A Survey of Artificial Intelligence for Prognostics

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Abstract

Integrated Systems Health Management includes as key elements fault detection, fault diagnostics, and failure prognostics. Whereas fault detection and diagnostics have been the subject of considerable emphasis in the Artificial Intelligence (AI) community in the past, prognostics has not enjoyed the same attention. The reason for this lack of attention is in part because prognostics as a discipline has only recently been recognized as a game-changing technology that can push the boundary of systems health management. This paper provides a survey of AI techniques applied to prognostics. The paper is an update to our previously published survey of data-driven prognostics.

Introduction

NASA is currently planning long-duration human space exploration missions to the Moon and Mars. Reliability of the spacecraft will be extremely important for these missions, since they will be away from the Earth for months or years at a time. An important contributor to that reliability will be an on-board Integrated Systems Health Management (ISHM) system. ISHM can provide two advantages. First, it can increase safety, by detecting problems, quickly diagnosing them, and assessing remaining life before they become serious, so that controllers can respond rapidly and prevent major failures. Second, it can reduce costs by enabling corrective action to be scheduled more efficiently. Corrective action such as maintenance scheduling is most important for reusable systems, such as aircraft or the Space Shuttle, but even expendable piloted spacecraft, such as Apollo or Soyuz, have had some maintenance actions that can be performed by the astronauts during a mission. Future air and space vehicle may also benefit from robotic or autonomic maintenance.

An ISHM system takes as input sensor values and the command stream, and ideally performs fault detection (detecting that something is wrong), fault isolation (determining the location of the fault), fault identification (determining what is wrong; that is, determining the fault mode), and fault prognostics (determining when a failure will occur based conditionally on anticipated future usage). We define diagnostics to include fault isolation and fault identification, so that full diagnostics requires determining the specific fault mode, rather than just reporting which sensor has an unusual value. We define prognostics to be detecting the precursors of a failure, and predicting how much time remains before a likely failure. Prognostics is the most difficult of these tasks. One must be able to detect faults before one can diagnose them. Similarly, one must be able to diagnose faults before one can perform prognostics. In addition to fault detection, diagnostics, and prognostics, ISHM also includes support for deciding what actions to take in response to a failure or a failure precursor. These actions can include reconfiguration of redundant or non-redundant hardware, maintenance actions performed by the crew, maintenance actions performed on the ground (for reusable vehicles), recalibration of sensor values or commanded values to compensate for degraded hardware, and mission replanning to accommodate degraded systems. The field of ISHM includes sensor development and optimization of sensor placement (Zhang, 2005), but this survey focuses only on the algorithms used for fault detection, diagnostics, and (especially) prognostics.

A simple form of prognostics, known as a life usage model, is widely in use. This method is applicable to components that have been mass produced. It gathers statistical information about the amount of time that a component lasts before failure, and uses these statistics collected from a large sample of components to make remaining life predictions for individual components. These predictions are based solely on the passage of time and/or measures of usage of the system or component. For example, for a timing belt on an automobile, the manufacturer may recommend that the belt be replaced after five years or 60,000 miles. The recommendations from these life usage models are not based on any measured characteristics of the individual component. This survey is primarily concerned with condition-based prognostic methods, i.e., methods that take advantage of measured characteristics of a particular system or component of interest in order to make predictions, and not on life usage models.

Frameworks that illustrate the use of computational intelligence algorithms within ISHM have been discussed in the literature. For example, Bonissone (2006) defines this framework in the cross product of the ISHM decision's time horizon and domain knowledge type and structure.

