Evaluating Predictive Technologies for PHM

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Prognostic health management (PHM) offers significant savings in maintenance costs, increased asset availability, and improved safety over traditional maintenance approaches for aerospace and other complex or critical systems. Prognostic management of equipment health should include both analysis of what is already occurring (diagnosis) and prediction of what might occur in the future (prognosis). For many applications, diagnostic technologies are now available that can detect an incipient fault well before it becomes severe enough to warrant maintenance action. However, technologies that accurately predict the future progression of a fault have lagged behind. The goal of this paper is to highlight some of the issues prognostics users may want to consider when evaluating predictive technologies.

It would be nice if PHM could tell us that a particular component or system will fail next Tuesday at 3:45 pm, but all predictions by their nature have some uncertainty. Regardless of how good our knowledge of the current system state is, the processes (such as fatigue) that transform the system from its current state to its future failed state are stochastic. We know that if we test 100 nominally identical components that have identical initial states under identical conditions, we will get a range of different outcomes. Figure 1 shows a hypothetical failure probability density function (PDF) from such a test. A predictive model that perfectly replicates the system degradation processes should generate the same PDF as the test data. A prediction with less uncertainty than the true PDF is incorrect and portrays a false sense of confidence in an inherently stochastic process.

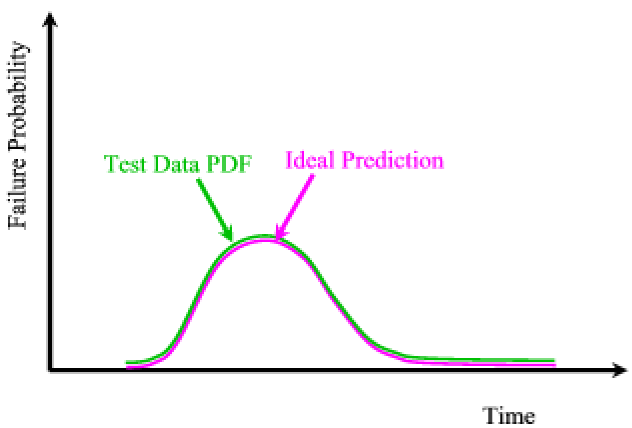

Figure 1. Baseline failure PDF derived from a carefully controlled set of tests and ideal prediction.

The PDF from the test data will of course change if we change *any* variable - the type of component, the initial state, or the conditions. The prediction from an ideal model should change in exactly the same way. Models based on first principles rather than simplistic curve fits are often adaptable to a different application (for example, changing the material of the target gear), which reduces the cost and risk of development. In addition, models that don’t replicate the underlying physics very well are usually only accurate over a small range of conditions. This must be compensated for by adding additional uncertainty to the prediction so that the “expanded” prediction encompasses the real results.

Uncertainty inflation reduces the value of prognostics. In predictive maintenance applications, decisions are not based on the most likely failure time, but on the time at which the *risk* of failure will exceed some threshold. The just-in-time (JIT) point in Figure 2 represents the latest time at which maintenance can be performed while keeping the risk below the allowable threshold, i.e. the point where (*allowable risk)*% of the area under the PDF curve has already passed (the shaded area). The time remaining before the JIT point is called the lead time; Figure 2 shows how the lead time is reduced if the uncertainty in the prediction is greater than the ideal. Many of the benefits of predictive maintenance and autonomic logistics result only if decisions and maintenance actions are proactive rather than reactive. We suggest that a minimum prognostic lead time of at least one complete mission cycle is needed to ensure sufficient time for planning and response, and that additional lead time would further reduce costs.

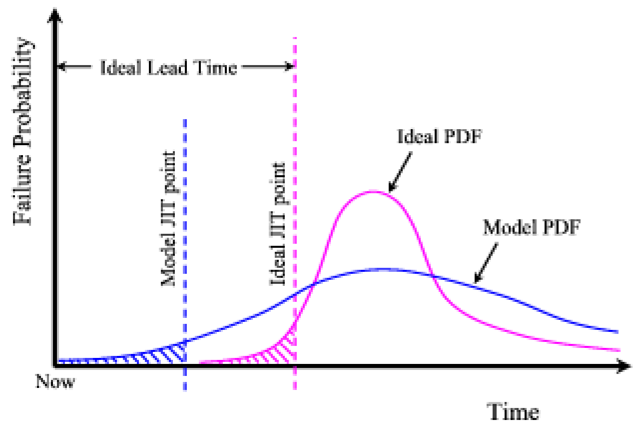

Figure 2. Reduction of prognostic lead time due to uncertainty inflation.

