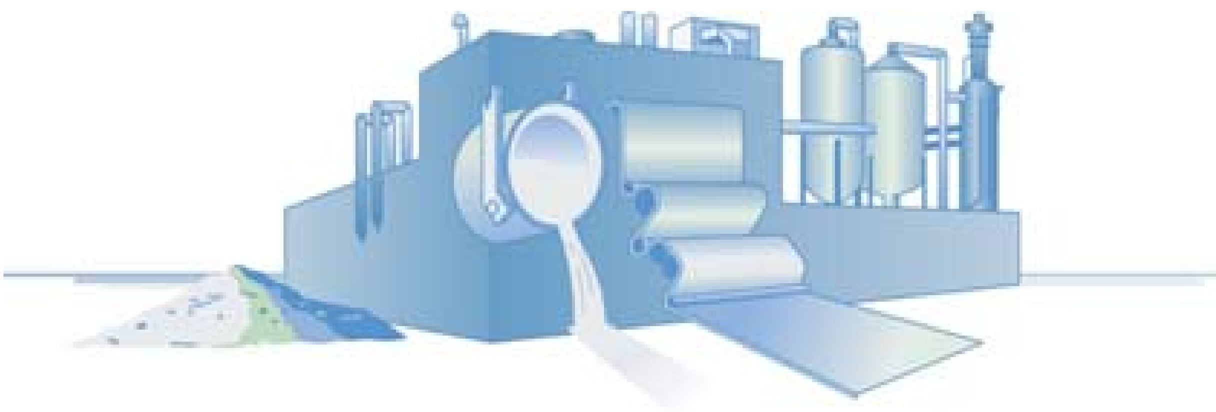
Workshop to Identify R&D Topics on Inferential Process Control



Industrial Technologies Program
Sensors & Automation

Workshop Report
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Executive Summary

Customers pay for product quality, but manufacturers are hardly ever able to measure this quality directly on-line. Instead they typically measure and control process variables, such as temperature and pressure. Process measurements usually do contain information related to product quality, but the data must be properly processed to extract the relevant information. Inferential process control uses a variety of data—on-line process measurements, delayed product property measurements, and even customer feedback—to predict, or infer, ultimate product quality. By controlling final product quality, inferential process control will improve quality, minimize waste, and save manufacturing energy and cost.

This report summarizes discussion during a March 22, 2006, workshop on inferential process control, organized as a Sensors and Automation activity of the Department of Energy's (DOE) Industrial Technologies Program (ITP). The workshop brought together experts from industry and research institutions to identify R&D needs and to clarify the goals and challenges anticipated in developing an industry-usable inferential process control system.

The workshop identified four main system components required to deploy a working inferential process control system: *data management* for the wide variety of available data, *inference technology* to integrate this data into a robust product quality estimator, a *control system* that uses information from the inference technology, and a *supervisory system* to guarantee functional robustness. Participants brainstormed key research needs for each of the four components. The research needs were edited down to a list of 33, and then participants voted to identify the most important ones. The R&D needs that received the most votes were: (1) robust inferential modeling, (2) data collection and integration, and (3) robust state estimation (techniques for using models to infer unknown quantities).

The workshop also discussed key aspects of proposals responding to a potential Industrial Technology Program solicitation on inferential process control. Proposed projects should have a plan for commercialization, and include both research and commercial partners. Given a typical period of performance of up to 5 years, projects may focus research on one or two of the system components, using other existing technology to complete the rest of the system. The majority of participants considered 3-5 years a reasonable timeframe for developing a working inferential process control system.

The Goal of Inferential Process Control

The goal of inferential process control is to achieve predictive control of product quality by making use of a variety of data—data of different types and time scales. The data available range from continuous, online process measurements to customer feedback, which has delays on the order of days and is discrete or binary in nature. In contrast to traditional inference-based process control, the DOE workshop focused on inferential control that would use data to control final product quality and anticipate the final customer response, not just to anticipate future values of process variables and reduce process variability.

Existing industrial process control methods focus mostly on the one of the two inner loops shown in Figure 1: disturbance rejection using process measurements *y* (Loop 1) and, less commonly, control of product quality *q* (Loop 2). These control loops are based on continuous process measurements from within the manufacturing environment combined with periodic predictions of product quality (as shown in the dashed line). The challenge in inferential process control is twofold: (i) to include product properties *w* in the second inner loop and make this a standard, integral part of the control system; and (ii) to expand to the outer loop (Loop 3) and actively include customer feedback *z* in the control system. These new data introduce time delays and come from sources outside the manufacturing organization, but have the potential to greatly improve quality performance. Instead of a delayed response to a disturbance in product properties or customer feedback, an inferential control system would use selected data to anticipate and correct for the disturbance in order to eliminate any variation in the output and customer response.

