Towards Defining and Allocating PHM Requirements for Military Systems

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ABSTRACT

Issues and methods of relating program requirements to PHM requirements and allocation of PHM requirements to lower system levels are discussed as alternatives to technology-driven approaches. This paper focuses on evaluating program requirements for improving reliability for military systems with a required maintenance free operating period. Reliability improvements are related to PHM attributes, which are condensed to two primary attributes: coverage and inefficiency. Methods of allocation of higher level PHM requirements to lower level requirements are examined, focusing on a normalized weighting approach. An alternative approach beginning with coverage estimates is also examined. A discrete-event simulation model is developed and exercised to confirm analytical results.*

1 INTRODUCTION

The application of Prognostics and Health Management (PHM) technology is largely technology driven – the focus of much of the effort in the field is on developing technologies which are hoped to transition to developing or fielded systems. One starts with a technology which appears promising or seems like a good idea, and then goes and looks for an application in which it can benefit the target system. But success in finding transition targets for technologies is dependent in a large degree on the ability to make the business case for its adoption, i.e., to justify its benefits using metrics such as return on investment (ROI). In this sense PHM seems very much like a solution looking for a problem where added value needs to be demonstrated in order to be adopted.

Another approach is to adopt PHM technology because of its general promise without any specific goal or requirement, such as the adoption of health usage monitoring systems (HUMS) in the US Army Blackhawk UH-60 program. On the basis of a general expected added value, large investments are made in building an infrastructure and diagnostic/prognostic capability into an existing fleet with the expectation of improvements in reduced manhours, mission aborts, etc., but without being driven specifically by required objectives and thresholds. In general, the approach is to define and use metrics from the fleet to look for evidence of a benefit, to justify after the fact that benefits are, in fact, being experienced.

Integrating PHM into a new system, subsystem, or component requires specific performance requirements for the PHM technology, which is recognized and described in (Di Lorenzo and Bayer, 2009). Those specific PHM performance requirements should be clearly related to system Key Performance Parameters (KPPs), and in fact, should be derived from them. This is often not the case, however, due to a lack of ability to quantify the relationship between PHM requirements and KPPs.

The purpose of this paper is to explore how PHM, prognostics in particular, can be represented by attributes which can be related to overall KPPs and to allocation of system reliability and maintainability requirements to lower levels during the design process.

2 DRIVING PHM REQUIREMENTS BY PROGRAM REQUIREMENTS

While PHM can yield benefits in program areas such as system safety, reliability, maintainability, logistics support, and training, the readiness KPP of operational availability (A_o) as defined in the RAM-C manual (DoD, 2009) is the focus of this paper. It should be noted that programs may use a more focused metric, such as the Joint Strike Fighter program, which elected to use Sortie Generate Rate (SGR) instead. The choice of SGR allowed for a more direct measure of the key parameter desired, which was the rate at which sorties could be flown from a representative squadron. The use of SGR rather than A_o allowed the inclusion of additional concepts such as flying window and periodic downtime for maintenance, which are more difficult to measure with a metric like A_o. In addition, the verification of SGR is performed via discrete-event simulation of operation and support of the JSF (ASCLCOM, 2010), which provides a more realistic assessment of the effect of constraining resources on the ability to achieve SGR objectives than a simple computation such as A_o. Nonetheless, its use in this paper allows for a simple analytical solution to compare to simulation results, while more complicated metrics, such as SGR, cannot be computed analytically.

The use of simulation to assess the impact of PHM on program KPPs is described in a separate paper (Luna, 2009). The focus of this paper is not on assessment of PHM impacts, but on approaches and methods for defining what PHM requirements should be, given what overall KPP requirements are. The use of simulation in this paper, however, serves to validate the simulation results with simple analytical solutions for A_o, which helps gain confidence in simulation results when more complex KPPs are used to evaluate the impact allocated PHM requirements can have.

2.1 Considerations of Operational Availability

Computation of A_o from the RAM-C manual is defined as the difference between operational uptime and operational downtime divided by operational uptime. The downtime in this case includes both scheduled and unscheduled maintenance. The benefits resulting from PHM can differ for each type of maintenance (a more detailed examination overall of prognostic benefit areas is provided in (Luna, 2009)). The primary benefit for unscheduled or corrective maintenance, particularly for mission aborting or mission affecting (i.e., critical) failures, is to avoid undesirable consequences of those failures by avoiding the loss of mission or ability to be assigned to a mission and/or by fixing at a convenient place and time.