Prediction uncertainty should gradually decrease during component life as diagnostic data is accumulated; this is referred to as convergence. Methods for fusing diagnostic data with predictive models vary, but the vendor should be able to demonstrate smooth and stable convergence over a range of examples using actual diagnostic and ground truth data. In some applications, diagnostic data may be unreliable or unavailable (e.g., sensor failure); the model should be able to generate some sort of reasonable prediction even in this case. Predictions are not terribly useful until they start converging on a relatively stable result. Figure 3 (from Engle, Gilmartin, Bongort, and Hess, 2000) shows the convergence of the JIT point to a stable, accurate result at about 225 minutes before failure. Predictions that jump around for no obvious reason are evidence that there is not enough uncertainty in the model, i.e. that it does not properly account for normal system variability.

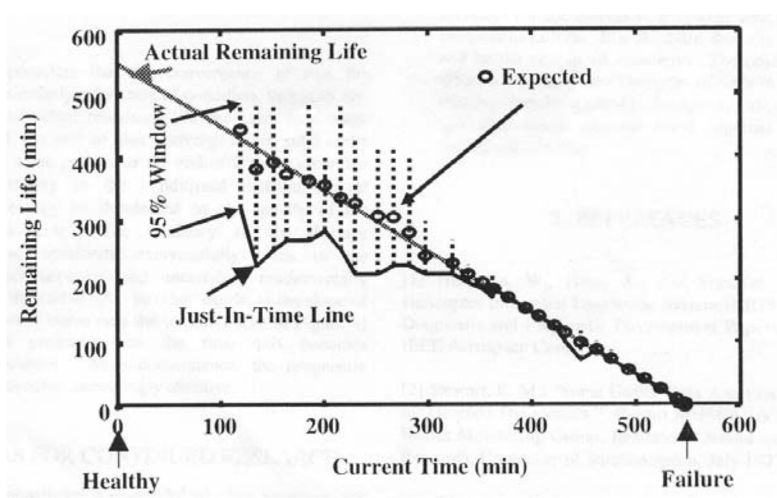

Figure 3. Prediction convergence as failure approaches (from Engle et al., 2000).

In PHM applications, a major source of added uncertainty is the estimated future usage of the system. If we knew exactly how the system would be used, then we could precisely account for that in the prediction. Unfortunately, that is usually not the case. If the model requires usage information, future usage may be estimated by the system and/or by users. The best approach depends on the particular application and the level of user involvement. Minimizing this added uncertainty improves prognostic lead time.

Data sets produced in carefully controlled lab tests might not replicate what happens in the real application, but they are extremely useful for measuring the degree to which the predictive model approaches the theoretical ideal. Plus, lab tests can be much more economical than running, say, 100 fully instrumented helicopters to failure. Of course, the closer the tests are to reality, the more valuable the data is. Faults should be allowed to develop naturally, although seeded fault tests are sometimes a necessary evil for rare fault types or those that take a very long time to develop. Lab tests should be run with the same components and operating conditions used in the target application whenever possible.

The PHM user should be able to specify the measure(s) of fault severity used to define failure as well as the failure criteria. For example, a bearing prognostics module might use fatigue spall length as the severity metric, with failure defined as a spall length > 5% of the total raceway length. The vendor should understand how fault severity affects performance so they can make a valid recommendation.

Finally, all models of system degradation processes have a limitation of scope. Some fault progression modes may be unforeseen, impossible to model, or too rare to justify consideration. In these situations, the model should (1) recognize that the fault progression is not within its scope, and (2) provide an alternate indication of future condition, or at least a warning that prognosis is not possible.

Summary of issues to consider when evaluating a predictive model:

1. How well does the model predict the results of a set of carefully controlled tests?
2. Over what range of operating conditions and initial states is the model accurate?
3. Is the predictive model based on first principles?
4. How much uncertainty does the model itself add? How does this effect lead time?
5. Does the prediction uncertainty decrease as failure approaches (convergence)?
6. Is the prediction stable over time? What happens if diagnostics are unreliable or unavailable?
7. Does the model require usage information? How is future usage estimated?
8. Can the vendor explain how the test data conditions differ from the application conditions and what the effects on real-world performance might be?
9. Can the user specify the fault severity metric and failure criteria? Can the vendor make a meaningful recommendation?
10. Does the model recognize fault progression modes that are outside its scope?

<u>Reference:</u>

Engle, S., Gilmartin, B., Bongort, K., and Hess, A., 2000, “Prognostics, the Real Issues Involved with Predicting Life Remaining”, *2000 IEEE Aerospace Conference*, Big Sky, MT, March.

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