Distributed Sensing for Quality and Productivity Improvements

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***Abstract*—Distributed sensing, a system-wide deployment of sensing devices, has resulted in both temporally and spatially dense data-rich environments. This new technology provides unprecedented opportunities for quality and productivity improvement. This paper discusses the state-of-the-art practice, research challenges, and future directions related to distributed sensing. The discussion includes the optimal design of distributed sensor systems, information criteria, and processing for distributed sensing and optimal decision making in distributed sensing. The discussion also provides applications based on the authors' research experiences.**

***Note to Practitioners*—This paper is based on a panel discussion on the topic of the emerging technology of distributed sensing and the associated challenges and opportunities. The panel, constituted by a group of leading researchers and practitioners with expertise in operations and statistics, convened during the Institute for Operations Research and the Management Sciences (INFORMS) 2003 annual meeting in Atlanta, GA. This panel focused its discussion on the information layer technology of distributed sensing for quality and productivity improvements, which differentiates this panel from other similar panels that were formed in a different society. The panelists provided their visions about the state-of-the-art practice, research challenges, and future research directions, and also discussed potential applications based on their own experiences.**

***Index Terms*—Decision making, distributed sensor systems, quality improvement, sensor optimization.**

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I. Introduction

SENSOR integration, coupled with unceasing electronic miniaturization and nanofabrication, makes it possible to produce inexpensive sensing devices. These inexpensive and smart devices with multiple heterogeneous onboard sensors, networked through wired or wireless links and deployable in large numbers, are distributed throughout physical systems to maintain the production performance, to ensure the life-cycle quality of products, and to improve the quality of management and service. This system-wide deployment of sensing devices is referred to as distributed sensing and the whole infrastructure is called a distributed sensor system. One example of using distributed sensing for quality improvements is in pharmaceutical manufacturing (more examples are presented in Section V), of which the standard deviation of vials filling processes should approach zero as positive deviations result in expensive material loss or overdose while negative deviations result in an insufficient dose. The use of distributed sensors at check weighs and filling nozzles will result in the minimization of the filling process [1]. In fact, MIT's *Technology Review* identifies the wireless distributed sensor network as one of the top ten emerging technologies that will change the world [2]. Indeed, this new technology has resulted in a data-rich environment with both temporally and spatially dense information [3]–[5] and provides unprecedented opportunities for quality and productivity improvement.

Major technologies associated with distributed sensor systems can be generally decomposed into three layers: 1) at the device layer: development and fabrication of sensing devices that can sense, process, and communicate; 2) at the network layer: networking architectures and protocols that ensure reliable, secured information transmission and communication; and 3) at the information layer: collaborative, multimodal, and fault-tolerant information processing that will complete the transition from the "data-rich" layer to the "information-rich" layer for optimal decision-making.

The general concept of networked sensor systems has attracted considerable attention such as the SensIT program [6], [7]. Prototypical distributed sensor systems are now available, for example WINS [8] and smart dust [9]. These provide hardware infrastructures for the device and network layers discussed above. The challenge now is to provide decision support capabilities that will allow the full potential of a distributed sensor system to be realized. More challenges need to be tackled at the information layer in order to realize a distributed sensor system to perform sophisticated and integrated tasks for monitoring, detection, diagnosis, and/or control in an

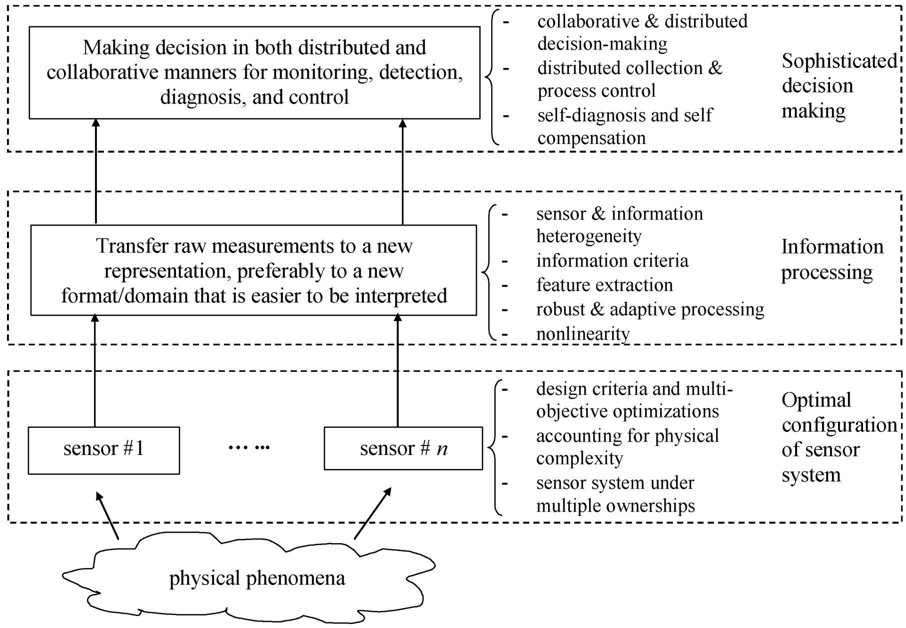


Fig. 1. Issues at the information layer of the distributed sensor network.

evolving and complicated physical environment. In particular, this involves the design problems of selecting the appropriate sensors, prescribing optimal sensor distribution (i.e., location) in a multilayer network and the intimately related data utilization problem of supporting effective decision-making in a distributed environment.

The design problem is crucial because a poorly designed system is likely to generate irrelevant, redundant, conflicting, and/or incomplete information. An optimal design must observe the imposed constraints, such as the resources available to install and operate a networked sensor system, the effective range and sensitivity of each type of sensor, and the critical features and tolerances of products/processes. The data utilization problem can be further classified into two subproblems: the information processing and the decision-making process. These two problems are closely related and their boundaries are sometimes difficult to draw. Information processing converts original sensor data into a format more conducive to data compression, feature extraction and interpretation, or pattern recognition. The decision-making process naturally follows information processing; in simple environments, the decision-making process becomes straightforward after appropriate information processing. However, there exists a more sophisticated decision-making process for a distributed sensor network, namely, data gathered by distributed sensors must be combined to support collaboration among different parts of the network, which is necessary to produce meaningful system-wide decisions.

More specific research issues are identified in the subsequent sections, which will address each of the three challenges associated with distributed sensing design and data utilization. In the design section, we will discuss design criteria, multi-objective optimizations, design methods of sensor systems accounting for the complexity of underlying physical systems, and designs under multiple ownerships. In the information processing section, we will elaborate the issues relevant to sensor and information heterogeneity, information criteria for feature preserving and model selection, feature extraction from data with complex structures, robust and adaptive information processing, and sensor characterization of nonlinearity. In the decision-making section, we will present thoughts on distributed and collaborative decision making, distributed data collection and process control, and self-diagnosis and self-compensation for high system reliability. Fig. 1 demonstrates these inter-related issues.

For general references in this paper, we define several terms used in Fig. 1 as well as the later sections. Monitoring refers to the task of overseeing, checking, and tracking the status of a parameter or a state variable. Detection refers to the task of revealing, discovering, and capturing a change in a parameter or a state variable that is being monitored. Diagnosis refers to the task of identifying the cause due to a change of a parameter or a variable upon its detection. Control refers to the task of exerting or directing adjustments and other necessary actions to a process so that it will stay in a desired course. In fact, the meanings of the terms used in this paper are consistent with their common meanings in the general literature.

This paper focuses on the design and data utilization challenges in a distributed sensing setting for quality and productivity improvement, and is organized as follows. Section II deals with optimal sensor configuration. Section III discusses the information processing issue. Section IV focuses on decision-making issues. Section V presents a few examples of applications based on the authors' research experiences. Section VI includes a few additional remarks.

