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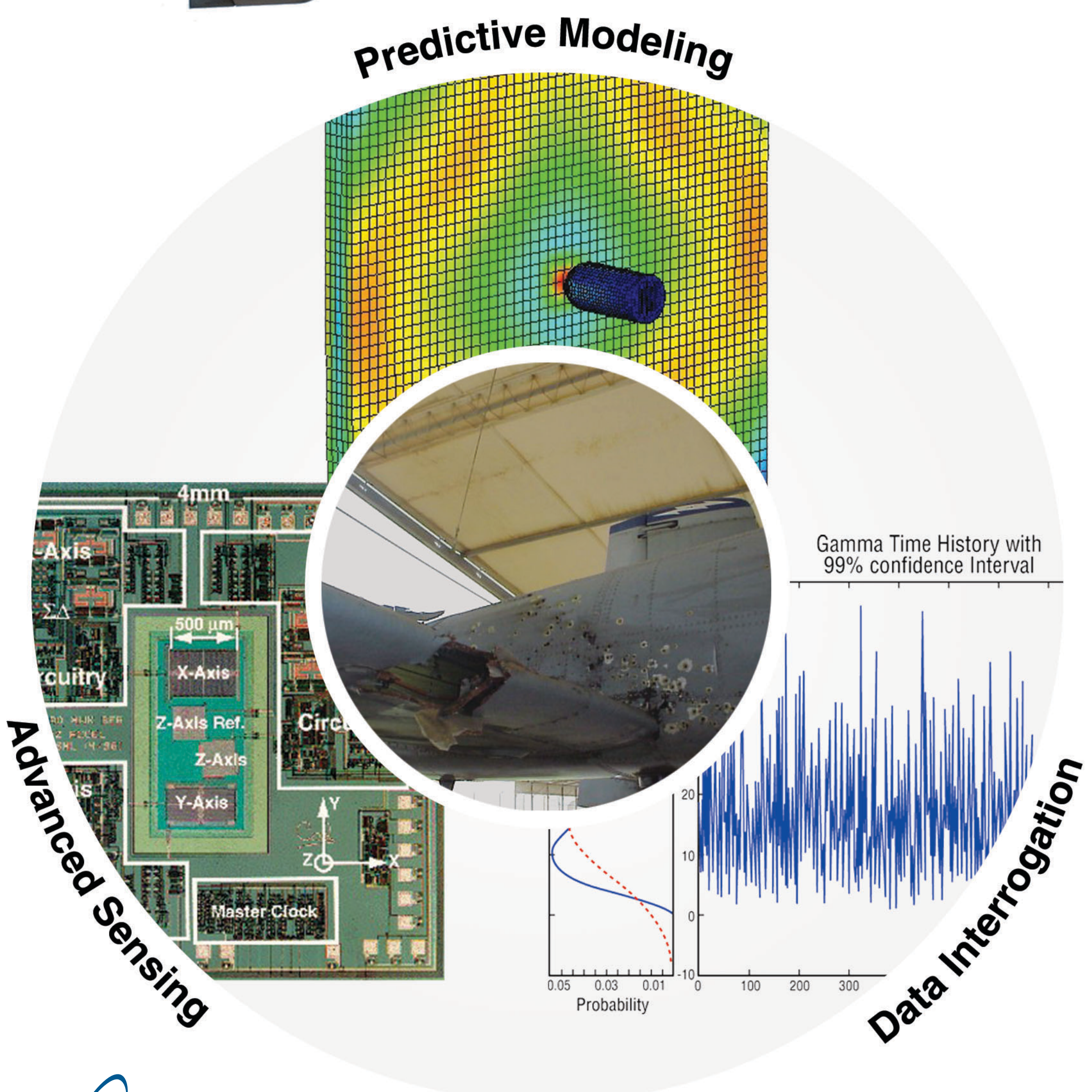
Damage Prognosis:
Current Status and Future Needs



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The cover photo shows damage sustained by an A-10 Thunderbolt during the 2003 Iraq War. Development of damage prognosis technology can potentially enhance combat asset readiness by providing operators and maintenance crews with rapid and quantifiable assessments of damage and its impact on future operations. The three major technology areas needed to develop damage prognosis solutions are shown in the ellipses.

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DAMAGE PROGNOSIS: CURRENT STATUS AND FUTURE NEEDS

by

Charles R. Farrar, Hoon Sohn, Francois M. Hemez, Mark C. Anderson, Matthew T. Bement, Phillip J. Cornwell, Scott W. Doebling, Nick Lieven, Amy N. Robertson, John F. Schultze

ABSTRACT

Damage prognosis will be an important engineering research topic in the near future because of the potential life-safety and economic advantages that this technology can provide. This report summarizes the authors' viewpoints on the technology development necessary to realize viable damage prognosis solutions. These viewpoints were developed, in part, as a result of discussions that took place at a damage prognosis workshop held in Phoenix, Arizona, March 27–29, 2001. The goal of the workshop was to bring together computer scientists, engineers, statisticians, and industry representatives working in the area of damage prognosis to identify the current state of the art as well as the technical challenges posed by the multidisciplinary nature of the damage prognosis problem.

A consensus definition of damage prognosis was agreed upon and is as follows: damage prognosis is the coupling of information from the system's original design loading environments, structural health monitoring; usage monitoring; past, current, and anticipated future environmental and operational conditions; previous component and system level testing and numerical modeling to estimate the remaining useful life of the system. The damage prognosis problem was divided into three technical areas: 1) sensing and processing hardware, 2) modeling and simulation, and 3) data interrogation. Issues pertaining to technology integration and applications were also considered. In the area of measurement and instrumentation, key challenges include increasing the sensor density and moving to an active sensing approach. Modeling and simulation challenges include predicting the evolution of component-level damage to system-level failures. Data interrogation challenges include managing large databases resulting from the increased numbers of sensors, developing reduced-order predictive models for embedment in microprocessors, and quantifying uncertainty for these models.

In summary, it is the authors' opinion that damage-prognosis solutions will not be developed on a short time scale (18–24 months). This opinion coupled with 1) the multidisciplinary approach to technology development that includes experimental, analytical, and computational methods; 2) the interest of this technology to a broad spectrum of industries for applications to their manufactured products as well as their manufacturing infrastructure; and 3) the fact that solving this problem will have significant economical and social impact, makes the development of damage prognosis solutions a grand challenge problem for engineers, material scientists, statisticians and computer scientists to solve in the twenty-first century.

1. INTRODUCTION

This report is intended to define the technology referred to as damage prognosis. Issues that are addressed in this document include the following:

1. A summary of the technologies that are needed to solve the damage-prognosis problem
2. A brief review of the state of the art in damage prognosis
3. A general solution approach to the problem while keeping the perspective that all damage-prognosis solutions are somewhat application specific
4. Limitations of the technologies that are required to address damage prognosis including key technology hurdles that must be overcome
5. A brief description of various applications for damage prognosis

Much of the information provided in this report is based on discussions that took place at the Damage Prognosis Workshop, sponsored by Los Alamos National Laboratory (LANL) and held in Phoenix, Arizona, on March 27–29, 2001. The workshop participants are listed in Appendix A. This report begins by defining several terms used throughout the document.

1.1 Definitions

Damage in a structural and mechanical system will be defined as intentional or unintentional changes to the material and/or geometric properties of the system, including changes to the boundary conditions and system connectivity, which adversely affect the current or future performance of that system. As an example, a crack that forms in a mechanical part produces a change in geometry that alters the stiffness characteristics of the part. Depending on the size and location of the crack and the loads applied to the system, the adverse effects of this damage can be either immediate or may take some time to alter the system's performance. In terms of length scales, all damage begins at the material level and then, under appropriate loading conditions, progresses to component- and system-level damage at various rates. In terms of time scales, as discussed in Section 5, damage can accumulate incrementally over long periods of time, such as damage associated with fatigue or corrosion. Damage can also occur on much shorter time scales as the result of scheduled discrete events, such as aircraft landings, and from unscheduled discrete events, such as enemy fire on a military vehicle. Implicit in this definition of damage is the concept that damage is not meaningful without a comparison between two different system states.

Usage monitoring is the process of measuring responses of, and in some cases the inputs to, a structure.

Structural health monitoring (SHM) is the process of damage detection for aerospace, civil, and mechanical engineering infrastructure. SHM involves the observation of a system over time using periodically sampled dynamic response measurements from an array of sensors, the extraction of damage-sensitive features from these measurements, and the statistical analysis of these features to determine the current state of the system. For long-term SHM, the output of this process is periodically updated information regarding the ability of the structure to perform its intended function in light of the inevitable aging and degradation resulting from operational environments. After extreme events, such as earthquakes or blast loading, SHM is used for rapid condition screening and aims to provide, in near real time, reliable information regarding the integrity of the structure. This process is also referred to as *condition monitoring,* particularly when it is applied to rotating machinery, or simply *diagnosis*.

Damage prognosis is the **estimate of a system's remaining useful life.** This estimate is based on the output of predictive models that develop such estimates by coupling information from usage monitoring; structural health monitoring; past, current, and anticipated future environmental and operational conditions; the original design assumptions regarding loading and operational environments, and previous component and system level testing. Also, "softer" information such as user "feel" for how the system is responding should be used to the greatest extend possible when developing damage-prognosis solutions. Stated another way, damage prognosis attempts to forecast system performance by measuring the current state of the system, estimating the future loading environments for that system, and predicting through simulation and past experience the remaining useful life of the system. Figure 1.1 depicts the relationship between usage monitoring, structural health monitoring, and damage prognosis.

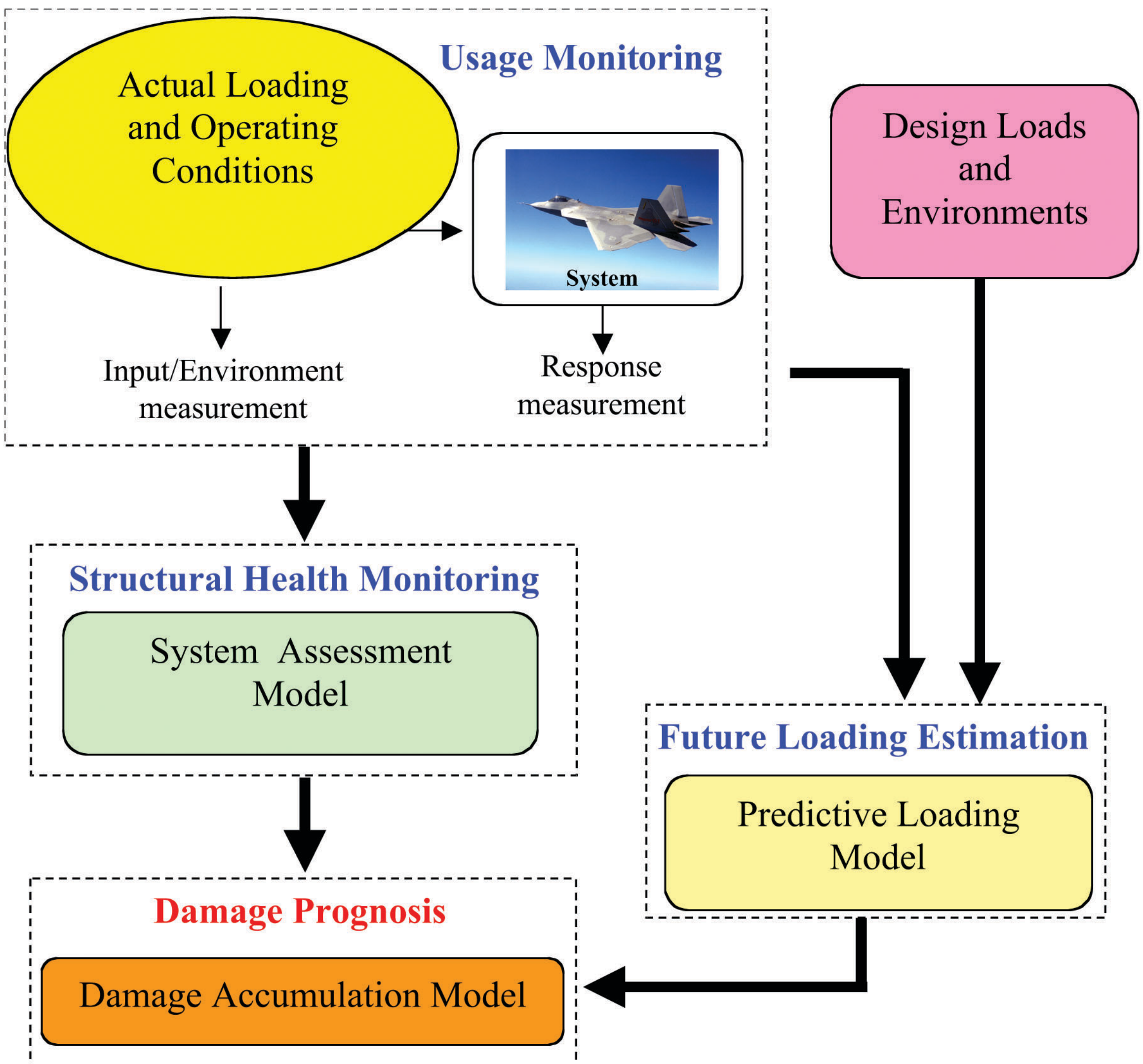

Figure 1.1 The relation between usage monitoring, structural health monitoring, and damage prognosis.

Figure 1.2, which shows damage to the USS Denver, emphasizes the challenge presented by damage prognosis. Clearly, it is not difficult to identify and locate such extreme damage. However, estimating the impact of this damage on various ship systems and coupling this information with estimates of the future loading to predict the remaining useful life of the ship, so that authorities can determine its ability to return safely to port, is a very difficult problem. This difficulty suggests that developing damage-prognosis solutions is an appropriate *grand challenge* problem for engineers involved with aerospace, civil, and mechanical infrastructure. Some features of a grand challenge problem include the following:

1. The problem must be difficult and something that will not be readily solved in the next few years
2. Solutions to the problem must be multidisciplinary in nature
3. Solutions to the problem must require developments in experimental, analytical and computational methods
4. There must be quantifiable measures indicating progress toward the problem solution
5. The problem must be of interest to many industries
6. Solving the problem will have significant economical and social impact

The authors believe that the development of damage-prognosis solutions meets the list of criteria for a grand challenge problem and that quantifiable measures can be developed to indicate that a solution has been developed.

Figure 1.2 Damage to the USS Denver.

1.2 The Damage-Prognosis Solution Process

The actual implementation of a damage-prognosis solution strategy will be application specific. However, there are major components of such a strategy that are generic to many applications; these components are outlined in Figure 1.3. In this figure, yellow boxes indicate system-specific information that will define how the three main technology components (shown in blue): instrumentation and data processing hardware, data interrogation, and predictive modeling are implemented in a damage-prognosis solution strategy.

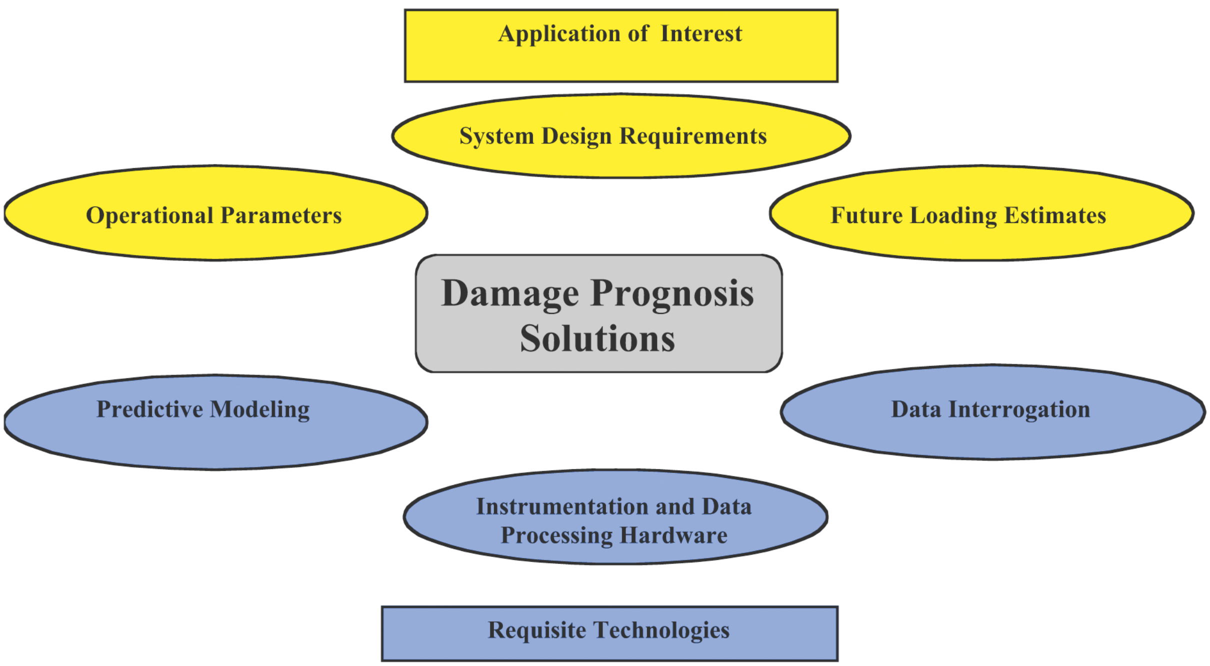

Figure 1.3 Major components of a damage-prognosis strategy.

An important first step in defining damage-prognosis solutions is the classification of the damage-prognosis problem. While it is unlikely that all or even most damage-prognosis applications will fit nicely within a rigid, precise classification scheme, through the course of the workshop, general categories were seen to emerge. To understand the categories, one must first answer three general questions: 1) what is causing the damage of concern, 2) what techniques should be used to assess and quantify the damage, and 3) once the damage has been assessed, what is the goal of the prognosis? Figure 1.4 represents these questions graphically. As discussed below, the categories do not have sharp boundaries, and many applications will overlap the various categories.

For each potential failure mode, the source of the damage falls into three general categories. The first category is gradual wear, where damage accumulates slowly at the material or component level, often on the microscopic scale. Examples of this damage source include fatigue cracking and corrosion. The second category is predictable discrete events. While the damage typically still originates on the microscopic scale, it accumulates at faster rates during sudden events that can be characterized a priori. Examples include aircraft landings and explosions in confinement vessels. Unpredictable discrete events make up the third category in which unknown and usually severe damage is inflicted upon the system at essentially unpredictable times. Examples include foreign-object-induced fan blade-off in turbine engines, earthquake-induced damage in civilian infrastructure, or battle damage in military hardware. Of course, there do exist applications where one failure scenario will fall into all three of these categories at various times. An example is damage to jet engine turbine blades caused by gradual thermal creep, increased bending stresses during takeoffs and landings, and impact with foreign objects.

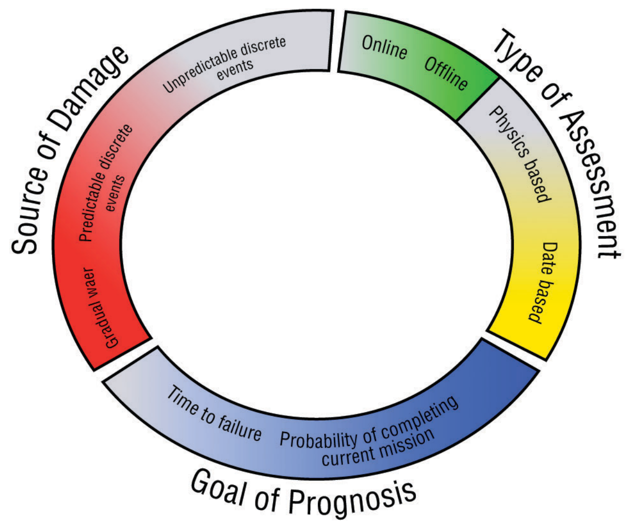

Figure 1.4 Classification of the damage-prognosis problem.

After identifying the type(s) and source(s) of damage, it is then important to determine which techniques should be used in the damage assessment. The first question that arises concerns whether the assessment should be done on-line, in near real time, or off-line at discrete intervals. This consideration will strongly influence the data acquisition and data processing requirements, as well as set limits on the computational requirements of potential assessment and prognosis techniques. While it is obvious that measurements should be taken on-line, the type of damage will influence whether the assessment needs to be done on-line. That is, for unpredictable discrete events, the assessment must be done on-line to be of any use, thus limiting the choice of the assessment techniques. However, for gradual wear, there are cases where the assessment need not be performed in near real time, and virtually any assessment technique may be used.

Assessment techniques can generally be classified as either physics-based or data-based, though practically speaking, a combination of the two will usually be employed. Physics-based assessment techniques, as their name implies, use mathematical equations that theoretically predict the system behavior by simulating the actual physical processes that govern the system response. These assessments are especially useful for predicting system response to new loading conditions and/or new system configurations (damage states). However, physics-based assessment techniques are typically computationally intensive.

Data-based assessment techniques, on the other hand, rely on previous measurements from the system to assess the current damage state, typically by means of some sort of pattern recognition method, such as neural networks. However, although data-based assessment techniques may be able to indicate a change in the presence of new loading conditions or system configurations, they will perform poorly when trying to classify the nature of the change. Thus, it is not uncommon to use the results from a physics-based model to "train" a data-based assessment technique to recognize damage cases for which no experimental data exists. Typically the balance between physics-based models and data-based techniques will depend on the amount of relevant data available and the level of confidence in the physics-based models, as illustrated in Figure 1.5.

Once the current damage state has been assessed, the prognosis problem can begin to be addressed by determining the goal for the prognosis. Perhaps the most obvious and desirable type of prognosis is an estimate of how much time remains until maintenance is required, the system fails, or the system is no longer usable. While this estimate is of high value in systems where damage accumulates gradually and at predictable rates, it is of less value in more extreme conditions such as aircraft in combat (see cover photo), where the users of the system (the pilot and mission commander) really want to know the probability of completing the current mission given the current assessment of the damage state. Because predictive models typically have more uncertainty associated with them when the structure responds in a nonlinear manner, as is often the case when damage accumulates, *an alternate goal might be to estimate how long the system can continue to safely perform in its anticipated environments before one no longer has confidence in the predictive capabilities of the models that are being used to perform the prognosis.*

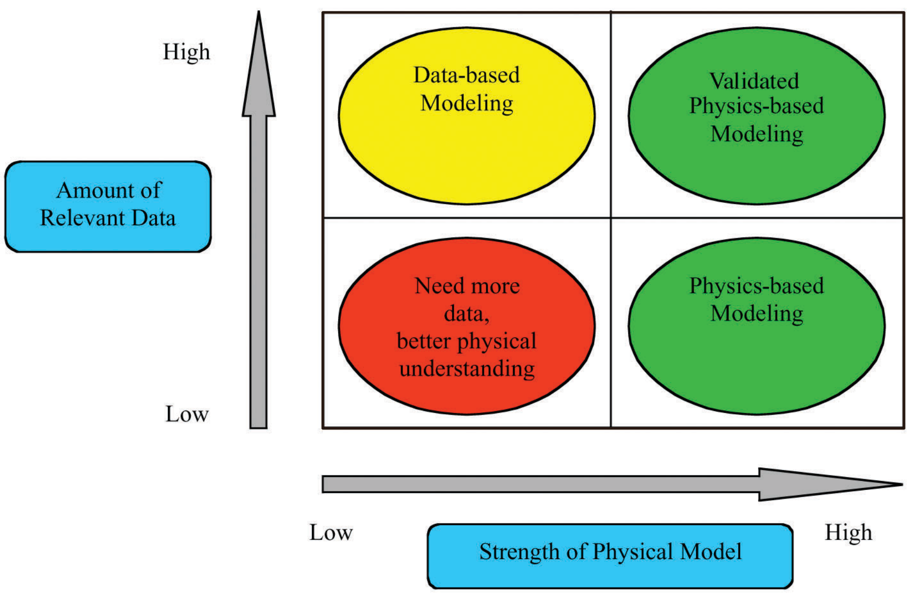

Figure 1.5 A comparison of regimes appropriate for physics-based modeling and regimes appropriate for data-based modeling.

Having classified the damage-prognosis problem for the purpose of identifying appropriate measurement, assessment, and prognostic techniques, a general solution procedure is depicted in Figure 1.6, where the relationship between data-based and physics-based assessments and predictions are identified. The process begins by collecting as much initial system information as possible. This information is used to develop initial physics-based numerical models of the system as well as to define the sensing system for state-awareness assessments and whatever additional sensors are need to monitor operational and environmental conditions. The physics-based models can also be used to define the necessary sensing system properties (e.g., sensor locations, bandwidth, sensitivity). As data become available from these sensing systems, they can be used to validate and update the physics-based models. These data, along with output from the physics-based models, can also be used to assess the current state of the structure (existence, location, type, and extent of damage). In addition, detailed information on system configurations and damage states may become available from time to time (e.g., via destructive testing, system overhauls, or system autopsies) that can be used to update the physics-based models. Data from the operational and environmental sensors can be used to develop data-based models that predict future system loading. The output of the future loading model, state awareness model, and the updated physics-based model can all be input into a reliability-based predictive tool that can be used to estimate the remaining system life. Note that "remaining life" can take on a variety of meanings depending on the specific application. From Figure 1.6 it is clear that various models have to be employed in the prognosis process. Also, the data-based and physics-based portions of the process are not independent. As is indicated, the solution process is iterative, relying on experience gained from past predictions to improve future predictions. It is again emphasized that results of past diagnoses and prognoses and their correlation with observed response can be used to continually enhance the system model.

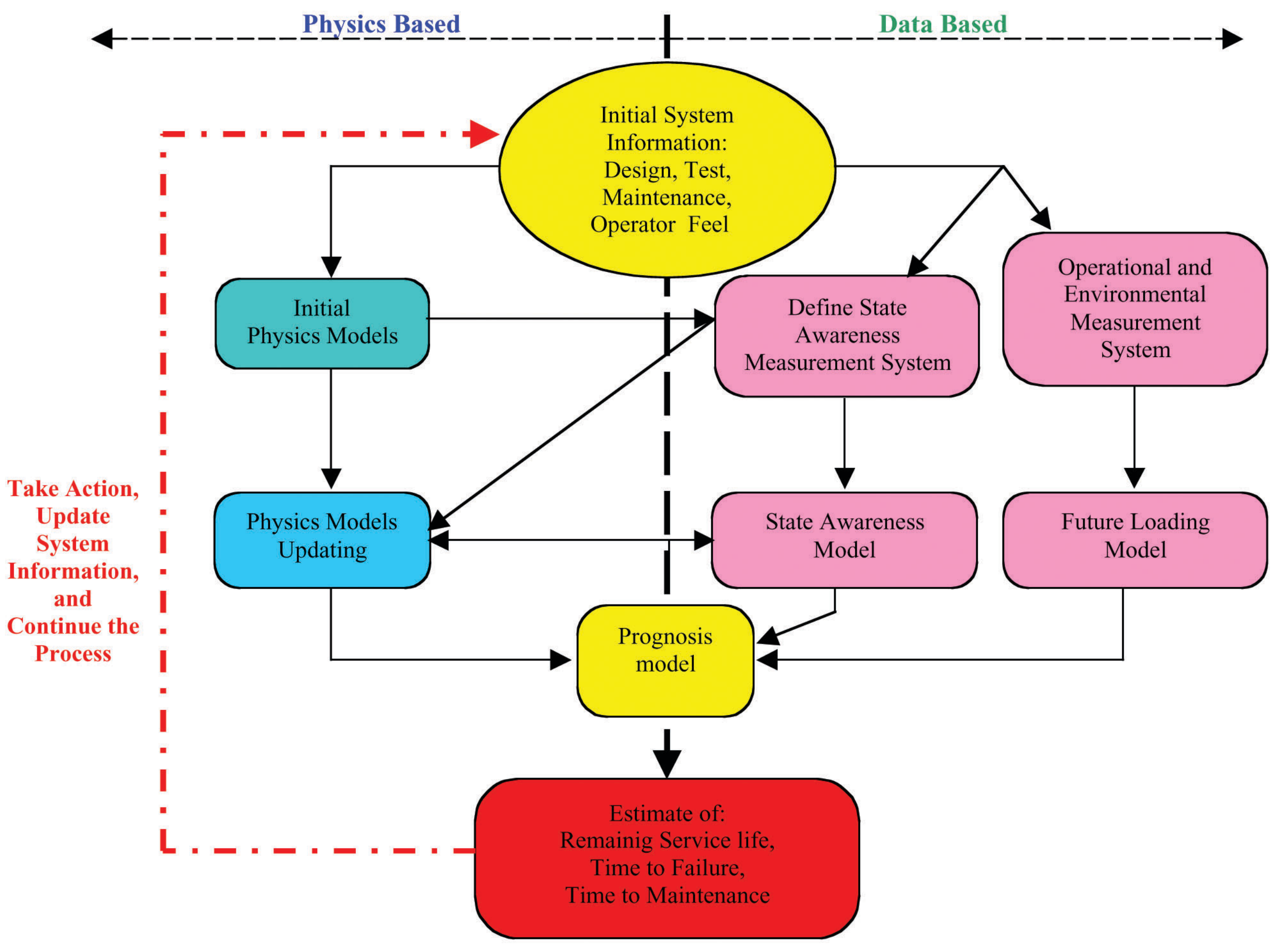

Figure 1.6 A general procedure for a damage-prognosis solution showing the interaction of data-based and physics-based assessments and predictions with the other issues.

Several additional points are brought out by this general solution procedure that should be mentioned:

1. As much information as possible should be used to describe the initial system state, including "soft" information such as operator "feel" for the system response
2. Damage prognosis will rely on numerous models of different forms
3. The sensing system that is used to assess damage may be different from the one used to monitor environmental and operational loading, but, most likely, the two systems will overlap
4. Both the sensing and predictive modeling portions of the process will have to be updated as more information become available
5. Numerical simulations will need to be used when defining the sensing system in order to have confidence that this system has adequate properties (e.g., resolution, bandwidth) to detect the damage of interest
6. Numerical simulations will have to be combined with data-based models in order to estimate the extent of damage in the SHM portion of the problem

1.3 Motivation for Damage-Prognosis Solutions

The interest in damage prognosis is based on the tremendous potential for life safety and economic benefits that this technology can provide. The consequences of an unpredicted system failure were graphically demonstrated by the Aloha Airlines fuselage separation in 1988 (see Figure 1.7). Despite the catastrophic failure of the structure, all but one of the passengers and crew survived. In response to this event the Federal Aviation Administration (FAA) established the Aging Aircraft Program to ensure that the integrity of aircraft are maintained throughout their useable lives. As part of this program, an Airworthiness Assurance Nondestructive Inspection (NDI) Validation Center was established.[1] The center was established to provide the developers, users, and regulators of aircraft with validated NDI, maintenance, and repair processes and with comprehensive, independent, and quantitative evaluations of new and enhanced inspection, maintenance, and repair techniques. Clearly, this catastrophic event has raised the importance of maintenance, reliability and safety to the public and industry alike.

Beyond the life-safety issues, the impetus from airframe and aircraft engine manufacturers, as well as other manufacturers of high capital-expenditure products, such as large construction equipment, for effective damage-prognosis capabilities is business models whereby manufacturers charge for usage by some type of lease arrangement and meet the cost of maintenance themselves. Damage prognosis will allow these manufacturers to move from time-based maintenance to the more cost-effective approach of condition-based maintenance. Also, with effective damage-prognosis capabilities these companies can establish leasing arrangements that charge by the amount of system life used during the lease instead of charging simply by the time duration of the lease.

[1] See http://www.sandia.gov/aanc/AANC.htm

Figure 1.7 Damage to Aloha Airline fuselage resulting from fatigue cracks.

The escalating cost of aging aircraft is not simply restricted to the civil fleet. The U.S. Air Force, through its Engine Rotor Life Extension program (ERLE) expects to commit 63% of its capital budget to sustainment, and 16% and 18% respectively on development and acquisition.[2] On this basis alone there will be a major thrust in the next few years in the aerospace and defense industries to reduce costs of maintenance. The current processes applied to military engine turbine rotors illustrate a need for new prognosis procedures. These rotors are safety critical components on the aircraft and failure through disc burst results in catastrophic loss of the engine at best, or the aircraft loss at worst. Guidelines outlined by Larson and Russ[6] dictate that a disc is discarded on the probability of a one-in-one-thousand chance of failure after inspection. The cost of a single disk is in the range of $300,000 to $400,000. In this case, the probability is that 999 out of 1,000 discs are being discarded before they have reached their full safe-operating life. On this basis, the minimum component cost saving—excluding benefits derived by reduced maintenance and inventory achieved by even a 10% increase in life resulting from improved prognosis methods—is approximately $30–40 million for 1000 discs.

Perhaps the most advanced and most scrutinized health monitoring systems are used in helicopters. The Health and Usage Monitoring Systems (HUMS) have already been operating successfully in transmission monitoring and engine applications. Their effectiveness and reliability has been endorsed by the Civil Aviation Authority (CAA) and FAA and are now being considered for more general structural health monitoring. The most recent cost estimates for implementation of HUMS depend on the level of coverage required:[3]

1. Specific HUMS: partial implementation of a specific component e.g. engine or transmission $10,000–$50,000/unit
2. Mid-Range HUMS: instrumentation of a range of structurally significant items (SSIs), but not full coverage, $75,000–$125,000/unit
3. Complete HUMS: $150,000–$250,000/unit

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[2] J. Larson, S. Russ, et al., "Engine Rotor Life Extension (ERLE)," Damage Prognosis Workshop, Phoenix, AZ, March 2001.
[3] G.F. Forsyth and S.A. Sutton, "Using Econometric Modeling to Determine and Demonstrate Affordability," Tiltrotor/Runway Aircraft Technology and Applications Specialists' Meeting of the American Helicopter Society, Arlington, VA, 2001.

Although the cost of these units is falling because of adoption of commercial off-the-shelf (COTS) technology, Forsyth identifies the data management as the largest single cost associated with these systems. This issue is significant because Forsyth acknowledges that "considerably more data" would be required for robust verification of parameters needed for prognosis. Currently such systems are used for identifying damage. Work is ongoing in the field to use HUMS for prognosis through the Seeded Defect Program[4] whereby electrical discharge machining (EDM) is used to introduce tightly defined faults within gears. The outcome of this program has been an effective demonstration of damage diagnosis and life extension. The options for prognosis have not been fully explored though HUMS, but the achieved life extension from the current implementation of usage monitoring of 73 SSIs has led to cost savings on replacement parts of US$175 per hour of operation, excluding the savings associated with installation and removal of components.[5] With multichannel component usage monitoring, White reports an average increase in available structural-fatigue life of 380% over the original design life. On this basis there seems to be an overwhelming argument in favor of development of robust, low-cost systems for health and usage monitoring.

