

## **A Maintenance Planning and Business Case Development Model for the Application of Prognostics and Health Management (PHM) to Electronic Systems**

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***Abstract*** - This paper presents a model that enables the optimal interpretation of Prognostics and Health Management (PHM) results for electronic systems. In this context, optimal interpretation of PHM results means translating PHM information into maintenance policies and decisions that minimize life cycle costs, or maximize availability or some other utility function. The electronics PHM problem is characterized by imperfect and partial monitoring, and a random/overstress failure component must be considered in the decision process. Given that the forecasting ability of PHM is subject to uncertainties in the sensor data collected, the failure and damage accumulation models applied, the material dimensions and properties used in the models, the decision model in this paper addresses how PHM results can best be interpreted to provide value to the system maintainer. The result of this model is a methodology for determining an optimal safety margin and prognostic distance for various PHM approaches in single and multiple socket systems where the LRU's in the various sockets that make up a system can incorporate different PHM approaches (or have no PHM structures at all).

The discrete event simulation model described in this paper provides the information needed to construct a business case showing the application-specific usefulness for various PHM approaches including health monitoring (HM) and life consumption monitoring (LCM) for electronic systems. An example business case analysis for a single-socket system is provided.

***Index Terms*** - Prognostic health management (PHM), life cycle cost, cost modeling, discrete event simulation, business case development, life consumption monitoring, health monitoring, maintenance planning.

## 1. Introduction

Prognostics is the estimation of Remaining Useful Life (RUL) in terms that are useful to the maintenance decision making process. The decision process can be tactical (real-time interpretation and feedback) or strategic (maintenance planning). All PHM approaches are essentially the extrapolation of trends based on recent observations to estimate RUL, [1]. Unfortunately, the calculation of RUL alone does not provide sufficient information to form a decision or to determine corrective action. Without comprehending the corresponding measures of the uncertainty associated with the calculation, RUL projections have little practical value, [1]. It is the comprehension of the corresponding uncertainties (decision making under uncertainty) that is at the heart of being able to develop a realistic business case that addresses prognostic requirements. The PHM approaches used to estimate RUL include: 1) Life Consumption Monitoring (LCM) forecasts based on physics-of-failure (PoF) models [2,3], 2) Health Monitoring (HM) forecasts based on precursor variable monitoring [4,5], and 3) HM forecasts based on failure mechanism specific fuses [6]. Vichare *et al.* [3] has shown how the uncertainty of an RUL forecast derived from LCM can be estimated. Mishra *et al.* [6] has shown how the uncertainty of a RUL forecast derived from failure mechanism specific fuse structures can be estimated.

Electronic systems have not traditionally been subject to PHM because their time to failure was assumed to be non-quantifiable and in any case, much longer than the system support life or technology refresh period (non-life limited). Most approaches to PHM are focused on monitoring failure precursor indications (i.e., HM), which does not require system failures to be deterministic in nature, but does require that the precursor selected has a deterministic link to the actual system failure. While there is considerable existing work on precursors for mechanical systems [4,5], relatively few attempts have been made to apply HM techniques to electronics, [6,7]. Alternatively, LCM, depends on the deterministic nature of system failures expressed through failure models. In LCM, a history of environmental stresses (e.g., thermal, vibration) is used in conjunction with physics of failure (PoF) models to compute accumulated damage and thereby forecast RUL, [2]. With the transition from military-specification parts to commercial-off-the-shelf (COTS) parts, many of which are now targeted by design for lifetimes in the 5 to 7 year range, wear-out of electronics may become a relevant concern for long field life systems, [8]. Also, it has long been known that interconnects are subject to fatigue failure from temperature cycling. In addition, PoF approaches to modeling electronic system reliability have shown that time-to-failure (TTF) for electronic parts and interconnects can be predicted within quantifiable bounds of uncertainty, [9].

Modeling to determine the optimum schedule for performing maintenance for systems is not a new concept. Examples of traditional applications of maintenance modeling include production equipment [10], and the hardware portions of engines and other propulsion systems [5]. However, maintenance modeling has not been widely applied to electronic systems where presumed random electronics failure is usually modeled as an unscheduled maintenance activity, and wear-out is assumed to be beyond the end of the system's support life.

Although many applicable models for single and multi-unit maintenance planning have appeared [11,12], the majority of the models assume that monitoring information is perfect (without uncertainty) and complete (all units are monitored the same), i.e., maintenance planning can be performed with perfect knowledge as to the state of each unit. For many types of systems, and especially electronic systems, these are not good assumptions and maintenance planning, if possible at all, becomes an exercise in decision making under uncertainty with sparse data. The perfect monitoring assumption is especially problematic when the PHM approach is LCM because LCM does not depend on precursors. Thus, for electronics, LCM processes do not deliver any measures that correspond exactly to the state of a specific instance of a system. Previous work that treats imperfect monitoring includes [4] and [13]. Perfect, but partial monitoring has been previously treated in [14].

This paper presents a new stochastic decision model that enables the optimal interpretation of LCM damage accumulation or HM precursor data, and applies to failure events that appear to be random or appear to be clearly caused by defects. Specifically the model is targeted at addressing the following two questions:

- How do we determine on an application-specific basis when the reliability of electronics has become predictable enough to warrant the application of PHM-based scheduled maintenance concepts? Note, we do not mean to imply that predictability in isolation is the criteria for PHM vs. non-PHM solutions, e.g., if the system reliability is predictable and very reliable, it would not make sense to implement a PHM solution.
- Given that the forecasting ability of PHM is subject to uncertainties in the sensor data collected, the data reduction methods, the failure models applied, the material parameters assumed in the models, etc., how can PHM results be interpreted so as to provide value, i.e., how can a business case be constructed? This boils down to determining an optimal safety margin on LCM prediction and prognostic distance for HM.

## 2. Model Formulation

The following maintenance planning model accommodates variable time-to-failure (TTF) of LRUs and variable RUL estimates associated with PHM approaches implemented within LRUs. The model considers both single and multiple sockets within a larger system. A “socket”, in our terminology, is a unique instance of an installation location, e.g., a Line Replaceable Unit (LRU). An example of an LRU could be an engine controller for a jet engine, one instance of a socket occupied by the engine controller is the location on a particular jet engine. This socket may be occupied by a single LRU during its lifetime (if the LRU never fails), or multiple LRU’s if one or more LRUs fail and needs to be replaced.

Discrete event simulation is used to follow the life of individual socket instances from the start of their field life to the end of their operation and support. Discrete event simulation implies the modeling of a system as it evolves over time by representing the changes as separate events (as opposed to continuous simulation where the system evolves as a continuous function). The evolutionary unit need not be time; it could be thermal cycles, or some other unit relevant to the particular failure mechanisms addressed by the PHM approach. Discrete event simulation has the advantage of defining the problem in terms of something intuitive, i.e., a sequence of events, thus avoiding the need for formal specification. Discrete event simulation is widely used for maintenance and operations modeling, e.g., [15-17], and has also previously been used to model PHM activities, [18].

The model use in this paper treats all inputs to the discrete event simulation as probability distributions, i.e., a stochastic analysis is used, implemented as a Monte Carlo simulation. Various maintenance interval and PHM approaches are distinguished by how sampled TTF values are used to model PHM RUL forecasting distributions. To assess PHM, relevant failure mechanisms are segregated into two types:

1. Failure mechanisms that are random from the view point of the PHM methodology. These are failure mechanisms that the PHM methodology is not collecting any information about (non-detection events). These failure mechanisms may be predictable, but are outside the scope of the PHM methods applied.
2. Failure mechanisms that are predictable from the view point of the PHM methodology, i.e., for which a probability distribution can be assigned.

