

A Framework for Prognostics-Integrated: Intelligent Aviation Services

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ABSTRACT

Advances in new sensor and wireless technologies—from auto-ID technologies to prognostics for anticipating product health—are ushering in a new generation of products that are “aware” of their current status and thus able to perform functions related to their use, health, and maintenance. At the same time, distributed intelligence and new information environments such as the cloud are enabling the coordination and synchronization of product-centered business processes, often remotely. By linking smart products to smart processes companies are creating a new platform for providing next-generation intelligent services to their customers. In this paper we present a framework for linking smart products (with embedded real-time diagnostics and prognostics based health management capabilities) to a service-provisioning system to create a system of “self-aware” product-centric systems. The framework includes a powerful “learning” engine capable of monitoring, analyzing and interpreting patterns of system/product behavior in real-time. The learning engine provides the capability of information feedback for real-time, “in-the-loop” control. This concept enables the service-provisioning network to provide customer services such as product health management at reduced maintenance costs, improved responsiveness to customer needs during use, and generally more efficient operations. This framework, being developed by the University of North Carolina, is a collaborative effort between the Center for Logistics and Digital Strategy and its partner companies to create the next generation of intelligent aviation services.

INTRODUCTION

Prognostics-integrated intelligent aviation services represent a significant opportunity to not only achieve significant cost savings and enhanced product reliability, but also to develop new revenue-generating service offerings. Developing these services requires companies to build “self-aware” product-centric systems that link prognostics-enabled “in the loop” products and intelligent support processes—in essence to build an intelligent envelope of smart services around a product. While the primary focus in this paper is on products, the concept is extendable to physical systems in general such as manufacturing systems or communications infrastructures.

The central driver of these trends is the benefit derived from real-time, closed-loop support in which prognostics and other analytics serve as an integral element in the feedback control scheme. In this context, closed-loop describes the capability of the complex product (for example, an aircraft) embedded in a smart support system (for example, a maintenance system) to self-monitor and regulate its activities based on a real-time comparison of the actual product performance with desired performance levels.

Self-aware product-centric systems are being enabled by the convergence of new sensor technologies, new information environments like the Cloud and, most importantly, by new software tools capable of real-time extraction of useful information from highly complex, large-scale datasets. Possibilities include the extraction of “significant details” from apparent noise, and hidden correlations across apparently unrelated sensor data. The availability of Internet-based Cloud Computing provides a vehicle not only for computation and analysis, but also for communication between the product, the user, and also the manufacturer or controlling enterprise. In essence, the Cloud makes it possible for a manufacturer to offer a range of services to the user across the product’s entire life cycle—from design and development through operational use until ultimate disposal or recycle.

The advent of Internet technology with its TCP/IP protocol-enabled open-architecture offered the ability to make information posting and access available anytime, anywhere, in single copy, and searchable. Thus, the ability to provide prognostics information along the chain, thereby closing the feedback loop, has been a reality for a several years. The recent emergence of cloud computing provides a new information environment for integrating products and services to better serve the customer—from aerospace manufacturers to producers of consumer products.

Until now, the bottleneck for prognostics-enabled services has been the human operator’s limitation in exploiting information in real time and recognizing complex relationships across large-scale information systems. A combination of rule-based, collaborative and learning technologies can be deployed as an underpinning to current business systems and as an enabler of a dynamic feedback loop—connecting, in real-time, all control elements from the in-use, onboard diagnostics/prognostics system to the upstream and downstream manufacturing and production logistics chain, use, maintenance and other support processes, such as engineering change management, and R&D support.

The goals of this paper are to: 1) advance the thinking about prognostics-enabled services in complex industries such as aviation; 2) provide decision-support capabilities for the intelligent use of sensed information in massively complex and distributed information environments; and 3) explore the potential for a new class of service offerings that envelop the product at all stages of its life cycle.

MOVING FROM DIAGNOSTICS TO PROGNOSTICS

As shown in Table 1 below, the general field of product health management has evolved as technical capabilities have become available. Until recently, many of the current applications focused on diagnostics, rather than prognostics. These technologies diagnose problems after failure or service degradation has occurred. In the commercial aircraft arena, for example, The Boeing Company has developed The Mechanics Compass, a system that facilitates the airplane maintenance process by automatically gathering, organizing and presenting the most pertinent information required by a mechanic to identify the source of a specific system failure, as identified by observable symptoms and findings. The Mechanics Compass uses technologies such as Bayesian Belief Networks and others that model probabilistic dependencies between the historical data linking cause and effect in order to correct failure.