In the civil engineering field, the driver for prognosis is largely governed by large-scale discrete events rather than more continuous degradation. Typical examples are aerodynamic gust loads on long span bridges and earthquake loading on all types of civil infrastructure. Although cyclic loads caused by traffic are also a consideration, the discrete events are the ones that require immediate prognosis for future use. Using the Kobe earthquake as an example, some buildings were subject to two years of scrutiny before a decision was made on their future use or demolition.[6] Clearly this delay had a significant commercial impact on the economic capacity of the city beyond the reconstruction costs. The most effective way to mitigate costs associated with building reoccupation is through timely prognosis of the system's load-bearing elements and connections. In this case, prognosis is required to ensure that the building can withstand the aftershock associated with a significant seismic event. This application requires a much denser array of sensors to identify local structural degradation than is typical for most current strong-motion instrumentation systems designed for seismic monitoring.[7] Current wired technology in the seismic field has a cost of $10,000 per node, including installation, which limits the sensor density for this application.[8] In California, the most densely instrumented structures have on the order of 10–30 sensors to measure seismic response. For damage prognosis, a one to two orders of magnitude increase in sensor density is required. It is the authors' opinion that this increase can only be achieved economically by the use of new sensing technology such as wireless, self-assembling, embedded devices based on integrated circuit (IC) fabrication technology.

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[4] A.J. Hess and W. Hardman, "SH-60 Helicopter Integrated Design System (HIDS) Program Experience and Results of Seeded Fault Testing," DSTO Workshop on Helicopter Health and Usage Monitoring Systems, Melbourne, Australia, 1999.
[5] D. White, "Helicopter Usage Monitoring Using the MaxLife System," DSTO Workshop on Helicopter Health and Usage Monitoring Systems, Melbourne, Australia, 1999.
[6] C.A. Taylor, Ed., "Shaking Table Modeling of Geotechnical Problems," ECOEST/PREC8, Report No. 3, p. 190, 1999.
[7] C.R. Farrar and H. Sohn, "Condition/Damage Monitoring Methodologies," *Proceedings Invited Workshop on Strong-Motion Instrumentation of Buildings*, J.C. Stepp and R.L. Nigbor Eds., The Consortium of Organizations for Strong Motion Observation Systems (COSMOS) publication CP-2001/04, Emeryville, CA ,November 2001.
[8] S.D. Glaser, "Smart Dust and Structural Health Monitoring," Damage Prognosis Workshop, Phoenix, AZ, March 2001.

Damage identification may significantly mitigate the economic impact of seismic disruption to civil engineering infrastructure. The figures shown below are the results of Coburn and Spence's[9] work developing models of the fiscal impact caused by earthquake damage. The average annual worldwide repair and reconstruction costs associated with mechanical failures and earthquake damage is in the region of $60 billion. This figure does not include consequential losses (e.g. loss of revenues resulting from damage to a manufacturing facility), and costs caused by operator errors. Significantly, in-service mechanical failures contribute 20%–40% of all losses within a given engineering sector. Some of the major components of the $60 billion loss are (approximately): $1.5 billion resulting from commercial aircraft hull losses, $1.5 billion resulting from repair and reconstruction following petrochemical industry disasters and $45 billion associated with earthquake damage. The trends of most concern in these statistics are the costs associated with the petrochemical industry, which have risen tenfold in real terms over the last 30 years, and with postearthquake costs, which are rising up to 20% per annum. During 1995, for example, the earthquakes in Northridge and Kobe were estimated to cost $220 billion. In 1999, the severe damage caused by earthquakes in Colombia, Turkey, Greece, and Taiwan showed that this is a problem of global proportions.

In Appendix B, some other applications that are of immediate interest for damage prognosis are outlined. These include creep rupture in turbine blades, fighter aircraft condition monitoring in hostile environments, flaw initiation and propagation in explosive containment vessels, and composite fuel tanks on reusable launch vehicles. All have the common attribute of being associated with safety-critical hardware where robust damage prognosis can provide high added value. Therefore, there is a considerable cost benefit to be obtained in developing effective damage-prognosis methods.

1.4 Disciplines Needed to Address Damage Prognosis

As discussed in detail in the body of this report, damage-prognosis solutions may be realized by the integration of a robust, densely populated sensing array and a system-specific adaptable modeling capability, both deployed on-board the system via advanced micro-electronic hardware. This integration requires that many disciplines be brought to bear on the damage-prognosis problem. These disciplines include, but are not limited to, the following:

1. **Engineering Mechanics**: transient nonlinear computer simulation, system performance analysis, and damage evolution material models
2. **Reliability Engineering**: probabilistic inference, probabilistic risk assessment, and reliability methods
3. **Electrical Engineering**: micro-electro-mechanical systems (MEMS), wireless telemetry, power management, and embedded computing hardware
4. **Computer Science**: networking, machine learning
5. **Information Science**: data compression and communication, large-scale data management, signal processing
6. **Material Science**: smart materials, material failure mechanisms, self-healing materials
7. **Statistics and Mathematics**: statistical process control, model reduction, pattern recognition, and uncertainty propagation

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[9] A. Coburn and R. Spence, *Earthquake Protection*, John Wiley, November 2002.

When so many disciplines are required to effectively tackle the damage-prognosis problem, technology integration becomes a major issue that must also be addressed.

1.5 Description of the Report

This report provides a brief summary of the current state of the art in damage prognosis. This summary will be followed by more detailed discussions of the three main technology areas that form the damage-prognosis solution: instrumentation and data processing hardware, data interrogation, and predictive modeling. In these discussions the authors have tried to capture the following:

1. The areas of these three respective technologies that are currently applied to the damage-prognosis problem
2. The portions of these technologies that must be further developed for more widespread applications of damage prognosis
3. Key technology hurdles
4. Issues associated with technology integration

The report concludes by citing some specific applications for damage prognosis and by providing a brief summary of damage prognosis demonstration problem being worked on at LANL.

2. BACKGROUND AND CURRENT STATE OF APPLICATION

The main findings of a brief review of the literature on damage prognosis are summarized in this section. One difficulty of such a review is that, like most emerging research and technology, damage prognosis is not well defined yet and the engineering community may not have adopted standard terminology for this technology. As an example, a search of the Engineering Index® electronic database from 1992 to the present on the key words "damage prognosis" (restricted to English) yields only three articles.[10,11,12] A similar search of the SciSearch® database yielded five articles, all of which were related to medical damage prognosis. These results clearly indicate that either the engineering community has not adopted the term damage prognosis or that very few studies have been published on this topic. The authors believe that the dearth of articles is related to some combination of these two issues, as it is known that there are applications of damage-prognosis technology to rotating machinery.

Many technologies could potentially contribute to the development of damage prognosis, such as high-fidelity modeling, computer science, statistical analysis, data interrogation, new instrumentation technologies and active control. The literature review reported herein does not attempt to summarize the state of the art and major accomplishments in each one of these sciences and technologies. Instead, we define what is generally meant by damage prognosis when it has been deployed for a particular application. This summary includes a brief description of the technologies that could potentially impact the development of damage prognosis. The summary of the main characteristics of each one of them does not constitute a thorough nor exhaustive review.

2.1 Scope of the Literature Review

To define which publications are relevant to the field of damage prognosis, it is first assumed that damage refers primarily to *structural damage*, as defined in the introduction, as opposed to damage to electrical components or failure of operating system software. Two key elements of damage prognosis are, first, *diagnosis* or the assessment of the current state of the structure and its history and, second, *prognosis,* which provides a predicted set of consequences for assumed future operational and environmental loading conditions.

The primary objective of structural diagnosis is to determine the current ability of a structure to carry loads. The structural-health monitoring literature has been addressing this problem for several decades. This technology development has been driven by applications from the aerospace, civil and mechanical engineering fields. Applications include both structures and machinery, with machinery applications referred to as *condition monitoring*. Extensive reviews on structural diagnosis are found in Doebling et al.,[13] Sohn et al., [14] and Housner et al. [15] There are numerous

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[10] J. Fu, A. Ray, and J.H. Spare, "Load Scheduling and Health Management of Electric Power Generation Systems," *Proc. of the American Control Conference*, **6**, pp. 4849–4854, 2002.
[11] F.M. Hemez and S.W. Doebling, "Model Validation and Uncertainty Quantification," *Proc. of the International Modal Analysis Conference—IMAC*, **2**, pp.1153–1158, 2001.
[12] D.E. Adams and M. Nataraju, "A Nonlinear Dynamical Systems Framework for Structural Diagnosis and Prognosis," *Int. J. of Engineering Science*, **40** (17), pp. 1919–1941, 2002.
[13] S.W. Doebling, C.R. Farrar, M.B. Prime, and D.W. Shevitz, "Damage Identification and Health Monitoring of Structural and Mechanical Systems From Changes in Their Vibration Characteristics: A Literature Review," Los Alamos National Laboratory report LA-13070-MS, May 1996. (Available at www.lanl.gov/projects/damage_id)

conferences[16,17,18,19] and more recently a refereed journal [20] dedicated to this topic. Technologies and methods generally involved in the development and deployment of diagnosis systems are instrumentation, data acquisition, finite element modeling, feature extraction, and test-analysis correlation for parametric calibration. One critical aspect of diagnosis is to assess not only the current "state" of the system, but also its history. Another critical aspect is to account for modeling, operational and environmental uncertainty. The importance of these aspects has only recently been recognized and only a small number of publications currently address these issues compared to the large body of work published on linear, history-independent, and deterministic approaches.

The primary objective of structural prognosis is to assess the ability of a system to carry out an intended function. This assessment is basically a decision-making process where answers must be provided to questions such as "Given an estimate of the current structural state of the bridge, how much future traffic loading can be tolerated?" or "Given a damage state of the bridge and a traffic load, what is the safety margin?" Prognosis is therefore a prediction or extrapolation problem, which generally presents challenges across all fields and necessitates a probabilistic approach. Various models of damage and estimations of future loading are combined to describe a space of potential operating conditions, and decisions are based on the outcome of each analysis analogous to probabilistic risk assessment. Other criteria such as economic, human, and safety factors and risk-versus-payoff analysis can be included in the decision-making process. The tools by which predictions and extrapolations are made are models and simulations. Models can be derived through measurement of a physical system, empirical observations, knowledge-based reasoning, or mathematical and numerical simulations.

The literature indicates that the only serious attempt at integrating damage prognosis around a predictive capability is encountered in the field of rotating machinery.[21] A recent account of the work performed in rotating machinery can be obtained from the literature.[22] The reason why successful applications of damage prognosis are documented in rotating machinery is because of the availability of large data sets from experiments, many of which include run-to-failure data. Also, rotating machines are typically operated in well-controlled environments and the future operational conditions and loading are often well defined. The databases can be used to develop regression models for failure prediction. Full-scale failure tests can be performed on critical components to augment these databases. One major drawback of this approach is that complicated systems that have multiple damage mechanisms can generally not be tested to failure.

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[14] H. Sohn et al., "A Review of Structural Health Monitoring Literature: 1996–2001," Los Alamos National Laboratory report LA-13976-MS (2003).
[15] G.W. Housner, et al., "Structural Control: Past, Present and Future," (Section 7, Health Monitoring) *Journal of Engineering Mechanics*, ASCE, **123** (9), pp. 897–971, 1997.
[16] The 4th International Structural Health Monitoring Workshop, Palo Alto, CA, 2003.
[17] The 6th International Symposium on Nondestructive Evaluation of Aging Infrastructure, San Diego, CA, 2003.
[18] The 5th International Conference on Damage Assessment of Structures, Southampton, UK, 2003.
[19] The 1st European Structural Health Monitoring Workshop, Paris, France, 2002.
[20] *The International Journal of Structural Health Monitoring*, F-K Chang Edt., Sage Publications.
[21] J.S. Mitchell, *Introduction to Machinery Analysis and Monitoring*, PenWel Books, Tulsa, OK, 1992.
[22] H.C. Pusey and R.B. Rao, *Proceedings of the 13th International Congress on Condition Monitoring and Diagnostic Engineering Management,* Houston, TX, December 3–8, 2000. Published by the Society for Machinery Failure Prevention Technology, Haymarket, Virginia.

2.2 Elements of Prognosis Technology

Based on the literature reviewed, eight subjects are identified as contributing to the deployment of damage-prognosis systems. The present literature review does not attempt to define the state of the art of each one of them because of the very large body of literature that would have to be examined. Instead, the efforts have been focused on collecting papers where damage prognosis is dealt with to some extent and on identifying which ones of these subjects are addressed. The list of publications reviewed is provided in Appendix C and Appendix D. A compilation of this analysis is also provided in Appendix C. The eight subjects considered are defined below.

1. **Advanced Modeling and Architectures**: Advanced constitutive models, multiple-scale models, coupled-field physics, fracture and damage evolution mechanics, high-fidelity models, innovative inverse problem solving, model updating, calibration experiments, and parallel processing.
2. **Data Interrogation**: Statistical analysis, outlier detection, data normalization, data fusion, group classification, and hypothesis testing.
3. **Elements of Prognosis Capability**: Implementation of predictive modeling, model validation experiments, assessment of future loading, calibration of reliability or failure criteria, and examples of decision making based on prognosis.
4. **Local Actuation and Processing**: Localized actuation and sensing, local data processing, programmable digital signal processing (DSP) chips, field programmable gate arrays, development of specialized chips, and system power.
5. **Novel Sensing and Telemetry Technology**: Micro electro-mechanical systems (MEMS), fiber optics, non-intrusive measurements, development of new sensor types, and wireless communication.
6. **System Integration**: Issues related to the integration and deployment of damage-prognosis technologies, integration of hardware and software components, data management, and evolution of models.
7. **Surrogate Modeling**: Surrogate models, metamodels, fast-running models, statistical models, data compression, feature extraction, and reduction of large data sets.
8. **Uncertainty Quantification**: Quantification of uncertainty, forward propagation of uncertainty, sampling strategies, design of experiments, and nonprobabilistic approaches.

In the summary tables presented in Appendix C, the eight subject categories are identified using the acronyms defined in Table 1. There may be some degree of redundancy between several of these categories. For example, the applicability of a novel sensing technology (5-NST) is often discussed in conjunction with system integration (6-SI). Therefore, there is a strong overlap between categories 5-NST and 6-SI. The number of categories could probably be reduced to four or five nonoverlapping ones. However, the current classification provides more flexibility, as some publications are very specific while others describe concepts and experiments in a broader sense.

Table 1. Methods and Technologies of Damage Prognosis	
Symbol	***Category***
1-AMA	Advanced Modeling and Architectures
2-DI	Data Interrogation
3-EPC	Elements of Prognosis Capability
4-LAP	Local Actuation and Processing
5-NST	Novel Sensing Technology
6-SI	System Integration
7-SM	Surrogate Modeling
8-UQ	Uncertainty Quantification

The only truly relevant category for this literature review is the third one, Elements of Prognosis Capability (3-EPC). Techniques that possess elements of a prognosis capability should present to some degree the development or application of predictive modeling to a particular problem. Very few papers have been found so far that discuss the deployment of a damage-prognosis system for an application other than rotating machinery. The very precise reasons why this deficiency exists are summarized in Section 2.3. The other categories are included because of the close connection to damage diagnosis and prognosis. Nevertheless, little work has currently been found that attempts to integrate several of these categories. *No publication has been found that addresses all eight categories.*

2.3 Analysis of the Literature

The instances of damage prognosis documented in the literature reviewed here consist of predicting criteria such as time to failure, remaining useful life, or safety margin based on information regarding the system and estimated future environmental and operational conditions. In the following discussion, the criterion predicted is denoted by the symbol y and the information required to make the prediction is denoted by the symbol p. Damage prognosis therefore consists of developing a model of the form $y = \mathrm{M}(p)$. Once the model has been developed, it is deployed for the application of interest. An instrumentation system or a combination of model predictions and measurements provide an estimate of the future p, and the model $y = \mathrm{M}(p)$ makes the next prediction. Adaptability is where the model is recalibrated or its functional form is revisited as soon as new data and predictions become available. Another important characteristic is that most applications presented in the literature deal with well-defined damage scenarios and operating conditions that can be adequately controlled.

Figure 2.1 illustrates this concept where data points that define an unknown relationship between an input parameter p and an output observation y are plotted. For example, a test bed can be developed to characterize the dynamics of typical gearbox mechanism when the system transitions from a healthy state to a damage state and, eventually, to total failure. A crack is initiated in one or several of the gear teeth and the vibration response of the gearbox is monitored. As the gear mechanism is subjected to loads, the cracks undergo high-fatigue cycles and damage progresses. Periodic measurements are collected and the features y extracted from the vibration response are tabulated for various crack lengths p. Next, a functional form $y = \mathrm{M}(p)$ is assumed and parameters of the model are calibrated. The objective of the calibration experiment is to obtain the optimal model that best matches the observation data. If the system investigated can be tested over a wide range of environmental and operating conditions, then the model will be able to make predictions for nominal operating conditions all the way to failure.

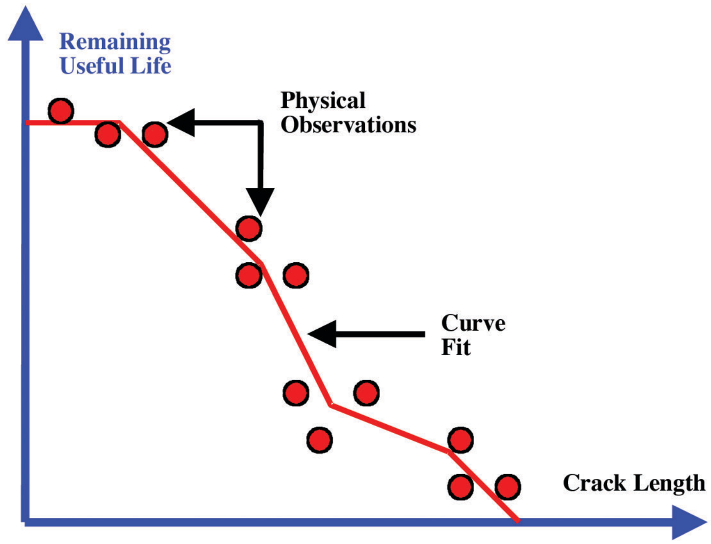

Figure 2.1 Failure model via curve fitting.

Figure 2.1 shows a representative curve fit where a continuous relationship is established between the damage indicator and the prognosis criterion. Several such curve-fitting methods are mentioned in the literature. They are collectively referred to as *continuous curve fitting* in this document. They include the least-squares and generalized least-squares approaches, statistical inference methods, and hypothesis testing methods. Prognosis models can also be developed that are not continuous. *Group classification* is an example of such discrete prognosis models. Figure 2.2 illustrates the case where the same data as previously shown in Figure 2.1 are classified in four groups. Such models would typically be developed based on group classification techniques. When a new measurement becomes available, the statistical estimation problem is essentially an orthogonal projection problem, where the distance between the new data and the existing subspaces is minimized in a multidimensional space.

The methods for constructing predictive models encountered in the damage-prognosis literature can be classified within the general paradigm of pattern recognition. Most often, data sets for training are generated by physical observation. In instances where the prognosis experiment can be run to failure, a complete characterization of the system is obtained from which a regression model can be developed. Very successful results are reported when such information is available.

As mentioned previously, the only successful application of damage prognosis consistently reported in the literature is the field of rotating machinery. Applications documented include machinery and industrial equipment that involves bearings, gearboxes, shafts, transmission lines, and blade assemblies. The main reason why damage-prognosis systems are successfully deployed is because failure testing of critical components is generally available. Failure scenarios and damage mechanisms have long been identified and it is possible to design model validation experiments in which the mechanical component under investigation is tested to failure. Because laboratory experiments can reproduce a wide range of environmental and operational conditions, the prediction models inferred from test data can be used with confidence. The availability of a large number of similar units is also an advantage. For example, large databases are available for turbine engines.

Because the damage mechanisms are relatively consistent, it is possible to treat the observations obtained from a large number of "similar" systems as replicate data and to estimate the probability distributions of failure. Computational failure and reliability prediction methods that are based on finite element analysis and probability approaches are applied with success to turbine engines because a large body of knowledge can be translated into prior distributions.

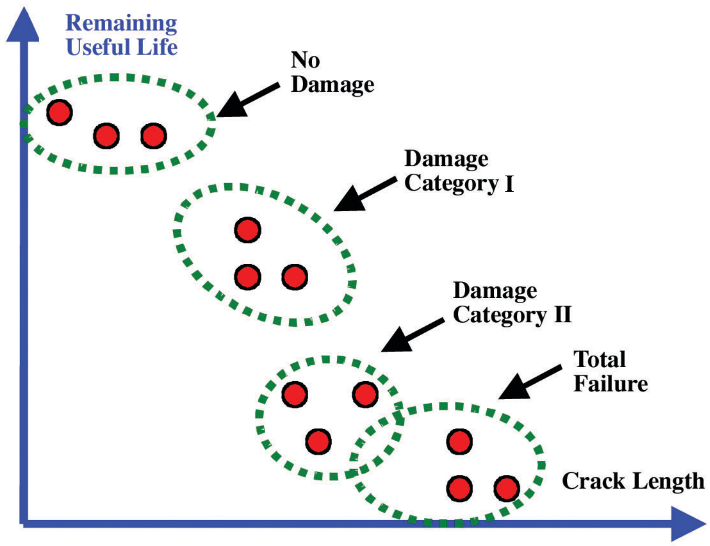

Figure 2.2 Failure model via group classification.

Several potential difficulties for the deployment of damage prognosis in applications other than rotating machinery are mentioned in the literature. They can be classified into four main categories:

1. Testing: For complex engineering applications, testing systems to failure may not be an option. It may be possible to isolate a critical component and to develop a specialized test bed. But in most cases, the interaction of a critical component with other components and the degree of variability of environmental and operating conditions will make such laboratory experiments of limited value. Numerical simulation is generally mentioned as the only alternative to limited or unavailable testing; however, it is not certain that complex systems can be modeled and analyzed numerically.

2. Sensing: It may not be possible to fulfill the objectives of damage diagnosis and prognosis using the currently available sensing technology. An example often mentioned is the assessment of damage using vibration measurement. A crack is visible only if the wavelength of the vibration measured is significantly less than the crack's length, which is a requirement that the conventional, modal based measurement and analysis techniques do not always satisfy. For this reason, many attempts at damage diagnosis are based on innovative sensing technologies such as fiber optics-based optical measurements or acoustic emission. Demonstrating their practicality for a real-world field application remains an open question. Communication and transmission of the data collected can also impose serious limitations on the type and number of sensors available. A constraint mentioned in the literature is the deployment of wires between sensors and the central data processing unit. Hardware compactness, packaging, and on-board integration are identified as important issues as well.

3. Variability: Unit-to-unit variability makes it difficult to develop a prognosis criterion because the causes of variability should theoretically be included in the prognosis model or criterion. Variability can originate from manufacturing and assembling processes. Maintenance history is also a significant source of variability because similar systems do not always receive the same maintenance, part replacement, and hardware upgrades at the same time. Even the acts of disassembly and reassembly can be a considerable source of uncertainty.

4. Confidence: Another consequence of variability is that it makes it difficult to assess with confidence the outcome of a prognosis. Confidence is generally represented by probability intervals. For example, Figure 2.3 illustrates the prognosis model shown in Figure 2.1 to which $\pm 2\sigma$ confidence intervals have been added. Confidence will typically decrease in regions where less data are available and where the sources of variability exhibit greater influence on the output prognosis feature. Probability-based assessment of confidence intervals is more difficult when the propagation of uncertainty methods cannot rely on repeatability.

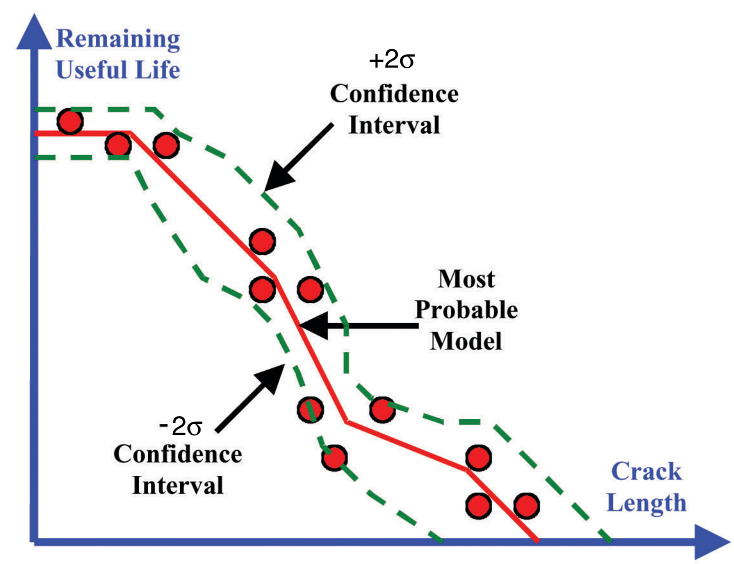

Figure 2.3 Assessment of confidence intervals in predictive modeling.

3. SENSING AND DATA ACQUISITION

Instrumentation and data acquisition issues are major concerns that must be addressed when developing damage-prognosis solutions. This report will address these concerns by presenting three different instrumentation strategies for damage detection and prognosis. These strategies are presented in increasing order of sophistication. The primary difference in these strategies is the up-front effort to integrate testing and numerical simulations, interdisciplinary communication, and to design instrumentation specifically for the system to be monitored. These strategies are then discussed in terms of conceptual issues associated with the development of a sensing and data acquisition system that are fundamental to making significant progress in damage prognosis. Next, more general challenges such as the technological issues of sensors, data acquisition and storage, data processing using feature extraction, and the combined role of testing/modeling in damage prognosis are addressed. This section concludes with a summary of the authors' opinions on the properties of a future sensing and instrumentation system for damage prognosis.

As previously mentioned, this report emphasizes structural dynamics while accepting that structural failures are not necessarily the dominant factor in many system failures. Therefore, the sensing issues that will be addressed are primarily related to detecting structural damage through some measure of kinematic quantities. Additional sensors will be needed to assess operational and environmental conditions in an effort to separate their effects from those caused by damage. The most fundamental issue that must be addressed when developing a sensing system for damage prognosis is the need to capture the structural response on widely varying length and time scales.

3.1 Sensing and Data Acquisition Strategies for Damage Prognosis.

3.1.1 Strategy I

A less effective, but often used, approach to deploying a sensing system for damage detection and prognosis consists of a sparse sensor array, installed on the structure after fabrication, possibly following an extended period of service. Sensors are typically chosen based on previous experience and availability. The selected sensing systems often have been commercially available for some time, and the technology may be twenty years old. Excitation is limited to that provided by the ambient operational environment. The physical quantities that are measured are often selected in an ad hoc manner without an a priori quantified definition of the damage that is to be detected or any a priori analysis that would indicate that these measured quantities are sensitive to the damage of interest. This approach dictates that damage-sensitive data features are selected "after the fact" using archived sensor data and ad hoc algorithms. This scenario represents many real-world systems, particularly those deployed on civil engineering infrastructure.

The common damage-detection approach associated with Strategy I is that a set of undamaged and damaged structures are subjected to nominally similar excitations and their responses measured. Features determined using trial and error or physical intuition are extracted from the measured response and correlated to damage using a variety of methods that vary in their level of mathematical sophistication. A comparison of power spectral density functions illustrates the type of basic data analysis associated with this sensing system strategy. When data are not available from the damaged structure, the damage detection process reverts to some form of outlier detection. In this case, trial and error or physical intuition is again used to define the damage-sensitive features that will be classified as outliers because of damage and to set thresholds that define when these features can be considered outliers. Despite the ad hoc nature of this process, Strategy I is sometimes effective for damage detection but typically shows limited success for damage location and quantification. This approach is often enhanced by a comprehensive historical database. For example, the availability of information regarding the damage state and corresponding measurement results for large numbers of nominally identical units will significantly improve the ability to detect damage in subsequent units when Strategy I is employed. A major drawback of this approach is that, typically, the sensing system is not designed to measure the parameters necessary to allow one to separate operationally and environmentally induced changes from changes caused by damage.

3.1.2 Strategy II

Strategy II is a more coupled analytical/experimental approach to defining the sensor system definition and incorporates some significant improvements over Strategy I. First, damage is well defined and to some extent quantified before the sensing system is designed. Next, the sensing system properties, including actuator properties, are defined based on the results of numerical simulations or physical experiments and are based on the data analysis procedures (e.g., feature extraction and statistical discrimination) that will be employed in the damage-detection application. This process of defining the sensor system properties will often be iterative. Sensor types and locations are chosen because the numerical simulations or physical tests show that the expected type of damage produces known, observable, and statistically significant effects in features derived from the measurements. Additional sensing requirements are then defined based on how changing operational and environmental conditions affect the damage detection process. However, all sensors are still chosen from the commercially available sensors that best match the defined sensing system requirements. Finally, as a result of this coupled approach to designing the sensing system, there is the possibility that the extent of the damage can be directly correlated to the sensor measurements through the numerical or physical models that were used to define the sensing system properties.

Strategy II incorporates several enhancements that will typically improve the probability of damage detection:

1. Well-defined and quantified damage information that is based on initial system design information, numerical simulation of the postulated damage process, qualification test results, maintenance records, and system autopsies
2. Sensors that are shown to be sensitive enough to identify the predefined damage when the measured data are coupled with the data analysis procedures
3. Active sensing that is incorporated into the process: a known input is used to excite the structure with an input waveform tailored to the damage detection process
4. Sensors that are placed at locations where responses are known from analysis, experiments, and past experience to be sensitive to damage
5. Features extracted from the measured data that are known to be sensitive damage indicators based on analysis, experiments, and past experience
6. Additional measurements that can be used to quantify changing operational and environmental conditions
7. Damage extent estimates that are obtained by correlating sensor readings with information from numerical or physical models of the damage and its effect on the system

The number of studies in the technical literature that take this approach to developing a sensing system to detect damage is quite small. In actuality, most sensing systems used to detect damage take an approach somewhere in between Strategy I and Strategy II. However, Strategy II still does not directly address the "predicting remaining life" issue of damage prognosis.

3.1.3 Strategy III

Strategy II is much more effective in damage detection than Strategy I, but does not specifically address the instrumentation issues associated with damage prognosis. Damage prognosis requires various validated models to predict future loading, damage accumulation, and remaining system life. The need to develop these models, update the models as new data become available and quantify the uncertainty in these models dictates the enhanced sensing system requirements associated with Strategy III. These models will incorporate the measurement data and produce a structural state estimate as in Strategy II. Then the model will be used to predict the evolution of this state through time, and finally to translate these progressive estimates into an estimate of remaining useful life.

In summary, Strategy III includes additional predictive capabilities that dictate sensing system requirements beyond those of Strategies I and II. The following are additional modeling capabilities and their associated sensing system requirements:

1. Numerical models, developed in conjunction with a series of nondestructive model validation experiments, that predict the damage evolution
2. A sensing system designed to provide information that can be used to develop future loading models
3. A procedure to validate the numerical damage prediction model through test-analysis correlation using measured system responses to a known set of physical excitations
4. The data processing and storage capabilities necessary to perform measurements on an ongoing basis
5. A procedure to extract damage-sensitive features from the measured data so the features can be used to monitor the evolution of damage
6. Reduced order models that can predict remaining system life

This strategy, which is the most sophisticated, clearly provides the most robust method for viable prognosis. Several serious challenges are involved in its implementation. The following section lists the major challenges related to sensing and data acquisition for damage prognosis.

3.2 Instrumentation: Conceptual Challenges

The above three strategies identify conceptual challenges to effective damage prognosis from a sensing system perspective. These challenges include the following:

1. The ability to capture local and system-level response; that is, the need to capture response on widely varying length and time scales
2. The need for a sensing system design methodology
3. The need to integrate the predictive-modeling and data-interrogation processes with the sensing-system design process
4. The ability to archive data in a consistent, retrievable manner for long-term analysis

These challenges are nontrivial because of the tendency for each technical discipline to work more or less in isolation. Therefore, an integrated systems-engineering approach to the damage prognosis process and regular, well-defined routes of information dissemination are essential. The subsequent portions of this section will address specific sensing-system issues associated with damage prognosis.

3.2.1 What Types of Data Should be Acquired

Instrumentation, which includes sensors and data acquisition hardware, first translates the system's dynamic response into a signal, such as an analog voltage signal, that is proportional to the measured quantities of interest. Next, the analog signal is discretely sampled to produce digital data. To begin defining a sensing system for damage prognosis, one must first define the types of data to be acquired. The data types fall into three general categories of kinematic, environmental and operational quantities. There are many traditional sensors that can be used to measure these various physical quantities, and there are emerging technologies that could have tremendous impact on the future of damage prognosis. Although this report focuses on more traditional sensing technology, it acknowledges that sensing technology is one of the most rapidly developing fields related to damage prognosis and therefore one must always be looking for new technologies that are applicable to the prognosis problem.

3.2.1.1 Kinematic Quantities

The "traditional" sensors used to measure kinematic quantities include wire resistance strain gauges, mechanical displacement transducers such a linear variable differential transducers, and piezoelectric accelerometers. In general, the accelerometers provide an absolute measurement at a point on the structure while the displacement and strain sensors provide relative measurements over typically short gage lengths. These sensors are used extensively for aerospace, civil, and mechanical engineering applications. Conditioning electronics for these sensors have evolved from bulky vacuum tube systems to small, sophisticated, solid-state devices. A wide variety of sensors that can accommodate many different applications are available off the shelf.

The principal emerging kinematic sensing technologies include micro-electro-mechanical systems (MEMS), piezoelectric (PZT) actuator/sensors (discussed in Section 3.2.6), and fiber optic strain sensors. Commercially available MEMS devices can measure strain, and rotational and linear acceleration. A MEMS accelerometer is shown in Figure 3.1. Once fully developed, MEMS sensors have the potential to impact a variety of sensing activities based on their versatility, small size, and low cost when manufactured in large numbers. These properties will allow the sensor density on a structural system to increase significantly, which is essential to improve damage-prognosis technology. MEMS can be integrated with on-board computing to make these sensors self-calibrating, and self-diagnosing. This integration of the sensor with microprocessors defines the "smart sensor" concept. Inhibiting MEMS use today are issues such as commercial availability, traceable calibration, and a track record of stability and ruggedness when used for long-term structural monitoring activities. In contrast, current commercially available traditional accelerometers have been proven to be reliable and stable. These accelerometers incorporate on-board signal conditioning and may soon have on-board A-D conversion. However, in comparison to anecdotal reports of MEMS sensors, the traditional accelerometers typically don't measure multiple parameters such as both rotational and linear acceleration. The traditional sensors are relatively expensive (hundreds of dollars for conventional piezoelectric accelerometers versus tens of dollars for MEMS accelerometers), and they are typically not integrated with microprocessors.