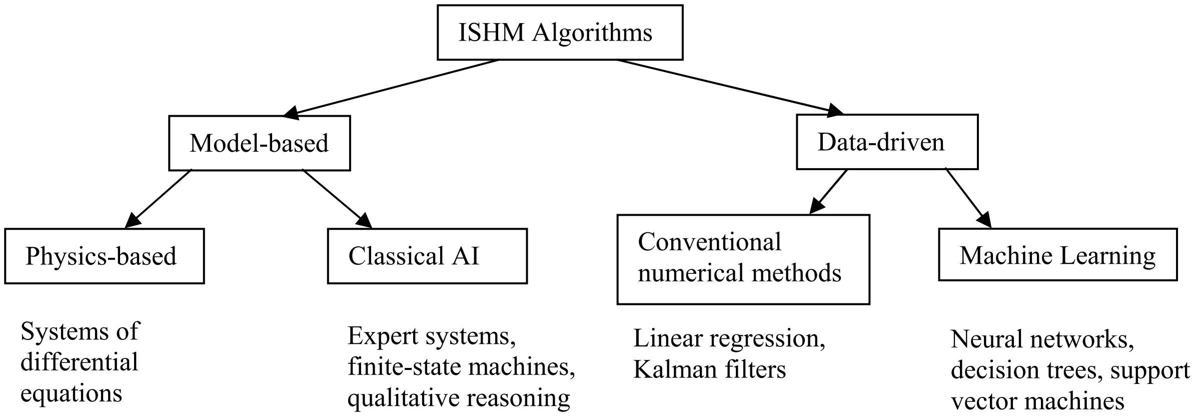

Figure 1: Taxonomy of ISHM algorithms. Examples of each of the four types are shown at the bottom of the figure.

Within this framework, the full range of ISHM functions are defined. In contrast, the present paper classifies different types of ISHM algorithms in a taxonomy shown in Figure 1. With the strong caveat that the boundaries between the different classes are not crisp, we distinguish here between algorithms that are model-based and algorithms that are data-driven. We use a narrow definition of the term "model-based" wherein algorithms encode human knowledge via a (more or less) hand-coded representation of the system. Such a model can be either physics-based (encapsulating first principles knowledge using systems of differential equations, for example), or based on techniques from Artificial Intelligence (AI). Since AI is notoriously ill-defined, we adopt for the purpose of this paper a definition (in contrast to the more strict Turing test) that subsumes elements of learning and the ability to deal with ambiguity, including elements from soft computing, computational intelligence, machine learning, etc. Model-based AI techniques include rule-based expert systems such as SHINE (James & Atkinson, 1990) and G2 (Gensym, 2007). Other examples of model-based AI techniques are finite-state machines, as in Livingstone (Williams & Nayak, 1996; Kurien & Nayak, 2000) and Qualitative Reasoning (Weld & de Kleer, 1989), where a hand-coded model uses qualitative, rather than numerical, variables to describe the physics of the system.

Data-driven approaches automatically fit a model of system behavior to historical data, rather than hand-coding a model. Data-driven approaches can either use "conventional" numerical algorithms, such as linear regression or Kalman filters, or they can use algorithms from the machine learning and data mining AI communities, such as neural networks, decision trees, and support vector machines. The term "machine learning" is ill-defined as well. We adopt here a definition of machine learning that imposes a degree of complexity on the learning aspect. That definition excludes linear regression and (marginally) Kalman filters, but it includes decision trees, case-based reasoning, clustering, and neural networks, for example.

In Table 1, we have constructed a matrix in which the rows represent the four types of algorithms from Figure 1, and the columns represent the three ISHM problems that we identified earlier in this section (fault detection, diagnostics, and prognostics). In each cell, we provide a representative (not exclusive) example of a method that uses the specified type of algorithm to solve the specified problem. Note that two cells are empty. There is little evidence of current activity in applying purely physics-based algorithms to diagnostics. This is not to say that it has not been done or could not be done. Indeed, one could imagine a diagnostic system that has a physics-based model of the nominal operation of a system and physics-based models of several fault modes. When the sensor data fails to match the nominal model, the system would simulate several candidate failure modes in parallel, and compare the simulated data from each failure mode with the sensor data. A match would result in a diagnosis. However, employing this approach to diagnostics may not be the most efficient way to accomplish diagnostics. One could also imagine a physics-based model augmented with if-then rules coded in a conventional programming language to perform diagnostics. Such a system would be considered a hybrid of a physics-based model and a very simple expert system.

The second empty entry in Table 1 is for AI-model-based prognostics for which no specific references are cited here. Again, one could of course imagine a rule-based

Table 1: An example method for each pair of ISHM problem (columns) and algorithm type (rows)

	Fault detection	**Diagnostics**	**Prognostics**
Physics-based	System Theory		Damage propagation models
AI-model-based	Expert systems	Finite state machines	
Conventional numerical	Linear regression	Logistic regression	Kalman filters
Machine learning	Clustering	Decision trees	Neural networks

expert system being used for prognostics. For example, such a system might employ a set of rules that specify that when certain sensor values first exceed a particular set of thresholds, a component has a given amount of remaining useful life. One could argue that rule-based systems are found in fuzzy logic systems. However, most of the fuzzy logic systems that are used for prognostics are encapsulated in a learning paradigm so that the overall system looks more like a machine learning system than an expert system.

Certainly, the work for which ample references are available in AI for prognostics—the subject of this symposium and of this survey—is in the domain of machine-learning.

This survey also includes hybrid methods that combine the machine learning approaches with one or more of the other approaches. For all methods, we are interested in the full spectrum of technology readiness levels, from basic research to deployed systems.

