Metrics, Models, and Scenarios for Evaluating PHM Effects on Logistics Support

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The growing potential of Prognostics and Health Management (PHM) technology to facilitate the maintenance and support of systems emphasizes the need for the ability to determine just what the impacts and benefits of PHM will be. In order to incorporate a capability to evaluate the effects of PHM in logistics support models, the abstraction of PHM metrics and functions is a necessary step. What are the essential prognostics metrics and functions within a logistics support system that will adequately model the effects of PHM? The purpose of this paper is identifying overall categories for understanding the different types of impacts and benefits a PHM system can have from a logistics support perspective. This paper also discusses how prognostics can be assessed by a modeling capability implemented in a legacy logistics support discrete-event simulation, and some examples and results for different support scenarios implementing a prognostics capability.

I. Introduction

THE growing potential of Prognostics and Health Management (PHM) technology to facilitate the maintenance and support of systems emphasizes the need for the ability to determine just what the impacts and benefits of PHM will be. Much of the effort to date has focused on the comparison of prognostics algorithms for the purpose of selecting the best algorithm for determining remaining useful life (RUL) [1-6] or on the economic benefits [7-11,22] (see in particular [9] for a summary of economic analyses of PHM to date). How to assess what impact prognostics will have on actual logistics support concepts, policy, and systems, however, is still fairly immature. Recurring themes of failure and cost avoidance, extended life, etc., can be observed in the literature but no general framework exists in which to place them. Initial efforts have been made to assess PHM within larger operational and support planning contexts [12-14,23], assess impact on sparing and inventory [15], and assess PHM versus reliability growth improvement [16]. A modeling approach to evaluate prognostics within a support context has been developed [7-9], and a general framework provided for understanding how prognostics can fit within a maintenance decision process [17]. One purpose of this paper is to provide a framework for organizing themes of PHM benefits by identifying overall categories for understanding the different types of impacts and benefits a PHM system can have from a logistics support perspective.

Many analyses make simplifying assumptions about the logistics support system in which a prognostics capability is to be implemented. In many cases, realistic scenarios cannot be adequately defined using analytical models; so that analysis approaches often must use discrete-event simulation to model the detailed and complex logistics support processes. In order to incorporate a capability to evaluate the effects of PHM in such logistics models, the abstraction of PHM metrics and functions is a necessary step. What are the essential prognostics metrics and functions that will adequately model the effects of PHM within a logistics support system? The purpose of this paper is also to show how prognostics can be assessed by a modeling capability implemented in a legacy logistics support discrete-event simulation, and some examples and results for different support scenarios implementing a prognostics capability.

II. Support Scenarios for Application of PHM

Often benefits of PHM are referenced without any clear idea of what exactly those benefits are and how they relate to the logistics support system. Without clearly understanding how PHM is intended to provide a benefit, it has the potential for actually becoming a detriment. Four support scenarios for the application of PHM are proposed. These scenarios are differentiated by the key benefit intended as a result of the application of PHM. More than one scenario may apply in a given PHM application, depending on the benefits desired and actions taken as a result of PHM implementation.

A. Reduce Lead Time

The key benefit of prognostics in this scenario is to identify the need for a resource that requires a nonnegligible lead time to acquire. An example of such a resource could be a replacement item (spare) or a maintenance resource that must come from off-site, such as a crane for wind turbine maintenance. Prognostics helps to reduce or eliminate the lead time, resulting in less downtime and in the case of spares, fewer pipeline spares. Items could still be allowed to run to failure.

B. Avoid Consequences of Failure

The benefit of prognostics in this scenario is the avoidance of a failure, such as increased downtime, loss of mission, more extensive damage to a higher level subsystem, or even loss of system or life. The system is not allowed to run to failure, but is repaired or replaced based upon the predicted RUL. Maintenance is scheduled for a time of least interference, particularly if the consequence to avoid is downtime. The resulting increased need for maintenance is offset by the reduction in downtime, overall reduced cost (whether because the cost of scheduled maintenance is less than unscheduled maintenance or because a more costly repair is avoided), or avoidance of a catastrophic event. The example considered in this paper is that of reducing unscheduled maintenance to achieve system performance goals for a squadron of military aircraft.

C. *Extend Life/Reduce Maintenance Frequency*

The benefit of prognostics in this scenario is to implement condition-based rather than time-based scheduled maintenance. By scheduling maintenance based upon each individual item's predicted RUL versus a population statistic, the period between maintenance is to be increased, thus reducing the frequency of maintenance (and its costs). If the item is replaced during maintenance, then the life of the item is extended because the time to replacement has been extended. This scenario is notionally depicted in Fig. 1. An example of a population statistic upon which time-based maintenance would be determined is the probability that very few failures will have occurred before maintenance. The maximum period between maintenance with prognostics will approach that of the mean time between failure (MTBF) of the item as prognostics is able to more perfectly predict failure. The smaller the population variance, the less benefit prognostics can yield.