For the purposes of cost model formulation, PHM approaches are categorized as: a) a Fixed-Schedule Maintenance Interval that is kept constant for all instances of the LRU’s occupying all socket instances throughout the system life cycle; b) a variable maintenance interval schedule for LRU instances that is based on inputs from a

Precursor to Failure methodology (e.g., HM or LRU-dependent fuses)); and c) a variable maintenance interval schedule for LRU instances that is based on an LRU-independent methodology (e.g., an LCM methodology or LRU-independent fuses).<sup>1</sup> Note, for simplicity, throughout this paper the model formulation is presented based on “time” to failure measured in operational hours, however, the relevant quantity could be a non-time measure such as thermal cycles.

The metrics computed are: life cycle cost, failures avoided, and operational availability. Appendix A provides a detailed description of the model implementation. The key features of the model’s formulation are described in Sections 2.1-2.3. Example results generated using all the approaches discussed in this section are presented in Sections 3 and 4.

### *2.1 Fixed-Schedule Maintenance Interval*

A fixed-schedule maintenance interval is selected that is kept constant for all instances of the LRU that occupy a socket throughout the system life cycle. In this case the LRU is replaced on a fixed interval (measured in operational hours), i.e., time-based prognostics. This is analogous to mileage based oil change in automobiles.

### *2.2 Precursor to Failure Monitoring*

Precursor to failure monitoring approaches are defined as a fuse or other monitored structure that is manufactured with or within the LRUs or as a monitored precursor variable that represents a non-reversible physical process, i.e., it is coupled to a particular LRU’s manufacturing or material variations. Health Monitoring (HM) and LRU-dependent fuses are examples of precursor to failure methods. The parameter to be determined (optimized) is prognostic distance. The prognostic distance is a measure of how long before system failure the prognostic structures or prognostic cell is expected to indicate failure (in operational hours for example). The precursor to failure monitoring methodology forecasts a unique TTF distribution for each instance of an LRU based on the instance’s TTF.<sup>2</sup> For illustration purposes, the precursor to failure monitoring forecast is represented as a symmetric triangular distribution with a most likely value (mode) set to the TTF of the LRU instance minus the prognostic

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<sup>1</sup> LRU-dependent fuses are fabricated concurrently with specific instances of LRUs, e.g., they would share LRU-specific variations in manufacturing and materials. LRU-independent fuses are fabricated separately from the LRUs and assembled into the LRUs, so they do not share any LRU-specific variations in manufacturing and materials.

<sup>2</sup> In the present model, all failing LRUs are assumed to be maintained via replacement or good as new repair, therefore, time between failure and time to failure are the same.

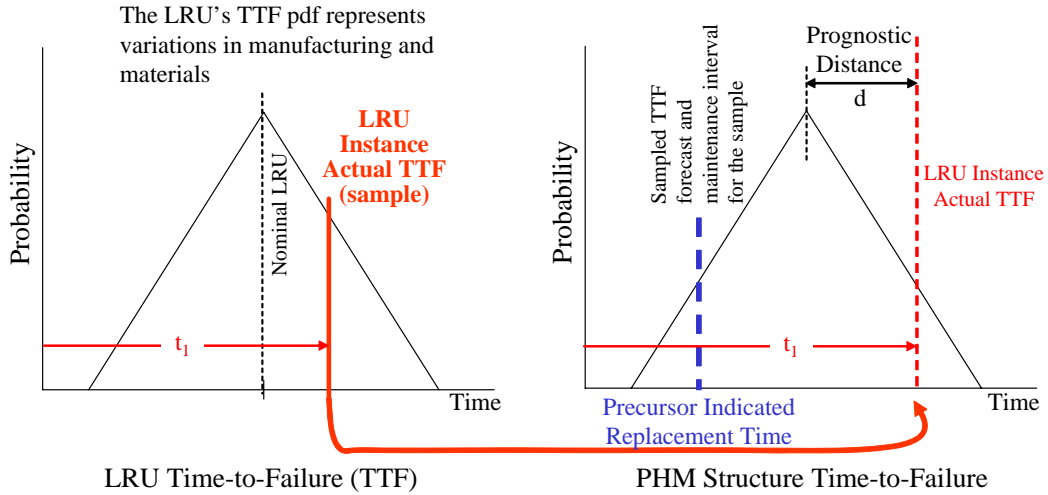


Fig. 1. Precursor to failure monitoring modeling approach. Symmetric triangular distributions are chosen for illustration. Note, the LRU TTF pdf (left) and the Precursor to failure TTF pdf (right) are not the same (they could have different shapes and sizes).

distance, Fig. 1. The precursor to failure monitoring distribution has a fixed width measured in the relevant environmental stress units (e.g., operational hours in our example) representing the probability of the prognostic structure correctly indicating the precursor to a failure. As a simple example, if the prognostic structure was a LRU-dependent fuse that is designed to fail at some prognostic distance earlier than the system it protects, then for this example the distribution on the right side of Fig. 1 represents the distribution of fuse failures (the TTF distribution of the fuse).

The parameter to be optimized in this case is the prognostic distance assumed for the precursor to failure monitoring forecasted TTF. The model proceeds in the following way: for each LRU TTF distribution sample ( $t_1$ ) taken from the left side of Fig. 1, a precursor to failure monitoring TTF distribution is created that is centered on the LRU TTF minus the prognostic distance ( $t_1-d$ ). The precursor to failure monitoring TTF distribution is then sampled and if the precursor to failure monitoring TTF sample is less than the actual TTF of the LRU instance then precursor to failure monitoring was successful. If the precursor to failure monitoring distribution TTF sample is greater than the actual TTF of the LRU instance then precursor to failure monitoring was unsuccessful. If successful, a scheduled maintenance activity is performed and the timeline for the socket is incremented by the precursor to failure monitoring sampled TTF. If unsuccessful, an unscheduled maintenance activity is performed and the timeline for the socket is incremented by the actual TTF of the LRU instance. At each maintenance activity, the relevant costs given in Table 1 (in Section 3) are accumulated.

### 2.3 LRU-Independent Methods

In LRU-independent PHM methods, the PHM structure (or sensors) are manufactured independent of the LRUs, i.e., the PHM structures are not coupled to a particular LRU's manufacturing or material variations. An example of a LRU-independent method is Life Consumption Monitoring (LCM). LCM is the process by which a history of environmental stresses (e.g., thermal, vibration) is used in conjunction with physics of failure (PoF) models to compute damage accumulated and thereby forecast RUL.