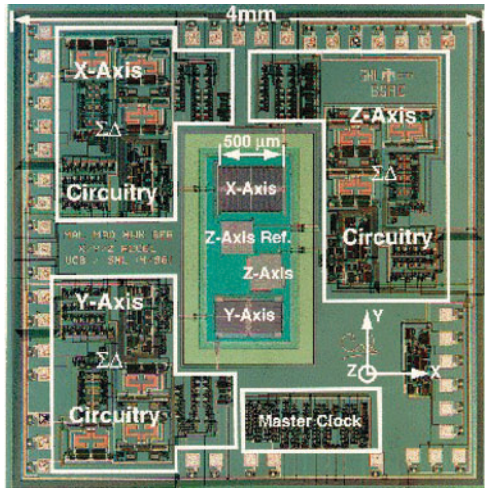

Figure 3.1 A MEMS accelerometer.

Fiber-optic strain gauges are mentioned here as a nearly commercially available emerging technology. In the most sophisticated type, a selectable gage length of a single long fiber is queried to obtain the strain (with picostrain accuracy). This technology could allow a single fiber with the length of a bridge girder to monitor strain at any location along the girder, or to embed sensors in manufactured parts that could measure strain later in selected regions using Bragg grating technology.[23] Multiple Bragg gratings can be placed in a single long fiber to obtain numerous discrete strain readings. These readings can be obtained with greater accuracy than electrical resistance strain gauges, the readings are immune to electromagnetic and RF interference, and the sensors are not a spark source, which is a key issue if monitoring is to be done near combustible materials. Also, these sensors are nonintrusive, extremely lightweight, and have proven to be very rugged.[24]

The previous discussion of measuring kinematic quantities has focused on local measurements. In addition, there are some global sensing technologies that are commercially available. More mature global sensing technologies include laser Doppler velocometers and acoustic field detectors. Global sensors can scan a surface of a structure, and in some cases with proper signal processing they can identify damaged areas. The disadvantages associated with global sensors include fairly high procurement cost, the need for a visual access to the measured part, and the need to remove the structure from service to carry out the test. An emerging technology in this area of global sensing is

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[23] M.D. Todd, G.A. Johnson, and B.L. Althouse, "A Novel Bragg Grating Sensor Interrogation System Utilizing a Scanning Filter, a Mach-Zehnder Interferometer, and a 3 × 3 Coupler," *Measurement Science and Technology*, **12** (7), pp. 771–777, 2001.

[24] G.A. Johnson, et al., "Surface Effect Ship Vibro-Impact Monitoring with Distributed Arrays of Fiber Bragg Gratings," *Proceedings of the 18th International Modal Analysis Conference*, San Antonio, TX, February 2000.

chemical coatings that emit a particular signature when cracked. This technology has already been demonstrated through the application of pressure-sensitive paints for wind tunnel testing.[25]

3.2.1.2 Environmental Quantities

If changes in environmental quantities produce changes in the damage-sensitive features similar to those produced by damage, a measure of the environmental quantity will be necessary to separate these effects. Such a case will necessitate that environmental quantities such as temperature, pressure, and moisture content be measured. Note that if damage changes the features that are in someway orthogonal to the changes produced by environmental effects, then a measure of the environmental parameters may not be necessary.

3.2.1.3 Operational Quantities

Similar to environmental quantities, operational quantities may also produce changes in damage-sensitive features and may therefore need to be measured. Operational quantities include such things as traffic volume for a bridge, mass loading of an off-shore oil platform, or amount of fuel in an airplane wing.

3.2.2 Define the Sensor Properties

One of the major challenges of defining sensor properties is that these properties need to be defined a priori and typically cannot be changed easily once a sensor system is in place. These properties of sensors include bandwidth, sensitivity (dynamic range), number, location, stability, reliability, power requirements, cost, telemetry, etc. To address this challenge, a significantly coupled analytical and experimental approach to the sensor system deployment should be used in contrast to the current ad hoc procedures used for most current damage-detection studies. This strategy should yield considerable improvements. First, critical failure modes of the system can be well defined and, to some extent, quantified using high-fidelity numerical simulations before the sensing system is designed. These high-fidelity numerical simulations can be used to define the required bandwidth, sensitivity, sensor location, and sensor number. Additional sensing requirements can also be ascertained if changing operational and environmental conditions are included in the models so as to determine how these conditions affect the damage detection process.

3.2.2.1 Required Bandwidth

Local response characteristics are required to identify the onset of damage, which tends to manifest itself in the higher-frequency portions of the response spectrum. Global response characteristics are required to capture the influence of damage on the system level performance and to predict future performance. The global system response is typically characterized by the lower-frequency portion of the response spectrum. Therefore sensors with a high-frequency range tend to be more sensitive to local response and therefore can detect the onset of damage. This sensitivity requires a sensor with a large bandwidth. Typically, as the bandwidth goes up, the sensitivity goes down. Also, it is harder to excite higher-frequency response of a structural system. This difficulty

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[25] R.H. Engler, C. Klein, and O. Trinks, “Pressure Sensitive Paint Systems for Pressure Distribution Measurements in Wind Tunnels and Turbomachines,” *Measurement Science and Technology*, **11** (7), pp. 1077–1085, 2000.

dictates that the excitation needs to be very local as is possible with PZT actuators (see Section 3.2.6). Both local and global response characteristics are required for damage prognosis.

3.2.2.2 Required Sensitivity

Adequate sensitivity and dynamic range is required to separate ambient vibration or low-level local excitation caused by damage (e.g., cracks opening and closing) from large-amplitude excitation such as that caused by impact or earthquake loading. Thirty-two bit sensors are able to resolve this sort of dynamic range, but issues remain concerning the calibration of the sensors over the entire range of possible inputs.

3.2.2.3 Number of Sensors and Sensor Locations

Two primary considerations when deciding on the number and location of sensors are whether or not the sensing system should be optimal and how much redundancy is desired. It is critical that the expected type of damage produces known, observable, and statistically significant effects in features derived from the measured quantities at the chosen transducer locations. For this reason, numerical simulations can be used to choose the number of sensors and sensor locations. It is well known from control theory that the observability of a system depends critically on the location of the sensors and the desired feature to be extracted. For instance, if one desires to measure the second resonant frequency of a structure and use this value as a metric for damage, mounting the sensor on the node of the second mode will doom any frequency-based algorithm to failure. This problem is partially addressed by the observability theory developed for control algorithms. However, this theory does not address performance, nor does it address the metric used to determine damage. The issues associated with integrating observability calculations for local damage and global behaviors of a system into the optimal sensing design, which has not been addressed in current damage identification practice, should be examined. Such methods may incorporate genetic algorithms[26] or neural networks with the ability to model the system in detail or the ability to examine the structure systematically.

Intuitively, sensors should be near expected damaged locations. With MEMS or Smart Dust[27] (tiny, wireless sensors) it may be possible to saturate the part with sensors to provide sensing redundancy, a clear issue for prognostics in civil aerospace applications, and to reduce the need for an optimal sensing system. As the number of sensors increases, the cost, reliability, and perhaps power requirements may become significant issues. Traditional sensing emphasizes relatively few, sophisticated sensors or scanning noncontact sensing. An alternative approach to attaching a sensor to a structure is the use of a probe. The structure is examined with a probe at numerous locations sequentially. This sensing approach is common practice in many industries; for example, condition monitoring of rotating machinery or local acoustic resonance spectroscopy. Clearly a probe requires a human operator and does not allow periodic data acquisition from a remote location or automatic data acquisition during a severe event such as an earthquake.

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[26] W.J. Staszewski, K. Worden, R. Wardle, and G.R. Tomlinson, "Fail-safe sensor distributions for impact detection in composite materials," *Smart Materials and Structures,* **9** (3), pp. 298–303, 2000.
[27] http://robotics.eecs.berkeley.edu/~pister/SmartDust/

3.2.3 Calibration and Stability

Most sensors are calibrated at a specialized calibration facility. This type of calibration is expected to endure but to be supplemented by self-checking and self-calibrating sensors. Calibration raises several important issues. It is not clear just what forms of calibration are essential, and what are superfluous. Some measurements are acceptable with 20% error, especially if sensor-to-sensor comparisons are accurate within a few percent. In other scenarios, absolute accuracies better than 1% are required. The calibration community needs to address these issues, including both precision and flexibility; for example, how to calibrate a 32-bit sensor over its entire dynamic range, and how to calibrate a precise sensor versus a coarse sensor.

3.2.4 Sensor Durability

Sensor survival is probably the major issue whose resolution is unclear. Confidence and robustness in the sensors are prime considerations for prognostics. If this part of the system is compromised, then the overall confidence in the system performance is undermined. For sensors implemented for prognostics, several durability considerations emerge:

1. The nontrivial problem of sensor selection for extreme environments; e.g., in service turbine blades
2. Sensors being less reliable than the part. For example, reliable parts may have failure rates of 1 in 100,000 over several years time. Sensors are often small, complex assemblies, so sensors may fail more often than the part to be sensed. Loss of sensor signal then falsely indicates part failure, not sensor failure
3. Sensors may fail through outright sensor destruction while the part being sensed endures
4. False indications of damage or damage precursors are extremely undesirable. If this occurs often, the sensor is either overtly or covertly ignored. The biggest cause of aircraft delay is a failed sensor. Sensor failure might be acceptable if its demise is simultaneous with the part failure, which would in itself provide an indication of damage

3.2.5 Define Data Sampling Parameters

Sampling issues include deciding how fast to discretize the data and when to take data. These issues will most likely change depending on the structure and the expected type of damage. If it is important to characterize the environmental or operational variability, then a lot of samples may need to be taken initially and data will need to be taken from all the expected environmental and operational conditions. Once a baseline has been established, data may be obtained either periodically or only after extreme or anomalous events such as an earthquake or new environmental conditions not previously experienced.

3.2.6 Define the Data Acquisition/Transmittal/Storage System

Multiple smart sensors produce an abundance of time history data to store and manage. Another field with this characteristic is satellite imaging, where huge volumes of image data are standard. Image-data processing may yield some insights valuable for processing smart mechanical sensor data.

Sensing, especially with a dense array of smart sensors, interacts with data acquisition. Smart sensors theoretically make it possible to extract, transmit, and store features, as well as to transmit raw time histories. Transmitting raw time histories clearly will require much more storage space but also allows the most flexibility for future data analysis. Continuous data transmission with Smart Dust could lead to information overload during analysis and storage. With smart, dense sensors the structure might be instrumented so densely that sensors are everywhere, so wherever damage occurs there is a nearby sensor.

Near-real-time data transmission for feature extraction and analysis has the potential to enhance real-time damage detection and to increase the value of testing. Currently, a test setup is often disassembled prior to data analysis, just to discover that some modification, like a different input type or level, or another transducer location, is required. Real-time analysis takes more upfront preparation time and better communications, but provides much more value from the test, because problems can be corrected during the test. Other issues that need to be addressed are the time synchronization of a large number of sensors, A-D conversion and onboard memory.

An example of an integrated sensing and processing system is the high-explosives radio telemetry (HERT)[28] system (see Figure 3.2) developed at LANL for weapons flight test monitoring. The HERT system currently can measure, record, process, and transmit data from 64 fiber optic sensor channels. A field-programmable gate array is used for local data processing.

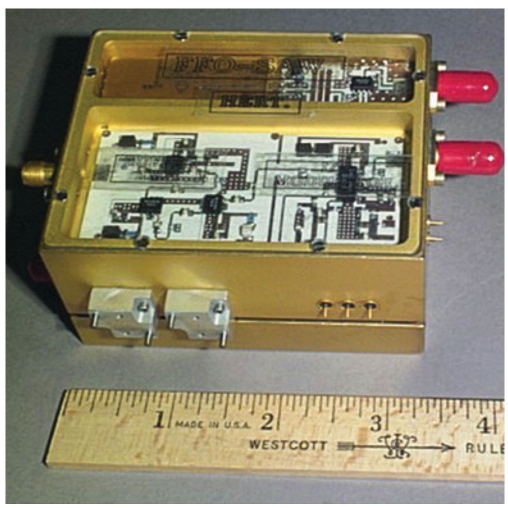

Figure 3.2 High-explosives radio telemetry system.

3.2.7 Active Versus Passive Sensing

Most field-deployed structural-health monitoring strategies examine changes in kinematic quantities such as strain or acceleration to detect and locate damage. These methods typically rely on the ambient loading environment as an excitation source and, hence, are referred to as passive sensing systems. The difficulty with using such excitation sources is that they are often nonstationary. The nonstationary nature of these signals requires robust data normalization

[28] R.R. Bracht, R.V. Pasquale, and T.L. Petersen, "QAM Multi-Path Characterization due to Ocean Scattering," *International Telemetering Conference*, San Diego, CA, October 2002.

procedures to be employed in an effort to determine that the change in the kinematic quantity is the result of damage as opposed to changing operational and environmental conditions. Also, there is no control over the excitation source, and it may not excite the type of system response useful for identifying damage at an early stage.

As an alternative, a sensing system can be designed to provide a local excitation tailored to the damage detection process. Piezoelectric (PZT) materials are frequently being used for such active sensing systems. Because PZT produces an electrical charge when deformed, PZT patches can be used as dynamic strain gauges. Conversely, the same PZT patches can also be used as actuators because a mechanical strain is produced when an electrical field is applied to the patch. This material can exert predefined excitation forces into the structure. The use of a known and repeatable input makes it much easier to process the signal for damage detection and prognosis. For instance, by exciting the structure in an ultrasonic frequency range, the sensing system can focus on monitoring changes of structural properties with minimum interference from global operational and environmental variations. These sensor/actuators are inexpensive (less than \$5 per PZT patch), generally require low power (less than 5 V), and are relatively nonintrusive (as shown in Figure 3.3).

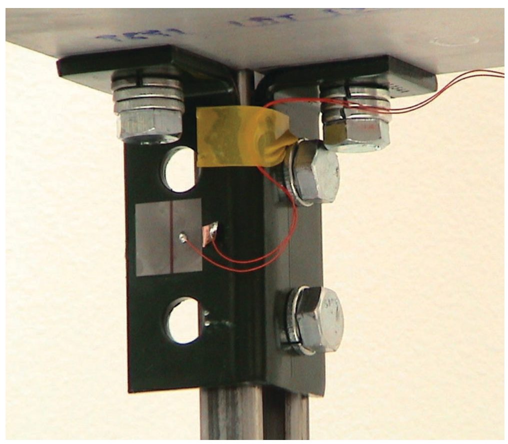

Figure 3.3 A PZT sensor/actuator being used to monitor a bolted connection.

Examples of documented successes in active local sensing for damage detection using PZT are the impedance-based method[29] and the Lamb wave-propagation method. [30] The impedance method monitors the variations in mechanical impedance resulting from damage, and the mechanical impedance is coupled with the electrical impedance of the PZT sensor/actuator. For this method, the PZT acts simultaneously as a discrete sensor and actuator. A schematic of the impedance method is shown in Figure 3.4. For the Lamb wave-propagation method, one PZT is activated as an actuator to launch elastic waves through the structure, and responses are measured by an array of the other PZT patches acting as sensors. The structure can be systematically surveyed by sequentially using each of the PZT patches as an actuator and the remaining PZT patches as sensors. The technique looks for possible damage by tracking changes in transmission velocity and wave attenuation/reflections.

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[29] G. Park, H. Sohn, C.R. Farrar, and D.J. Inman, "Overview of Piezoelectric Impedance-Based Health Monitoring and Path Forward," accepted for publication in *The Shock and Vibration Digest,* 2003.
[30] J.R. Wait, G. Park, H. Sohn, and C.R. Farrar, "Active Sensing System Development for Damage Prognosis," *Proceedings of 4th International Workshop on Structural Health Monitoring*, Stanford, CA, September 2003.

A composite plate with a PZT sensor layer is shown in Figure 3.5. Both methods operate in the high frequency range (typically above 30 kHz) where there are measurable changes in structural responses for even incipient damage associated with crack formation, debonding, delamination, and loose connections.

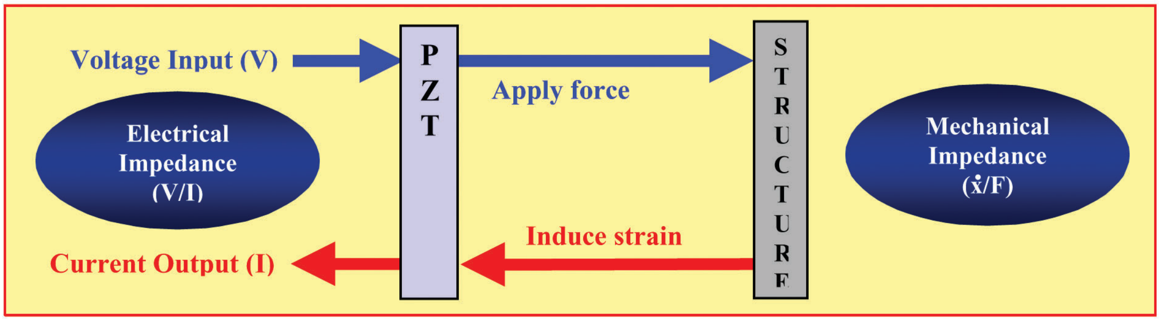

Figure 3.4 Schematic of the impedance method.

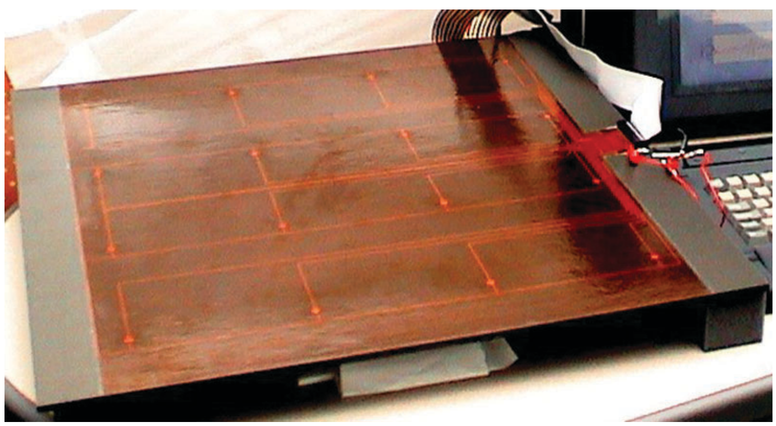

Figure 3.5 A composite plate with a PZT sensor layer.

Once structural damage has begun and is detected, numerical models can be used to capture the influence of damage on the system level performance and to predict future performance. This procedure necessitates the measurement of global system-level response. It may be possible to use these same PZT patches in both an active and passive mode. When used in the passive mode, the sensors detect strain resulting from ambient loading conditions and can be used to monitor the global response of a system. In the active mode, the same sensors can be used to detect and locate damage on local level as described above.

3.2.8 Sensor Communication

The typical way of instrumenting a system is to run wires between the local sensors and a centralized data acquisition unit. This approach can impose serious limitations on damage prognosis since it is highly desirable to have a very large number of sensors. Recent advances in wireless communication can alleviate most of these limitations. With wireless technology, the local sensing and processing units can communicate with a centralized processing unit and each other. Potential constraints on wireless systems include the maximum range, amount of bandwidth available, energy requirement, and susceptibility to electromagnetic interference.

3.2.9 Powering the Sensing System

A major consideration in using a dense sensor array is the problem of providing power to the sensors. This demand leads to the concept of "information as a form of energy." Deriving information costs energy. If the only way to provide power is by direct connections, then the need for wireless protocols is eliminated, as the cabled power link can also be used for the transmission of data. Hence, the development of micropower generators is a key factor for the development of the hardware if wireless communication is to be used. A possible solution to the problem of localized power generation is technologies that enable harvesting ambient energy to power the instrumentation.[31,32] Forms of energy that may be harvested include thermal, vibration, acoustic, and solar. Although this is new technology, the overriding consideration of reliability still exists, as it does with any condition monitoring system. With two-way communication capability, the local sensing and processing units can also turn themselves off-line for energy conservation and they can be resuscitated when a "wake-up" signal is broadcast.

3.2.10 Data Cleansing

In this section the term "data cleansing" refers to what is done electronically and not the data cleansing associated with software and data analysis. Data processing includes filtering, amplifying, and perhaps changing the signal source impedance. Historically, data processing prepared the signal for recording (on analog magnetic tape) or digitizing and storage (for digital acquisition). More sophisticated data processing incorporates "smart processing" using a sensor/computer combination for amplification, A/D conversion, overload detection, transmission of time series data, and feature selection. A "transformation matrix" preprocesses the raw sensor data into physical quantities of interest. This matrix is sensor specific and conceptually includes frequency response compensation, bounds on the sensor error, and automatic removal of out-of-band signals.

3.2.11 Sensor System Definition

Standards for definition of the sensor system are needed. A standard system defines sensor types, sensor locations, physical parameter sensed, sensor transition matrix (a matrix for translation of sensor readings to estimated physical parameters) and any other important sensor characteristics. Extensible Markup Language (XML) and Institute of Electrical & Electronics Engineers (IEEE) 1451.2 are potential templates for a standard sensor system.

Although XML was originally designed to improve the functionality of the Web by providing more flexible and adaptable information identification, it can also be used to store any kind of

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[31] H. Sodano, E.A. Magliula, G. Park, and D.J. Inman, "Electric Power Generation using Piezoelectric Devices," *Proceedings of 13th International Conference on Adaptive Structures and Technologies,* Berlin, Germany, October 7–9 2002.

[32] H. Sodano, G. Park, D.J. Leo, and D.J. Inman, "Use of Piezoelectric Energy Harvesting Devices for Power Storage in Batteries," *Proceedings of 10th SPIE Conference on Smart Structures and Materials*, San Diego, CA, March 2–6, 2003.

structured information and to enclose or encapsulate information in order to pass it between different computing systems, which would otherwise be unable to communicate.

IEEE 1451.2 standard defines smart transducer elements that can be treated as network-independent devices. The IEEE wrote 1451.2 to reduce the complexity of establishing communications between transducers in a networked environment. The specification addresses wiring, installation, and what is needed to calibrate a networked sensor. Essentially, the standard specifies a digital interface that can be used to access what might be called an electronic data sheet (nonvolatile memory as a transducer electronic data sheet, or TEDS). The specification also defines how a device reads sensor data and how it sets downstream actuators.

3.3 Summary: Sensing and Data Acquisition

Fundamentally, the key issue for developing a sensor system for damage prognosis is the ability to capture system response on widely varying length and time scales. Special purpose sensing is a development of a "smart sensor" philosophy, in which the sensor array is sensitive to and reports the presence of damage. Current developments in sensor technology indicate that MEMS devices will soon be integrated with signal processing, data interrogation, and telemetry capabilities and fabricated on the same silicon substrate. Such "systems on a chip" may significantly improve the sensing and processing capabilities for prognostic applications by providing a dense-array of sensors with low cost and low maintenance. Depending on the application, the telemetry can be accomplished either in a wired or wireless manner. For wireless telemetry, a major concern is the power source for such systems. Microparasitic generators being developed elsewhere may, when integrated with the system on a chip, provide the power that will enable a truly self-contained sensing capability. For in-service prognostics, it is possible that ambient vibration will provide both the power source and excitation for the structure. However, the authors' believe that the use of local actuation with waveforms tailored to the damage-prognosis activity will provide a more robust damage- detection and damage-monitoring capability.

Current modeling technology is not well integrated with developing sensor technology. In most cases, without the precise model of a system, it is difficult to know what exactly to measure. Sensors that directly measure crack properties or corrosion are non-existent. Damage prognosis requires sensors that measure the physical properties that are more directly related to the most probable damage scenarios, rather than sensors that measure only strain, strain rate, and acceleration. In addition, sensors are needed that use multiple materials or sensing elements to get increased dynamic range, and range of properties. There may be an evolution of sensor types in damage prognosis, for example, expensive, accurate sophisticated sensors initially, replaced by cheap special purpose sensor in the longer term, with the special purpose sensors targeting specific damage types.

At the "front line" of any damage detection or prognosis system is ability to acquire data that encapsulates any change in system properties that may affect its life or operation. Although simple sensor configurations with a limited number of sensors will provide an indicator of change to the global properties, higher-density sensor arrays are required, not only to provide localized information relating to damage, but also to provide for redundancy. Perhaps the most important aspect of the sensing system is that it must be more reliable than the system being monitored.

4. DATA INTERROGATION

The main issue of data interrogation is how to utilize a combination of simulated and empirical data for damage diagnosis and prognosis. Figure 4.1 shows the interaction of data interrogation with the other tasks. First, model updating and refinement requires experimental test data to adjust and validate the numerical model. In this process, data interrogation condenses the massive numerical data and extracts features from physical measurements for comparison with features extracted from the numerical data. The data interrogation component of the damage diagnosis process also defines damage-sensitive features and formulates statistical procedures to determine the existence, location, and extent of damage. Damage prognosis requires coupling the current system state, determined from the damage diagnosis process, with estimated future loading information and the predictive capability of the previously refined model. Future loading can be forecast using various data-driven prediction modeling techniques. Then, a decision analysis similar to the one in the damage diagnosis step can be designed to synthesize all this information in an effort to make damage prognosis. The data interrogation methods needed for this process are data validation, feature extraction, data normalization, characterization of feature distributions, statistical inference for decision making, and prediction modeling for future loading estimates. These issues are discussed more in detail in the following sections.

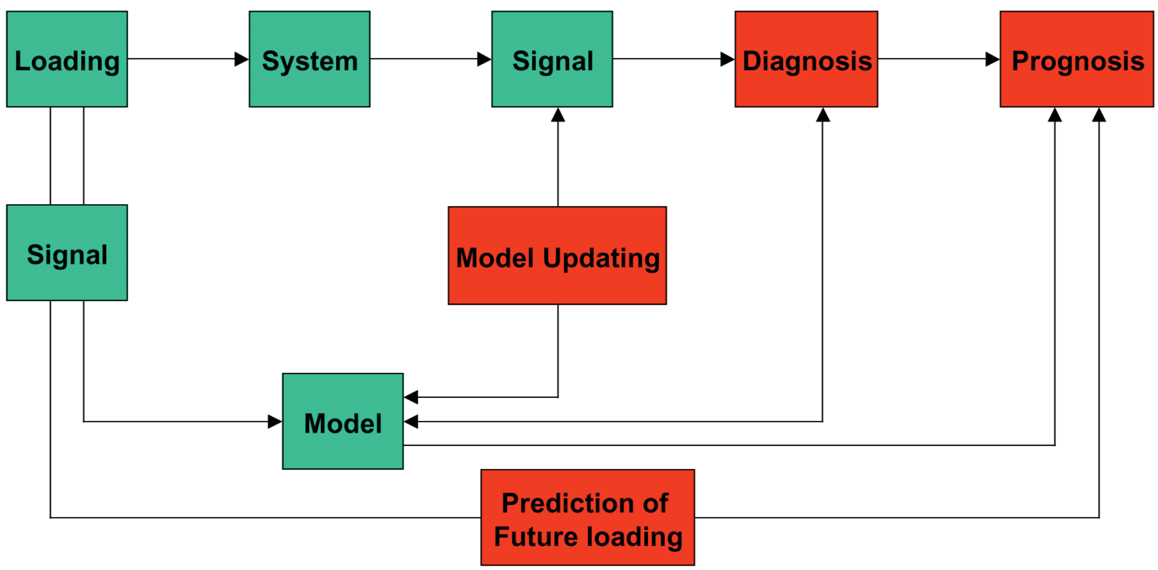

Figure 4.1 Interaction of data interrogation with the other issues (the major roles of data interrogation are highlighted in red).

4.1 Data Validation

The first step in data interrogation is to inspect data obtained from sensing devices or numerical simulations. The data validation step should ensure that the recorded data possesses information relevant to subsequent analyses. For instance, measured acceleration data can have anomalies because of electromagnetic interference, missing values because of disrupted RF transmission, or DC offset caused by drift. This step is closely tied with the sensing and data acquisition issues discussed in the previous chapter. Data validation techniques can also be conducted to monitor the functionality of sensors themselves or the bonding condition of the instruments to the host structure. For instance, some standard features such as autospectra, frequency response functions, modes, and response probability density will be available in near real time to analysts and statisticians, allowing data validation during data acquisition, not after the fact when it is too late to modify test measurement parameters. Statistical inference techniques such as outlier analysis[33] and novelty detection can be used in this data validation process.

4.2 Feature Extraction

Because new sensing technologies allow structures to be instrumented with large sensor arrays, and new computation capabilities produce substantial amounts of numerical data, it is essential to compress these data for subsequent analyses, keeping the information that is relevant to later analyses. Feature extraction refers to identifying the salient features of data so that it may be used in subsequent analyses; in the current case, damage diagnosis and prognosis.[34] That is, features are a set of variables derived from the original data set, and they are supposed to capture the relevant information contained in the original data. Almost all feature extraction procedures inherently perform some form of data compression. Compressing data into feature vectors of small dimension is necessary if accurate estimates of the feature's statistical distribution are to be obtained. The aspects of a specific problem must be considered in the feature extraction process. Also, nonlinear features may be necessary for damage detection because the propagation of damage often produces nonlinear system responses. Data interrogation techniques will assist analysts with various tools such as linear/nonlinear principle component analysis,[35] Fisher's discriminant,[36] and independent component analysis.[37]

4.3 Data Normalization

Damage diagnosis is based on the examination of a system's dynamic response to determine if the system significantly deviates from an initial baseline condition. In reality, the system is often subject to changing environmental and operation conditions that affect its dynamic characteristics. Such variations include changes in loading, boundary conditions, temperature, and moisture. Most damage diagnosis techniques, however, generally neglect the effects of these changing ambient conditions. For the development of robust monitoring systems, these natural variations of the system responses should be explicitly taken into account in order to minimize false positive indications of true system changes. Autoassociative neural networks[38] and a combination of autoregressive (AR) and autoregressive with exogenous inputs (ARX) models[39] have been employed to address this data normalization issue. Furthermore, time-dependent autoregressive

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[33] V. Barnett and T. Lewis, *Outliers in Statistical Data*, John Wiley & Sons, Chichester, UK, 1994.
[34] C.M. Bishop, *Neural Networks for Pattern Recognition*, Oxford University Press, Oxford, UK, 1995.
[35] M. Kramer, "Nonlinear Principal Component Analysis using Autoassociative Neural Networks," *AIChE Journal*, **37**, pp. 233–243, 1991.
[36] K. Fukunaga, *Statistical Pattern Recognition*, Academic Press, San Diego, CA, 1990.
[37] A.D. Back and A.S. Weigend, "A First Application of Independent Component Analysis to Extracting Structure from Stock Returns," *Int. J. on Neural Systems*, **8**(4), pp. 473–484, 1998.
[38] H. Sohn, C.R. Farrar, and K. Worden, "Novelty Detection Under Changing Environmental Conditions" *Proceedings of SPIE's 8th Annual International Symposium on Smart Structures and Materials*, Newport Beach, CA, 2001a.
[39] H. Sohn, C.R. Farrar, N.F. Hunter, and K. Worden, "Structural Health Monitoring Using Statistical Pattern Recognition Techniques" submitted for publication in *ASME Journal of Dynamic Systems*, Measurement and Control*: Special Issue on Identification of Mechanical Systems*, 2001b.

moving-average (TARMA) models[40] and evolutionary spectral analysis [41] have potential to address this issue. These nonstationary time series and spectral analyses have found wide applications in modeling of nonstationary process and various naturally occurring phenomena.

4.4 Characterization of Feature Distributions

Because of inherent uncertainties involved in data measurements and physical model development, the decision-making procedures for the following damage diagnosis and prognosis should be based on statistical modeling of feature spaces. There are a variety of tools for decision analysis. A few are hypothesis testing,[42] outlier and novelty detection,[43,44] sequential probability ratio tests,[45] statistical process control, [46] group clustering, and Bayesian decision theory. [47] These techniques require parametric or non-parametric characterization of feature distributions or estimates of statistical properties of the assumed distribution. For example, outlier analysis requires the estimation of a probability density function for the features corresponding to an undamaged state of a structure. Furthermore, inherent uncertainties should be addressed in this decision-making process. For example, how does uncertainty in damage diagnosis propagate through to uncertainty in damage prognosis? A review of uncertainties in dynamic analysis can be found in Langley[48] and this issue of uncertainty quantification is further discussed in Section 6.

4.5 Statistical Inference for Damage Diagnosis

Statistical inference is concerned with the implementation of the algorithms that analyze the distribution of extracted features in an effort to make decisions on damage diagnosis and prognosis. The algorithms used in statistical model development fall into the three general categories: (1) group classification, (2) regression analysis, and (3) outlier detection. The appropriate algorithm to use will depend on the ability to perform *supervised* or *unsupervised* learning. Here, supervised learning refers to the case where examples of data from damaged and undamaged structures are available. Unsupervised learning refers to the case where data are only available from the undamaged structure.[34] The success of decision making can be assessed by (1) overall misclassification rate (false positive or negative indications of damage or system failure), (2) receiver operating characteristic[49] curves (ROC), and (3) confidence intervals on prediction.

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[40] K.A. Petsounis and S.D. Fassois, "Non-Stationary Functional Series TARMA Vibration Modeling and Analysis in a Planar Manipulator," *Journal of Sound and Vibration*, **231**(5), pp. 1355–1376, 2000.
[41] S. Adak, "Time Dependent Spectral Analysis of Non-stationary Time Series," *Journal of the American Statistical Association*, **93**, pp. 1488–1501, 1998.
[42] R.G. Miller, *Beyond ANOVA: Basics of Applied Statistics*, Chapman&Hall/CRC, New York, NY, 1997.
[43] V. Barnett and T. Lewis, *Outliers in Statistical Data*, John Wiley & Sons, Chichester, 1994.
[44] K. Worden, G. Manson, and N.R.J. Fieller, "Damage Detection Using Outlier Analysis," *Journal of Sound and Vibration*, **229** (3), pp. 647–667, 2000.
[45] K. Humenik, and K.C. Gross, "Sequential Probability Ratio Tests for Reactor Signal Validation and Sensor Surveillance Applications," *Nuclear Science and Engineering*, **105**, pp. 383–390, 1990.
[46] D.C. Montgomery, *Introduction to Statistical Quality Control*, John Wiley & Sons, Inc., New York, NY, 1996.
[47] R.O. Duda and P.E. Hart, *Pattern Classification and Scene Analysis*, John Wiley & Sons, Inc., New York, NY, 1973.
[48] R.S. Langley, "The Dynamic Analysis of Uncertain Structures," *Proceedings of the 7th International Conference on Recent Advances in Structural Dynamics*, University of Southampton, Southampton, UK, 2000.
[49] J.P. Egan, *Signal Detection Theory and ROC Analysis*, Academic Press, New York, NY, 1975.

