Sense of Sensing: From Data to Informed Decisions for the Built Environment

Steven D. Glaser[1] and Anne Tolman[2]

Abstract: There is currently an explosion of research on microsensor and wireless network technology, and methods of discerning structural state from such data. Besides the inherent interest in such fascinating technology, the question remains as to why an owner, operator, or user of the built environment should care. The construction industry is now adopting new types of contracting practice. Previously the contractor simply implemented a given design, but the current trend is for clients to commission certain performance requirements to be met with performance-based design. The emphasis of the industry is becoming the delivery of certain structural behavior states rather than simply building to a client's set plans. The contracting process becomes the determination of the performance criteria, and delivery becomes a long-term fulfillment of these criteria. This can only take place if the performance states can be measured, and the measurement utilized in a decision-making process. The tools needed for both the evaluation of the delivery after construction and during operation are changing accordingly. The process is increasingly dependent on densely spaced sensor data, valid models to turn the data into physical behavior, and decision-making tools to determine whether the performance requirements are being met. This process must take place in order to satisfy all stakeholders. This paper describes the approaches in monitoring the performance, the obtaining of data and refining into information for decision making. Example cases concern the continuous performance and condition monitoring within buildings and civil structures, and indicators of the economical impacts of informed decisions including structural safety, hygrothermal, and energy aspects. A case study of structural health monitoring of the Golden Gate Bridge is also presented. The enabling sensor technology is described, and the exploitation of the data for life cycle needs is discussed.

DOI: 10.1061/(ASCE)1076-0342(2008)14:1(4)

CE Database subject headings: Information management; Life cycles; Infrastructure; Performance characteristics; Project management; Sensors; Structural behavior.

Introduction

The creation of small, cheap, and accurate sensors and wirelessly linked sensor networks has allowed fantastic technological feats and innovations. Although allowing for the intrinsic value of such knowledge, a fundamental question must be addressed. Why should owners, contractors, designers, and users care and foot the bill? The purpose of the paper is to address just this problem, not to propose new techniques of sensing and data interpretation or to serve as a state-of-the-art compendium on these subjects. This is done overtly, and much better, by papers such as Lynch and Loh (2006) or Glaser et al. (2005).

All stakeholders want to know what their structures are doing. By stakeholders we mean owner, architect, engineer, zoning board, user, insurer, safety personnel—everyone involved with the structure from inception to demolition. "Structure - anything built by people, from a dam built of earth or a pyramid of stone to a power station or an earth satellite." (Scott 1993). The purpose of this paper is to discuss new aspects of measuring structural performance, the sensor data produced, and the conversion of such data into the useful information needed by the stakeholders. Current enabling technologies, and obstacles of data exploitation for valid decision making, are described in the context of two developed countries, the United States and Finland. Concrete cases of collection and utilization of data transformed into information are used to demonstrate the state of the art. Aspects of ownership, publicity and privacy of data, and refined information are also discussed.

[1]Professor, Dept. of Civil and Environmental Engineering and the Center for Information Technology Research in the Interest of Society, Univ. of California, Berkeley, Berkeley, CA 94720. E-mail: glaser@berkeley.edu

[2]Senior Research Scientist, Business and Process Management, VTT Technical Research Center of Finland, P.O. Box 1100, FI-90571 Oulu, Finland. E-mail: Anne-tolman@vtt.fi

Note. Discussion open until August 1, 2008. Separate discussions must be submitted for individual papers. To extend the closing date by one month, a written request must be filed with the ASCE Managing Editor. The manuscript for this paper was submitted for review and possible publication on January 25, 2007; approved on July 27, 2007. This paper is part of the ***Journal of Infrastructure Systems***, Vol. 14, No. 1, March 1, 2008. ©ASCE, ISSN 1076-0342/2008/1-4–14/$25.00.

Why We Need Sensors

Performance-Based Building

The necessity for improved performance and condition monitoring in structures arises from the recent performance-based building methodologies. Performance-based building has come to the fore over the last 10 years, when changes in the client–provider relationship were mandated by the World Trade Organization (WTO 1997) with the 1997 Agreement on Tariffs and Trade. "Whenever appropriate, Members shall specify technical regulations based on product requirements in terms of performance rather than design or descriptive characteristics." Since 2000, in the Federal Acquisition regulations, the United States government has made performance-based contractiong mandatory. In Europe, there are many initiatives, both at the national and at the Union level, such as the Construction Product Directive, to promote the same end. This necessitates a standardization effort to describe the target performance rather than the structural solution, and has led to developments such as the CIB Proactive Programme for Performance Based Building Codes and Standards (Foliente et al. 1998).

Performance-based building (PBB) differs from traditional practice in that it does not prescribe how to get things done. A prescriptive approach "describes means as opposed to ends, and [is] concerned with type and quality of materials, method of construction, workmanship, etc." (Gibson 1982). In a performance-based approach, all decisions, choices, and tradeoffs start with the required behavior-in-use rather than prescribed solutions for how to meet the stated needs. The supplier responds with an offering that includes the estimated performance of that offering. A validation method, through measurement, calculation, or testing, is necessary to evaluate the performance (over time) and to compare alternative solutions (Szigeti and Davis 2005). How that performance is established, verified, and validated is one of the areas that needs much further research (Szigeti and Davis 2005).

Whether the PBB approach is used explicitly or not, a required performance is always embedded in the building process. It is important for the project delivery team to be able to predict not only the performance of the parts, but also how the whole will perform when all the parts are synthesized (Szigeti and Davis 2001). During operation, both performance and condition must be monitored with sensors. The statements of user requirements [i.e., according to definitions per ISO (1984)] provide the reference point of a facility or constructed asset, as a complete product. PBB changes the time scale of the contracting process. Traditionally the contractor produces a structure to some stated specifications as to materials, assembly method, finish, etc., mandated by the architect/engineer. Once the building is accepted by the owner, the design/build team no longer plays a role. In the PBB environment the design/build team must warrantee and maintain structural performance to the level stated in the contract, for the extended duration of the contract. This requires measurement, hence sensors.

An example is the recent contracts for the E18 motorway near Helsinki, Finland. The Finnish Road Administration (Tiehallinto) E18 Muurla-Lohja project includes the construction of 51.3 km of new motorway, seven motorway tunnels with a total length of 5.2 km, eight interchanges, and 48 bridge sites. In February, 2004, the Government Ministerial Committee on Economic Policy, Finland, decided that the project will be implemented as a Design Build Finance and Operate (DBFO)-based life-cycle contract. A DBFO represents a fundamentally different alternative mode of project delivery and should not be regarded as a mere variation of traditional project delivery (Murtoaro 2006). The contractor is the service provider; the client (in this case, Finnish Road Administration) pays an annual charge, and no toll is collected from the actual users. The customer defines the quality of service and pays the service provider according to whether the agreed level has been achieved (Tiehallinto, Finnish Road Administration 2006). The service provider delivers a transportation corridor meeting quality standards such as surface reflectivity and roughness, skid resistance in a snow storm, salt runoff, etc., for a period of over 20 years. The service provider is responsible for not only designing and constructing, but also for funding the investment, and for the related routine and periodical maintenance operations from the date the agreement enters into force until the date on which the period of agreement ends. The service provider is also responsible for any needed repairs during the agreement period. At the end of the period, the motorway is transferred to the client (Tiehallinto, Finnish Road Administration 2004) after the service provider proves the roadway meets the quality requirements set by the initial contract (Tiehallinto, Finnish Road Administration 2006).

The actual performance assurance relies heavily upon sensor data. Modern traffic and road monitoring equipment will collect data both on the road and in the tunnels to provide traffic information, direct traffic, and deal with emergencies and safety. For example, performance of the thermal insulation of the tunnels is considered critical. Because of the long and severe winters in Finland, ice may form behind the insulation layers (despite the layers of water barriers and thermal insulation) and cause severe damage endangering the traffic zone. The tunnels are therefore equipped with two types of sensor systems on each structural component. The basic sensing is a permanent wired system, and a wireless sensor system is utilized for critical and emergency conditions as needed. The sensor data will be used for documenting performance and for improving the technical design of the structures, whereas an interactive graphical user interface supports continuous decision making (Vupio, personal communication, 2007). Thus the sensor system serves the needs of both the customer and the service provider.