Table 1. From Diagnostics to Self-Aware Systems

Stage	Description	Enabling Technology	Capabilities
Diagnostics	Sensored Product	Bayesian belief networks, statistical models, etc.	Diagnose failure after the fact based on post-failure analysis
Prognostics	Product-in-the-Loop	Neural networks, machine learning, etc.	Anticipate failure or other state that requires action to maintain design performance specifications
Self-Cognizance	Online Product-in-the-Loop Intelligent Support Processes	Cloud computing, machine learning, etc.	Closed loop information feedback system creates integrated support system

Prognostics implies a framework of methodologies embedded within an information environment that permits the reliability of a system to be evaluated and communicated in real time based on its life-cycle state and relevant environmental conditions. Prognostics about future states enable the user to take any necessary actions ranging from averting failure in the event of broad performance deterioration

to changing operating conditions or environment to achieve performance improvements and reduce life cycle costs.

Thus, prognostics involves [do we use prognostics as a plural or singular term?] the process of predicting the future state of the system. A prognostics system is comprised of sensors, a data acquisition system, and micro-processor-based software to perform sensor fusion, analysis, and reporting/interpreting of results. Smart Sensors are typically built into products with the ability to relay this information to an operating base, thus enabling on-board diagnostics and prognostics. [generally smart sensors have built-in A/D conversion for bus interface, but not actual computational capabilities]

We refer to prognostics-enabled products as “products-in-the-loop” systems because the products have the ability to assess their own health and to direct that information to appropriate functions or organizations that make decisions about how to respond. After an action is taken, usually, but not necessarily, initiated by a human, the product is able to sense its new state and continue to self-monitor for changes in health or other conditions.

Offline prognostics for vehicle health monitoring, as well as remote diagnostics, are used extensively in complex products like aircraft engines and long haul vehicles for both surface and rail transport, and on defense products such as weapons platforms and munitions. More recently this technology is infusing commercial products such as washing machines, personal automobiles and even buildings.

“CLOUD” CONNECTED PRODUCT HEALTH MANAGEMENT

Today, Cloud Computing broadly refers to a trend in service delivery where application services are moved onto the Internet—termed the Cloud. Yet Cloud Computing also holds the promise of advancing physical systems diagnostics and prognostics to a new level of speed and cost-effectiveness.

Up till now there has been a progression of prognostics capabilities for complex physical systems such as aircraft, ships, automobiles, and related complex manufacturing systems starting with bench level analysis and mathematical model based prognostics. The subsequent generation introduced diagnostics downloads to base stations, either on location (e.g. CARB-based diagnostics downloads via data cable in the auto industry) or online, for faster response and corrective action.

The more recent prognostics concepts allowing for onboard real time computation, alerts, and prognostics, including alerts to maintenance and C&C, are those described so far in this paper. These approaches rely on a real time “observe, learn, interpret, and act” methodology enabled by product embedded intelligence. A drawback of such embedded systems is the added complexity within the product and the associated cost.

With emerging “Cloud Computation”, such disadvantages may be overcome. Cloud embedded computational software can process either continuously or batch transmitted data, so that the only required product embedded capability is sensing and internet connectivity. For example, the use of Cloud-embedded associative memory based learning agent software discussed above can be used for a fleet of vehicles (aircraft, automobiles, etc.), or a number of machines in a manufacturing system, without having it installed on each machine or even base station.

Thus, intelligent products with embedded diagnostic software are replaced by “street smart” products, saving cost and letting the “cloud” do the work – a form of “cyber-outsourcing”. A similar argument holds for base station embedded software; using the “Cloud” avoids software redundancy and eliminates the need for local software maintenance, updating and the associated manpower.

So we see the promise of “street smart” products as the future truly intelligent and self-aware entities in the physical world of machines, be they planes or cars or manufacturing systems, communications infrastructures, or the power grid.

THE EVOLUTION OF SELF-AWARE SYSTEMS

With the advent of Internet based connectivity and the emergence of Cloud-based near real-time computation, sensed products are increasingly being integrated within a (near) real-time information and computational environment with intelligent support processes which allows for autonomous intervention (c.f. change in operating characteristics) with little or no human intervention. The prognostics and analytics that support self-aware systems may be simple rules that link an aware state with a response. Increasingly, however, these intelligent support systems are differentiated by the ability to learn from past experience the “best” action to restore normal operating modes or avert failure.

Another barrier beyond speed is the ability to process extremely the extremely large set of parameters that are required to represent the operating state of a complex system—and learn. The emergence of new tools, in particular associative memory, that can fully exploit the information content and MEANING in these extremely large, complex and distributed datasets. Most, if not all, current data mining and other pattern recognition techniques are ineffective—and expensive—because they are unable to process the voluminous amounts of information typical of large-scale, sensed environments.