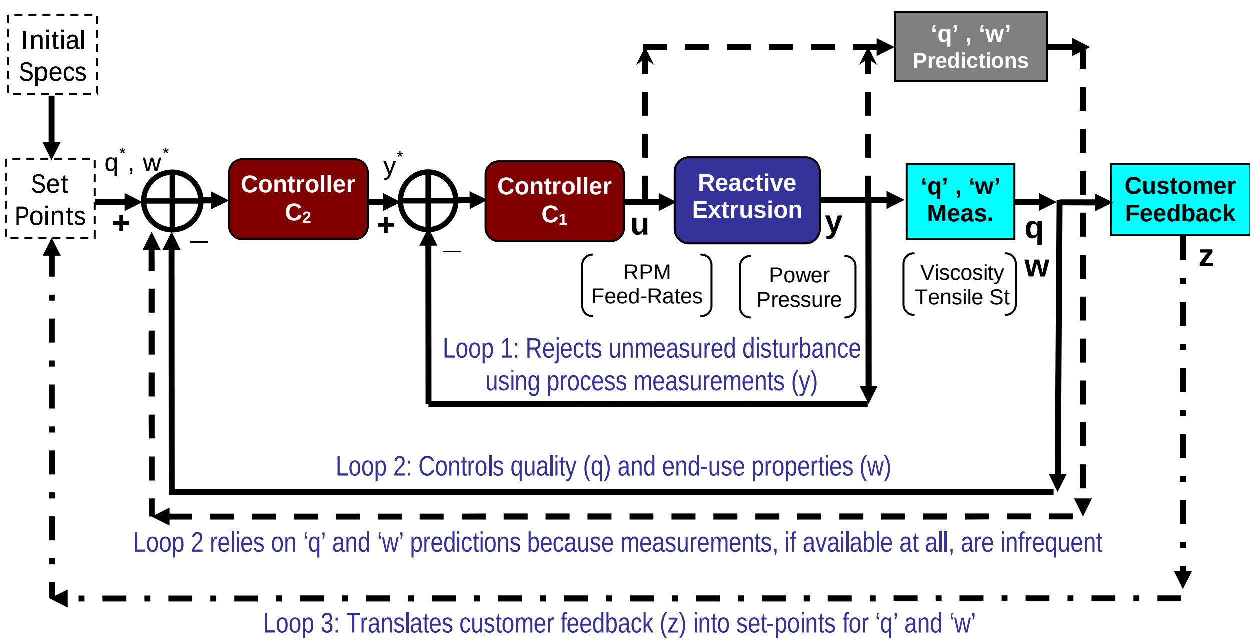

Figure 1. Inferential control structure for a reactive extrusion process, showing nested feedback loops for incorporating product quality and customer feedback data. (Source: Ogunnaike, B. A., Workshop to Identify R&D Topics on Inferential Process Control, 2006)

Components of an Inferential Process Control System

In order to achieve working inferential process control, four key components are required: data management, inference technology, the control system, and a supervisory system to deal with uncertainty. In addition to these four components, there are other important implementation issues that need to be addressed to ensure effective commercialization. Workshop discussion on the four components is summarized below, and each component is explained in greater depth in the following *R&D Needs* section of this document.

Data Management: Integrating customer feedback with routine on-line process and off-line product quality measurements poses special data management challenges. In contrast to process data, customer feedback data may have unknown uncertainty; long, varying time delays; varying format; and binary nature (positive/negative). Additional data may be obtained from process equipment (e.g., motors) or novel use of existing sensors. The data management challenge is to collect, integrate, and align the data and then extract relevant information. This component also involves prescreening and validating the data and then quantifying its value.

Inference Technology: The inference technology component takes all the appropriate data and process information and integrates it into a robust product quality estimator, in order to provide useful information for process control. The inferential model must be able to respond to the delayed customer feedback through a model maintenance or development mechanism. When this customer feedback eventually arrives, the system must respond to it and learn from it. When responding to such data, the system must distinguish between transient disturbances and true feedback information requiring adjustment of the model.