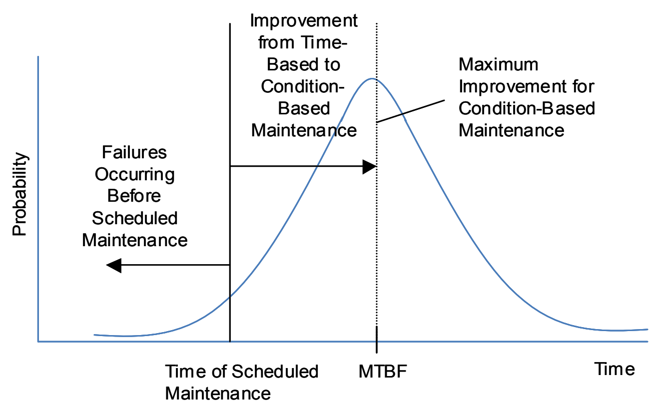

Figure 1. Extending Life by Transitioning to Condition-Based Maintenance.

D. *Optimize Resource Use*

The benefit prognostics is to provide in this scenario is to optimize resource use by the ability to schedule the resource for an optimal time or to consolidate failures for repair to minimize the number of times a resource is needed. For example, acquiring a crane for turbine repairs on a wind farm can be quite costly. If it can be known in advance what potential future repairs will be needed, the use of the crane can be optimized by conducting those repairs as well (in advance of their predicted failure) when the crane is already on the premises.

Scenarios *Avoid Consequences of Failure* and *Extend Life/ Reduce Maintenance Frequency* will be examined in greater detail via specific examples in Sections V and VI.

III. Modeling the Impacts and Benefits of PHM

As identified earlier, this paper is concerned with the modeling of PHM to be used to perform quantitative analyses on the effect PHM will have on a logistics support system. In an earlier paper, a general probabilistic model was proposed as the basis for implementation in a discrete-event simulation model [17]. The probabilistic model is in general agreement with other similar models [1,7,18,19]. The integration of a PHM model within a larger logistics analysis model, however, is still uncommon and not well documented. Only three such models are known to the author [7,18,20]. Therefore, it is important to identify what are the key attributes and metrics, events, and functions of PHM that are relevant for use in logistics analysis models. These are followed by a description of implementation in the Logistics Composite Model (LCOM) [21], a discrete-event simulation model for logistics analysis of systems such as military aircraft.

A. *PHM Attributes and Metrics*

The attributes and metrics for evaluation of PHM within a logistics support context are related to those proposed for evaluation and comparison of PHM algorithms [1,2]. In particular, the following serve as a basis for the attributes/metrics for modeling:

1) *Probability that a failure occurs before its prediction*

This metric is also referred to as *false negatives* [2] and *missed estimation rate* [1]. This metric refers to the proportion of predictions that fail, i.e., that the actual failure occurs before the prediction. It can also include predictions that are later than some critical threshold.

2) *Accuracy and Precision*

There are a number of metrics that relate the failure prediction to the actual failure [2]. It is common to describe

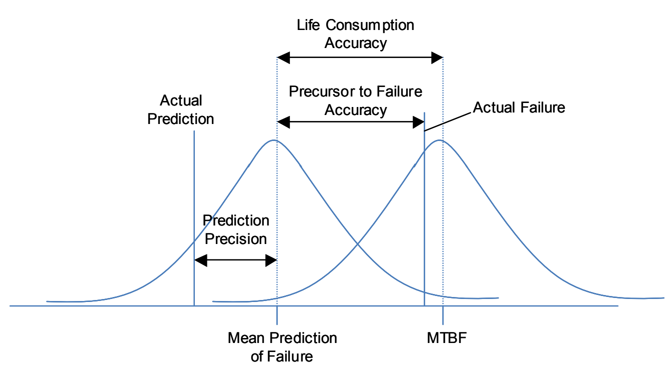

Figure 2. Depicting accuracy and precision in stochastic modeling.

this relationship in terms of a mean with confidence levels for the failure prediction with respect to the actual failure [1,9,17].

For the purpose of stochastic modeling, accuracy and precision are most easily defined as attributes of probability distributions for actual failures and failure predictions as shown in Fig. 2. The precision is defined by the variance of the failure probability density function (p.d.f) and the accuracy is defined by the distance between means of the failure prediction and actual failure (the failure event for Precursor to Failure and the failure p.d.f for Life Consumption [9]).

3) Time of first prediction and prediction lead time

The point at which a prediction of RUL is first available is the time of first prediction (it is not meant to include the time between detection and prediction). It is identified as te in [1], tP in [2], and time Z in [17]. This point is particularly important for modeling, in that it defines the earliest point at which any maintenance planning or scheduling can occur, and thus the greatest value for logistics lead times. The prediction lead time is the time between the time of first prediction and the failure prediction. Note that time may refer either to calendar time or to a usage basis (such as hours of operation).

4) False alarm

This metric is the percentage of predictions for which the corresponding actual failure is later than some specified maximum [1,2]. From a modeling perspective, this is the number of times a prediction is made for which there is no corresponding actual failure (such as a Cannot Duplicate). If a false alarm can be identified as such before a maintenance action is taken, the consequence of a false alarm can be averted. This may support definition of an interval after a prediction is first made to increase confidence that it is not a false alarm.

B. Maintenance Attributes and Metrics

The key events related to logistics support must also be identified in relation to PHM events.

1) Logistics lead time

The time in advance of a failure prediction that can be used to plan for and perform maintenance and supply actions. This time is referred to as *alert time* in [1], and is based on a user defining a minimum time before a predicted failure required to schedule maintenance. This time is considered as a window for maintenance opportunities (L) in [17] to assess the likelihood maintenance and supply actions could take place within the allowable lead time. Actually, there can be more than one lead time, depending on the corresponding action (such as for different PHM application scenarios). For example, the lead time for ordering replacement spares could be different than that for scheduling maintenance for a least disruptive time. If the logistics lead time is greater than the prediction lead time, then it is presumed that the corresponding maintenance action cannot be performed. It is important to note that the units of the logistics lead time (the basis for maintenance actions, typically calendar time) may be different than the units for the prediction (which may be based on operational hours).

