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Perspective

Smart Plant Operations: Vision, Progress and Challenges

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Introduction

The process industry is involved with the conversion of raw materials, through a series of chemical processing steps, to valued products and is a key economic sector in the U.S. and globally. The global market share and business performance of the process industry is heavily based on the value that can be generated from its assets which are comprised of process sites, people and materials, as well as intellectual property in the form of product knowledge, process expertise and physical properties of materials. While the range of valuable assets is large, nearly all the economic value in terms of operating profit in the process industry is a direct result of plant operations. This realization has motivated extensive research, over the last 40 years, on the development of advanced operation and control strategies to achieve economically optimal plant operation by regulating process variables at appropriate values. Figure 1 depicts the existing paradigm that couples plant management with process feedback control. This paradigm has been widely adopted by the process industries and extensively studied by the process systems engineering community. This paradigm features two distinct levels of plant operations: a plant management level and a process control level. At the plant management level, an optimization problem is solved on the basis of a (typically) steady state model of the plant to compute the economically optimal values for the process variables, while in the process control level, feedback control systems are used to regulate the process variables at the specified values. Additionally, the important task of plant monitoring — that is the determination of abnormal, potentially faulty plant behavior by proper analysis of plant sensor data — and the incorporation of plant operator input take place at the plant management level.

While the paradigm of Figure 1 has undoubtedly been a successful one, over the last few years there have been numerous calls (e.g.,[1,2]) for expanding this paradigm in a number of directions. Specifically, while economic prosperity has always

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been and will continue to be a key driver that strongly influences plant operations, it is becoming increasingly important to develop plant management strategies that balance the need for maximizing operating profit with sustainable Environmental, Health and Safety (EH&S) performance and corporate social responsibility. Specific EH&S targets may include: (a) no damage to facilities and processes or injury to personnel, (b) no releases of toxic materials to the environment, (c) no negative impact to communities adjacent to operating facilities, (d) no physical or cyber-security breaches, and (e) no unplanned outages. While incorporating EH&S performance targets explicitly in the plant management level is the right thing to do from a personnel health and safety point of view as well as from a process safety perspective, it can also lead to enormous economic benefits since abnormal situations cost the process industries billions of dollars yearly; for example, the U.S. petrochemical industry loses an estimated $20 billion per year because of unplanned outages at oil refineries and chemical plants.[3] In addition to the direct positive impact resulting from elimination of incidents including both large incidents, and numerous minor process disturbances that have a significant accumulated effect on production loss and excess energy use over time, there is an inferred positive impact on asset productivity, cost of manufacture and product quality. Beyond incorporating EH&S performance targets in the plant management level, another important direction of augmenting the traditional paradigm to plant operations is the tighter integration of business systems that provide real-time information of market demand and conditions with the plant management system. Today, by operating plants primarily via their process variables, optimal business decisions may not be fully explored or even missed. With the development of a properly designed company and industry cyber-infrastructure, the use of real-time sensor and communication networks, and shifting human involvement from a process to a business focus, business considerations can be fully integrated into real-time plant management and balanced with critical process considerations.

Expanding the traditional paradigm of Figure 1 into these directions marks a transition to a new paradigm, where the tight real-time integration of process control, plant operations and business systems is enabled by the rapid advances in cyber-infrastructure and communication technologies. We will refer to this emerging paradigm as the "Smart Plant" and present a realization of a "Smart Plant" in Figure 2. The objective of a "Smart Plant" is to make optimal use of the plant assets first and foremost to approach zero-incident and sustained EH&S targets, and maximize the economic operating value of the plant. Ideally, in a "Smart Plant", each asset — from the smallest pipe or pump, to a single process unit and to collections of processes — not only executes its basic process function, but also provides feedback and predictive information, through real-time communication networks, on the current and expected performance of that asset to the plant management system. This, in turn, will allow the plant management system, together with human decision-making, to maximize, based on the current and future collective performance of all assets, the use (and, thus, the value) of each asset as business conditions change and warrant.

