Paper presented at the International Society of Logistics (SOLE) 1999 Symposium, Las Vegas, Nevada, August 30 – September 2, 1999.

Development of a Framework for Predicting Life of Mechanical Systems: Life Extension Analysis and Prognostics (LEAP)

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Abstract—The focus of this paper is on health monitoring of complex mechanical systems for diagnostics, prognostics, and maintenance scheduling. We discuss challenges faced in developing and implementing a general methodology for predicting the remaining useful life of mechanical systems, and challenges to institutional and logistical processes for exploiting prognostics.

Introduction

Prognostics is the process of predicting the future state of a system. Prognostics systems comprise sensors, a data acquisition system, and microprocessor-based software to perform sensor fusion, analysis, and reporting/interpreting of results with little or no human intervention in real-time or near real-time. It offers the promise of minimizing failures (especially failures "in the field"), extending the time between maintenance overhauls, and reducing life-cycle costs. But prognostics is still in a research and development phase, and implementing prognostics is a monumental task on several levels—the technical challenges involving hardware and sensor technologies, the analytical challenges involving predictive methods, and the logistical challenges centering on how to make use of prognostic information.

Advances in Data Collection

Advancements in electronics, sensors, computer processing speed and memory, and communications are enabling more reliable and less expensive field data collection to support diagnostics and prognostics. Some examples of such advancements are smart microsensors, ultrasonic sensors, acoustic emission sensors, smart memory cards, radio-frequency tags/multi-sensor modules, and cellular data links. With control microprocessors, these sensors and instrument packages may be fabricated within a size, cost, weight, and power requirement that will allow deployment directly onboard host equipment.

Data Analysis Methods

As hardware and sensor technologies make it more feasible to collect critically needed field data, interest has grown in improving analysis techniques. A hardware and software architecture for diagnostic and prognostic analysis of sensor data for a turbine engine application has a system-level architecture that is sufficiently general to apply to a variety of mechanical systems (Greitzer et al., 1999). Analysis proceeds through a series of stages or components, beginning with sensor validation and progressing through diagnostics and prognostics analyses. This system, called TEDANN (Turbine Engine Diagnostics using Artificial Neural Networks) uses artificial neural networks (ANNs), rule-based algorithms, and model-based approaches at each of these stages. The prognostics output is based on trending of parameters that are output from the diagnostic module. Both short-term and long-term trends are computed using linear regression, which attempts to predict the time until components fail or will fall below operational specifications. It is recognized that more sophisticated analyses may enhance the value of the prognostics output, and a current internal research project (LEAP, for Life Extension Analysis and Prognostics) at the Pacific Northwest National Laboratory is investigating more advanced approaches.

Prediction may be addressed using any of a variety of statistical techniques, depending upon the prognostic goals/requirements. Examples of goals are: (a) predict the value of parameter **Y** at time **t**; (b) predict the time **t** when system performance/efficiency will be at level **Y**; (c) predict the time until the next overhaul is needed; or (d) predict the cost-benefit ratio of removing equipment from service at time **t**. Of course, the use of the term "time" may be misleading, as it is clear that elapsed time or calendar time is a poor unit of measure for a mechanical system. Better manifestations of the variable "time" might be "running time" or "cycles" or a measure of "work" produced (e.g., joules or torque-time).

Candidate statistical methods include multivariate regression, Bayesian regression methods, time-series analysis, and discrimination or clustering analysis. Analysis may focus on a single parameter or multiple parameters. For single parameter prognostics, statistical analyses may be performed simultaneously on each real-time data source. As data are collected, regression models are applied to the data to determine trends (see Figure 1(a)). This is compared, in

