Diagnostics Driven PHM

The Balanced Solution

Jim Lauffer

DSI International, Inc.
Orange, California 92867, USA
jlauffer@dsiintl.com

ABSTRACT

Much effort has been made to develop technologies and define metrics for Prognostics Health Management (PHM). The problem is that most of this effort has focused on theoretical and high risk concepts of Prognostics performance while ignoring the real needs in "System Health Management". In the wake of this technological attention, the importance of true Integrated Systems Health Management (ISHM) has been masked by the focus on single failure mode physics of failure solutions. The critical PHM metrics, derived from Integrated Systems Diagnostics Design (ISDD) have mostly been ignored. These critical metrics include Reliability, Safety, Testability, and System Maintainability & Sustainment, as well as the impact of prognostics performance on Systems Diagnostics. A key point to be made is that the ISDD process is much larger than just developing metrics. ISDD results in a well-designed system that meets true health management needs, as well as significantly lowering development costs, and the cost of ownership. Another point that needs to be made is that the core of ISDD is a proven and highly effective analysis solution in Model Based Diagnostics. This paper discusses the approach of using Model Based Diagnostics in the ISDD process to determine the best balance of the Health Management design. It will be shown how the impact and effectiveness of prognostics as integrated with the ISDD process provides true value to performance and cost avoidance.

1. THE SKEWED PHM TECHNOLOGIES

New York University mathematics physicist, Alan Sokal, submitted an article on current physics and mathematics based around quantum mechanics / chaos theory (Sokal, 1994&1995). Sokal's article was republished by top scientist in 1996 citing Sokal's article as a credit to scientific research. Soon after Sokal explained in a new article that his publication had been salted with nonsense, and in his opinion was accepted because: (a) it sounded good and (b) it flattered the editor's ideological preconceptions.

It turns out that Sokal's Hoax served a public purpose to attract attention to what Sokal saw as a decline of standards of rigor in the academic community. Today, this philosophy of Sokal's Hoax can easily be applied to Government, Industry and Academia on the subject of Prognostics Health Management. Far too many technologists and business managers fall into the "hoax" that systems can be prognosed to predict, within a known Remaining Useful Life (RUL) parametric, for any and all failures; then to go on to promote this RUL prediction of precluding all failures that will prevent system operational failures and enhance sustainment.

Back about thirty years ago this author had his first experience with prognostics based on signature analysis. As a result of this operation, the U.S. Navy looked into using signature analyses from the ship's noise propagation to predict a signature shift that could possibly be leading to a failure. After much trial and error on this concept, and after unnecessary consumption of spare parts and maintenance labor hours, it was decided that this form of "prognostics" was not working.

A major U.S. project was based on PHM being the core to the prevention of catastrophic failures and system aborts through prognostics. This PHM system would also provide the operational data needed to drive an Advanced Logistics Information System (Gill, 2003). After investing untold millions in U.S. dollars, it is recognized that the planned PHM path must be modified. The realization that you cannot prognose an entire system is finally coming into focus. The idea of using the proven technology of Model Based Diagnostics was discarded early in the program due to the same philosophy Sokal exposed. By the way, the original definition of PHM was Diagnostics and Prognostics Health Management. It did not take long for diagnostics to be displaced by the more "exciting" prognostics exclusivity.

If you have read this far, you are probably thinking that this author is anti-technology development and is only trying to promote an old method for determining the Health Management of a system. This is far from the intent of this paper! This author has been a proponent of advanced technology development from the 50s during the early transition from vacuum tubes (valves as some say) to solid state technology, and on to today's prognostic technologies. He has attended courses at Georgia Tech and has worked with prognostics professionals. From all of this, it has to be said that prognostics plays a very powerful role in PHM and is the way of the future. With that said, it is also apparent that prognostics is not a "Systems" health management technology. It is limited to selected failure modes that must not be allowed to fail due to system criticality. In depth physics of failure analysis, proper sensors, and precise processing needs to be in place to determine RUL when a single failure mode approaches a critical state. Keep in mind that the focus is on a single failure mode, and even into the molecular structure of this single mode. Even then, this processed single failure mode effect must be observable at the system level to be considered a functional component of PHM.

This is in contrast to a typical operational platform with tens of thousands, or even hundreds of thousands of failure modes. It is obvious that the prognostics technologies are far from capable of performing system level PHM. There have been attempts in AI, Bayesian Networks, Boolean Logic, and others to perform this PHM System analysis. But, these have been shown to be ineffective, at a very high cost and risk.

As stated, there is a need for integrated prognostics that can map a prognosed event to overall System PHM. Investment into prognostics must be accountable, not just bought in to satisfy study funding. Thousands of pages have been written on prognostics but those studies have had a difficult, if not impossible, time performing in a fielded system, let alone contribute any value to design influence.

