Using Value Assessment to Drive PHM System Development in Early Design

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Abstract

Prognostics and Health Management (PHM) systems have been shown to provide many benefits to the reliability, performance, and life of engineered systems. However, because of trade-offs between up-front design and implementation costs, operational performance, and reliability, it may not be obvious in the early design phase whether one PHM system will be more beneficial to another, or whether a PHM system will provide benefit compared to a traditional reliability approach. These trade-offs make the commitment required to pursue PHM features in the early design phase difficult to justify. In this paper, a cost model incorporating trade-offs among design cost, operational performance, and failure risk is used to provide a comprehensive value comparison of health management options to motivate design decision-making. This approach is then demonstrated in a simple case study comparing the use of a PHM system for condition-based maintenance or diagnostic-based recovery with implementing redundancy and increased inspection in the design. Then the effect of different model inputs and assumptions is varied and the resulting design choices are shown, illustrating the usefulness of cost modelling to capture design trade-offs. Using this approach, decisions about pursuing PHM can be made early, enabling the benefits to be fully leveraged in the design process to achieve increased operational resilience.

1. Introduction

Prognostics and health management systems (PHM) have shown great promise towards making engineered systems more safe and economical. Unfortunately, however, while such systems have been implemented on a variety of technologically complex systems, such as the Joint Strike Fighter (Hess & Fila, 2002), Railroads (Brahimi, Medjaher, Leouatni, & Zerhouni, 2017), Smart Manufacturing (Jin, Weiss, Siegel, & Lee, 2016) and Nuclear Power Plants (Coble, Ramuhalli, Bond, Hines, & Ipadhyaya, 2015), they have yet to achieve widespread adoption. While much of this lack of adoption could be attributed to lack of knowledge and technical inappropriateness (e.g. for cheap reliable products), the primary concern from the perspective of project management is the lack of being able to directly quantify and compare the overall utility of PHM compared to more "traditional" approaches to risk and maintenance. Up-front costs to design and implement PHM systems, which comes from the labourious effort of characterizing the system with models and/or data and developing the necessary hardware and software, and as a result it may be difficult to have certainty in the early design phase that such an approach will be appropriate. As a result most PHM solutions today are "retrofit" solutions being integrated after a system has been deployed, when operators realize that insufficient insight into operations is a salient problem that a condition-based maintenance strategy could solve.

Nevertheless, when designing a new system, the choice to use a PHM system should be made in the early design phase, when the design team has the most ability to integrate it with the rest of the design (e.g. taking advantage of performance gains associated with prognostics over redundancy) and to allow resources to be allocated to prognostics teams early so that their work may be done concurrently with (rather than after) the traditional design process. As a result, the initial decision to pursue the PHM system should occur in the initial concept selection and requirements development process along with the rest of the system. To make this decision appropriately, the up-front design costs must be weighed against the operational, maintenance, and safety benefits they will provide in the final design (Feldman & Sandborn, 2008) (Kurien & R-Moreno, 2008).

Justification of prognostic systems using cost-benefit analysis has been presented in previous work, as outlined in Section 2.2. While previous work has shown how to quantify the economic case for prognostics systems, it has not shown how to use this economic case to drive system development in the early design phase, when one has high-level design requirements that must be considered and a number of design options to consider. This paper provides this approach, which works by associating the requirements related to the PHM system with an underlying value model that can be used to choose between design options and set targets for the design. This process is demonstrated on a simple value model under a variety of design scenarios, showing how the design choices given by this process will change based on the PHM system's internal requirements and external technical and market environment. This paper is organized as follows: Section 2 provides background into the early design decision-making process and cost-benefit analysis in PHM. Section 3 provides the general approach to generating and choosing between design options. Section 4 then demonstrates the approach and shows how design choices change based on parameter values and assumptions. Finally, Section 5 provides some conclusions and directions for future work for this approach.

2. BACKGROUND

Before presenting the details of the method, some context is provided here about early design decision-making and previously-developed cost models in PHM.