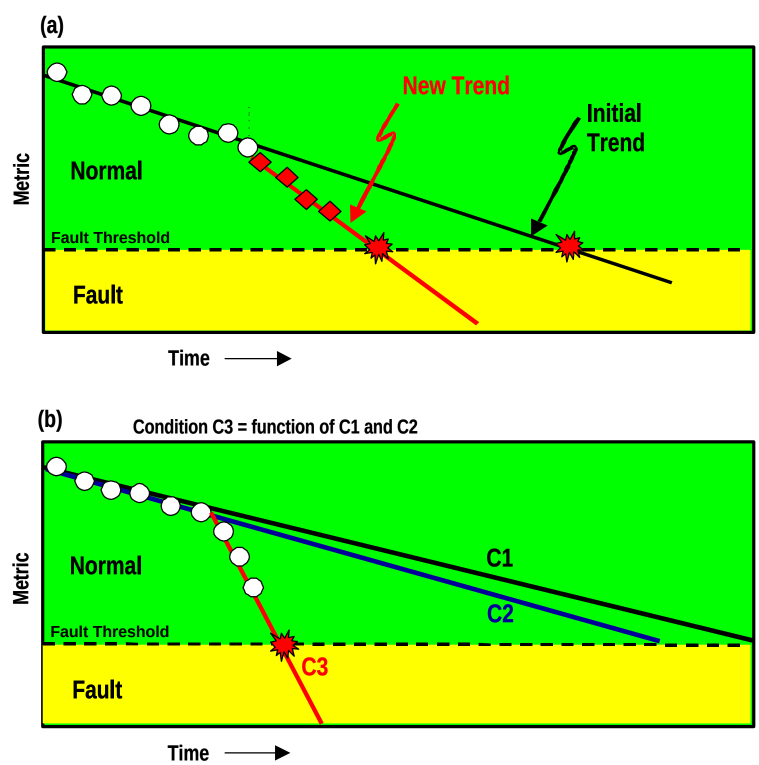

Figure 1. (a) Single-Metric or Univariate Prognostics and (b) Multivariate Prognostics

real-time, to a metric failure limit that is established offline. The point of predicted failure is calculated as the intersection of these two lines. If an unexpected event occurs that dramatically increases degradation, it is immediately identified and addressed.

For multivariate prognostics, interactions among individual equipment parameters are sought. This is illustrated in Figure 1(b). In this example, two parameters, C1 and C2, are being monitored. Separate analyses of each do not indicate a pending failure. Taken together, however, failure is imminent because a slight degradation of both parameters is symptomatic of a drastic change in performance. In certain cases, this could be described by a relatively simple algorithmic model that reflects the physics underlying the relationship among the parameters. For example, engine efficiency is a commonly used indicator of engine health that is calculated from multiple thermodynamic data sources. In these cases, the data would be used to estimate the parameter values while still closely reflecting the physics-based model. In other cases, however, the underlying physics model may be too complex to be determined by a simple algorithm. Effective analytical approaches may require empirically-driven, non-linear, non-parametric regressions such as artificial neural networks or other multivariate statistical techniques—including partial least squares, seemingly unrelated regressions, and canonical correlation.

In each of these cases, the response of the system depends on the severity and consequences of the impending failure. For example, if a failure is not estimated to affect immediate operations, the prognostics program may only notify the central scheduling process. If the failure is estimated to affect immediate operations, the operator is notified, or in extreme cases, the machine may shut itself down to prevent catastrophic failure. In general, it is obvious that in order to benefit from prognostics information, appropriate action must be taken. This leads to the third major issue to be addressed.

Impact/Application of Prognostics

Traditional maintenance practice is either a function of a somewhat arbitrary rule-of-thumb (e.g.; maintenance every 90 days or 1000 hours of operation) or reactive—equipment is not fixed until it breaks, and parts, supplies, personnel and tools required for maintenance are not placed in the pipeline until maintenance is scheduled. As a result, when the actual demand is greater than expected and parts begin to fail early, the ramp-up time for maintenance may be steep and inefficient, particularly when personnel, parts, materials or other resources are not available or located nearby. If parts do not exist, this can result in a large production deficit and substantially increase delays and costs (see Figure 2). On the other hand, when the actual demand is less than expected, a traditional maintenance and acquisition system may suffer unnecessary costs associated with idle personnel and parts being purchased too early.