It may not be simple to specify a logistics lead time. For example, it may be desirable to wait for a number of failures to occur before acquiring a long-lead or high cost resource. In that case, logistics lead time should be the time it takes to accumulate predictions for that number of failures.

2) Mean predicted failure with confidence (MPFWC)

This metric is new and is being proposed as a reference point in logistics planning for determining when maintenance and supply actions should occur. The reference point is proposed as the predicted failure time that is fixed with respect to the actual failure by an allowed number of failures that occur before the predicted failure. This metric combines the accuracy and precision metrics with the false negatives metric to identify a point before which a logistics planner can have a high confidence that an actual failure will not occur (see Fig. 3).

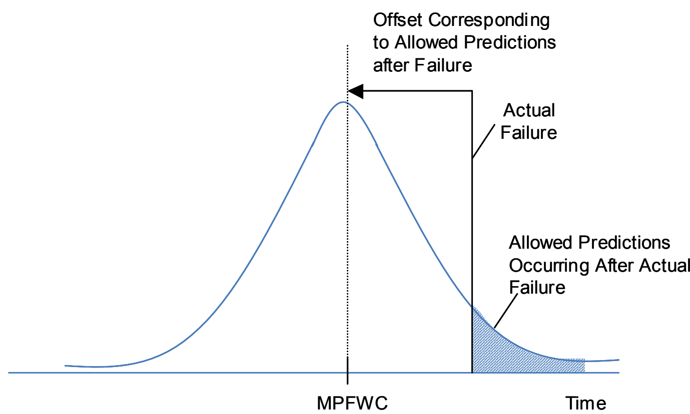

Figure 3. MPFWC is fixed relative to actual failure by allowed predictions occurring after actual failure (or *false negatives*).

3) Coverage

This metric concerns the percentage of total failure rate that PHM addresses. Coverage of the failure modes for a single item concerns the percentage of total failure modes that PHM can address. The coverage value for an item will directly affect the percentage benefit for each item, for example for the number of repairs or replacements. Benefits for system-level measures such as downtime (and thus availability) and total cost are impacted more by coverage across items (from the perspective of a higher system level) unless the item has a high degree of impact on downtime, cost, or resource usage.

C. Benefit Metrics

Examples of benefit metrics for each of the support scenarios for PHM application from Section II are provided below. It should be noted that metrics related to and potentially influenced by downtime, such as availability and numbers of missions completed, are not mentioned since they can vary depending on the program requirements for the system.

1) Reduced lead time

For spares, benefits could reduce the effective resupply time by ordering the spares in advance of the failures. Reducing the effective resupply time should reduce pipeline spares quantities and associated costs (theoretically, with sufficient lead time and full coverage for a unit, pipeline spares for that unit should be able to be eliminated). The number of replacements or maintenance actions remains the same since the unit is allowed to run to failure.

For acquisition of a resource, the key benefit metric should be reduced or eliminated downtime for acquisition of the resource.

2) Avoid Consequences of Failure

A key metric for this scenario is the mean time between unit replacement (MTBUR) or mean time between maintenance events (MTBME), or number of repairs/replacements for a given timeframe (the metric used in this paper). These metrics especially should be used to compare with corresponding values based upon the mean time between failure (MTBF) without PHM. The expectation is that with PHM these metrics will show an increase in the number of repairs/replacements. The benefit metric is reduction in downtime since unscheduled maintenance is being shifted to less disruptive times. Another benefit metric is cost – there will be improved cost if a differential in the per unit costs for scheduled versus unscheduled maintenance accounts for the increase in the number of maintenance events.

3) Extend Life/Reduce Maintenance Frequency

Metrics for this scenario include time between repair/replacement (which should increase), and numbers of maintenance events (which should decrease with corresponding costs). Note that this is exactly the opposite effect from *Avoid Consequences of Failures*. There is a potential decrease in downtime as well.

4) Optimize Resource Use

Since maintenance is to be performed in advance, as in *Avoid Consequences of Failures*, the metrics are also the same. In addition, metrics related to reduced frequency of the use of selected resources with corresponding costs and potentially reduced downtime are also important.

D. Modeling PHM and Logistics Support

A general framework for implementing a PHM assessment capability in stochastic support models [17] is shown in Fig. 4.

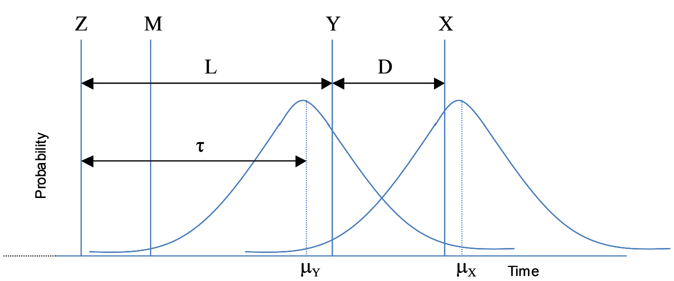

Figure 4. Model relating PHM events (time of prediction Z and predicted time of failure Y), failure event (X), maintenance opportunity (M), and times between them.

