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Title: Statistical Tools for Prognostics and Health Management of Complex Systems

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STATISTICAL TOOLS FOR PROGNOSTICS AND HEALTH MANAGEMENT OF COMPLEX SYSTEMS

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ABSTRACT

Prognostics and Health Management (PHM) is increasingly important for understanding and managing today's complex systems. These systems are typically mission- or safety-critical, expensive to replace, and operate in environments where reliability and cost-effectiveness are a priority. We present background on PHM and a suite of applicable statistical tools and methods. Our primary focus is on predicting future states of the system (e.g., the probability of being operational at a future time, or the expected remaining system life) using heterogeneous data from a variety of sources. We discuss component reliability models incorporating physical understanding, condition measurements from sensors, and environmental covariates; system reliability models that allow prediction of system failure time distributions from component failure models; and the use of Bayesian techniques to incorporate expert judgments into component and system models.

INTRODUCTION

We begin by defining some terms. A *system* is a group of components that interact to function as a whole; for example, aircraft, motor vehicles, and machine guns are systems. A *component* is an entity that is part of a larger whole. A *subsystem* is a component composed of interacting subcomponents. We use the term *unit* to refer to a system, subsystem, or component. These terms are hierarchical in a flexible way: something that is a system from one point of view may be a subsystem or component when viewed as part of a larger system. For example, an M230 automatic gun can be seen as a system by itself, but is a subsystem when installed in an Apache helicopter. The term "component" mainly reflects the fact that we are considering something as a non-decomposable unit, rather than as a composite of interacting parts.

The term *complex system* is defined in various ways in different disciplines (e.g., computer science versus biology). In the context of this paper, a complex system is composed of many components, has a multilevel hierarchy of subsystems, and is difficult to understand and manage.

Components of a complex system have varying amounts of interdependence. Operation of one may be almost completely independent of another, for example the headlights and tires of an automobile; or they may be highly dependent, for example the fuel and ignition subsystems. Interdependence may be such that a partial failure of several components results in complete failure of a system. Boundary conditions for complex systems, such as environmental conditions and interfaces to other systems, are significant. In fact, *where* the boundary is drawn may be significant, since failures may occur at the interface between systems.

Complex systems typically present large, heterogeneous collections of data to the analyst. Data are of different types, including records from sensors monitoring internal conditions, environmental data on temperature and humidity, system test data, component test data, measurements of degradation due to metal fatigue or corrosion, etc. The challenge is to integrate and analyze these multiple data sources, many of which may not be complete, to produce credible health assessments for systems, and aid decision-making in areas such as maintenance, logistics, and long-term planning for replacement systems.

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EXAMPLE: A MUNITIONS SYSTEM

We use as an example of a complex system the M789 30mm HEDP (high explosive dual purpose) round[1,2,3], used in the M230 automatic gun mounted in AH-64 Apache helicopters.

The 30 mm cartridge itself is a moderately complex system, consisting of several subsystems and many components—see Figure 1. The cartridge(s) plus the M230 gun comprise a more complex system, including an interface involving a chain feed for the cartridges and an electrical system, since the cartridge primer is electrically initiated. Cartridges plus gun plus the helicopter comprise an extremely complex system, many elements of which interact in complex ways to affect performance of the cartridge from the user's point of view (the warfighter), whose concerns are delivery of the projectile to a target, with maximum safety for the operator of the gun.

Note that the system context can be broadened to include human operators, the supply chain, etc. As an example of events beyond the cartridge/gun/helicopter system boundary, the cartridge has an aluminum case which may be damaged by improper handling, causing gun malfunctions. Thus corrective actions for certain gun failures include education of personnel loading and unloading rounds from the helicopter[2].