The next three sections are each devoted to one of the AI-related approaches described above. Since many systems use a combination of these approaches, they could fit into more than one of these sections. We have chosen, however, to include each system in the one section in which we feel it best fits.

Most ISHM systems devote a large amount of effort to pre-processing the data using various algorithms including signal processing algorithms in order to extract the features that can be used for fault detection, diagnostics, and prognostics. While pre-processing is extremely important to the success of an ISHM system, it is not the focus of this study.

We previously published a survey of data-driven prognostics in 2005 (Schwabacher, 2005). The present paper briefly summarizes that survey paper, and adds new work that has been published in the past two years. It also focuses more on work that uses the AI approach. Other recent survey papers have focused on the application of prognostics and other parts of ISHM to particular applications, such as heating, ventilation, and air conditioning (Katipamula & Brambley, 2005a; Katipamula & Brambley, 2005b), electronics (Vichare & Pecht, 2006), manufacturing (Goh et al., 2006), and wheeled mobile robots (Luo et al., 2005). Patterson-Hine, et al. (2005) presented a survey of diagnostic techniques for ISHM.

Data-Driven Prognostics

One of the most popular machine-learning approaches to prognostics is to use artificial neural networks to model the system (Bonissone & Goebel, 2002; Byington et al., 2004b; Byington et al., 2004c; Byington et al., 2003; Chinnam & Baruah, 2003; Chinnam & Mohan, 2002; Gebraeel et al., 2004; Goebel et al., 2007; Kallappa & Hailu, 2005; Khawaja et al., 2005; Kozlowski et al., 2001; Lavretsky & Chidambaram, 2002; Lee, 1996; Naipei et al., 2003; Roemer et al., 2005a; Shao & Nezu, 2000; Sharda, 1994; Stone & Jamshidid, 2005; Studer & Masulli, 1996; Watson & Byington, 2005; Weigend & Gershenfeld, 1993; Werbos, 1988). Artificial neural networks are a type of (typically non-linear) model that establishes a set of interconnected functional relationships between input stimuli and desired output where the parameters of the functional relationship need to be adjusted for optimal performance. This adjustment is typically accomplished by exposing the network to a set of examples, observing the response of the network, and readjusting the parameters to minimize the error. Several techniques can be employed to adjust (or "train") these parameters, including a range of gradient descent techniques and optimization techniques (Bishop, 1995).

Another machine-learning approach is anomaly detection algorithms (also known as novelty detection or outlier detection algorithms). These algorithms learn a model of the nominal behavior of the system, and then notice when new sensor data fail to match the model, indicating an anomaly that could be a failure precursor (Bock et al., 2006; Clifton, 2006; Volponi, 2005). Other machine-learning techniques used for prognostics include reinforcement learning (Bock et al., 2005; Kalgren & Byington, 2005), classification (Watson & Byington, 2005), clustering (Byington et al., 2003), and Bayesian methods (Amin et al., 2005; Gebraeel, 2006).

Data mining algorithms seek to discover hidden patterns in large data sets (Hand & Smyth, 2000). Some authors have addressed the use of data mining algorithms to assemble and process the data needed to train data-driven prognostic algorithms (Reichard et al., 2005b; Sandborn et al., 2005).

Another popular AI technique that is used for prognostics is fuzzy logic (Amin et al., 2005; Bonissone & Goebel, 2002; Byington et al., 2004b; Byington et al., 2004c; Byington et al., 2003; Chinnam & Baruah, 2003; Frelicot, 1996; Kozlowski et al., 2001; Studer & Masulli, 1996; Volponi, 2005). Fuzzy logic provides a language (with syntax and local semantics) into which one can translate qualitative knowledge about the problem to be solved. In particular, fuzzy logic allows the use of linguistic variables to model dynamic systems. These variables take fuzzy values that are characterized by a sentence and a membership function. The meaning of a linguistic variable may be interpreted as an elastic constraint on its value. These constraints are propagated by fuzzy inference operations. The resulting reasoning mechanism has powerful interpolation properties that in turn give fuzzy logic a remarkable robustness with respect to variations in the system's parameters, disturbances, etc.