In this framework, a random failure event X occurs with probability density function (p.d.f) f_X, mean μ_x, and standard deviation σ_x. No assumption is made regarding the type of p.d.f. X occurs relative to a start or renewal not shown in the figure. At time Z, a PHM system predicts a random failure event Y, with p.d.f f_Y, mean μ_Y, and standard deviation σ_Y. Similar to X, no assumption is made regarding the type of p.d.f. This prediction is made at random time L (with p.d.f f_L and mean τ) before the predicted failure (Y). A maintenance opportunity M can occur during the interval L, that is, between time of prediction Z and predicted failure Y, based upon a p.d.f or events within a discrete-event simulation model. Logistics lead time is the time between event M and prediction Y. There can be one or more M events, or none, depending on the distributions of M and L. It is assumed that a planned maintenance event can only occur if the maintenance opportunity M were to occur before predicted failure Y. In other words, while a maintenance event could occur because of a maintenance opportunity after predicted failure Y and before actual failure X, it is not a planned event. The relationship between X, Y, and M can change if the prediction is updated over time.

IV. Implementation in LCOM

Since more realistic scenarios cannot be adequately defined using analytical models as described above, a capability for defining PHM systems in the context of specific operation and support scenarios for military aircraft was developed. The discrete-event simulation model used in this case is LCOM, a large-scale stochastic model which allows the analyst to define any number of operational, maintenance and support activities as interconnected tasks, usually at the squadron level [21]. Analysts typically create tens of thousands of tasks for thousands of removable/replaceable items. Each item, equivalent to an LRU, has a defined failure distribution. When a failure occurs in the simulation, a maintenance activity is either conducted right away or postponed to a time when the aircraft are not flying (usually end of day), depending on its criticality. Implementing PHM provides a means for the user to model predicted failures, which can then be used as a basis for scheduling maintenance events in the simulation.

A. Generation of a Predicted Failure

At the time that an LRU is repaired or replaced (assuming complete renewal), the next actual failure (event X in Fig. 4) is randomly drawn from a user specified distribution. At that time, a predicted failure (event Y) is also randomly drawn from a separate distribution that has been offset from the value for the drawn actual failure as shown in Fig. 3. As described earlier, the predicted failure distribution is defined by the user in terms of a standard deviation and probability that actual failure will occur before the predicted failure (P_f), or false negatives rate. The actual and predicted failures both have the same usage basis (number of sorties, flying hours, number of rounds, etc.). A user specified lead time is then subtracted from the predicted failure time to establish the time of first prediction (event Z). This lead time also has the same usage basis as the actual and predicted failures.

B. Generation of a Maintenance Opportunity

Once the predicted failure has been set, user specified maintenance opportunities can be initiated at specified lead times. These are implemented in LCOM in two different ways, corresponding to an event or a state. Events, called triggers, initiate user defined processes in the discrete event simulation which can model the repair process itself or schedule the repair for a later time. States, called modes, are passive in that they do not initiate any action per se, but are set to an 'on' state for a prespecified period of time. The user can develop processes that check for the value of the state, such as at the end of the day, to see which LRUs are in need of maintenance. For both triggers and modes, a check is made to see if the lead time has already been passed. If so, the mode or trigger is not scheduled.

V. Unscheduled Maintenance Avoidance

A. *Description of Scenario*

A six aircraft squadron is scheduled to fly missions throughout each day with a flying window specified for 0600 (6 a.m.) to 2000 (8 p.m.). The flight schedule is for 10 sorties per aircraft per day (a sortie generation rate, or SGR, of 10), scheduled one and a half hours apart, with each sortie one hour in length. An hour past the scheduled takeoff time is allowed for any late aircraft. Pre-sortie processing is 5 minutes and post-sortie is 25 minutes if there is no failure, so one complete cycle is one and a half hours. If there is a failure, post-sortie processing takes an additional 20 minutes. The flying window allows a half hour slack to accomplish 10 one-hour sorties, so the squadron can experience one failure of one aircraft in a day and still meet the goal of 10 sorties (since a delay to takeoff is allowed past the time lost to additional post-sortie processing). If more than one aircraft fails in a day, one of the scheduled missions will be lost and the goal of 10 sorties per aircraft per day will not be met. Maintenance can be performed during the day and at night. Resources such as manpower, parts, support equipment, and facilities are not constrained (i.e., assume there are enough).

Failures are grouped into a critical and non-critical status. Critical failures occur at 100 flying hours on average with a normal distribution where the standard deviation is varied. Non-critical failures occur at a constant 10 flying hours. Critical failures must be repaired/replaced immediately, especially during the flying window. Non-critical failures can be deferred until outside the flying window. The non-critical failures occur at ten times the rate of the critical failures. Critical failures have a PHM capability with a prediction lead time of 50 flying hours, and a 5% probability of an actual failure occurring before the failure prediction (false negatives). The precision of the prediction and the logistics lead time for repair/replacement of a critical failure are varied.

B. *Description of Analysis*

The first step was to establish a baseline case where there is no PHM capability. In this case, the average SGR achieved is 8.61, well below the goal of 10. For comparison purposes, the critical MTBF was increased to determine at what value an SGR goal of 10 could be met, which was 5500 flying hours. This means that increasing reliability, such as through a reliability growth program, must increase the MTBF by a factor of 55 in order to meet the SGR goal.