To accomplish this "Smart Plant" vision, the paradigm of Figure 2 consists of three distinct levels: the process control level, the plant management level and the corporate office level. At the process control level, local area networks handle the real-time feedback control of process units via wired and/or wireless communication. These control networks are linked with a plant-wide network to exchange real-time information, such as sending process sensor data to the plant management level and receiving operating set points, constraints and fault-tolerant control commands. Industry standards for an automation architecture become critical at this level. At the plant management level, operating constraints and conditions are set based on the operator, economic and EH&S restrictions, as well as product requirements based on business strategies and market demand as determined by the corporate office level. It is important to note here that while described in terms of three distinct levels, the overall "Smart Plant" paradigm is not hierarchical with respect to information flows. Rather, through extensive interconnected communications and networks individual assets can self-evaluate their individual and collective performances, both current and expected, toward the business goals of the plant. This increasing interlinkage brings its own set of problems since the interdependence of all plant elements leading to a large-scale, complex system has to be carefully considered. Decision-making, however, is structured to encompass the broadest view of the collective impact and expectations of the asset base toward all goals.

The transition to the "Smart Plant" paradigm opens up new opportunities for process control and operations, but also poses a number of challenges. The focus of this article is to elaborate on the current progress and major unresolved issues toward the realization of the "Smart Plant" vision. Progress is aided by a number of important recent developments in the underlying component research areas, including model-based controller design, plant-wide optimization and supervisory control, process monitoring, fault-tolerant control and operator decision support tools. In the next section, we provide an overview of results in these areas pertaining to the paradigms of Figures 1 and 2, and elaborate on the kinds of problems that they can address. This will naturally set the stage in the Research Challenges section for a discussion of the main research challenges that need to be confronted and addressed to make the "Smart Plant" paradigm a reality.

Recent Developments

Process Control. Most of the research in the field of process control over the last 20 years has focused on the design of feedback control systems on the basis of increasingly more accurate process modeling descriptions. The basic premise of this model-based control approach is that closed-loop performance can be substantially improved if the controller structure is tailored specifically for the process that it is applied to since in this way the controller accounts for the dominant process characteristics. Therefore, since chemical processes very often exhibit nonlinear behavior, are characterized by inaccurate modeling descriptions, and also need to satisfy operational constraints (dictated by performance considerations or due to the limited capacity of control actuators), most of the research in process control has focused on the development of nonlinear geometric control methods for dealing explicitly with process nonlinearities (e.g.,[4,5,6]), model predictive control methods for dealing explicitly with control actuator and state variable constraints (e.g.,[7,8]), and Lyapunov-based control