A robust product quality estimator is developed using a model that is based on a large pool of data, but also must take into account the fundamental physical relationships between process variables and product attributes. Rather than allowing either fundamental models or empirical models to dominate, there should be a balance or interplay between the two. The data provide vital information, but should be augmented with the fundamental physics and chemistry. For example, a model based on fundamentals could include an adaptive component that uses streaming data to provide the real-time process dynamics. Another possibility is to develop methods of analyzing the data to indicate the causal relationships even if the fundamentals are not known before-hand.

Control System: The control system will take information from the inference technology and use it to manipulate the process. This can be done using existing control methods or by developing new control strategies that incorporate inferential techniques.

Supervisory System: This supervisory component monitors the performance of the whole system and takes compensatory action when necessary. It involves process and sensor fault detection and identification to ensure robust control. The whole control system should be robust, and robustness should be built into each component. But a complete inferential process control system also needs a mechanism for handling uncertainty in the data. There may be a variety of ways to implement this component, but it is essential for monitoring the system and providing an indication of the reliability of the control action. This component may be passive or active: passively providing advice or reliability information, or actively overriding control action.

Implementation: In many discrete manufacturing processes, the control system seeks to replace the human operator entirely. Continuous manufacturing processes (such as chemical industry processes) have much more variability and uncertainty in raw materials, reactions, etc. Thus, the operator is still an important part of the process and needs to be considered when designing and implementing inferential process control. In addition, the technical skills of operators are rising, and the operator's role is expanding to include maintenance and supervisory roles. For a new control system to work, the operator needs to be comfortable with it—to understand its advantages and the basics of how it works. To achieve this comfort and understanding, the system must be simple (with only a few adjustment parameters) and transparent (using model visualization).

Commercialization and Project Discussion

Commercialization: Successful ITP technologies save energy. In order to save energy, a technology must be commercialized and adopted by industry. A potential ITP solicitation would therefore not just seek to advance the state of inference-based process control, but would favor proposals that are likely to result in implemented systems. A good proposal would include both technical expertise (to develop the system) and industrial partners (to take the system to the market). Tools such as the Oak Ridge National Laboratory commercialization partnership web site may be useful in helping form these partnerships.

Because commercialization is the goal, teams would need to demonstrate the technology in a commercial process. This would require them to customize their system for a particular application, though the technology should ideally be universally applicable. As with model predictive control, the controls platform may be general, and be customized by putting in process specifics. Teams would also need to consider how to move beyond the initial demonstration. After this demonstration, the commercial partner is expected to take ownership of the project, and would be responsible for applying the platform to other processes or industries. Industries often do not recognize their similarity to other industries, posing a challenge to broader application of a system.

Project Scope: The key goal of a potential solicitation would be the ultimate emergence of an inferential control system for industry use. The period of performance for projects resulting from a solicitation would be limited to five years. Given this constraint, a project need not have major advances or novelty in all four components. A project team could focus on developing an innovative solution for just one or two of the components, using less novel, or even existing, components for the rest of the system. A project with innovation in all four components could allow more novelty in the interaction between components, but could also extend beyond the five year limit and have an uncertainty of completion beyond acceptable levels. The potential benefit of a project must be weighed against its probability of success. Whether a project introduces novelty in one component or in all four, the components must be systematically integrated into a working system.

Time scale: The majority of workshop participants considered 3-5 years a reasonable timeframe for developing a working inferential process control system (perhaps a demonstration unit for one process). The remainder considered 5-10 years a more reasonable estimate.

Inferential Process Control R&D Needs

This section summarizes research and development needs that were identified during the workshop. The R&D needs are organized under the four main components of an inferential process control system. Four working groups of workshop participants edited the lists and wrote the descriptions for each subsection.

Following the workshop, participants voted on these lists to identify the most important R&D needs. The needs that received the most votes were: robust inferential modeling (R&D need number 9, below), data collection and integration (number 2, below), and robust state estimation (techniques for using models to infer unknown quantities; number 10, below). The complete voting results are given at the end of this section.

Data Management

Product quality measurements will play a key role in future process control systems driven by the desire to improve process efficiency, reduce waste, and increase energy savings. It is known from process control industry experience that direct product quality measurements are difficult and sometimes cost prohibitive for any practical use. An alternative is to look for early indications of product quality from related process variables. For instance, motor parameters can carry extremely useful product information in many heavily motor-driven process industries.