Over the last decade or so, the demand for increased prognostics within complex, critical systems has resulted not only in changes to how these systems are developed, but also to the way in which designs are analyzed as they are developed. In particular, system analysis practices have been moving away from true System Health Management values, such as reliability, testability, maintainability, sustainment and the critical parametric today - Cost. Some critical systems have focused on prognostics details while, to the most extent, ignored the ISDD process. System designs now either pursue high cost and risk custom solutions to focus on prognostics, incorporate prognostic details into other calculations, or ignore prognostics altogether. This issue is amplified by the fact that much of the value in reliability and testability analysis can best be realized when design feedback is available relatively early in the development cycle. On the other hand, prognostic development and the evaluation of prognostic performance take years of operational time to obtain any metrics of value. It is unlikely that information derived from formal prognostic performance metrics (Saxena, et al, 2010) can be incorporated into systems engineering analyses to profitably impact system development and decision-making. At the same time, un-validated prognostics can lead to low Availability and high sustainment cost due to false removals. This results in notoriously time-consuming and costly prognostic performance

As an alternative, some projects have implemented custom solutions, modifying design-time engineering analyses to account for the expected impact of prognostics concurrently under development. There is, however, no standardized or officially sanctioned approach to accounting for prognostics performance. For each project, systems analysts must ask a series of questions; for example, diagnostic analysts must decide whether fault detection & isolation metrics should take full or partial credit for prognosed failures, or whether testability analysis can be constrained to cover only the non-prognosed portion of the design. In either case, should prognostic horizon and/or accuracy be taken into consideration?

If so, then how is the end user or maintainer expected to respond to prognostic notifications without questioning them? Will there be cases in which some sort of confirmation will be required before a maintenance action is performed? Then the key question is, should diagnostic analysis be consulted when determining the optimal areas in which to develop prognostic measurements or will only criticality considerations be involved in the selection of prognostic candidates?

The root of these, and other related questions is the lack of realistic and cost effective requirements, and the lack of systems diagnostics understanding. So, what is the solution to effective and affordable PHM? The answer is obvious – Model Based Diagnostics. This Model Based Diagnostics is a proven technology that has been in use for decades. In the past 20 plus years it has come to be recognized as the systems engineering tool of choice throughout industry.

Without going off track on the balancing of prognostics and diagnostics in PHM development, it needs to be mentioned that there is once again a push for something new in the field of diagnostics analysis. There has been talk of Model Based Diagnostics falling out of "fashion" within the same community that has proliferated prognostics. Also, Model Based Diagnostics has received some bad press from entry level tools whose use has been attempted on projects where the tools failed to perform. Unfortunately, these unproven tools resulted in high costs with no acceptable results.

These failures to perform lead the technology community to downplay the use of Model Based Diagnostics and they became vulnerable to high cost and high risk solutions. They are told Model Based Diagnostics is considered obsolete due to construed higher order mathematical solutions. The issue is these "non-model based" solutions have significant problems with development skill needs, high cost, lack of system integration, and are limited to small scale analyses. Just as prognostics entered as the "new and improved" health management solution, other analytical solutions are continuing to be pushed into the new wave of thinking without the understanding of a systems engineering approach.

One such solution attempt has been tried over the years in several research communities and this is based on Bayesian Networks. As with prognostics, a Bayesian Network requires extensive development and cannot begin until the design is well defined. Then, if there is a design change, the analysis needs to start all over again. Even if a network can be completed, it is limited to smaller systems, cannot provide knowledge to the Logistics sustainment solution, and still requires years of learning to "fine tune" the results.

2. DIAGNOSTICS DRIVEN PHM

Now that this author has ripped "stand alone" attempts at prognostic solutions, the following discussion focuses on effective diagnostics driven PHM based on Model Based Diagnostics. This ISDD process is centered on a proven tool suite and process that brings the system design into an optimized PHM solution. This solution provides the confidence needed for fault detection and isolation at the system level that includes the impact of prognostics on diagnostics. This ISDD process identifies the candidates needed for an effective prognostics analysis. It also provides the parametrics used for and Operational and Support Simulation. This simulation capability is shown in section 5.

For the system design to be optimized for effective health management and sustainment, the diagnostics design process needs to begin early in the design process. This is something prognostics cannot do. The diagnostics analysis results in a selection of candidates for prognostics analysis. See Figure 1 for this diagnostics informed prognostics analysis process.

As emphasized, for optimum results in design influence, the ISDD process needs to begin at the start of the project's design phase. This is where PHM and sustainment must be considered to be effective and affordable. Along with testability requirements (the probability of fault detection, isolation to a defined ambiguity set, and false alarm constraints), PHM and logistics requirements must be understood.

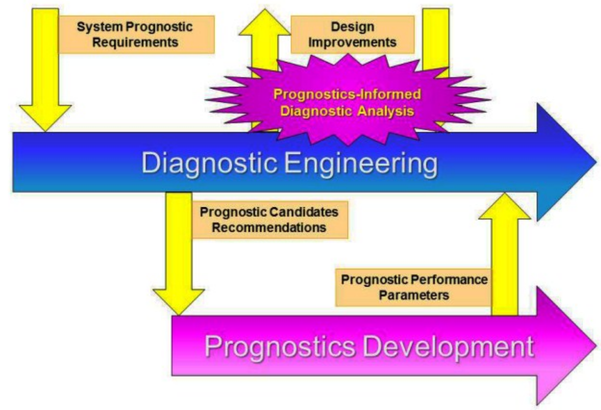

Figure 1. Diagnostics selection of prognostics candidates

With this in mind, and to keep this paper on track, the following discussion focuses on system prognostics requirements as driven by the ISDD process.