PBB evaluations can and should be performed in a routine manner. In practice, evaluations are often made only as part of commissioning or shortly thereafter, or when there is a problem. In order for any measurement and evaluation to be truly meaningful, they should refer to explicit requirement levels against which they can be judged. The performance of a building has some physical factors that serve as principle indicators. For condition monitoring, temperature and humidity are key indicators, which are also major factors for performance evaluation. In the use phase, maintenance and energy consumption are the main cost components, and directly relate to user comfort and services. All these items can be objectively evaluated from sensor-provided data. In all, the only way to quantify performance is to measure performance indicators. This requires proper sensors and measurement techniques. The wider the variety of performance metrics that need to be determined, the more sensors are needed. This requires small, inexpensive sensors placed in dense arrays, with simple communications (Glaser et al. 2005).

Sensors

The scenario just described opens a new perspective for overall optimal life-cycle management, and the need for operational data is magnified. The new approach to commissioning and managing the built environment creates a demand for objective factual performance data. The client may wish to measure the output values of ready-made constructions. The contractor may demonstrate the compliance to the required performance. The facility manager starts utilizing the performance data to optimize operation-phased maintenance and economy. Proactive interventions can be made when performance indicators start to deviate (e.g., Yanev 2003). Alarms can be generated based on deviations in the performance data, and repair plans augmented with actual real time data. The obvious needs for sensor-generated data offers business potentials for an entire new category of performance and condition monitoring services.

In order to determine the state of a structure, pertinent parameters must be measured. For this measuring devices called transducers are used. A transducer is a primary sensing element that receives energy from the measure and, and performs a deterministic mapping of the input to some output in a more useful energy domain (transducer–transducera–to change). For example, in a simple bathroom scale a spring deforms in proportion to your weight, and the deformation is transformed into a movement of a dial past an indicator. In order to develop useful transducers, it is critical to first understand the physics of the parameters to be measured. Only then can appropriate transducers with the necessary operability be developed.

A scale is an example of a mechanical transducer—mechanical in, mechanical out. Mechanical sensors require remarkably complex linkages and mechanisms to do their work (e.g., Brown 1987). Over the last 75 years, electromechanical transducers have come to the fore. The measurand is still some mechanical or chemical variable, but now the measurand is transformed into an electrical signal—opening up enormous varieties of signal output for the user. An example might be a linear variable transducer that transforms linear motion into a proportional voltage signal. Regardless of type, transducers all have the same logical elements. It must also be noted that any transduction process always costs energy, and any transduction process always affects the signal being measured (e.g., Fraden 1993).

Engineers are now in a position to refine the existing measurement paradigms by utilizing micromechanics and microcircuitry made possible by microelectromechanical systems technology (MEMS). MEMS are micron-scale mechanical devices "machined" out of silicon by the same processes used to fabricate integrated circuits (Senturia 2003). These are often the same mechanical subassemblies that are part of the traditional macrotransducer. The process also allows near-seamless integration of electrical and electromechanical components to the mechanical. An example might be the interdigitated electrostatic drive/sense plates in an Analog Devices ADXL 202e accelerometer (Analog Devices, Cambridge, MA, 2006). Because the process elements and internal linkage movements are now small, these MEMS-based transducers consume very little power. Because of the nature of the production process, like for an integrated circuit, a large manufacturing run means very low piece costs (if the pieces are actually sold). The low cost, low power, and small size of MEMS-based transducers have revolutionized what can now be measured.

Traditionally the term sensor has been synonymous with transducer. However, a "sensor" will here be defined as comprising the traditional transduction elements along with substantial signal processing and computational ability (e.g., Glaser et al. 2005). These sensors can also be combined into comprehensive miniature sensing platforms incorporating transduction, signal processing, computational power, and wireless communication—platforms that are called Motes (e.g., Glaser et al. 2005; Lynch and Loh 2006; Huang 2003; Hill et al. 2000). In turn, Motes are combined into large, organic, networks which allow dense, detailed sensing, opening a new paradigm where the network is the sensor. Smart devices that self-assemble into networks is a concept that the research community is not necessarily familiar with. The paradigm of sensor networking allows engineers and scientists to move beyond the idea of a sensor as a single instrument that measures one thing, to a system of many small nodes working cooperatively. Mote networks have been used in all varieties of ingenious applications such as monitoring the falls of the elderly (Jafari et al. 2007), measuring accelerations at a hundred points along the Golden Gate Bridge (Pakzad et al. 2008), environmental conditions in a Redwood grove (Szewczyk et al. 2004), structural health of bridges (Kim et al. 2006; Garcia and Stubbs 1997), etc. The Mote is now becoming ubiquitous, with several companies, large and small, selling them, e.g., Shinkawa Sensor Technologies, Dust Networks, Telos, Crossbow, and Microsense. In this paper, it is the revolutionary flexible Mote sensor platform that will measure structural state and provide corresponding data. It should be noted that the rapidly deployable Mote networks are perfect for any sudden or temporary monitoring situation. They are therefore an important tool in emergency applications such as reacting to typhoons, earthquakes, landslides, traffic incidents, man-made disasters, etc.

Given the second law of thermodynamics, there is a limit to the amount of information that is present in a signal. It is possible to quantify this using the signal-to-noise ratio (S/N). This implies that the finest resolution of the measurand can be no smaller than the noise level. For large civil structures in everyday use, the noise levels are large whereas the signals from localized damage are small, resulting in a small S/N. By using spatially dense sensing networks of inexpensive wireless Motes, the finer granularity supplies additional information whereas the noise remains constant.

With power and bandwidth at a premium in a network of battery powered Motes, embedding some local processing capabilities within the sensor networks is desirable. For example, the temperature data gathered from numerous sensors could be fed into one or more other sensors on the network for processing. A weighted average could then be calculated and transmitted to the user, significantly reducing the amount of data flying around the network. Further, software users must be able to query the sensor network as a user-friendly virtual database rich with raw information about the world of interest.

An interesting example of network processing is presented by Zimmerman et al. (2008). They describe an experiment to determine the modal behavior of the large balcony of the historic Fox Theater in Detroit. Because interprocess communication costs for a network of Motes is much greater in terms of power compared with local processing, the authors chose to solve a local output-only system identification model at each Mote. Each Mote identified the local frequency response function, which were then combined in the network to calculate the balcony's overall modal response. For this experiment of examining distributed processing three different output-only algorithms, peak picking, random decrement, and frequency domain decomposition, were adapted to use a minimum amount of Mote energy.

While offering many important benefits, it must be noted that wireless is not the only or best solution for a given situation. rf transmission uses great amounts of power compared to sensors (MEMS-based transducers and a microcontroller). There are problems ensuring privacy of the data transmission that have not yet been satisfactorily addressed. The quality of low power rf transmission is quite variable and susceptible to seemingly insignificant changes in surroundings. Such variables include orientation of antenna, distance from antenna to nearby structural elements, proximity of water-bearing bodies, fog, etc. (Kim et al. 2006; Ikegawa et al. 2006). Data transmission rates over low power rf networks are quite limited compared to the simplest wired bus. A single receiver can only receive one signal at a time, making true real-time operation impossible. In the huge realm of sensor possibilities, applications define network design.

Data and Information

The output of a transducer is raw data—analog or discrete numerical values proportional to the measurand with some statistically defined accuracy and variability (noise). Data analysis is the act of transforming data with the aim of extracting useful information and facilitating conclusions (decisions) (e.g., Berthold and Hand 2004). Depending on the type of data and the need for inference, this might include application of statistical methods, parametric and nonparametric parameter estimation, model-based inversion, selecting or discarding certain subsets based on specific criteria, or other techniques. To paraphrase Poincare, as a house is made of stones, information is made up of data; but a pile of stones is no more a house that lots of data is information. In comparison to data mining (e.g., Cherkassy and Mulier 1998), data analysis is usually narrowly focused. Whereas data mining is attempting to discover unforeseen patterns hidden in the data, data analysis is an attempt to verify or disprove an existing model, or to the extract parameters necessary to adapt a theoretical model describing (experimental) reality (e.g., Pierce 1980).