II. Optimal Configuration of Distributed Sensing

Even if sensors generally become smaller and inexpensive due to advances in electronic miniaturization techniques, the entire sensor network and its maintenance could still be costly if not carefully designed. Design of a sensor system is realized through the design and determination of 1) an individual sensor unit; 2) the number of sensors needed; 3) sensor locations; and 4) operational strategies. Problem 1) is a device layer issue which is not dealt with in this paper. Problems 2)–3) have a broader relevance and will be the focus of this section. For Problem 4), some of the operational aspects such as how often measurements will be taken may seem straightforward when in-process automated sensing devices are used to measure a 100% product in production [10]. Challenges will arise in many situations where such measurements might indeed exceed the memory storage and power requirements that deem it impossible to implement. The discussion of other operation strategies related to decision-making will be presented in Section IV.

As stated before, Problems 2) and 3), which focus on the determination of the number and locations of sensors, are usually called the problem of "sensor placement" in engineering practice [11], [12]. It is important to note that the "location of a sensor" bears two meanings in the literature. It may refer to the location of a physical feature that a sensor measures or the place where a sensor is physically installed. In this paper, the first meaning is more relevant and, thus, is often implied.

Previous work primarily incorporates limited sensor collaboration, for example, sensors on the same workstation, for single objective monitoring missions [12]–[17]. The theoretical foundation of design criteria was initially developed in the research of optimal experimental design [18], [19], where the Fisher Information Matrix is used to characterize the estimation/prediction accuracy for a linear regression model. Certain measures of the Fisher Information Matrix, known as the D-, E-, A-optimality, are then used as the criteria for optimal sensor placement so that estimation/prediction accuracy can be optimized.

Given the new paradigm of distributed sensing, the sensor location is no longer limited to a localized area. They may form sensor clusters. Nagel [20] presented a discussion of the seven items involved in microsensor clusters: the multiple sensors, interface electronics for sensor excitation and signal conditioning (amplification), a microcontroller or a computational unit with associated memory, a means of communicating information out or receiving commands, a source of power, and a printed-circuit board (PCB) and housing. More important, sensor clusters are distributed throughout a system, either at different levels in a hierarchical network or along a production line with multiple sensors clustered at individual workstations. This new setup of sensor system design is called "optimal configuration of distributed sensing" or "optimal strategy for sensor distribution."

In this paper, we identify the following major challenges related to the optimal configuration of distributed sensing: 1) develop design criteria and formulate multiobjective optimizations; 2) network structure design accounting for the complexity of underlying physical systems; and 3) characterization and design of sensor systems under multiple ownerships.

A. Design Criteria and Multiobjective Formulations

One aspect related to the performance of a sensor system is to quantify sensor collaboration. Two sets of related performance indices were developed before—observability in control theory [21] and identifiability/estimability in estimation theory [22], where observability refers to the capability of discovering or tracking unknown state variables in a dynamic yet usually deterministic system, whereas the identifiability/estimability, with its root in statistics, refers to the capability of uniquely identifying the fixed or random effects in a linear static system. New research is needed to translate these indices such that they are directly connected to the performance evaluation of a distributed sensor system. Recently, an analysis of diagnosability was performed for distributed sensor system in multistage manufacturing processes [23], [24]. The diagnosability of a distributed sensor system is defined for the mean and variance components of the random system inputs. Diagnosability is mathematically similar to the concept of identifiability/estimability in statistics but the new term better suits the mission of fault diagnosis. Higher order statistics may be used to provide additional information or account for the lack of knowledge of a system model [25]—an approach known as blind source separation, wherein another criterion of separability is proposed [26].

Another aspect is the reliability of a sensor system. Unlike most of the reliability models of electronic components, there are no basic failure modes which are common to sensors designed for different purposes and operating at the same conditions. For example, each sensor family, such as flow sensors, inertial sensors, pressure or radiation sensors, is normally based on a very specific flow of process steps. Even within a sensor family, processes can differ drastically when they are based on various preferential technologies, such as bulk or surface micromachining as it is the case for inertial sensor for example [27]. Therefore, reliability prediction of a class of sensors is obtained with high uncertainty. Then, improved performance of sensor systems is likely to be obtained through system redundancy. Redundancy is a natural way to improve sensor system reliability because a multisensor setup will allow the sensor to watch over each other and identify the failing sensors based on their own outputs—a procedure known as sensor self-diagnosis [28], [29]. A possible performance index could be self-diagnosability, which measures how healthy the sensor redundancy is. Simply put, too little redundancy may not allow self-diagnosis and too much redundancy could impose unnecessary costs. Thus, reliability estimates of distributed sensor networks need further investigation in terms of sensor locations, individual sensor reliability, network configuration, and redundancy level (where and how many). Determination of the bounds of the reliability estimates is a challenge for further research as difficulties increase with the level of uncertainty in an individual sensor's reliability and the size of the configurable network.

A distributed sensor system, especially for those enterprise-wide implementations, is usually too complicated for a single scalar measure to adequately characterize its performance in both the local level and the global level. It is desirable to decompose a system-wide index into subsystem levels, for instance, between-station and within-station diagnosability in a multistage manufacturing or within-layer and across-layer diagnosability in a hierarchical network [23].

With various criteria depicting different aspects of distributed sensor systems and constraints of being low cost and potentially low maintenance, optimal sensor system design will unavoidably take a multiobjective formulation (e.g., design for diagnosability, design for self-diagnosability, design for sensitivity), the establishment of which is a major task in itself.

B. Complexity of Underlying Physical Systems

Most real-life problems, such as manufacturing/production systems, are complex, nonlinear, and dynamic. The complexity generates considerable difficulty for optimally designing a distributed sensor system to monitor the underlying physical systems. Understanding the interaction between the distributed sensor system and the physical process plays an important role in making the resulting sensor system more effective.

The information flow in a physical system is determined by the nature of each physical action and the topology of the physical system. The information related to key processes and product features is evolving with or without the presence of a sensor system. With a sensor system in place, however, this dynamically evolving information will be retrieved at different locations and could be pieced together for revealing the status of the physical system. Therefore, the overall detection capability of a distributed sensor system depends not only on how much information sensors can retrieve from the process at selected locations but also on how the information is transmitted through the process. The latter is determined by the physical system instead of the deployment of a sensor system.

Aware of this interaction, a strategy has recently been proposed by Ding *et al.* [30] for sensor distribution in a serial production system. The information chain linking process changes to sensor measurements can be tentatively partitioned into two consequent steps: 1) information transmission from station i to station k, characterized by transmissibility ratio $\lambda_{i|k}$ and 2) information detection through sensors on station k, characterized by detecting power $\tau_k > 0$. Fig. 2(a) shows an example of sensor distribution in multistage manufacturing. Process faults occur on station i and propagate to station k. The overall diagnosability relies on both across-station transmissibility and detecting powers on individual stations. Optimal sensor distribution strategy should be developed to identify stations at which the fault information is not completely transmitted and then decide the optimal detecting power on that station. Fig. 2(b) shows an iteratively propagating strategy to identify those missing sensors (i.e., $\lambda_{i|k} < 100\%$) at which a saturation in diagnosability could be observed. The installation of new sensors at those locations will complete the broken information chain and improve the system-wide diagnosability. Therefore, investigating the placement of sensors in order to achieve complete information propagation in the minimum number of sensors presents a challenging area of research. It should be noted that this system resembles those studied under consecutive k-out-of-n: F system in reliability engineering [31].