The focus in this paper is largely on avoiding loss of mission or ability to be assigned to a mission due to maintenance of a mission affecting failure. In other words, in consideration of A_o, the operational uptime is considered that time that the system is desired to operate maintenance free. For example, the operational use concept of a ground radar system may be to be able to operate the radar maintenance free for 23 hours, followed by an allowed downtime of 1 hour. The failures that occur in that 23 hours that must be fixed in that 23 hour window are of critical importance, since they cause the system to be down during the time that it is required to be up. Similarly, a squadron of military aircraft may need to fly missions during a 16 hour flying window, followed by an allowed downtime to perform maintenance. Any failures that cause an aircraft to be unavailable in the flying window are also considered critical. Since the downtime in the Ao computation involves both scheduled and unscheduled downtime, an availability measure which specifically targets the unscheduled downtime is particularly relevant to identifying the benefits of PHM in predicting the unscheduled failures in advance and repairing them during an allowed downtime so as not to impact the maintenance free period. For this reason, the following availability (A_{ocrit}) is defined,

$$A_{ocrit} = (uptime - downtime_{unsched\_crit})/uptime \qquad (1)$$

where *uptime* is the maintenance free period and $downtime_{unsched\_crit}$ is the time that the system is down during the maintenance free period due to unscheduled maintenance of mission aborting or mission affecting failures. This downtime is given by,

$$downtime_{unsched\_crit} = \lambda_{ucrit} * uptime * MDT_{crit} \qquad (2)$$

where λ_{ucrit} is the rate at which critical failures occur, *uptime* is the maintenance free period, and MDT_{crit} is the mean time the system is down to repair critical failures. Rearranging Eq. (1) and substituting in Eq. (2) yields

$$A_{ocrit} = 1 - \lambda_{ucrit} * MDT_{crit} \qquad (3)$$

At this point it is worth noting that A_{ocrit} can be increased by decreasing λ_{ucrit} or MDT_{crit} or both. Improved diagnostics or advanced warning for reductions in administrative or logistics lead times can be used to reduce MDT_{crit}, while using indications of failure in advance to perform maintenance outside of the maintenance free operating period reduces λ_{ucrit}. Conversely, if Ao is held fixed, decreasing λ_{ucrit} or MDT_{crit} or both results in allowing for an increase in uptime, or an increase in the maintenance free period. It is important to remember that the improvement of A_{ocrit} or extension of the maintenance free period occurs in the context of an identified allowable scheduled downtime for performing the maintenance outside of the maintenance free period.

2.2 Operational Availability Allocation

As seen from the previous section, PHM can be applied to increase maintainability (by reducing MDT_{crit}) or reliability (by reducing λ_{ucrit}) or both. Current methods for allocating reliability and maintainability requirements to achieve availability goals can be used to similarly help identify the focus of PHM benefit desired. In this paper, the focus will be on using reliability requirements to allocate PHM requirements.

2.3 Reliability Improvement and Allocation

Perhaps it is a misnomer to refer to reducing λ_{ucrit} by means of effectively converting unscheduled to scheduled maintenance as reliability improvement, since there is no actual reliability improvement involved. Yet, the effect on A_{ocrit} is the same as if λ_{ucrit} were reduced by means of reliability improvement. What is different is that the frequency of maintenance actions is not reduced, and may be increased depending on the point at which the maintenance is performed relative to the actual failure.

The application of PHM for effective reliability improvement then must be considered as part of the overall reliability allocation and improvement for a system. In (Bedard, 2009), prognostics is considered as an alternative to actual reliability improvement via reliability growth, with a rule-based screening process as the basis for deciding which components are best for prognostics versus reliability growth. The use of more sophisticated methods involving cost estimates for incremental reliability improvements, such as in (Ebeling, 1997), can be extended to include PHM as an alternative as well, although the development of such an approach is considered outside the scope of this paper.