When applied to prognostics, fuzzy logic is typically applied in conjunction with a machine learning method, and is used to deal with some of the uncertainty that all prognostics estimates face. Indeed, uncertainty representation and management is at the core of performing successful prognostics. Long-term prediction of the time to failure entails large-grain uncertainty that must be represented effectively and managed efficiently. For example, as more information about past damage propagation and about future use becomes available, means must be devised to narrow the uncertainty bounds. Prognostic performance metrics should take the width of the uncertainty bounds into account. Khawaja et al (2005) introduced a confidence prediction neural network that employs confidence distribution nodes based on Parzen estimates to represent uncertainty. The learning algorithm is implemented as a lazy or Q-learning routine that improves uncertainty of online prognostics estimates over time. Alternative techniques for dealing with uncertainty include Dempster-Shafer theory (Goebel et al., 2006; Kallappa & Hailu, 2005), or using a Bayesian framework with relevance vector machines combined with particle filters (Saha et al., 2007). In another effort to reduce uncertainty, the concept of prognostic fusion has been introduced (Goebel and Eklund, 2007; Xue et al., 2007). Here, similar to multiple classifier fusion, the output from several different prognostic algorithms is fused such that the resulting output is more accurate and has tighter uncertainty bounds than on average the output of any individual algorithm alone.

It is not uncommon to find that researchers have been trying to extend tools commonly found in diagnostics to prognostics. For example, Przytula and Choi (2007) suggest the use of a Bayesian Belief Net (BBN) for prognostics where the past and future usage need to be discretized and inference on remaining life can be accomplished within the framework of BBNs.

In a similar vein, case-based reasoning (and its variants such as instance-based reasoning), an important tool in the domain of diagnostics, has been proposed for use in a diagnostic setting. Saxena et al. (2005) propose the use of time history traces as cases that can be used to perform prognosis. Xue et al. (2007) propose an instance-based model that they test out on aircraft engine date. In contrast to Saxena, the particular local models proposed here are not based on individual models that consider the track history of a specific engine nor are they based on a global model that would consider the collective track history of all the engines. Instead, the authors use local fuzzy models that are based on clusters of peers where a peer is described by similar instances with comparable operational characteristics and performance. A collection of competing instances is generated that are evaluated with respect to their performance in light of the currently available data. The models are refined using evolutionary search, and the best one is selected after a finite number of iterations. The best model at the end of the evolutionary process is used at run time to estimate remaining useful life.

Some of the conventional numerical techniques used for data-driven prognostics include wavelets (Wang & Vachtsevanos, 2001; Chinnam & Mohan, 2002; Roemer et al., 2005a; Sheldon et al., 2007), Kalman filters (Byington et al., 2004b; Byington et al., 2004c), particle filters (Orchard et al., 2005; Saha et al., 2007), regression (Brown et al., 2006; Goebel et al., 2006; Veaux et al., 1998), demodulation (Roemer & Byington, 2007; Sheldon et al., 2007), and statistical methods (Byington et al., 2004a; Kallappa & Hailu, 2005; Watson et al., 2004). Hernandez & Gebraeel (2006) combined a life usage model with a data-driven technique by using sensor data to automatically update the life usage model.

Another area where prognostics intersect with artificial intelligence techniques is in the area of post-prognostic decision support. Challenges arise from the large amount of different information pieces upon which a decision maker has to act. Conflicting information from on-board and off-board ISHM modules, seemingly contradictory and changing requirements from operations as well as maintenance for a multitude of different systems within strict time constraints make operational decision-making a difficult undertaking. Post-prognostic decision support will enable the user to make optimal decisions based on his expression of rigorous trade-offs between different prognostic and external information sources. This can be accomplished through guided evaluation of different optimal decision alternatives under operational boundary conditions using user-specific and interactive collaboration. Iyer et al. (2006) present some preliminary results of the use of such a decision support tool. Tang et al (2007) describe a control reconfiguration that is based on prognostic information. Short-term objectives and long-term objectives are dealt with in separate reasoners which are optimized to simultaneously accomplish several different goals.

Some authors have collected laboratory data to be used for data-driven prognostics, but have not yet applied any algorithms to the data (Kalgren et al., 2007; Nanduri et al., 2007). Some data repositories are being made publicly available which can be used to baseline different data-driven algorithms (NASA Ames Research Center, 2007)

Prognostic Architectures

Several authors have proposed architectures for health management that include fault detection, diagnostics, and prognostics, and that can use both AI methods and conventional methods (Beshears & Butler, 2005; Bock et al., 2005; Brotherton et al., 2005; Byington et al., 2005; Byington et al., 2004a; Kalgren et al., 2006; Reichard et al., 2005a). BEAM (Beacon-based Exception Analysis for Multimissions) is a system developed at JPL that has nine components that use nine different approaches to fault detection, including supervised learning, unsupervised learning, and physics-based models (Mackey et al., 2000). BEAM has been tested on various space applications, including using historical data from the Space Shuttle Main Engine (Park et al., 2002).