One of the main issues in this decision-making procedure is to establish decision threshold values. In particular, extreme value statistics[50] can be employed to establish decision boundaries to minimize false positive and negative indications of damage. Statistical inference is often based on the assumption that the underlying distribution of data is Gaussian. However, the assumption of normality imposes potentially misleading behavior on the extreme values of the data; namely, those points in the tails of the distribution (illustrated in Figure 4.2). As the problem of damage identification specifically focuses attention on these tails, the assumption of normality is likely to lead any analyses astray. An alternative approach based on Extreme Value Statistics is developed to specifically model behavior in the tails of the distribution of interest. Furthermore, the development of statistical models should vary depending on the targeted damage scenarios. For example, it will be necessary to track trends in feature spaces for the detection of slowly accumulating deterioration over long time periods as opposed to sudden anomalies in features resulting from a discrete event. Uncertainties and propagation of uncertainties also need to be taken into account in the establishment of decision criteria.

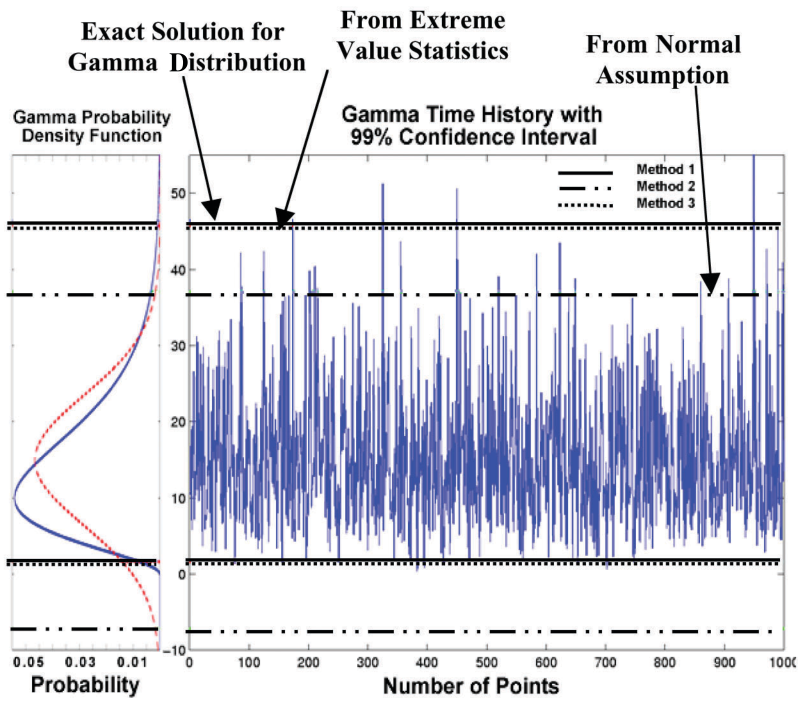

Figure 4.2 The increasing false-positive and false-negative outlier detection if confidence limits are based on a normality assumption when underlying feature has a Gamma distribution. Extreme value statistics based on Gumbel distribution accurately represent the true thresholds.

[50] K. Worden, D.W. Allen, H. Sohn, and C.R. Farrar, "Extreme value statistics for damage detection in mechanical structures," Los Alamos National Laboratory report LA-13903-MS, August 2002.

4.6 Prediction Modeling for Future Loading Estimates

A successful damage prognosis requires the measurements of the current system state, and the prediction of the system deterioration when subjected to future loading. Based on the analysis of previous loading histories, future loading can be forecast using various data-driven prediction modeling techniques. For example, surrogate modeling such as state space representation[51] and multivariate ARMA models[52] can be employed to track previous loading and predict future loading for this purpose. Then, a decision analysis similar to the one in damage diagnosis step should be designed synthesizing all these information. Estimating remaining useful service life is a wide-open area for future research because little work is being done in this prognosis area. It might be possible to cast the damage-prognosis problem in the context of risk analysis. In a risk analysis, the failure state of a system is represented by a function of the response known as the safety margin. Then, the probability of failure is the integral of the response space over the unsafe region bounded by the safety margin. The first-order reliability method (FORM) approximates this integral by seeking the shortest distance from the origin of the response space to the surface of the safety margin. Various refinements of the FORM exist, including the approximation of the safety margin surface to a quadratic surface (using the second-order reliability method, or SORM) and the use of multiple failure-surfaces to represent different failure mechanisms.[53] Unlike damage diagnosis, it is difficult to obtain experimental data near the failure of a system. Therefore, the prognosis aspect of this problem most likely will be cast in an unsupervised learning mode.

4.7 Summary

The purpose of data interrogation is to extract pertinent features from numerically generated and experimentally measured data and to build statistical inference models for damage diagnosis and prognosis. The feature extraction procedure involves identifying salient features of data that can be used for numerical model updating, damage detection, or damage prognosis. Condensation of data, which reduces the dimensionality of the feature space, is another important aspect of data interrogation. This data compression is beneficial for reliable statistical modeling of the feature space. Once a statistical model is built, it can be used for subsequent statistical inference and decision making. Another major role of data interrogation is to address the issue of data normalization, which can severely hinder the deployment of a robust monitoring system on real-world applications. The authors strongly believe that this data normalization issue needs to be explicitly taken into account to minimize false positive indications of damage. Furthermore, decision-making procedures in damage detection and prognosis should be based on rigorous statistical modeling in the face of measurement, loading, and modeling uncertainties. Currently, little work has been done in the area of future loading estimation, although the successful deployment of a damage-prognosis solution absolutely depends on the prediction of future loading characteristics and as such further research on this topic is warranted.

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[51] L. Ljung, *System Identification-Theory for the User*, Prentice Hall, Upper Saddle River, NJ, 1999.
[52] G.E. Box, G.M. Jenkins, and G.C. Reinsel, *Time Series Analysis—Forecasting and Control*, Prentice Hall, NJ, 1994.
[53] H.O. Madsen, S. Krenk, and N.C. Lind, *Methods of Structural Safety*, Prentice Hall, NJ, 1986.

5. MODELING AND SIMULATION

The purpose of this section is to present the definitions, issues, and research needs relating to modeling and simulation for damage prognosis. The discussion is restricted to structural damage prognosis where a structure is defined as a mechanical system whose primary purpose is to carry loads as opposed to computer operating system failure or failure of electronic circuit boards.

The primary objective of structural health monitoring is to determine the current condition of a structure. One critical aspect of SHM is to be able to assess not only the current state of the system, but also to assess its operational and environmental loading history. Also, knowledge of the historical evolution of the damage states may be as important as the knowledge of the current system state. Beyond this first step, structural prognosis aims to assess the ability of a system to carry out it future intended function. Modeling and simulation are the tools by which predictions are made. Predicting the remaining useful life of a structure or the ability of a system to carry out its intended function must rely on a combination of numerical models and physical observations when direct service-life experimentation of the fully integrated system is not an option.

5.1 Decisions to Support

It is generally agreed that damage diagnosis and damage prognosis are application-dependent technologies. Therefore, success will depend to a large extent on the ability to define the damage scenario, how it occurs and its potential modes of propagation. Examples of damage mechanisms that may require the development of appropriate models are creep, fatigue, corrosion, wear, brittle and ductile fracture, buckling, and embrittlement. It is not realistic to believe that a single model will, in the foreseeable future, be able to capture all these different damage mechanisms. Therefore, research and development should first attempt to demonstrate the damage-prognosis technology and assess its limitations for a particular application and a particular damage mode.

Once the damage of concern has been defined, the next step is the assessment of how that damage initiates and propagates. Models used for this portion of the study will differ depending on what causes damage to appear and the type of damage that is present. In almost all cases damage is related to exceeding some strength, deformation or stability criteria. With these general failure mechanisms in mind, three main categories of damage evolution will be described in terms of the types of loading that occur:

1. Incremental damage accumulation: High-cycle fatigue (HCF) is an example of incremental damage accumulation mechanism where cracks form from initial flaws and then open and close as the system goes through its load cycles. Because plastic deformation accumulates, the crack reaches an equilibrium state before eventually propagating further through the material. This mode of propagation relates to the loading experienced by the structure. If the damage scenario and its mode of propagation are well defined, numerical models and diagnosis systems can be developed and tailored for a particular application that can predict the damage evolution and periodically update estimates of the current system state.

2. Scheduled discrete damage accumulation: Damage can be the result of scheduled discrete events such as aircraft landings or missile stage separations. This category must be kept separate from the next one because events that are planned will typically be easier to control and monitor than unexpected events. During the times between such events, for example, it might be possible to implement damage prevention and countermeasures with little interference to the system's intended use.

3. Unscheduled discrete damage accumulation: Typical unscheduled discrete events would include natural loading and phenomena hazards such as earthquakes, small arms fire on aircraft structures, and foreign object intrusion in turbine blades. The occurrence of such events and the resulting loads applied to the system are difficult to measure or predict. The consequences might range from insignificant (the mechanical response remains elastic), to moderate (a small crack is initiated) to severe (total failure). Other propagation modes can be initiated as the result of discrete events. This is, for example, the case of an impact that initiates a series of small cracks, some of which will then start propagating and coalescing in an incremental fashion or as further discrete events are encountered. An illustration of these three categories of damage is shown in Figure 5.1.

Figure 5.1 Illustration of three categories of damage. From left to right, (a) incremental damage accumulation in rotating machinery, (b) scheduled discrete damage accumulation resulting from an F-14 Tomcat landing on a carrier, and (c) unscheduled discrete damage accumulation resulting from a collision of the USS Denver.

Figure 5.2 illustrates the concept that appropriate models generally have to be developed depending on which damage scenario and propagation mechanism is considered. Other dimensions may have to be considered given the targeted application. In particular, models might have to be somewhat purpose-specific where the implementation of a particular model might depend on the decisions that the simulations are required to support.

After defining the damage scenario, propagation mode, and expected occurrence type, the numerical models developed must satisfy specific requirements. First, past experience must be translated into useful modeling rules as much as possible. This task may be achieved by learning the state-of-the-art technology available for a particular application or incorporating existing databases or expert opinion. Second, the purpose of the model must be clearly identified. This identification includes defining the required model output, defining the confidence level that is required to support a particular decision and, possibly, defining which features of the system's numerically simulated response can be observed experimentally to complement and validate numerical predictions. Finally, techniques must be developed and implemented to help manage the evolution of models. Examples of configuration management include tracking which numerical models are implemented, tracking which algorithms are used, tracking how the models evolve such that they can capture system evolution (mix of old, retrofitted, and new parts) and tracing the status of specific hardware changes. These requirements are captured in the following six questions:

1. What is the state of the art of the problem and what can be learned from it?
2. What decisions will the model support?
3. What specific response features should be extracted from the numerical data?
4. What level of confidence is required for the simulation output?
5. What response quantities should be experimentally measured?
6. How should the evolution of the model be managed?

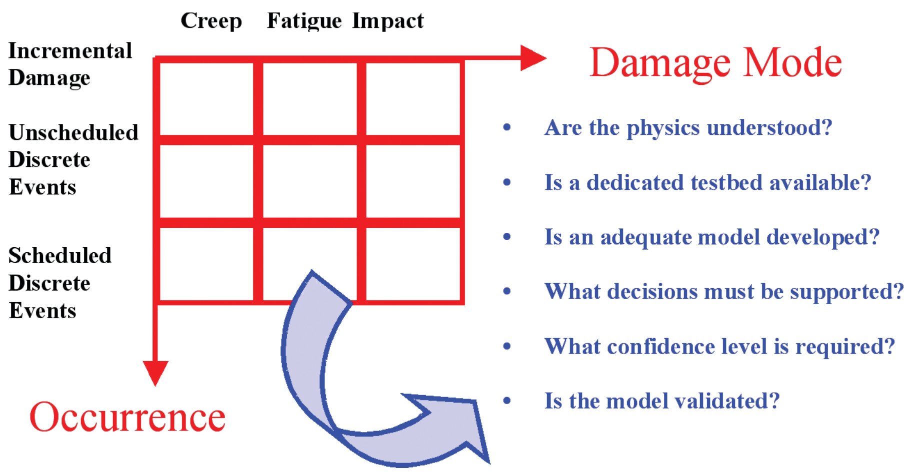

Figure 5.2 Matrix of damage model development.

5.2 Modeling and Simulation

In this section, model requirements for damage prognosis are discussed. We start by discussing in Section 5.2.1 the various types of models and some of their characteristics and requirements. Issues such as the input data needed to develop and maintain the models and the integration of modeling and sensing are discussed in Sections 5.2.2 and 5.2.3.

5.2.1 Types of Models

A model is defined here in a broad sense as the relationship between output features denoted by the symbol y and a set of input parameters denoted by the symbol p. This relationship can be written as $y = \mathrm{M}(p)$. Output features represent any combination of averaged, integral quantities (for example, the mean von Mises stress calculated over the entire mesh), scalar responses (such as the length of a crack or its energy dissipation rate), time-series (for example, the history of acceleration at specific locations), statistical information or discrete variables (such as a flag equal to either "go" or "abort" that would answer a specific question). The input parameters include physical parameters, numerical parameters and measurements. Inputs such as environmental variables and loads can be considered as part of the model or they can be parameterized and included in the definition of p. The only requirement when defining the input is to make sure that all parameters whose variations are likely to influence the outcome of the model are included. This requirement ties into the notions of sensitivity, variability and uncertainty quantification as explained below (see Section 5.3).

Damage-prognosis solutions are likely to rely heavily on numerical modeling and simulation because damage and its evolution cannot always be measured directly. Even if the presence and severity of structural damage can be inferred from physical observation, the effect that damage might have on the future performance of the system is generally assessed though simulation. The models required for damage prognosis, whether they are derived from a mathematical theory, experimentation, empirical observations or expert knowledge, will belong to different categories depending on what they are supposed to represent, their purpose and the decisions they support. The following model types have been identified:

1. Physically based models: Physically based models attempt to mathematically describe the fundamental mechanisms of a phenomenon with as little approximation as possible. This class of models is often referred to as "first principle" modeling, as opposed to models that are developed from macroscopic conservation laws, empirical observation, or expert knowledge. Physically based models must provide a resolution in terms of fundamental mechanics, spatial discretization, temporal discretization, and energy bandwidth that fully describes the damage mechanism of interest. To achieve the requisite predicative capability for damage prognosis, the integration of information from models capturing the physical phenomena of interest on various length scales will be necessary. The integration of models that predict different physical phenomena may also be necessary to achieve a damage-prognosis capability. Alternatively, the simulations will have to be carried out on large-scale computing platforms, such as those being developed as part of the Department of Energy's Advanced Simulation and Computing Program (ASCI),[54] with sufficient capability to run codes to capture multiscale physics.

Examples of physics-based and surrogate models are shown in Figures 5.3 and 5.4. A detail of the computational grid for a finite element analysis of a pressure vessel is shown in Figure 5.3. The surrogate model shown in Figure 5.4 is a multivariate statistical metamodel developed to replace a finite element simulation. The model predicts peak acceleration of a test item as a function of the input parameters. Because the polynomial's coefficients are characterized by statistical distributions, the model can be sampled to produce the family of response surfaces shown in Figure 5.4.

[54] See http://www.lanl.gov/asci/

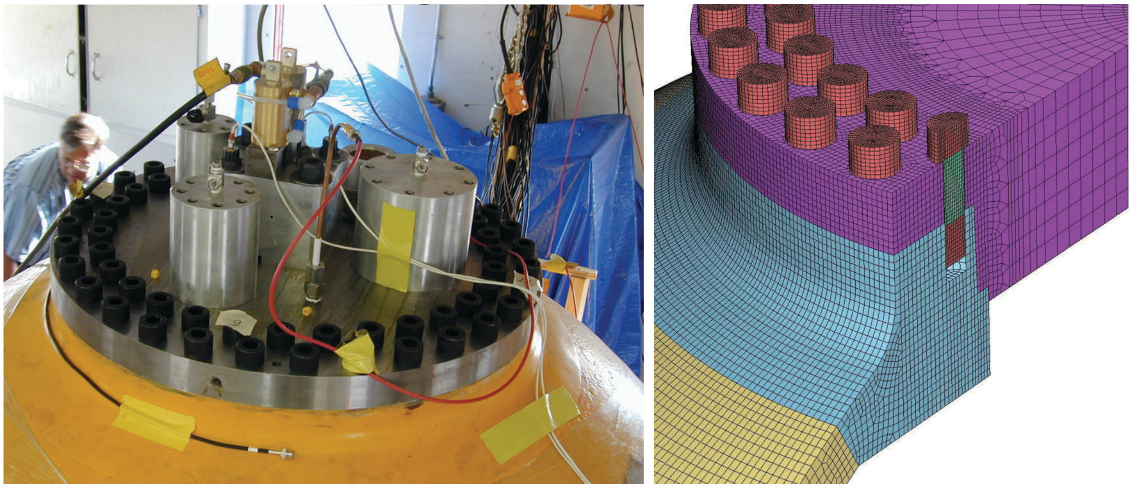

Figure 5.3 The flanged portal of a pressure vessel and a detail of the computational grid of a finite element model of the vessel.

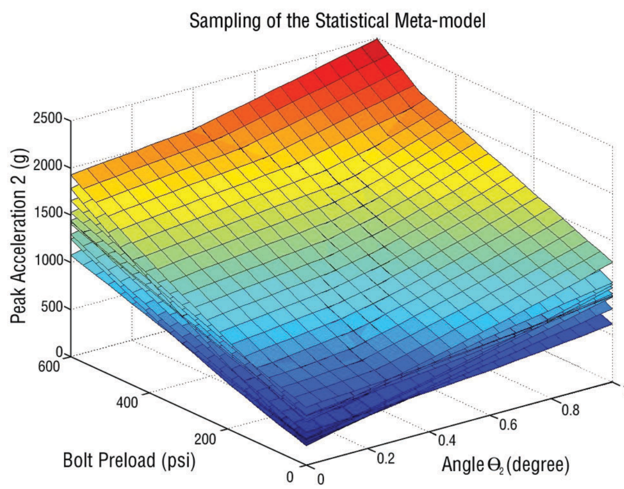

Figure 5.4 Multivariate statistical metamodel.

2. Surrogate models: Surrogate models are also referred to as "reduced-order," "fast-running models," or "metamodels" in some scientific communities. The purpose of a surrogate model is to replace a more complex physically based model and to improve computational efficiency for parametric study, sensitivity analysis, and numerical optimization. Surrogate models are not derived from first principles, nor should they be based on complicated computational procedures. They are generally obtained after condensing information or fitting predefined and parameterized functional relationships to data sets. Surrogate models can be obtained in ways such as fitting a polynomial function $y = a_0+b_1x+c_2x^2$ through a distribution of data points $\{x_k; y_k\}$ in an effort to define the functional relationship between x and y. Some of the more recent and more sophisticated techniques employed in engineering include, but are not restricted to, neural networks, support vector machines and statistically accurate models capable of predicting an output feature together with its probability information. Surrogate models may be derived from computational models or observed data.

However, the accuracy of these models is a direct function of the data used to develop the model and there is no guarantee that the surrogate model will extrapolate beyond the data used in its development. The authors envision that for damage prognosis, surrogate models will provide a bridge between detailed physics-based models and measured system response data. The computational efficiency of surrogate models will allow for local data processing capabilities, through programmable digital signal processing (DSP) chips that can be integrated directly with the sensing system. Coupling the surrogate model with the sensing system will allow for near-real-time system assessment based on the measured system response and previous physically based numerical simulations whose information is captured in the surrogate model.

Surrogate models must be "trained," to identify their unknown parameters. Their quality must also be evaluated independently from the training step. Because analyzing a detailed finite element model at every combination of input variables is computationally prohibitive, training is generally based on a subset of carefully selected runs. Design of experiments (DoE)[55] techniques can be used to explore large design spaces and to select a judicious subset of finite element analyses. Surrogate modeling and effect screening can be performed using DoE because identifying the effects and interactions that capture a particular input-output relationship controls the functional form of the surrogate model.

3. Coupled models: The key to success when modeling and analyzing complex phenomena is, to a great extent, in the formulation of a multidisciplinary approach to the problem. As mentioned previously, damage prognosis will require a high degree of integration and coupling between various models. The coupled models might represent several scales of a phenomenon as, for example, when macroscopic mechanical models are coupled with a microscopic and probabilistic description of a material and, possibly, with a nanoscale representation of atomic interactions. Models might also have to be coupled because of interaction between two or more physical phenomena. An example of this coupling is provided by the field of aeroelasticity that specializes in studying the interaction between fluid-dynamic equations and solid mechanics equations.

4. Knowledge-based models: The fourth class of models considered does not, as the previous ones do, rely on formal descriptions of input-output relationships, partial differential equations or empirical descriptions of data sets. Knowledge-based models are developed from gathered data or expert opinion and analyzed using tools such as neural networks, fuzzy logic, and case-based reasoning. The primary objective of knowledge-based modeling is to capture heuristic understanding and codify it. An example where case-based reasoning is being applied with some success is the monitoring of engine breakdown.[56] Although automobiles are theoretically replications of the same system, unit-to-unit variability during the manufacturing, assembling processes, and during the operating life of each individual system makes it impossible to rely on a single model for diagnostics. Valuable information can be gained from recording the causes and consequences of breakdowns as they occur and inferring reasoning rules from the observed data. Means must be found to make formal and knowledge-based models better interact with each other.

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[55] C.F.J. Wu and M. Hamada, *Experiments: Planning, Analysis, and Parameter Design Optimization,* John Wiley & Sons, Inc., New York, NY, 2000.
[56] M.A. Meyer and J.M. Booker, "Eliciting and Analyzing Expert Judgment: A Practical Guide." Published by the Society of Industrial and Applied Mathematics, Philadelphia, PA, 2001.

Figure 5.5 illustrates the coupling between different physics-based models. Each is developed to model physical and mechanical phenomena occurring in their own time scale, spatial resolution, and energy bandwidth. Capturing the evolution of damage from small time and spatial scales to system-level failure may also require the ability to manage the evolution and coupling of different models.

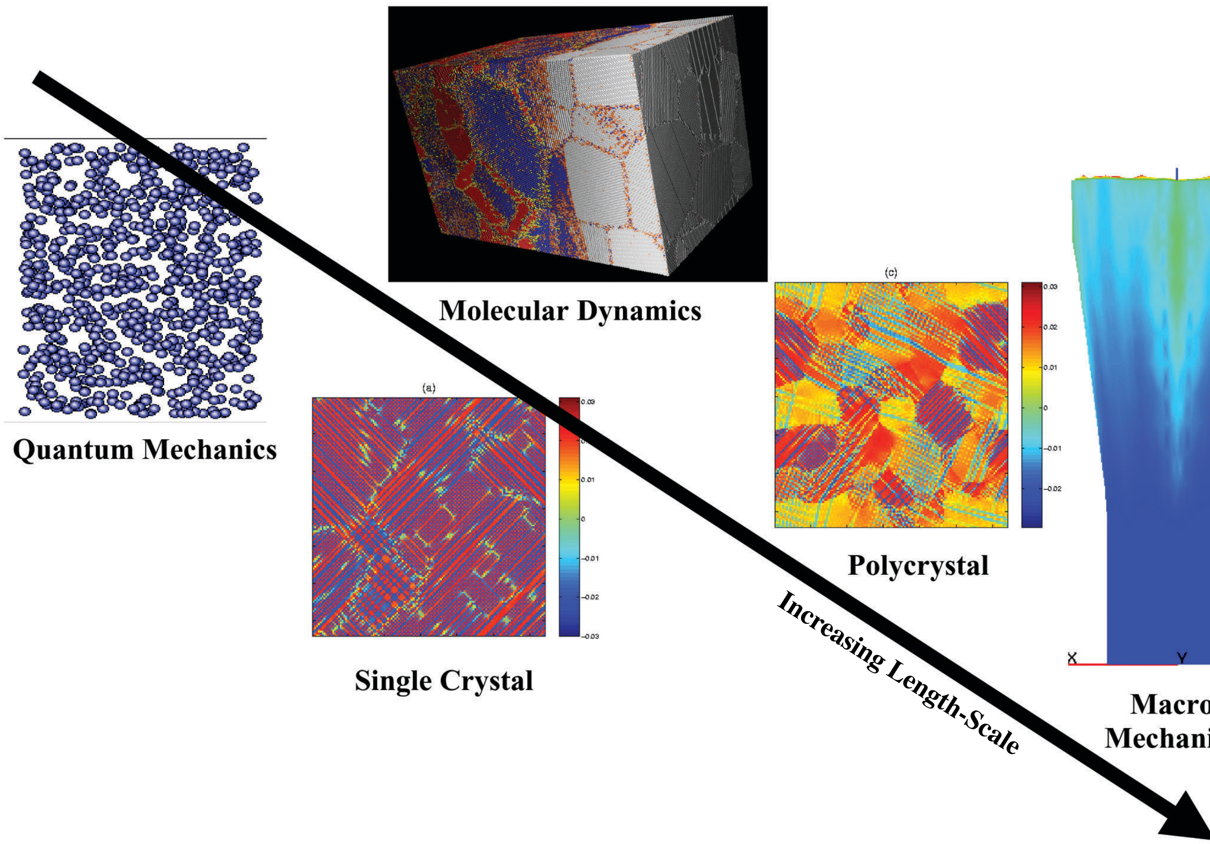

Figure 5.5 Illustration of the required coupling between multiscale, multiphysics models.

5.2.2 Input Data

Care must be taken when specifying the parameters and inputs required to adequately define a simulation and the subsequent solution to a problem. These parameters and inputs include initial conditions, boundary conditions, problem domain, material properties, forcing functions, and prior probability information. Parameters and inputs must be defined adequately no matter what types of models are used (physically-based, surrogate or knowledge-based models).

Complex, physics-based models and surrogate models generally depend on input parameters to which a clear physical meaning cannot be attributed. Other input parameters are often encountered that cannot be measured directly and whose values are associated with extreme uncertainty. In both cases, dedicated calibration experiments are required to infer the parameter values that are most consistent with the physical observation.

Structural prognosis relies on the assessment of the system's current state and the estimation of future loading to make predictions such as remaining useful life, safety margin, and future performance characteristics. Estimating future loading scenarios is a difficult problem. Current loads, future loads, and their probability information can be inferred from direct measurement to some extent. Even so, the loads estimated are likely to vary significantly from their nominal values. During prognosis, the uncertainty associated with input loading must be propagated through forward simulations to provide confidence bounds around the predicted model output.

5.2.3 Integration of Modeling and Sensing

The importance of integrating numerical modeling and sensing is recognized. Two levels of interaction are possible that would contribute to improving the analysis capability. First, numerical models can be used to specify what one would *ideally* like to measure. Of course, this specification will depend on the damage scenario considered, the damage propagation mode, and the intended purpose of the numerical model. A direct measure of damage will always be preferred to an indirect physical observation because it can be easily quantified and compared to model output. It should also be more reliable than a value inferred from indirect measurements. Hence, models and numerical simulations can be used to explicitly define the measurement required for each damage scenario and propagation mode. For example, current models for analyzing creep damage are based on predicting creep strains. Are sensors available that would provide a direct measure of creep strain? Can they be developed?

Beyond this first step, numerical simulations can also be used to determine the specifications of a measurement system given specific deployment and damage detection constraints. High-fidelity simulations can be analyzed for predicting the effect of crack damage for a particular application, determining the minimum crack length that the measurement system should be able to detect, optimizing the location of actuators and sensors, and finally, determining the measurement system's specifications in terms of sensitivity, bandwidth, and frequency content.

The second potential level of integration between modeling and sensing resides in the integration of software and hardware components. Once the actuation and sensing capability has been selected, their locations have been optimized and the specifications of the data acquisition system have been met, it may be advantageous to integrate model output and sensing information as much as possible. For example, surrogate models can be programmed on local DSP chips and their predictions can be compared to sensor output in real time. One obvious benefit would be to minimize the amount of communication by integrating the analysis capability with real-time sensing. Figure 5.6 shows a comparison of predictions of a polynomial response surface and features extracted from experimental measurements. In an integrated approach, features can be extracted from sensing information and numerical simulation. Test-analysis comparison and parameter calibration can then be performed locally, which would greatly increase the efficiency of damage detection.

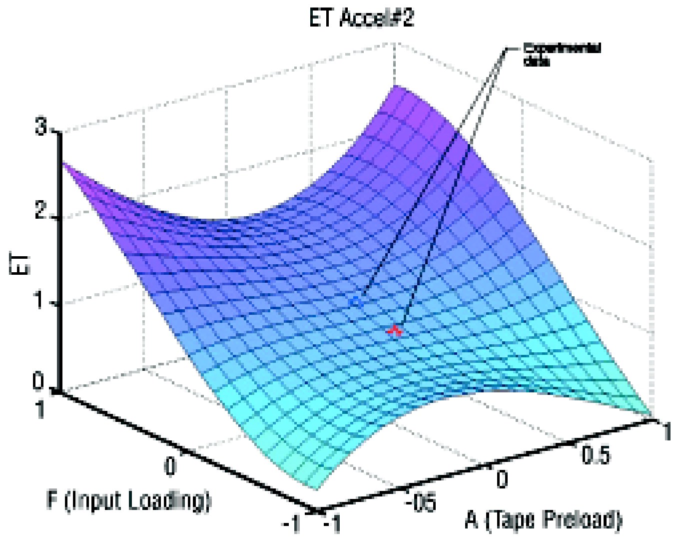

Figure 5.6 Integration of measurements and predictions. The vertical axis, ET, is the first temporal moment.

5.3. Uncertainty Analysis

Uncertainty in models and computer simulations generally arises from the combination of environmental variability, parametric uncertainty, and modeling lack of knowledge. Section 6 discusses these categories and overviews the theories available to represent uncertainty. A brief discussion of uncertainty is provided here to emphasize implications in terms of reliability assessment and decision-making capabilities.

Environmental variability includes the uncertainty associated with environmental variables such as temperature and humidity. For the purpose of this discussion, it also includes measurement errors, data processing errors and uncertainty associated with the description of loads and boundary conditions. Most environmental variability can be dealt with as parametric uncertainty. Uncertainty that cannot be modeled easily is generally accounted for by perturbing the available information with a random process.

Parametric variability is defined as the uncertainty associated with the input parameters of a particular model. It is dealt with by sampling each input parameter's probability density function or intervals of possible values. Enough analyses must be performed to provide an adequate representation of variations in the input parameter space. Uncertainty introduced through manufacturing and assembling processes can be considered under this category if it can be properly modeled.

Modeling uncertainty or lack of knowledge refers to the uncertainty associated with the functional form of the models implemented. Examples are inadequate model forms, unknown interaction between state variables or physical phenomena, and model order truncation. Modeling consists of translating observations or reasoning into formal rules and equations through the formulation of hypotheses. To assess the confidence in simulation results, the uncertainty associated with each hypothesis and modeling assumption must be assessed and propagated through the simulation.

Because decisions about the future performance of the structure can involve various sources of uncertainty, the decision-making procedure should be thought of in terms of an assessment of system *reliability*. Reliability analysis estimates the probability of failure in the context of uncertainty. Failure refers to, for example, catastrophic failure, or not meeting a performance requirement, or exceeding an allowable crack size. A numerical integration procedure is required to propagate the sources of variability, uncertainty and lack of knowledge through the numerical simulation and estimate the probability that the failure criterion is met or not. The scenario of modeling uncertainty based on probability has been extensively studied, and sampling-based as well as approximation-based techniques are available to estimate the probability of failure. On the other hand, few techniques are available to deal with nonprobabilistic uncertainty, make decisions that maximize the robustness to uncertainty, and account for modeling lack of knowledge.

Uncertainty analysis for damage prognosis is further discussed in Section 6. The formulation of reliability problems and decision making for damage prognosis is further discussed in Section 7.

5.4 Verification and Validation

Replacing physical observations with computer modeling requires that the models and simulations adequately match the system's response. If simulations are used to support decisions in life-threatening or mission-critical situations, the computational models on which they rely must be validated and their degree of predictability must be assessed. This study will conform to the U.S. Department of Energy's definition of validation, which makes a clear distinction between *verification* and *validation*. Here, model verification addresses the issue of assessing that the equations implemented are being solved correctly. In contrast, model validation is concerned with estimating that the equations correctly represent reality.

5.4.1 Verification

Before a decision can be confidently based on numerical results, it must be verified that the computer hardware, computational models, and numerical simulations are implemented correctly. Model verification addresses issues associated to programming bugs, communication errors, human interaction errors, discretization errors, computational errors, and the convergence of numerical solvers. In structural dynamics, for example, finite element-based simulations must ensure that discretization is adequate both spatially and temporally and that the energy content is captured over an adequate bandwidth. Figure 5.7 shows a comparison of predictions obtained with several computational grids to check that the numerical solutions asymptotically converge. It had been demonstrated that a posteriori and interpolation-based error estimators can be used to efficiently demonstrate mesh convergence for elliptic problems. However, such indicators can not typically be applied to other types of equations (parabolic, hyperbolic) with arbitrarily complex geometries.[57]

It may be argued that guaranteeing a 100% error-free simulation using a 100% bug-free code is not realistic. Nevertheless, a statistical treatment can assess the confidence in code output or measurement system output. Ideally, each model should be developed with its own verification plan

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[57] O.C. Zienkiewicz, and Taylor, *The Finite Element Method*, McGraw-Hill Publishers, New York, NY, 1991.

to ensure traceability (adequately documenting changes), and to guarantee that once linked with other models errors are not accumulated or transmitted to other parts of the simulation.