Data are a message transmitted and understood. Information, as used here, can be defined as an interpretation of data bits from which conclusions may be drawn. Information is the result of processing, manipulating, and organizing data in a way that adds to the knowledge of the person receiving it. Data are a set of transduced values, and are of no use until they are analyzed to establish relationships. Once a model reveals meaningful relationships among data, the data may be converted into information. These same data can be used for different purposes. Until the data lead to some information, they are not useful.

Data are valuable only if they are used. Given thousands of transducing devices, what will researchers do with all the data that's streaming in? Who is going to look at it all? For example, how much data does NASA throw away every day that nobody has ever looked at? To manage the fire hose of incoming numbers, data integration in a broad sense—processing and concentrating the data locally within the network—is needed. In the end, the user wants information, not numbers. One approach is to synthesize our design models with the data to be collected—sensing is a link between the real world and an abstract world. The user can then predict through simulations the expected system properties and whether the data interrogation is useful. This synthesis leads to adaptive data interrogation systems where the interpretive section of the loop can tell the sensor system to record on a different granularity or measure different variables. In any instance some aspects of the system—sensors or model—will be system independent whereas others will be system specific.

Data Ownership

Data have value both in-and-of-themselves, and, more important, when they are converted into particular information. Application of these data has different value to different stakeholders. The buyer of a property might put value on knowing past and present states of the structure; a maintenance firm might want to know what needs repair now, and when an item was last replaced (maintenance value); certainly the insurance company wants to know the physical state of the property, as does the mortgage company. The owner needs to know the state of their property for many reasons. Society, the variety of users, needs to know the state of safety or performance of a property. Finally there is bling value, where a trend-conscious owner wants to be able to tout the unique information they have about their property.

The ownership of data is not a clear concept. If a company is collecting data with sensors, does the company own the measurement results? Or are the results (data and information) owned by the client? Often this is not specified when a measurement task is commissioned. The client does get the data, but the data are also in the hands of the supplier. The delivery of the data does not mean that it has been removed from the supplier; data may exist both with the client and the supplier. If the government collects data for regulatory purposes, do the data then belong to the general public? There are also privately run utilities that end up being a private/government blend since by providing essential services they are under direct governmental oversight. This is especially true for electric, water, telecommunications, and gas utilities. In the United States, air transportation is greatly subsidized by the government through public support of airports and the air traffic control system. Privately owned toll roads are becoming more popular in the United States. Who owns data from them and who can use it, since in this case knowledge of where people are going is the start of a police state?

Informed Decisions

Decision making is the cognitive process leading to the selection of a course of action among alternatives. Etymologically, the verb "decide" is derived from Latin prefix "de" meaning "off" and the word "caedo" meaning "to cut." In this sense, decision making is some cognitive process to cut off a particular course of action from a set of possible alternatives. Every decision-making process implies a choice, which becomes the final decision upon implementation. Decision making is a reasoning process which is often classified into being either rational or irrational. However, rationality is closely related to subjectively expected utility; items may seem irrational in a technical or economical sense, but may yet serve some aspect of subjective satisfaction and therefore be subjectively rational. Decisions can be based on explicit or tacit assumptions, propositions held true. In this paper, the concept of rationality is limited to technical and/or economical aspects of the built environment, and subjective aspirations of the decision maker are excluded from the discussion.

Information is carried by symbols and is an objective (although abstract) commodity that exists independently of any person who may interpret the symbols. The information carried by a symbol is causally implied by the occurrence of a symbol (e.g., Pierce 1980). The information carried by a symbol relates to who produces it, why and how it was produced, and its relationship to the real world system state it signifies. Information reflects the intentions of the creator of the symbols. It is the propositional content of a symbol—that which is implied by the occurrence of the sign (Mingers 1995).

Information can be defined in terms of semiotics. Semiotics is the study of symbols, and semiotic theory concerns the use of symbols to convey knowledge. Stamper (1992) define six layers of properties for analyzing symbols. These layers are the physical, empirical, syntactic, semantic, pragmatic, and social levels. They note that all signs depend upon physical phenomena so that there is a layer of properties that are essentially studied by the physical sciences. The semantic level of representation concerns the meaning of symbols (Shanks 1999). The goal for the semantic level is that the representation is complete and accurate at particular points in time (Lindland et al. 1994; Shanks and Darke 1998).

The symbols and symbolic systems can be classified in relation to the way they are transmitted. Data which can be automatically processed by the application system correspond to the syntax level, i.e., the rules that govern the way words combine to form phrases and phrases combine to form sentences. In the context of an individual who interprets the data they become information, which correspond to the semantic level referring to the aspects of meaning that are expressed in a language, code, or other form of representation. Information becomes knowledge when an individual knows (understands) and evaluates the information (e.g., for a specific task). This corresponds to the pragmatic level.

The systems that provide means to automate the processing of data toward informed decisions are called decision support systems (DSS) or expert support systems. DSS have been under development for some decades (e.g., Simon 1978). DSS typically applies algorithms to reduce the effort of the decision maker. They have been successfully developed for practical applications in a variety of data-intensive fields such as in winter maintenance of roads (MDSS 2006), patenting (i.e., Chau et al. 2006), logistics (da Costa Sousa et al. 2003), marketing (Moutinho et al. 2000; Beifus et al. 1997), financial management (SmartQuant 2006), etc. Decision support systems may be simply information systems for processing data or knowledge-based expert support systems that, in a very different manner, support decision-making activities.

Reducing Data into Information

Model-Based Methods

Perhaps the major challenge in estimating the state of civil engineering structures (gaining information about) lies in developing robust condition models. For most typical civil engineering structures under hazard or normal (aging) conditions, there are no obvious models (e.g., Ciloglu et al. 2001). We do not even have a good definition of damage for many civil engineering structures. Once a structural state can be defined, it is possible to rationally address what to measure and how to directly interpret or relate the measured signals to the condition of given structures. The goal of structural state identification is to infer characteristics of structural systems, which cannot be measured directly, through the correlation of mathematical models and experimental response data. The model-based state detection methods often require updating a large number of parameters, especially when the structure has many structural members (e.g., Fritzen and Bohle 1999).

Model updating techniques require judgment for choosing likely parameters and locations in the structure that are potentially interesting (Beck and Katafygiotis 1998). The analytical model is typically highly idealized, and about which there exist significant uncertainties that cannot be fully validated with experimental data. For instance, one of the common underlying assumptions for system identification/finite element model updating is whether there exists a sufficient correlation between the measurable responses of the structure (e.g., displacement, strain, acceleration, etc.) and the desired unmeasurable attribute (e.g., structural parameters and damage), such that the attribute can be uniquely inferred through the system identification process (Friswell and Mottershead 1995). This correlation, however, is a function of the configuration, complexity, and redundancy, of the specific structure as well as the configuration, location, type, and number of sensors. For example, an ideal structure may show a strong and distinguishable correlation between natural frequencies and boundary conditions, whereas this correlation may be diluted or masked for a structure with significant levels of nonlinearity (Arici and Mosalam 2005).

Data-Driven Methods

Some users attempt to avoid the dependence on analytical models by performing data driven unsupervised learning. These approaches include novelty/outlier analysis (Sohn et al. 2006; Ruotolo and Surace 1997), statistical process control charts (Sohn et al. 2000), auto-associative neural networks (Bishop 1995; Chan et al. 1999), and simple hypothesis testing (Lapin 1990), and they have been shown to be very effective for identifying the onset of structural damage. Unsupervised learning can also be applied to data containing examples from a structure known to be undamaged, but this approach is inherently limited to only identifying the presence of change, which may be sufficient for many practical applications (Hastie et al. 2001). In supervised learning the model is trained with data from a state known to be healthy, and the divergence from this state quantified by reference to a constitutive-based model. In this methodology, data are from both the initial and changed condition, the supervised learning approach can be taken to classify and quantify system condition.