Figure 1 shows these prognostic requirements being defined at the beginning of the diagnostics engineering development. This is a critical point in PHM design and is where the customer typically falls short in requirements definitions. Very few customer project managers understand prognostics well enough to flow down cohesive prognostic requirements. To be effective, these initial prognostics requirements now need to be included in the diagnostics test definitions in the form of prognostic tests. These prognostic parametrics are defined in section 3.1.

As the diagnostics analysis is developed, prognostic candidates are developed as part of the optimized diagnostics results. The prognostics candidates are prioritized based on the failure mode severity and the failure rate. The primary candidates are those failure modes that cannot be allowed to progress to failure, and failure mitigation through functional redundancy is not practical or possible. An example of a prognostics candidate list derived from the diagnostics analysis is shown in Figure 2. This example is not intended to be an eye test but is used to show the format of a typical candidate list. Note that in the example, two Loss of Life severities are listed below the Loss of Equipment candidates. This is not to suggest Loss of Life is less important, it is just listed based on the lower failure rates. In an actual prognostics assessment, these two candidates would certainly be considered important. But, at the same time, if their Loss of Life failure probability is very low, the prognostics for this failure mode may not be cost effective.

Prognostic Candidates				
##	Failure Mode	Item	Maximum Severity	Failure Probability
1	Pad squeeling	Front Pads	Loss of Equipment	0.020211
2	Pad Squeeling	Front Pads	Loss of Equipment	0.020211
3	Pad Squeeling	Front Pads	Loss of Equipment	0.020211
4	Pad Squeeling	Front Pads	Loss of Equipment	0.020211
5	Pad Squeeling	Rear Pads	Loss of Equipment	0.020211
6	Pad Squeeling	Rear Pads	Loss of Equipment	0.020211
7	Pad Squeeling	Rear Pads	Loss of Equipment	0.020211
8	Pad Squeeling	Rear Pads	Loss of Equipment	0.020211
9	Switch Fails Open	R Pump	Loss of Life	0.009600
10	Pedal Linkage Failure	Brk Pedal	Loss of Life	0.005775

Figure 2. Prognostic Candidate List from Diagnostics

Continuing in the diagnostics engineering process, the diagnostics analysis results, along with selected prognostics tests, are fed into the product design to support the PHM design solution. This provides the all-important design trade study process that builds a well-balanced, diagnostics driven, PHM solution. Later in the process it is shown where prognostics parameters may be available to further optimize the diagnostics analysis.

3. SYSTEM PROGNOSTIC REQUIREMENTS

The following discussion focuses on the approach to incorporating prognostic considerations into areas such as reliability, testability, maintainability and sustainment analyses. This is accomplished by representing expected prognostic behavior in terms derived from system prognostic requirements. This will show how these parameters can be used to define prognostic behavior within a diagnostic engineering process. Finally, this will show how these prognostic definitions can be used to modify the results of standard measures of diagnostic effectiveness using fault detection and isolation metrics defined within IEEE Standard 1522-2004. This also looks into informed simulation-based approaches for assessing the impact of different prognostic, diagnostic and maintenance strategies. The following definition of requirements, parameters and example are based on a paper by Eric Gould who has developed advanced prognostic influence capabilities in the DSI ***eXpress*** Diagnostics Engineering tool (Gould, 2011). This previous paper is being paraphrased in some sections to provide specific information needed to understand how prognostics is used in the ISDD process.

Even though the academic technology of system prognostics has been around with study support since the 1990s, the understanding of prognostics requirements are relatively new to design development projects. This is compared to system diagnostic and testability requirements which have been around since the 1980s. It is therefore not surprising that there has been a fair amount of variance in the definitions of desired prognostic capabilities from one project to another.

For effective prognostics requirements to be defined, a process for the derivation of these requirements must be understood and followed. Aspects covered by these qualitative descriptions include 1) whether the prognostics shall be embedded in the system, 2) whether prognostics shall be automated or initiated, 3) whether prognostics shall be developed solely for the determination of mission-readiness or also for the optimization of Logistics, 4) whether prognostics results shall be reported to the crew, maintenance technicians, and/or mission planners, and 5) whether prognostics shall consist solely of condition-based observations of failure precursors or whether it can also contain predictions based on the failure rates and stress histories of individual components. Although information of this type is essential for describing the prognostic capability required for each project, it is not relevant to the following discussion. In the example shown in section 3.2, the requirements have been trimmed down to include only the information needed for a quantitative evaluation of a system's prognostics capability, and the impact of prognostics on systems diagnostics in PHM.