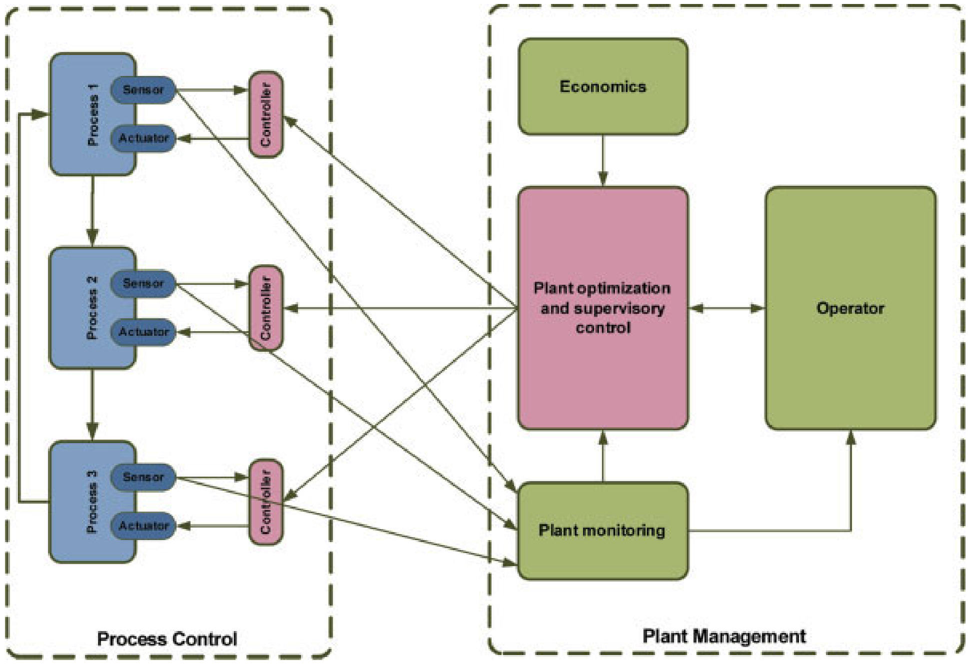

Figure 1. Existing plant operations paradigm: process control system uses dedicated, point-to-point communication links, plant monitoring is based on sensor data transmitted to the plant management system through wired networks, and plant-wide optimization is based on economic considerations.

methods for dealing simultaneously with nonlinearities, model uncertainty and actuator constraints (e.g.,[9]). In addition to these results, significant recent efforts have focused on the design of feedback control systems on the basis of process modeling descriptions that go beyond linear/nonlinear ordinary differential equation systems, including nonlinear differential-algebraic equation systems,[10] and nonlinear distributed parameter systems.[11,12]

Plant-Wide Optimization and Supervisory Control. Going beyond the design of model-based control algorithms that facilitate steering process variables to the desired set points, an important question is how the set points for the process

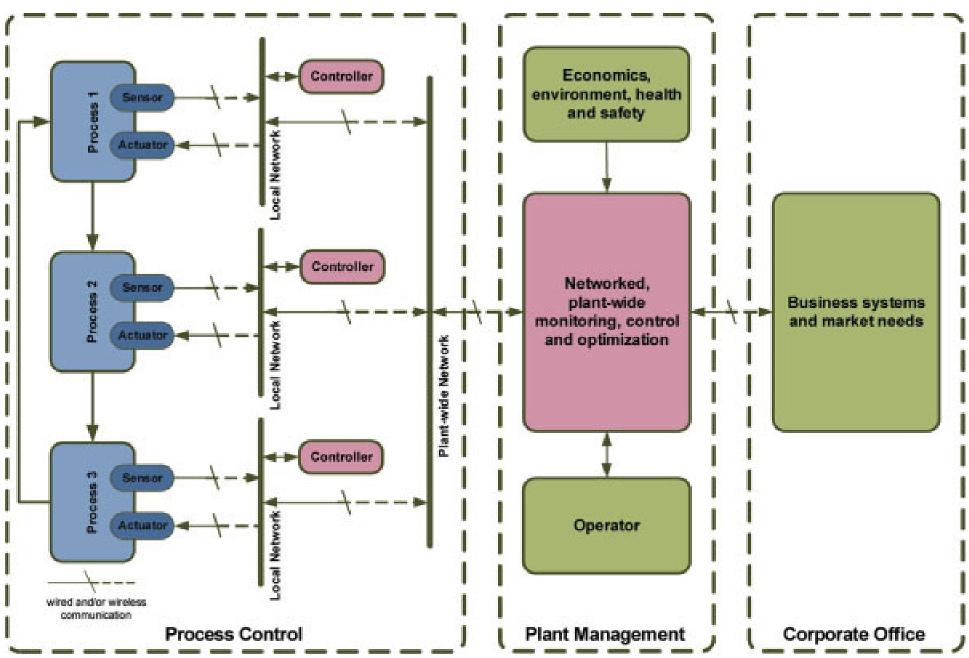

Figure 2. "Smart Plant" paradigm: process control, plant-wide management and corporate office systems communicate in real-time through wired and wireless networks to satisfy economic and EH&S objectives and deal with market changes.