For manufacturing with more complicated topologies, a promising approach is to use the concept of agent—an autonomous element which can sense and respond. An agent system is constituted by a large number of simple-functional elements (called agent) but can otherwise fulfill highly sophisticated tasks. The objective of sensing is to respond to

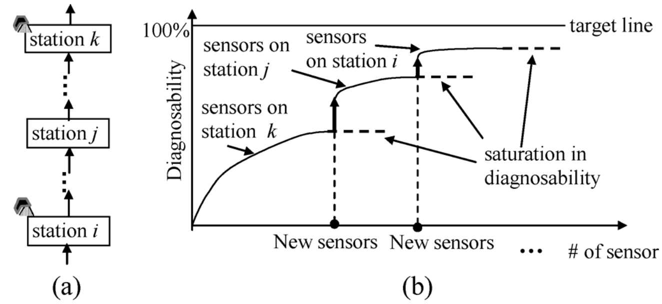


Fig. 2. Information flow in multistation network.

anomalies and problems. As the system is distributed, it becomes imperative that local information processing assumes an important role. Given an anomaly, it may be necessary to schedule alternatives processing, materials, facilities, tools, and manpower. Agents such as software entities can reside on the equipment and collect data, extract features, and send the anomaly information to a distributed coordinator. This coordinator can invoke anomaly (diagnosis) detection and invoke the appropriate scheduling of resources to enforce replacement and control. Each agent will be autonomous and communicate when an event gets triggered. A collaborative agent platform can be developed where, in interactive resource allocation agents, manpower agents, tools agents, facilities agents, and scheduling agents can work together to take the information from the sensors and respond appropriately [32]–[34]. We envision future systems having multiscale and multilevel capability for diagnosis and control starting from sensing to procurement from the supply chain.

C. Characterization and Design Under Multiple Ownerships

The current assumption for sensor and process components ownership is that they are owned by the same organization. However, the global economy concept has resulted in the physical separation of many manufacturing operations for the same organization. As a result, data and information collection from various sensors distributed globally present new and interesting research problems, such as the configuration of the dynamic system networks where data are collected at different time zones which might have a direct impact on processes operating in close proximity. This might make it difficult, if not impossible, to make timely changes in dependent processes. We need to note that the information collected from various sensors will be used in many situations by different organizations and rethink the design criteria (and multiobjective formulation) and the complexity of the system. Suppose that some variations in the upstream manufacturing processes will be critical to the downstream manufacturing processes. However, two different organizations own these two streams of processes. In the upstream operations, when we design the sensors to collect information without considering the needs in the downstream operations, there is a chance that some important data are not collected for understanding how the variations are propagated throughout the processes. Therefore, it is important to determine the optimal location of the sensors in order to detect such variations as early as possible in the production process. Other challenging issues include how to characterize the design in different organizations and how to build a robust sensor system for handling possible sensor malfunction (providing imperfect data).

Under multiple ownerships, there is usually a large number of sensors to be allocated among processes and the optimization problem for sensor distribution thus becomes inherently difficult due to the curse of dimensionality. Meanwhile, with a multi-objective formulation, the objective function is likely nonlinear and accompanied by complicated physical and geometrical constraints. As an example, a Knapsack formulation [35], the same as in resource allocation, is often used in the problem of maximum coverage of a detecting area [36]. However, the Knapsack problem is inherently NP-hard. In order to solve the large-scale problem, optimization algorithms need to be scalable, namely, it should remain effective when the scale of the problem (e.g., the number of decisions) has dramatically increased. This would be one of the key components to be developed because distributed sensing will generally result in a large-scale problem with many decision variables or massive datasets.

III. Information Processing in Distributed Sensing

As we mentioned in Section I, information processing and decision-making can be hardly separated completely. We include in this section information processing and the simple subsequent decision-making. More complicated decision-making tasks (e.g., collaborative decision-making in distributed environments, sensor self-diagnosis, and real-time process control) are discussed in Section IV.

We identify the following major challenges related to information processing for distributed sensing: 1) sensor and information heterogeneity; 2) information criteria for feature preserving and model selection; 3) feature extraction from data with complex structures; 4) robust and adaptive information processing; and 5) sensor characterization of nonlinearity.

A. Sensor and Information Heterogeneity

The implementation of a diverse variety of heterogeneous sensors is desired because a heterogeneous sensor system can provide both complementary and competitive information about a physical system. Complementary information refers to measurements of different characteristics of the process while competitive information refers to measurements of the same characteristic but from different sensor units. A heterogeneous sensor system will provide a more reliable and accurate view of operational status of physical processes. For instance, one physical machine fault (say, an unbalanced shaft) may generate different symptoms (e.g., vibration, temperature changes, motor force, etc.) and can be measured by different sensors (e.g., an accelerometer, thermal couples, and current, respectively). On the other hand, one sensor may sense different types of machine faults occurring simultaneously with similar symptoms.

In [12], it is usually assumed that sensor noises are independent and have equal variance (i.e., $\boldsymbol{\varepsilon} \sim (\mathbf{0}, \sigma^2 \cdot \mathbf{I})$), where $\boldsymbol{\varepsilon}$ is the sensor noise vector, σ^2 is the variance, and $\mathbf{I}$ is an identity matrix. This assumption is usually made for the system of which all of the sensors must measure the same physical variable through the same transduction method. A sensor system under this circumstance is generally called a homogenous sensor system. A heterogeneous sensor system will likely violate the above assumption on $\boldsymbol{\varepsilon}$ because heterogeneous sensors in a distributed sensor system will surely have different statistical characteristics. Even for the same types of sensors, they may be at a different stage of their service life so that their measurement precisions are different. Of course, no actual sensor system is absolutely homogenous since no two sensors are identical. A widely used statistical hypothesis testing procedure, the likelihood ratio test [37] (with the alternative hypothesis set as "there is a change in the model (or the parameter value) describing the sensor data"), can be used to verify when the above homogeneity assumption holds and when it is violated.

The sensor heterogeneity in a distributed sensor system will introduce information heterogeneity. The information heterogeneity will take more dramatic manifestation than the sensors. To name but a few, some information is represented by a periodic temporal signal and the others may be a collection of spatial point measurements, or some may take continuous values and the others could be categorical, or some are real physical measurements and the others could be from pseudomeasurements (i.e., the design information or outputs from deterministic simulations without random errors).

The effect of sensor and information heterogeneity on information processing has not yet been adequately addressed. Systematic modeling of sensor and information heterogeneity needs to be investigated. In a recent development [38], it is shown that when sensor heterogeneity comes into play, the original diagnosability condition of a sensor system no longer holds. Weighted least-squares estimation is probably the most widely used method to account for this heterogeneity. In dynamic systems, Kalman filters [39] may be developed for individual sensors. System states will be estimated and updated using a weighting function determined from specific characteristics of individual sensors. At a higher inference level, a generalized Bayesian inference framework, also known as the Dempster–Shafer theory [40], [41], is used to produce a belief interval, which corresponds to the upper and lower bound of the posterior probability, based on the conditional probability of heterogeneous measurements.

B. Information Criterion for Feature Preserving and Model Selection

This information quantification is different from the performance quantification of sensor systems discussed in the previous section. Here, we refer to the criteria or measures to quantify the "usefulness" of information in measured signals or data. The purpose of information processing is to either extract the features from raw signals or establish empirical characterization of system behavior. For this reason, information quantification serves as the basis for information processing techniques.

Information quantification is intended to define the boundary between a useful feature and irrelevant information, or significant terms in empirical models versus those insignificant ones. The currently available information criteria usually try to make a distinction between systematic signals and pure noises. For instance, one such criterion is entropy from Shannon's information theory [42], with applications primarily in communication. Entropy is defined as $-\Sigma_{x_i \in \aleph} p(x_i) \log p(x_i)$, where $\aleph$ is the set of all possible x_i's and $p(x_i)$ is the probability density of x_i. Pure noise will have the largest entropy and a constant signal will have zero entropy. Other types of criteria used in denosing include the SURE [43], the AMDL [44], and a modification of Donoho's denoising approach [45].