3.1. Prognostic Parameters

With the quantitative aspects of the requirement broken down into individual parameters, it was determined that five basic parameters were sufficient for describing any of the sample requirement statements:

Scope – the set of possible failures to which a given requirement applies. Common scopes include mission critical failures, essential function failures, or failures that necessitate a system abort.

Category – the set of prognoses to which a given requirement applies, such as embedded or sensor-based prognoses.

Horizon – the time before failure that prognosis must occur. This can either be a fixed value (e.g., 72 hours prior to failure) or a calculated value, based on both the desired mission length and the corrective action time associated with each failure.

Coverage – the percentage of failures in the specified scope that must be prognosed. This parameter can either be failure probability-weighted (so that there is greater credit for failures that occur more frequently) or non-weighted (so that all failures in the specified scope are counted equally).

Accuracy – the desired confidence/correctness of the overall prognostic capability (typically defined as a percentage of accuracy). In some requirement statements, Accuracy is bundled with Coverage as a single percentage of failures prognosed.

3.2. An Example of Prognostic Requirements

The following example examines the individual prognostic requirements, parsing each statement into the related parameters and discussing any interpretive peculiarities. All threshold/objective parameters have been simplified so that they are expressed as a single goal.

1) Requirement Example
Prognostics shall predict at least 80% of the mission critical failures 96 hours in advance of occurrence with 90% probability.

Scope: Mission Critical Failures

Horizon: 96 hours

Coverage: 80%

Accuracy: 90%

This prognostic requirements statement has four parameters that collectively specify the expected behavior of the prognostics. Because it reads like a performance requirement — one that specifies the expected performance of a fielded system, greater credit should be given to prognosed failures that occur more frequently than to those that occur relatively infrequently. So, when calculated as an engineering metric, the prognostic coverage should be weighted by the failure probability of each individual failure. The overall coverage can thus be calculated by summing the failure rates of the failures in the scope that can be prognosed, divided by the sum of the failure rates for all failures in the scope.

4. PROGNOSTIC DEFINITIONS

Now let's take a look at how prognostic definitions can be defined within a proven diagnostic engineering tool. There are several reasons why support for prognostics should be added to tools that are used primarily for the creation, assessment and optimization of system diagnostics. First of all, if the tool has been designed for system-level diagnostic analysis, then it already has the infrastructure in place to perform an analysis of system-level prognostic performance. Data from individual prognostic definitions is compiled across the entire system to produce overall measures of prognostic effectiveness— measures that can be easily compared to system prognostic requirements to determine contract compliance.

A second (and perhaps more significant) advantage to representing prognostic measurements within a Diagnostic Engineering tool is that the Reliability, Testability, and Maintainability evaluations performed within the tool will be able to reflect the expected performance of systems for which mission readiness is assured using prognostics. Moreover, diagnostic procedures developed within the tool can be optimized based on the assumption that prognostics will be employed based on real needs.

For example, prior to developing prognostic sensor and algorithm requirements, an analysis of the system can be used to determine the set of failures for which prognosis is most desirable. This takes into consideration not only the criticality and frequency of failures, but also how successfully the system can diagnose and remediate the failures without prognostics. Later, if the bottom line changes and you need to reconsider the value of developing some of the more expensive prognostic sensing and algorithms, you can easily reevaluate the PHM performance that would be achieved if the system were to not have this capability.

A third advantage of adding prognostic definitions to a diagnostic engineering tool's model or database is that this information can be easily exported for analysis within an external tool. For example, simulation-based case studies can be performed using different health management approaches. This will allow PHM analysts to evaluate different combinations of diagnostics, prognostics and preventative maintenance to determine which combinations are most effective, not only from the perspectives of availability or mission readiness, but also sustainment and cost effectiveness. Section 5 describes some of this simulation capability.

4.1. Tests and Prognoses

In proven and accepted model-based diagnostic engineering tools, test definitions are used to represent diagnostic knowledge. To be effective, each individual test definition must specify the coverage of a corresponding fielded operational test or measurement. This coverage identifies the specific functions or failure modes that should be exonerated (removed from suspicion) or indicted (called into suspicion) when that test passes or fails. Tests are organized into different test sets so that they can be easily selected as groups to support different diagnostic case studies. Examples given relate to ***eXpress***, DSI International's Diagnostics Modeling and Analysis tool, and to DSI's STAGE Operations and Support Simulation tool.

Prognostic measurements can be represented using a special type of test definition. This is basically a test definition to which prognostic parameters have been attached. The coverage for each prognosis is represented the same way as it would be for a diagnostic test; the only difference being that the coverage now represents the specific functions or failure modes for which failures can be predicted using prognostics. As with diagnostic tests, prognostic measurements can also be organized into test sets. When a project has prognostic requirements that utilize the Category parameter, the individual measurements should be grouped into sets by category. The analysis can then be constrained by simply selecting the sets that correspond to the desired prognostic categories.