See also figure 3 for a partial decomposition of the system into subsystems and components

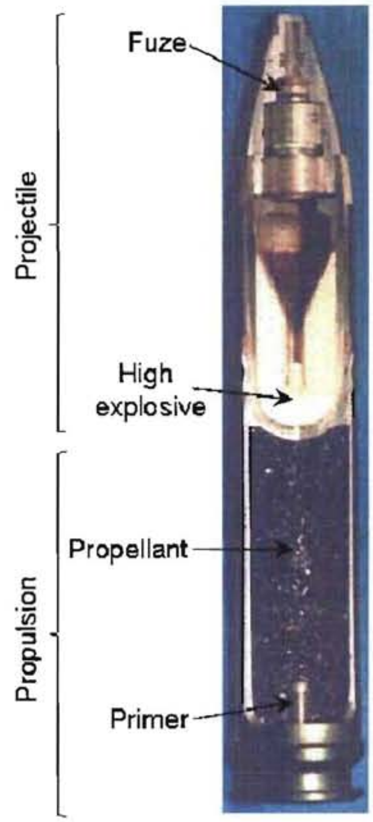

Figure 1 M789 cartridge

Prognostics and Health Management (PHM) requires first of all a definition of what constitutes "health," and techniques for measuring it.

A general definition of system health[4] will most likely include the following items:

- Adequate safety margins for intended uses of the system, taking into account uncertainties in measurements of system integrity, load levels and environmental conditions.
- Absence of observable damage or material changes to components of the system. "Observable" may include observation by such means as radiography or ultrasound.
- Operating performance within specified ranges.
- Predicted reliability within a specified range over the probable life of the system.
- No predicted degradation that would compromise system integrity, reliability, or safety within a specified time period

Application of these desiderata is context-dependent, of course; for each type of system, terms such as "adequate" and "specified time period" must be carefully defined in terms of measurable criteria. For example, assessment of the health of ammunition is based on acceptably low safety risk, low failure rate (jams, misfires, excessive bore pressure, etc.), and ability to function as specified (muzzle velocity, accuracy, etc.) over its expected life. There may be many mission profiles for a multi-use item such as a cartridge used in various guns, and careful consideration should be given to how system health is calibrated to the requirements of the various missions.

Taking the M789 cartridge as an example, aspects of health can be assessed by visual inspection for damage or corrosion, test-firing of samples, and analysis of field failure reports. Predictive models may also be feasible: since chemical changes in propellants are fairly well-understood, the age and history of storage conditions such as temperature enables prediction of the probable reliable life of the ammunition[5]. All of these methods used in conjunction provide a more complete picture of health.

The *prognostics* component of PHM is the prediction of future health conditions based on current and historic environmental and condition data, using physical and statistical models. *Health management* is the use of prognostics to manage maintenance and logistics for increased reliability and reduced cost.

A variety of statistical and other techniques come under the PHM umbrella, such as reliability centered maintenance (maintenance driven by functional reliability needs), condition-based maintenance ("just in time" maintenance based on monitoring of component conditions), automated logistics (logistics decisions based on condition monitoring and predictive models), prediction of remaining useful life of a system, and uncertainty quantification (quantitative specification of the uncertainty in predictions).

In the next section, we discuss primarily statistical tools associated with PHM. The discussion is at a high level, with some examples of specific techniques, and references for more detailed information.

RESULTS AND DISCUSSION

The simplest model of a system is as a "black box," whose inputs and outputs are known, but whose internal structure is assumed unknown. We very rarely use black-box models for systems of significant complexity, but they may be useful as first approximations for components, particularly those that are sealed and intended to be replaced as a unit. In predicting, say, reliability for a unit of this type, we generally use test data, which may be drawn from repeated tests of one unit, of from observation of the continuous operation of the unit. In the case of units such as cartridges, testing is destructive, so we have results from many units assumed to have come from a homogeneous population, and subjected to the same mission or test conditions.

In addition to the characteristics of the unit itself, test results may be influenced by factors that violate the assumption of a homogeneous population. For example, temperature, humidity, ambient vibration, and other environmental conditions may affect reliability and performance (measurements of output). Other covariates may be relevant too, such as storage and handling conditions, age, variations in mission conditions, etc.

Test or observational results may include any of the following:

- Pass/fail binary data: the unit worked satisfactorily, or it did not.
- Lifetime data: the length of time the unit performed satisfactorily in continuous operation before failing.
- Degradation data: measurements of fatigue cracking, corrosion, chemical changes, etc., with respect to operating, standby, or storage time.
- Measurements of environmental conditions and other covariates.

- Computer simulation data: though less relevant for black-box models, in general if an accurate physical or empirical model exists for the unit, computer results may replace or augment testing data from the actual unit.
- Expert judgment as to testing results that would occur under given conditions, based on experience with the unit, or with units of similar type; where system testing is difficult, expensive, or impossible under mission conditions, the judgment of experienced engineers and scientists can be a valuable adjunct to other forms of data.