The focus of this paper is to look at reliability allocation methods for applicability to allocating PHM requirements, in particular, the Base Apportionment method as described in (Crowe, 2008). This method represents several other methods as well, such as the Equal Apportionment and ARINC methods, since it is based on defining a set of normalized weighting factors at each level which are applied to the higher level's allocated failure rate, where the source of the values for the weighting factors differs based on the approach.

3 PHM ATTRIBUTES

Before going further, the specific PHM attributes being considered in this paper need to be defined. In (Luna, 2010), five different attributes, as shown in Table 1, were defined for evaluating the relationship of PHM attributes with cost attributes. For the purpose of this paper, these five attributes were condensed into two (coverage and inefficiency) based on the observation that the effects of the latter four attributes were inversely related to coverage (that is, as increases in coverage increase cost avoidance, there is a corresponding increase in the effects of the latter four attributes which serve to decrease cost avoidance. The method of condensing these attributes is explained in the next section.

Table 1: Summary of Prognostic Attributes

Factor	*Symbol*	*Description*
Coverage	f	The fraction of failures in item failure rate (λ) which are designed to be or can be detected by prognostics
Missed failure	α	Probability or fraction of failures that occur before predicted failure
Wasted life	γ	Ratio of average rate of wasted life (or inverse of mean wasted life per failure) to item failure rate (λ)
False alarm	δ_{fa}	Ratio of false alarms to 'covered' failures - i.e., of the failures that are designed to be or could have been detected by PHM (whether actually detected or not)
PHM failure	δ_{pf}	Ratio of PHM failures to 'covered' item failures - i.e., of the failures that are designed to be or could have been detected by PHM (whether actually detected or not).

3.1 Considerations of the Effects of the PHM Attributes on Critical Unscheduled Failure Rate (λ_{ucrit})

The effects of the PHM attributes on critical unscheduled maintenance can be formulated readily. In this paper, point values (representing average values) are used to provide greater clarity and insight into the relationships between the PHM attributes and availability measures. In fact, the attributes are likely to be probabilistic, which is addressed by the use of stochastic simulation later in the paper. First, the 'covered' failures, that is, those failures for which PHM is intended to detect and predict, can be simply defined by the failure rate (λ_{ucrit}) multiplied by the coverage factor (f). Of those failures that are intended to be predicted so that they can be scheduled to be repaired during an allowed downtime, a portion will be missed (factored by α), so that the rate of missed failures is given by,

$$\lambda_{ucrit\_missed} = \lambda_{ucrit} * f * \alpha \tag{4}$$

Similarly, assuming failures due to the PHM technology itself are not detected or predicted by the PHM technology (e.g., sensor failures), the rate of PHM failures is given by,

$$\lambda_{ucrit\_phm\_fail} = \lambda_{ucrit} * f * \delta_{pf} \quad (5)$$

Likewise, false alarms which cause a fix action during the maintenance free operating period are given by,

$$\lambda_{ucrit\_false\_alarm} = \lambda_{ucrit} * f * \delta_{fa} \quad (6)$$

It should be noted that false alarms could also result in a fix action during allowed downtime, but in this paper the worst case is assumed that false alarms result in unscheduled downtime. Those failures which are not intended to be predicted by the PHM technology, or, are not 'covered', are given by,

$$\lambda_{ucrit\_not\_covered} = \lambda_{ucrit} * (1\text{-}f) \quad (7)$$

So that together, the sum of Eq.s (4) – (7) constitute the unscheduled maintenance, which can be reformulated as,

$$\lambda_{ucrit\_phm} = \lambda_{ucrit} * (1\text{-}f*(1\text{-}\varepsilon)) \quad (8)$$

where ε is the inefficiency attribute mentioned earlier and is given by,

$$\varepsilon = \alpha + \delta_{pf} + \delta_{fa} \quad (9)$$

It can be seen more clearly from Eq. (8) that missed failures, PHM technology failures, and false alarms act to reduce the positive effect of coverage in reducing the critical failures that occur during the maintenance free period. Eq. (8) was then used as the basis for examining the surface of reliability improvement as a function of coverage and inefficiency.