4.2. Prognostic Terms

For each prognostic definition, the analyst must specify one or more Horizons, each accompanied by three variables—Confidence, Correctness and Accuracy—that collectively describe the expected behavior of the given prognostic measurement at that Horizon. See Figure 3 for an example of Prognostic Settings in ***eXpress*** with single horizon.

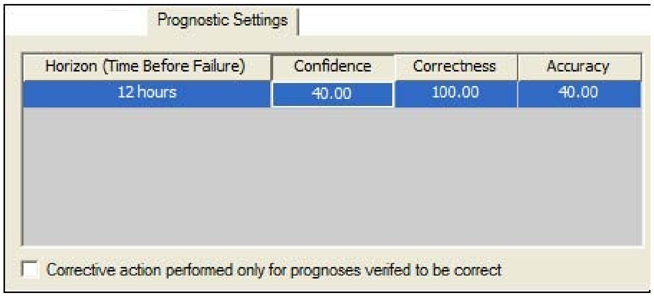

Figure 3. Prognostic Settings in ***eXpress*** with single horizon

The value of the specified Horizon is similar to the Horizon parameter within a prognostic requirement; it represents a time interval before failure that the given prognosis might occur. The Confidence represents the likelihood that the given prognosis will predict the covered failure(s) at or before the specified Horizon. It is expected that Confidence increases as the Horizon decreases; in other words, that predictions become more confident as a prediction approaches the time of failure.

The Correctness variable is used to represent the expected percentage of prognoses that are correct; that is, not *too* early. By default, the Correctness setting affects neither the prognostic nor diagnostic analysis performed using that measurement. The Correctness value, however, can still be used to categorize prognoses within a simulation-based assessment of a proposed PHM approach. Note that excessively early prognoses leads to false aborts and wasted maintenance cost and time.

The calculated Accuracy value corresponds to the Accuracy parameter within a prognostic requirement. Unlike the other two values used to describe a given Horizon, Confidence and Correctness, the Accuracy variable is not defined by the analyst, but rather calculated automatically by the analysis.

A prognostic condition that must be addressed is the need for corrective action to be performed only for prognoses verified to be correct. This is the case when a given prognosis is not only independently verifiable, but will be verified before corrective action is performed. As an example, think of the brake pads on an automobile. As the pads wear past a given point, they begin to squeal when the breaks are applied. This is an intentional design characteristic that allows the owner of the car to identify when the pads need to be replaced. This relates to the squealing of the brake pad as a condition-based prognosis of a pending failure. Now, imagine that, when your brakes start to squeal you inspect the pads and see that there is plenty of life left—the squeal came *too early.* Would you still replace the pads?

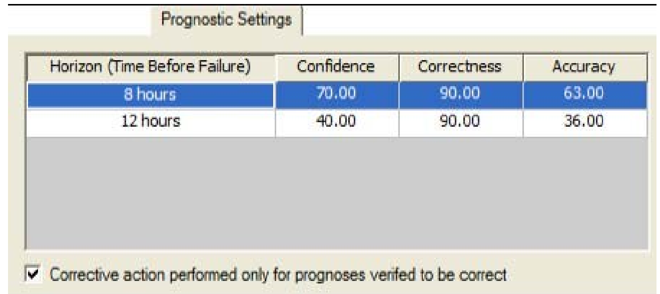

Figure 4. Accuracy calculated using both Confidence and Correctness

From a purely realistic standpoint, the Accuracy of your prognosis would be equal to your Confidence that prognosis would occur prior to failure. If, however, if you only replace the pads when they have truly worn down (when the prognosis was correct) then the accuracy of your prognosis must be adjusted down to account the possibility of these false squeals.

So, when this prognostic condition is selected in the analysis, the calculated Accuracy is equal to the product of the Confidence and Correctness percentages. See Figure 4 for an example of Accuracy calculations. Accuracy then represents the likelihood that the prognosis occurs early enough (Confidence), but not too early (Correctness).

Of course, the real value of incorporating prognostics into a diagnostic engineering model is not so much to facilitate the prognostic analysis itself as it is to develop, assess and optimize systems diagnostics capability This is based on the assumption that a given level of prognosis can and will be achieved.

5. Simulation of Prognostic impact on diagnostics

Figure 5 shows a section of an automotive braking system that has been modeled for diagnostics analysis. The pink highlighted items (1, Brake Pads, 2, Tires) are identified for prognostic testing. The diagnostic results from this analysis were exported in an XML schema (DiagML) to be used for PHM software development and for use in other tools. One of these tools, DSI STAGE, takes the analysis results and performs a Monte Carlo simulation using developed calculations for specific simulation results. Some of these results are presented below to show the diagnostics behavior for systems that are to be supported using selected prognostics derived from the analysis. Note that the simulation graphs shown are for representation of example analyses. Do to scaling of the graphs, the scale legends are not legible and are for reference only. The typical simulation time is 4000 hours of brake operational use.