Traditionally, scheduled maintenance based on mean-time-between-failure (MTBF) statistics attempts to reduce this problem, but this typically results in equipment being replaced before it is necessary or (more typically) is ineffective when equipment breaks before the expected time. Inevitably, over time both will happen. When a schedule is based on an averages (in this case, MTBF), it will be too high about half the time and too low about half the time. As a consequence, either too few or too many repair/maintenance activities will be scheduled almost all of

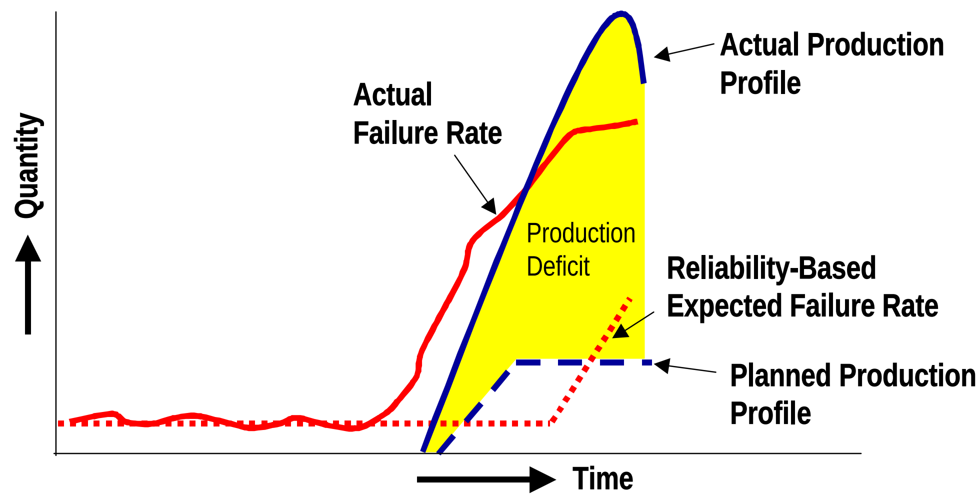

Figure 2. Reactive Acquisition Processes Suffer Production Deficits or Delays

the time. This MTBF-based system is illustrated in Figure 3, where historical data are used to calculate MTBF statistics that drive maintenance, acquisition, and resource scheduling decisions. To minimize the impact of failures, maintenance must be scheduled early, which incurs unnecessary costs.

In contrast, Figure 4 illustrates how prognostics can impact the process of scheduling maintenance, ordering parts, and using resources. Included is the prognostics framework for predicting future wear. The left side of Figure 4 shows the *non-real-time* activity of establishing wear models. Although data may be collected in real-time, many months of data from many pieces of equipment are required to develop accurate and comprehensive wear models. Once these models are developed, they are downloaded to each piece of equipment for use in the real-time prognostics module.