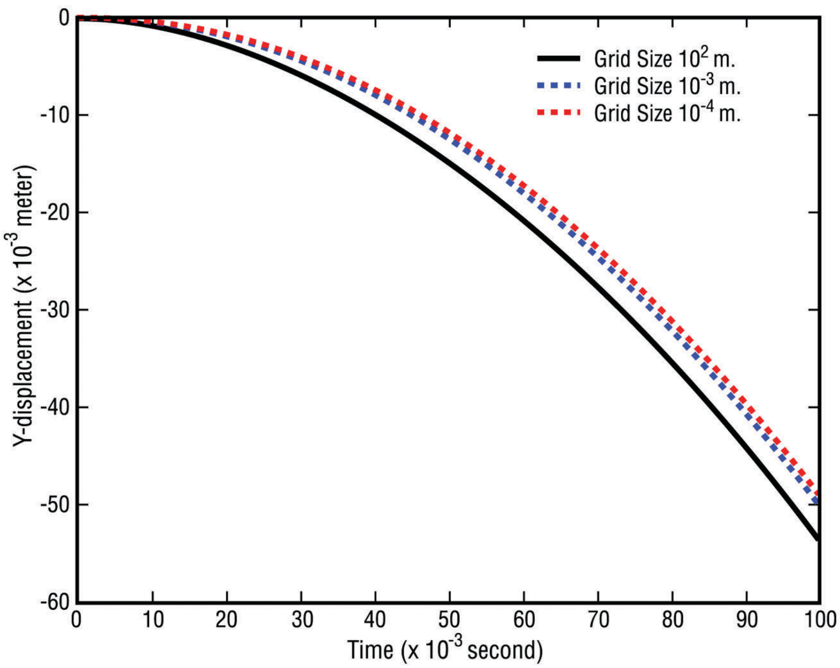

Figure 5.7 Study of the convergence of a computational grid.

5.4.2 Validation

The definition of model validation is generally centered about the question: "Are the appropriate equations being solved?" Answering this question necessitates some sort of comparison between physical measurements and prediction output. However, it is emphasized that a model should never be considered validated if the validation experiment establishes *only* that the model output matches experimental results. Techniques such as finite element model updating, parameter identification and parameter "tuning" are useful tools for model validation and they will be collectively referred to as *calibration* tools.[58] Nevertheless, by no means does a calibration experiment constitute a validation experiment. Generally, calibration adjusts some of the model's input parameters through one of many inverse problem-solving techniques to make the numerical predictions consistent with physical observations. Model validation, on the other hand, aims to assess the accuracy of the model's predictions throughout the operational space.

The relationship among modeling, variability, and uncertainty has already been discussed in Section 5.3. Because it is unrealistic to believe that a model, no matter how sophisticated, will ever represent reality perfectly, the statistical analysis of modeling uncertainty should be systematically included. Uncertainty analysis during model development and validation helps to assess regions of the design space that are predicted with acceptable accuracy and those that would require further refinement. Similarly, all potential sources of variability (e.g., environmental changes,

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[58] M.I. Friswell and J.E. Mottershead, *Finite Element Model Updating in Structural Dynamics*, Series on Solid Mechanics and Its Applications, Kluwer Academic Publishers, June 1995.

manufacturing tolerances, and assembling variability) should be represented to help estimate the probability information contained in the model output.

This supposition implies that physical testing is not needed so much for the purpose of calibration or verification, as is usually the case in test-analysis correlation studies, but for assessing the statistical adequacy between model predictions and system response over as much of the design space as possible.

Clearly, model validation requires well-defined validation experiments. The validation experiments should provide physical observations over the entire operational range of the system. The experiments must also be designed to capture potential sources of variability and isolate the separable physics before consideration of more complex interactions. The statistical design of experiments, together with numerical simulation, can be useful for planning an adequate matrix of physical tests that will then feed the validation study. In Figure 5.8, the predictive accuracy of a high-rate, high-temperature plasticity model is assessed over a domain of potential temperatures and strain rates. Validation experiments are performed at several temperatures and strain rates to calibrate the parameters of the numerical model. A metamodel of predictive accuracy is developed to estimate the prediction error. It is very likely that model validation will have to be carried out at each level of modeling. Probable scales of validated models will represent basic, separable physics; elementary components; subassemblies; and, if possible, the full system.

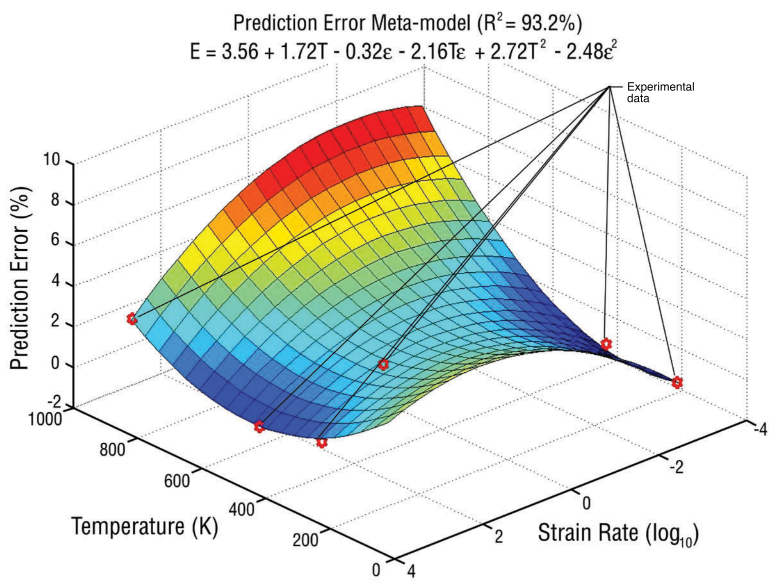

Figure 5.8 Assessment of predictive accuracy of a constitutive model.

Typical outcomes of a validation experiments include assessing the accuracy of the constitutive equations, the functional form of the partial differential equations, and the conceptual form of the model (especially, in the case of surrogate modeling). Another important issue is that the models required for analyzing the response of a system to real operating conditions might be significantly different from the models developed for non-operating conditions or laboratory experiments. If the models and simulations are validated using laboratory validation experiments, the question remains as to how the predictive accuracy for the real system can be assessed. Other elements of model validation include the following:

1. **Feature extraction:** In the context of damage prognosis, *features* are defined as any quantities extracted from physical measurements or numerical predictions that support the assessment of the current health of the system. Generally, low-dimensionality features are sought to provide an efficient compression or reduction of large data sets and to allow the subsequent statistical analysis. Of course, the features selected must also reflect the purpose intended for the model. Conventional features in structural health monitoring are peak values in time histories, mode shapes, or resonant frequencies. However, these metrics are not appropriate indicators of damage in complicated systems characterized by nonlinear, nonstationary responses and a high degree of variability. Response characterization and feature extraction are important components of damage diagnosis and prognosis.

2. **Correlation metrics:** During a calibration or validation experiment, a correlation metric is used to compare the distances between features derived from physical measurements and numerical simulations. Conventionally, least-squares metrics, maximum likelihood, or Bayesian metrics are defined for formulating inverse problems as optimization problems. As the importance of building statistically accurate models is recognized, other correlation metrics should be investigated to capture the consistency between model predictions and reality. Capturing this consistency ties directly into the statistical activities of hypothesis testing and group classification. Statistical tests that have been proposed as correlation metrics include, but are not restricted to, the Chernov entropy,[59] the Kullback-Leibner entropy,[60] or the Mahanalobis test[37] that simplifies into a conventional Bayesian posterior distribution when probability information is normally distributed.

3. **Error localization:** One of the objectives of calibration and validation experiments is to identify the areas of the model that are responsible for the discrepancies between physical observations and model predictions. In a calibration experiment, the discrepancy is attributed to erroneous input parameters. Error sources might also include erroneous initial and boundary conditions, incorrect geometry description, inadequate discretization and inadequate model form. Some of these error sources can be addressed with an appropriate verification plan (that would, for example, be the case of discretization errors) while others are clearly validation issues. Generally, error sources are assumed a priori and an appropriate correction strategy is implemented. For example, a posteriori error estimators and mesh adaptivity address the problem of discretization convergence while finite-element model updating addresses the problem of parameter calibration. Currently, there is little published research that attempts to either classify error sources or develop general-purpose error localization strategies.

4. **Calibration:** Calibration has been recognized as an important tool for model verification and validation. Calibration applies to those input parameters whose values can be inferred from physical observation. In general, parametric calibration is formulated as an optimization

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[59] N. Chernov, "Invariant measures for hyperbolic dynamical systems" in: Handbook of Dynamical Systems, A. Katok and B. Hasselblatt, Eds., Elsevier, 2002.
[60] T.M. Cover and J.A. Thomas, *Elements of Information Theory*, Wiley Series in Communications, 2^{nd} Edition, 1991.

problem, although other approaches via adjoint modeling[61,62] or two-point boundary value problems[63] sometimes appear more relevant. In structural dynamics, finite-element model updating[64] is an example of a calibration technique that has been applied with some success to structural health monitoring. Issues in calibration include adopting an appropriate framework through the choice of correlation metrics, numerical optimization efficiency and convergence, local versus global search techniques, and the propagation of uncertainty and probability information. Figure 5.9 shows an example of a test-analysis comparison and the improved result obtained through parametric calibration.

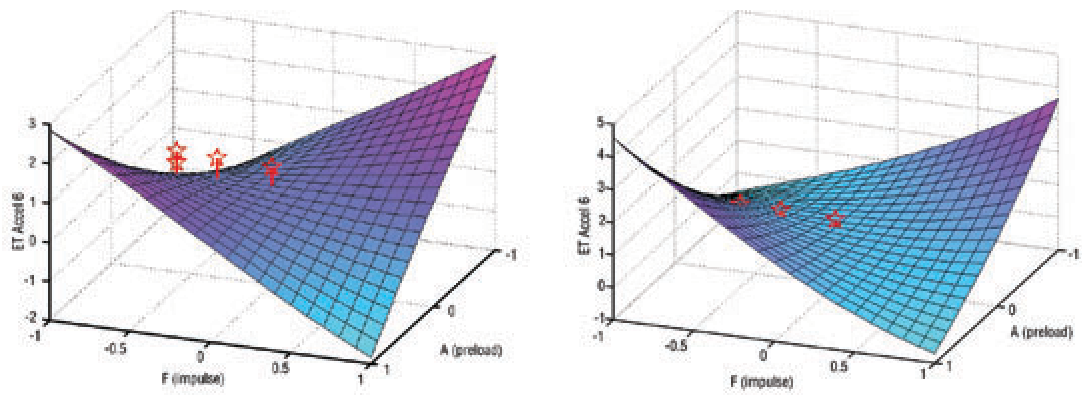

Figure 5.9 Illustration of test-analysis comparison and parametric calibration. The stars correspond to experimental data points. The vertical axis, ET, is the first temporal moment. Left: Test-analysis comparison before parameter calibration. Right: Test-analysis comparison after calibrating the parameters of the metamodel.

5. **Sensitivity:** Sensitivity information is very valuable whenever optimization problems are solved or design questions must be answered. *Sensitivity* can be defined as the local gradient information obtained from an analytical formulation, adjoint differentiation, or numeric computation via finite-difference schemes. Here, sensitivity also refers to the broader notion of statistical variance, which is an integral measure of influence averaged over the entire design space. Analysis of variance techniques can also provide important information regarding which input parameters are responsible for the statistical variance of an output feature. Obviously, convergence and computational resources can impose serious limitations on the amount of sensitivity information available. Nevertheless, validated models should be required to represent the output features of interest adequately together with their statistical distribution and sensitivity information. Figure 5.10 shows results from

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[61] R.J. Henninger, P.J. Maudlin, and M.L. Rightley, "Accuracy of Differential Sensitivity for One-dimensional Shock Problems," *Shock Compression of Condensed Matter*, S.C. Schmidt, Ed., American Institute of Physics, Woodbury, NY, 1998.

[62] M.L. Rightley, R.J. Henninger, and K.M. Hanson, "Adjoint Differentiation of Hydrodynamic Codes," Newsletter of the Center for Nonlinear Studies, Los Alamos National Laboratory, Los Alamos, NM, November 1997. http://cnls.lanl.gov/Publications/newsletters.html.

[63] K.D. Dippery and S.W. Smith, "An Optimal Control Approach to Nonlinear System Identification," *Proceedings of the 16th SEM International Modal Analysis Conference,* pp. 637–643, Santa Barbara, CA, February 2–5, 1998,

[64] M.I. Friswell and J. Mottershead, *Finite Element Updating in Structural Dynamics*, Kluwer Academic Publishers, 1995

a main effect screening analysis of a large-size finite element model to 12 parameters. These 12 input parameters are screened to analyze which ones produce the greatest change in several response features over a range of possible values. A design-of-computer-experiment is used to determine the necessary finite element simulation runs. Results are analyzed using a Bayesian screening technique. Large vertical bars indicate input parameters that strongly influence the values of the output features throughout the operational domain.

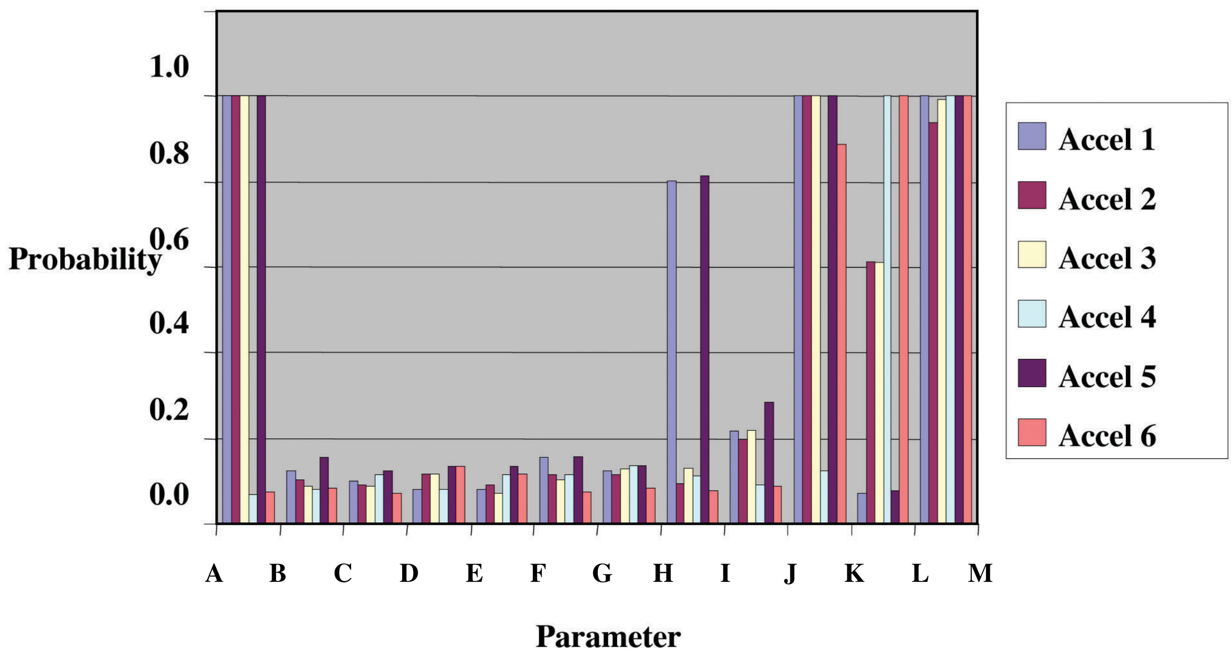

Figure 5.10 Results of a main effect screening experiment.

5.5 Hardware and Data Management

In this section damage prognosis issues related to hardware, software and data management will be discussed. It is believed that some of the problems generated by the deployment of large numbers of actuators and sensors can be more efficiently resolved if hardware integration is taken into account early in the process of designing a damage-prognosis system. Similarly, the vast amounts of data generated by massive number of sensors and numerical models require specific data handling procedures. Integration of hardware and software, process streamlining, and modularity are some of the aspects addressed below.

5.5.1 Architectures

Large-scale computational resources and high-fidelity modeling are increasingly available. An example is the U.S. Department of Energy's ASCI program.[54] Figure 5.11 shows the Department of Energy's ASCI Q massively parallel platform at Los Alamos National Laboratory. This machine is capable of 20 teraops ($20 \times 10^{+12}$ floating-point operations per second). Even without access to massively parallel architectures, computational power and modeling capability have increased by several orders of magnitude in compared to just a decade ago. Lower costs for memory and disk space, massive integration of transistors on computer chips, and high-speed networking are mainly responsible for this continuing improvement. Many of these achievements are motivated by new technologies and the consumer market place. Examples are high-speed Internet, voice streaming, video games, cellular phone applications and, soon to come, video streaming. These are examples of technologies that are readily available, for the most part, and that can have a significant impact on the deployment of damage-prognosis systems.

Figure 5.11 The Department of Energy's ASCI Q computer.

Further research and development is also needed in computer science and software engineering to develop robust and general-purpose production codes capable of analyzing very large practical problems based on massively parallel architectures.

On the other end of the spectrum, specialized hardware must be developed for specific applications. Great efficiency can be achieved by tailoring both hardware and data processing to the application of interest. The technology that has the potential to impact damage prognosis the most is the development of micro-electro-mechanical systems (MEMS), as discussed in Section 3. Among all possible chips that could potentially be developed for damage prognosis, specialized chips dedicated to finite element analysis, impedance models, and advanced signal processing techniques would be the most useful.

5.5.2 Data Handling

Massive instrumentation and high-fidelity numerical simulations tend to generate vast amounts of numerical data that must be accessed and processed. Here, data handling collectively refers to communication, security, storage, compression, visualization, human interaction, and archiving of the data. Data handling issues are classified in four groups:

1. **Communication:** The conventional approach to monitoring that consists of running wires between the local sensors and a centralized data acquisition unit can impose serious limitations on damage prognosis, a corner stone of which is the deployment of massive instrumentation. Recent advances in wireless communication can alleviate most of these limitations. With wireless technology, the local sensing and processing units can communicate with a centralized processing unit and with each other. With two-way communication capability, the local sensing and processing units can also take themselves off-line to conserve energy, and they can be resuscitated when a "wake-up" signal is

broadcast. Potential constraints are the maximum range, amount of bandwidth available, energy requirement, and susceptibility to electromagnetic interference.

2. **Security:** Beyond the health monitoring of civil engineering systems, potential applications for damage prognosis include critical machinery and equipment in industrial facilities and military systems. Broadcasting information about such systems may betray innovative production techniques, competitive advantages, or national security concerns. It is therefore very unlikely that damage-prognosis systems will ever be deployed if sensitive information is prone to unauthorized interception. Sensitive components must be identified as such and protected by adequate encryption techniques. The security procedures implemented must also be able to adapt to evolving threats.

3. **Visualization**: Understanding what data or measurements tell us can be made quite difficult by an inappropriate presentation of the results, especially when large amounts of data are presented. Too much information can hide what is really important to know about the system and impede decision making. The interaction between humans and computers can be tailored for maximum efficiency given a particular application and the corresponding measurement systems and computer simulations. Current developments of multi-media technology offer many possibilities that should be used. Depending on the environment considered (computer laboratory, prototyping, deployment on the field, etc.), an efficient presentation of results could include high-fidelity graphics, three-dimensional (3-D) immersion chambers, simple visual messages such as a red-yellow-green light, or vocal messages. Obviously, greater efficiency can also be achieved through feature extraction techniques.

4. **Accessibility:** Large data sets generally require sophisticated or innovative storage capabilities not just to physically store the information but also to access it efficiently. Storage and accessibility are therefore important components of damage prognosis. Compression algorithms will most likely be required to improve the efficiency with which large data sets are stored and accessed. Law enforcement authorities' storage of large fingerprint databases is an example where, through wavelet-based image compression, over 99% of the information can be retrieved using a fraction of the bits of the original image.[65] This data compression ties directly into the pattern recognition and feature extraction technology that has already been mentioned. Archiving as much as possible of the data collected and generated is also important. Analysts must be allowed to revisit past data sets for further, in-depth analysis if an abnormality is detected in the future. It is also likely that the preferred features will evolve throughout the life of the structural system and new features cannot be analyzed if the raw data have not been archived.

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[65] R.A. DeVore, B. Jawerth, and B.J. Lucier, "Image Compression Through Wavelet Transform Coding," *IEEE Trans. Inform. Theory*, **38** (2), pp. 719–746, 1992.

5.5.3 Evolution

Finally, the models, sensing configuration, and the associated computational hardware must be designed to be flexible and modular. One major challenge is that the full system simulations must account for retrofits and other potential hardware updates. Simulations should reflect the maintenance history, which implies modularity of the family of models implemented. For example, the action of replacing a particular hardware component in the full system should be accounted for in the numerical simulation. This requirement will most certainly have important implications in terms of databases and information management.

Similarly, model validation procedures and numerical predictions should theoretically be revisited as soon as new measurements and new data from the damaged system become available. These iterations should not be restricted to parametric calibration experiments. When new measurements become available, the values of calibrated parameters can surely be confirmed or re-calibrated. In addition, the model form should also be allowed to evolve. For example, when it is assessed that a crack has formed and is growing, a material model that represents the mechanism by which energy is dissipated through friction or impact between two components should be augmented with a crack propagation model.

5.6. Key Technology Deficits

The following aspects of modeling and simulation are identified as crucial to the success of damage prognosis:

1. Integration of models: Generally, several models must be integrated to characterize the features of a particular damage scenario, the evolution of structural damage, and the resulting effect on system performance. This integration is required because each model is constructed to capture a particular phenomenon. Models may also be formulated using different physics (mechanical fields, thermal fields, electro-magnetic fields, etc.) and different scales (macroscopic, microscopic, nanoscale, etc.). Therefore, procedures must be established to ensure that adequate models are developed and integrated into the full system simulation. In addition, the simulations must represent the causal instigators completely. Modularity is also critical to ensure flexibility and adaptability. For example, similar systems may require several perturbed models to reflect the past maintenance history of sub-systems or individual components. Models and numerical simulations must be managed in a flexible and modular way to ensure that retrofits, maintenance history, and other potential updates are fully accounted for.

2. Computational limitations: Limitations in computational power and resources needed for real-time prediction are obvious bottlenecks if damage prognosis is to rely heavily on numerical analysis as opposed to full-scale testing. On the high-end computing side, computational resources and networking capabilities limit the level of detail that can be included in the numerical simulations. On the fast modeling and diagnosis side, the constraints include the amount of data that can reasonably be processed by specialized DSP chips. Because of the required high degree of integration between modeling and sensing, instrumentation limitations might also adversely impact modeling.

3. Confidence in results: It is essential to quantify the confidence in experimental and simulation results. This quantification is required because some of the models implemented may be stochastic in nature to reflect the fact that future environmental and operating conditions are uncertain. Damage states, history, and evolution scenarios may also be uncertain. In addition, measuring and modeling complex systems always requires the formulation of hypotheses and approximations such as model reduction, truncation, and order selection, no matter how much testing and computational resources are available. These approximations explain why uncertainty is not just the manifestation of variability and partial knowledge, but also the result of the formulating approximations. Decision making based on experimentation and simulation requires the knowledge of confidence intervals associated with the data. This requirement ties into sensor and data acquisition selection, model validation and predictability.

4. Knowledge acquisition: Knowledge acquisition refers not only to the activity of performing physical experiments and developing mathematical and numerical models but also to data "mining," data "fusing," and documentation. Capturing the human experience also fits under this category. Opinions and subjective information are difficult to collect, exploit, and combine with formal models. Special models might have to be developed for this purpose.

5. System Reliability: Because of the numerous sources of variability and uncertainty previously mentioned, the decisions supported by measurements and simulations become reliability assessments. Instead of providing deterministic answers, the decision models estimate the probability of "failure" and whether such risk is worth taking. Little to no research is currently available to formulate damage prognosis as a problem of system reliability and this should be further investigated. In particular, there are few if any procedures to include modeling uncertainty and nonprobabilistic descriptions of uncertainty into reliability assessment and decision making.

6. UNCERTAINTY QUANTIFICATION

Robust model predictions and a quantifiable level of conservatism are necessary for the practical adoption of damage-prognosis technology. Furthermore, the business case for damage prognosis as envisioned in the present context requires greater robustness and demonstrably less conservatism than the current technology. Achieving this enhanced robustness and reduced conservatism necessitates the quantification of the uncertainties inherent in all phases of damage-prognosis modeling.

The phases of the modeling process relevant to damage prognosis are depicted in Figure 6.1. Uncertainty is present in all of these phases including the observation of nature, the abstraction of this observation into a conceptual model, and its symbolic representation as a mathematical model, as well as the concomitant numerical and surrogate models and their evaluation. The uncertainty associated with this process may be divided into four areas, including those caused by measurement, modeling, parameters, and evaluation. In this section, some of the general considerations associated with uncertainty quantification and specific issues related to measurement, model, parameter, evaluation, and overall, or total, uncertainty will be discussed.

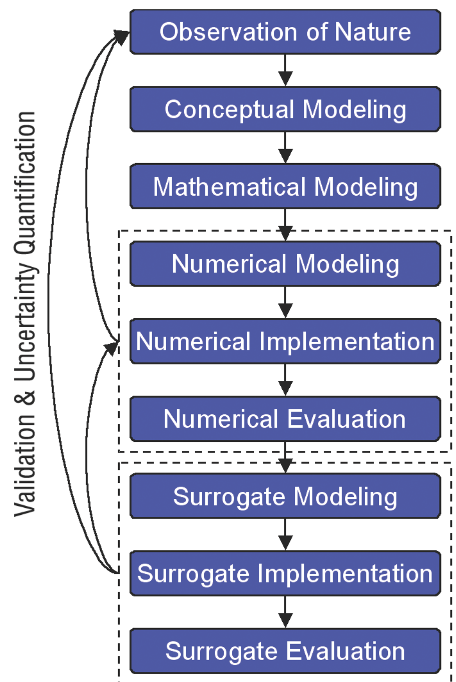
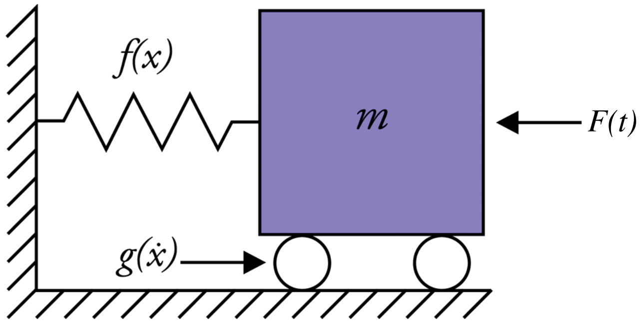


Figure 6.1 Phases of the modeling process for prognosis.

To illustrate these concepts more concretely, consider the simplified mechanical system depicted in Figure 6.2. A priori measurement of the forcing function and response will likely be contaminated by noise, deterministic anomalies, and artifacts of the measurement system, all leading to an approximation of the true load. This variability is an example of measurement uncertainty. The conceptual and mathematical models are typically formulated without regard to the friction in the wheels and usually assume no slippage between the wheels and the ground surface. Also, such a model is often formulated linearly because the spring nonlinearity at small deflections is considered negligible. These two approximations result in inadequacies of model form; i.e., one type of modeling uncertainty. Because of the conceptual disregard for wheel friction any nonzero offset in the spring is neglected, leading to uncertainty in the initial conditions, another form of modeling uncertainty. The system parameters are typically calculated from the geometric and material properties of the mass and spring using handbook values for density and elastic modulus. These values represent mean estimates from statistical distributions defined by material tests (themselves subject to measurement uncertainty) and are a source of parametric uncertainty. Note that the geometry of the actual system as well as the specific material composition may be subject to measurement uncertainty or to manufacturing variability if the system is modeled from a nominal design. Finally, unless the forcing function is particularly simple, the equations will usually be solved numerically. For the present example this will entail the choice of an approximate integration scheme and temporal discretization, as well as introducing numerical round-off and truncation errors. These factors are examples of evaluation or solution uncertainty.



1. "TRUTH" MODEL

$$m\ddot{x} + f(x) + g(\dot{x}) = F(t)$$
$$x(0) = x_0, \dot{x}(0) = 0$$

2. APPROXIMATE MODEL

$$\hat{m}\ddot{x} + \hat{k}x = \hat{F}(t)$$
$$x(0) = 0, \dot{x}(0) = 0$$

Figure 6.2 Examples of uncertainty in a simple physical problem.

6.1 General Consideration

The uncertainty associated with a given model, or collection of models, can be viewed either as a compendium arising from the various sources or as a whole without regard to origin. Both viewpoints will be required for successful implementation of damage-prognosis technology. The various types of uncertainties can be roughly classified into three categories, including aleatoric uncertainty (irreducible, inherent variability), epistemic uncertainty (potentially reducible lack of knowledge), and simple error (reducible error or bias). In the foregoing example, noisy measurements, statistically distributed properties, and manufacturing variability are examples of aleatoric uncertainty. Epistemic uncertainty and error are represented by the model form and initial condition approximations and by the numerical approximations necessary for solution. The classification of the latter uncertainty group into error or epistemic uncertainty is largely a matter of taste, although one might argue that the model-related uncertainties are epistemic, while those concerning the solution are simple error.

Several classes of methods are available for formulating the logical and computational framework of uncertainty analysis.[66] Measure theoretical methods are more applicable to aleatoric uncertainty. Such methods include classical probability theory in its various guises (frequentist, Bayesian, etc.), Dempster-Schafer theory, and possibility theory. An axiomatic comparison of standard probability theory and Dempster-Schafer theory is given in Table 2 as an example. Also contained in the family of measure theoretic methods and usually associated with classical probability theory are information and entropy theory.[67] Set theoretic methods[68] include those based

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[66] H.G. Natke and Y. Ben-Haim, Eds., "Uncertainty: Models and Measures," Mathematical Research, **99**, Akademie Verlag, 1997.
[67] S. Kullback, *Information Theory and Statistics*, Dover Publications, 1997.

on fuzzy sets, interval arithmetic, and convex sets or convex modeling. Set theoretic methods are primarily applicable to the treatment of epistemic uncertainty. Also available for handling epistemic uncertainty is a relatively new approach called information gap theory.[69] Hybrid methods, capable of treating both aleatoric and epistemic uncertainty, based on a combination of fuzzy set theory and fuzzy measure theory are also being investigated.[70] Dynamical systems methods [71] are applicable to unpredictability because of sensitive dependence on initial conditions and deterministic chaos; i.e., to some of the uncertainties arising from model evaluation. Candidate methods from dynamical systems include strange attractor theory, the Liapunov exponent, and complexity theory.[72] Complimenting methods for treating specific uncertainties is a recently developed method for quantifying the total uncertainty;[73] i.e., the total difference between measured data and model predictions, in a generic sense.

Table 2. Axiomatic comparison of probability theory and Dempster-Schafer theory.

Probability Theory	Dempster-Schafer Theory
$\mathrm{Pr}: 2^X \to [0,1]\ \mathrm{Pr}(\varnothing) = 0,\ \mathrm{Pr}(X) = 1$	$\mathrm{Bel}: 2^X \to [0,1]\ \mathrm{Bel}(\varnothing) = 0,\ \mathrm{Bel}(X) = 1$ $\mathrm{Pl}: 2^X \to [0,1]\ \mathrm{Pl}(\varnothing) = 0,\ \mathrm{Pl}(X) = 1$
$\mathrm{Pr}\left(\bigcup_i A_i\right) = \sum_i \mathrm{Pr}(A_i) - \sum_{j<k} \mathrm{Pr}(A_j \cap A_k) + \cdots + (-1)^{n+1}\,\mathrm{Pr}\left(\bigcap_i A_i\right)$	$\mathrm{Bel}\left(\bigcup_i A_i\right) \geq \sum_i \mathrm{Bel}(A_i) - \sum_{j<k} \mathrm{Bel}(A_j \cap A_k) + \cdots + (-1)^{n+1}\,\mathrm{Bel}\left(\bigcap_i A_i\right)$
$\mathrm{Pr}\left(\bigcap_i A_i\right) = \sum_i \mathrm{Pr}(A_i) - \sum_{j<k} \mathrm{Pr}(A_j \cup A_k) + \cdots + (-1)^{n+1}\,\mathrm{Pr}\left(\bigcup_i A_i\right)$	$\mathrm{Pl}\left(\bigcap_i A_i\right) \leq \sum_i \mathrm{Pl}(A_i) - \sum_{j<k} \mathrm{Pl}(A_j \cup A_k) + \cdots + (-1)^{n+1}\,\mathrm{Pl}\left(\bigcup_i A_i\right)$

In addition to a logical and mathematical framework for uncertainty characterization, a metric for measuring uncertainty is required for quantitative comparisons and for the decision process for damage prognosis. In a probabilistic context, the standard deviation of a variable is often taken as the relevant metric. The related concept of confidence intervals may also be used. The situation is not so clear for nonprobabilistic uncertainty, however. A variety of metrics are available for finite

[68] T.J. Ross, J.M. Booker, and W.J. Parkinson, Eds., *Fuzzy Logic and Probability Applications: Bridging the Gap*, ASA-SIAM Series on Statistics and Applied Probability 11, SIAM Publishing, Philadelphia, PA, 2003.

[69] Y. Ben-Haim, *Information-Gap Decision Theory: Decisions Under Severe Uncertainty*, Series on Decision and Risk, Academic Press, 2001.

[70] G.J. Klir, "Uncertainty Theories, Measures, and Principles: An Overview of Personal Views and Contributions," in "Uncertainty: Models and Measures," H.G. Natke and Y. Ben-Haim, Eds., Mathematical Research, Vol. 99, Akademie Verlag, 1997.

[71] A. Katok and B. Hasselblatt, "Introduction to the Modern Theory of Dynamical Systems," Cambridge University Press, 1995.

[72] W.H. Zurek, Ed., "Complexity, Entropy and the Physics of Information," Santa Fe Institute Studies in the Sciences of Complexity, Proceedings Vol. 8, Addison-Wesley, 1990.

[73] M.C. Anderson, T.K. Hasselman, and W. Gan, "Statistical Analysis of Modeling Uncertainty and Predictive Accuracy for Nonlinear Finite Element Models," *Proceedings of the 69th Shock and Vibration Symposium*, October 1998.

sets of alternatives. Examples of some of these metrics for finite sets are listed in Table 3. Corresponding metrics for countable and uncountable infinite sets are generally unavailable.

Table 3. Examples of uncertainty metrics for finite sets.