3.2 Prognostic Horizon and Take Action Points (TAPs)

One PHM attribute that may seem noticeably absent is prognostic horizon, which figures prominently in other efforts to define PHM attributes and metrics for decision making (Saxena, *et al*., 2009). While the concept of prognostic horizon makes sense for evaluating and comparing prognostic algorithms, it makes less sense in an operational and support concept. There will already be specific types of actions that a decision maker (i.e., an operator or maintainer) will want to take, such as order a spare in advance, preposition resources, fix immediately, fix before the next mission, fix at the next scheduled downtime, or fix when already fixing something else (opportunistic maintenance). The point at which a decision maker will want to take action, or Take Action Points (TAPs), are dependent on the maintenance and supply opportunities defined by the maintenance concept and operation. For example, the TAP for ordering a spare is dependent on the spare lead time (the time it takes to order and receive a spare). The TAP for mission aborting or mission affecting failures is the time between allowed downtimes, at a minimum. The decision maker is only interested in knowing in advance of a given TAP with a sufficient degree of confidence whether or not to take that action. The more uncertain the prediction, the more in advance of a TAP a decision maker will need to make a decision if the same level of confidence is desired. An example of an evaluation of the effect of uncertainty on increased time before decision points is provided in (Luna, 2009).

4 DERIVING SYSTEM LEVEL PHM REQUIREMENTS FROM AVAILABILITY REQUIREMENTS

Using Eq. (8) to relate coverage and inefficiency to λ_{ucrit_phm} and Eq. (3) to relate λ_{ucrit_phm} to A_{ocrit} by substituting λ_{ucrit_phm} for λ_{ucrit}, the relationship between required coverage and inefficiency values can be determined. Figure 1 shows the coverage required for a range of inefficiencies for A_{ocrit} ranging from 0.991 to 0.999 where MDT_{crit} = 1 hour, and λ_{ucrit} = 0.01 failures per hour (MTBCF = 100 hours).

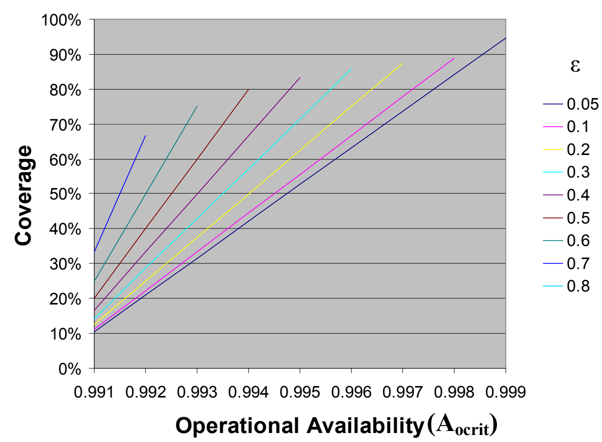

Figure 1: System Coverage Requirements from Availability Requirements

For very low inefficiency (0.05), the coverage required to meet A_{ocrit} requirements varies linearly from about 10% for A_{ocrit} = 0.991 to above 90% for A_{ocrit} = 0.999. As inefficiency increases, the requirement for coverage increases more rapidly as seen by the increasing slope of the plotted lines. It can also be seen that the minimum acceptable coverage also increases, ranging from 10% for low inefficiency up to about 25% for A_{ocrit} = 0.991. This means that the worse your PHM capability is, the more the coverage requirement is driven up.

It is interesting to compare these results with the increase in MTBCF (the inverse of λ_{ucrit}) required to meet the same A_{ocrit} objectives, as shown in Figure 2. While fairly linear for low A_{ocrit} values, it becomes highly nonlinear from about 0.996 or 0.997. If the costs to implement vary with coverage and MTBCF increases, then small improvements may be more economical to accomplish through increasing inherent reliability than applying PHM, while larger improvements may be more economical to implement with PHM.