In the end, all state evaluation can be viewed as problems in statistical pattern recognition (Glaser et al. 2005; Sohn et al. 2000; Bishop 1995), in which the present state of the system is inferred by comparing test data with baseline data. Subtle signal changes due to changes in the variable representing the property of interest could be masked by larger operational and environmental variations of the in-service structure (considered "noise" in this case). It might also take several years of data collection before the test data corresponding to a damage case can be compared with baseline data recorded many years ago.

From the statistical point of view, data collected by sensor systems can be analyzed using either parametric or nonparametric approaches (Shumway and Stoffer 2006). The former rely on a specified physical model or functional form with parameters quantifying relationships between variables, whereas the latter make no outright assumptions about the system the analysis results will be applied to. The benefit of the nonparametric approach is that it does not require a priori physical models or mathematical functional form (e.g., Hung et al. 2003; Nakamura et al. 1998). This approach does require a significant quantity of measured behaviors containing signature information from both acceptable and nonacceptable conditions in order to detect and identify abnormal events. On the other hand, parametric models can be concise in expression and easy to interpret by using physical relationships to map data into useful information, which enables both spatial and temporal variations to be considered simultaneously (Liu and Yao 1978; Ljung 1987). Semiparametric models have also been used to characterize a changing system (e.g., Ching and Glaser 2003b). As physical models are approximations of real structures, uncertainty is introduced into the system which can be minimized by sharpening model assumptions using results of system response from known inputs. Addressing and characterizing uncertainties (model errors, measurement errors, unexpected operational and environmental variability) in these scenarios can be a key aspect for matching sensor data with analytical results (Ciloglu et al. 2001).

Reduction of Information into Decision Criteria

As the utilization of the condition and performance data has a variety of motivations, the information derived from the data has to be tailor-fit for the intended purpose. This can be solved through intelligent user interfaces to the sensor data. An important component of collected data is the metadata—data about data. Metadata describes how and when and by whom a particular set of data was collected, and how the data are formatted. Sets of metadata are useful to help describe characteristics of information-bearing entities to aid in the identification, discovery, assessment, and management of the described entities (Shanks and Darke 1998). For example, metadata can be created within a single server allowing limited access to various stakeholders with a relevant user interface. With multiple user groups, metadata describe all aspects of the system—data, activities, people and organizations involved, locations of data and processes, access methods, limitations, timing and events, as well as motivation and rules.

The decision-makers strive to achieve an optimum—the best (subjectively) expected utility. The criterion for the decision completely depends on the nature of the optimum. If perfect comfort is the aim, temperature and humidity are set according to the feelings of the experiencing person. But if economy is a key matter, the optimum is lowering the cost, allowing lower ambient temperature than what would be preferred for comfort alone. The constitution of decision-making rules is not quite trivial if subjective aspirations are given a significant role. However, here the intention is to limit the discussion to technical and economical optimality.

Business intelligence is the process of analyzing large amounts of corporate data, usually stored in large databases such as a data warehouse, tracking business performance, detecting patterns and trends, and helping enterprise business users make more informed decisions (e.g., Wilson and McDonald 2001; Berry and Gordon 1997). Business intelligence metadata describes how data are queried, filtered, analyzed, and displayed by business intelligence software tools, such as reporting tools, and on-line analytical processing (OLAP) tools. It is decision support software that allows the user to quickly analyze information that has been summarized into multidimensional views and hierarchies (i.e., Lau et al. 2002; Trujillo et al. 2001). OLAP is an approach to quickly provide the answer to analytical queries that are dimensional in nature. These business-driven data management tools may prove to be useful for the management of the built environment as well, as facilities management is becoming increasingly professional and also more prone to need technical description of actual performance.

Data mining [which is also called knowledge-discovery in databases (KDD) or knowledge-discovery and data mining] is the process of automatically searching large volumes of data for patterns such as association rules (e.g., Menzies and Hu 2003; Smirnoff and Maher 1998). KDD involves the identification of potentially useful and understandable patterns in these data (Simoff and Maher 1998); although it is a fairly recent topic in computer science, KDD applies many older computational techniques from statistics, information retrieval, machine learning and pattern recognition. Examples of such include location-aware computing (Patterson et al. 2003), and ontology-based multimedia data mining for design information retrieval from building product models (Simoff and Maher 1998). The vision of the Finnish Rail Authority includes data warehousing of environmental data, maintenance data, measurement data, and other data sets (Hyvärinen et al. 2006) which allows utilization of KDD. These infrastructure condition data registers are currently utilized for management analysis, following condition trends, design of rehabilitation, and for quality control if contracts.

As structural health monitoring (SHM) data collected in the field or laboratory can have as many forms as there are different transducers, data fusion may be a necessary preliminary step toward more refined analysis (e.g., Durrant-Whyte 1988). Use of a Bayesian approach recently received tremendous attention due to Markov Chain Monte Carlo methods, which enables an efficient computational implementation (e.g., Ching and Glaser 2003a; Beck and Katafygiotis 1998; Sohn and Law 1997). Bayesian inference utilizes a numerical estimate of the degree of belief in a hypothesis before evidence has been observed, and calculates a numerical estimate of the degree of belief in the hypothesis after evidence has been observed (by sensors). Bayesian statisticians believe probabilities can have an objective value and therefore Bayesian inference can provide an objective method of induction (Gelman et al. 2003). Tackling SHM problems in the framework of Bayesian decision-making would allow subjective knowledge and uncertainty to be incorporated into the modeling process in a natural way. Altunok et al. (2006) introduced a method that accommodates uncertainties due to ambiguity, vagueness, and fuzziness, which are statistically nondescribable. The proposed method deals primarily with epistemic uncertainty. The method improves damage identification by performing damage pattern recognition using fuzzy sets. In this approach, healthy observations are used to construct a fuzzy set representing healthy performance characteristics.

Case Study One: Sensing of Performance in Buildings

Compliance in Performance-Based Building

Two key parameters for estimating the performance of a building are humidity and temperature. Hygrothermal analyses are becoming more important in building design as moisture damage is one of the main causes of building deterioration. Water and moisture can cause structural damage, reduce the thermal resistance of building materials, change the physical properties of materials, and deform materials. It is estimated (Ronald 1994; Bomberg and Brown 1993) that 75–80% of all the problems with building envelopes are related to excess moisture. In Haverinen's cross-sectional analyses of moisture findings in the Finnish housing stock (Haverinen 2002), it is reported that some 38% of detached houses and 26% of apartments have notable or significant moisture problems. Similar results are found in other Nordic countries. The presence of home dampness and/or molds (that is damp spots, visible mold or mildew, invisible but health-damaging mold, water damage, and flooding) was reported in 38% of the structures in a Canadian study (Dales et al. 1991).

These estimates show that moisture problems are a serious issue and have strong economic effects. Repair of the existing problems is very expensive. According to estimates by Pirinen et al. (2005), expenses to repair microbiological problems causing health effects are on the order of €10,000–€40,000 per case. Even worse are the excessive moisture-related health effects on the occupants. The evidence of a causal association between dampness and health effects is strong. Common symptoms associated with moisture problems are respiratory symptoms, sensitization to house dust mites, asthmatic symptoms or emergency room visits due to asthma, as well as tiredness and headaches. Causal association between dampness and health effects shows that avoidance and control of moisture problems should be an essential concern in public health issues.

Hygrothermal models are useful tools in assessing the heat and moisture performance of building envelope systems and optimizing these systems for maximum hygrothermal performance and longer service life, but they require accurate climatic data for boundary conditions. Moisture conditions in building envelopes depend strongly on indoor and outdoor climatic conditions. Standardized methodology for dynamic moisture design and hygrothermal loads does not exist yet (Kalamees et al. 2006).