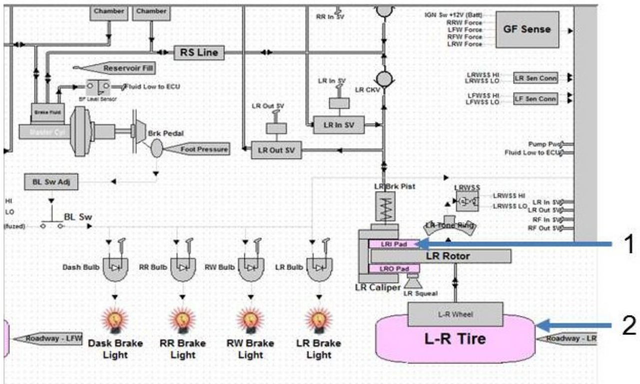

Figure 5. Section of *eXpress* diagnostics model showing targeted prognostic candidates

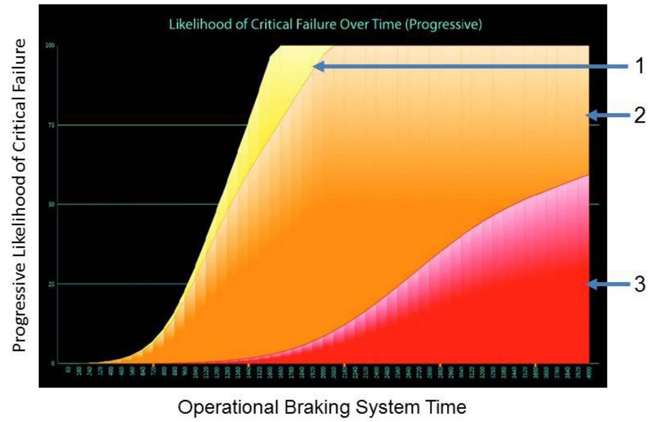

Figure 6. Simulation results showing likelihood of Critical failures over time

This capability of analyzing prognostic performance as part of diagnostics in PHM provides PHM optimization based on both requirements and constraints. Through simulation, the overall PHM solution is evaluated based on how well PHM meets system requirements and how well it can be implemented within cost constraints. Some typical simulation calculations include: Prognostic Effectiveness, Fault Detection and Isolation, Diagnostic False Alarms, Critical Failures, System Aborts, Mission Success, Mean Time Between Failure, Mean Time to Repair, System Availability, Development Costs, Sustainment Costs, and Total Cost of Ownership, plus many more to meet analysis needs.

The following charts are from simulation runs based on the diagnostics results from the model shown in Figure 4. The simulation was run with 500 iterations of an operational time of 4000 hours. The simulation was randomly seeded. The calculations used where: Likelihood of Critical Failures Over Time (progressive), Critical Failures Prognosed Over Time (number), System Aborts Over Time (number), Critical Failure Prognosed per Failure Entity (number), Mean Time Between Prognostics/Maintenance Actions Over Time, and Faults (Despite Prognostics) Over Time.

The use of effective prognostics developed condition based maintenance can reduce the likelihood of critical failures. As seen in Figure 6, the critical failure events on this analysis begin with loss of operation (1–yellow) and loss of equipment (2-Orange), beginning with low probability in the systems operational life cycle. Then, as the system ages, the probability of Loss of operation increases rapidly, followed by loss of equipment. Finally, the loss of life severity (3-red) begins to increase further into the operational life cycle. This is where the assessment of prognostics needs to be performed for those failure modes contributing to these critical failures.

Where the simulation shown in Figure 6 shows total failures progressively over time by severity, Figure 7 shows the number of critical failures over time, and also shows those failures detected by prognoses (4, magenta). These prognosed failures are calculated as being repaired prior to critical failure. Since it well known that prognostics is not 100% correct, other critical failures did occur. These failures are shown by number of failures at a specific point in time. These failures are also identified by severity (1, yellow, loss of operation; 2, orange, loss of equipment; 3, red, loss of life). With the ability to observe types of failures over time, it is now possible to re-analyze the diagnostics, and possibly improve the prognostics effectiveness.