variables can be determined. This is the subject of plant-wide optimization which is typically based on more elaborate, but steady state, models, accounting for EH&S, logistics, and plant economics considerations. In practice, plant-wide optimizations are carried out much less frequently than the control calculations, typically only once a cycle to update the set points being sent to the control level, to account for plant-model mismatch and process changes. While the frequency of plant-wide optimization is low, the problems to be solved are large, and often include both continuous variables (e.g., the set points for various processes), as well as discrete variables (e.g., whether to use a certain stream or not) and could be based on linear or nonlinear models. The complexity associated with solving such optimization problems, and the importance of obtaining meaningful solutions have fostered a large and growing body of research work (e.g.,[13,14]). Furthermore, motivated by the increasing trends toward interconnected and tightly integrated process networks, there have been several efforts toward exploiting the underlying structure of such networks in the context of distributed control strategies (e.g.,[15]), and also toward accounting for the core network dynamics during transitions at a supervisory control level (e.g., [16,17,18]). These developments provide promising avenues for a tighter coordination between the plant-wide optimization and supervisory control levels.

Process Monitoring. Process monitoring is a key task at the plant management level and deals with the issues of fault detection and isolation (FDI) in systems subject to random disturbances. FDI structures are essentially based on comparing the actual evolution of the process with the expected evolution in the absence of faults using data-based or model-based approaches. Methods of process monitoring allow for common cause variation within the system while accurately detecting the presence of abnormal behavior. Generally, these methods involve some form of statistical process control (SPC) that uses the known or estimated mean and variance for the system to predict when the system has breached the bounds of normal operation (e.g.,[19,20,21]). State-of-the-art control room discussions are shifting from process issues, e.g., what is the reflux ratio, to business issues, i.e., where are we on costs.

While an effective approach to fault detection is elusive in practice because of the changing conditions of the data and the plant operation, the use of SPC is taking hold, and the problems of false positives and negatives are being addressed. Fault isolation, on the other hand, is more difficult. Methods for fault isolation can again be categorized as either model-based or data-based. Model-based methods use a mathematical model of the process to design dynamic filters and compute residuals that relate to specific faults (e.g.,[22,23]). Data-based methods are primarily based on analyzing measured data to find and compare the location and direction of the system in the state-space with past behavior under faulty operation (e.g.,[20,24,25,26]).

Fault-Tolerant Process Control. In general, existing methods for handling faults can be categorized within the robust/reliable control approaches and reconfiguration-based control approaches. Robust/reliable control approaches (e.g.,[27]) can be utilized when the faults do not impinge upon the ability to implement control and sufficient control action remains available through multiplicity and redundancy of active control loops. Active fault-tolerant control approaches, on the other hand, handle faults explicitly through control system reconfiguration (e.g.,[28,29,30,31]), and are suited for the case when faults erode the control authority to the extent that closed-loop stability cannot be preserved by simply retuning the controller in the active control configuration. In this case, activating a suitable fallback control configuration is required to maintain closed-loop stability. The control reconfiguration problem can be formulated and solved within the framework of hybrid systems, wherein the process nonlinearity, the presence of constraints, as well as uncertainty are accounted for in the choice of the fallback control configuration. When multiple fallback configurations are feasible, performance considerations can be incorporated in the reconfiguration logic. In addition to these results, recent efforts have also focused on the design of fault-tolerant control architectures for spatially distributed processes modeled by nonlinear partial-differential equations (e.g.,[32]).