Optimization of Energy Consumption

A key economic performance indicator of a building is energy consumption. According to the Common European Energy Policy Green Paper, the major guidelines of the energy policy are sustainable development, competitiveness, and security of supply (European Commission 2006). To achieve that goal, the consumers need to be motivated and able to make choices. A large fraction of the potential savings from rational use of energy can be attained if governments give the responsibility for implementation to the proper actors. A proper actor is one who does not suffer a financial loss due to implementation. To be able to act rationally, the actual energy consumption and costs need to be known to the decision makers. If the provision of the needed information comes with ease and at minimal cost, the demand-side management decisions can be guided to actual energy savings.

For electricity, production and consumption is simultaneous—it is not readily storable. In the Nordic countries, the peak consumption of electricity is reached only on a few winter days of the year, namely the coldest morning and afternoon hours. In many industrialized countries with warm climate, the peak consumption occurs on the hottest summer days as a consequence of cooling systems operating during times of high consumption of electricity for other purposes. There are obvious reasons why these instances are problematic—high peak demand requires commissioning expensive power plants to be used only for peak periods. (There are also elaborate pump-storage and compressed air schemes, but they also are enormously expensive.)

In California, peak load is strongly dominated by air conditioning, followed by commercial lighting and "miscellaneous." Residential air conditioning alone accounts for nearly as large a portion of peak load as the entire industrial sector (Brown and Koomey 2003). Although high power rates remain a focus for the state, the challenge of ensuring adequate electricity supplies, especially during high-demand peak periods, has emerged as the critical issue. The *2004 Energy Report Update* expressed serious concern over dangerously low reserve margins, especially in light of the expected retirement of aging power plants.

Demand rates are usually cheapest during the hours between 10 p.m. and 7 a.m., when grid demand is lowest. In Finland there are specific winter rates valid from the beginning of November until the end of March. The intention is to cut peak consumption rates, in particular during the coldest periods, with the incentive of cheaper nighttime rates. Preferably, domestic heating will be mostly during the night, with massive structures and hot water containers to store the heat.

The use of locally measured data has the potential to spur a reduction in electricity consumption during the peak hours. In Finland this means reduction of heating and unessential electronic equipment during the coldest times. In California this would lead to lower consumption of domestic electricity during the hottest hours. To truly motivate the users, there needs to be clear real-time indication of both the consumption and its cost.

Solution for Performance Monitoring and Optimization

Dense sensing offers a powerful mechanism to observe the actual hygrothermal performance, building safety in the structural and occupational sense, and power consumption. In order to monitor hygrothermal conditions in real time and with fine granularity, VTT (Technical Research Centre of Finland) commissioned a Mote called WirCur (Tolman et al. 2006; Parkkila 2007). This is a multisensor Mote, including electric current flow, temperature, humidity, and illumination transducers, and data transmission via Zigbee radio. This device can be manufactured for a reasonable cost as MEMS technology makes available inexpensive and accurate transducers to measure all these variables. For instance, hygrothermal data are extremely simple to measure with current sensors, such as the Sensirion SHT15 relative humidity sensor (range 0–100% rH, accuracy ±2%), which also measures temperature with an accuracy of ±0.3°C, linearizes and temperature compensates the data, and digitizes it, at a cost of $12. The described WirCur Mote can be utilized for several needs. It is a tool for observation of performance compliance which has enabled proactive condition control for several environmental variables, and serves as a source of data for optimizing energy consumption. The same data can be refined into relevant information for various user groups through user interfaces which enable genuine decision support.

The WirCur Mote is not unique in the sense that a similar operating sensor system has been developed and utilized at the University of California, Berkeley (Wright 2006). Simultaneous to the development of WirCur, Wright spearheaded a CITRIS project for the California Energy Commission to optimize domestic energy use. The balancing of occupant comfort versus energy price has been made simple with user-friendly displays and a preference slider for user-controlled adjustments of conditions, as well as automated control of various energy sinks. Within each house, the electricity meters are capable of receiving real-time electricity tariffs and automatically initiating responses that reduce overall energy cost, while being responsive to occupants' preferences. The meters also act as a platform to support other sensors and actuators, with a good portion of the development effort spent on providing a user interface that is clear and intuitive to typical residential users (Arens et al. 2005). The system will be rolled out state wide beginning in 2008.

Case Study Two: Monitoring the Golden Gate Bridge

During 2006 a Mote network was designed, implemented, deployed, and tested on the Golden Gate Bridge (GGB) in order to monitor its structural condition. The work was performed by a broad interdisciplinary group from University of California, Berkeley (see Kim et al. 2006). The goal was to determine the response of the 70-year-old structure to ambient and extreme conditions and compare actual behavior to design predictions. This will result in greater public safety as well as improving the state of knowledge of the structural engineering profession. The network measured ambient structural vibration from wind load at closely spaced locations along the main span, as well as being prepared for strong shaking from a possible earthquake, all at low cost and without interfering with the operation of the bridge. For this deployment, 64 Motes were distributed over the main span and southern tower (see Fig. 1), and is the largest wireless sensor network ever installed for structural health monitoring purposes.

The bridge is located in a hostile environment; gusty wind,

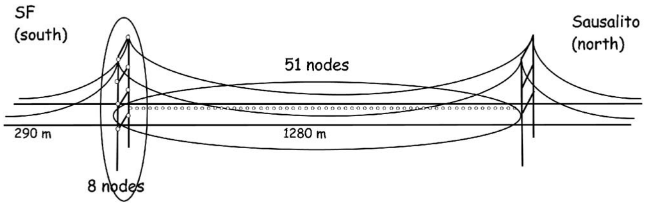

Fig. 1. The Golden Gate Bridge and layout of Motes on the main span and tower. To cover the 1,300 m midspan, an extended linear data transmission topology needed to be used.

strong fog, and rain present serious engineering challenges for deployment and maintenance of an electronic system. The combination of sea fog and strong wind resulted in quick condensation of salty water and rapid oxidation of metallic components. As the bridge has a linear topology, radio communication only needs to be bidirectional, therefore an external bidirectional patch antenna was used, adding signal splitters when necessary for changing directions. There is a very narrow passage along the side of the bridge which provides limited line of sight for the bidirectional antennas. This space is, of course, surrounded by tons of steel components and reinforced concrete slabs, and at some places it is obstructed by tools and materials belonging to the maintenance crew. The range of the radio in that harsh environment is severely limited, with the functional range of the Crossbow MicaZ Mote used in this project being 15–30 m. For details see Pakzad et al. (2008).

Dynamic monitoring of structural motion required constant measurement as it is not possible to predict when an earthquake will occur, and all the data-to-information conversion schemes require very large amounts of data. This results in data sets that are between two to four orders of magnitude larger than that of an environmental monitoring application (Kim et al. 2006). The higher data volume requires either sophisticated onboard computation with a distributed system identification algorithm, or to be transmitted to a base station for further processing, which is even more power-expensive. Energy supply is therefore a vitally important issue. Although hard-wiring is always preferable, the use of batteries or other renewable sources of power is justified for quick and temporary applications, or where a more permanent power source cannot be provided.

For monitoring structural performance during seismic events, loss of data is not acceptable. Many structural events happen rarely and the data are too important to be lost during communication. On the bridge, the system must be able to detect signals with peaks as low as 500 μg (Abdel-Ghaffar and Scanlan 1985). The GGB system measures acceleration for the two orthogonal horizontal directions synchronously at a 1 ks/s rate, with less than 10 μs of time jitter, and with an accuracy of 30 μg. The sampled data are collected over a 45 hop network, with a bandwidth of 461B/s at the 45th hop using pipelining (Kim et al. 2006). Every 10 samples are averaged, and the average stored for later transmission to the aggregator using error correction techniques. Communication over a linear, 45 hop network is a challenging problem because the data from the far Mote must be daisy-chained all the way to the aggregator. The two important aspects of such a protocol are channel capacity and scalability of the number of hops over the network. Increasing the packet size is an attractive way of increasing the bandwidth per joule, but this increases the data loss rate (Pakzad et al. 2008).