A practical data management system will address communication, data representation, storage, and security of offline and online data essential for building a powerful inferential process control system. This comprehensive system should have the capability to go beyond a typical process plant for data gathering: the data-gathering network should also collect data from sources such as product end-users, OEMs, equipment suppliers, and energy vendors.

The communication backbone for this system is expected to carry data from these diverse sources and from many different, yet relevant, sensors. These sensors can output heterogeneous discrete and analog data in temporal, spectral, and spatial domains. The system must be able to gather and deliver these data in a secure, reliable, and timely manner to infer product and process knowledge. The deployment of the system in existing facilities should be accomplished with minimal disruptions to the stakeholders. The goal is to develop a system that is self-configurable and self-healing, needing little or no human intervention during installation, start-up, and operation.

Data representation becomes especially important since the data originates from varied sensors/sources and existing process archives. These diverse data need to be consolidated into a single unified representation prior to any further processing. Sophisticated data prescreening and categorization approaches need to be developed to extract information-rich data from these sources in order to reduce redundancy. This data organization process will allow experts to drill down into information rich areas quickly and efficiently.

Removal of redundancy is also an important step towards building innovative data visualization tools. These tools will help to highlight data concentrations or hot spots that need extra care for assuring continuous operation. Furthermore, these tools will also have the capability to discover areas for additional sensor allocation to achieve optimal sensing coverage. In order to achieve a high degree of availability, the system should provide innovative tools and methods for remote data management. These tools will be used for maintenance and rapid diagnostics of this infrastructure.

Data Management R&D Needs:

1. Data representation: being able to get data in different formats, and viewing it in a unified way; diverse temporal, spectral, and spatial resolution.
2. Data collection and integration across different parts of the organization and platforms: continuous data, categorical data, discrete data, data from the process, data from marketing and sales departments, data from the end users
3. Data prescreening and outlier detection, validation, integrity, security
4. Data compression and alignment
5. Quantifying value of data, data mining, determining the relevant process variables based on raw data, and statistical analysis
6. Reliable, secure, low-cost communication backbone for data collection
7. Integration of control and communication network tailored to process

Inference Technology

An *effective* inferential process control system ensures consistent attainment of desired end-use attributes in the manufactured product even though *actual* product quality and end-use attribute measurements are neither available immediately, nor frequently enough, for direct use in a classic feedback control configuration. The inferential scheme will succeed to the extent that the "inference technology" is effective in encapsulating the relationship between process variables and product characteristics in a manner that can be exploited (i) directly for providing reliable estimates of the unavailable process *and* product information; and (ii) as a basis for determining appropriate control action required to ensure consistent attainment of desired end-use product characteristics. The challenge of the inference technology component is therefore two fold:

- to provide a means for developing *an integrated collection of models* that can reliably infer product characteristics from all available process measurements (across all levels of granularity), infrequent product quality measurements, and customer feedback; and
- to provide a basis for rational decisions regarding appropriate control action across the entire production chain, from base level regulatory control through process output control to product quality control incorporating customer feedback.

The inference technology component of a solicitation will need to address the issue of *how* to create and maintain an "inference engine" that integrates multiple sources of process and product quality information (multi-scale; high, medium, low frequency; continuous, discrete, categorical process and product data) into a high-fidelity dynamic process and product quality model. Important aspects of the system are likely to include *data modeling strategies* (involving the identification of information rich interactions between variables and how to encapsulate these in quantitative form); *hybrid modeling strategies*, where first-principle knowledge is combined with data to create an appropriate model; *adaptation strategies* (how to integrate fresh information from streaming, real-time empirical data from all sources to adapt to process changes as necessary). Some key desirable attributes of the inference engine include *flexibility and* *scalability* (to accommodate large data volumes and disparate data types) and *model transparency* to enhance process understanding (especially important for effectiveness as a basis for robust control).