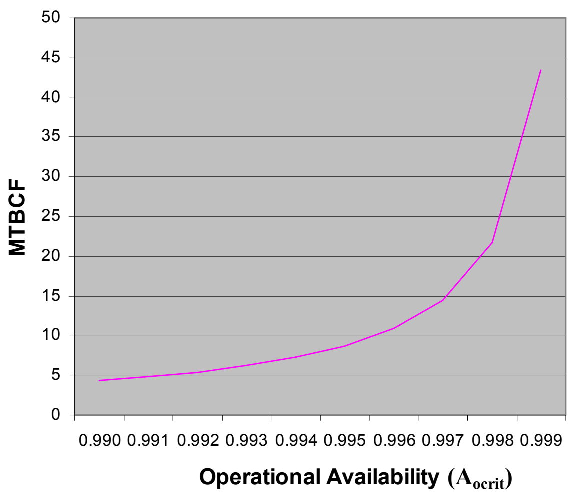

Figure 2: Reliability Design Requirements from Availability Requirements

In any case, Figure 1 shows that PHM requirements (in terms of the two attributes coverage and inefficiency) can be derived from availability requirements when the goal is to reduce downtime during a maintenance free period.

5 ALLOCATING PHM REQUIREMENTS

Once PHM requirements for the system have been derived, how can they be allocated to lower levels, such as to subsystems and components? One obvious source of potential methods to apply is from the area of reliability allocation. Several classic methods exist which rely on the normalized weighting of lower level failure rates, such as the Equal Apportionment, Base Apportionment, and ARINC methods (Ebeling, 1997; Crowe, 2008), which can be summarized by the following,

$$\lambda_{sys} = w_1\lambda_1 + w_2\lambda_2 + \ldots + w_n\lambda_n \qquad (10)$$

where there are n subsystems (or lower levels to which λ_{sys} is to be allocated) and $\sum w_i = 1$. The key to this approach is the source of information to determine the values for the weights, which can be set to be equal (1/n), a proportion of the subsystem to system failure rate (λ_i/λ_{sys}), or by some other means determined by the user. Each of these approaches is considered in the sections that follow.

The example used to examine each approach to allocating PHM requirements is that of a radar system composed of four components (antenna, transmitter, receiver, and processor). While a significantly larger number than four components could have been used in the example, a smaller number allows for simplicity and greater clarity. An improvement in λ_{ucrit} among the four components is desired for the radar system with a MTBCF of about 150 hours. The components of the radar system have existing or predicted MTBCFs of 3500, 750, 300, and 595 hours for the antenna, transmitter, receiver, and processor, respectively. The desired improvement is a 15% increase in MTBCF, which would yield an improved MTBCF = 173 hours. With a MDT_{crit} = 2 hours (1 hour for administrative delay and setup and 1 hour for repair), the resulting baseline A_{ocrit} is computed using Eq. 3 as 0.9867, while the improved A_{ocrit} is computed to be 0.9885. The recommended allocations are computed analytically, and then confirmed via logistics simulation of the radar system using the discrete-event simulation ASC LCOM (ASCLCOM, 2010) previously described in performing PHM benefit analysis in (Luna, 2009).

5.1 Equal Weighting

In this approach, the amount of reliability improvement desired is equally divided among the four components, as shown in Table 2. The MTBCF is shown for each component in the first column, along with its inverse (λ_{ucrit}) in the second column. The weight for each component is provided in the third column, which is used to multiply the overall λ_{sys} = 0.006633 to determine the reduction in each component's λ_{ucrit}, which is then subtracted from the original λ_{ucrit} to get the new reduced λ_{ucrit}. This value is inverted to get the new MTBCF in the fourth column, and then the percentage increase from the original to the improved MTBCF is shown in the fifth column.

Table 2: Equal Weighting

MTBCF	λ_{ucrit}	*w*	*New MTBCF*	*MTBCF increase*
3500	0.000286	0.25	14405	312%
750	0.001333	0.25	895	19%
300	0.003333	0.25	321	7%
595	0.001680	0.25	683	15%

The requirements on PHM to produce such MTBCF increases in each component can be evaluated using a similar approach to that described earlier for λ_{ucrit} , but based on a percentage increase in MTBCF, as shown in Figure 3. In this figure, coverage requirements are shown along the vertical axis, while the required MTBCF increase is shown along the long horizontal axis for different inefficiency values along the short horizontal axis. Using the percentage MTBCF improvement requirements from the fifth column of Table 2 and the equations to related percentage MTBCF to coverage and inefficiency requirements from Figure 3, the coverage requirements would be 80%, 17%, 7%, and 14% for the four components respectively for a low inefficiency ($\varepsilon = 0.05$). Different coverage requirements for different inefficiency values could be obtained for the same desired component MTBCF improvement, and could be used to evaluate various PHM technologies to satisfy those requirements.