Operator Monitoring Support Systems. Beyond automatic fault-tolerant control systems, plant operators play a very important role in monitoring abnormal event situations. Operator monitoring support systems translate sensor information into plausible scenarios of process malfunction and help operators diagnose abnormal events. Specifically, a comprehensive operator support framework for rapid understanding of abnormal plant situations is accomplished (e.g.,[33]) through early detection of an abnormal situation, assimilation of relevant information for quick understanding, rapid assessment and diagnostic localization. Diagnostic localization is a less granular form of diagnosis focusing on a broadened set of feasible and prioritized scenarios, information on the nature of an abnormal event and a diagnostic narrowing to a malfunctioning system and explanatory detail that is sufficient for action. Identification of a failed component is a possible outcome but is not the primary focus. Diagnostic localization combines data interpretation, causal pattern generation and causal pattern interpretation.[34] The task involves aggregating evidence from sensor measurements,[35] and applying the information to a process model. Using these input sources, a localization algorithm operates on a causal process model to assimilate data into possible process behaviors and generate diagnostic hypotheses that can help operators handle abnormal situations.

Research Challenges

In this section, we discuss the key research challenges that need to be addressed to make the vision of "Smart Plant" operations a reality.

Networked Process Control. An important feature of the "Smart Plant" depicted in Figure 2 is the increased reliance on sensors, actuators and control systems that are accessed over real-time communication networks (wired and/or wireless) rather than dedicated, point-to-point links. The insertion of a communication network in the sensor-controller and controller-actuator links gives rise to a networked control system and can substantially improve the flexibility and fault-tolerance of an industrial control system, in addition to reducing the installation, reconfiguration and maintenance time and costs. Currently, process control systems utilize dedicated, wired control networks to achieve key closed-loop properties like stability, set point tracking and robustness to disturbances. With the advent of wireless communication technology, however, and the push for wireless adoption by major industrial organizations, there is a growing realization that low-cost wireless sensor and actuator networks can play an important auxiliary role to the existing control system by collecting and transferring additional data to the control system.[36] The deployment of more devices to monitor and control more process variables provides an opportunity for substantially improving the performance and fault-tolerance capabilities of the closed-loop system beyond what is achievable with dedicated control networks.

However, augmenting existing control networks with real-time wireless sensor/actuator networks challenges many of the assumptions in traditional process control methods dealing with dynamical systems linked through ideal channels with flawless, synchronous communication. In wireless networks, key issues that are important for process control include robustness, reliability and power usage. Robustness and reliability are major concerns because the interference in the process field and the consequence of a failure can be severe. Interference caused by environmental events and other wireless signals impacts timely data transmission which directly challenges the objective of real-time process control (see[37] for results on handling data losses within a model predictive control framework). Power issues related to real-time control include the contingency handling of power outage and data transmission delay variance due to battery levels. The limited processing and energy resources of a wireless sensor/actuator network, together with the difficulty of frequent battery replacement in a plant environment, require the development of resource-aware control algorithms that can extend the lifetime of the network as much as possible.

Deployment of Real-Time Sensor Networks. The use of real-time wireless sensor networks in industrial plants will also require the development of systematic strategies for deploying sensor networks including the determination of measured process variables, their optimal locations, and frequency and timing of measurement and the specification of precision, mean time to failure and maintenance. Sensor networks must be integrated with data communications and operational and planning systems. Such development should be based on existing results on sensor network design (e.g.,[38,39]), which are primarily based on open-loop considerations and metrics. There is significant potential with deploying sensor networks to take advantage of wired-based communications network architectures, but there is substantial new potential with wireless networks allowing sensors to communicate with each other, self-aggregate information and report higher-level interpretations. Sensor networks should also be integrated with abnormal situation management systems. Abnormal situations include the handling of malfunctions in the sensors themselves, and resulting losses of data and issues related to the topology, reliability and performance of the underlying wired and wireless communications network. Furthermore, control of the network itself to achieve time synchronization and buffering/interpolation of sensor measurements and actuator commands can play a key role in aiding the control algorithms to deal with communication malfunctions and facilitating the controller design task (e.g.,[40]).