The LRU-independent methodology forecasts a unique TTF distribution for each instance of an LRU based on its unique environmental stress history. For illustration purposes, the LRU-independent TTF forecast is represented as a symmetric triangular distribution with a most likely value (mode) set relative to the TTF of the nominal LRU and a fixed width measured in operational hours, (Fig. 2).<sup>3</sup> Other distributions may be chosen and [3] has shown how this distribution may also be derived from recorded environment history. The shape and width of the LRU-independent method distribution depends on the uncertainties associated with the sensing technologies and uncertainties in the prediction of the damage accumulated (data and model uncertainty). The variable to be optimized in this case is the safety margin assumed on the LRU-independent method forecasted TTF, i.e., the length

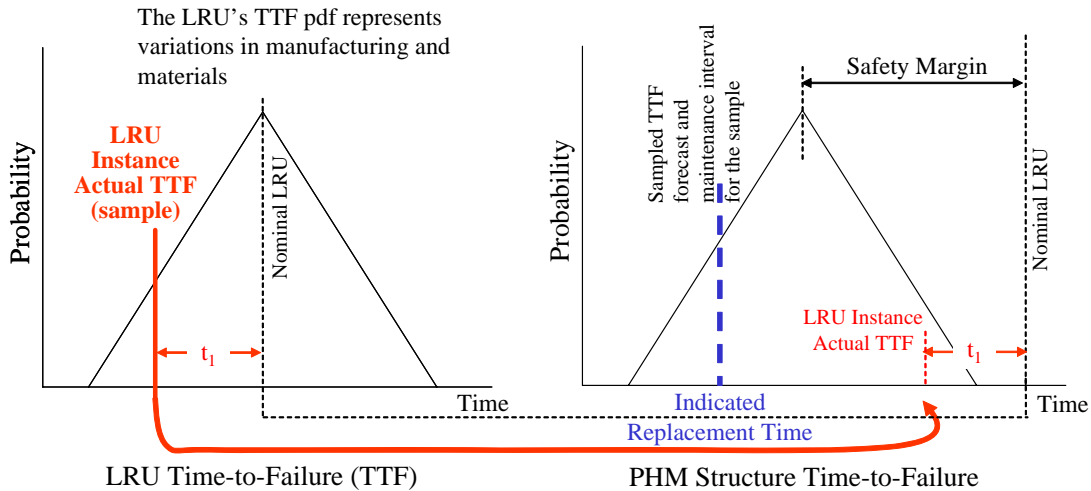


Fig. 2. LRU-independent modeling approach. Symmetric triangular distributions are chosen for illustration. Note, the LRU TTF pdf (left) and the LRU-independent method TTF pdf (right) are not the same (they could have different shapes and sizes).

<sup>3</sup> A preliminary version of this work, [19], suggested a different model for Life Consumption Monitoring (LCM), which is not applicable to LCM as defined in this paper. The model for LCM used in [19] is mathematically identical to the model presented for precursor to failure methods in Fig. 1.

of time (e.g., in operation hours) before the LRU-independent method forecasted TTF the unit should be replaced.

The LRU-independent model proceeds in the following way: for each LRU TTF distribution sample (left side of Fig. 2), an LRU-independent method TTF distribution is created that is centered on the TTF of the nominal LRU minus the safety margin – right side of Fig. 2 (note, the LRU-independent methods only know about the nominal LRU, not about how a specific instance of a LRU varies from the nominal). The LRU-independent method TTF distribution is then sampled and if the LRU-independent method TTF sample is less than the actual TTF of the LRU instance then LRU-independent method was successful (failure avoided). If the LRU-independent method TTF distribution sample is greater than the actual TTF of the LRU instance then LRU-independent method was unsuccessful. If successful, a scheduled maintenance activity is performed and the timeline for the socket is incremented by the LRU-independent method sampled TTF. If unsuccessful, an unscheduled maintenance activity is performed and the timeline for the socket is incremented by the actual TTF of the LRU instance.

In all the maintenance models discussed, a random failure component may also be superimposed (see Appendix A). The fixed scheduled maintenance, precursor to failure monitoring and LRU-independent method model is implemented as stochastic simulations, in which a statistically relevant number of sockets are considered in order to construct histograms of costs, availability, and failures avoided. At each maintenance activity, the relevant costs according to Table 1 are accumulated.

The fundamental difference between the precursor to failure and LRU-independent models is that in the precursor to failure models the TTF distribution associated with the PHM structure (or sensor) is unique to each LRU instance; whereas in the LRU-independent models the TTF distribution associated with the PHM structure (or sensor) is tied to the nominal LRU and knows nothing about manufacturing or material variations between LRU instances.



### 3. Single Socket Model Results

The baseline data assumptions used to demonstrate the model in this paper are given in Table 1.

TABLE 1. Data assumptions for example cases presented in this paper.

Variable in the model	Value used for example analysis	
Production cost (per unit)	\$10,000	
Time to failure (TTF)	5000 operational hours = the most likely value (symmetric triangular distribution with variable distribution width)	
Operational hours per year	2500	
Sustainment life	25 years	
	Unscheduled	Scheduled
Value of each hour out of service	\$10,000	\$500
Time to repair	6 hours	4 hours
Time to replace	1 hour	0.7 hours
Cost of repair (materials cost)	\$500	\$350
Fraction of repairs requiring replacement of the LRU (as opposed to repair of the LRU)	1.0	0.7

All of the variable inputs to the model can be treated as probability distributions or as fixed values, however, for example purposes, only the TTFs of the LRUs and the PHM structures have been characterized by probability distributions. Note, all the life cycle cost results provided in the remainder of this paper are the mean life cycle cost from a probability distribution of life cycle costs generated by the model.

Figure 3 shows the fixed scheduled maintenance interval results. 10,000 sockets were simulated in a Monte Carlo analysis and the mean life cycle costs are plotted. The general characteristics in Fig. 3 are intuitive: For short scheduled maintenance intervals, virtually no expensive unscheduled maintenance occurs, but the life cycle cost per unit is high because large amounts of RUL in the LRUs are thrown away. For long scheduled maintenance intervals virtually every LRU instance in a socket fails prior to the scheduled maintenance activity and the life cycle cost per unit becomes equivalent to unscheduled maintenance. For some scheduled maintenance interval between the extremes, the life cycle cost per unit is minimized. If the TTF distribution for the LRU had a width of zero, then the optimum fixed scheduled maintenance interval would be exactly equal to the forecasted TTF. As the forecasted TTF distribution for the LRU becomes wider (i.e., the forecast is less well defined), a practical fixed scheduled maintenance interval becomes more difficult to find and the best solution approaches an unscheduled maintenance model.

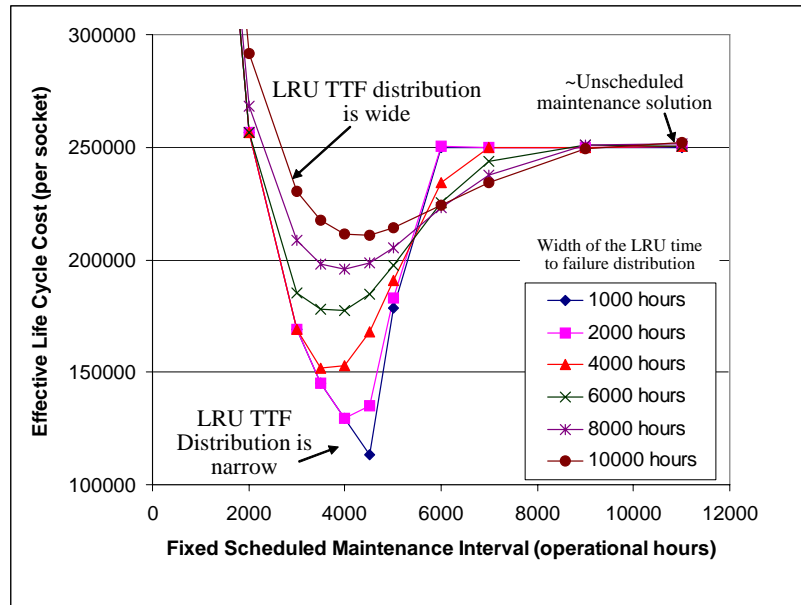


Fig. 3. Variation of the effective life cycle cost per socket with the fixed scheduled maintenance interval (10,000 sockets simulation). No random failures assumed.