For complex systems, the desired model is a "white box," whose internal structure and function is understood. This means we know what components comprise the system, how they are structurally connected, and how the structure affects reliability or other performance measures. Ideally we know how interactions between components affect both component and system health. This kind of model is illustrated in Figure 2, which also indicates that system inputs/outputs, environmental data, and other covariates are present as in the black-box model. (In fact, by blacking out the inside of the system box, it becomes a black-box model.)

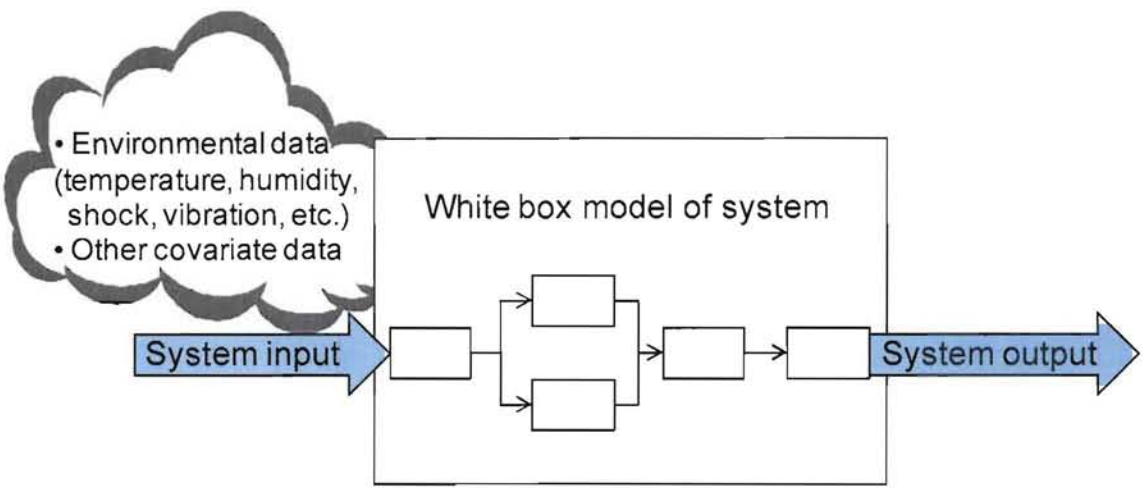

Figure 2 A system model for PHM

The figure conveys structural understanding by a reliability block diagram, indicating how components of the system are connected in series (all must work or the system fails) and in parallel (the system can still function when one or more of a set of redundant units has failed). Blocks inside the white box may be composite, in which case they can be further decomposed into white-box sub-models, or non-composite. Ideally, for each non-composite block we have a functional science or engineering model (i.e., mechanical, electronic, etc.) that enables prediction under given input and environmental conditions. If not, the block is a black box which can be modeled empirically based on the data described above.

Returning to the M789 cartridge, Figure 3 shows part of a white-box model. The propulsion subsystem includes propellant and ignition subsystems. The propellant, though physically homogeneous in appearance, is actually a complex blend of base propellant, stabilizer, and deterrent. Ignition is accomplished by electrically detonating a primer which initiates an igniter in a sealed flash tube, which ruptures the seal and ignites the main propellant[6].

Extensive data has been collected in the course of various studies to increase the reliability of the M789 and the M230 gun[2,3,6]. Data were collected both under field conditions (i.e., when the cartridge is fired from the M230) and in various laboratory test rigs designed to accurately measure parameters such as bore pressure and muzzle velocity. Note that with respect to the types of data described above, we are primarily interested in pass/fail tests, subject to the constraint of operating within specifications (muzzle velocity, rounds per minute, etc.), and degradation data (mainly chemical) which can be used to predict failures.