2.1. Requirements Specification

A key part of the design process is defining a quantitative model of preference from customer requirements that can be used to benchmark products and choose between design concepts. The most well-known of these processes is the Quality Functional Deployment, which correlates design specifications to customer requirements, which are then weighted by importance and then used to develop a target benchmark for ongoing design work (Ullman, 2010, Chapter 6). The main tool used to perform this process is the House of Quality, which is a visual representation of the correlation between customer requirements and engineering specifications, the correlation between different engineering specifications, preferences for requirements from different customers, current products' ability to meet requirements, and the resulting target benchmark (Ullman, 2010, Chapter 6). Similarly, in the concept selection process (after infeasible or obviously poor solutions are removed), Pugh Matrices (Ullman, 2010, Chapter 8), Value analysis (Pahl & Beitz, 2007, Chapter 3), and Utility-based selection (Otto et al., 2003, Chapter 11) are often used to compare between design alternatives, which work by quantifying the importance of each criteria in a table or tree structure, rating each concept along each criteria, and then combining the scores as a weighted sum.

Recently, the validity of these design procedures has been challenged. As is identified in (Olewnik & Lewis, 2008), the fact that the true relationship between technical attributes and customer attributes (and preferences) is not identified in the House of Quality make it prone to giving poor recommendations. Additionally, the House of Quality, Pugh Matrices, and other traditionally-used engineering decision-making methods are internally inconsistent (Hazelrigg, 2010) and often subject to assumptions regarding independence and linearity of criteria which may not be generally applicable to all design cases (P. Collopy, 2009). Value-driven design has been presented as a solution to these issues, where a model of the actual realized costs and revenues generated by the system is developed and parameterized in terms of system attributes (P. D. Collopy & Hollingsworth, 2011). In this method, requirements are removed from the design to allow for optimization, remove cost growth and performance erosion due to an inability to meet requirements, and resolve trade-offs between objectives (P. D. Collopy & Hollingsworth, 2011), however methods also exist that augment the traditional quality functional deployment process with explicit value models, retaining the benefits of having a clear set of requirements and benchmark design (C. J. Hoyle & Chen, 2009). In this paper, the value-driven design process is adapted to the early design PHM systems–not necessarily removing specifications per se (since it is often useful to solidify the design to allow work to proceed in an integrated way), but by using system value to justify their development.

2.2. Cost Modelling in PHM

Cost modelling for PHM systems is an active area of research, and a literature review is provided in (Saxena et al., 2010). As identified by (Feldman & Sandborn, 2008) and (Kurien & R-Moreno, 2008), because of PHM systems' large up-front cost and technological unfamiliarity, it becomes important to quantify the trade-offs of PHM to determine whether there will be a good return-on-investment. A variety of approaches have been presented to quantify and use these metrics for design and decision-making. A multi-objective trade-space tool was previously used to investigate where PHM systems had the most benefit, showing that the greatest return-on-investment is achieved when the system has a long operational time horizon, large numbers manufactured and in use, and a high failure rate (Banks & Merenich, 2007). A comparison of PHM systems and traditional reliability approaches is provided in (Scanff et al., 2007) for aircraft avionics, finding the preferability of PHM systems to be dependent on the underlying failure distribution, with a normal-approximating Weibull distribution centered around the expected mean-time-to-failure and high "random" failure rates resulting in less value from the PHM system, and an exponential model of expected mean-time-to-failure resulting in more value from the PHM system.

A study of the effect of PHM coverage rate (the percent of faults a PHM system would be able to prevent) and false alarm rate (accidental unneeded maintenance and replacement due to the PHM system) is provided in (Hölzel, Schilling, Neuheuser, Gollnick, & Lufthansa Technik, 2012), finding a large dependency between these attributes and the net present value of the resulting strategy (not including the up-front design cost). The value of flexibility has further been quantified in previous work in the context of windfarm maintenance to make decisions about maintenance in response to the variable internal (e.g. health) and external conditions of the windfarm over time using decision trees and Monte Carlo simulation (Haddad, Sandborn, & Pecht, 2012). This approach found that the time given by the prognostic indication before failure itself has value in enabling the operators to choose to perform maintenance at an optimal time given external conditions (Lei, Sandborn, Bakhshi, & Kashani-Pour, 2015).