Figure 4 shows example results for various widths of the LRU TTF distribution as a function of the safety margin and prognostic distances associated with the precursor to failure and LRU-independent models. Several general trends are apparent. First, the width of the LRU TTF distribution has little effect on the precursor to failure PHM method results. This result is intuitive since in the precursor to failure case the PHM structures are coupled to the LRU instances and track whatever manufacturing or material variation they have, so they also track the LRU TTF distribution (the degree to which the LRU-to-LRU variations are removed from the problem depends on the degree of coupling between the LRU manufacturing/materials and the PHM structure manufacturing/materials). Alternatively, the LRU-independent PHM method is sensitive to the LRU TTF distribution width since it is uncoupled from the specific LRU instance and can only base its forecast of failure on the performance of a nominal LRU. A second observation is that the optimum safety margin decreases as the width of the LRU TTF distribution decreases. This is also intuitive, since as the reliability becomes more predictable (i.e., narrower forecasted LRU TTF distribution width), the safety margin that needs to be applied to the PHM predictions also drops.

Figure 5 shows example results for various widths of the PHM associated distribution (constant LRU TTF distribution width) as a function of the safety margin and prognostic distances associated with the precursor to failure and LRU-independent models. In this case, both PHM approaches are sensitive to the width of their distributions.

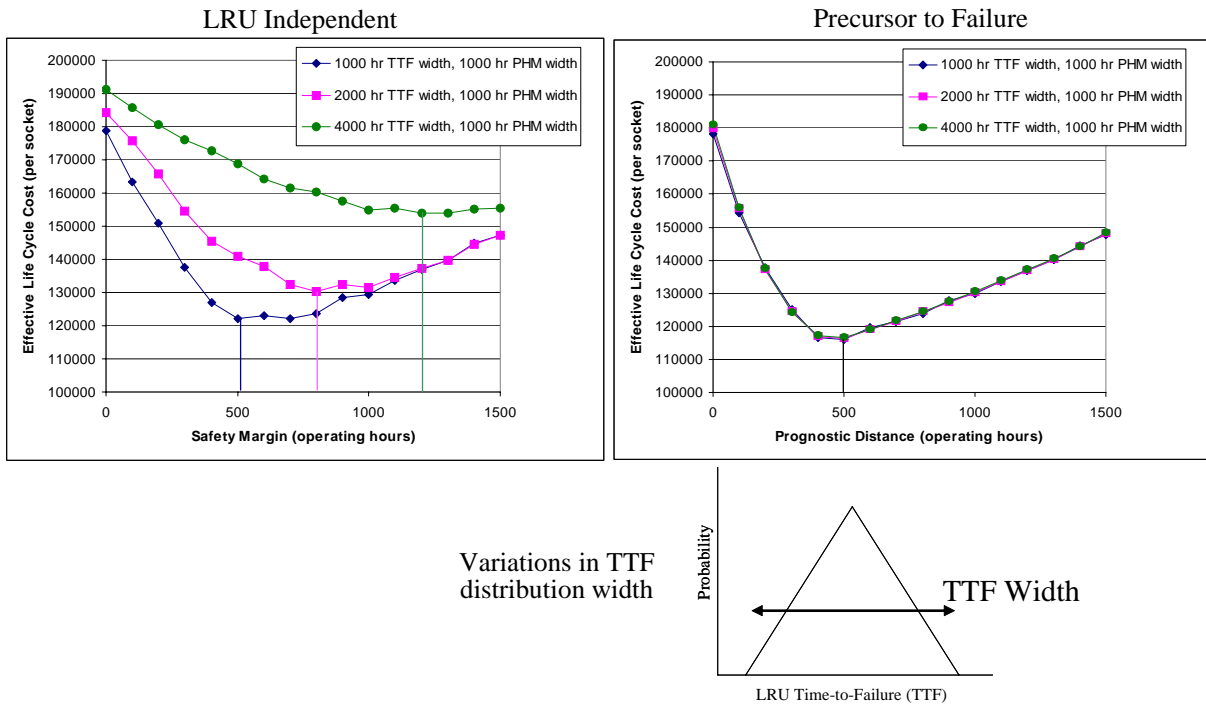


Fig. 4. Variation of the effective life cycle cost per socket with the safety margin and prognostic distance for various LRU TTF distribution widths and constant PHM structure TTF width (10,000 sockets simulated).

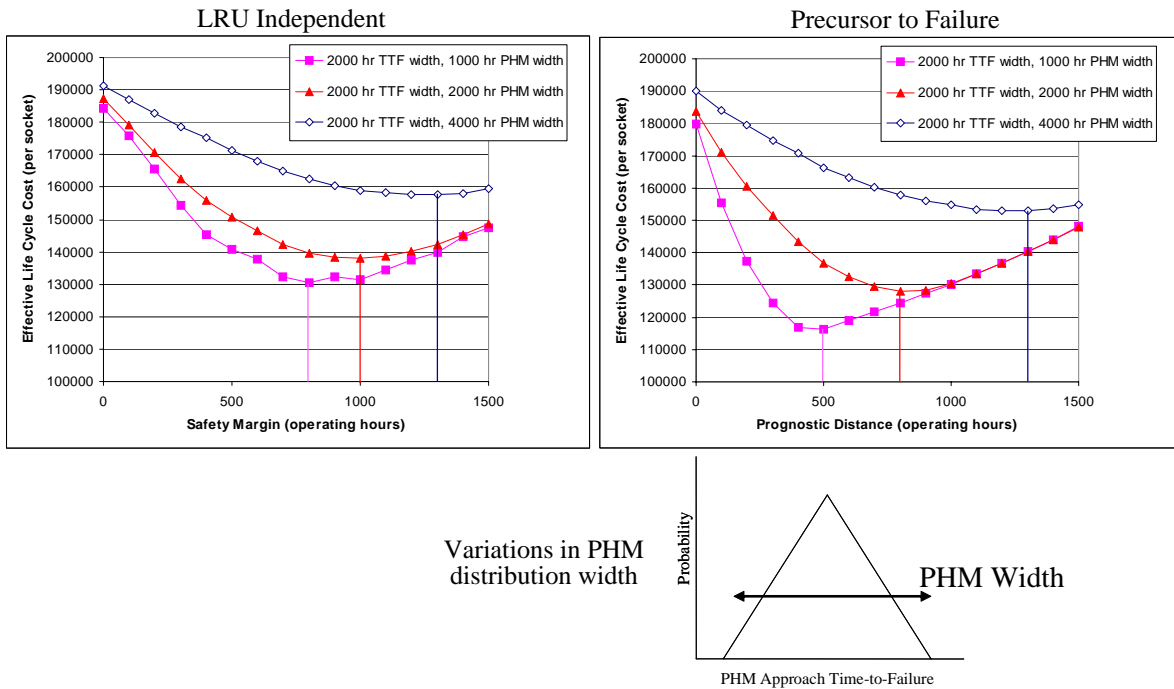


Fig. 5. Variation of the effective life cycle cost per socket with the safety margin and prognostic distance for various PHM structure TTF and constant LRU TTF distribution widths (10,000 sockets simulated).

General observations from Figures 4 and 5 are that:

- 1) The LRU-independent model is highly dependent on the LRU's TTF distribution
- 2) Precursor to failure methods are approximately independent of the LRU's TTF distribution
- 3) All things equal, optimum prognostic distances for precursor methods are always smaller than optimum safety margins for LRU-independent methods, and therefore, all things equal, precursor to failure PHM methods will always result in lower life cycle cost solutions than LRU-independent methods.