Name	Formula	Purpose
Hartley Measure	$H(A) = \log_2 \lvert A \rvert, \lvert A \rvert$ is cardinality of A	Nonspecificity
Generalized Hartley Measure	$N(m) = \sum_{A \in 2^X} m(A) \log_2 \lvert A \rvert, m: 2^X \rightarrow [0,1] m(\varnothing) = 0, \sum_{A \in 2^X} m(A)$	Nonspecificity in Dempster-Schafer theory
U-uncertainty Measure	$U(r) = \sum_{i=2}^{n} (r_i - r_{i+1}) \log_2 i, r(x) = \mathrm{Pos}(\{x\}), r_i \geq r_{i+1} \forall i$	Nonspecificity in possibility theory
Shannon Entropy	$S(p) = -\sum_{x \in X} p(x) \log_2 p(x)$	Total uncertainty in probability theory
Generalized Shannon Entropy	$AU(\mathrm{Bel}) = \max_{p_x} \left(-\sum_{x \in X} p_x \log_2 p_x \right), Bel(A) \leq \sum_{x \in A} p_x \forall A \in 2^X$	Total uncertainty in Dempster-Schafer theory
Hamming Distance	$f(A) = \sum_{x \in X} [1 - \lvert 2A(x) - 1 \rvert], A(x)$ is membership function	Fuzzy sets

A variety of hurdles stand between the current state of the art for uncertainty quantification and its meaningful implementation as an integral part of damage prognosis. These hurdles include the problems of identification, classification, and attribution; incomplete theoretical development and a lack of practical tools for some of the methods of treating uncertainty; and the endemic problem of sparse or nonexistent data. Identification of uncertainty, its type classification, and its attribution of source will require the collaboration of classical subject matter experts and a new breed of uncertainty experts. Completion of the theoretical framework and the development of practical tools for treating the myriad aspects of uncertainty are ongoing areas of research and require only time and the proper impetus, such as the problem of damage prognosis. The lack of sufficient data, on the other hand, is a problem that is impractical to overcome by mere data gathering. The only tenable solution to this problem for the foreseeable future is the proper use of expert elicitation and development of methods for fusing expert "data" with measured data.[74]

Nevertheless, uncertainty should not be dissociated from the modeling issues discussed in Section 5.3. The attempt to explain a complex physical experiment by mathematical models implicitly defines uncertainty. Modeling consists of translating observations or reasoning into formal rules and equations through the formulation of a series of hypotheses. The probabilities, or other representations of uncertainty, associated with assumptions and modeling rules should therefore be included in the numerical simulation. Uncertainty also originates from several processes commonly adopted during modeling, discussed below.

1. **Selecting an inadequate model form:** If a phenomenon or an interaction between variables is not known precisely, an inadequate model form is likely to be implemented. This error generates discrepancies between the "true" system and its mathematical representation. Parameter calibration is commonly used to correct model form errors. However, this

[74] L.A. Klein, *Sensor and Data Fusion: Concepts and Applications*, Second Edition, TT14, SPIE Press, 1999.

strategy may not be an appropriate approach, as it will often lead to physically unrealistic parameter values. Uncertainty analysis may provide an efficient means of detecting inadequate model forms and implementing corrective action.

2. **Truncating the model order:** Second order dynamics are generally truncated when it is believed that they do not have a significant influence on the primary dynamics of interest. Order truncation is therefore a common practice in numerical modeling. Truncation typically consists of restricting the degrees of freedom of a problem to a subset of "master" degrees of freedom and somehow condensing or approximating the information represented by the omitted equations. Model order selection in autoregressive models and component mode synthesis are examples of truncation methods in linear structural dynamics.

3. **Approximating equations:** Equations are often approximated for computational efficiency, model order truncation, or because the exact functional relationship is unknown. In the case of model order truncation, for example, a coupling force might be replaced with its expected value, conditioned by the functional relationship between primary and secondary variables. In essence, this approach defines an approximated system where the original differential equations are solved "on average" instead of exactly. The second main class of approximation is numerical approximation where the mathematical operators, spatial fields, temporal fields, and energy content must be discretized for numerical implementation. In both cases, the practice of associating an uncertainty model with the approximation and analyzing the model accordingly should be promoted.

6.2 Measurement Uncertainty

Measurement uncertainty refers to the uncertainties arising from the measurement process itself. Aleatoric uncertainty, or inherent variability, can come from noise in the measurement process that is due to factors such as thermal instability, internal or external electromagnetic fields, and quantization noise. Error and epistemic uncertainty can arise from electrical bias, gain errors, and signal processing artifacts. Examples of the latter include aliasing introduced by sampling at too low a rate, or contamination by signals outside the frequency range of interest, amplitude and phase distortion from explicit filtering or the frequency response of the measurement system, numerical processing of the measured data, and a myriad of other factors including human error.

The treatment of measurement uncertainties has a history almost as long as measurement itself. The most common method of treating bias, gain, and temporal or frequency errors is by calibration of each piece of measurement equipment with respect to known standards. Less common is the end-to-end calibration of the entire measurement system. Externally generated noise can be dealt with in some cases by using first principles modeling or independent measurement for deterministic or statistical characterization of noise. So-called "dummy" transducers are often employed for independent measurement. Aliasing errors can be avoided by use of the proper sampling rates or analog anti-aliasing filters. A conceptually obvious, but little used, technique for minimizing measurement uncertainties is "inverse" signal processing. In this technique, all or part of the measurement system is modeled mathematically and the model is "inverted" to infer the "true" signal from the processed one. In general, a wide variety of best practices have been devised for many measurement schemes. While some of these techniques are common knowledge, some are rather arcane or specific to a particular measurement instrument or scheme.

The foregoing comments are pertinent to direct measurement of the quantities of interest. In many applications, the desired quantities cannot be measured directly but must be inferred indirectly based on available data. This inference is usually facilitated by the use of a physical and/or empirical model of some sort. Thus, indirect measurements are subject not only to the usual measurement uncertainties, but also to those typically associated with mathematical and numerical models.

Measurement uncertainty is a significant part of the overall uncertainty picture. In many situations, measured data are taken as absolute truth. This approach is obviously not correct because measurements rely on the characteristics of real hardware, and on the physical or empirical models underlying the design of that equipment. An honest quantification of measurement uncertainty is crucial to a meaningful characterization of uncertainty as a whole.

6.3 Modeling Uncertainty

Modeling uncertainty is a catch-all term that describes all uncertainty not associated with measurements, the parameters of the model, or the numerical solution of the model. This type of uncertainty can be introduced during either the conceptual or mathematical modeling processes. Because it is not possible to model complex, realistic systems at the level of elementary particles, most real-world mathematical models are comprised of a set of field equations and associated boundary and initial conditions, all used as an empirical surrogate for a physical model. These equations are approximations of the complicated physics of the real world. The fidelity with which they can predict the outcome of real world situations is limited and usually application dependent.

A variety of uncertainties can arise from the physical modeling process. Many of these can be classified as epistemic uncertainty or outright error, although the use of a deterministic model for a scenario that has stochastic elements (such as stochastically distributed parameters) leads to aleatoric uncertainty. Modeling uncertainty can arise from approximations or errors in the form of the model equations, the applied loads and the boundary and initial conditions. Form errors can be attributed to known, but not modeled, physics (simple error or aleatoric uncertainty) or to unknown effects (epistemic or aleatoric uncertainty). In either case the results are the same: induced discrepancies between model predictions and reality.

There are few methods available for the systematic treatment of uncertainty in physical models. Clearly, if the uncertainty is due to physics that are known, but not modeled, either the model can be revised to include these physics or an attempt can be made to characterize the uncertainty induced by their exclusion. However, if the excluded physics are not known, little can be done to characterize the concomitant uncertainty.

Surrogate models also suffer from modeling uncertainty. However, the situation is exacerbated for surrogate models because the model form or possible forms are specified a priori and are not based on first principles. This process leads to both training errors and generalization errors. Training errors arise because the specified model form is incapable of accurately reproducing the training data generated by a physical system or model with a different underlying functional form. Training errors can be minimized by many techniques (e.g., least squares) as long as sufficient data are available. Generalization errors (i.e., interpolation or extrapolation errors) also arise because of form errors but cannot be minimized by additional data at the training points. There is often a tradeoff between accuracy at the training points and the generalization potential of a surrogate model. The optimal choice is application dependent.

An array of techniques is available for the characterization and minimization of uncertainty in surrogate models. Most of these address the parameter estimation problem for these models.[75,76,77] Most of the parameter estimation methods rely on probabilistic concepts, but a few based on fuzzy methods are available. At least one general theory is being developed to encompass the uncertainty of surrogate models,[78] although this theory only addresses probabilistic uncertainty.

6.4 Parameter Uncertainty

The term parametric uncertainty refers simply to uncertainty in the input parameters of a model. Once a model's form has been specified by a complete set of mathematical equations, all that remains for a complete mathematical statement of the problem is numerical quantification of the various constants. These constants may be geometric or material properties, or they may be those that characterize the applied loads, or boundary or initial conditions. Note that if enough information is available it may also be possible to explicitly model other types of uncertainty in a parameterized form and include them in the problem formulation. No matter where they appear in the formulation of a problem, uncertainties in the numerical constants will lead to uncertainties in model predictions. These uncertainties differ from those due to modeling or evaluation uncertainties that are not explicitly included in the problem.

Parametric uncertainty is perhaps the most widely studied aspect of uncertainty. The characterization of the effect of this type of uncertainty on model predictions is amenable to a wide variety of techniques such as sensitivity and effects analysis,[79] Monte Carlo methods, [80] reliability-based methods,[81] fuzzy set, and interval propagation methods, [82] and stochastic finite elements. [83] The sampling techniques collectively known as design-of-experiments can be powerful tools for performing sensitivity and effects analysis and estimating the probability information of an output feature. Such methods include orthogonal array sampling and Latin hypercube sampling. Effects analysis techniques such as the analysis of variance and differential sensitivity analysis provide means to assess the global influence of an input parameter on an output feature. This information generalizes the conventional sensitivity information that provides a local gradient and direction at a sample point in the design space.

Formulating and solving inverse problems in the context of uncertainty analysis is still an area of active research. In a probabilistic context the problem consists in calculating the posterior distribution of input parameters such that predictions of the numerical simulation are statistically

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[75] E. Walter and L. Pronzato, *Identification of Parametric Models from Experimental Data*, Springer-Verlag, 1997.
[76] S. Haykin, *Neural Networks, A Comprehensive Foundation*, Prentice Hall, 1999.
[77] V. Cherkassky and F. Mulier, *Learning from Data: Concepts, Theory, and Methods*, Wiley Interscience, 1998.
[78] V.N. Vapnik, *Statistical Learning Theory*, Wiley Interscience, 1998.
[79] G.E.P. Box, W.G. Hunter, and J.S. Hunter, *Statistics for Experimenters, An Introduction to Design, Data Analysis, and Model Building*, Wiley Interscience, 1978.
[80] C.P. Robert and G. Casella, *Monte Carlo Statistical Methods*, Springer-Verlag, 1999.
[81] W.R. Blischke and D.N.P. Murthy, *Reliability: Modeling, Prediction, and Optimization* , Wiley, 2000.
[82] G.J. Klir and B. Yuan, *Fuzzy Sets and Fuzzy Logic: Theory and Applications*, Prentice Hall, 1995.
[83] R.G. Ghanem and P.D. Spanos, *Stochastic Finite Elements: A Spectral Approach*, Springer-Verlag, 1991.

most consistent with physical observations over the largest possible region of the input space. Bayesian inference,[84] where the posterior distribution is expressed as the product of the prior distribution and the likelihood function, is generally the formulation of choice. A significant hurdle is the computational limitation introduced by multivariate statistical analysis that rapidly requires very large numbers of simulation runs. Recent promising techniques include the Markov Chain Monte Carlo algorithm and its many variants that can sample a posterior distribution without assuming anything about its functional form.

The probabilistic approach is only one of many available for treating parametric uncertainty. Other frameworks that may offer attractive alternatives to the theory of probability, especially in the event of uncertainty from lack of knowledge (epistemic uncertainty) are available for quantifying and propagating uncertainty. Dempster-Schafer theory, possibility theory, fuzzy sets, interval methods, convex models of uncertainty, and information gap theory are potential alternatives.

6.5 Evaluation Uncertainty

Although discrepancies caused by solution methods and numerical errors have always been acknowledged to exist, they have rarely been considered in an uncertainty context until recently. Approximate formulations include spatial discretization techniques such as the finite difference and finite element methods. These methods are sometimes accompanied by auxiliary model order truncation, such as the modal truncation commonly used in the solution of linear eigenvalue problems. Various types of temporal discretization are used to facilitate the integration of dynamic equations, along with a myriad of approximate integration techniques. Examples of these integration methods include the Runge-Kutta, Newmark beta, and Monte Carlo techniques. Truncation and round-off errors appear whenever a finite machine is used to compute solutions to a specific set of approximate equations. Error estimates have long been available for some of these approximations and numerical errors,[85,86] although many of them are not sharp enough to be useful in estimating uncertainty realistically.

A relatively new area of interest with regard to the uncertainty arising from model evaluation is complexity and indeterminacy arising from the mathematical or numerical equations treated as dynamic systems. An enormous amount of research into the sensitive dependence on initial conditions, commonly called deterministic chaos, and other sources of complexity has been conducted in the last four decades. Useful techniques for characterizing the uncertainty inherent in the solution of these systems are emerging. Examples of these methods include the Liapunov exponent, strange attractor theory, and Melnikov's method.[87,88,89] Although their application to the study of uncertainty is in its infancy, these methods hold promise for application to particular classes of problems.

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[84] A. Gelman et al., *Bayesian Data Analysis*, Chapman & Hall/CRC, 1995.
[85] G. Dahlquist and A. Bjorck, *Numerical Methods*, Prentice Hall, 1974.
[86] G. Strang and G.J. Fix, *An Analysis of the Finite Element Method*, Wellesley-Cambridge Press, 1988.
[87] A.J. Lichtenberg and M.A. Lieberman, *Regular and Stochastic Motion*, Springer-Verlag, 1983.
[88] S. Wiggins, *An Introduction to Applied Nonlinear Dynamical Systems and Chaos*, Springer-Verlag, 1990.
[89] A. Katok and B. Hasselblatt, *Introduction to the Modern Theory of Dynamical Systems*, Cambridge University Press, 1995.

The greatest difficulty in characterizing the uncertainty caused by the approximate, numerical solution of mathematical problems is the lack of exact solutions that can serve as references. Such solutions are available only for a few linear equations and simple geometries. In other cases, the order of convergence can be established theoretically and verified numerically using multiple computational grids or time stepping strategies. The issue then becomes to assess whether the discrete solution is "close enough" to the (unknown) solution of the continuous equations and to quantify the numerical uncertainty. Techniques such as the grid convergence index[90] have been proposed to verify the adequacy of a numerical solution but their application to arbitrary fluid mechanics and structural mechanics problems remains incomplete.

When several discrete solutions are provided, extrapolation techniques such as Richardson's extrapolation can estimate the true-but-unknown solution of the continuous equations. The main drawback is that convergence verification and extrapolation methods rely on multiple computational grids and numerical evaluations. Because the model is evaluated, such approaches are generally referred to as a posteriori error estimates. A priori estimates of solution error can also be derived in particular cases. They do not rely on computed solutions and use, instead, the mathematical properties of the equations solved. Practical issues such as mesh distortion, however, rapidly deteriorate theoretical estimates and it is generally prudent to verify numerically the evaluation uncertainty. This situation cannot be avoided, but might be mollified to some extent by the use of expert data.

6.6 Total Uncertainty

The breakdown of uncertainty into that associated with measurement, modeling, parameters, and evaluation represents a bottom-up view of uncertainty. It is also possible, and may even be more practical, to look at uncertainty from the top down. This is accomplished by characterizing uncertainty as a whole, without regard to origin. The term *total uncertainty* has been applied to this viewpoint. The obvious problem with a total uncertainty approach is the lack of sufficient data to characterize the various specific uncertainties that may arise. One approach is to augment real data with expert opinion. Another approach is to treat uncertainty generically,[91,92] although the only known development relies on a probabilistic formulation.

The generic approach to total uncertainty does not require an inordinate amount of data for a specific problem. Rather, it utilizes comparisons of pairs of corresponding measurements and model predictions for a class of problems generically similar to the one of interest. To be meaningful, the generic data must contain a variety of model-measurement pairs with the various sources of uncertainty adequately represented. Examples of classes of generic uncertainty considered to date include truss-type space structures, reinforced concrete structures subjected to blast loading, and car crash simulations.

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[90] P.J. Roache, *Verification and Validation in Computational Science and Engineering*, Hemosa Publishers, Albuquerque, NM, 1998.
[91] T.K. Hasselman and M.C. Anderson, "Assessing the Accuracy of Numerical Simulations," *Proceedings of the 70th Shock and Vibration Symposium*, October 1999.
[92] T.K. Hasselman, "Quantification of Uncertainty in Structural Dynamic Models," *ASCE Journal of Aerospace Engineering*, October 2001.

The existing method for characterizing generic total uncertainty normalizes the information in both the measurements and model predictions by computing the singular value decomposition of each measurement and prediction, estimating the statistics of the differences of the components of the decomposition, expanding the model representation as a function of these normalized quantities, and propagating the uncertainty through the model of interest to estimate the second order statistics of the uncertainty. Uncertainty propagation may be affected by a first order Taylor series approximation, interval propagation, or Monte Carlo methods. This approach has the additional advantage of being able to treat both spatially and temporally distributed quantities. It remains to incorporate nonprobabilistic uncertainty into the methods formulation.

Besides the endemic problem of obtaining a sufficient uncertainty database, the generic approach to total uncertainty suffers from two potential drawbacks. One of these drawbacks is the interpretation and use of generic uncertainty information. This problem can be solved by developing consensus standards for interpretation of the information for each generic class, a task that is application dependent and requires expert opinion. The second potential problem is one of attribution. Reduction of uncertainty requires understanding the origin of the uncertainty. This information is lost in a total uncertainty characterization. However, if used in conjunction with specific treatments of measurement, parametric, and evaluation uncertainties, it may be possible to use a total uncertainty characterization to estimate the contribution of modeling uncertainty to the overall uncertainty.

7. RELIABILITY ASSESSMENT AND DECISION MAKING

As mentioned previously, damage prognosis faces numerous sources of variability, uncertainty, and lack of knowledge. Examples are experimental variability, parametric uncertainty, unknown functional forms of the mathematical models, and extrapolated future loading and environments. The discussion of damage prognosis would therefore be incomplete without addressing the issue of decision making under uncertainty. This section summarizes the framework of reliability analysis then discusses the needs for other decision-making frameworks that do not necessarily rely on a probabilistic description of uncertainty.

Some of the difficulties of decision making discussed in this section include the mathematical representation of the failure criterion or criteria, the statistical sampling of the corresponding failure domain, and the formulation of decision-making strategies in the context of nonprobabilistic uncertainty. Note that "failure" is used in a broad sense here. It can refer to the conditions leading to structural failure but also, generally speaking, to the situation where a demand, D, exceeds a capacity, C, as illustrated in Figure 7.1, no matter how "demand" and "capacity" are defined.

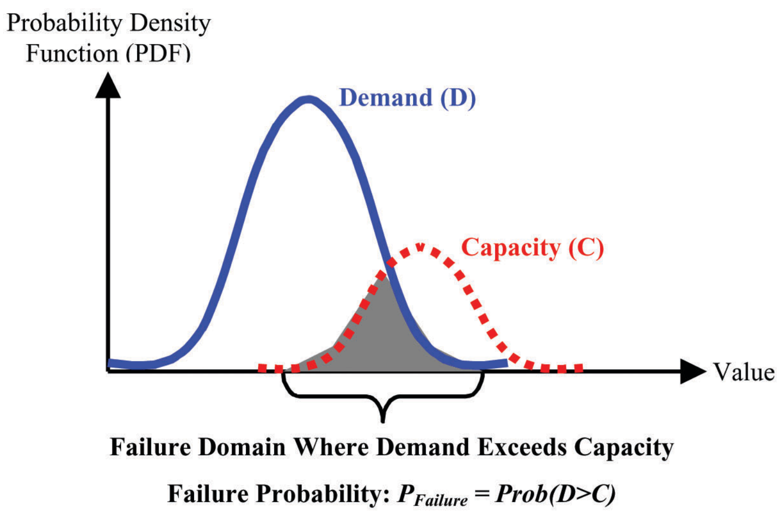

Figure 7.1 Illustration of the concepts of demand, capacity, and failure of a system.

Section 7.1 presents the concept of reliability analysis for decision making under probabilistic uncertainty and discusses the computational approaches commonly available to solve this problem. Section 7.2 addresses the role of surrogate modeling (also known as metamodeling) for integrating the experimental diagnostics, modeling and simulation, data interrogation, and reliability assessment into a practical damage-prognosis solution. Finally Section 7.3 briefly addresses cost-benefit analysis as well as the need for nonprobabilistic decision-making strategies.

7.1 Reliability Assessment

In reliability analysis, the failure state of a system is represented by a function of the response known as the limit state. Figure 7.1 simplistically defines a limit state as the structural conditions or operating environments that lead to the demand exceeding the system's capacity. The limit state is generally expressed as $g = C\text{-}D$ such that negative values ($g < 0$) of the function g denote the failure or unsafe operating mode of the system.

The first challenge is to express the limit state g in terms of a mathematical equation or set of equations. This formulation is generally straightforward when failure is defined through a physical criterion, such as "the maximum size of a crack or delamination area should not exceed a given level" or "the speed of the aircraft should not lead to the occurrence of wing flutter." When the definition of the limit state involves non-physical criteria, subjective performance evaluations, or linguistic ambiguities, translating the definition into a set of equations that can be implemented in a reliability code can be more challenging. Clearly the derivation of a limit state or multiple limit states is application-specific.

Once the limit state has been defined, reliability analysis consists of estimating the probability of failure; that is, the probability that demand will exceed the system's capacity. Decision making then answers questions such as "Is the probability of failure acceptable?" or "Which scenario, configuration of the system, or operating condition leads to an acceptable probability of failure?" Decision making relies on estimates of reliability, as well as quantifying its confidence, to decide which course of action should be taken. The second challenge is therefore to calculate the probability of failure, not only because of the combinatorial complexity of integrating a complex function in a multiple-dimension space, but also because it involves computing rare events located in the tails of the statistical distributions.

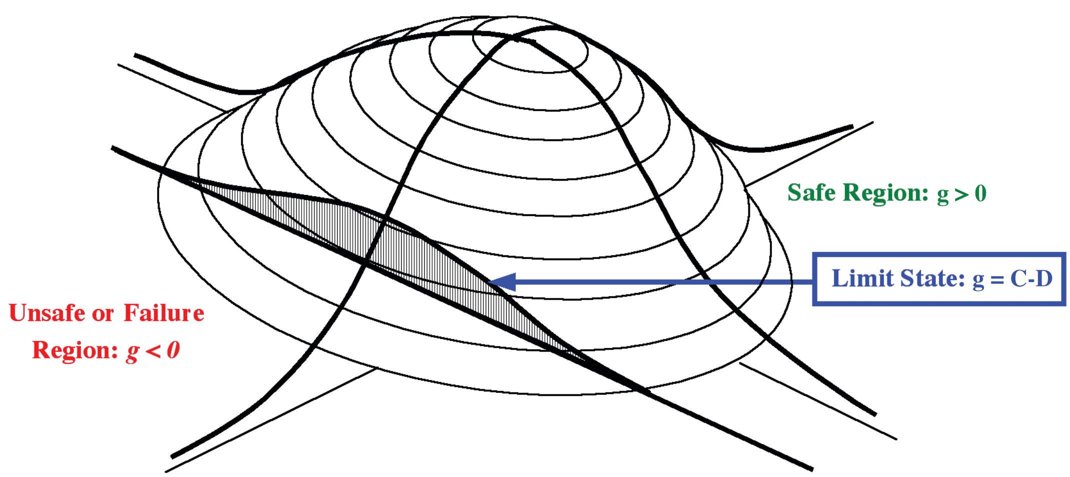

Figure 7.2 Joint probability density function of demand (D) and capacity (C) and limit state $g = C–D$ that separates the safe region from the failure region.

The probability of failure $P_{Failure}$ is defined as the integral of the Joint Probability Density Function (JPDF) of demand D and capacity C over the failure or unsafe region. As mentioned previously the failure region is mathematically defined as $g < 0$ and it is the region bounded by the limit state $g = 0$, as shown in Figure 7.2. If failure is defined, for example, in terms of a wing flutter condition, then reliability analysis consists of estimating the probability of reaching this limit state given uncertainties about the predictive model, current health of the system, and expected loading. The analysis begins with identification of the failure modes (such as wing flutter caused by delamination) and the random variables of the models and numerical simulations that affect these failure modes. Examples are parameters of a wind gust model for flutter analysis, or ply orientation angles and homogenized elasticity parameters in the delamination of a fiber-composite component. Reliability analysis requires the incorporation of the failure model into a finite element model or other model to build a relationship between system response and damage level. Interfacing the analysis model and the calculation of a limit state can be a significant computational and software integration challenge. In addition, input uncertainty must be described by a JPDF probability law, which can impose serious limitations on the representation of nonprobabilistic sources of uncertainty.

Integration of the JPDF across all random variables for the failure region $g < 0$ of the parameter space gives the probability of failure $P_{Failure}$. The reliability of the system is then simply defined as one minus the probability of failure. Because closed form representations of the limit state g and the failure domain ($g < 0$) are generally not available for complex systems, an approximation must be sought. Two computational strategies commonly available to estimate the reliability are briefly discussed below.

The first approximation strategy consists of numerically integrating the probability of failure through statistical sampling. A series of simulations are run to find the percentage of results that fall within or outside the failure region of the response space. The simplest sampling method is the Monte Carlo simulation, which chooses which simulations to run by randomly sampling the probability distributions of the input parameters. A theoretical proof of convergence is available, which can be taken advantage of to estimate convergence of the probability of failure. The main limitation is that Monte Carlo sampling can require more simulation runs than can reasonably be performed, especially when the number of random variables is large (typically, more than ten). Stratified sampling techniques, such as the Latin hypercube sampling (LHS), and fractional factorial designs of experiments can provide a trade-off between convergence of the numerical integration and the number of computational simulations. Another way of limiting the number of simulations is by intelligently choosing the computer runs. There are adaptive sampling techniques that can sample simulations mainly around the limit state and failure domain, leading to an accelerated rate of convergence compared to purely random sampling.

The second approximation strategy relies on Taylor series expansions of the limit state to reduce the potentially significant computational burden of sampling-based integration. The probability of failure is approximated by estimating the system's most probable point (MPP), which is the location on the limit state $g = 0$ that is closest to the origin, if the limit state is transformed to standard normal space. In standard normal space, the JPDF is decaying as it progresses out from the origin, so the closest location to the origin is the "most probable" system state. This calculation is illustrated in Figure 7.3. First, the random variables X of the simulation are transformed into an uncorrelated, standard normal space described by the random variables u. The standard normal multivariate JPDF of normalized variables u is denoted by Φ. Second, the MPP is estimated by solving a minimum distance optimization problem as shown in Figure 7.3. Third, the distance β between the MPP and the origin is calculated. Finally the probability of failure is estimated by finding the standard normal cumulative distribution value at β, that is, $P_{Failure} = \Phi(-\beta)$.

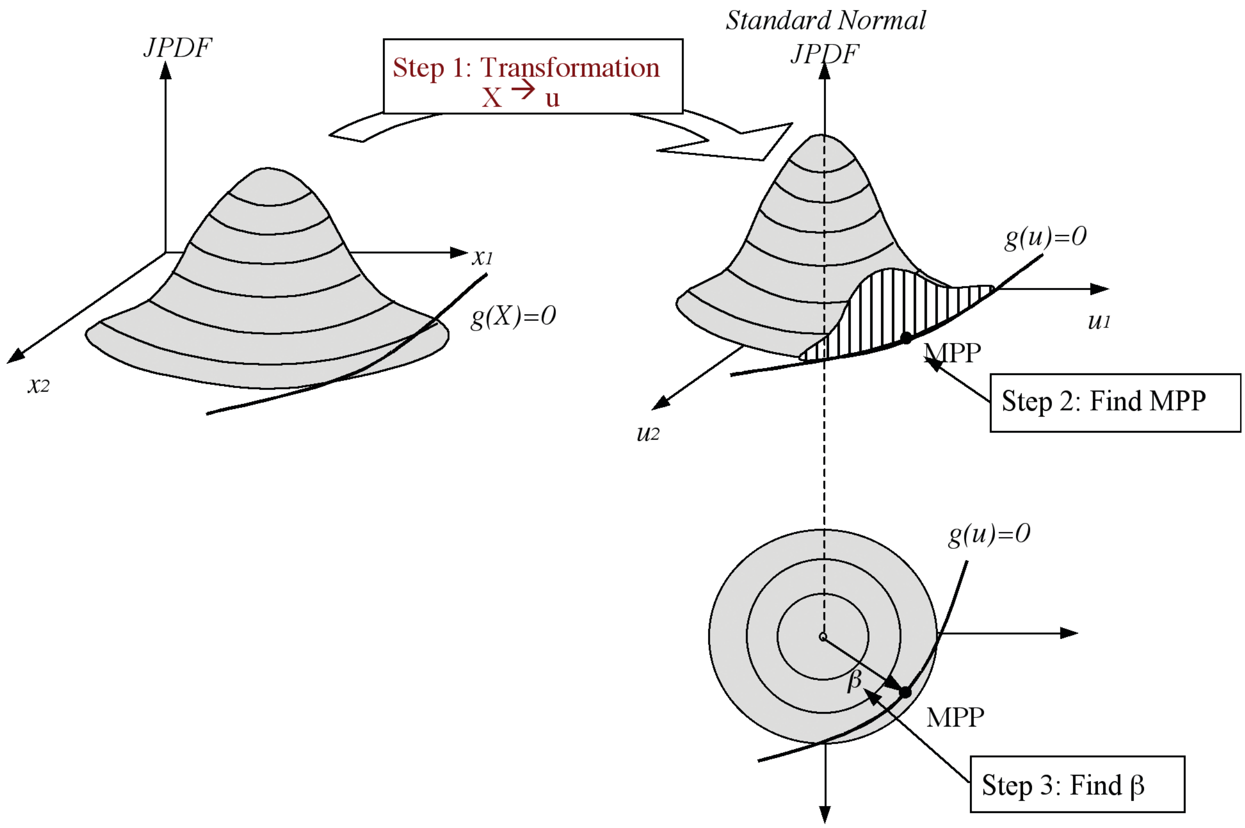

Figure 7.3 Concept of fast probability integration for reliability analysis.

Expansion-based approximations such as the first-order reliability method (FORM), second-order reliability method (SORM), and advanced mean value (AMV) follow the principle of these calculations and are collectively referred to as fast probability integration (FPI) methods. FPI methods differ by the order of the polynomial expansion used in the neighborhood of the MPP and other details.[93] Generally the limit state $g = 0$ is approximated using either a first-order or second-order Taylor series expansion about the MPP (FORM and SORM). Expansions about the mean values of the input random variables, rather than the MPP, are also possible with the AMV method. In this context, runs of the simulation code are performed to estimate the derivatives needed for the Taylor series expansion, instead of sampling the probability distributions. This explains the significant computational savings that can be achieved compared to sampling-based approaches.

The computational savings of expansion-based FPI methods, however, are provided at the expense of formal proofs of convergence. Another potentially devastating limitation is the accuracy with which linear and quadratic polynomials can approximate nonlinear limit-state functions. A solution that deserves further research and development could be to provide more flexibility in the way implicit limit state functions (such as those generally provided by finite element simulations) are approximated. Libraries of response surface methods, fractional functions, exponential decays, neural networks, and radial basis functions, for example, could be implemented to augment the limited capability of first-order and second-order polynomial approximations.

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[93] Y.T. Wu, "Advanced Probabilistic Structural Analysis Method for Implicit Performance Functions," *AIAA Journal*, **28** (9), 1990.

Finally, the value of hybrid methods for reliability analysis is recognized. Hybrid methods refer to the integration of sampling-based and expansion-based approaches to concentrate the effort of statistical sampling in areas of the reliability domain where it is most needed; that is, along the limit state. More information about the limit state, in turn, makes it possible to fit with better accuracy the polynomial models that approximate the true but unknown limit-state function.

7.2 The Role of Metamodeling for Information Integration

Approximations implemented to reduce the cost of a reliability assessment do not, however, reduce the computational burden of a single numerical simulation. When the prognosis of damage involves the analysis of large finite-element models or other physics-based models, the number of runs that can be executed in a reasonable time might be limited. It may then be advantageous to spend the available computational resources on developing fast-running surrogates to the computational mechanics simulation, as discussed in Section 5, rather than attempting to directly estimate the reliability of the system. Reliability assessments based on fast-running metamodels then become computationally efficient.

Metamodels therefore play a central role in the integration of information from the sensing network and the predictive modeling capability. This concept is illustrated in Figure 7.4 by showing the integration of experimental diagnostics, modeling and simulation, data interrogation, and reliability assessment on local sensing and computing nodes. The sensing and computational capabilities of such nodes can be tailored to monitor particular aspects of the system, such as a critical joint, and can be made robust to external sources of variability, such as ambient vibration.

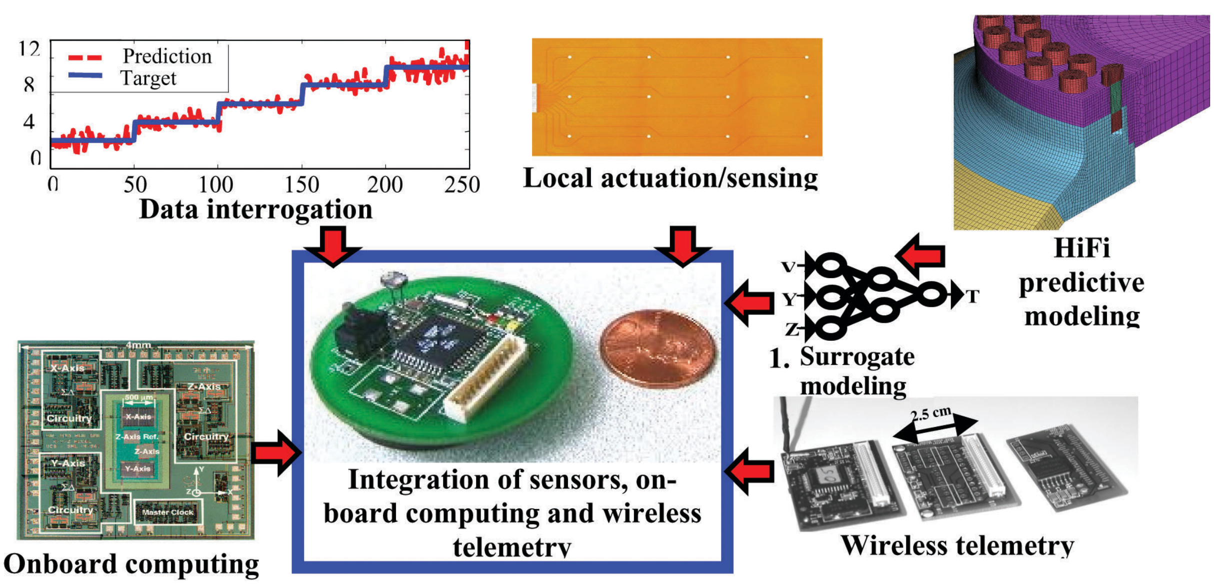

Figure 7.4 Integration of experimental diagnostics, modeling and simulation, data interrogation, and reliability assessment on local sensing and computing units for damage-prognosis solutions.