The usefulness of information obtained from sensors also lies in the empirical characterization of system behavior. Although certain physical laws characterize process behaviors of components (or subsystems), the variations of the components and their propagation over the (successive) systems at multiple stages require empirical data for its characterization. Moreover, some of the physical laws are not well understood (especially in new process development) and, thus, from a data-mining point of view, sensor data are very useful in understanding the effect of the process conditions on its performance. This is particularly important when the system under the surveillance of a distributed sensor system is large and complicated, where the experimental design activities cover only a part of the system. Typical criteria for model selection include the Akaike information criterion (AIC) [46] and the Bayesian information criterion (BIC) [47]; these two are closely related. The AIC/BIC criterion is usually used for parameterizing a signal with an empirical model, namely, it selects an appropriate empirical model while preventing the overfitting problem, the occurrence of which will deteriorate a model's predictive capability upon new observations [46, Ch. 7].

The aforementioned information criteria largely define the boundary between a systematic signal and pure random noises, which is one aspect of information quantification. However, applying these criteria directly in information processing has the tendency to overfit the data and retains an excessive number of coefficients [48]. Thus, they may not serve well in distributed sensor systems. In fact, the "irrelevant" information in many physical systems could be more than pure random noises. For example, in a fault diagnosis application in the stamping process [49], researchers found that the relevant information for the fault diagnosis purpose is by and large associated with the peak/valley areas of a tonnage signal curve (refer to Section V-B and Fig. 5 for more details). This motivates research emphasis on investigating approaches for combining engineering knowledge and information processing requirements in redefining "usefulness" versus "irrelevance" of information so that a more efficient data model can be developed to represent the original data.

C. Feature Extraction From Data With Complex Structures

The ultimate goal in information processing is feature extraction. Development of feature extraction methods can be classified into spatial analysis [50], [51] and temporal analysis [52], [53]. Spatial analysis relies mainly on the crosscorrelations of measurements at different locations. Multivariate statistical methods, such as principal component analysis [54] (PCA)-based pattern recognition [55], factor analysis [56], [57], variance components analysis [22], [24], and signature metrics approach [58], [59], have been used to extract process operation patterns from correlation matrices. Temporal analysis methods, which analyze autocorrelated data, include time-series methods [60] such as exponential smoothing [61], autoregressive moving average (ARMA) modeling [62], or Kalman filtering [39], [62], and time–frequency analysis, such as wavelet transform [63], [64].

Note the difference between two aforementioned multivariate analysis methods: factor analysis and the PCA-based pattern recognition. The factor analysis method refers to the procedure of using system outputs' data alone to fit a linear model structure that can provide more insightful interpretations of the data. PCA is often included as an intermediate step in the factor analysis to find the subset of the most important factors. The PCA-based pattern recognition is different in the sense that it will treat the eigenvectors associated with the few largest principal components as the fault patterns and then use them for the diagnosis purpose.

Wavelet analysis is a key method among the temporal analysis methods for information processing and feature extraction [48], [49], [65], [66]. Unlike the Fourier transform where the basis function is only a sinusoidal wave, a choice can be made of the wavelet shape to suit the features of the signal. In addition, the Fourier transform describes the average characteristics of the signal over the time history, but the wavelet transform identifies the local features of the signal. In a sense, the wavelet transform is a windowed Fourier transform but with adaptive window sizes so that different time–frequency components can be localized. When the size and shape of a wavelet are similar to an event inside the signal, the transform identifies large amplitude, a property can be used to detect transients in a signal. By simply dilating the wavelet size in the transform, local features with different time-scales can be described by the distribution in the "time–frequency" plane. These features of wavelet analysis can be advantageous for examining the nonstationary signal where a large-scale or small-scale change occurs when localized or distributed anomalies are introduced during operations. To that end, Kamarthi *et al.* [69], Suh *et al.* [45], and Bukkaptnam *et al.* [70], [71] showed several applications of wavelets in manufacturing with reference to enforcing online real-time quality control. In addition, in nonliner systems, it is possible to observe self-similarity of signal features. In such a case, it will be very effective to use fractal dimensions, such as information, correlation, and capacity dimensions. These give excellent features which will be very effective in terms of storage and transmission in real-time analysis [70].

Traditionally, spatial and temporal analyses have followed separate paths. Since a distributed sensor system is capable of monitoring both spatial and temporal evolutions of a physical process, it is highly desirable to perform a joint spatio-temporal analysis using data gathered through the distributed sensor system. Joint spatio-temporal analyses were initially developed in geostatistics [50], [67] and were mainly applied in meteorology [68] for forecasting spatially and temporally evolving weather conditions. A more complete work of applying spatio-temporal methods to other applications is not yet broadly reported.

D. Robust and Adaptive Information Processing

Information processing is complicated by the fact that signals exhibit different physical characteristics and are associated with the inherent information uncertainty. Many parameters and thresholds are involved in transforming the original data into a set of features or a collection of feature-preserving coefficients. The determination of those parameters and thresholds itself depends to a great extent on the physical environments and information-processing requirements. A set of optimal thresholds under one circumstance may not be optimal when the process changes; or, an optimal estimator may lose its optimality when there are outliers or sensor anomalies. For example, the optimum threshold degradation level of the light intensity of light-emitting diodes (LEDs) for their replacements when they are infrequently used is different from the optimum level when they are in continuous use. In a constantly changing physical world, it is challenging yet desirable to develop information processing techniques that are more robust and adaptive.

Robust information processing refers to the techniques that are insensitive to measurement outliers and is related to sensor self-diagnosis, which will be discussed in the next section. The difference is that robust information processing may not need to make the decision about which sensor has failed. A simple example is that a sample median is a more robust statistic than a sample mean. Yet, many current information processing procedures focused on modeling mean sensor data, which is not robust against abnormalities (e.g., extremely large or small data in the two tails of the sensor data distribution). The concept of median should be extended to more complicated information processing scenarios. References [72] and [73] show the possibilities of using median polish in spatial data modeling suitable for image analyses. Since the median does not use the values of the extreme data, these types of procedures are more robust to abnormalities. Much of the ongoing work is in the area of robust statistics [74] or robust estimation [75].

Adaptive thresholding will also help to improve the robustness of information processing. Determining the optimum thresholds for process diagnostics and improvements based on sensors data and the conditions of the process is a difficult task. This is due to many factors, such as errors in sensors' observations and lack of perfect correlation between the process parameters, environmental conditions, and the sensors' measurements. More important, in many situations, it becomes necessary to have adaptive thresholds as the process conditions and parameters change according to some patterns. Consider the case when a machine is being monitored using multiple sensors. The machine condition is assessed by the symptom limit value S_L and its two components: the alarm value S_a and the breakdown value S_b. If a running machine reaches the alarm value, it is an indication that it experiences intensive wearing. Hence, the type and advancement of the fault must be identified in order to prepare the maintenance procedure. If a machine reaches the second limit value S_b, the shutdown of a machine for maintenance becomes necessary. The knowledge of these two limit values is of great importance for critical machines which run continuously with automatic monitoring and shutdown system. However, in most cases of diagnostic implementation, for large and expensive machinery in particular, it is difficult to perform active diagnostic experiments, which means establishing the S_L on the basis of the known machine condition. Hence, the determination of S_L is possible only as the result of passive diagnostic experiments, where the values of S are observed on the group of running machines without knowledge of their condition [76].