Where “all things equal” means the same LRUs with the same shape and size distribution associated with the PHM approach. Any comparison between the precursor to failure approach and the LRU-independent approach, assumes that you have a choice between the two, i.e., that there is a precursor to failure method that is applicable – there may not be (especially for application to electronic systems). Appendix B provides an example business case construction for the single socket case.

Figure 6 shows an example with 10% random failures included. Figure 6 also includes the associated failures avoided. In all cases the failures avoided when random failures are included is lower than when random failures are not included, however, the change in the optimum safety margin or prognostic distance is small. As the safety margin or prognostic distance increase the failures avoided limits to 100% in all cases (with and without random failures included). However, for the example data used in this paper, safety margins or prognostic distances must be increased substantially beyond the range plotted in Fig. 6 for the cases with random failures to approach 100%.

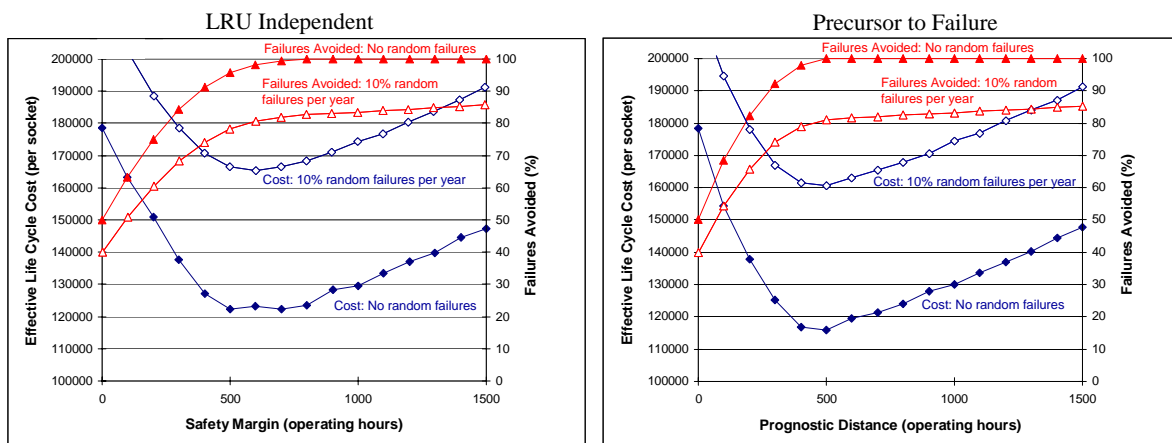


Fig. 6. Variation of the effective life cycle cost per socket and failures avoided, with the safety margin and prognostic distance for 2000 hour LRU TTF distribution widths and 1000 hour PHM distribution widths, with and without random failures included (10,000 sockets simulated).

#### 4. Multiple Socket Model Results

Real systems are composed of multiple sockets, where the sockets are occupied by mixture of LRUs, some with no PHM structures or strategies, and others with fixed interval strategies, precursor to failure structures or LRU independent structures. Maintenance, even when it is scheduled, is expensive. Therefore, when the system is removed from service to perform a maintenance activity for one socket it may be desirable to address multiple sockets (even if some have not reached their most desirable individual maintenance point).

First we address, how to use the single socket models developed in Section 2 to optimize a system composed of multiple sockets, where we are assuming that all the LRUs that occupy a particular socket have the same PHM approach (but approaches can vary from socket to socket). To address this problem we introduce the concept of a coincident time. The coincident time is the time interval within which different sockets should be treated by the same maintenance action. If,

$$\text{Time}_{\text{coincident}} > \text{Time}_{\text{required maintenance action on LRU } i} - \text{Time}_{\text{current maintenance action}} \quad (1)$$

then the LRU  $i$  is addressed at the current maintenance action. A coincident time of 0 means that each socket is treated independently. A coincident time of infinity means that any time any LRU in any socket in the system demands to be maintained; all sockets are maintained no matter what remaining life expectancy they have. In the discrete event simulation, the time of the current maintenance and the future times for the required maintenance actions on other LRUs are known or forecasted and application-specific optimum coincident times can be found.

Implementation of the above constraint in the discrete event simulation is identical to the single socket simulation except we follow more than one socket at a time (see Appendix A). When the first LRU in the multiple socket system indicates that it needs to be maintained by RUL forecast or actually does fail, a maintenance activity is performed on all sockets in which the LRUs forecast the need for maintenance within a user specified coincident time, e.g., Fig. 7. Our model assumes that LRUs replaced at a maintenance event are good-as-new and that the damage accumulated by portions of the system not addressed by a maintenance event are not affected by the maintenance event. Costs are accumulated for scheduled and unscheduled maintenance activities and a final total life cycle cost computed. In practice, the future maintenance actions times for LRUs, other than the one indicating the need for maintenance, need to be determined from reliability forecasting (note, however, there is greater uncertainty in these forecasts the further from the present you go).

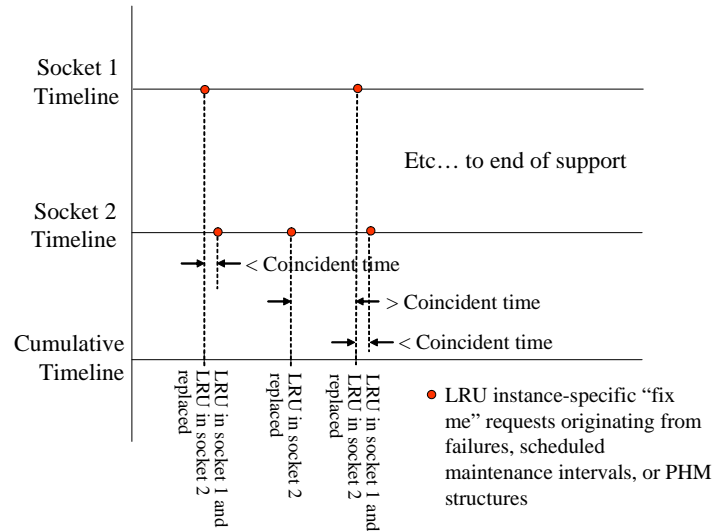


Fig. 7. Multi-socket timeline example.

Analysis of multi-socket systems demonstrates that three types of system responses are possible for three types of systems: dissimilar LRUs, similar LRUs, and optimizable mixed systems of LRUs. Consider systems built from the two different sockets shown in Fig. 8. For the examples in this section, with the exception of the LRU TTF distribution, all the data is given in Table 1. With LRU TTFs defined as shown in Fig. 8, a system composed of sockets #1 and #2 is considered to be dissimilar (LRUs with substantially different reliabilities and different PHM approaches). The first step in analyzing a multi-socket system is to determine what prognostic distance/safety margins to use for the individual sockets – we have observed no differences between the optimum prognostic