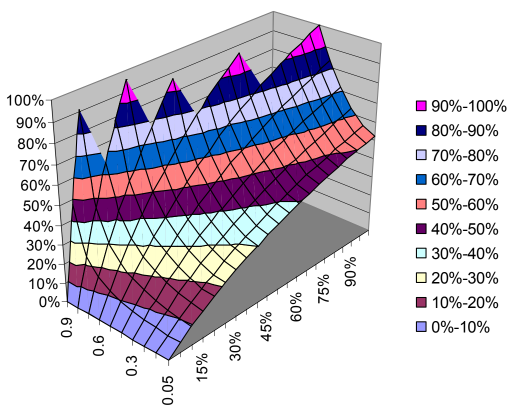

Figure 3: Reliability Design Requirements from Availability Requirements

It can be seen that using this method results in a requirement for quite a significant increase to the MTBCF of the antenna, the first component, which in turn results in a significant coverage requirement of 80%. Such a high coverage requirement may not be technically feasible. A weakness in this approach, then, is the allocation of requirements which may have unacceptably high technical risks.

5.2 Simulation

A discrete-event simulation model of the radar system with four components operating in a maintenance free environment as described earlier was developed to assess the actual impacts of coverage and inefficiency. An obvious advantage of simulation is to model uncertainty connected with PHM attributes which was not reflected in the simple analytical equations. In addition, simulation also provides not only single point values for A_{ocrit}, but also confidence values for A_{ocrit} based on the variation of PHM attributes as well as uncertainties in the system's operation and support. The simulation model explicitly handles the prediction of failures and performance of maintenance during allowed downtimes to examine whether the coverage and inefficiency values determined above are reasonable for estimating improvement to A_{ocrit}. Most modeling approaches model the effects of PHM in terms of non-PHM attributes, such as reduced lead times and larger MTBFs, while ASC LCOM is one of the few models that actually models the mechanisms of PHM as they apply to operational and logistics decision making based on the PHM attributes. The way in which these modeling mechanisms are implemented is discussed briefly below, but in more detail in (Luna, 2008; Luna, 2009).

5.2.1 Times to Fail and Coverage

Stochastic values for time to failure are generated for each of the four components in the simulation model. An exponential distribution was used to generate each of the stochastic times to fail, although a number of other distributions could have been used. A new time to fail for a given component is generated initially at the start of the simulation, and subsequently whenever it is replaced, whether in advance of failure during scheduled downtime, or when it fails during the maintenance free operating period. The covered failures were modeled separately from failures that are not covered, so that two distributions were needed for each component. This required dividing the component MTBFs between covered and not covered. This was implemented by dividing the current MTBF by the coverage value obtained above for the covered values, i.e., for component i,

$$MTBCF_{i\_covered} = MTBCF_i/coverage \qquad (11)$$

which for the first component yielded an $MTBCF_{covered}$ = 3500/80% = 4392 hours. The MTBCF for the uncovered values were derived by dividing by 100 minus the coverage percent, which for the first component yielded $MTBCF_{uncovered}$ = 3500/20% = 17231 hours. These two values were used to drive the failure mechanisms in the simulation (only a single parameter was required since exponential distributions were used for covered and uncovered failures). It should be noted that coverage was not implemented as a random variable within the simulation. To account for variation in coverage, different coverage percentages could be used to compute the parameters for the failure time distributions. Alternatively, logic could be defined in the model input file which allows failures for each component to be randomly assigned as covered or not covered based on the coverage percentage.

5.2.2 Missed Failure

The value for missed failure probability (α) is defined by the user as an input, and is used to define the offset of the component's prediction distribution from the component's actual time to failure as shown in Figure 4. When the actual failure (the solid vertical line in Figure 4) has been randomly generated by the simulation, a corresponding prediction of time to failure is also randomly generated from a prediction distribution. The first parameter (mean predicted failure with confidence, or MPFWC, in Figure 4) of the predicted failure time is fixed by the simulation with respect to the actual failure by α (referred to as "allowed predictions occurring after failure" in Figure 4) and by the standard deviation of the prediction distribution (also entered by the user as input). The standard deviation of the prediction distribution accounts for the precision of the prediction distribution and the offset accounts for the accuracy.