Metamodels take the form of polynomial response surfaces (illustrated in Figure 7.5). Other functional forms, such as fractional models, exponential decays, neural networks, statistics-based models, and radial basis functions, to name only a few, can be considered depending on the type of input-output relationship considered. The design-of-experiment techniques discussed in Section 5 can greatly improve the efficacy of the training step by choosing intelligently a subset of simulation runs based on the type of metamodels trained and the level of fidelity required. Metamodels make it feasible to perform sampling-based reliability estimates, therefore guaranteeing a converged estimate of the system's probability of failure. The accuracy then depends on how well the metamodels estimate the response of the computational model at parameter values not used for training. Fortunately, validation criteria and goodness-of-fit indicators are available to control the quality of training and level of fidelity. The adequacy of metamodels can be assessed prior to their deployment on the damage-prognosis nodes and their integration with the sensing system.

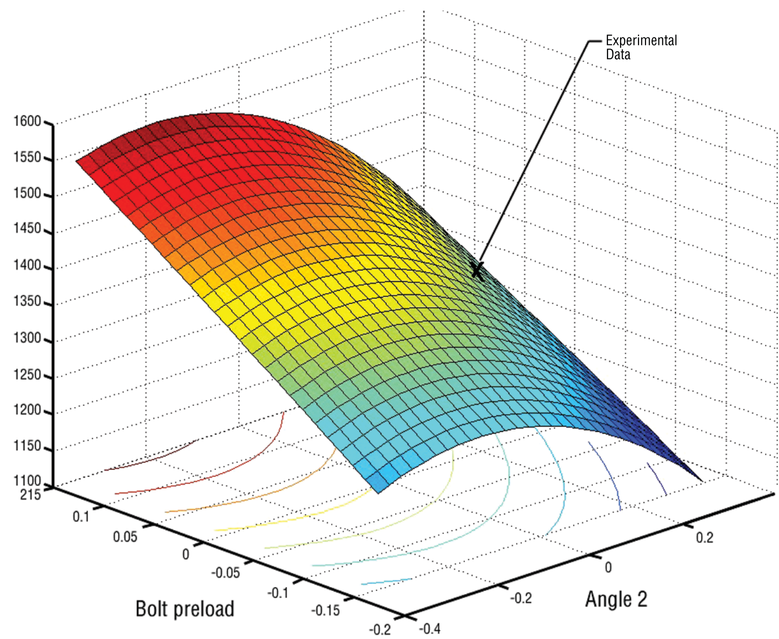

Figure 7.5 Response surface developed as a surrogate to a finite element analysis.

Because reliability analysis is applicable to many engineering problems, general-purpose software is being developed to perform sampling-based and expansion-based sensitivity, uncertainty quantification, and reliability assessments. The software packages NESSUS®[94] and Design Analysis Kit for Optimization and Terascale Applications (DAKOTA)[95] are two examples of software that can be interfaced with a variety of general-purpose finite-element packages. These and other uncertainty quantification, reliability, and numerical optimization packages also include limited capabilities for metamodeling that can be taken advantage of.

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[94] *NESSUS User's Manual*, Version 2.4, Southwest Research Institute, San Antonio, TX, 1998.

[95] M.S. Eldred, A.A. Giunta, B.G. Van Bloemen Waanders, S.F. Wojtkiewicz, W.E. Hart, and M.P. Alleva, *DAKOTA User's Manual, A Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis*, Version 3.0, Sandia National Laboratories report SAND-2001-3796, April 2002. http://endo.sandia.gov/DAKOTA/.

7.3 Decision Making Under Uncertainty

Formulating decision making in terms of a reliability assessment is attractive because it can handle the sources of experimental variability and modeling uncertainty. Reliability analysis also provides a well-defined computational framework. The main constraint, however, is the characterization of the sources of uncertainty with probability laws.

Situations may arise where there is no evidence that suggests that a source of uncertainty can be represented as a probability function. Three situations are listed here where this may be the case. First, testing may be limited, impractical, or too expensive, hence impeding the collection of multiple data sets from which statistics can be established. Second, some components of the decision-making process may originate from judgment or expert knowledge. The uncertainty associated with subjective opinions such as "the surface finish is smooth" or "the temperature is too high" is generally not expressed in terms of probabilities. A third essential category of nonprobabilistic uncertainty is the lack of knowledge associated with the unknown functional form of a mathematical model. An example might be the assumptions made to develop a turbulence model or a contact algorithm. Such assumptions may be somewhat arbitrary because of our imperfect knowledge of the underlying physical phenomena. Therefore, they introduce sources of uncertainty, but it is generally not possible to define a probability law that describes the likelihood that a particular assumption is better than the others. Section 6 provides other examples of modeling uncertainty.

One source of uncertainty that is likely to seriously affect the experimental and simulation results of any damage prognosis is the initial condition of the structure in terms of residual stress state and distribution of initial flaws. It may not be possible to account for such complex initial conditions in the models. Furthermore, deriving probabilistic information about a distribution of residual stresses and initial flaws might require a prohibitive number of physical specimens and destructive evaluations. If evidence in terms of experimental data, expert opinion, or first-principle physics is not available to suggest a specific probability structure, simply assuming a structure does not solve the problem because it can lead to the under-prediction of the probability of failure, as illustrated by a number of authors.[96] One could easily think of many other effects that even well-controlled experiments or high-fidelity models will not be able to account for in a probabilistic manner.

The reliability framework, because of its reliance on the theory of probability, cannot handle such situations. Procedures must be developed for decision making in the face of nonprobabilistic uncertainty. Clearly, the first step is to represent the variability, uncertainty, and lack of knowledge with theories other than probability theory. Within the last three decades, alternate theories have been developed to represent uncertainty. Section 6 lists several of them, such as the theory of random sets, the Dempster-Shafer theory of evidence, the theory of possibility, fuzzy logic, and interval arithmetic. Figure 7.6 illustrates how uncertainty about a numeric or linguistic variable (whose value can be equal to either A, B, C, or D) would be represented by these previous theories.

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[96] W.L. Oberkampf, J.C. Helton, and K. Sentz, "Mathematical Representation of Uncertainty," *42nd AIAA/ ASME/ ASCE/ AHS/ ASC Structures, Structural Dynamics, and Materials Conference*, AIAA-2001-1645, Seattle, WA, April 16–19, 2001.

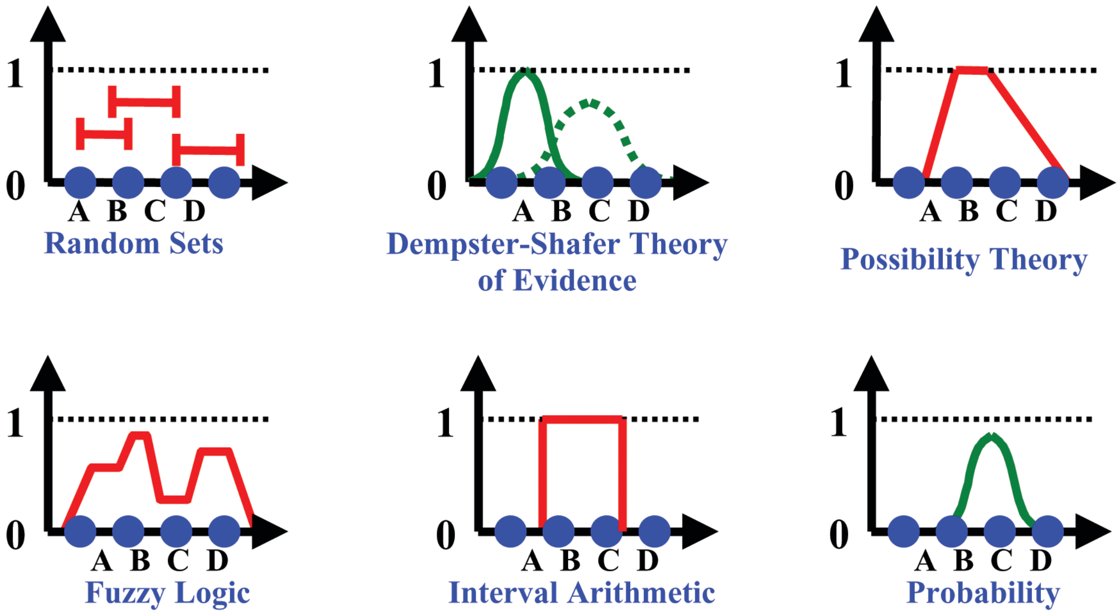

Figure 7.6 Representing uncertainty with various theories. A random variable can take the values A, B, C, or D. Functions are defined to express the degree of evidence, belief, possibility, or probability of each value. In all cases, a degree equal to one indicates certainty, while zero indicates impossibility.

The second step is the aggregation (or combination) of various sources of nonprobabilistic uncertainty. Although this is an open area, research in generalized information theory (GIT) suggests that mechanisms might be found to link the different theories together. Information integration is essential to solve any practical damage-prognosis problem where the uncertainty about some components of a complex engineered system are represented with probabilities while other sources of uncertainty are represented differently. For example, a bridge has recently been proposed through the Bayesian theorem of posterior probabilities to link the membership functions of fuzzy logic to probability density functions.[97] Such a link makes it possible to combine expert judgment with probabilistic information in reliability analysis.[98] Unfortunately bridges between other GIT representations of uncertainty either do not yet exist or they do not currently offer computational procedures that can be implemented for practical problem solving.

In this context the question is not so much how to represent the uncertainty, but rather what the effect of these “unknown unknowns” is on the decision. This potential roadblock can be addressed by applying decision theories that focus on decision making instead of attempting to represent the uncertainty with a nonprobabilistic theory. An example is information-gap theory where the clustering of uncertain events is modeled instead of their occurrence,[99] Information gap is defined as the lack of knowledge between the information available and what is needed to support the

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[97] T.J. Ross, J.M. Booker, and W.J. Parkinson, Eds., *Fuzzy Logic and Probability Applications: Bridging the Gap*, ASA-SIAM Series on Statistics and Applied Probability 11, SIAM Publishing, Philadelphia, PA, 2003.

[98] M.A. Meyer and J.M. Booker, *Eliciting and Analyzing Expert Judgment: A Practical Guide*, Society of Industrial and Applied Mathematics, Philadelphia, PA, 2001.

[99] Y. Ben-Haim, *Information-Gap Decision Theory: Decisions Under Severe Uncertainty*, Series on Decision and Risk, Academic Press, 2001.

decision. Clearly such a definition is very broad and it can encompass most sources of uncertainty. Information-gap theory offers a framework that, while computationally expensive, allows us to study the robustness of a decision to probabilistic or nonprobabilistic sources of uncertainty.

Figure 7.7 compares the robustness of four decisions to a nonprobabilistic uncertainty. The performance might, for example, represent the reliability of an aging system given a prognosis of its damage state and a forecast of future operating conditions. The decisions might, for example, be to field the original system or to retrofit components believed to be potentially faulty in hope of improving the overall system reliability. The uncertainty considered in this calculation is a modeling uncertainty; specifically, the unknown functional form of a submodel included in the numerical simulation.[100] Such uncertainty represents a lack of knowledge that cannot be described by a probability density function. Instead a generic "horizon-of-uncertainty" parameter is defined to express how much the model can deviate from the current knowledge. Figure 7.7 illustrates that one decision (decision 3) leads to a total loss of performance. Other decisions, while witnessing deterioration in performance, have levels of uncertainty that are somewhat robust to moderate.

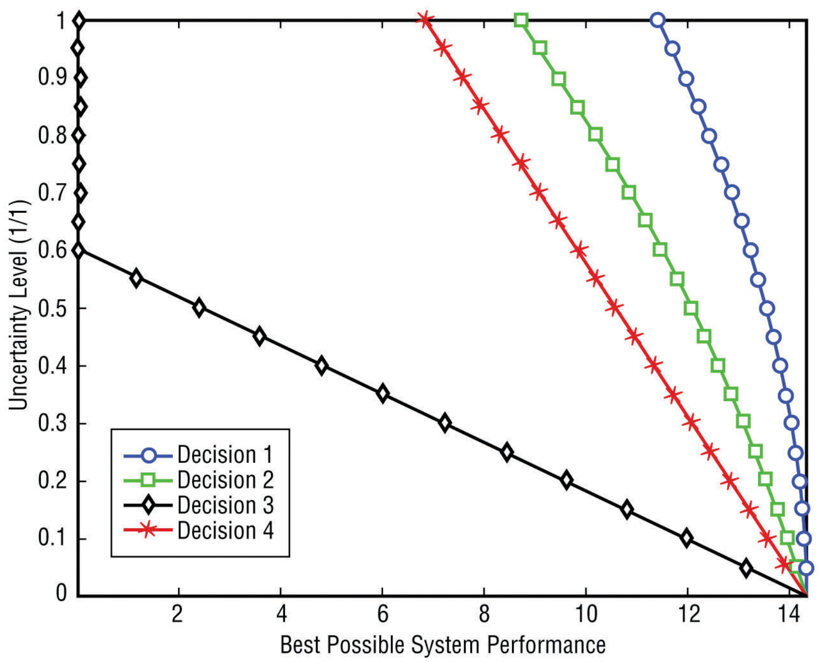

Figure 7.7 Example of nonprobabilistic cost-benefit analysis.

Results such as those illustrated in Figure 7.7 lead to cost-benefit analysis. Typically no more than a given horizon of uncertainty (whether it is defined in terms of probabilistic or GIT measures) is allowable to guarantee a minimum performance. Tolerating no more than a given uncertainty level comes at a cost. To better understand, and hopefully reduce, the uncertainty and its effect on system performance, more testing, additional modeling, or a combination of both is recommended. Some decisions might also be more expensive or less practical to implement. Damage-prognosis

[100] F.M. Hemez, Y. Ben-Haim, and S. Cogan, "Information-Gap Robustness for the Test-Analysis Correlation of a Non-Linear Transient Simulation," 9^{th} *AIAA/ISSMO Symposium on Multidisciplinary Analysis and Optimization*, AIAA-2002-5420, Atlanta, GA, September 4–6, 2002.

solutions must integrate the means of performing cost-benefit analyses with probabilistic and GIT representations of uncertainty to provide decision makers with the information they need about the future remaining life and performance of their systems.

8. CONCLUDING REMARKS

The aim of this report has been to define the concept of damage prognosis and highlight the necessary technologies required to develop damage-prognosis solutions. There exists a clear and increasing need for prognosis in a range of applications in which extending the life of the system would result in economic benefits, risk reduction, and improved human safety. The wide variety of possible applications in military and civil infrastructure implies the need for a multidisciplinary technology development.

Damage-prognosis solutions will require the integration of the following three technology areas:

1. Sensing and data acquisition
2. Data interrogation techniques
3. Predictive modeling and uncertainty analysis

The expected solution is likely to consist of an array of autonomous sensing devices that can interpret the measured system response and transmit decisions about the state of the structure. These decisions are then assembled and interrogated to determine whether the structure has accrued damage. The output of the interrogation is then coupled to a refined damage-evolution model that can predict the remaining useful life with quantified uncertainty, given the interpreted state of the structure and knowledge of its history (e.g., past loading, maintenance, modifications) and anticipated future loads. Within each of these areas there are still major technical challenges that need to be addressed before damage-prognosis solutions can be realized.

There are many issues to be considered in the area of sensing systems and the development of data-acquisition hardware. To begin, there is a need to build autonomous, intelligent sensor systems that transmit decisions rather than streaming data. Fortunately, the integration of MEMS technology with microprocessors may provide such sensor systems in the foreseeable future. To date, almost all sensor systems deployed for damage detection monitor the system's response to its ambient environmental and operational conditions. Improved capabilities may be realized though the use of active sensing, in which actuators that provide an input tailored to the damage detection activity are deployed on the structure. In addition, the sensor-system design must consider telemetry issues. In the cases that necessitate wireless telemetry, there are still many outstanding issues regarding the robustness of communications protocols. The integration of all of these technologies into single, intelligent devices will require a source of power. The most amenable technology for localized power is the use of parasitic generators that derive energy from ambient vibration. Note that if power needs to be provided by direct connections, then the need for wireless telemetry is eliminated, as the cabled link can also be used for the transmission of data. Hence, the development of micropower generators is a key factor for the development of the hardware. Because various portions of the sensing and data-acquisition system represent new technologies, the overriding consideration of reliability still exists, as it does with any condition monitoring system. The hardware configuration must be more reliable than the system it is monitoring. One means of obtaining this reliability is through the use of redundant sensor hardware. Therefore, the tradeoff between an optimal and redundant sensor system must be considered as part of the damage-prognosis process.

The primary role of data interrogation is to extract pertinent features from numerically generated and experimentally measured data and build statistical models that can be used to define the location and extent of damage. Significant challenges are associated with the a priori definition of damage sensitive features when data from a degraded structure are not available. One must also be able to define decision boundaries associated with the feature distribution that indicate damage. Such definitions are again difficult when data from the degraded system are not available. Numerical modeling may be useful to address this issue. The feature extraction process must consider the issue of dimensionality. Reducing the data dimension can improve data transmission, statistical classification, and test-analysis correlation. Major technological challenges also are associated with data normalization because the measured response characteristics are not necessarily produced by a known input spectrum or known operational and environmental conditions. Finally, to obtain a prognostic capability, statistical models must be developed that can define the future loading the system will experience.

Numerical modeling development needs to occur at both local and global levels using physics-based and surrogate reduced-order models. This need implies that a variety of models will most likely be employed in the damage-prognosis process. Challenges associated with physics-based models include simulating the initiation of damage on a local level while at the same time capturing the effects of this damage on the global system response. Currently, such models are computationally demanding for even the most powerful parallel processor systems. In order to deploy a prognosis capability onboard a structural system, the input-output relationships defined by multiple runs of the detailed physics-based model must be captured with surrogate reduced-order models. Surrogate models, which may take the form of neural networks, support vector machines or fuzzy inference systems, require significant computational resources for their training. The prognostics part of the modeling requires updating the estimate of remaining useful life as subsequent loading is applied and further degradation occurs. Implicit in this prognosis process is uncertainty, and how it propagates through the modeling process. Uncertainty can be introduced into the modeling process at all stages. Also, there are sources of uncertainty that will be difficult, if not impossible, to quantify, such as the distribution of initial flaws or residual stresses within a material. Currently, uncertainty quantification is the focus of several large-scale research efforts, but it has yet to be demonstrated that uncertainty can be accurately quantified for large, multicomponent structural systems. Reliability methods provide a framework for predicting the system's remaining useful life with quantified uncertainty and will most likely become an integral part of the damage prognosis.

Finally, the three technology areas discussed above must be developed in an integrated manner to realize damage-prognosis solutions. Currently, there is a tremendous amount of research being conducted in these three technology areas, but in general this research is not being conducted with damage prognosis as the end goal. The integration of these technologies is necessary because many system characteristics will not be known at the onset (e.g., sensing system processing requirements, numerical damage model parameters, and statistical model decision boundaries). The integrated approach will facilitate the design of damage-prognosis systems in a way that will better define these characteristics, particularly when information from damaged systems is not available. In addition, if these technologies are developed for general purpose applications, they most likely will not be optimized for damage prognosis and will not necessarily represent the most cost-effective solution for this problem.

Although this report has concentrated on the technological aspects of damage prognosis, several related financial and human factors will need to be explored in parallel. Clearly each application will require a cost-benefit analysis. Even though the potential benefits of prognosis are enormous, the occurrence of false-negative and false-positive damage indications can have significant adverse consequences. The false-negative indications of damage clearly will produce adverse effects in terms of preventing damage and mitigating injury to users. False-positive indications will cause a loss of confidence in the prognosis system and will unnecessarily reduce asset readiness. A consideration from the human factors perspective is that the decision-making process is potentially taken away from the system operator, which may not be well received, and may give rise to issues of liability and certification. For safety-critical systems, such as aircraft and nuclear installations, the damage-prognosis technology will have to go through an extensive demonstration period. It is more than likely that the damage-prognosis process will have to be deployed in parallel with more traditional maintenance procedures until the added advantages of the process can be established. Therefore, an initial goal might be to develop damage-prognosis solutions for systems in which failure does not have adverse life or safety implications.

Fundamentally, damage prognosis requires the ability to measure and model system response on widely varying length and time scales. Such problems are difficult, and hence in closing it will be reiterated that the authors believe that developing damage-prognosis solutions is a “grand challenge” problem for engineers, material scientists, statisticians and information technologists in this century.

ACKNOWLEDGEMENT

The Damage Prognosis Workshop, the time needed to prepare this report, and Los Alamos National Laboratory’s current efforts related to damage-prognosis solutions were supported and continue to be supported through Los Alamos’s Institutional Program Development funds and Laboratory Directed Research and Development funds. We are indebted to all the participants in the Damage Prognosis Workshop for their contributions to our understanding of the damage-prognosis problem.

ACRONYMS

3-D	three-dimensional
A-D	analog-digital
AMV	advanced mean value
AR	autoregressive
ARX	autoregressive with exogenous inputs
ASCI	Advanced Scientific Computing program
CAA	Civil Aviation Authority
COST	Conference on System Identification and Structural Health Monitoring
COTS	commercial-off-the-shelf (technology)
DAKOTA	Design Analysis Kit for Optimization and Terascale Applications
DAMAS	International Conference on Structural Damage Assessment Using Advanced Signal Processing Procedures
DC	a constant offset in a signal
DoE	design of experiment
DSP	digital signal processing
EDM	electrical discharge machining
EPC	elements of prognosis capability
ERLE	Engine Rotor Life Extension program
FAA	Federal Aviation Administration
FE	finite element
FORM	first-order reliability method
FPI	fast probability method
GIT	generalized information theory
HCF	high-cycle fatigue
HERT	high-explosives radio telemetry
HUMS	health and usage monitoring system
IC	integrated circuit
IEEE	Institute of Electrical & Electronics Engineers
IJF	International Journal of Fatigue
JEM	Journal of Engineering Mechanics
JPDF	joint probability density function
LANL	Los Alamos National Laboratory
LHF	Latin hypercube sampling
MEMS	micro-electro-mechanical systems
MPP	most probable point
MSSP	Mechanical Systems and Signal Processing
NDI	nondestructive inspection
NESSUS®	a software program developed by Southwest Research Institute
NST	novel sensing technology
PZT	piezoelectric
RF	radiofrequency
ROC	receiver operating characteristic
SHM	structural health monitoring
SI	system integration
SORM	second-order reliability method

SPIE	Proceedings of SPIE, Nondestructive Evaluation of Highways, Utilities and Pipelines IV
SSIs	structurally significant items
STAN	Proceedings of the Second International Workshop on Structural Health Monitoring, Stanford University
TARMA	time-dependent auto-regressive moving average
XML	extensible markup language

APPENDIX A: WORKSHOP PARTICIPANTS AND THEIR AFFILIATIONS

DAMAGE PROGNOSIS WORKSHOP ATTENDEES		
NAME	***AFFILIATION***	***TECHNICAL SPECIALTY***
Adams, Douglas E.	Purdue University, School of Mechanical Engineering	Data Mining/Damage Prognosis
Addessio, Frank L.	Los Alamos National Laboratory	Computational Continuum Mechanics
Anderson, Mark C.	Los Alamos National Laboratory	Data Interrogation & Analysis
Barber, Laura J.	Los Alamos National Laboratory	Licensing Executive
Bement, Matthew T.	Los Alamos National Laboratory, Engineering Analysis Group	Controls
Brown, David L.	University of Cincinnati, Dept. of Mechanical Engineering	Vibration Testing
Butler, Thomas A.	Los Alamos National Laboratory, Engineering Analysis Group	Computational Structural Dynamics
Cafeo, John A.	General Motors Research & Development Center	Testing, Model V&V in Automotive Applications
Childs, Dara W.	Texas A&M University, Mechanical Engineering Dept.	Dynamics of Rotating Machinery
Christensen, Ronald	University of New Mexico, Dept. of Math & Statistics	Statistics
Christodoulou, Leo	DARPA	Materials
Cornwell, Phillip J.	Rose-Hulman Institute of Technology, Dept. of Mechanical Engineering	Structural Dynamics, Engineering Education
Crow, Eddie C.	Penn State Applied Research Laboratory	Intelligent Systems Monitoring
Diness, Arthur M.	Institute of Defense Analyses	Materials-microstructural Development
Doebling, Scott W.	Los Alamos National Laboratory, Engineering Analysis Group	Model Validation, Uncertainty Quantification
Ewins, David J.	Imperial College of Science, Tech & Medicine Dept. of Mechanical Engineering	Vibration Engineering
Farrar, Charles R.	Los Alamos National Laboratory, Engineering Analysis Group	Structural Health Monitoring
Fugate, Michael L.	Los Alamos National Laboratory	Linear Statistical Models
Girrens, Steven P.	Los Alamos National Laboratory, Engineering Analysis Group	Large Scale Numerical Modeling
Glaser, Steven D.	University of California, Berkeley, Dept. of Civil & Environmental Eng.	Monitoring & Instrumentation, Technology Integration
Hemez, Francois M.	Los Alamos National Laboratory, Engineering Analysis Group	Modeling & Validation
Hjelm, Lawrence N.	Hjelm Engineering, Consultant	Aerospace Materials and Processes
Hunter, Norman F., Jr.	Los Alamos National Laboratory,	Vibration Testing & Signal

	Measurement and Testing Group	Processing
Hush, Donald R.	Los Alamos National Laboratory	Machine Learning
Inman, Daniel J.	Virginia Tech, CIMSS	Structural Health Monitoring and Smart Structures (vibration)
Kenny, Thomas	Stanford University, Dept. of Mechanical Engineering	Sensing & Diagnostics
Kosmatka, John B.	University of California, San Diego, Dept. of Structural Eng.	Structural Damage Determination
Kulowitch, Paul J.	Naval Air Systems Command, Naval Air Warfare Center Aircraft Division	NDI, Technology Integration & Applications
Larsen, James M.	U.S. Air Force, Air Force Research Laboratory	Life Prediction and Durability
Law, Kincho H.	Stanford University, Dept. of Civil & Environmental Engineering	Damage Detection, System Integration
Lee, Eui W.	Naval Air Systems Command	Technology Integration & Applications
Lieven, Nicholas A.J.	University of Bristol, Dept. of Aerospace Engineering	Modal Testing/Analysis of Stressed Structures
Liu, Cheng	Los Alamos National Laboratory	Dynamic Fracture Mechanics, Constitutive Modeling of Materials
Martinez, David R.	Sandia National Laboratories	Analytical Structural Dynamics
Matic, Peter	Naval Research Laboratory, Multifunctional Materials Branch	Materials & Solid Mechanics
McConnell, Kenneth G.	Iowa State University, Professor Vibration Engineering, Aerospace & Mechanics (Retired)	Monitoring & Instrumentation, Vibration Testing, Frequency & Modal Analysis
Meilunas, Ray	Naval Air Systems Command	Fiber Optic Sensors/Composites
Orisamolu, Irewole R.	United Technologies Research Center	Prognostics, Probabilistic Mechanics
Paez, Thomas	Sandia National Laboratories	Prognostics, Probabilistic Mechanics
Parlos, Alexander G.	Texas A&M University, Department of Mechanical Engineering	Diagnosis and Prognosis of Rotating Machines
Rabern, Donald A.	Montana State University, Dept. of Civil Engineering	Structural Health Monitoring, Dynamic Fracture Mechanics
Rasmussen, Bruce A.	U.S. Air Force, Air Force Research Laboratory	Turbine Engine Materials & Manufacturing
Schreyer, Howard L.	University of New Mexico, Dept. of Mechanical Engineering (Retired)	Computational Mechanics, Damage Mechanics
Schultze, John G.	Los Alamos National Laboratory, Engineering Analysis Group	Structural Dynamics
Shumway, Robert H.	University of California, Davis, Dept. of Statistics	Time Series Analysis, Signal Processing, Seismic & Infrasound Arrays, Nuclear

		Monitoring
Smallwood, David O.	Sandia National Laboratories	Signal Processing, Testing
Sohn, Hoon	Los Alamos National Laboratory, Engineering Analysis Group	Structural Health Monitoring
Stoffer, David S.	University Of Pittsburgh, Dept. of Statistics	Statistics
Swanson, David C.	Penn State Applied Research Laboratory	Acoustic & Signal Processing
Todd, Michael D.	Naval Research Laboratory	Fiber Optic Structural Sensors & Structural Health Monitoring
White, Edward V.	The Boeing Company	Smart Structures
Womack, Kathie	Los Alamos National Laboratory	Admin Support
Worden, Keith	University of Sheffield, Dept. of Mechanical Engineering	Signal Processing
Zimmerman, David C.	University of Houston, Dept. of Mechanical Engineering	Modeling & Inverse Problems

APPENDIX B: DAMAGE-PROGNOSIS APPLICATIONS

B1: Creep Rupture in Turbine Blades

Problem: Turbine blades typically must function in high-temperature environments (>1000 K) for tens of thousands of hours. A jet engine layout and typical turbine blade are shown in Figures B1 and B2 respectively. Modern turbine blades are often grown as a single crystal of a nickel superalloy. Even so, the harsh thermal environment necessarily makes creep and therefore creep rupture a major consideration. From a damage-prognosis standpoint, the primary goal is to determine the current creep and then estimate the remaining time to failure, given anticipated operating conditions.

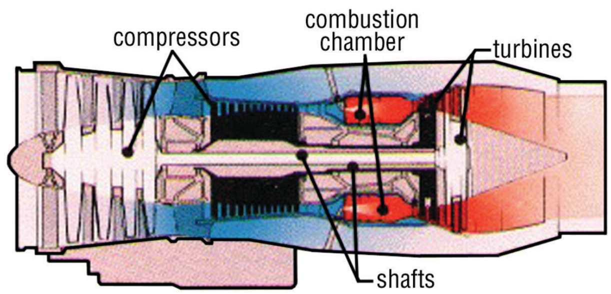

Figure B1 Jet engine layout.

Figure B2 Turbine blade.

Motivation: Catastrophic failures of turbines can have very high direct and indirect economic costs (greater than $10 million) as well as very high human costs (hundreds of lives).

Challenges:

- Placement of sensors on the turbine blades is very difficult due to high operating temperatures, as well as the manufacturing process of the blades.
- Extracting data features that are indicative of creep deformation and impending creep rupture is difficult in the absence of direct strain measurements.

Current online monitoring techniques:

- Thermal radiation monitoring products are available to directly assess blade temperature (e.g., Land Infrared, Land Instruments, Intl.), to facilitate creep estimation.
- Reflected light during blade passage has been used to determine blade vibration (Arnold Engineering Development Center, Arnold Air Force Base, Tullahoma, Tennessee).

B2: Fighter Aircraft Condition Monitoring in Hostile Environments

Problem: Combat aircraft operating in hostile environment may, not surprisingly, incur damage from enemy fire. From a damage-prognosis standpoint, the primary goal is to detect and quantify damage to give a reconfigurable control system the updated system model it needs to maximize aircraft life and performance. A reconfigurable control system automatically changes the control laws that govern the behavior of the control surfaces as the system or operating condition changes. Figure B3 shows a Vista F-16 landing with a failed left-side stabilator.

Motivation: In combat situations, it is critical to maximize aircraft and pilot survivability for economic, human, and national security reasons, as well as to ensure completion of the mission.

Challenges:

- Damage location is unknown.
- Multiple types of failure are possible.
    - Many sensors will be required to monitor different failure types, leading to issues associated with data fusion and management.
    - Failure types may interact; e.g., "Could a plausibly survivable structural failure cause a critical hydraulic or electrical failure?"
- The operational environment is uncertain.
- Prognosis must be done in near real time.
- There are already stringent operational constraints on hardware (weight, electrical characteristics, etc.) associated with fighter aircraft design.

Current technologies:

- AFRL and others have made significant research efforts in the areas of integrated diagnostics and reconfigurable control.

Figure B3 Vista F-16 with a failed left-side stabilator landing successfully with the use of reconfigurable control.

B3: Flaw Initiation and Propagation in Explosive Containment Vessels

Problem: Pressure vessels like those shown in Figure B4 are used to contain the blast, fragments, and toxic byproducts of explosive experiments. Rupture of such vessels is obviously a major concern, although some leakage is often permitted. Explosive-containment vessels are large, relatively thick metallic structures and inevitably contain flaws such as pores and cracks of various sizes. This is especially true in weld zones where material properties vary significantly from those of the parent material and are less well understood. These flaws become more severe under load, eventually growing to the point where a significant load event would induce a catastrophic failure. Standard design models, and even high-fidelity physics-based finite element models (see Figure B5), are currently incapable of predicting damage accumulation and eventual failure with an acceptable degree of reliability.

Figure B4 Explosive-containment pressure vessels.

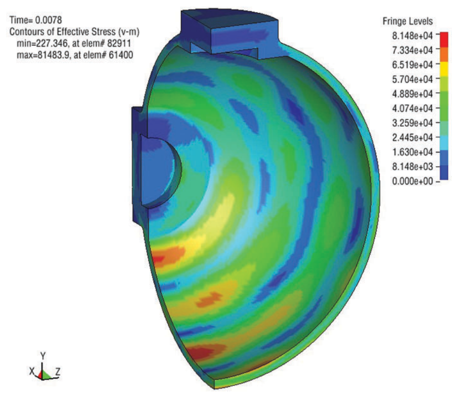

Figure B5 Results from a high-fidelity finite-element (FE) model.

Motivation: Fabrication of these vessels using a design that meets all relevant criteria is at the edge of current capabilities, both for forming and welding. Also, in the current regulatory environment, qualification of new designs and acceptance of deliverable hardware are complicated processes. Therefore, explosive-containment vessels are quite expensive and maximal reuse is a major priority.

Challenges: While it is possible to inspect for flaw initiation and growth after a significant load event, the ability to predict damage before an event, not to mention the remaining useful life with respect to a series of anticipated load events, is hampered by several technical challenges. These challenges include the following:

Monitoring and instrumentation

- Initial characterization of flaws
- Measurement of transient pressure and fragment impact loads
- Global and local response measurements
- Detection of flaw growth and damage accumulation

Modeling and simulation

- Damage, damage accumulation, and damage propagation models
- Material failure models
- Mapping from global response to local damage and failure
- Validation of models

Data interrogation and analysis

- Determination of optimal load and response features for damage identification
- Metrics for comparison of measured and simulated features
- Quantification of uncertainties associated with models, tests, and hardware

B4: Health Monitoring of Composite Fuel Tanks on Reusable Launch Vehicles

Problem: The goals of NASA's second-generation reusable launch vehicle (RLV) program (see Figure B6) require the ability to employ each vehicle in a quick-turnaround mode. To significantly reduce the time for inspection of RLV structures between flights, an integrated vehicle health management (IVHM) system will be employed to aid diagnosis of structural damage. One aspect of this inspection system is the detection of flaws and delamination in the composite tanks that house cryogenic fuels. Nothing is known about the possible use of this data for prognosis of structural performance.