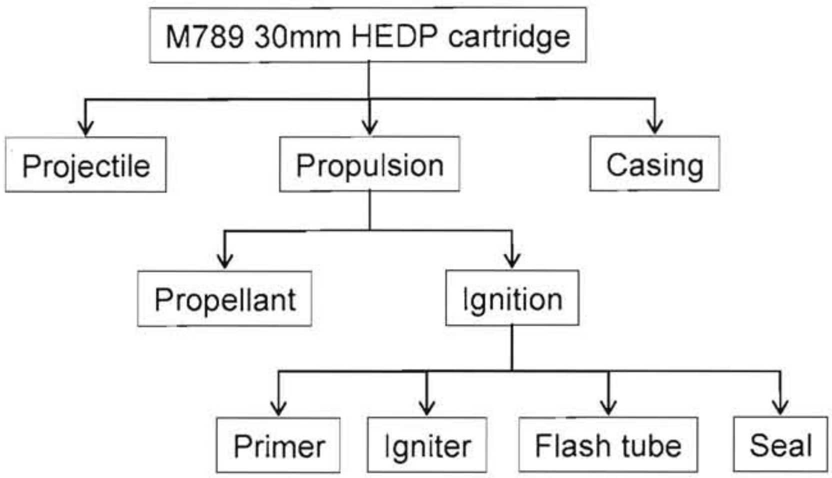

Figure 3 System decomposition of M789 cartridge

Data collected include:

- At the system (cartridge) level, field reports of misfires, etc., pass/fail test results, and ballistic measures such as muzzle velocity.
- Also at the system level, covariate values: lot (year of manufacture), storage time and temperature, and general qualitative storage and handling conditions.
- For the propellant, measures of chemical composition and degradation, and bore pressures in a test barrel.
- For the ignition subsystem, chemical composition /degradation, and flash tube pressures and seal performance. The flash tube and seal were also inspected visually (after disassembly) and radiographically.

THE CHALLENGE OF HETEROGENEOUS DATA

"New statistical methods and research are needed that can span and integrate data and knowledge from computational models, theoretical models, physical experiments, observational studies, expert judgment, and other sources. These methods must include . . . some way to highlight where our ignorance lies." This statement by Sally Keller-McNulty[7] in a panel discussion on industrial statistics nicely summarizes some of the new challenges confronting statisticians in implementing prognostics and health management. Operational managers, engineers, and funding agencies need information in a form that is useful for decision-making. This means that the plethora of testing and other data available for systems need to be analyzed and summarized in a useful form, which may include:

- An overall assessment of system health, including current operational readiness and predicted performance out to some appropriate time horizon.

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- Predictive information that can be used to develop optimum maintenance and logistics policies, as well as to extrapolate how the system would perform under conditions not yet encountered.
- Measurements of uncertainty regarding predictions, to enable decision-makers to assess risks.
- Assessment of the relative values of acquiring new data of given types, so that resources can be allocated intelligently to increase the accuracy of predictions and reduce the cost of sensors and testing.

In recent years, significant progress has been made toward developing statistical methodology to satisfy these goals, though much remains to be done. In the interest of space and keeping this paper non-technical, we merely sketch a number of methods here. We refer the reader to the papers by Anderson-Cook[8] and Wilson *et al.*[9] for further details, references, and examples.

For units that operate continuously, the classical black-box model is the lifetime distribution, a continuous probability distribution that expresses, for any time *t*, the probability of failure at or before *t*. From this can be derived the probability density function (pdf) $f(t)$, the reliability function $R(t)$ giving the probability of survival without failure beyond *t*, and the hazard rate $h(t)$ giving the probability of failure within a small interval $(t, t + dt)$. Typical lifetime distributions include the exponential, which has a constant hazard rate (often used for electronic components that do not wear out), and the Weibull, which has been found to be a good model for many applications, including mechanical devices subject to wearing out.

A lifetime distribution may be chosen as a predictive model based on physical insight into how a component fails, or empirically, as a good fit to observed data. This is illustrated by the following example.

EXAMPLE: WEIBULL LIFETIME DISTRIBUTION

The Weibull density and reliability functions are given by

$$f(t) = e^{-(t/\beta)^{\alpha}}\, t^{\alpha-1}\alpha\beta^{-\alpha} = 0.002624e^{-0.001381t^{1.9}}\, t^{0.9}$$

$$R(t) = e^{-(t/\beta)^{\alpha}} \qquad = e^{-0.001381t^{1.9}}$$

The first form on each line is the general parametric model, with α and β to be specified. The second form is a specific model, plotted below in Figure 4. The graph is the pdf, and the histogram shows a sample of 200 points drawn from the distribution. The parameters α and β may be estimated in various ways. They can be related to a physical failure model, based on the "weakest link" property[10]. They can also be estimated from the data (e.g., if we had the data in the histogram but did not know α and β). For certain types of physical model, parameter values may be determined by covariates, e.g., temperature τ: $\alpha = \alpha(\tau) = c_0 + c_1\tau$.