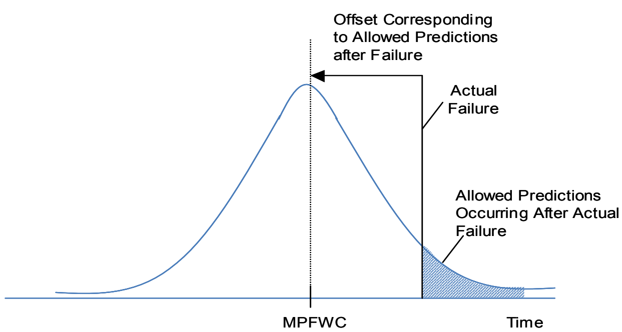

Figure 4. MPFWC is fixed relative to actual failure by allowed predictions occurring after actual failure (or *false negatives*).

5.2.3 Taking Maintenance Action

The user also specifies states of the aircraft with corresponding maintenance actions. In this example, the state 'PHMFIX', which means to fix at the first opportunity outside of the maintenance free operating period, is specified to begin 48 hours in advance of predicted failure. The user specifies maintenance tasks which look to see if the aircraft is in a 'PHMFIX' state, or, whether there is an opportunity to fix outside of the maintenance free operating period. When such an opportunity occurs (once every day for one hour), the administrative delay is assumed to have occurred prior to the scheduled maintenance for that downtime, so that the aircraft is only down for the one hour. Since the one hour of repair is conducted in the allowed one hour of downtime, the result is that A_{ocrit} is not impacted by predicted failures which can be fixed outside of the flying window. Failures that are not predicted should impact A_{ocrit}, whether it is because they are not covered or not predicted in time to fix outside of the flying window.

5.2.4 The Other Attributes

The other attributes from Table 1 were also considered for simulation. Wasted life (γ) was excluded because it concerns maintenance actions outside the maintenance free operating period, whereas this paper is concerned with failures that occur *within* the maintenance free operating period. Wasted life, however, is an important attribute when considering economic impacts. Both PHM failures and false alarms (δ_{pf}, δ_{fa}) were also excluded because they can be modeled as increases to non-covered failures, and since non-covered failures are already being modeled, they are not necessary for validation of the simulation with the analytic equations. They would be important factors, however, in an analysis where factors contributing to inefficiency are examined using the simulation.

5.2.5 Simulation of Equal Weighting

The MTBCF values for each component were computed based on the coverage allocations for low inefficiency ($\varepsilon = 0.05$) where α was set to 5% and PHM induced failures and false alarms were not modeled (δ_{fa}, $\delta_{pf} = 0$). A special measure was defined for the modified availability (to only count the downtime that occurs in the maintenance free operating period) and used to collect statistics. Assuming sufficient resources otherwise (parts, manpower, support equipment), the resulting mean A_{ocrit} for 30 replications of 180 days each was 0.9895, with low and high confidence (95%) values of 0.9888 and 0.990, respectively. Since the improved A_{ocrit} was expected to be 0.9885 (below the lowest confidence value), the difference between the values was investigated. Further review of the model showed that downtime is only counted in the simulation when there is maintenance performed, so that the system continued to operate during the scheduled downtimes when there was no critical maintenance to be performed. Examination of the baseline case confirmed this, where for no PHM capability, A_{ocrit} was reported as a mean of 0.9878 (with low and high confidence values of 0.9870 and 0.9886, respectively) versus the expected value computed earlier of 0.9867. Therefore, accounting for this difference between the mean and computed values for A_{ocrit}, the simulation results from modeling the PHM mechanisms matched well with the computed values of A_{ocrit}.

5.3 Equal Coverage

In this approach, the amount of reliability improvement desired is divided among the four components such that equal percent of MTBCF improvement is provided, as shown in Table 3. The resulting required coverage for each component would then be 14% based on a low inefficiency ($\varepsilon = 0.05$).