Inference Technology R&D Needs:

8. Strategic data acquisition (*Since most of the model development will be data-based*)
   - Sensor placement for maximizing information content
   - Sensor and analyzer innovation for measuring critical process variables (along with a framework for rational cost-benefit analyses: the identification of crucial process measurements, and the requisite frequency; the benefits of having these measurements at the indicated frequencies; and the cost)
   - Rapid analytical methods for product quality determination as a supplement to process variable measurements
   - Information characterization: (Determination of information content in the data set prior to model building – design of experiments and inputs)
9. Robust inferential modeling (*Techniques for model development*)
   - Hybrid modeling (joint empirical/mechanistic modeling); combine both mechanistic knowledge with data
   - Adaptive modeling (time-varying compensation, iterative learning)
   - Multivariate data correlation
   - Integrated economic models
10. Robust state estimation (*Techniques for using the model to infer unknown quantities*)
    - Multiple time and length scales
    - Reconciliation of estimates
    - Sensor-fault-tolerant estimation
    - Plant wide state estimation
11. Inferencing system architecture (*Structure of the inference engine*)
    - Adaptive inferencing (updating both model estimates and the model itself)
    - System reconfiguration in the presence of sensor failure
    - Distributed inference
    - Integration with control theory (control-relevant inferential system architecture).
12. Knowledge extraction
    - Analysis: predictive capability, as well elucidating process principles and fundamentals
    - Model visualization

Control System

Given a robust inferential method to infer/estimate important unmeasured variables from available frequent and infrequent measurements, a robust control system that is capable of using the inferred/estimated information is needed. The system is desired to be sensor- and process-fault tolerant, require little modeling effort, be applicable to a wide class of processes, have flexible structure with respect to the model (as one accumulates knowledge of the process, one should be able integrate that knowledge in a seamless way, incrementally adding knowledge to the controller), be easy to implement and maintain, and be operator friendly. The control system should ensure the profitability of an entire plant through producing higher quality products at higher production rates but at lower operating (e.g., raw material and energy) costs.

Control System R&D Needs:

13. Sensor- and process-fault-tolerant control schemes
14. Multi-rate control
15. Control systems robust to unmeasured disturbances and unknown parameters
16. Data-driven control system design
17. Model-based control based on simplified models (model reduction for control)
18. Hybrid (discrete plus continuous) control
19. High fidelity distributed-parameter control
20. Control of processes with unequal number of manipulated inputs and controlled outputs
21. Distributed wireless/wired network control systems with variable time delay
22. Proactive agent-based distributed control

Supervisory System

The objective of the supervisory system is to guarantee functional robustness of the inferential control system toward sensor failures, model and control performance deterioration, low quality data, operator missteps, and minor process changes. In order to satisfy the defined objective, the following key blocks are needed:

- Overall system diagnostics, based on sensors, models, and controllers diagnostics
- Performance self-assessment, based on different metrics on data quality, inferential sensors performance, and control system performance
- Data integrity assessment, based on appropriate data organization and interactions at different levels and time scales to get robust control
- Uncertainty analysis using an integrated model of control and plant process
- High quality human interface technology capable of conveying critical, succinct indications of status and recommending operator actions with quantifiable confidence

Supervisory System R&D needs:

23. Rapid multi-level hierarchical model-based diagnostics
24. Fault-tolerant and robustness analysis
25. Estimating and compensating for unmeasured disturbances
26. Estimating covariance properties of signals from on-line data
27. Deterministic rather than stochastic modeling for communication
28. Have confidence limits of estimation values and how these limits fit into the control loop; define some thresholds for the limits
29. Incorporating probabilistic reasoning into the models
30. Uncertainty analysis using an integrated model of control and plant process
31. Modeling and control system output validation
32. Agent-based diagnostic system; must capture in some sense the knowledge gained from the operators from using this system
33. Human interface technologies for displaying and quantifying status and recommendations

R&D Needs Voting

Workshop participants were asked to choose the three most important R&D needs from the list above. Their responses are summarized in Table 1.

Table 1. Summary of workshop participants' votes on R&D needs

R&D Need		Number of votes
9	Robust inferential modeling	9
2	Data collection and integration across different parts of the organization and platform	4
10	Robust state estimation	4
13	Sensor- and process-fault-tolerant control schemes	3
5	Quantifying value of data, data mining, determining relevant variables, and statistical analysis	2
8	Strategic data acquisition	2
17	Model-based control based on simplified models	2
11	Inferencing system architecture	2
23	Rapid multi-level hierarchical model-based diagnostics	2
19	High fidelity distributed-parameter control	2
16	Data-driven control system design	2
7	Integration of control and communication network tailored to process	1
15	Control systems robust to unmeasured disturbances and unknown parameters	1
12	Knowledge extraction	1
21	Distributed wireless/wired network control systems with variable time delay	1
22	Proactive agent-based distributed control	1
24	Fault-tolerant and robustness analysis	1
27	Deterministic rather than stochastic modeling for communication	1

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