Most benefits quantified in the research are related to longer usage time, greater availability, less required maintenance, flexibility in maintenance schedule, and longer operational life, and most existing literature covering cost-benefit analysis of PHM systems is about quantifying the benefit of a condition-based maintenance approach with traditional maintenance approaches. A repeated area of interest in the literature is evaluating the cost-benefit of PHM systems against "traditional" designed features, and use in early design, however few studies have yet been performed in this area. A study of using prognostics to replace redundancies in an aircraft is provided in (Bodden, Hadden, Grube, & Clements, 2006), finding that the use of prognostics could reduce weight without violating reliability and availability constraints. However, the trade-offs in this study were not quantified using an economic model for decision-making. A framework for design optimization has been presented by (Yu, Honda, Zubair, Sharqawy, & Yang, 2013) for use in design, however it did not consider comparing differing sets of functions, instead focusing on optimization of parameters. A cost-based framework is proposed in (C. Hoyle, Tumer, Mehr, & Chen, 2009) to determine the allocation of system health features in a system. In previous work, we developed a design framework for comparing resilient features in the early design stage to consider the cost-benefit of different design features in the early design phase (Hulse, Hoyle, Goebel, & Tumer, 2018) (Hulse, Hoyle, Goebel, & Tumer, 2019). In this work we will build on this work to specifically compare the costs and benefits of different designed features and PHM approaches.

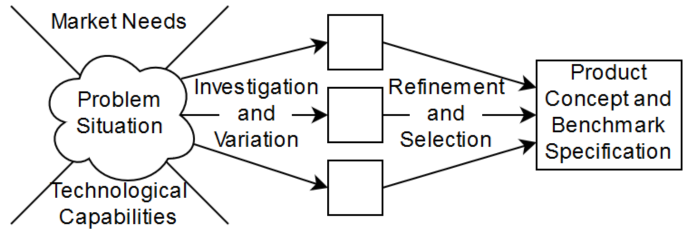

Figure 1. The Early Design Concept Generation and Selection Process

3. APPROACH

Whether and how to implement a PHM system in a new system will occur in the early design process, when the design team has the most ability to consider a variety of different design concepts. Figure 1 shows a simple representation of a traditional early design process (Otto et al., 2003) (Pahl & Beitz, 2007). The designers begin by clarifying the problem into high-level goals and objectives based on the market and organizational need for the product and the capabilities that can be realized by various technologies. This problem definition drives design decision-making throughout the process, defining which designs will be feasible and most fit to the given task. To solve this problem, a variety of different concepts are generated and investigated then refined and selected. In this selection process, each concept is modelled, benchmarked along a set of selection criteria, and chosen based on those criteria. After this choice is made, the design is solidified and design work proceeds to realize that concept the embodiment design phase (Pahl & Beitz, 2007). In the approach presented here, the need for the system is clarified into an explicit cost model in terms of the selection criteria concurrently with design work, and then used in the concept selection process to select the best concepts. The details of this modelling and design approach will be discussed in the next subsections.

3.1. Developing a Value Model from System Attributes

Using value to drive PHM design decisions requires developing a model of the profit generated by the system based on early design requirements. Requirements for a system will depend on the product situation, as discussed in (Saxena et al., 2010). For example, if there are ethical considerations that must be considered in the design of the product (such as safety, privacy, sustainability, or security) identified in (Goebel, Smith, & Bajwa, 2019), the costs associated with those attributes also need to be quantified and incorporated in the overall cost model. However in a generic design scenario there are three major requirements to consider, as shown in Figure 2 with an integrated cost model:

Resilience–the mitigation of faults by the system, including

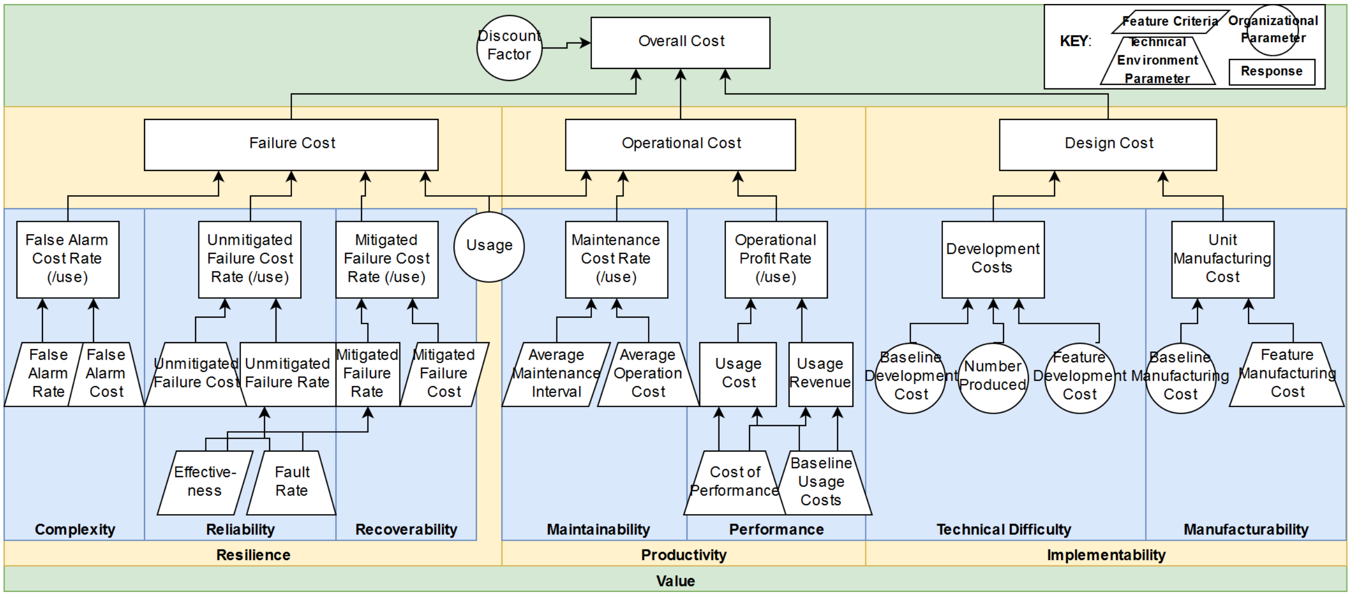

Figure 2. Constructing a value model aligned with PHM system requirements.

reliability (the reduction of unmitigated fault probability by the system), recoverability (the decrease in fault effect severity by the system), and complexity (the introduction of faults by the system). In this generic model, the value of resilience a system can be quantified by considering the expected costs of the system in the total set of faults. To quantify this fault cost over any set of fault scenarios, the expected cost of faults is:

$$C_F = T * r_a \sum P_{s|a} * C_s + \sum T * r_u * C_u \tag{1}$$

where T is the life-cycle time, r_a is the occurrence rate for fault a, $P_{s|a}$ is the probability that the system will end up in an end-state s in a scenario, C_s is the cost of that scenario, r_u is the rate of a given undesired mitigation feature being used, and C_u is the cost of the undesired mitigation feature being used.

In the single-fault case, these fault costs C_F are the sum of expected failure scenario costs (2), mitigated fault scenario cost (3), and false alarm cost for the system (4):

$$C_F = T * r_f * P_{fs|f} * C_{fs} \tag{2}$$
$$+T * r_f * P_{ms|f} * C_{ms} \tag{3}$$
$$+T * r_u * C_u \tag{4}$$

where T is the lifecycle usage time, r_f is the fault rate, $P_{fs|f}$ is the probability of the fault scenario fs occurring unmitigated (or, $1 - E$, where E is the effectiveness of the mitigating feature) with cost C_{fs}, $P_{ms|f}$ is the probability of the mitigated scenario ms given the fault occurs (E) which has cost C_{ms}, r_u is the false alarm rate, and C_u is the cost of a false alarm. Considering a model at this level of detail, then, controllable PHM benchmarks include effectiveness E, mitigated fault severities C_{ms}, and false alarm rate r_u, although other parameters may be controllable through the design of the rest of the system (lifecycle time, false alarm costs, failure costs, etc) and may occur at lower levels of a more detailed resilience-based cost model (e.g. critical prediction horizon, etc).

Productivity–the operational practicality of the system, including maintainability (the cost and frequency of operations in a "smarter" maintenance strategy) and performance (the ability to use the system to increase functionality and/or efficiency). In a value model, the productivity of the system is modeled as operational cost. In a simple model, the operational costs C_O is the result of costs and revenues from use (5) as well as the cost of maintenance (6):

$$C_O = T * (c_o - r_o) \tag{5}$$
$$+(T/t_m) * C_m \tag{6}$$

where c_o is the per-hour cost of operations, r_o is the per-hour cost of revenue, t_m is the maintenance interval, and C_m is the cost per maintenance interval. For more detailed benchmark specification of PHM systems, the cost of performance can result in benchmarks on hardware weight, volume, and other performance-related parameters while the maintenance can be specified here using the average intervals for each required operation and the costs of each of those operations.