In this example, or in general whenever parameter values must be estimated or postulated, we can account for uncertainty with a Bayesian analysis: we use prior probability distributions on α and β to account for mean values and associated uncertainty; see Hamada *et al.*[11] for details and examples. Prior distributions also provide a mechanism for capturing and representing the judgment of experts.

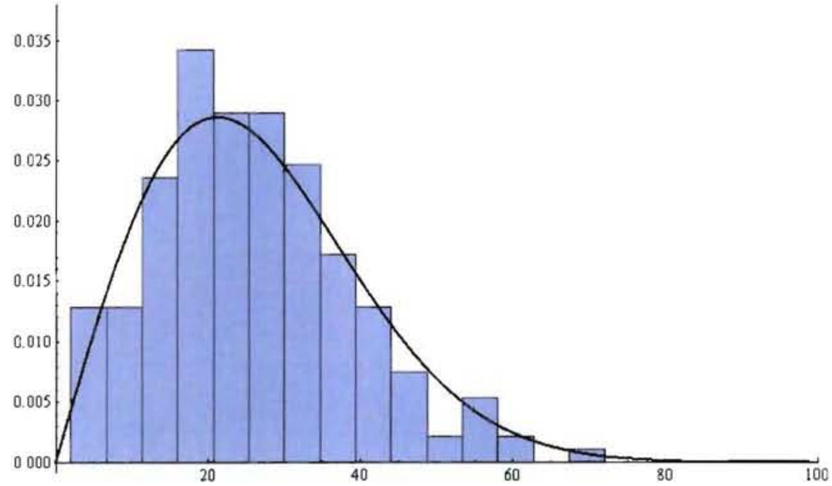

Figure 4 Weibull probability density function and sample histogram

Regression models are often used to model the effect of covariates on lifetimes or binary pass/fail. The model above, using temperature to determine one of the Weibull parameters, is a simple example. General regression models include logistic and probit for binary data, lifetime regression models such as the Weibull, and others involving, e.g., logarithmic transformation of the data. Nonparametric regression is also used, which fits a curve to data without any assumption of a particular parametric model.

There are many types of structural (white box) models, including reliability block diagrams, fault trees, path/cut sets, structure functions, and others; see Hamada *et al.*[10] for details and examples. These tend to be most useful for systems that can be easily decomposed into combinations of functional modules connected in series or parallel. A problem that immediately arises in such models is how to *combine* different types of data into an overall assessment. For example, suppose we know the system structure and have data on system reliability from system testing, plus component reliability data (e.g., from unit testing) for some, but perhaps not all, components. The paper by Wilson *et al.*[9] gives many scenarios of this type, with appropriate statistical methods for combining the data to obtain the most informative reliability assessment. Bayesian methods, in particular, enable the computation of a predictive distribution for system reliability, thus also providing uncertainty estimates.

Block diagrams, fault trees and similar representations fail to capture significant aspects of system structure. For example, it may be that relationships between component reliabilities are not of the simple deterministic type that goes with series and parallel structures. Bayesian network analysis can capture conditional probabilities for component interactions, thus providing a much more flexible modeling methodology; see Hamada *et al.*[11] for details and examples.

Block diagrams and the like, and also Bayesian networks, do not capture event-driven aspects of system performance, e.g., the effect of repairing a component when it fails. Viewing system structure as a succession of states, rather than a collection of components, provides a useful perspective which is described below.

EXAMPLE: STATISTICAL FLOWGRAPH MODELS

Representation of system states rather than physical units can capture structure in time that is not representable in decompositions such as block diagrams. For example, repair actions, holding time distributions in states, probabilities of state changes, and recurrent events such as shocks or electrical surges can be captured in multistate stochastic models. Statistical flowgraphs[12] comprise a conceptually simple framework for analyzing these multistate models.