A detailed description of condition inference techniques and the use of statistical methods to estimate the limit symptom value S_L can be found in Cempel [77]–[80]. A simple solution for determining S_L is given by Dabrowski [81]. It is determined in the way its tail probability does not exceed a given small level $\alpha : P_r(S > S_L) \leq \alpha$. Another possible way of determining S_L from passive experimental data is based on the Neyman–Pearson technique [82] of the statistical decision theory. It minimizes the number of breakdowns at an assumed and allowed percent of needless repairs A by means of a proper choice of the breakdown symptom value S_b. According to [78], this condition of minimizing the breakdown number can be written as follows:

$$A = P_g \int_{S_b}^{\infty} p(s)ds \tag{1}$$

where $p(s)$ is the probability density function of the condition parameter S, and P_g is the probability of good machine condition. Cempel [79] treated observed symptoms as an outcome of the Weibull-type stochastic process and estimated S_b using (1). Additionally, he defined the alarm symptom value S_a and estimated it using

$$A = P_g \int_{S_a}^{S_b} p(s)ds. \tag{2}$$

E. Sensor Characterization of Nonlinearity

We have discussed several techniques such as ARMA models, Fourier transforms, and wavelets for feature extraction in distributed sensor networks. One fundamental question relates to the nonlinearity of processes. Most physical systems that we interface with, including ourselves, are complex. They are composed of various interdependent entities whose collective behavior and functionality portray a significantly larger variety compared to each entity. Large-scale distributed sensor networks fall into this category of complex systems. Developing models of these systems, computational or otherwise, is the main imperative for harnessing these systems. The use of the first-principles knowledge, including the underlying physics and biology alone, to model these sensor networks is a futile exercise. This is because such systems, from first principles standpoint tend to have infinite degrees of freedom (i.e., if we want to develop rules to track the evolution of such systems, we need to develop infinitely many of these). Further, these systems are characterized by multifariously related entities and events, and the evolution of their behaviors, defined in terms of states and statuses of their underlying processes, distinctly marks their dynamics. As these states evolve, the emergent behaviors seldom follow periodic or similar regular patterns. This is because most of the real-world processes exhibit nonlinear and chaotic dynamics. Consequently, even medium-term predictions of their emergent behaviors can be extremely cumbersome and almost impossible. Evidently, this type of system cannot be easily harnessed or controlled. Chaos theory can provide us with rigorous analytical tools and methods to develop models of sensor networks which are nonlinear and complex and, hence, can enable us to control them. The key idea here is that under steady operating conditions, a complex system is usually governed by significantly fewer active degrees of freedom than those in the first-principles models. In other words, only a few of the infinitely many, at least several, degrees of freedom govern the evolution of these systems under operating conditions. In fact, if we use chaos theory, we can capture all of the complicated emergent behaviors of a system using nonlinear models that have two to four degrees of freedom. Extraneous noise can be captured completely.

In order to understand the underlying dynamics, thorough sensor signal characterization will be necessary. Sensitive dependence to initial conditions, false nearest neighbor tests, Lyapunov exponents will help in characterizing sensor signals. Bukkapatnam *et al.* [83], [84] report the characterization of sensor signals in machining context and prove the existence of chaos in machining. Such an analysis will be very useful in real-time situations as the features can be now Lyapunov exponents, and fractal dimensions. These features will better capture the inherent nonlinearity of the sensor data than the traditional feature extraction techniques alone.

IV. Decision Making in Distributed Sensing

We will discuss decision-making tasks involving a large number of sensors in a network hierarchy in this section. The sheer number of sensors requires a new paradigm to support decentralized information processing and distributed decision making, first at each sensor node and then with collaboration among the relevant devices in the network, to produce meaningful, system-wide results. Sensor collaboration plays a central role in making a distributed sensor system more informative. It will take full advantage of both temporal and spatial information obtained from different sensors at different stages in a process and respond rapidly according to different urgency levels, should it be an immediate, intermediate, or slow response. Sensor collaboration also provides redundancy and, thus, enables sensor system self-diagnosis or self-compensation, leading to a higher fidelity estimation of the true process status. Sensor distribution strategies, as we discussed in Section II, should aim at optimizing the collaboration among sensors in a network.

This paper identifies the following major challenges related to decision making for distributed sensing: 1) distributed and collaborative decision making; 2) distributed data collection and process control; 3) self-diagnosis and self compensation for high system reliability.

A. Distributed and Collaborative Decision Making

A distributed sensor system usually adopts a multilayer, hierarchical structure so that it can easily adapt to complicated topologies of manufacturing or other physical processes. Aggregating all of the data at the central controller for decision-making may not satisfy the timeliness requirements for rapid responses to catastrophic events. Additionally, passing along all of the data with unnecessary redundancy to the central controller will certainly put a burden on network communication and could cause serve data congestion and delay, especially for Internet-based remote diagnosis systems or when wireless sensors are being used.

Ideally, certain event of interest will be detected in a distributed manner based on the local measurements of smart sensors equipped with local processors. By local information processing and exchange, a consensus on a reduced dataset will be made and sent to a cluster head at the next layer. The cluster head (serves as an intermediate fusion center) will combine the decision from the sensors in the same vicinity and decide on what type of information is to be transmitted to the next layer and what kind of control decision should be fed back to individual sensors. In this way, the cluster heads could further compress the preprocessed data to avoid the creation of a communication bottleneck within the network. Certainly, it is also of interest to consider the case where the local decisions made at a number of sensors are communicated to multiple cluster heads for data fusion.

The hierarchical architecture designed above enables us to combine the benefits of the fully distributed and fully centralized configurations. The fundamentals of distributed detection and estimation are given in [85]. Either the Bayesian hierarchical model or the Neyman–Pearson criterion can be used to combine local decisions at a fusion center to generate a global decision. Usually, a set of hypotheses will be initiated. Upon new observations, new hypotheses may be formed and old ones will be updated, combined, or eliminated so that the new set of hypotheses will generally have a higher probability confidence. One approach using the Neyman–Pearson formulation is to determine the optimum local and global decision rules that minimize the global probability of miss detection (or equivalently maximize the global probability of detection). When the sensors are deployed so that one observation is independently conditioned on observations from other sensors, one can show that the data-fusion rules are threshold rules based on likelihood ratios [37] and then the problem now becomes one of determining the optimal threshold at each sensor, as well as at the fusion center. For the recent development of hierarchical data modeling methods for supporting multilevel decisions, please refer to Wang *et al.* [86].

B. Distributed Data Collection and Process Control

The advancement of distributed sensing techniques also provides opportunities for inline automatic control of complex manufacturing systems. In general, an automatic control strategy is widely used to control an individual machine or device, where the dynamic equations are readily available to describe the system behavior. However, it is difficult to obtain a model to describe a complex manufacturing system where multiple machines, or variables, are interrelated in a process level. For such a system, the design of experiment (DOE) methods [87] is normally employed, performing experiments and obtaining empirical models to describe the interrelationships among various variables. When distributed sensing is available, the inline sensing capability is greatly improved and some noise variables can be either directly measured or estimated through measured quantities. The concepts of DOE-based automatic process control are introduced recently to adjust the controllable variables during production based on inline sensing data [88], [89]. Fenner, Jeong, and Lu [90] provided a framework of developing two-stage automatic control schemes, where the state-space model was used for incorporating sensor data collected at several process stages.

In building the state-space model of sensor data collected at various stages for developing a multistage process control rule, it is important to include the knowledge from the physical processes for designing distributed data-collection schemes. For example, when some of the process stages are critical, but placing sensors there could be technically difficult or costly, sometimes the physical model, such as the chemical kinetics $SiH_4 \Rightarrow Si + 2H_2$, allows us to locate other measurable variables (see [91] for details). In this example, when one Si atom is deposited, there are two H_2 molecules released in the gas phase. Thus, the sensor on H_2^+ intensity can tell us how much the Si atom is deposited.

For handling the possibility of multiple goals and ownerships in different process stages, the work in [92] of using the game theory [93] to structure the negotiation and coordination between partners is needed. This reference provides a framework of how partners can work together to decide robust process conditions for each process stage. The ideas presented in this section need to be extended to general distributed framework beyond serially connected multistage manufacturing systems.