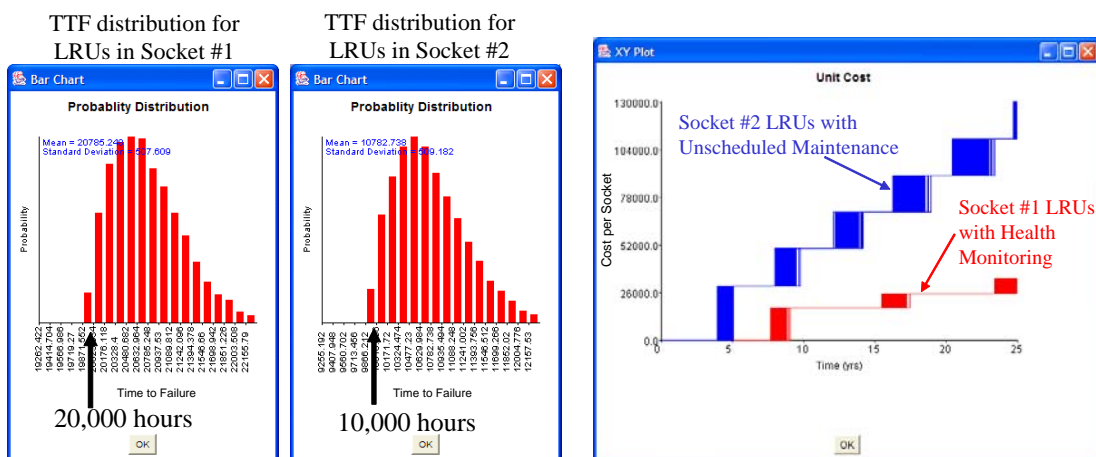


Fig. 8. Time to failure (TTF) distributions for LRUs used in multi-socket analysis examples. The plot on the right shows the cost of single socket systems made from these two LRUs as a function of time using a prognostic distance of 500 hour for the LRU in socket #1 (note, the results for 10,000 instance of each socket are shown). All data other than the LRU TTF is given in Table 1.

distance/safety margins determined analyzing individual sockets or the sockets within larger systems. For the case shown in Fig. 8, the optimum prognostic distance for the LRU in socket #1 was 500 hours.

Figures 9-11 plot the mean life cycle cost for a system of sockets. The mean life cycle cost is the mean of a

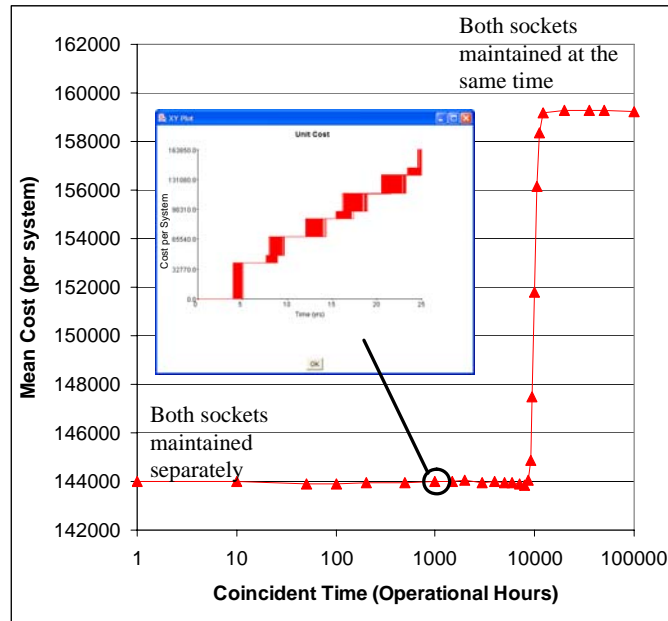


Fig. 9. Mean life cycle cost per system of two dissimilar sockets. Socket #1 LRU, location parameter = 19900 hours (health monitoring); socket #2 LRU, FFOP = 9900 hours (unscheduled maintenance). (10,000 systems simulated).

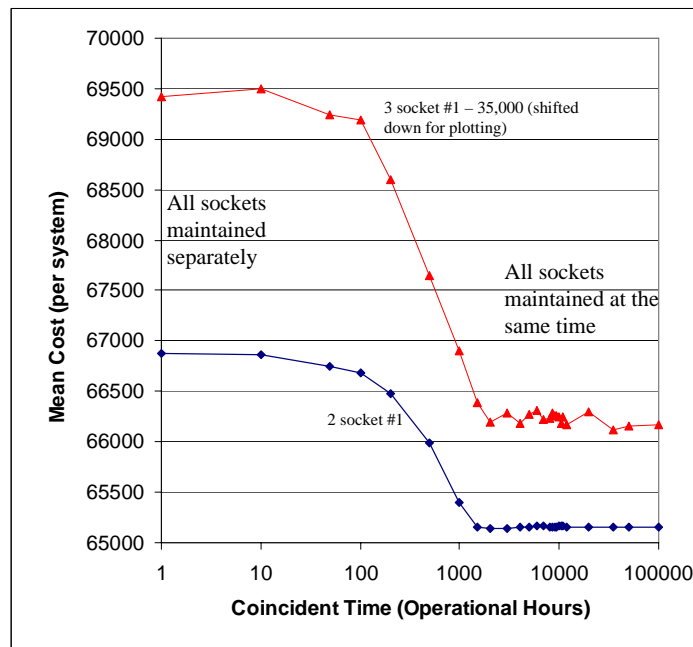


Fig. 10. Mean life cycle cost per system of two or three similar sockets. All LRUs, location parameter = 19900 hours (health monitoring). (10,000 systems simulated).

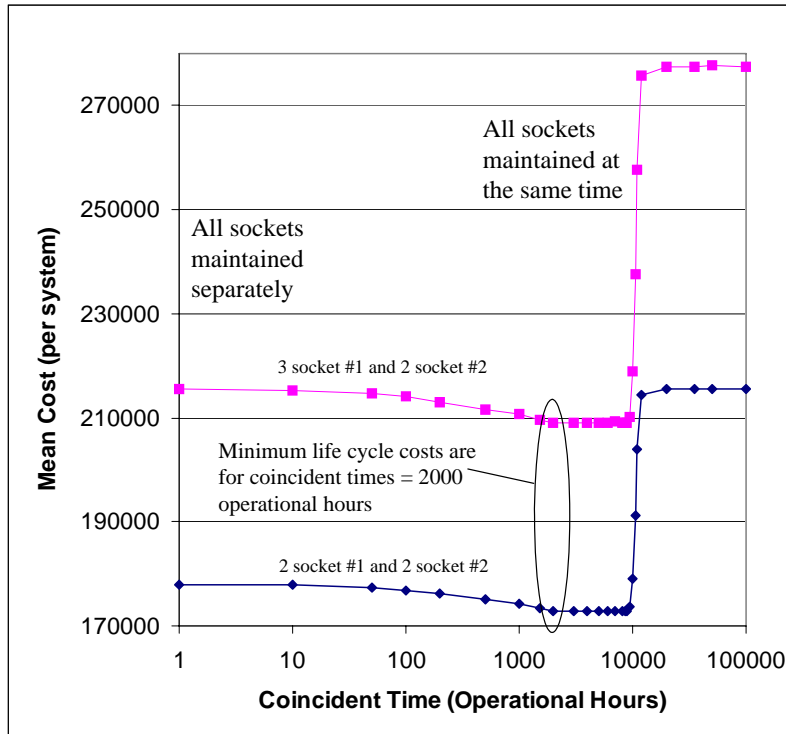


Fig. 11. Mean life cycle cost per system of mixed sockets. (10,000 systems simulated).

distribution of life cycle costs computed for a population of 10,000 systems. Figure 9 shows the most common life cycle cost characteristic for dissimilar systems. For small coincident times, both sockets are being maintained separately, for large coincident times, LRUs in both sockets are replaced anytime either socket requires maintenance. Obviously, dissimilar systems prefer small coincident time (this is intuitive).