Table 3: Equal Coverage

MTBCF	λ_{ucrit}	*w*	***New MTBCF***	***MTBCF increase***
3500	0.000286	0.04	4025	15%
750	0.001333	0.20	863	15%
300	0.003333	0.50	345	15%
595	0.001680	0.25	684	15%

The coverage values were again used to compute MTBFs for the simulation, and confirmed by exercising the simulation that the expected A_{ocrit} was obtained.

5.4 Likely Coverage

The problem with the previous approaches is that they rely on methods to weight the allocation of reliability improvement with coverage as a result, rather than starting with what is likely coverage that can be obtained, and then computing what the resulting MTBCF improvements might be. An approach, which takes into account the desired coverage, as well as an estimate on the likelihood of obtaining it, was developed as shown in Table 4.

In this approach, one starts with estimates of what are possible coverage values based on PHM technology available, the type of equipment (mechanical, electro-mechanical, etc.), and any other factors that are considered relevant. These estimates can be developed by subject matter experts, market survey results, or through the use of tools such as MADe (Hess et al., 2008), and hypothetical estimates are shown in the first column for the four components.

Table 4: Likely Coverage

Estim. Covg.	***Prob. of Success***	***Alloc. Covg.***	***Ineff.***	***MTBCF increase***
15%	0.9	13.5%	0.30	10%
20%	0.8	16%	0.05	18%
50%	0.5	25%	0.25	23%
20%	0.7	14%	0.10	14%

In addition, a likelihood of achieving that coverage can be specified, based on factors such as the maturity of the PHM technology, which are shown in the second column. These are multiplied together to compute maximum allocated coverage, shown in the third column. In addition, estimates on inefficiency are provided which correspond with the coverage values provided. In this example, inefficiencies hypothetically vary from low (0.05 for the second component) to fairly high (0.30 for the first component). The coverage and inefficiency together can then be used to compute an estimated maximum achievable MTBCF for the component, as shown in the fifth column. These values can then be used to compute an overall MTBCF increase (19%) to a value of 180 hours, which is slightly larger than the previously stated goal of 173 hours. If the maximum achievable MTBCF does not meet the goal, then other reliability improvement means need to be identified or reassessment of PHM technologies. If the MTBCF is much higher than the goal, then the estimated coverages can be reduced based on probability of success, cost, or other relevant factors.

These coverage values were again used to compute MTBFs for the simulation, and confirmed by exercising the simulation that the expected A_{ocrit} (0.9896, slightly higher than 0.9895, with low and high confidence values of 0.9888 and 0.9903, respectively) was obtained.

5.5 Using Cost in Allocation Decision

There are reliability allocation methods that take costs into account (Ebeling, 1997; Mettas, 2000), but it often involves either estimating a general cost function for reliability increase, or obtaining detailed cost data that is often not available. The same is true for PHM technologies as well – there is still little in terms of actual cost data or cost estimating relationships to use as a basis for cost functions to help evaluate reliability allocation alternatives. It is a subject of future research to review methods for estimating and using cost functions to perform such evaluations.

6 CONCLUSION

Issues and methods of relating program requirements to PHM requirements and allocation of PHM requirements to lower system levels have been discussed. This paper focused on evaluating program requirements for improving reliability in a maintenance free operating period, although other benefit areas will also be examined in this ongoing effort (such as extending a maintenance free operating period, reducing downtime due to improved or replaced scheduled inspections, extending scheduled maintenance intervals by moving to condition-based maintenance). Reliability improvements were related to PHM attributes, which were condensed to two primary attributes: coverage and inefficiency. Methods of allocation of higher level PHM requirements to lower level requirements were examined, where lower level requirements were translated into component coverage and efficiency requirements which could guide PHM design. Methods of allocation focused on a normalized weighting approach. An alternative approach beginning with coverage estimates was also examined. A discrete-event simulation model was developed and exercised to confirm analytical results and to demonstrate that more extensive and complicated systems could be modeled.

The work described in this paper is part of a larger effort to define a framework and methodology for identifying and quantifying PHM benefits to military systems. Further efforts will involve identifying what tools and data are required in the proposed seven step process, including methods for tying to cost models in order to perform cost benefit analysis, as well as decision analysis tools for identifying high driver candidates for PHM application and the most promising PHM technologies.

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