C. Self-Diagnosis and Self Compensation for System Reliability

Even if a single sensor is relatively reliable, the large number of sensors in a distributed sensor system presents a high probability that at least some sensors may malfunction. Without isolating sensor anomalies from underlying process changes, abnormal sensor readings can cause frequent false alarms and jeopardize information fidelity. Sensor self-diagnosis identifies malfunctioning sensors and, thus, improves sensor system reliability.

Traditionally, sensor system reliability has been ensured by employing offline gage repeatability and reproducibility (R&R) calibration [94]. But this can be time consuming and costly for a distributed sensor system. A sensor failure can be diagnosed by including built-in test equipment and monitoring a few vital physical parameters such as voltage or current [95], [96]. However, several problems arise in implementing such a "hardware" approach. The monitoring system itself is subject to failure, monitoring of which requires another test system. This would prevent adequate monitoring that assures the system work as intended under all conditions.

Sensor redundancy in a distributed sensor system is the fundamental reason to enable sensor self-diagnosis (i.e., it allows for decisions regarding sensor failure to be based on the outputs of sensors themselves). The key to detecting sensor failures is to analyze the residual based on actual redundant observations. Under normal work conditions, sensor noise should have zero mean and also show close agreement between the observation and expected nominal behavior of the system. Any residual reconstructed from the observation that indicates a discrepancy between observed and expected system behaviors can help track the sensor failure that is responsible.

It is noted that residual analysis is also used in statistical process control (SPC) monitoring for an autocorrelated process [97], [98]. The difference is that the SPC approach assumes that sensors are working as intended and the changes are from the underlying process that is being monitored by the sensors. For sensor system self-diagnosis, however, we need to project an observed signal into a subspace that contains only the sensor noise so that sensor failures can be isolated from the underlying process changes. To that end, parity space approaches [28], [29], [99]–[101] developed from control theory for detecting abrupt changes [102] appear to meet this requirement and may be a promising technique that is worth further exploring.

According to each type of sensor anomalies (e.g., drift, shift, or wild reading), subsequent actions for compensation will decide if the reading should be completely discarded or if it may provide partial information for process fault diagnosis. Prior information from the historical sensor data, their anomalies, and corrective actions could be formulated into probability distributions by using cluster analysis. Combining this distribution with new sensor data described by the likelihood model characterizing the current data distribution, one can formulate Bayesian posterior distributions for predicting sensor failure probabilities and deciding appropriate corrective actions.

V. Examples of Applications and Opportunities

This section will present a few examples of applications of distributed sensor systems. They are mainly based on the research experiences of the authors. The intention is to provide engineering backgrounds and outline potential applications to the above discussions on technical challenges and theoretical developments. It is not intended here to cover the application domains all inclusively. For a more comprehensive discussion on applications, please refer to [4], [103], and [104].

A. Structural Damage Monitoring and Maintenance

One of the interesting applications of determining the optimal locations of sensors is related to the monitoring of the structural "health" of engineering structures [105]. Researchers have presented several methods for determining the optimal number and location of sensors in engineering structures, such as towers, high-rise buildings, tunnels, and bridges. These methods are based on different optimization techniques. In most of these published studies, many variables have been investigated. These include the number and location of sensors, number of structural degrees of freedom, number of tests, and number of structural modes. Almost all of these studies assume that the location and the magnitude of damage are known *a priori,* before locating the sensors [106]. However, the variability of the location of the loading source has not been well investigated. We illustrate how the optimal locations of sensors (issues related to Section II) in a complex engineering structure are determined by citing Ettouney *et al.*'s paper [106]. They investigate a suspension bridge (Fig. 3) subject to two loading conditions, and their combination. The first loading condition is the vertically applied dead load (DL) and the second is the horizontal seismic

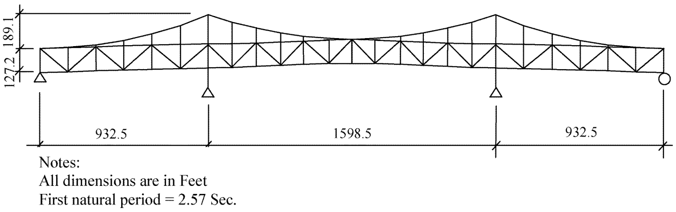


Fig. 3. Suspension bridge body.

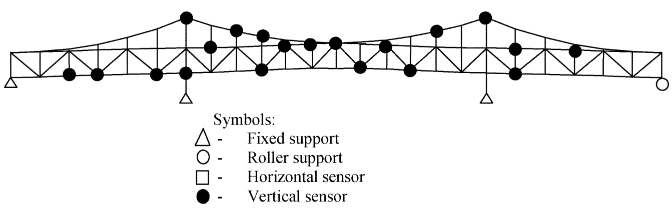


Fig. 4. Optimum sensors location under uniform damage criterion.

loading (SL). The combination of these two loading conditions is assumed as the basis for any damage that might occur to the bridge.

They also assume that the number of available sensors for damage detecting is 20 and that the optimal sensor location is determined independently from the loading conditions. Fig. 4 shows the optimal sensor location (OSL) when uniform damage in all of the structural elements is assumed. The figure also shows that all of the sensors that were computed with the uniformity assumption are vertical sensors.

Ettouney *et al.* [106] use the goal programming technique to determine the optimal locations of the sensors under the two loading conditions. The weighting factors for each of the two optimum conditions were the design load factors applicable to each loading condition. The resulting OSL for the combined case utilizes only horizontal sensors and their locations are different than those shown in Fig. 4. Further information is given in [106].

B. Diagnosis and Prognosis for Equipment and Facility Through Multisensor Data Fusion

Example 1. Complex Cycle-Based Signals in Sheet Metal Stamping: Sheet metal stamping is a complex manufacturing process widely used in the automobile, aerospace, and appliance industry to produce the metal product by deforming the sheet metal according to the prefabricated geometry of a die. Stamping tonnage sensors are used to monitor process changes and potential process faults. A stamping press with some process variables is shown in Fig. 5. Four tonnage sensors (strain gauge sensors) are distributed on the four press uprights (or on the two linkages). The total stamping force is obtained by the summation of these tonnage forces. The right graph insert shows one cycle of a total tonnage signal measured from a double-action forming process. Based on engineering understanding, a few features related to certain process faults are indicated therein. For more details of a stamping process, please refer to [107].

The tonnage signal is generally known as a functional signal. Characterization and control of functional signals present