The focus of this analysis was to examine the effects that the precision of the prediction has on the ability to meet the SGR goal of 10 and the effects of increasing logistics lead time for different population standard deviation values. Values for prediction precision are measured as the ratio of the prediction standard deviation to the critical MTBF, or $STMR_{pred}$, expressed as a percent. The value of 0% precision corresponds to perfect PHM – the failure prediction is aligned with the actual failure, and there is no variation about the prediction. Other precision STMRpred values included 1%, 5%, and 10% of the population mean (i.e., 1, 5, and 10 flying hours, respectively). Logistics lead time for repair/replacement of a critical failure was varied in steps of 2 hours beginning with 2 flying hours up to 36 flying hours (which at a rate of 10 flying hours per day means from less than a day to over 3 days). The standard deviation of the critical failures was also varied as ratios over the critical MTBF, or $STMR_{crit}$. These values included 0% deviation (or constant TBF), 1%, 5%, and 10%. A horizon of 90 days and 50 replications were used for each run.

For each aircraft, when the value of the actual failure is obtained (at the beginning of the simulation, or when a fix is performed), the value of the predicted failure is also obtained based upon the 5% false negatives goal and the precision of the prediction as described earlier for MPFWC. At this same point, the beginning of a maintenance opportunity window is scheduled to occur the specified logistics lead time prior to the MPFWC. As the simulation runs, the rate of flying hours to calendar time is monitored, and if it varies beyond a set tolerance, a new estimate is made for the beginning of the maintenance opportunity relative to the predicted failure and is rescheduled within the simulation. At the scheduled simulation time, the maintenance opportunity begins. This is implemented by a unique attribute of the aircraft, which the simulation maintains, and is used to test within the flow of post-sortie tasks the aircraft performs. Once that attribute indicates that a maintenance opportunity exists, a fix is identified to be performed at the next opportunity outside of the flying window. Thus, if the attribute is encountered in any given day, a fix will be performed outside the flying window of that same day. Thus, a fix is performed at the first opportunity after indication that is needed. It should be noted that the time of the indication and the time of the fix are not the same. If the actual failure occurs before the first opportunity to fix it, the fix will be conducted immediately.

Primary outputs examined were SGR and mean number of fixes. The mean flying hours between maintenance events (MFHBME - computed from a tailored output which measured the flying hours between fixes) was used with the total flying hours (900), when SGR of 10 was achieved, to determine the mean number of fixes.

C. Results

1) Varying Population Variance

The first comparison is of varying population variance ($STMR_{crit}$) as a function of lead time and prediction precision ($STMR_{pred}$). The results are interesting although not surprising as shown in Fig. 5. The graph for each case only begins at the flying hours before predicted failure where the SGR goal of 10 is met. There are four cases where the prediction is assumed to be perfect (a $STMR_{pred}$ of 0% for a constant critical time to failure, and $STMR_{crit}$ values of 1%, 5%, and 10%), and two cases where the prediction precision is 10% of the MTBF (a $STMR_{pred}$ of 10% for a constant critical time to failure and $STMR_{crit}$ of 10% of MTBF). Interestingly, for perfect prediction and very low critical standard deviation, the number

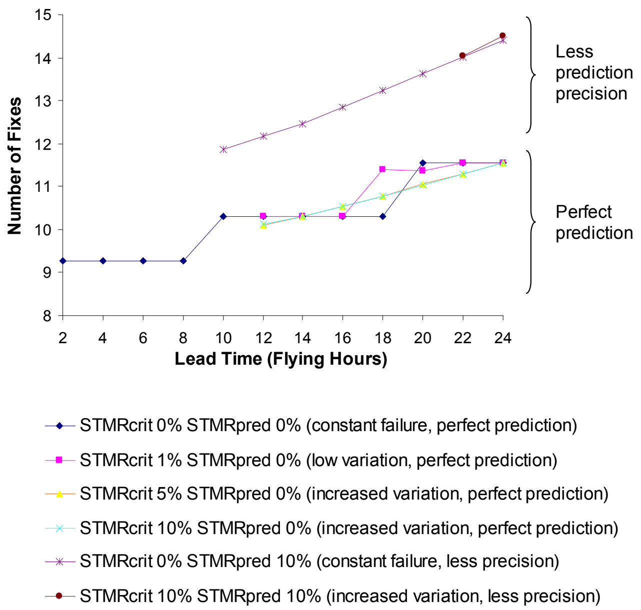

Figure 5. Number of fixes for varying population variance ($STMR_{crit}$) by lead time and prediction precision ($STMR_{pred}$).