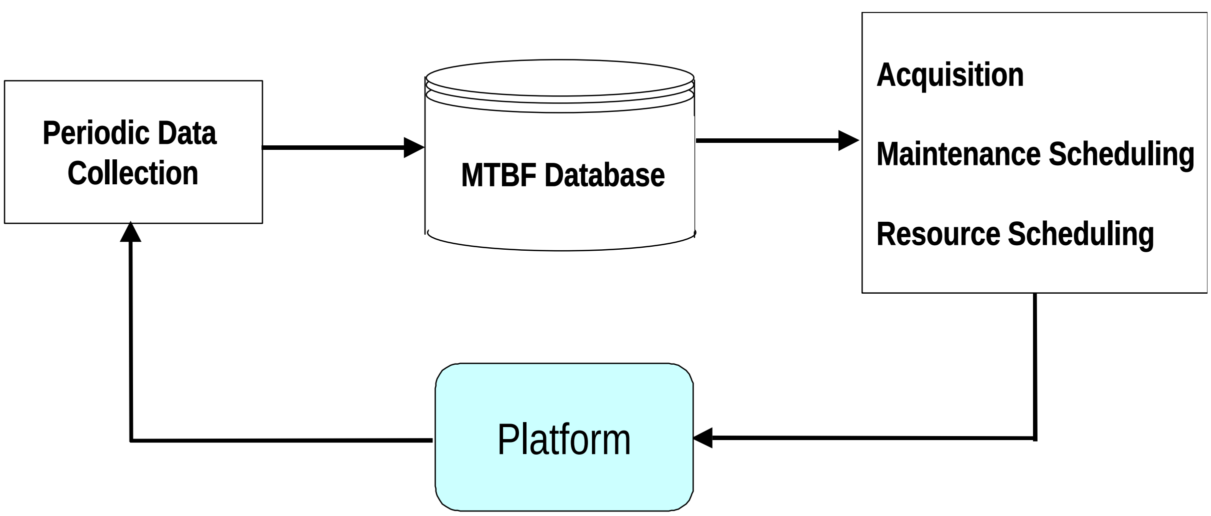

Figure 3. Traditional Scheduling Framework

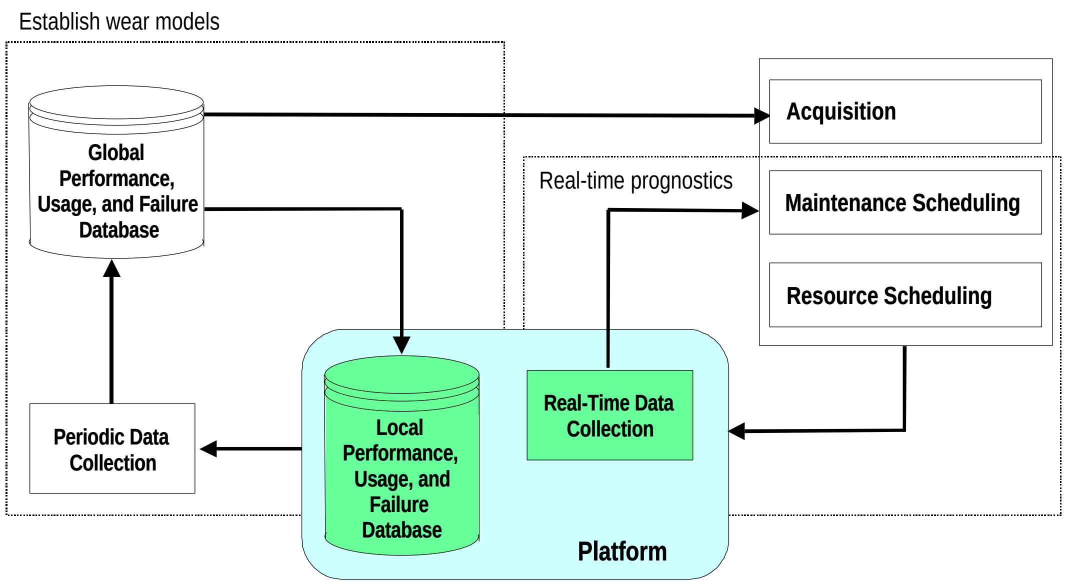

Figure 4. Prognostics-Enabled Scheduling

The right side of Figure 4 illustrates the use of *real-time* prognostics. Onboard the system, data from sensors, current usage, and the environment are used in conjunction with the wear models to predict performance and wear in real-time. Once a failure or excessive degradation is predicted, data about the impending event may be forwarded to a central logistics system. There, maintenance is scheduled based on these data, and necessary equipment and parts are ordered to arrive just in time for the maintenance.

Figure 5 illustrates the benefits of a proactive acquisition process that is driven by prognostics. Here, failures may be predicted early so that maintenance and acquisition systems can be primed, significantly reducing maintenance ramp-up time because parts are available in the pipeline to meet projected demand. The ability to benefit from prognostics requires proactive business practices. Organizations need to evolve beyond their reactive processes and adopt new proactive objectives.