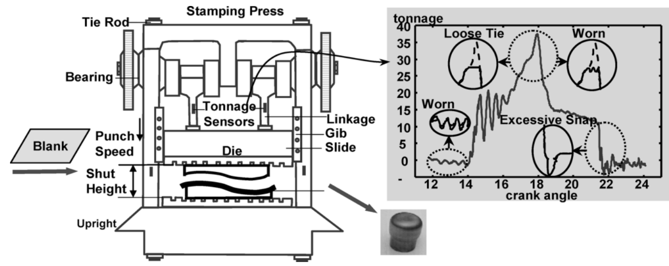


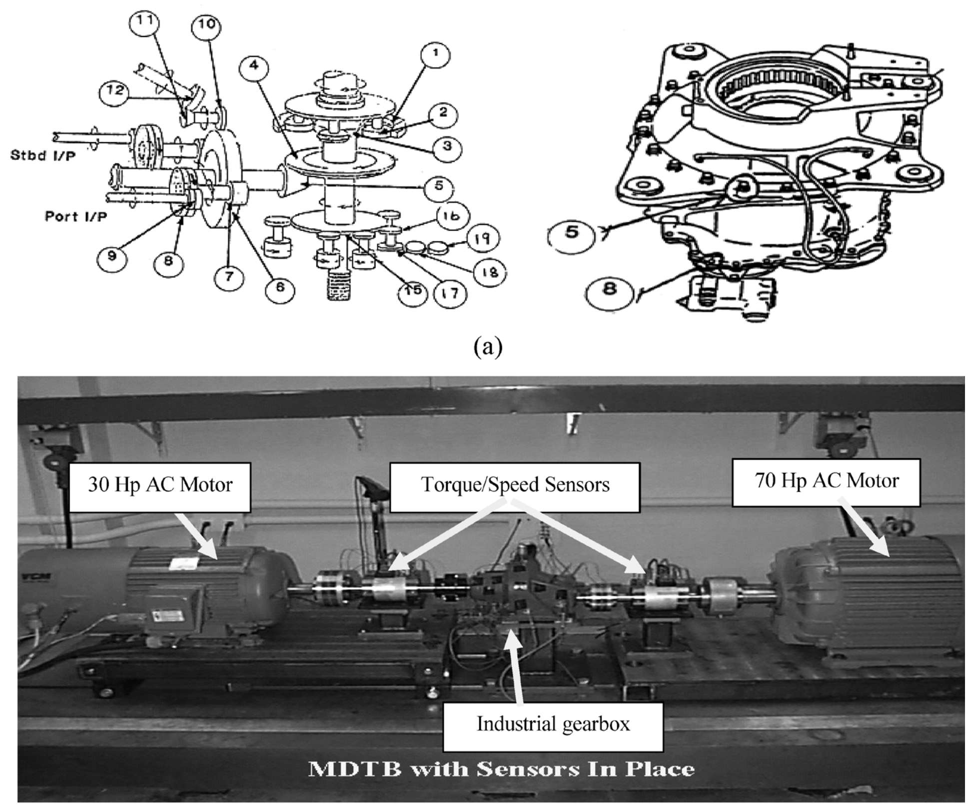
Fig. 5. Stamping press and tonnage signal features.

challenges related to information processing criteria (Section III-B) and feature extraction technique (Section III-C). Given its complicated contour, it is difficult to benchmark the shape of the signal under a normal process variation so that a multivariate statistical control can be established for detection and monitoring. It is more challenging to develop sensible information criteria for feature characterization, extraction, and data compression. Some recent developments are made mainly using wavelet transform techniques, including multilayer coefficient selection criterion based on signal segmentation [49] as well as a criterion called relative reconstruction error [48]. Empirical evidences showed that they achieved a much higher data-compression ratio if appropriately implemented. The tonnage signal was also used for the purpose of process monitoring and fault diagnosis through efforts such as feature extraction [108], [109], sensor fusion [110], and signal decomposition [111], [112].

Example 2. Diagnostics for Westland Helicopter Main Transmission: Sensor data representation and data fusion is critical to the distributed sensor problem. Fig. 6 represents two test scenarios. For a detailed discussion, the reader is referred to [45] and [113].

Westland Data obtained from Westland CH-46E aft main transmission consists of eight accelerometer signals for each of the 68 no-fault and seeded-fault runs. Only one faulted component is embedded in the gearbox during data collection. The types of fault embedded are 1) planetary bearing corrosion, 2) input pinion bearing corrosion, 3) spiral bevel input pinion spoiling, 4) helical input pinion chipping, 5) collector gear crack, 6) quill shaft crack, and 7) no defect. During every experimental run, vibration signals were collected from eight accelerometers, mounted at different locations on the transmission at 103 116.08-Hz sampling rate with 16-b quantization.

Mechanical Diagnostics Test Bed (MDTB) is constructed at the Applied Research Lab (ARL) at Penn State University to generate a gearbox's mechanical failure test data. MDTB is composed of a 30-hp, 1750-r/min ac motor and a 75-hp, 1750-r/min ac motor. The gearbox is driven by the 30-hp ac drive motor and the torque is provided by the 70-hp ac absorption motor. The gearbox tested is the Dodge single reduction helical gearbox with a reduction ratio of 1:1.5 and a maximum power rating of 10 hp with an input speed of 1750 r/min. The motors and gearbox are hard-mounted and aligned on a bedplate which is able to prevent vibration transmission to the floor. Ten accelerometers are placed on different locations on the gearbox and torque sensors are mounted on the input and output sides of the gearbox. The gearbox was run at different loading levels



(a)

(b)

Fig. 6. Sensor locations for Westland helicopter gearbox and mechanical diagnostics test bed.

in order to accelerate gearbox failures. The data is collected in 10-s windows at set times and triggered by accelerometer root-mean-square (rms) thresholds.

The sensor signals in both of these experimental setups were represented using wavelet transforms (WTs). The WT is capable of decomposing a signal into different frequencies with different resolutions [multiresolution analysis (MRA)] (i.e., it provides time-scale (frequency) representation of a signal). Moreover, when an orthogonal WT is used, Parseval's theorem is readily applicable such that the energy of a signal $x(t)$ can be related to the energy in wavelet coefficients and the energy in the transformed domain is partitioned in time and scale space. This distribution of energy of the signal can be displayed in the form of two (time–scale plane) or three (time-scale-amplitude) dimensional plots called a wavelet scalogram. Patterns in the scalogram make it possible to visually interpret important signal attributes, such as the pattern of the signal evolution due to a fault in the gearbox. The scalogram thus can help identify robust features to be used in diagnosis and prognosis.

In this example, the Morlet wavelet is used as a prototype function (mother wavelet). The Morlet wavelet is defined as the product of a complex exponential and a Gaussian envelope. The computation of wavelet coefficients is performed by convolving the signal $x(t)$ with the Morlet wavelet samples. Patterns in the scalogram make it possible to visually interpret important signal attributes such as the pattern of the signal evolution due to a fault in the gearbox and, thus, the scalogram helps identify robust features to be used in the classifier as well as the predictor. The leakage of energy into different bands of frequencies has a slowly increasing trend in the beginning and as the condition of the gear reaches imminent failure condition, the slope tends to be steeper. Based on this observation, a fault severity index is computed. If the value of the fault severity index crosses the threshold, it indicates that a defect in the gear is severe and failure is imminent so that appropriate maintenance action needs to be taken. The information obtained from the fault severity index is useful in implementing an anticipatory maintenance system.

C. Distributed Sensing in Multistage Hot Deformation Processes

In a hot deformation process (e.g., forging and rolling), there are multiple, different types of sensors embedded in manufacturing equipment and processes. As for the example shown in Fig. 7, more than 50 sensors are distributed along the production line of a crankshaft forging process, which includes two parallel induction heating lines, six forging stations, two quality inspection stations, plus a number of material handlings and cooling stations. The duplications of individual sensors are indicated by a number in the legend of Fig. 7.

The hot deformation process exemplifies many characteristics of a general multistage manufacturing process (MMP) and the associated distributed sensor system therein. It is usually difficult to identify the manufacturing root causes in an MMP since quality defects that are detected on the current station could be caused by variation transmission and accumulation from upstream stations. When in-process heterogeneous sensors are deployed along the production line to measure quality characteristics of intermediate products, a distributed sensor system pro-

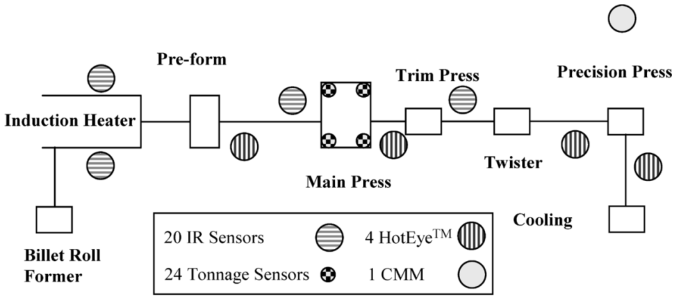


Fig. 7. Sensor distribution in a forging process, where IR stands for infrared and HotEye is a type of imaging sensor that can measure high-temperature subjects.

vides a greater capability of tracing down a root cause by processing quality information retrieved at different stations.