A new sensor board was designed for the GGB application (GGB 2006). The board was made up of two sets of accelerometers, each with vertical and transverse sensitivity, and a thermometer to facilitate temperature compensation of the accelerometers. A pair of SiliconDesigns 1221L accelerometers was used to resolve low-amplitude ambient vibrations, and ADXL 202E accelerometers to measure possible earthquake strong motion. To measure the static noise floor of the devices, the board was calibrated in the Berkeley Seismology Laboratory's Byerley underground vault (BKS 2006), which provides an isolated, calibrated environment with minimal ambient vibration.

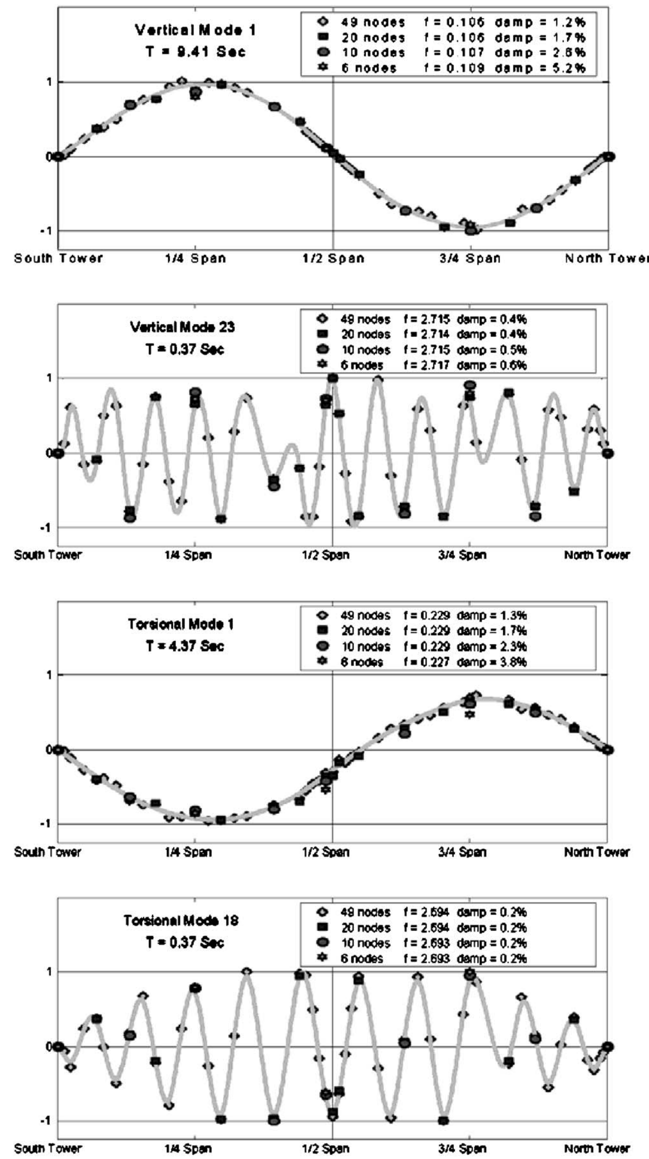

Fig. 2. Estimated vertical and torsional Mode shapes of the main span of the Golden Gate Bridge. The data are plotted for four different spatial densities.

The signals delivered by the GGB network have a good signal/noise ratio with about 11.5 usable bits of dynamic range, and the power spectral density estimates show clearly defined peaks in the low frequencies, where the natural modes of vibrations of the bridge are expected to reside. The spatially dense array allows increased precision in defining the actual mode shapes, as is shown in Fig. 2 which was computed from for 250 s of data. The end result is an improvement in effective S/N analogous to the improvements seen by signal stacking in seismology. The use of spatially dense sensing allows the higher modes, both vertical and torsional, to be analyzed easily and accurately. More extensive analysis of the data is on going.

Conclusions

Sensing is becoming an essential element in facility management, from procurement to operation. Its importance is obvious for validating outcomes in performance-based commissioning and construction, which is being pushed by agencies in the United States and the European Union. Sensing provides a tool to observe the output of the entire system in actual operation, which is the actual target of commissioning and continuous commissioning. In case of disputes, all parties benefit from sensor data. The ability to observe actual performance, and in particular the changes in the behavior of the entire system (i.e., of a building or bridge), enables proactive facility management, and makes reactive operation more efficient.

The future scenario for the construction industry is that increasingly more clients will purchase the performance of the structures instead of just the physical means for providing it. In this scenario decision-making during the operation phase becomes an integrated part of the initial design and construction. When the operation phase of the structure is taken into consideration, being able to proactively plan for changing circumstances becomes more critical. Sensor data are rapidly becoming essential for professional operation of built environment.

Note that data at present do not appear to carry monetary value with it. It is not a capital item; it is rather a "consumable" in the process of facility management. The value of sensor data at first glance appears to be transitory, thus the need for long-term storage may appear to be so arbitrary that it does not create a business opportunity either for the first collector of the data or a downstream vendor of a market commodity. The business potential seems to be mostly in the equipment industry, rather than in data management.

It is sometimes possible to estimate the economic value of having the data available. Such cases include the savings in energy costs when avoiding peak time consumption, demonstrating compliance or noncompliance to required performance standards and avoiding structural failures. Often the benefits remain speculative, like saving lives in case of fire. Notably, the benefits often accrue to parties who are not carrying the costs. The saving of peak consumption energy benefits all the users regardless of their own investment on the matter, as the general market price becomes lower. If the need for an extra power plant is avoided by leveling the peak consumption through voluntary initiatives based on cost advantage, the savings for entire society are huge. The costs of fire rescue systems fall to the society at large, the costs of the sensors (some $80/room) for the owner of the building, and the benefits (sometimes the invaluable saving of lives) for persons involved in cases.

A potential business might sit within data mining, where data would be collected at a large scale with adequate structuring (nomenclature, metadata for addressed search options, and means to observe trends and deviations). This kind of activity would be analogous to currently operating business intelligence systems. Currently the drive for such a business is largely lacking, as the data collection of large scale management of build environment is too scattered and currently relies on more traditional means than sensor technology. This situation will be changing as the enabling technology develops, becomes cheaper (both in enabling sensors and data storage; and energy sources for sensing and transmission of data) yielding abundant data needed for data mining. The challenge remains in the sphere of allocating the true costs to the de facto beneficiaries.

Acknowledgments

The writers would like to acknowledge NSF Grant No. CMS-0624985 for making this work possible and the Academy of Finland for support to Data Management and Exploitation During the Use of a Facility in KITARA research program. Help from Shamim Pakzad and Sukun Kim is appreciated.

References

Abdel-Ghaffar, A. M., and Scanlan, R. H. (1985). "Ambient vibration studies of Golden Gate Bridge: II. Pier-tower structure." *J. Eng. Mech.*, 111(4), 483–499.

Altunok, E., Taha, M. M. R., Epp, D. S., Mayes, R. L., and Baca, T. J. (2006). "Damage pattern recognition for structural health monitoring using fuzzy similarity prescription." *Comput. Aided Civ. Infrastruct. Eng.*, 21(8), 549.

Arens, E., Federspiel, C. C., Wang, D., and Huizenga, C. (2005). "How ambient intelligence will improve habitability and energy efficiency in buildings." *Ambient intelligence*, W. Weber, J. M. Rabay, and E. Aarts, eds., Springer, New York, 63–80.

Arici, Y., and Mosalam, K. M. (2005). "Modal identification of bridge systems using state-space methods." *Struct. Control and Health Monit.*, 12(3-4), 381–404.

Beck, J. L., and Katafygiotis, L. S. (1998). "Updating models and their uncertainties. I: Bayesian statistical framework." *J. Eng. Mech.*, 124(4), 455–461.

Beifus, S., Proskurowski, W., and Udwadia, F. E. (1997). "A fuzzy logic approach to incorporating managerial thinking in prediction and control: A case study of market penetration." *J. Optim. Theory Appl.*, 92(2), 225–248.