of fixes is a step function of the flying hours before predicted failure. This makes sense because each day there is a very high likelihood that the critical failure will occur at the end of the day (after 100 flying hours, or the end of the tenth, twentieth, etc. days). Any indications that a critical failure is going to occur within that day will still result in the same time for the fix (i.e. at the end of the day). For each day, therefore, there is little effect on the number of fixes for indications within that day. As the variation about the MTBF increases, however, the likelihood that the critical failure will occur at the end of the day becomes much less, and so the effect on the number of fixes becomes more linear. In this case, this occurred by an $STMR_{crit}$ of 5%. Also of interest is when the prognostic is less precise ($STMR_{pred}$ = 10%). Even for constant failure (when the $STMR_{crit}$ is zero), the effect of lead time (flying hours before predicted failure) on the number of fixes is now fairly linear. This can be explained by the fact that the alert for maintenance is tied to the failure prediction, and not to the actual failure itself. Even though for $STMR_{crit}$ = 0 the actual failure still occurs at the end of the day, the MPFWC can occur throughout the day due to the increase in variation of the prediction, and thus the alerts are also occurring throughout the day. This also explains why the SGR goal of 10 is achieved much earlier for constant failure ($STMR_{crit}$ of zero) versus failures with increased variation ($STMR_{crit}$ of 10%) when the prediction is less precise ($STMR_{pred}$ = 10%). For $STMR_{crit}$ close to zero, the actual failures occur at the end of the day, outside of the flying window. For larger $STMR_{crit}$ values, the actual failures can occur throughout the day (albeit rarely because of the 5% false negative rate), and thus can impact the ability to meet the SGR goal of 10. It should be noted that while not meeting the goal, a very high SGR value can be obtained earlier than a lead time of 22 flying hours (9.953 at a lead time of 10 flying hours).

2) Varying Prediction Precision

For failures with increased variation ($STMR_{crit}$ of 10%), cases of decreasing precision (or increasing $STMR_{pred}$) are shown in Fig. 6. The minimum lead time at which an SGR of

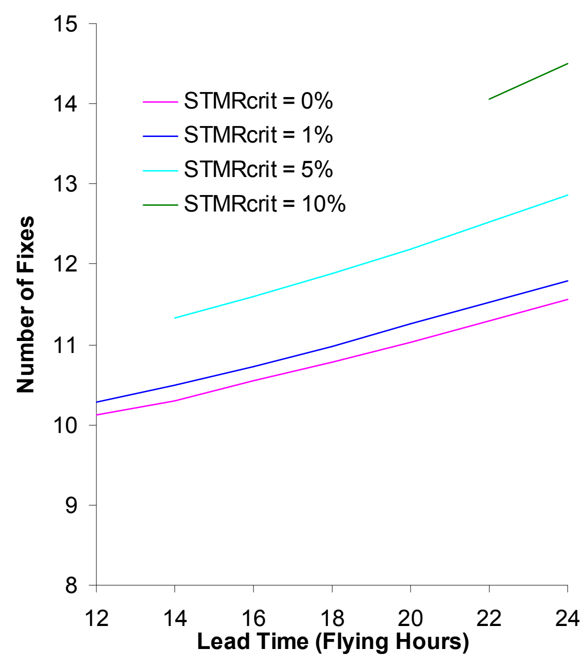

Figure 6. Number of fixes for varying prediction precision ($STMR_{pred}$) by lead time for $STMR_{crit}$ of 10%.

10 can be achieved appears to increase nonlinearly with $STMR_{pred}$ ($STMR_{pred}$ values of 0-5% result in minimum lead times of 12-14 flying hours, while an $STMR_{pred}$ value of 10% results in a minimum lead time of 22 flying hours). The numbers of fixes corresponding to the minimum lead time also appear to grow nonlinearly with linear increases in $STMR_{pred}$. For each $STMR_{pred}$ value however, the number of fixes grow relatively linearly with the lead time.

Overall it can be observed that increasing the lead time tends to increase the number of fixes, as expected. This is true for perfect prediction as well. Increases in lack of precision for the prediction also results in increased number of fixes, both in terms of the number of fixes for the same lead time, and for the longer lead time required to meet the SGR goal. It might be slightly more difficult to detect that the increase in number of fixes for a linear increase in $STMR_{pred}$ is in fact nonlinear, although slightly so.

3) Cost Benefit

From these results, the relative benefit of improvements to precision can be measured as the reduction in the number of fixes. If the cost of a level of precision is far greater than the cost of the corresponding number of replacements gained, then the increase in precision may not be cost effective. The cost of implementing a prognostic capability can also be compared to the cost of a non-prognostic alternative, such as reliability growth.

VI. Time-Based Versus Condition-Based Maintenance

A. Description of Scenario and Analysis

A continuously operating system, such as a wind turbine or a computer system, is scheduled for periodic maintenance based upon a MTBF and a safety factor. For a normal distribution, the safety factor can be expressed in terms of numbers of standard deviations ($n_{fail}*s_{fail}$) from the mean (M_{fail}, or MTBF), and the period, T_{sched}, is given by $M_{fail} - n_{fail}*s_{fail}$ (notionally depicted in Fig. 1). For values of a 95% probability the scheduled maintenance occurs before a failure, M_{fail} of 12 days, and s_{fail} of 1.2 days ($STMR_{fail}$ = 10%), T_{sched} is 10 days. Periodic maintenance takes 24 hours (admittedly, not very realistic, but adequate for illustrative purposes) so with no prognostics, for every 11 days the system is up for 10 days and down 1 day, yielding an availability of 10/11 = 0.909.