Networked Process Monitoring. While augmenting the existing wired control networks with real-time wireless sensor networks offers additional information that can help achieve improved fault detection and diagnosis, the transfer of this information over a potentially unreliable communication medium can limit the potential benefits to process monitoring. From the point of view of FDI, for example, the complex dynamics and errors introduced by the network make the design of FDI residuals and their evaluation more challenging than in conventional control systems with dedicated links. Some faults are induced by the network itself, such as packet losses which are comparable to — and may be difficult to distinguish from — an intermittent sensor failure. A process monitoring scheme designed to take advantage of the additional data from a networked control system must be robust with respect to asynchronous behavior in the sensor data, and must adequately discriminate between network-induced errors and faults. Beyond robustness issues, efficient algorithms for managing the abundance of data available through the network must be developed. Key issues in this direction include handling more data interaction and interpretation, the increased potential for conflicting data and data overload situations. Also, delays resulting from using more sophisticated data processing techniques should be taken into account by the diagnosis algorithms.

Networked Plant-Wide Fault-Tolerant Control and Operations. The overall reliability of a chemical plant is strongly dependent on the phenomenon of fault propagation where the occurrence of a fault in some part of the plant puts the system in a working mode in which other faults are more likely to happen elsewhere, thus increasing the likelihood of a plant-wide failure. The need to prevent shutdown and enforce a smooth transition to normal operation after fault recovery calls for the development of "safe-park" plant-wide fault-tolerant control methods. An important consideration in the implementation of such an approach is that of determining the "zone" where the plant can and should be safe-parked. Key problems to be investigated include whether the process can be stabilized at the point of safe-parking using the available control action, whether the plant states can be steered from the nominal operating condition to the point of safe-parking and back in an optimal fashion and how the extra information — communicated via the wireless networks — about the states of the plant units can be utilized in choosing the safe-parking point.

In addition to automatic fault-tolerant control decisions, the use of networked sensors that provide real-time information about the state of the plant assets motivate incorporating EH&S performance and business/market considerations directly in the plant management decisions. That is, in a "Smart Plant" the assets also provide feedback and predictive information on the expected performance of that asset and its aggregated assets. This will allow the plant management system to proactively alter the use of the asset to maximize its value as conditions change and warrant (e.g., a type of proactive fault-tolerance). The challenge in the long run is shifting how information is concentrated, interpreted and shared so that operations can be run based on EH&S and business considerations and proactive asset information and not just process variables.

Network and Cyber-Infrastructure Security. The integration of dedicated local area control networks with wireless real-time sensor networks and the integration of plant management and business systems, while beneficial from a plant performance point of view, poses a number of security challenges owing to the open nature of wireless networks. The process industries must continue to operate in a managed-risk environment to provide the market with goods and services, yet do so with the confidence of minimal and decreasing potential of adverse impact. The communication network and cyber-infrastructure security challenge spans the entire global chemicals industry (including pharma/biotech) and petroleum production representing nearly $3 trillion in economic impact. No complete solution to the security problem exists. Yet, it is clear that the solution to these issues of security, whether cyber or physical, must be layered around scalable solutions that themselves are also "smart" and do not intrude or impede in any way on authorized use. Lastly, given the complexity of modern information systems and corresponding difficulty in achieving absolute security, plant and data structures need to be designed to deal with the possibility (albeit low) of intrusion and effectively mitigate negative effects. There must be knowledge, technology and procedures to respond to security situations very quickly. Efforts in the area of network and cyber infrastructure security for the process industries are underway (e.g., see http://www.chemicalcybersecurity.com/).

Operator Situational Awareness and Management Systems. Creating improved methods and interfaces that can substantially facilitate operator decision-making is another important research challenge. Such operator decision support interfaces should be tightly integrated with automatic fault-tolerant control systems. Operator situational awareness refers to the objective of having operators understand the state of a plant operation at any given time with sufficient information to make strategic plant operation decisions and/or management decisions about impending or occurring fault situations. The objective is the reduction of the decision-making time constant. Problems must be assessed, data gathered, constraints assessed, and criteria applied. Integrating these decisions across the entire organization arrives at a composite plant time constant for decisions. The "smart plant" will allow for the shrinking of that time constant over time. A corollary of this phenomenon will be that as the time constant shrinks, more and more of the repetitive decisions will be off-loaded from the humans to the system. As pointed out, the system will learn, and begin to recognize patterns of decision making, and automatically close the loop on a decision with no or very little human intervention. This frees the human to tackle more difficult and nonrepetitive problems, empowered but not replaced by systems.