Berry, M. J. A., and Gordon, S. L. (1997). *Data mining techniques: For marketing, sales, and customer relationship management*, Wiley, New York.

Berthold, M., and Hand, D. (2004). *Intelligent data analysis*, Springer, Berlin.

Bishop, C. M. (1995). *Neural networks for pattern recognition*, Oxford University Press, New York.

BKS. (2006). ⟨http://seismo.berkeley.edu/bdsn/station_book/bks.html⟩.

Bomberg, M., and Borwin, W. (1993). "Building envelope and environmental control. 1: Heat, air and moisture interactions." *Constr. Canada*, 35(1), 15–18.

Brown, H. T. (1987). *507 mechanical movements: Mechanisms and devices*, Dover, New York.

Brown, R. E., and Koomey, J. G. (2003). "Electricity use in California: Past trends and present usage patterns." *Energy Policy*, 31(9), 849–864.

Chan, T. H., Ni, Y. Q., and Ko, J. M. (1999). "Neural network novelty filtering for anomaly detection of Tsing Ma Bridge cablescables." *Structural health monitoring 2000*, Stanford Univ., Palo Alto, Calif., 430–439.

Chau, M., Huang, Z., Qin, J., Zhou, Y., and Chen, H. (2006). *Building a scientific knowledge web portal: The NanoPort experience*. Elsevier B.V. Decision Support Systems, Amsterdam, The Netherlands, ⟨www.elsevier.com/locate.dsw⟩.

Cherkassky, V., and Mulier, F. (1998). *Learning from data*, Wiley, New York.

Ching, J., and Glaser, S. D. (2003a). "Identification of soil degradation

during earthquake excitations by Baysian inference." *Earthquake Eng. Struct. Dyn.*, 32, 845–869.
Ching, J., and Glaser, S. D. (2003b). "Tracking rapidly changing dynamical systems using a semi-parametric statistical method based on wavelets." *Earthquake Eng. Struct. Dyn.*, 32, 2377–2406.
Ciloglu, K., Catbas, F. N. Pervizpour, M., Wang, A., and Aktan, A. (2001). "Structural identification of phenomenological physical models with controlled mechanisms of uncertainty." *6th Annual SPIE Int. Symp. on NDE for Health Monitoring and Diagnostics*, Newport Beach, Calif.
da Costa Sousa, J. M., Palm, R., Silva, C., and Runkler, T. A. (2003). "Optimizing logistic processes using a fuzzy decision making approach." *IEEE Trans. Syst. Man Cybern., Part A. Syst. Humans*, 33(2), 245–256.
Dales, R. E., Burnett, R., and Zwanenburg, M. (1991). "Adverse health effects among adults exposed to home dampness and molds." *Am. Rev. Respir. Dis.*, 143, 505–509.
Durrant-Whyte, H. F. (1988). "Sensor models and multisensor integration." *Int. J. Robot. Res.*, 7(6), 97–113.
European Commission. (2006). "A European strategy for sustainable, competitive and secure energy." *Green Paper*, Commission of the European Communities, Brussels.
Foliente, G. C., Leicester, R. H., and Pham, L. (1998). *Development of the CIB proactive programme for performance based building codes and standards*, Council for Research and Innovation in Building and Construction (CIB), CSIRO Building, Construction and Engineering, Canberra, Australia.
Fraden, J. (2003). *AIP handbook of modern sensors: Physics, designs, and applications*, 2nd Ed., American Institute of Physics, New York.
Friswell, M., and Mottershead, J. (1995). *Finite element model updating in structural dynamics*, Kluwer, Dordrecht, The Netherlands.
Fritzen, C.-P., and Bohle, K. (1999). "Identification of damage in large scale structures by means of measured FRFs-procedure and application to the I40-Highway bridge." *Damage Assessment of Structures, Proc., Int. Conf. on Damage Assessment of Structures (DAMAS'99)*, Dublin, Ireland, 310–319.
Garcia, G., and Stubbs, N. (1997). "Application and evaluation of classification algorithms to a finite element model of a three-dimensional truss structure for nondestructive damage detection. Smart systems for bridges, structures, and highways." *Proc. SPIE*, 3,043, 205–216.
Gelman, A., Carlin, J. B., Stern, H. S., and Rubin, D. B. (2003). *Bayesian data analysis*, 2nd Ed., Chapman & Hall, London.
Golden Gate Bridge (GGB). (2006). ⟨http://www.tinyos.net/scoop/special/hardware⟩.
Gibson, E. J. (1982). "Working with the performance approach in building." *CIB Rep. No. 64*, CIB (International Council for Research and Innovation in Building and Construction), Rotterdam, The Netherlands.
Glaser, S. D., Shoureshi, R., and Pescovitz, D. (2005). "Future sensing systems." *Smart Struct. Sys.*, 1(1), 103–120.
Hastie, T., Tibshirani, R., and Friedman, J. H. (2001). *The elements of statistical learning*, Springer, Berlin.
Haverinen, U. (2002). "Modeling moisture damage observations and their association with health symptoms." Doctoral thesis, National Public Health Institute, Dept. of Environmental Health, Univ. of Kuopio, Kuopio, Finland, *Rep. No. A10/2002*.
Hill, J., Szewcyzk, R., Woo, A., Hollar, S., Culler, D., and Pister, K. J. S. (2000). "System architecture directions for networked sensors." *Proc., 9th Int. Conf. on Architectural Support for Programming Languages and Operating Systems*, 93–104.
Huang, G. (2003). "Casting the wireless sensor net." *MIT technology review*, ⟨http://www.technologyreview.com/InfoTech/13235/⟩ (July, 12).
Hung, S.-L., Huang, C. S., Wen, C. M., and Hsu, Y. C. (2003). "Nonparametric identification of a building structure from experimental data using wavelet neural network." *Comput. Aided Civ. Infrastruct. Eng.*, 18(5).
Hyvärinen, J., Porkka, J., Pienimäki, M., Korkiala-Tanttu, L., Mäkeläinen, T., and Kiviniemi, A. (2006). *Infra PDM Analysis. Rep. No. 1: Objectives and Ramifications of Product Model-Based System in Finnish Infra-Sector*, VTT Technical Research Centre of Finland, Espoo, Finland.
Ikegawa, Y., Glaser, S. D., Karasaki, K., Ito, K., Aoki, H., and Sawada, M. (2006). "Proposal for ubiquitous monitoring of ground environments and its wireless communication test." *Proc., 35th Symp. on Rock Mechanics*, Japan Society for Rock Mechanics, Kyoto, Japan, 383–388.
ISO. (1984). "Performance standards in building—Principles for their preparation and factors to be considered." *ISO 6241-1984(E)*.
Jafari, R., Li, W., Bajcsy, R., Glaser, S., and Sastry, S. (2007). "Physical activity monitoring for assisted living at home." *4th Int. Workshop on Wearable and Implantable Body Sensor Networks*, Aachen, Germany.
Kalamees, T., Vinha, J., and Kurnitski, J. (2006). "Indoor humidity loads and moisture production in lightweight timber-frame detached houses." *J. Build. Phys.*, 29(3), 219–246.
Kim, S., Pakzad, S., Culler, D. E., Demmel, J., Fenves, G., Glaser, S., and Turon, M. (2006). "Health monitoring of civil infrastructures using wireless sensor networks." *Technical Rep. No. UCB/EECS-2006-121*, EECS Dept., Univ. of California, Berkeley, Calif., ⟨http://www.eecs.berkeley.edu/Pubs/TechRpts/2006/EECS-2006-121.pdf⟩.
Lapin, L. L. (1990). *Probability and statistics for modern engineering*, PWS-Kent, Boston.
Lau, H. C. W., Ip, R. W. L., and Chan, F. T. C. (2002). "An intelligent information infrastructure to support knowledge discovery." *Expert Sys. Applic.*, 22(1), 1–10.
Lindland, O., Sindre, G., and Solvberg, A. (1994). "Understanding quality in conceptual modelling." *IEEE Software*, 11(2), 42–49.
Liu, S. C., and Yao, J. T. P. (1978). "Structural identification concept." *J. Struct. Div.*, 104(12), 1845–858.
Ljung, L. (1987). *System identification, theory for the user*, Prentice-Hall, New York.
Lynch, J. P., and Loh, K. J. (2006). "A summary review of wireless sensors and sensor networks for structural health monitoring." *Shock Vib.*, 38(2), 91–128.
MDSS National Laboratory Consortium (MDSS). (2006). "MDSS prototype release-4.0, technical description." Federal Highway Administration Road Weather Management Program, ⟨www.rap.ucar.edu/projects/rdwx_mdss/documents/MDSS_Tech_Description_13Feb06.pdf⟩.
Menzies, T., and Hu, Y. (2003). "Data mining for very busy people." *IEEE Comput.*, 36(11), 18–25.
Mingers, J. C. (1995). "Information and meaning: Foundations for an intersubjective account." *Inf. Sys. J.*, 5, 285–306.
Moutinho, L., Goode, M., and Davies, F. (2000). *Quantitative analysis in marketing management*, Wiley, New York.
Murtoaro, J. (2006). "Public-private partnership a study on the economics and financing alternatives of transport infrastructure production." Helsinki Univ. of Technology. Laboratory of Industrial Management, *Rep. No. 2006/3*, Espoo, Finland.
Nakamura, M., Masri, S. F., Chassiakos, A. G., and Caughey, T. K. (1998). "A method for nonparametric damage detection through the use of neural networks." *Earthquake Eng. Struct. Dyn.*, 27, 997–1010.
Pakzad, S. N., Fenves, G. L., Kim, S., and Culler, D. E. (2008). "Design and implementation of scalable wireless sensor network for structural monitoring." *J. Infrastruct. Syst.*, 14(1), 89–101.
Parkkila, T. (2007). "Damex—Inspection and commissioning services." *VTT Seminar on Services for Housing*, 15.2.2007 Dipoli, Espoo, Finland, ⟨http://www.vtt.fi/uutta/tapahtumat/aineisto/Kotiseminaari_15022007/Parkkila_Huoneistokohtainen_mittauskonsepti.pdf[2007, 08/17]⟩.
Patterson, C. A., Muntz, R. R., and Pancake, C. M. (2003). "Challenges in location-aware computing." *IEEE Pervasive Comput.*, 2(2), 80–89.
Pierce, J. R. (1980). *An introduction to information theory*, Dover, New York.
Pirinen, J., Karjalainen, J., Kärki, J. P., Öhman, H., and Riippa, T. (2005).