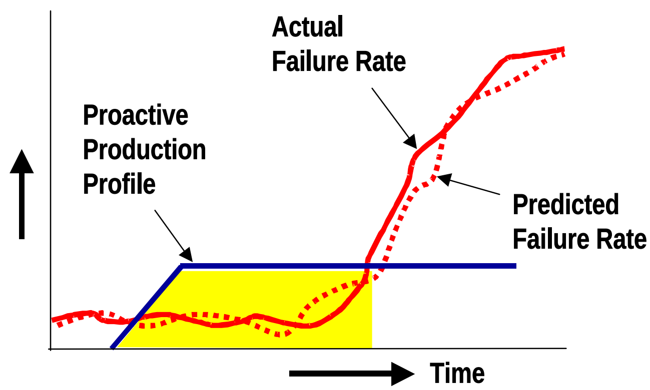

Figure 5. Prognostics-Enabled Proactive maintenance/Acquisition Process has Reduced Ramp-Up Time and Greater Resource Availability

LEAP Project

The Pacific Northwest National Laboratory's LEAP project is developing a system architecture for prognostic predictions that will support different applications and include several analytical methods. The system is initially focused on two rather different types of applications. One application is for the gas turbine engine used in the US Army M1 Abrams tank (Greitzer et al. 1999). This application uses data acquired in real-time from a set of 48 sensors (temperatures, pressures, etc.) onboard the engine. A second application is for a large diesel electric engine used in locomotives. The data acquired for the diesel locomotive engine application is restricted to a set of specialized in situ oil analysis sensors (Wilson et al. 1999). The oil analysis sensors use X-Ray fluorescence, viscometery, and non-dispersive infrared analysis to measure wear metals, viscosity, and lube oil oxidation, nitration, and sulfate formation. These are critical indicators of the health and status of the engine that may be linked to specific fault or degraded conditions.

Summary and Conclusions

Increasingly, economic considerations do not allow owners to replace equipment in their aging fleets, and thus there is pressure to extend the life of equipment well beyond the initially expected life. This is true for many kinds of complex mechanical systems including military tanks, aircraft, ships, locomotives, and heavy earth-moving equipment. Today the focus is on high-value systems. As technology is advanced to reduce size, weight and cost, and increase reliability of prognostics systems, the applications will migrate to more plentiful, lower-value systems with potential for greater cost savings.

To extend the life of complex mechanical systems and to reduce operational/life cycle costs, solutions must be found to reduce or eliminate premature failures and associated collateral damage, as well as to reduce or eliminate the down time that results from an inefficient maintenance/resupply process. Private industry and the military are realizing that maintenance/logistics systems must factor in the cost of "wait time" or "down time." This will increase emphasis on predictive maintenance—where parts, tools, and personnel are scheduled to be at the right place and at the right time to effect repairs. This requires real-time, onboard prognostics systems that monitor the health of equipment and are able to diagnose degradations in performance and predict faults, so that appropriate upkeep may be scheduled. Equally important, it requires that organizations be responsive to available prognostics information. For most organizations, achieving this proactive status amounts to a major transition that needs to be planned and managed. This will require workforce planning, training, scheduling and deployment to meet the new needs of the organization. Logistics, maintenance, procurement, and acquisition systems must be re-engineered for proactive operations.

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Acknowledgement

This research and development was conducted as internally-funded Laboratory-Directed Research and Development at the Pacific Northwest National Laboratory (PNNL). Pacific Northwest National Laboratory is operated by Battelle for the U.S. Department of Energy under contract DE-AC06-76RLO1830.

About the Author

Frank L. Greitzer is a Staff Scientist at Pacific Northwest National Laboratory. He holds a BS degree in Mathematics and a PhD degree in Mathematical Psychology. His professional experience includes twenty years of research and development in performance support systems, including artificial intelligence/expert systems applications. Dr. Greitzer is currently the Project Manager for the TEDANN project and Principal Investigator for an internally-funded research and development project called LEAP (Life Extension Analysis and Prognostics), aimed at developing a methodology for predicting the remaining useful life of mechanical systems.