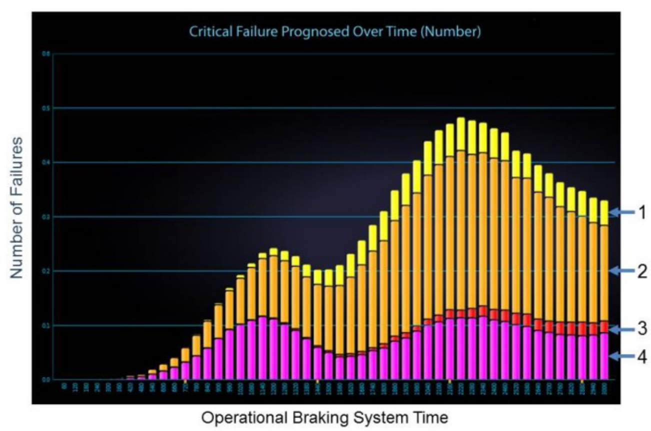

Figure 7. Number of critical failures prognosed over time

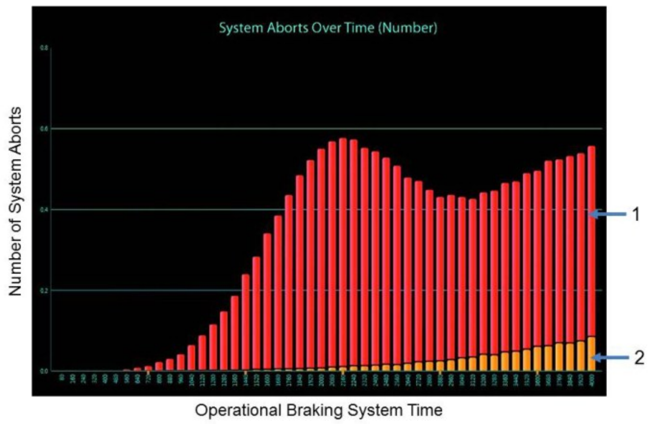

Figure 8. System aborts contributed to inadequate PHM

Figure 8 shows the simulation results for system aborts over Time. This calculation is based on the accuracy of prognostic tests defined in the diagnostics analysis. The "true" system aborts are projected over time as shown at the bottom of the graph (2-orange).

The system aborts contributed to false prognostics are shown in the top of the graph (1-red). This is a design condition that can be corrected by improving the prognostic tests and therefore the accuracy of these tests. Once the prognostics have been assessed for improvement, the diagnostics analysis would be adjusted based on new test parameters. The simulation would then be re-run to validate the results for improvement in system aborts. During this diagnostics update, the "true" system aborts can be assessed. Even though the number of true aborts is low, there may be opportunities for improvement.

Figure 9 shows the number of critical failures over time by failure entity (failed item) and by failure severity. Note that the diagnostic analysis performed on the sample automotive braking system is used for demonstration only and does not necessarily represent actual operational parameters for this system. This statement is made to keep people from arguing about the actual diagnostic values rather than paying attention to the message being presented!

The failures shown are the same as those contributing to the simulation results in the other charts, except these are identified by specific parts. Those item failures prognosed are identified in magenta (2). The groups of four are the brake pads (four right and four left, front and rear). The prognostic test for these is quite basic. Each pad contains a low pad thickness metallic "scraper" or "squealer". When the brakes squeal, it is time for inspection. The added failures shown for the brake pads (1, orange, loss of equipment), are based on actual pad failure to where they are scraping the disk rotor (very expensive repair). These "running to failure" events can be minimized through better prognostics.

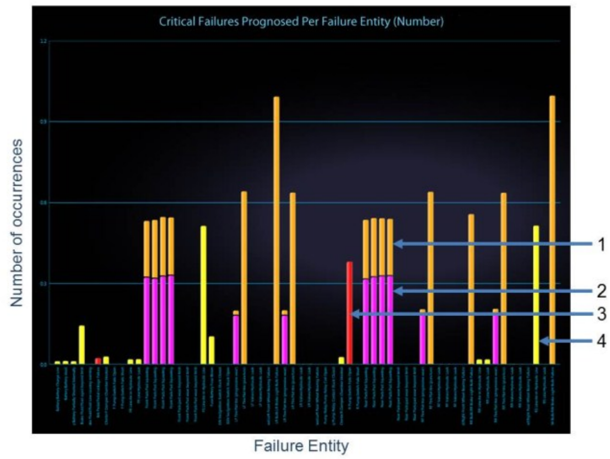

Figure 9. Number of critical failures by item and severity

In fact, existing, more sophisticated, brake pad wear detection does exist in the form of optical sensing.

There is a loss of life (3, red) failure that involves the Antilock Brake System hydraulic pump. There is a possible loss of braking control if this pump fails. It does have a low probability of failure, but this would be a candidate for additional prognostics.

The lager loss of operation, or degraded operation (4, yellow), failures noted are for air in the hydraulic lines.

There are two items shown with higher failure rate for loss of equipment (orange). These are the rear brake lights. The burnt out bulb failure mode would be difficult to prognose but some automobiles do have detection sensors that provide a warning on the dashboard. The use of LEDs significantly reduces the failure rate for these items. But, again, this shows the value of running a simulation of diagnostics results to provide a graphical representation of diagnostics, prognostics and maintenance actions over a specified operational time. The simulation results are not limited to charts. Each calculation result has a detailed report defining events and values.