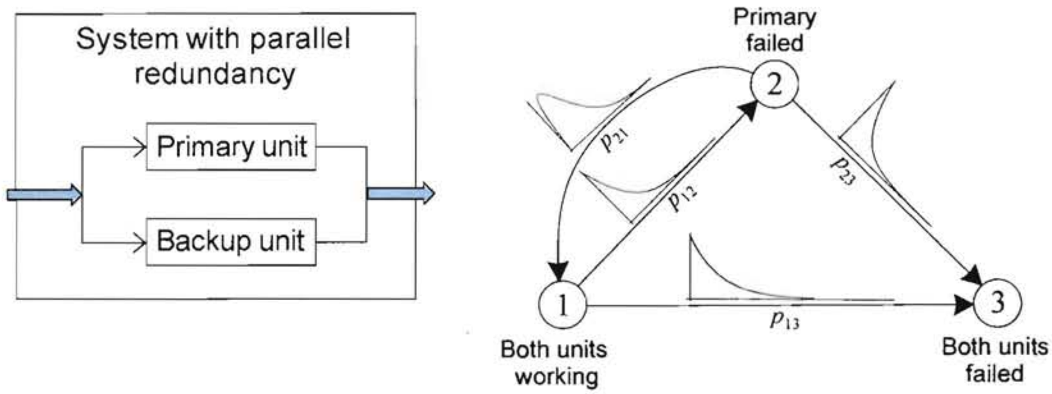

Figure 4 Block diagram versus flowgraph

Figure 4 shows an example. On the left is a block diagram of a system with parallel redundancy—either the primary or backup unit can handle the system load, so if one fails, the system continues to operate. Now suppose that we want to add to the model the fact that if a failed unit is repaired before the second unit fails, the system can recover from any number of failures (until the second unit fails before the repair is complete, or both units fail simultaneously). This cannot be done with anything like a block diagram.

On the right in the figure is a flowgraph model for this system. Each transition between states is labeled with the probability of making that transition, and a plot of the pdf of the holding time in a state before the transition is made. Note particularly the feedback loop from state 2 to 1, representing repair of a failed unit. Our main interest is in the probability distribution for the time until state 3 (system failure) is reached, starting in state 1. The statistical flowgraph framework provides algorithms for computing distributions for first passage between arbitrary states; see Huzurbazar[12] for details.

Though details are beyond the scope of this paper, these methods can be used synergistically to develop performance predictions and quantifications of uncertainty for complex systems. In addition, as described in Wilson *et al.*[9], methods are available for assessing the value (in terms of better predictions and less uncertainty) of additional data of a given type. Looking back at the M789 example, the various tests that have been performed are all expensive. Knowing the statistical value of types of test in advance allows decision-makers to sensibly allocate resources to get the maximum value from each test.

SUMMARY AND CONCLUSIONS

Prognostics and Health Management (PHM) is increasingly important for understanding and managing today's complex systems. These systems are typically mission- or safety-critical, expensive to replace, and operate in environments where reliability and cost-effectiveness are a priority. In recent decades, great advances have been made in sensor and monitoring technology, for example, in real-time condition monitoring of aircraft engines, as well as in off-line diagnostic testing. For systems such as military aircraft this results in large, heterogeneous datasets containing information on internal vibration, chemical composition of propellants and lubricants, corrosion, etc., as well as environmental data such as ambient temperature and humidity. Even systems without real-time sensing or diagnostic technology typically present large, heterogeneous collections of data based on testing and field reports. The challenge for PHM is to filter and integrate this data to drive predictive models for scheduling inspections, maintenance, and replacement of parts or of the entire system, and for assessing mission failure probabilities and operational readiness. The cost justification for PHM is its facilitation of decision-making regarding maintenance and logistics.

We have presented background on PHM and a suite of applicable statistical tools and methods. Our primary focus is on predicting future states of the system such as the probability of being operational at a future time, or the expected remaining system life, using data from a variety of sources. We discussed component reliability models incorporating physical understanding, condition measurements, and environmental covariates; system reliability models such as flowgraphs, which allow prediction of system failure time distributions from the component failure models; and the use of Bayesian techniques to incorporate expert judgments into component and system models.

Our ongoing work aims at development of more robust predictive methods, improved integration and usability of tools, and quantification of the uncertainty associated with models based on heterogeneous data types.

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