Figure 10 shows the cases of two and three similar LRUs in a system. In this case the multiple sockets that make up the system are all populated with LRU #1 in Fig. 8. In this case, the solution prefers to maintain the LRUs in all the sockets at the same time, i.e., when the LRU in one socket indicates that it needs to be maintained, the LRUs in all the sockets are maintained. Note the height of the step depends on the number of hours to perform scheduled maintenance and the cost of those hours.

Figure 11 shows the results for a mixed system that has a non-trivial optima in the coincident time. In this case there is a clear minima in the mean life cycle cost that is not at zero or infinity.



## 5. Discussion

Previous work has demonstrated that PHM approaches can be successfully applied to electronic systems, [2,3,6]. However, the previous work has not addressed if (or exactly how) a specific application's life cycle cost can actually be reduced and/or operational availability increased by using PHM. Such an analysis becomes non-trivial when one considers that the RUL predictions are based on imperfect and partial monitoring conditions and thus are themselves subject to uncertainty. Schemes for interpreting and applying PHM results to maintenance decisions will have to balance the risk of unscheduled failure with the substantial uncertainties present in the PHM results.

The single and multi-socket models presented in this paper provide insight into the maintenance decision process when complex systems use various PHM approaches within their subsystems. To be complete, models like those presented in this paper will ultimately need to address additional issues including:

- What is the right shape and size of distributions associated with PHM approaches?
- How to treat redundancy and what exactly constitutes a failure?
- Second order uncertainty (uncertainty about uncertainty) may be a real issue in the treatment of this problem.
- The effects of repair, i.e., LRUs with a mixed age population of sub-assemblies.
- More detailed revenue models are needed to model the cost of maintenance, e.g., simply costing scheduled and unscheduled maintenance is oversimplified for modeling the maintenance planning of commercial enterprises.
- The present analysis has not addressed a calculation of the actual implementation costs of PHM, i.e., this analysis has only discussed the "return on" part of the return on investment problem.

## Appendix A – Model Implementation Details

This appendix provides a detailed description of the general model implementation. In the model, the time-to-failure (TTF) distribution is assumed to represent manufacturing and material variations from LRU to LRU. The range of possible environmental stress histories that sockets may see are modeled using an environmental stress history distribution. Note, the environmental stress history distribution need not be used if the TTF distribution for the LRUs includes environmental stress variations. The environmental stress history distribution is not used with the precursor to failure or LRU-independent models. Random TTFs are characterized by a uniform distribution with a height equal to the average random failure rate per year and a width equal to the inverse of the average random failure rate.

The model follows the history of a single socket or a group of sockets from time zero to the end of support life for the system. To generate meaningful results, a statistically relevant number of sockets (or systems of sockets) are modeled and the resulting cost and other metrics are presented in the form of histograms. Figure A.1 provides a detailed flow chart for the simulation performed.

The scheduled and unscheduled costs computed for the sockets are given by,

$$C_{\text{socket } i} = fC_{\text{LRU } i} + (1 - f)C_{\text{LRU } i \text{ repair}} + fT_{\text{replace } i}V + (1 - f)T_{\text{repair } i}V \quad (\text{A.1})$$

where,

$C_{\text{socket } i}$	= Life cycle cost of socket $i$
$C_{\text{LRU } i}$	= Cost of procuring a new LRU for socket $i$
$C_{\text{LRU } i \text{ repair}}$	= Cost of repairing an LRU in socket $i$
$f$	= Fraction of maintenance events on socket $i$ that require replacement of the LRU in socket $i$ with a new LRU
$T_{\text{replace } i}$	= Time to replace the LRU in socket $i$
$T_{\text{repair } i}$	= Time to repair the LRU in socket $i$
$V$	= Value of time out of service.

Note, the values of  $f$  and  $V$  generally differ depending on whether the maintenance activity is scheduled or unscheduled. For simplicity, (A.1) is written assuming that quantity of replaced LRUs in socket  $i$  is one, however, in general, the socket could receive many LRUs during its lifetime.

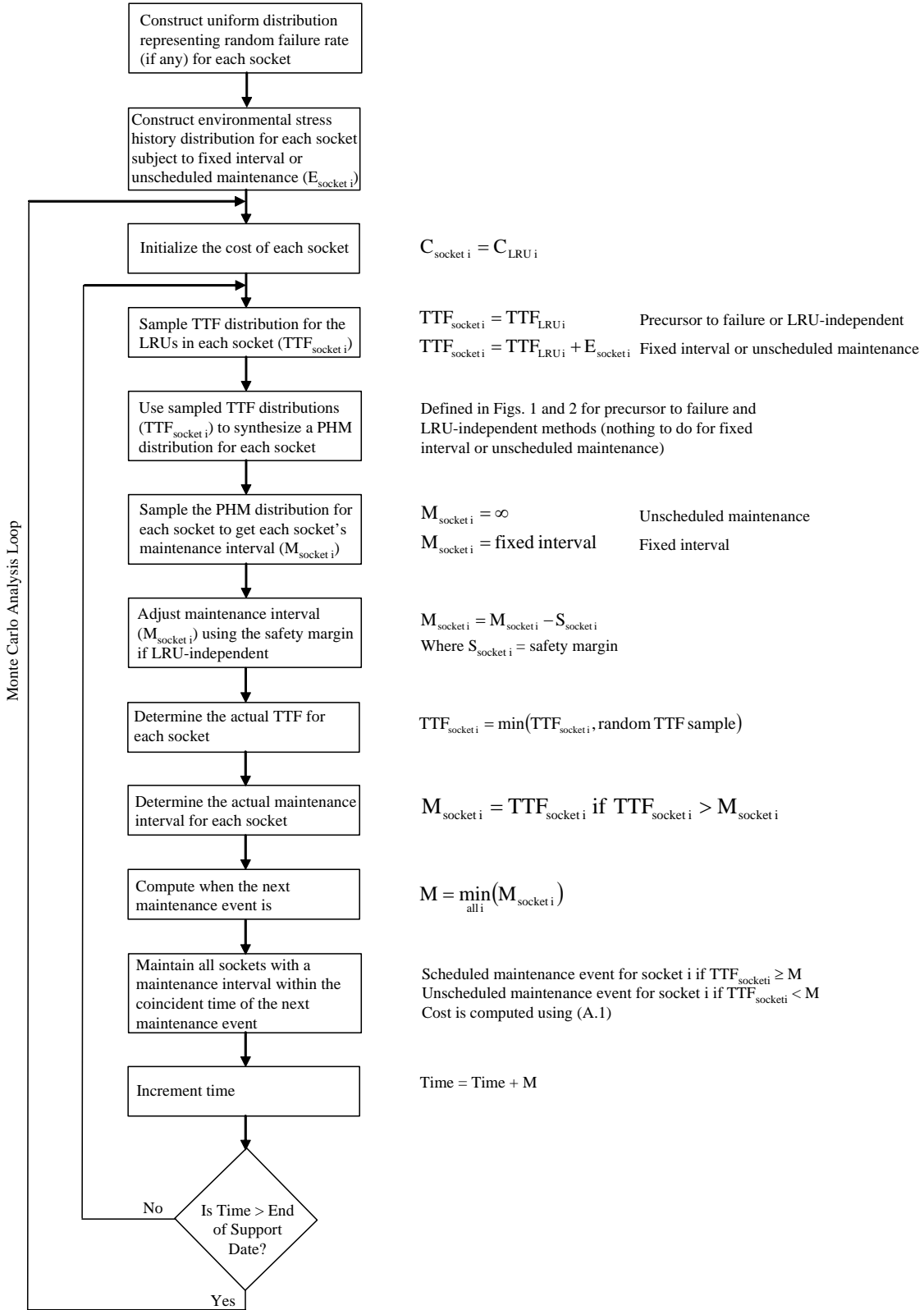


Fig. A.1. Model implementation detail.