Figure 10 shows calculation results for frequent failures that are prognosed but without a maintenance plan. These prognosed items are repaired without opportunistic maintenance or an effective level of repair definition. Since actual physics of failure prognostics typically looks at molecular level single failure modes, the analysis considers only single failure modes with no repair concept. Reliable items that were not repaired as a balanced maintenance action will begin to fail as the operating system matures, resulting in increased prognostic related failures and low Mean Time Between Maintenance Action (2, green) and Mean Time Between Prognostic events (1, magenta)

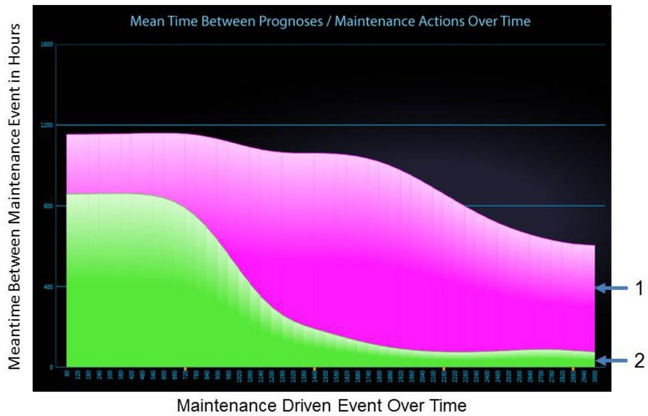

Figure 10. Mean time between a prognostics maintenance action over time

If this were calculated for Mission Success and Availability, It would show a direct correlation to reduced performance from the lack of maintenance understanding in a prognostics analysis. This is mitigated through the integration of prognostics and diagnostics in an effective ISDD process.

Figure 11 shows the calculation results of failure modes that are prognosed but the failure was not detected prior to failure. The loss of equipment failure severity (2, orange) is shown for those failure modes that need to be reassessed for possible prognostics improvement. The grey areas indicate no failure effect (1).

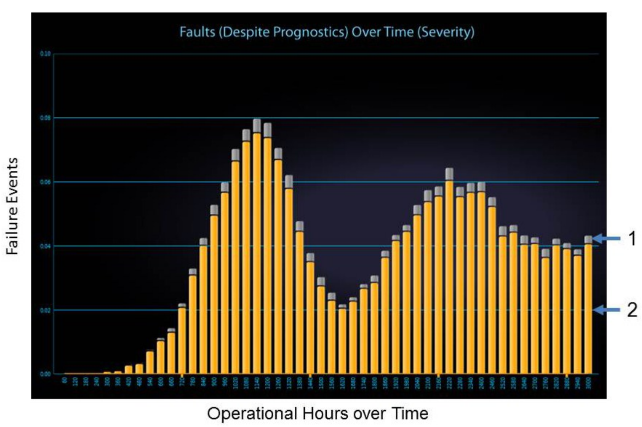

Figure 11. Faults over time by severity despite prognostics

6.0. CONCLUSIONS

There are currently no real guidelines for the calculation of diagnostic-related metrics for systems whose critical failures are covered by prognostics. More important is the lack of prognostics selection based on intelligent diagnostics analysis. Not only have approaches not yet been standardized, but many of the alternatives may not have even been discussed in the public arena. Existing standards describing diagnostic analysis, such as the IEEE Testability standard (IEEE Std. 1552, 2004), do not yet account for prognostics in any way. As a result, diagnostic engineering analysis and simulation tools have been enhanced to address this issue.

As more systems are planned for embedded prognostics, questions about the relationship between prognostics and diagnostics, and even beyond into sustainment, are likely to become even more prominent. A common practice will begin to emerge with subsequent efforts at standardization. It is important that the relationship between prognostic and diagnostic analysis be worked as an integrated solution. Based on subjective, experience driven research, previous methods for assessing diagnostic-related prognostics behavior remain in question, and suppliers, customers and the companies that supply their tools also remain in question.

The main point of all of this is to break out of the “Sokal Hoax” syndrome and work the technologies with the goal of a balanced Health Management and Sustainment solution. The end result will be significantly lower development, operation, and support costs, while experiencing higher Mission Success and Operational Availability!

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BIOGRAPHY

James R. Lauffer (Jim) began the technology journey in Ohio, USA, on New Year's Day, 1941. Jim received his Ham Radio license at the age of 12 and designed many antennas and radio systems. He entered the Air Force at 17 and worked in the Strategic Air Command as a maintainer of B47s and anything else that landed on the base. He entered industry in 1962 and spent the next 40 years in Logistics, Reliability, Maintainability and finally Systems Engineering. This career began with North American Aviation in 1962, then Rockwell and finally Boeing. Much of the engineering time was in combat system development on international programs, field operations testing, and then in management trying to get all of these technologies to work together. Much of the field testing work involved passive sonar sea trails in the Atlantic and the Mediterranean. He also worked aircraft avionics upgrades for the Royal Australian Air Force. Jim retired from Boeing in 2001 and agreed to help out a small engineering business called DSI. This was 11 years ago and he still has not figured out how to retire. But, this past eleven years have resulted in a wealth of knowledge related to the diagnostics technologies and the resulting health management and sustainment systems. Jim's formal education is a bit thin compared to others in this field. He started in the world of Applied Physics but due to work and family, ended up with a business degree. I guess you would say he has several PhD degrees in experience. Jim is a past member of the Society of Logistics Engineers, Society of Reliability Engineers, and the Association of Old Crows (Electronic Warfare), IEEE, and presently The American Institute of Aeronautics and Astronautics (AIAA). To this day Jim continues to study and attend courses in the sciences. He is still active in Ham Radio with his Extra Class license and is always looking for new and balanced PHM solutions.