Implementability–the ease of implementing the PHM system, including technical difficulty (the design and research effort required to achieve system requirements) and manufacturability (the procurement, assembly, and testing costs of integrating the PHM system). The implementability of a system can be quantified by considering design costs. In a simple model the design costs C_D are a function of the per-unit baseline manufacturing cost C_{mb}, feature manufacturing costs C_{mf} and the overall baseline development costs C_{db} and feature development costs C_{df} that result from the expected time, cost, and risk of developing the technology:

$$C_D = (C_{db} + C_{df})/n + (C_{mb} + C_{mf}) \tag{7}$$

where n is the total number of systems manufactured. The implementability of the system are related as much to the project as to the technology, however a more detailed consideration could result in benchmark plan for hardware and software costs, as well as the product schedule and development resource use.

Value–The overall value is a result of the resilience, productivity, and implementability quantified as failure, operational, and design costs. While design costs only occur at the beginning of design, operational and failure costs occur throughout the system's lifecycle. As a result, to consider the overall value of a design, the time value of returns should be considered using the net present value formula:

$$V = -NPV(C_F, i, T) - NPV(C_O, i, T) - C_D \tag{8}$$

where i is the yearly discount factor.

3.2. Generating and Assessing Design Variants

Early system design involves covering a large space of different design options in order to find the design that will be the best. For this to occur, a variety of health management approaches should be investigated in early design to see what will be most appropriate to the application, including PHM systems, traditional reliability approaches, and diagnostic-enabled failure tolerance and recovery in the system. The general sequence performed in developing a concept to the point where it can be compared with others using a traditional design process (Pahl & Beitz, 2007) includes determining:

1. Functions Performed–Will the system recommend and schedule maintenance, or also take the system offline in use? What faults will the system attempt to predict, avoid, or detect?
2. Solution Principles Used–How will the system form the prognostic? Will it be a model-based, data-based, or hybrid approach? What types of sensors will be used?
3. Integration and Feasibility–Can performance measures and analyses be trusted? Will an off-the-shelf or external solution be used or will it be internally developed? Will the PHM system integrate with the rest of the system as desired?

A design that answers each of these questions has completed the conceptual design process and is developed enough to be compared with others. After going through this process the system can then be rated on how well it will perform along various criteria (detection rate, false alarm rate, prediction horizon, etc), which are then used as inputs to cost model for decision-making.

4. DEMONSTRATION

To demonstrate how a cost model can be used to drive early PHM design decisions, a simple example on a generic system considering one fault with the model presented in 3.1 to see how PHM-based solutions compare with others. The baseline values and demonstration of the model is shown in Table 1. In this situation the system is expected to run consistently at a moderate scale ($n = 200$ systems) over a long life ($T = 25000$ hours over a 17 year life) at high reliability ($r_f = 5 * 10^{-6}$ faults/hr) by an established company ($i = 5\%$). However, if the system fails there will be a large cost due to safety effects ($16M dollars). This is typical of the design situation for aviation.

4.1. Design Options and Results

A variety of different potential functions are considered in the assessment in Table 1 to the system to increase system resilience, including:

1. **Baseline Design:** The baseline design in which no risk-mitigation strategy is provided.
2. **Increased Inspection:** The baseline design in which risk is reduced through frequent inspection. This results in considerable operational costs due to the heavy maintenance schedule but is given a low effectiveness ($E = 0.5$) since not all faults will be apparent to inspectors in the time immediately before the event occurs.
3. **PHM System (CBM):** A design with a PHM system implementing a condition-based maintenance strategy. This approach is given moderate effectiveness ($E = 0.95$) because while the underlying model may characterize and track degradation of the system well, there are still "random" errors that will occur unpredictably. This also has a minor effect on operational costs due to weight and sensor maintenance.
4. **Hot Redundancy:** A design with a hot redundancy that is constantly running and managed to activate immediately when a fault occurs in the active component. This has high effectiveness (assuming total independence of faults) but results in higher operational costs due to greater parts replacement and cost of weight. However, there is less up-front design cost since redundancy circuits are well-developed technology.
5. **PHM System (Recovery):** A design with a diagnostic-based recovery system leveraging flexibility or reconfigurability in the system. The implementation of such a system is contingent on the rest of the system having functionality that can be reconfigured. In this demon-

stration it is considered that a high effectiveness can be achieved using this approach with less maintenance and performance cost than a redundancy. However, the chance of partial recovery makes the mitigated fault cost higher than it would be otherwise, and there is a high up-front design cost to develop the system.