Motivation: For the RLV, the goal is to reduce the cost of delivering a pound of payload to low Earth orbit from today's $10,000 to $1000 by the year 2010. For the IVHM, the goal is to improve the expected safety of launch so that by the year 2010 the probability of losing a crew is no worse than 1 in 10,000 missions.

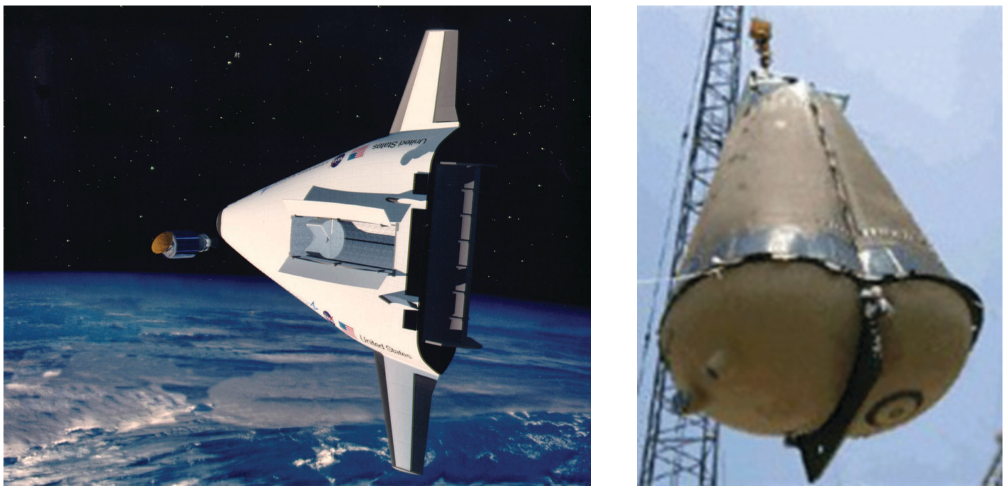

Figure B6 (Left) Concept art for the X-33 Venture Star Reusable Launch Vehicle. (Right) Composite liquid hydrogen tanks for X-33.

Challenges:
- Sensors must be robust for the space flight environment, yet lightweight, low power, and free of electrical spark sources.
- Embedding sensors in composites introduces uncertainties into the structural response calculations.
- Damage-diagnosis technique must detect flaws both on the surface and through the thickness of the structure.
- Flaws are typically small with respect to the size of the tank.
- Time constraints for inspection are tight.

Currently proposed inspection techniques:
Bragg-grating fiber optics embedded or wound on tanks to measure local strains.

B5: Electric Motors and Driven Loads

Problem: Electric motors and motor-driven loads (e.g. pumps, compressors, fans, conveyor belts, etc.) represent the most common industrial machines, with over 6 billion units installed worldwide . Such machines operate in harsh environments and they are often critical for the operation of various processes. From a damage prognosis standpoint, the primary goal is to determine the present electrical and mechanical condition of the motor-coupling-load system and then estimate the remaining time to failure, given anticipated operating conditions. Two typical damage scenarios are shown in Figures B7 and B8.

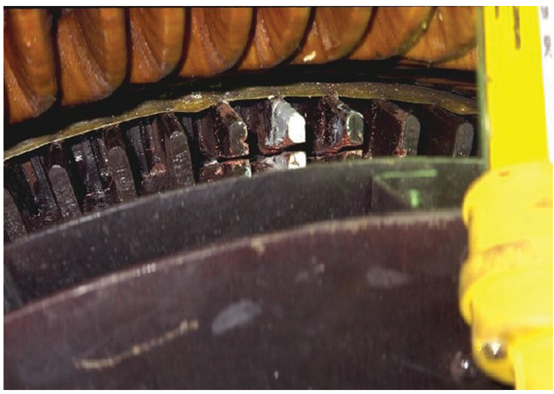

Figure B7 Staged broken rotor bar fault.

Figure B8 Staged stator insulation fault.

Motivation: Catastrophic failures of electric motors or motor-driven loads can have very high economic costs because of process downtime, emergency maintenance costs, and in some instances, high human costs. Operating the system with developing incipient faults also impacts the system's energy efficiency.

Challenges:

- The lack of sensors for mechanical condition monitoring; only the largest and most expensive motor-load systems have permanent sensors beyond those needed for over-current protection. Industry is not willing to retrofit systems with additional sensors, and manufacturers are skeptical about adding more sensors, because of the cost.
- The significant variability found in the components of mass-produced systems, and the associated fault and damage signatures.
- Detailed design parameters are not available to the users of systems already installed.

Current online monitoring techniques:

- No continuous online monitoring.
- Portable current transformers and potential transformers are used in electric current monitoring to detect electrical faults, and portable accelerometers are used for vibration monitoring.
- Present monitoring techniques are about 50%–60% effective in detecting and diagnosing motor and driven-load faults.

B6: Composite Plate Structures

Problem: This project will begin to demonstrate damage-prognosis solutions by applying the developed sensing and instrumentation, data interrogation, and predictive modeling technologies to a series of tests on composite plates.

Motivation: These tests were motivated by input LANL engineers received from aerospace companies about predicting the evolution of damage resulting from impact and subsequent fatigue.

Challenges:
Experimental: Seventy-centimeter-square, 6-mm-thick composite plates will be subjected to impact from a 200-gm steel projectile fired at 30–50 m/s using the LANL gas gun facility. The projectile has a 25-mm hemispherical impact surface. After seeding damage through the impact, the plate will be subjected to a sinusoidal loading.

Analytical/Computational: Finite element analysis (FEA) will be used to train surrogate models, neural networks, or support vector machines to predict impact location and velocity from strain sensor readings as depicted in Figure B9. The surrogate models are also referred to metamodels. FEA will then be used to develop surrogate models that can locate and quantify damage based on strain-sensor readings and knowledge of the impact location and velocity (depicted in Figure B9). An additional surrogate model will be developed that can predict fatigue-damage accumulation based on known initial damage and strain measurements that were made during fatigue loading (shown in Figure B10). Pre-established thresholds for fatigue-damage accumulation will signal failure for the system, and the surrogate model will predict the time to reach this threshold under the given loading environment (summarized in Figure B11). A snapshot from an explicit finite-element run showing the projectile impacting a composite plate is shown in Figure B12.

The benefits of ASCI computing are evident when one considers the numerical simulation of the damage initiation by the projectile impact. This 50,000-element explicit calculation was run for 0.5 ms. Using six 195-MHz processors on an SGI Origin 2000 computing system, each run takes over 12 hours to complete. Using 200 processors on the ASCI Blue Mountain computer reduces this run time to 15 minutes. This time savings is significant when one considers that 1000 simulations were used to train the neural network that estimates impact location and velocity based on the nine sensor readings.

Current online monitoring techniques:

Nine biaxial strain gauges will be evenly placed on the structure to monitor its response to the impact and to the subsequent harmonic input. In addition, local active-sensing systems using PZT sensor/actuators will be employed for postimpact and postharmonic test damage-interrogation. Figure B13 shows the PZT sensing system mounted on the composite plate and the associated data-acquisition system.

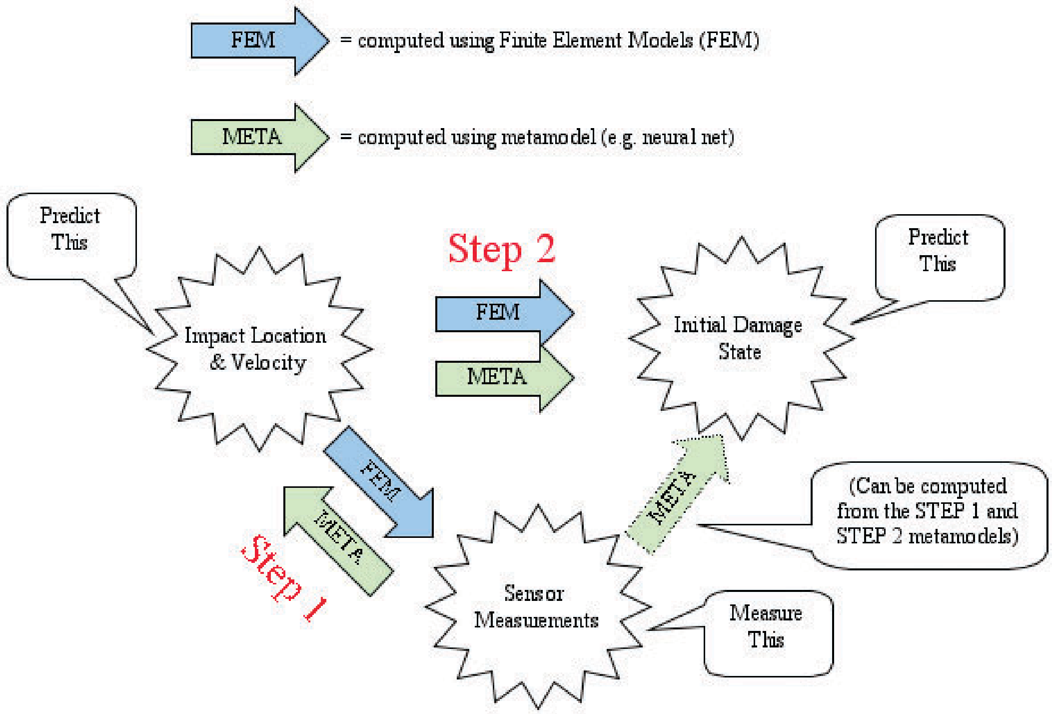

Figure B9 Development of surrogate models that identify impact velocity and location as well as initial damage state. Surrogate models are trained with finite-element analysis.

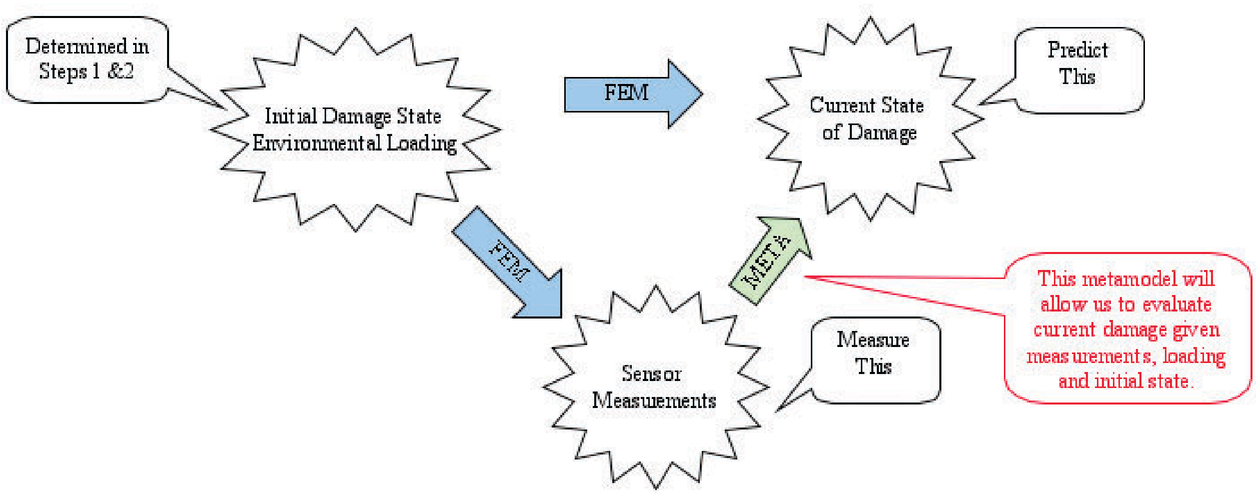

Figure B10 Process of updating estimates of the damage state during subsequent fatigue loading.

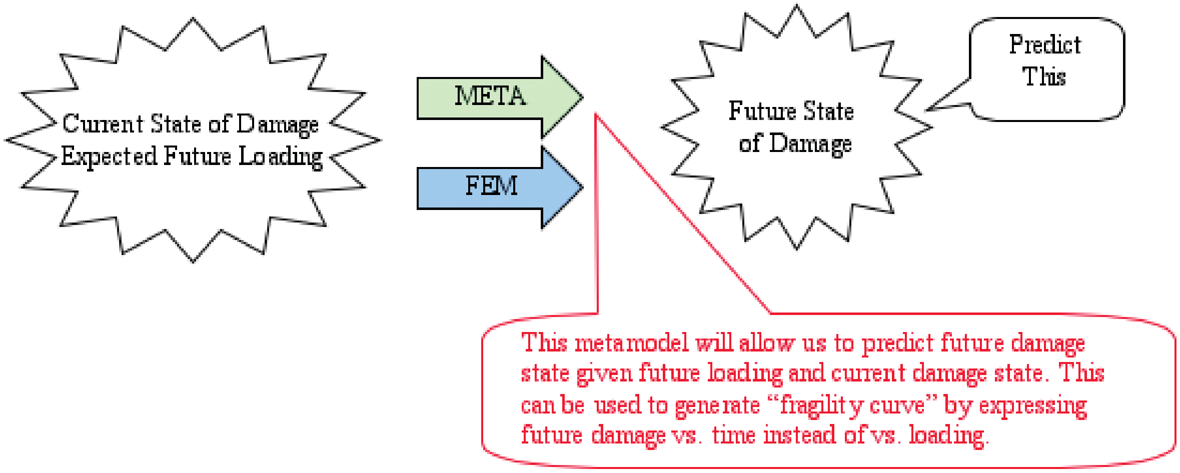

Figure B11 Process of updating estimates of the damage state during subsequent fatigue loading.

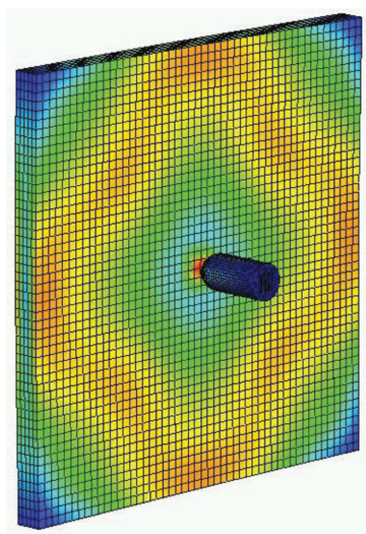

Figure B12 Finite-element model of a projectile impacting a composite plate.

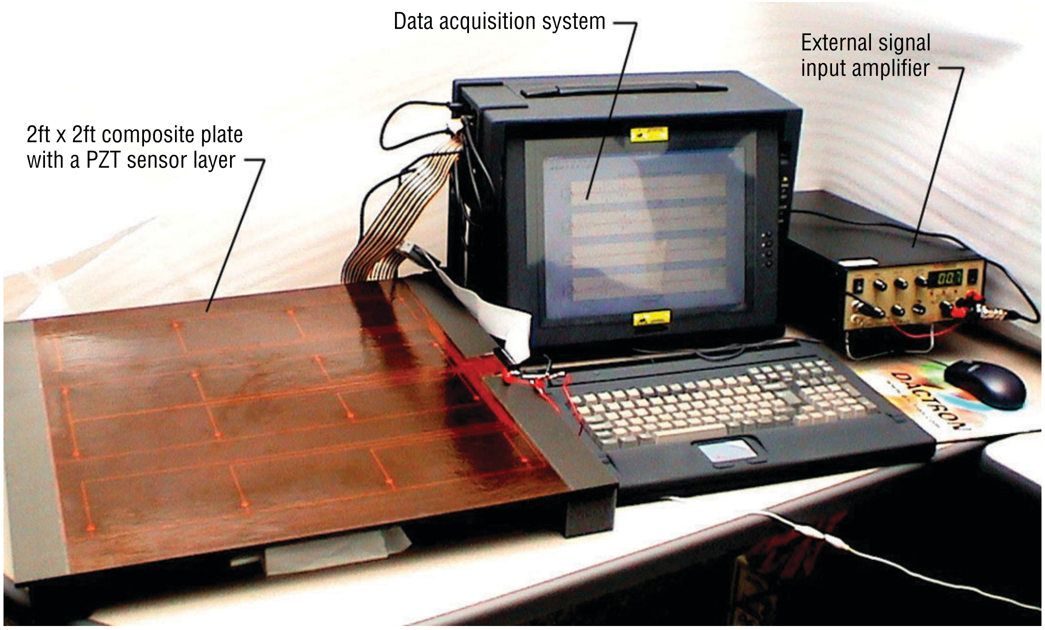

Figure B13 Active PZT sensing system developed by Acellent Technologies, Inc., mounted on a composite plate, and the associated data-acquisition system.

APPENDIX C: LIST OF RESOURCES RESEARCHED

Elements of Damage-Prognosis Technology

Table C-1 Elements of Damage-Prognosis Technology.

Paper	1-AMA	2-DI	3-EPC	4-LAP	5-NST	6-SI	7-SM	8-UQ
1	X		X		X			
2					X			
3					X			
4					X			
5				X	X			
6					X	X		
7			X					
8					X			
9								X
10						X		X
11			X		X			
12		X					X	X
13		X					X	
14							X	
15		X						
16			X					
17				X			X	
18							X	X
19	X							
20	X							X
21	X							X
22			X		X			X
23					X			
24								X
25					X			
26			X					
27								X
28				X		X		
29			X					
30			X					
31		X					X	
32								X
33			X					
34							X	
35		X					X	
36		X					X	
37								X
38		X					X	X
39		X						
40								X
41		X						
42			X			X		
43			X_			X		
44		X_					X	
45								X
46		X					X	

Table C-1. Elements of Damage-Prognosis Technology (cont.)

Paper	1-AMA	2-DI	3-EPC	4-LAP	5-NST	6-SI	7-SM	8-UQ
47	X		X					
48	X		X					
49		X					X	
50	X		X					
51							X	
52							X	
53							X	
54							X	
55		X					X	
56								X
57								X
58							X	
59							X	
60	X		X					
61		X						
62							X	
63							X	
64							X	
65							X	X
66			X					X
67			X					
Total	8	14	17	3	11	5	24	18

Symbols: 1-AMA, Advanced Modeling and Architectures
2-DI, Data Interrogation
3-EPC, Elements of Prognosis Capability
4-LAP, Local Actuation and Processing
5-NST, Novel Sensing Technology
6-SI, System Integration
7-SM, Surrogate Modeling
8-UQ, Uncertainty Quantification

Table C-2 List of Resources Researched.

Identifier	Year(s)	Journal, Conference, or Database	Number of Papers	3-EPC Papers
STAN-99	1999	Proceedings of the 2nd International Workshop on Structural Health Monitoring, Stanford University, Stanford, California, September 8-10, 1999, Edited by F.K. Chang, Technomic Publishing Company, Inc., Lancaster, Pennsylvania	102	4
STAN-97	1997	Proceedings of the 1st International Workshop on Structural Health Monitoring, Stanford University, Stanford, California, September 18-20, 1997, Edited by F.K. Chang, Technomic Publishing Company, Inc., Lancaster, Pennsylvania	67	4
DAMAS-97	1997	Proceedings of DAMAS '97, International Conference on Structural Damage Assessment Using Advanced Signal Processing Procedures, University of Sheffield, Sheffield, U.K., June 30-July 2, 1997, Edited by J.M. Dulieu-Smith, W.J. Staszewski, and K. Worden, Sheffield Academic Press, Sheffield, U.K.	39	1
COST-00	2000	Proceedings of the European COST-F3 Conference on System Identification and Structural Health Monitoring, Universidad Politécnica de Madrid, Madrid, Spain, June 6-9, 2000, Edited by J.A. Guemes, and S.L. Gráficas, Madrid, Spain	76	2
JEM-00	2000	ASCE Journal of Engineering Mechanics, Vol. 126, No. 7, July 2000	2	0
IJF-01	2001	International Journal of Fatigue, Vol. 23, 2001	2	2
SPIE-00	2000	Proceedings of SPIE, Nondestructive Evaluation of Highways, Utilities and Pipelines IV, March 2000, Vol. 3995, Edited by A.E. Aktan and S.R. Gosselin	2	1
MSSP-97	1997	Mechanical Systems and Signal Processing, Vol. 11: No. 1, January 1997; No. 2, March 1997; No. 3, May 1997; No. 4, July 1997; No. 5, September 1997; No. 6, November 1997	64	0
MSSP-98	1998	Mechanical Systems and Signal Processing, Vol. 12: No. 1, January 1998; No. 2, March 1998; No. 3, May 1998; No. 4, July 1998; No. 5, September 1998; No. 6, November 1998	52	0
MSSP-99	1999	Mechanical Systems and Signal Processing, Vol. 13: No. 1, January 1999; No. 2, March 1999; No. 3, May 1999; No. 4, July 1999; No. 5, September 1999; No. 6, November 1999	59	1
MSSP-00	2000	Mechanical Systems and Signal Processing, Vol. 14: No. 1, January 2000; No. 2, March 2000; No. 3, May 2000; No. 4, July 2000; No. 5, September 2000; No. 6, November 2000	57	2
MSSP-01	2001	Mechanical Systems and Signal Processing, Vol. 15, No. 1, January 2001	16	0
Total			**538**	**17**

APPENDIX D: LIST OF PAPERS REVIEWED

Table D-1. List of Papers Reviewed.

Paper	Author(s)	Title	Publication	Reference
1	R. Ikegami	"Structural Health Monitoring: Assessment of Aircraft Customer Needs"	STAN-99	pp. 12-23, Review Paper
2	P.D. Foote	"Structural Health Monitoring: Tales From Europe"	STAN-99	pp. 24-35, Review Paper
3	S.C. Liu	"Natural Hazard Mitigation: Exploring the Technological Frontiers"	STAN-99	pp. 36-55, Review Paper
4	A. Mita	" Emerging Needs in Japan for Health Monitoring Technologies in Civil and Building Structures"	STAN-99	pp. 36-67, Review Paper
5	V.K. Varadan V.V. Varadan	"Wireless Remotely Readable and Programmable Microsensors and MEMS for Health Monitoring of Aircraft Structures"	STAN-99	pp. 96-105, Review Paper
6	J.N. Kudva M.J. Grage M.M. Roberts	"Aircraft Structural Health Monitoring and Other Smart Structures Technologies — Perspectives on Development of Future Smart Aircraft"	STAN-99	pp. 106-119, Review Paper
7	E. Robeson B. Thompson	"Tools for the 21st Century: MH-17E SUMS"	STAN-99	pp. 179-189
8	G.A. Johnson K. Pran G. Wang G.B. Havsgård S.T. Vohra	"Structural Monitoring of a Composite Hull Air Cushion Catamaran With a Multi-Channel Fiber Bragg Grating Sensor System"	STAN-99	pp. 190-198
9	C. Papadimitriou L.S. Katafygiotis K.V. Yuen	"Optimal Instrumentation Strategies for Structural Health Monitoring Applications"	STAN-99	pp. 543-552
10	A. Todoroki Y. Shimamura T. Inada	"Plug and Monitor System Via Ethernet With Distributed Sensors and CCD Cameras"	STAN-99	pp. 571-580
11	M.R. Carlos R.D. Finlayson R.K. Miller M.A. Friesel LL. Klokus	"Acoustic Emission On-Line Monitoring Systems (AEOLMS)"	STAN-99	pp. 581-593
12	C.R. Farrar T.A. Duffey S.W. Doebling D.A. Nix	"A Statistical Pattern Recognition Paradigm for Vibration-Based Structural Health Monitoring"	STAN-99	pp. 764-773, Review Paper
13	K. Worden G. Manson R. Wardle W. Staszewski D. Allman	"Experimental Validation of Two Structural Health Monitoring Methods"	STAN-99	pp. 784-799

Table D-1 List of Papers Reviewed (cont.)

Paper	Author(s)	Title	Publication	Reference
14	H.T. Vincent S.L.J. Hu Z. Hou	"Damage Detection Using Empirical Mode Decomposition Method and a Comparison With Wavelet Analysis"	STAN-99	pp. 891-900
15	R.A. DeCallafon	"On-Line Damage Identification Using Model-Based Orthonormal Functions"	STAN-99	pp. 912-920
16	C. Zhang T.R. Kurfess S. Danyluk S.Y. Liang	"Dynamic Modeling of Vibration Signals for Bearing Condition Monitoring"	STAN-99	pp. 926-935
17	V. Lopes G. Park H.H,. Cudney D.J. Inman	"Smart Structures Health Monitoring Using Artificial Neural Network"	STAN-99	pp. 976-985
18	T. Inada Y. Shimamura A. Todoroki H. Kobayashi H. Nakamura	"Damage Identification Method for Smart Composite Cantilever Beams With Piezoelectric Materials"	STAN-99	pp. 986-994
19	K.C. Park G.W. Reich K.F. Alvin	"Structural Damage Detection Using Localized Flexibilities"	STAN-97	pp. 125-139
20	M.W. Vanik J.L. Beck	"A Bayesian Probabilistic Approach to Structural Health Monitoring"	STAN-97	pp. 140-151
21	L.S. Katafygiotis H.F. Lam	"A Probabilistic Approach to Structural Health Monitoring Using Dynamic Data"	STAN-97	pp. 152-163
22	J.D. Achenbach B. Moran A. Zulfiqar	"Techniques and Instrumentation for Structural Diagnostics"	STAN-97	pp. 179-190, Review Paper
23	T.L. Vandiver	"Health Monitoring of U.S. Army Missile Systems"	STAN-97	pp. 191-196, Review Paper
24	S.W. Doebling C.R. Farrar P.J. Cornwell	"A Computer Toolbox for Damage Identification Based on Changes in Vibration Characteristics"	STAN-97	pp. 241-254
25	I. Searle S. Ziola S. May	"Damage Detection Experiments and Analysis for the F-16"	STAN-97	pp. 310-324
26	H. Bach R. Markert	"Determination of the Fault Position in Rotors for the Example of a Transverse Crack"	STAN-97	pp. 325-335
27	C.R. FarrarS.W. Doebling	"Lessons Learned From Applications of Vibration-Based Damage Identification Methods to a Large Bridge Structure"	STAN-97	pp. 351-370, Review Paper

Table D-1. List of Papers Reviewed (cont.)

Paper	Author(s)	Title	Publication	Reference
28	P. Neuzil F.M. Serry O. Krenek G.J. Maclay	"An Integrated Circuit to Operate a Transponder With Embeddable MEMS Microsensors for Structural Health Monitoring"	STAN-97	pp. 492-501
29	C. Boller C. Biemans	"Structural Health Monitoring in Aircraft — State-of-the-Art, Perspectives and Benefits"	STAN-97	pp. 541-552, Review Paper
30	T. Simmermacher G.H. James III J.E. Hurtado	"Structural Health Monitoring of Wind Turbines"	STAN-97	pp. 788-797
31	S.G. Pierce W.J. Staszewski K. Worden W.R. Philip B. Culshaw G.R. Tomlinson	"Lamb Wave Testing of Composite Plates Using Optical Fiber Sensors"	DAMAS-97	pp. 41-52
32	S.W. Doebling C.R. Farrar	"Using Statistical Analysis to Enhance Modal-Based Damage Identification"	DAMAS-97	pp. 199-211
33	M. Pirner O. Fischer	"Monitoring Stresses in GRP Extension of the Prague TV Tower"	DAMAS-97	pp. 451-460
34	K. Worden	"Nonlinearity in Structural Dynamics: The Last Ten Years"	COST-00	pp. 29-51, Review Paper
35	H. Sohn C.R. Farrar	"Statistical Process Control and Projection Techniques for Damage Detection"	COST-00	pp. 105-114
36	K. Worden A.J. Lane	"Damage Identification Using Support Vector Machines"	COST-00	pp. 201-211
37	J.B. Bodeux J.C. Golinval	"ARMAV Model Technique for System Identification and Damage Detection"	COST-00	pp. 303-312
38	J.S. Sakellariou S.D. Fassois	"Parametric Output Error-Based Identification and Fault Detection in Structures Under Earthquake Excitation"	COST-00	pp. 323-332
39	B. Peeters J. Maeck G. De Roeck	"Dynamic Monitoring of the Z-24 Bridge: Separating Temperature Effects From Damage"	COST-00	pp. 377-386
40	S.W. Doebling F.M. Hemez W. Rhee	"Statistical Model Updating and Validation Applied to Nonlinear Transient Structural Dynamics"	COST-00	pp. 409-418
41	L. Mevel A. BenvenisteM. Basseville M. Goursat	"In Operation Structural Damage Detection and Diagnosis"	COST-00	pp. 641-650
42	S.R. Hunt I.G. Hebden	"Validation of the Eurofighter Typhoon Structural Health and Usage Monitoring System"	COST-00	pp. 743-752

Table D-1. List of Papers Reviewed (cont.)

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43	M.J. Iglesias A. Palomino	"SHMS, A Good Chance to Gain Experience to Optimize the Aircraft Structural Capability"	COST-00	pp. 753-771
44	S.J. Hickinbotham J. Austin	"Novelty Detection for Flight Data From Airframe Strain Gauges"	COST-00	pp. 772-780
45	M.W. Vanik J.L.Beck S.K. Au	"Bayesian Probabilistic Approach to Structural Health Monitoring"	JEM-00	pp. 738-745
46	S.F. Masri A.W. Smyth A.G. Chassiakos T.K. Caughey N.F. Hunter	"Application of Neural Networks for Detection of Changes in Nonlinear Systems"	JEM-00	pp. 666-676
47	Z.X. Li T.H.T. Chan J.M. Ko	"Fatigue Analysis and Life Prediction of Bridges With Structural Health Monitoring Data — Part I: Methodology and Strategy"	IJF-01	pp. 45-53
48	T.H.T. Chan Z.X. Li J.M. Ko	"Fatigue Analysis and Life Prediction of Bridges With Structural Health Monitoring Data — Part II: Application"	IJF-01	pp. 55-64
49	D.M. McCann N.P. Jones J.H. Ellis	"Evaluating the Utility of Global Damage Detection for Highway Bridges"	SPIE-00	pp. 28-36
50	Z.X. Li T.H.T. Chan J.M. Ko	"Health Monitoring and Fatigue Damage Assessment of Bridge-Deck Sections"	SPIE-00	pp. 346-357
51	G. Dalpiaz A. Rivola	"Condition Monitoring and Diagnostics in Automatic Machines: Comparison of Vibration Analysis Techniques"	MSSP-97	pp. 53-73, Vol. 11, No. 1 (Jan. 1997)
52	W.J. Staszewski G.R. Tomlinson	"Local Tooth Fault Detection in Gearboxes Using a Moving Window Procedure"	MSSP-97	pp. 331-350, Vol. 11, No. 3 (May 1997)
53	N. Sarkar R.E. Ellis T.N. Moore	"Backslash Detection in Geared Mechanisms: Modeling, Simulation and Experimentation"	MSSP-97	pp. 391-408, Vol. 11, No. 3 (May 1997)
54	S.K. Lee P.R. White	"Higher-Order Time-Frequency Analysis and its Application to Fault Detection in Rotating Machinery"	MSSP-97	pp. 637-650, Vol. 11, No. 4 (July 1997)
55	W.J. Staszewski K. Worden G.R. Tomlinson	"Time-Frequency Analysis in Gearbox Fault Detection Using the Wigner-Ville Distribution and Pattern Recognition"	MSSP-97	pp. 673-692, Vol. 11, No. 5 (Nov. 1997)
56	Y. Ben-Haim S. Cogan L. Sanseigne	"Usability of Mathematical Models in Mechanical Decision Processes"	MSSP-98	pp. 121-134, Vol. 12, No. 1 (Jan. 1998)

Table D-1. List of Papers Reviewed (cont.)

Paper	Author(s)	Title	Publication	Reference
57	Y. Ben-Haim	“Sequential Tests Based on Convex Models of Uncertainty”	MSSP-98	pp. 427-448, Vol. 12, No. 3, (May 1998)
58	M.C. Pan H. Van Brussel P. Sas	“Intelligent Joint Fault Diagnosis of Industrial Robots”	MSSP-98	pp. 571-588, Vol. 12, No. 4 (July 1998)
59	T.I. Liu W.Y. Chen K.S. Anatharaman	“Intelligent Detection of Drill Wear”	MSSP-98	pp. 863-873 Vol. 12, No. 6 (Nov. 1998)
60	Y. Li S. Billington C. Zhang T. Kurfess S. Danyluk S. Liang	“Adaptive Prognostics for Rolling Element Bearing Condition”	MSSP-99	pp. 103-113 Vol. 13, No. 1 (Jan. 1999)
61	G.M. Lloyd M.L. Wang T.L. Paez	“Minimization of Decision Errors in a Probabilistic Neural Network for Change Point Detection in Mechanical Systems”	MSSP-99	pp. 943-954 Vol. 13, No. 6 (Nov. 1999)
62	K. Shibata A. Takahashi T. Shirai	“Fault Diagnosis of Rotating Machinery Through Visualization of Sound Signals”	MSSP-00	pp. 229-241 Vol. 14, No. 2 (March 2000)
63	G. Dalpiaz A. Rivola R. Rubini	“Effectiveness and Sensitivity of Vibration Processing Techniques for Local Fault Detection in Gears”	MSSP-00	pp. 387-412 Vol. 14, No. 3 (May 2000)
64	P. Simard E. Le Tavernier	“Fractal Approach for Signal Processing and Application to the Diagnosis of Cavitation”	MSSP-00	pp. 459-469 Vol. 14, No. 3 (May 2000)
65	A. Lucifredi C. Mazzieri M. Rossi	“Application of Multi-regressive Linear Models, Dynamic Kriging Models and Neural Networks to Predictive Maintenance of Hydroelectric Power Systems”	MSSP-00	pp. 471-494 Vol. 14, No. 3 (May 2000)
66	Y. Li T.R. Kurfess S.Y. Liang	“Stochastic Prognostics for Rolling Element Bearings”	MSSP-00	pp. 747-762 Vol. 14, No. 5 (Sept. 2000)
67	D.C. Swanson J.M. Spencer S.H. Arzoumanian	“Prognostic Modeling of Crack Growth in a Tensioned Steel Band”	MSSP-00	pp. 789-803 Vol. 14, No. 5 (Sept. 2000)

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