Many of today’s prognostics use technology that is based on statistical inference in which observed events in the past are used to assess statistical probabilities (Bayesian approaches) or to fit statistical models (regression or neural nets, for example). These approaches cannot handle large data sets efficiently, may involve model building, and often require off-line analysis. Innovative new technologies, such as associative memory technology, bridge these barriers thereby enabling real-time in-the-loop autonomous control of complex products and their physical support processes through

its ability to discern patterns in large-scale, distributed, dynamic data that are not detected by traditional methods.

Machine learning methods (c.f. artificial neural networks, genetic algorithms, and decision trees) typically learn from an incomplete set of examples. These technologies, like neural nets, have had limited success with extremely large-scale datasets. At their current state of development, neural computing approaches have limited suitability for massively complex, large-scale problems due to an inherent problem with scaling. For example, patterns involving as hundreds or thousands of factors such as airframe vibrations, engine temperatures, oil viscosities, oil pressures and so forth, can signal the impending shut-down of an engine or catastrophic part failure, allowing the pilot and/or ground crews to avoid unanticipated failure.

One pattern recognition technology, referred to as associative memory, has proved to be highly scalable and efficient in cases of extremely large datasets. The implementation of associative memory used by the authors was developed by Saffron Technology in Cary, North Carolina. Details of the technology and its applications are provided on the company web site (www.saffrontechnology.com).

Saffron's associative memory, modeled after the human brain, exploits a proprietary lossless (i.e. does not lose information) compression routine that is capable of creating extremely compact models. Further, the Saffron implementation is able to operate on compressed datasets, unlike other pattern recognition technologies, thereby enabling dramatic reduction in storage and CPU hardware, thus enabling the application of associative memory technology in a distributed, "on-board", environment.

PROGNOSTICS-INTEGRATED INTELLIGENT AVIATION SERVICES

While the fully-sensored and always connected "things" has received a lot of attention lately, largely under the heading of "internet of things," what hasn't received a lot of attention are the new business models and revenue-generating opportunities that will be possible in this world of self-aware products. Self-aware products change the traditional pathways of information flow in companies. But, more importantly, they change the traditional pathways of information flow between products and customers, between customers and manufacturer, AND between products and manufacturer. At the heart of the change is the fact that the basic ownership model between product and customer is broken and redefined in three dimensions as follows:

Products and Customers. Under the old ownership model, the product was the responsibility of the owner upon purchase. While warranties could provide an extension of the ownership, the customer assumed control of the product through its useful life. Further, the operation and use of the product was controlled directly by the customer. As an example, when a customer bought a product s/he must often

adjust the settings to personalize it. A self-aware product linked to the user's personal cloud would automatically adapt the product to the user's specifications based on a retained profile, or even adapt the product's settings based on the context of its use. In the example of prognostics and health management, products could automatically adjust operating parameters in order to enhance reliability.

Customers and Manufacturers. Under the old ownership model, after the arms-length purchase transaction the company and consumer relationship had been completed. However, the self-aware product provides a continuing link between the company and the customer that can serve as a source of additional revenue through the provision of a range of services over the product's lifetime. In the example of prognostics and health management, a current example is the relationship between engine manufacturers like General Electric and airframe manufacturers like Boeing in which GE monitors the operating characteristics of an in-flight engine for potential engine failures.

Products and Manufacturer. While the manufacturer has acquired new opportunities to gain additional revenues under the new model, its product responsibilities also increase. The company may now find itself responsible for the lifetime care of every product that it manufactures even as the product acquires multiple users over its lifetime. The company will retain the complete lifecycle data from operation and maintenance. The company may now also be responsible for disposal and end-use practices. For example, in the care of prognostics and health management, an airframe manufacturer may be required to tag and track all materials for appropriate recycle or disposal upon disposal, or to track sustainability metrics over the lifetime of the product.

CONCLUSION

The convergence of new sensor technology, cloud computing, and powerful learning-capable pattern recognition technology is making it possible for companies to make better health decisions about their assets and products across their entire life cycle—from manufacture through useful lifetime and, finally, disposal. Sensor technology has made large strides, as has communications technologies. Currently, software is reaching a level of maturity in which prognostics can move into more widespread use in commercial applications. And information environments like the cloud enable a pervasive environment for data management. The Center for Logistics and Digital Strategy at the University of North Carolina is working with its clients to develop new concepts and technologies that can help to transform business practices with new prognostics-enabled self-aware systems in both commercial and defense sectors.

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