Homevauriot suomalaisissa pientaloissa (Mold damages in Finnish detached houses), RAKLI, Helsinki, Finland.
Ronald, P. T. (1994). *Relevant moisture properties of building construction materials. Moisture control in buildings*, ASTM Manual Series, MNL 18, Philadelphia.
Ruotolo, R., and Surace, C. (1997). “Damage assessment of multi-cracked beams using combinatorial optimization. Structural damage assessment using advanced signal processing procedures.” *Proc., DAMAS ’97*, Univ. of Sheffield, Sheffield, U.K., 77–86.
Scott, J. S. (1993). *The VNR dictionary of civil engineering*, Van Nostrand-Reinhold, New York.
Senturia, S. (2001). *Microsystem design*, Kluwer Academic, Boston.
Shanks, G. (1999). “Semiotic approach to understanding representation in information systems.” *Proc., Information Systems Foundations Workshop on Ontology, Semiotics and Practice*, Melbourn, ⟨http://www.comp.mq.edu.au/isf99/Shanks.htm⟩.
Shanks, G., and Darke, P. (1998). “Understanding metadata and data quality in a data warehouse.” *Aust. Comput. J.*, 30(4), 122–128.
Shumway, R. H., and Stoffer, D. S. (2006). *Time series analysis and its applications*, 2nd Ed., Springer, New York.
Simoff, S. J., and Maher, M. L. (1998). “Ontology-based multimedia data mining for design information retrieval.” *Proc. Computing in Civil Engineering*, ASCE, Reston, Va., 212–223.
Simon, H. A. (1978). “Rational decision making in business organizations.” Nobel Memorial Lecture, Stockholm, Sweeden.
SmartQuant. (2006). ⟨http://www.smartquant.com/⟩.
Sohn, H., Czarnecki, J., and Farrar, C. R. (2000). “Structural health monitoring using statistical process control.” *J. Struct. Eng.*, 126(11), 1356–1363.
Sohn, H., and Law, K. L. (1997). A Bayesian probabilistic approach for structure damage detection.” *Earthquake Eng. Struct. Dyn.*, 26(12), 1259–1281.
Sohn, H., Park, P., and Kim, S. (2006). “Application of outlier analysis for baseline-free damage diagnosis.” *SPIE Int. Symp., Smart Structures & Materials and Nondestructive Evaluation for Health Monitoring and Diagnostics*, San Diego.
Stamper, R. (1992). “Signs, organizations, norms and information systems.” *Proc., 3rd Australian Conf. on Information Systems*, Wollongong.
Szewczyk, R., Polastre, J., Mainwaring, A., and Culler, D. (2004). “Lessons from a sensor network expedition. Wireless sensor networks.” *Lect. Notes Comput. Sci.*, 2920, 207–322.
Szigeti, F., and Davis, G. (2001). “Functionality and serviceability standards: Tools for stating functional requirements and for evaluating facilities.” *Federal Facilities Council, Technical Rep. No. 145*, Learning From Our Buildings: A State-of-the-Art Practice Summary of Post-Occupancy Evaluation, National Academy Press, Washington, D.C.
Szigeti, F., and Davis, G. (2005). “Performance based building: Conceptual framework.” *Final Rep.*, Performance Based Building Thematic Network, EUR 21990, Brussels, Belgium.
Tiehallinto, Finnish Road Administration. (2004). “E18 Muurla–Lohja Palvelusopimus.” Ohje Esivalintaan Osallistuville, Helsinki, Finland, ⟨www.tiehallinto.fi/e18⟩ (last accessed October 2007).
Tiehallinto, Finnish Road Administration. (2006). *Life-cycle contract open up new possibilities*, Rakennusteollisuuden viestintäkeskus Oy, Helsinki, Finland.
Tolman, A., Möttönen, V., and Tulla, K. (2006). “Data management in facility management.” *Proc., Facility Management Conf. 2006*, Frankfurt, Germany, 81–187, VDE Verlag GMBH, Berlin.
Trujillo, J., Palomar, M., Gomez, J., and Song, I. (2001). “Designing data warehouses with OO conceptual models.” *Computer*, 34(12), 66–75.
Wilson, H. N., and McDonald, M. H. B. (2001). “An evaluation of styles of IT support for marketing planning.” *Eur. J. Market.*, 35(7/8), 815–842.
World Trade Organization (WTO). (1997). “First triennial review of the operation and implementation of agreement on technical barriers to trade.” *Document No. G/TBT/5 Attachment*, Committee on Technical Barriers to Trade. World Trade Organization. Geneva, Switzerland.
Wright, P. (2006). “The built environment, energy, and sustainability, or, intelligent infrastructures.” *CITRIS in Europe*, ⟨http://www.citris-uc.org/files/2006-0620-CITRIS-Europe/6.1-PAUL-WRIGHT.pdf⟩.
Yanev, B. (2003). “Structural health monitoring as a bridge management tool.” *Proc. of the First Int. Conf. on Struct. Health Monitoring and Int. Infrastructure*, Tokyo, Japan, Z. S. Wu and M. Abe, eds., Balkema, Lisse.
Zimmerman, A. T., Shiraishi, M., Swartz, R. A., and Lynch, J. P. (2008). “Automated modal parameter estimation by parallel processing within wireless monitoring systems.” *J. Infrastruct. Syst.*, 14(1), 102–113.