Applications of Prognostics

Automated prognostics has been applied to several different types of engineered systems, including actuators (Byington et al., 2004b; Byington et al., 2004c; Watson & Byington, 2005), aerospace structures (Roemer et al., 2005a), aircraft engines (Kallappa & Hailu, 2005; Volponi, 2005), batteries (Kozlowski et al., 2001), bearings (Gebraeel, 2006; Roemer & Byington, 2007; Sheldon et al., 2007), clutch systems (Watson et al., 2004), cracks in rotating machinery (Orchard et al., 2005), electronics (Brown et al., 2005; Brown et al., 2006; Byington et al., 2005; Hernandez & Gebraeel, 2006; Kalgren & Byington, 2005; Kalgren et al., 2007; Nanduri et al., 2007; Sandborn et al., 2005; Vichare & Pecht, 2006), gas turbines (Byington et al., 2004a; Clifton, 2006; Roemer et al., 2006), hydraulic pumps and motors (Amin et al., 2005; Byington et al., 2003), military aircraft turbofan oil systems (Bock et al., 2006), semiconductor manufacturing (Stone & Jamshidid, 2005), heating, ventilation, and air conditioning (Katipamula & Brambley, 2005a; Katipamula & Brambley, 2005b), wheeled mobile robots (Luo et al., 2005), and Unmanned Aerial Vehicle (UAV) propulsion (Brotherton et al., 2005). Some authors tested their systems on more than one application. Khawaja et al. (2005) tested their system on a Navy chiller and a helicopter gearbox. Ginart et al. (2006) applied their system to power electronics and electric machinery.

The Joint Strike Fighter (JSF) aircraft is currently under development (JSF, 2007). It will be used by the U.S. Air Force, Navy, and Marines, and by certain U.S. allies. The current plan for it is to have a Prognostics and Health Management (PHM) system that provides fault detection and isolation for every major system and subsystem on the aircraft, and prognostics for selected components. PHM is a key element in the justification for the choice of a single-engine aircraft and it is intended to both improve safety and reduce maintenance costs. It will use model-based, rule-based, and data-driven approaches. The proposed architecture includes an off-board PHM system (OBPHM), which will use data mining techniques. Recent publications in the area of prognostics for the JSF include (Bock et al., 2005; Hess et al., 2005).

Conclusion

In our 2005 survey, we concluded that prognostics is extremely difficult, and noted that although much research had been done in the area, we were not aware of any deployed prognostic systems that take advantage of measured characteristics of the systems being monitored (but there are of course deployed life usage models). In the two years since then, we have been encouraged to see that more researchers have gotten to the point of building prototype systems that make predictions of remaining useful life, such as (Gebraeel, 2006; Amin et al., 2005). Other researches have built prototype systems that estimate the current level of degradation on a numerical scale, without making the final step of predicting the remaining useful life (Brown et al., 2006; Byington et al., 2003). However, we are still not aware of any deployed prognostic system, i.e., systems at a high technology readiness level (TRL 7-9). Some of the systems reviewed here are proposed architectures that have not yet been built (Beshears & Butler, 2005; Brotherton et al., 2005; Byington et al., 2005; Kalgren et al., 2006; Reichard et al., 2005a), some are systems that have been tested using laboratory data (Kalgren et al., 2007; Kozlowski et al., 2001; Nanduri et al., 2007; Roemer & Byington, 2007; Sheldon et al., 2007), and some are systems that have been tested using simulated data (Kallappa & Hailu, 2005; Watson et al., 2004). Simulations and laboratory tests offer the opportunity to simulate or induce faults that have never occurred in flight. Using real flight data, however, forces researchers to address all of the nuances that occur in real flight, such as noise and unexpected signals from unrelated subsystems. Prognostics of complex engineered systems remains an area in which much more research and development is needed. AI and related techniques can offer an important part of the solution, in conjunction with more conventional methods.

One of the biggest challenges for AI-based prognostics and for the rest of ISHM is verification and validation (V&V). The complexity of AI systems makes them very difficult to verify and validate before deployment. AI-based V&V may offer the potential to help solve this problem. Some research has been done in using the AI approach to verifying diagnostics models (Pecheur et al., 2000).

Another possible area for future AI research is the question of what to do after detecting a failure precursor. The research in AI planning and scheduling could be very relevant to planning maintenance actions or replanning the mission. Some research has been done in automatically planning the recovery actions to take after diagnosing a failure (Muscettola et al., 1998).

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