PHM was added to the system in order to move to condition-based maintenance rather than the time-based maintenance described above. First of all, it should be noted that even with a perfect prognostics capability, the average time between maintenance will be equal to the MTBF as shown in Fig. 1. Thus, the most a perfect PHM can do is to increase the period of 10 days for time-based to 12 days for condition-based maintenance. This means that on average for every 13 days, the system is up for 12 days and down 1 day, yielding an average availability of 12/13 = 0.923. Since PHM cannot be assumed to be perfect, the prediction with confidence can be determined as described earlier in the paper, where MPFWC is obtained by subtracting a number of prediction standard deviations ($n_{pred}*s_{pred}$) from the time of failure, where n_{pred} is determined by the desired false negatives rate. The mean of those predictions (T_{pred}) then is given by $M_{fail} - n_{pred}*s_{pred}$, which has the same form as that for T_{sched} given above. The life of the system is extended when $T_{pred} > T_{sched}$, and for the same confidence, this can be simplified to the case where $s_{pred} < s_{fail}$. It is expected that when the prediction standard deviation and the failure standard deviations are the same, that the availability will be the same, and that when prediction standard deviation is less, the availability will be greater, and that when it is greater, the availability will be less. For perfect PHM (zero prediction standard deviation), availability should correspond to $T_{pred} = M_{fail}$. It is also expected that as the failure standard deviation increases, availability will go down but that the relationship between prediction and failure standard deviations will remain the same.

B. Analysis and Results

In order to evaluate the effects of precision and the population variance on availability, prediction precision values were varied (prediction standard deviation as percentages of the failure standard deviation from 0 to 140%) for three different values of population standard deviation ($STMR_{fail}$ of 10%, 20%, and 30%). A confidence level of 95% is assumed for both.

1) Availability as a function of prediction precision

For a range of values of prediction precision (prediction standard deviation as percentages of the failure standard deviation, or $s_{pred}/s_{fail}*100$) from 0 to 140%, availability values are shown in Fig. 7. Three different cases of $STMR_{fail}$ are

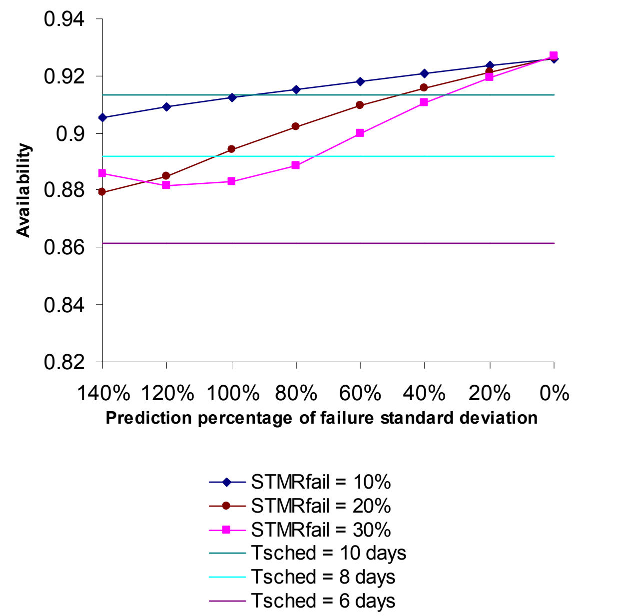

Figure 7. Availability for varying prediction percentage of failure standard deviation by $STMR_{fail}$.

shown (10%, 20%, 30%) with availability values demarcated for corresponding T_{sched} values (10 days, 8.1 days, and 6.1 days respectively). Starting with a $STMR_{fail}$ of 10%, it can be seen that when s_{pred} and s_{fail} are equal (prediction is 100% of failure standard deviation), the condition-based and time-based approaches yield the same availability. For $s_{pred} > s_{fail}$ (percentage > 100%), the time-based approach yields a higher availability, while for $s_{pred} < s_{fail}$ (percentage < 100%), the condition-based approach yields a higher availability. As expected, the bound for perfect prediction (percentage = 0) yields the maximum availability attainable, corresponding to $T_{pred} = M_{fail}$. It should be noted that availability results diminish as s_{pred} decreases with respect to s_{fail}, requiring greater investment for equal increases in precision.

For greater values of $STMR_{fail}$, the same general behavior is observed except for the change in slope at prediction percentage of 120% for $STMR_{fail}$ of 20% and prediction percentage of 80% for $STMR_{fail}$ of 30%. In fact, for $STMR_{fail}$ of 30%, the availability actually increases when $s_{pred} > s_{fail}$ (between 120% and 140%), which seems incorrect, as well as the fact that it never reaches the availability corresponding to T_{sched} when $s_{pred} = s_{fail}$. This can be explained by the increase in $STMR_{fail}$, which for $s_{pred} << s_{fail}$ still behaves as expected, but as s_{pred} approaches s_{fail}, the likelihood increases that the MPFWC will be beyond the renewal point, resulting in a false negative. This can be seen in Fig. 8, where the false negatives increase dramatically for $STMR_{fail}$ = 30% beyond a prediction percentage of 40%.

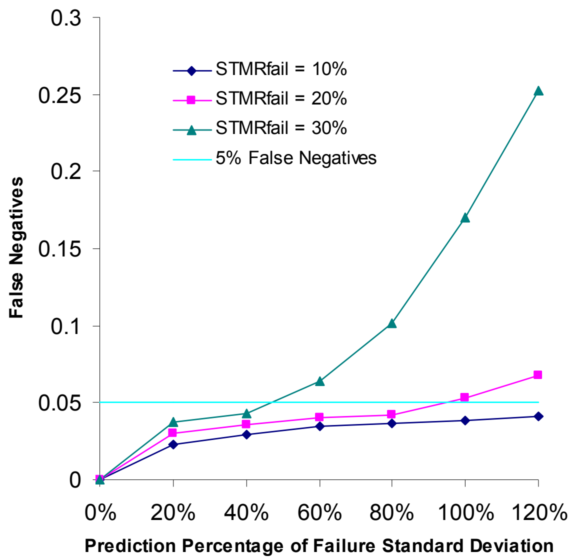

Figure 8. False negatives for varying prediction percentage of failure standard deviation by $STMR_{fail}$.