Practically, decision-making support and presentation can be managed with a decomposition that distributes the monitoring, detection, interpretation and decision support into a set of focused, but coordinated problem solving tasks including: (a) detection of nonnormal process behavior, (b) identification of classes of non-normal plant behaviors, (c) rapid reporting to the operators of what functional or operational objectives are changing or being impacted, (d) diagnostic localization, and (e) operator decision making that directly utilizes plant objectives and control system reconfiguration options from the automatic fault-tolerant control systems. Much has evolved with incorporating the operator as a critical component of the overall "Smart Plant" paradigm but the technologies are still in an early development and implementation phases.

Operator Simulation Training Tools. While addressing the above problems would contribute a lot in developing a comprehensive "Smart Plant" solution, even if a perfect "Smart Plant" solution were available today, it would be decades before most plants fully incorporated the technology. One reason for the slow adoption of newer technologies is the fact that it is difficult to prove the value of the technology, when the technology is aimed at preventing costs of relatively rare and unpredictable problems. For example, the process industry does not have near miss reporting like that in the airline industry. It is, therefore, important to develop advanced analysis software in the industry that can alert plant operations personnel to impending problems in plant assets and/or the process so that corrective action can be taken in adequate time. It must also be noted that human operators are a crucial part of the automation system at a chemical plant. They become particularly crucial when the automation system cannot handle a situation. Therefore, there is great opportunity for cyber-infrastructure advances that will enable affordable simulation training for plant operators to improve their ability to handle abnormal situations.

Concluding Remarks

The increasing need to balance economic prosperity with sustainable EH&S performance and corporate social responsibility together with recent advances in the manufacturing of wireless sensor/actuator networks provide a strong motivation for introducing a new paradigm for networked, plant-wide monitoring and control. While the development of such a paradigm requires the solution of a series of intellectually challenging problems, this approach could deeply impact the operation of process industries in the 21st century. The nature of "Smart Plant" technologies, the research that is needed, the development that needs to be coordinated and the interoperability requirements for implementation are such that without an overall plan, efforts tend to be unsuccessful at producing the fundamental change demanded by these problems. What is needed, therefore, is better coordination of resources between academia and other technology providers, standards groups, industry, suppliers and marketplace, and a centralized process for ensuring that research and development follows a coherent plan that will be of use to the broader industry.

In addition to technological needs, several other factors bode well with the increasing interest in and practical impact of "Smart Plant" methodologies and solutions including: (a) the development of easy-to-use software that makes system modeling and control routine and easy-to-incorporate in the chemical engineering curriculum, as well as in an industrial environment, (b) the availability of low-cost computing power that allows fast simulation of entire plants and testing of fault-tolerant control scenarios, (c) advances in wireless sensors and actuators that make networked monitoring and supervisory control feasible and practical, and (d) the current funding trends toward integration of physical and cyber systems including NSF's cyber infrastructure initiative. Training the next generation of chemical engineers that can manage networked process control and monitoring systems effectively is also a major challenge. The introduction of courses on advanced networking technologies and sensor networks in the curriculum will be essential for chemical engineers to develop and implement "Smart Plant" solutions to process industries. Also, the "operator" of tomorrow will be much more of a proprietor with a business to run rather than a process to manage. Last, but not least, the development and implementation of "Smart Plant" solutions should be accompanied by changes in human behavior and perception at all levels of the corporate hierarchy including management misconceptions about safety, incorporation of safety concerns in cost estimates, improved communication among personnel and the creation of a culture where EH&S issues can be openly surfaced.

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