Conventional solutions attempt to apply the statistical control technique to every single station in an MMP since the root cause within a single station is easier to identify. The implementation of this solution is neither necessary nor economical since it involves obtaining the measurement, constructing the controller, and implementing control charts at each station. In fact, this solution overlooks the inherent relationship among different stations. As a result, a vast amount of useful information is not fully utilized to reduce the number of sensors, actuators, and control charts. In other words, the in-process data analyzed by statistical tools will not be effective if there are no methodologies to determine the types of data needed and the location where they should come from. Fundamental research issues (related to Sections II, III-A, III-B, IV-C) can be summarized as: 1) how to coordinate the information obtained at different stations; 2) how to quantify the performance of a distributed sensor system in MMPs [23], [24], [114]; and 3) how to optimally distribute sensing stations and determine the sensor number at each sensing station [30], [115], [116]. The application of distributed sensor systems in MMPs has drawn considerable recent attention, some of which addresses this hot deformation process specifically [117], [118].

D. Factory- or Enterprise-Level Distributed Sensing and Coordinated Decision

Sections V-B and V-C illustrated examples with mechanical systems. This section utilizes semiconductor manufacturing systems to show the potential of the procedures presented in Sections III and IV in factory- or enterprise-level operations. A typical factory for manufacturing semiconductor devices (e.g., microprocessors, memory chips, and microcontrollers) is organized around many workstations coordinated with each other for production scheduling, material handling, and inventory control policies. Most of the machines in the workstations are equipped with sensors and controllers for monitoring and controlling production. Each batch of products is routed through these workstations as the devices are built up layer by layer on the wafer surface. For efficient use of machines, a lot usually revisits the workstations many times for different layers of processing. Due to the possibility of products being rejected or requiring rework, these routes are often probabilistic. Thus, there are usually many different classes of lots in the queue of each workstation waiting for further processing. The classes are differentiated by product type and, within each type, are differentiated by which stages in the process the products have gone through.

In real-life applications, various production scheduling algorithms decide which machine shall work on what lot next when it finishes processing the last lot (or finishes being repaired, which may happen all too often). Inventory control rules make decisions on when to release a new lot of semifinished products into the manufacturing line and when to order new raw materials and components upstream in the factory and supply chain. Until now, in the semiconductor factory, most production scheduling and inventory control models plan for a shift or a day ahead of schedule. With the data collected from various sensors, one can extend the scheduling and inventory models to dispatch production lots and order supplies in real time. The decision models established in Sections III and IV from various sensor data provide the real-time status of the product, machine, and process quality. When these models built on sensor data make predictions about future changes in machine availability or product yield, the scheduling and inventory models can include those predictions in its parameter set so that decisions can be made based on both current and future conditions.

The extended scheduling and inventory models will help us realize the impact of the sensor information and will drive new production control policies. For example, when a machine quality model (built from sensor data) indicates that this machine is not doing well (such as when many SPC alarms have occurred), the scheduling algorithm should request preventive maintenance (and expect an increased likelihood of a failure until the maintenance occurs). For the workstation containing the machine, its average throughput will suffer. Thus, the scheduling algorithm should re-route some of the lots at upstream workstations to slow down the use of this workstation. If the problematic workstation is a bottleneck, the inventory control algorithm shall cut down the release of new lots into the factory and reduce the orders of raw materials and components from the supply chain.

In conclusion, sensor data models will provide a better understanding of the functional status of the manufacturing systems. The average cycle time and inventory cost (and their variations) should become lower than that without the models built with sensor information.

E. Integrate Cyber and Physical Spaces Through Wireless Sensors

Wireless sensors provide an interface between cyber space and the physical world. Cyber space is built primarily for communications purpose. The physical world, where data/information are generated, includes both natural and manmade systems. The promise of (wireless) sensor networks is to enable the person-to-things and things-to-things communication by embedding processing and communication into the physical world or equivalently presenting the physical world in cyber space [119], [120]. One application area in the industrial monitoring and control is the heating, ventilating, and air conditioning (HVAC) of buildings [121].

In most, if not all, buildings with HVAC systems, the number of sensor nodes (thermostats and humidistats) used to control the HVAC system is mainly limited due to the cost associated with their wiring connection to the rest of the HVAC system. Generally, there is less than one sensor node per room in office areas. As a result, the location configuration of these sensors, as well as the air handlers and dampers, has to be optimized in order to have proper HVAC control. However, such a configuration optimization can be quite challenging due to the dynamic nature of heat sources (moving of people and equipment) and the frequent physical changes in the buildings, such as the addition and removal of walls and conversion of office areas to lab and factory areas or vice-versa. This will lead to an inconsistent and/or nonuniform HVAC environment conditions. The underlining root cause is the lack of sufficient information about the environment in the building for the HVAC system to make proper control adjustments at various locations.

By eliminating wiring and, thus, the associated cost, a large number of wireless sensors may be employed to solve the above problems. The addition, relocation, and removal of wireless sensors are quite effortless. Redundant nodes may be deployed for the fault-tolerance purpose. Furthermore, people and equipment with wireless sensor and/or communication nodes will be able to communicate with the HVAC system regarding their needs and environment conditions. An HVAC system will measure its performance according to the comfort level of all objects (people, equipments, etc.) it serves. The HVAC system may not satisfy the needs of all objects in its environment but will inform the objects the possible environment condition changes due to its upcoming actions. The objects may take certain actions, such as moving to different locations or changing the physical conditions of the environment (e.g., opening doors, etc.).

The low cost, abundance, and convenience of wireless sensors are not coming without new challenges. Most of the wireless sensors do not know their physical positions at the deployment except their topological links to other nodes in the wireless sensor networks. Also, they may be moved around for various reasons. Therefore, a mapping of the physical world onto the cyber space must be done [119]. The system may be overloaded with data collected, fundamentally due to the fact that the physical world generates an unlimited quantity of data for observation, monitoring, and control. In some cases, the available sensor nodes are overly redundant as to deteriorate the communication quality, and the system may need to selectively silence or lower the transmission frequency of some sensors. These challenges align with issues addressed in Sections III-A, III-B, and IV-A. Which sensors are to be selected is again the problem of the optimal sensor configuration but viewed from a different angle. The data collected by multiple sensor nodes monitoring the same room may be inconsistent. The wireless actuators, such as handlers and dampers, may not have a geometrically correct association with the wireless sensors and, thus, may lead to the HVAC changes in the unintended areas. These challenges will thus demand more robust, collaborative processing (Section III-D) and reliable decision-making enabled by self-diagnosis and self-compensation capability (Section IV-C).

VI. Concluding Remarks

This paper is based on a panel discussion which was convened during the 2003 annual meeting of the Institute for Operations Research and the Management Sciences (INFORMS) in Atlanta, GA. It discussed the technical challenges related to distributed sensing, which are grouped into three inter-related categories of optimal sensor distribution, information processing, and optimal decision-making.

Advancements in distributed sensing will be expected to generate a far-reaching and long-lasting impact on every aspect of our lives. The panel feels that the following factors and their intricate interactions contribute to the challenges related to distributed sensing: the complexity of physical systems, the uncertainty and heterogeneity of information, the high dimensionality of sensor space and information space, and the increasing expectation and requirement on decision-making capability. A technological breakthrough in distributed sensing will be likely made by innovatively integrating knowledge and methods of physical modeling, statistics, operations research, and information technology. Consequently, for addressing the wide range of technical challenges, specific application domains will be explored first and methodology integration will come later.

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