2) Availability as a function of $STMR_{fail}$

Also of interest is the rate of decrease in availability over increases in $STMR_{fail}$ for each of the prediction percentages.

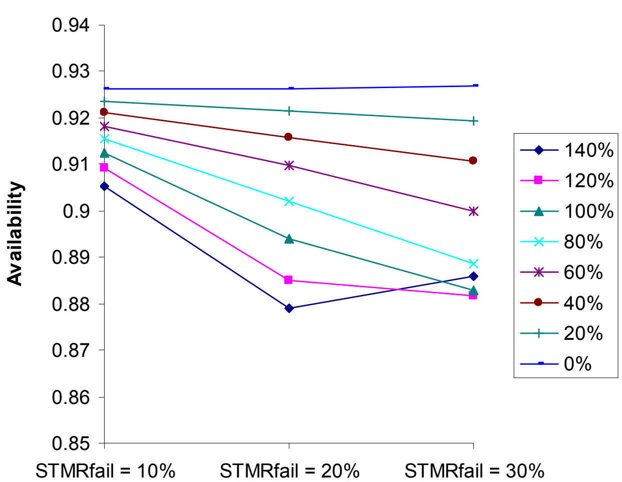

Figure 9. Availability for increasing $STMR_{fail}$ by prediction percentage of failure standard deviation.

As shown in Fig. 9, there is very little effect on availability from increases in the failure variation when the prediction precision is very good (low prediction percentage), but for decreasing precision, the failure variation becomes more of a factor in decreasing availability. The exceptions for higher $STMR_{fail}$ and prediction percentages are again due to the increasing false negative rate described earlier. In general, better precision is good if the failure variation is not well understood.

C. *Other than full coverage for a single item*

The analysis and discussion thus far for extending life with PHM has centered on the assumption that the PHM coverage is 100% for a single item (that is, with PHM, scheduling maintenance to occur before failure is performed at one time). If coverage is not 100%, or if there are multiple items that require scheduled maintenance at the same time, or both, then the benefit of condition-based maintenance becomes a little less clear. If coverage is less than 100% for a single item, that item may still need scheduled maintenance in addition to the condition-based maintenance. If the condition-based maintenance cannot be scheduled for an off time, then availability is potentially impacted negatively by the increase in downtime (for both the time-based and condition-based maintenance). If there are multiple items, a similar argument can be made. In fact, if there are multiple items that even have 100% coverage with PHM, the single scheduled maintenance event is replaced by potentially many scheduled maintenance events, decreasing availability due to increased downtime. This scenario is actually the opposite of the *optimize resource use* scenario which aims to consolidate repairs. For example, if there are 5 items, and one of those items has perfect PHM, then 4 of the items will get time-based maintenance at 10 days (assuming as before a normal distribution, 95% probability maintenance occurs before failure, MTBF of 12 days, and a failure standard deviation of 1.2 days), and one item will get condition-based maintenance on average every 12 days. Availability of this mixed scenario then on average for every 14 days is up for 12 days and down for 2 days, for an average availability of 12/14 = 0.857. The availability for full time-based maintenance of 0.909 from earlier then decreases with this scenario where PHM can only be partially applied.

Even if the intent is to fix all of the items at one time as condition-based maintenance, the life extended is compromised by the number of items. For increasing numbers of items, each with their own individual times to failure, the time that all items will be fixed will be driven by the least time to failure. The average number of fixes over time will be driven by the minimum time to fail rather than the average time to fail. For the scenario describe above of 5 items, fixing all items when the first one fails yielded an average availability of 0.848 versus 0.909 for a single item with 100% coverage. Thus, care needs to be taken in evaluating the benefits of extending life when PHM coverage is not 100% or involves multiple items.

VII. Conclusion

Overall categories for identifying and understanding the different types of impacts and benefits a PHM system can have from a logistics support perspective were presented, which are: *Reduce Lead Time*, *Avoid Consequences of Failure*, *Extend Life/Reduce Maintenance Frequency*, and *Optimize Resource Use*. A method for how prognostics can be assessed by a modeling capability that is implemented in discrete-event simulation models was presented, including identification of key attributes and metrics.

Examples and results for different support scenarios implementing a prognostics capability were provided. For the *Avoid Consequences of Failure* scenario, it was observed that increasing the lead time tends to increase the number of fixes (assuming maintenance is performed at the first opportunity). Increases in lack of precision for the prediction also result in increased number of fixes, both in terms of the number of fixes for the same lead time and the longer lead time required to meet the performance goal (SGR). For the *Extend Life/Reduce Maintenance Frequency* scenario, it was observed that when the prediction standard deviation and the failure standard deviations are the same, that the availability will be the same, and that when prediction standard deviation is less, the availability will be greater, and that when it is greater, the availability will be less. It is also observed that as the failure standard deviation increases, availability will go down but that the relationship between prediction and failure standard deviations will remain the same. It was identified that care needs to be taken in evaluating the benefits of extending life when PHM coverage is not 100% or involves multiple items. In both scenarios, it could be concluded that better precision is good if the failure variation is not well understood

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