## Appendix B – Example PHM Business Case Construction

Commitments to implement and support PHM approaches cannot be made without the development of a supporting business case justifying it to management. One important attribute of most business cases is the development of an economic justification. The economic justification of PHM has been previously discussed by several authors, e.g., [20-24]. These previous business case discussions provide useful insight into the issues influencing the implementation, management, and return associated with PHM and present some application-specific results, but do not approach the problem from a simulation or stochastic view. This appendix presents an example of the use of the discrete event simulation model to contribute to business case development. The objective of this example is to determine what the cost of implementing a PHM structure has to be in order for it to be viable from a life cycle cost viewpoint. Consider a single socket containing instances of an LRU characterized by the TTF distribution shown in Fig. B.1. The sockets that are occupied by instances of this LRU see a range (distribution) of environmental stress profiles. Figure B.1 shows a fixed maintenance interval analysis performed using the process described in Section 2.1. We will use the best fixed interval maintenance solution as the metric that the PHM approaches must achieve.

The second step in the business case construction is shown in Fig. B.2. In Fig. B.2 we show four example PHM approaches, two with a precursor to failure approach (costing either \$0 or \$1000 per LRU instance to implement)

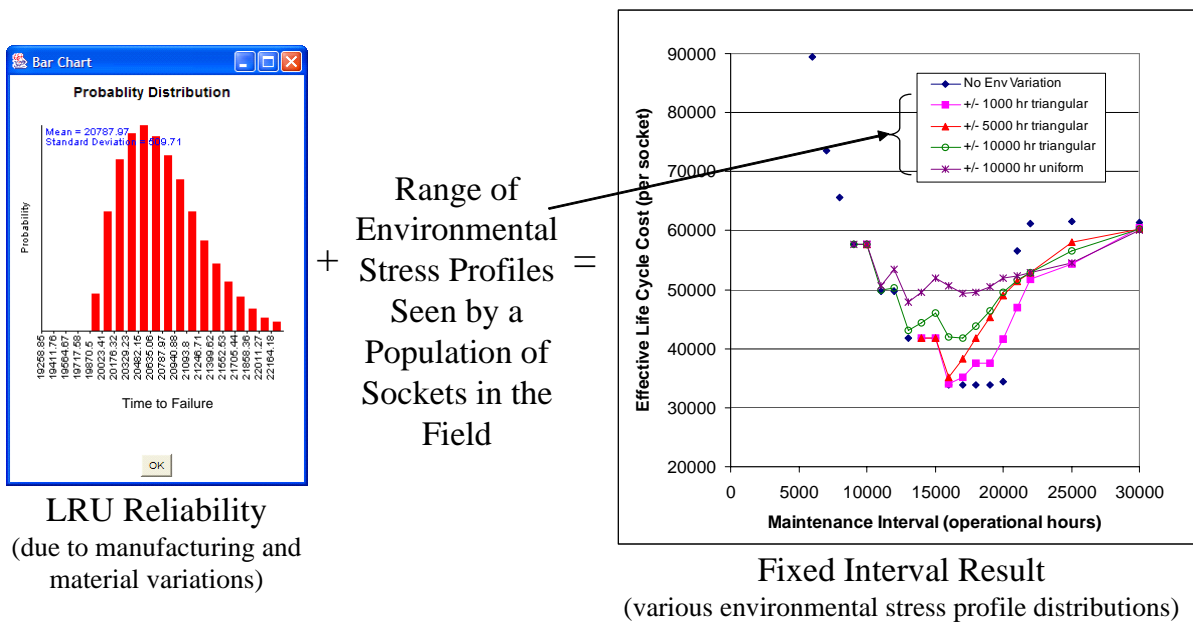


Fig. B.1. Single-socket timeline example. This result indicates that the mean unscheduled maintenance cost per socket is \$61,696. (10,000 sockets simulated).

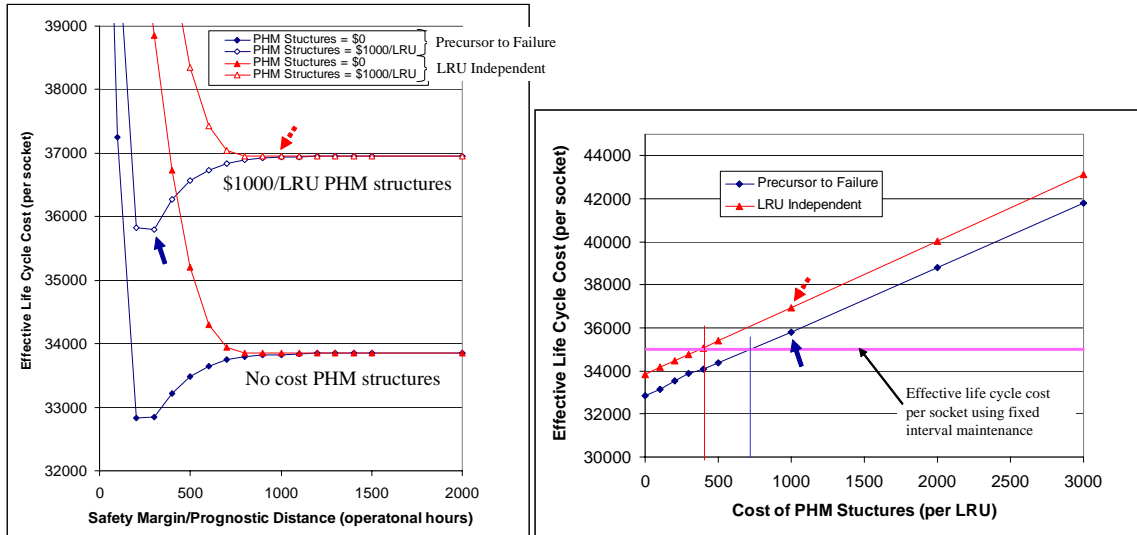


Fig. B.2. The effective life cycle cost associated with precursor to failure and LRU independent PHM approaches. The left plot shows PHM approaches costing either \$0 or \$1000 per LRU instance to implement. Note, from Table 1, \$1000/LRU = 10% of the LRU's recurring cost. The right plot shows a generalization of the left plot where just the lowest life cycle cost solutions are plotted. The small arrows indicate points on the left plot that are mapped to (common with) points on the right plot. (10,000 sockets simulated).

and two with a LRU independent approach (again, costing either \$0 or \$1000 per LRU instance to implement). The right side of Fig. B.2 also generalizes the result by considering a continuum of PHM implementation costs and plotting the minimum life cycle cost solution corresponding to each one. Figure B.2 also shows the life cycle cost of the best fixed interval maintenance solutions for the  $\pm 5000$  hr triangularly distributed environmental stress distribution case from Fig. B.1. The intersection of the fixed interval maintenance line and the precursor to failure and LRU independent lines in the graph on the right side of Fig. B.2 tells us what we can spend on the PHM approaches. The precursor to failure is economically practical if it can be implemented for  $< \$730/\text{LRU}$  (7.3% of recurring LRU cost) and LRU independent methods are practical if they can be implemented for  $< \$400/\text{LRU}$  (4% of recurring LRU cost). It should be stressed that this is an application-specific result.

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