A comparison of the various systems using some example numbers is shown in Table 1. As shown, in this design situation, the total NPV is greatly improved by the implementation of any fault-mitigating feature due to the high failure cost, and the health management functions (CBM System, Hot Redundancy, and Recovery System) each have a comparable overall NPV, with the recovery system having the highest.

4.2. Consideration of Possible Design Scenarios

To show how a value model can incorporate the particular needs of the market as well as technical challenges of a given design situation into the decision-making process, the effect of a variety of design situations on the resulting chosen design will be shown here. These situations can be grouped into ones based on the internal technical benchmarked criteria of the feature, external technical environment of the feature, and the overall market and organizational environment of the product, as listed below. The preferability of these features (and overall cost score of each option) in the different point-cases assessed is shown in Figure 3. The individual parameters, explanation, and interpretation of each case is discussed below:

- **Situation 1: Nominal Scenario**
  In the baseline case, high failure costs and moderate performance costs make the combination recovery system preferable due to the low effect on performance and moderate effectiveness compared to the redundancy scheme.

Feature Criteria

- **Situation 2: High False Alarm Rate**
  ($r_u = 5 * 10^{-4}$)
  When the rate of false alarms given by a system is high, the introduced cost has a significant effect on the preferability of a recovery system, since the cost of accidental recovery is higher than the cost of accidental prevention.
- **Situation 3: High Effectiveness, Common Mode Errors**
  (CBM $E = 0.99$, Red. $E = 0.9$)
  In the baseline case, the preferability of a redundancy is a result of higher effectiveness due to assumptions about independence and prognostic effectiveness. However, when the fault rate for each redundancy is not independent and a high effectiveness can be achieved, the prognostic system becomes preferable.
- **Situation 4: Low Mitigatability**
  (Red., Recovery $E = 0.8$)
  When a fault is difficult to recover from, the effectiveness of fault masking and recovery options is low. As a result, a prognostic approach becomes preferred.
- **Situation 5: Low Cost of Recovery**
  (Recovery $C_u, C_{ms} = 1000$)
  The assumption for the recovery system in the baseline case is that there will be some additional cost taken on by entering the recovery state (e.g. by triggering a safety system). When this cost is low, the recovery system becomes preferred.

Technical Environment

- **Situation 6: High Fault Rate**
  ($r_f = 1 * 10^{-4}$)
  In the high rate situation, expected failure costs become even more dominant, making less effective features even less preferable. This reverses in low-rate situations, where maintenance, performance, and manufacturing costs are more likely to be a consideration.
- **Situation 7: Low Cost of Failure**
  ($C_{fs} = 500,000$, Recovery $C_u, C_{ms} = 20,000$)
  A low cost of failure situation (as with a low rate situation) leads other concerns to be the dominant factor, leading PHM to be the most preferable option, though the difference between each is relatively marginal.
- **Situation 8: High Cost of Performance**
  (Red. $c_o = 450, r_o = 475$)
  The preferability of a redundancy system is sensitive to the cost of performance–the amount of cost or decreased revenue incurred in the operation of the system due to, for example, increased weight causing more energy use or increased use of space leading to less capacity.
- **Situation 9: High Maintenance**
  (t_m = Baseline $t_m/10$, Ins$C_m = 1000$, CBM $C_m = 1100$, Red $C_m = 2000$, Rec $C_m = 1500$)
  When the cost of each maintenance operation is high, reducing the amount of maintenance required has significant influence on the decision. In this case, the prognostic system becomes preferable to a redundancy system due to less required maintenance.
- **Situation 10: High Manufacturing Cost**
  ($C_{mb} = 500000$, CBM and Rec. $C_{mf} = 5000$, Red. $C_{mb} = 50000$)
  When the underlying system is costly to manufacture, redundancy costs increase, leading the recovery system to be preferable.

Market/Organizational Situation

- **Situation 11: Low Scale, High Cost**
  ($n = 10$, $c_{db} = 10,000,000$, CBM, Rec $c_{db} = 5,000,000$)
  Manufacturing at a low scale causes the development costs required to implement a health management system to factor more into the overall cost.

Table 1. Comparison of Design Options Using Cost Model for Resilient Features in Baseline Scenario

Fault Costs	**Baseline Design**	**Increased Inspection**	**PHM (CBM)**	**Hot Redundancy**	**PHM (Recovery)**
New Fault Rate	5.00E-06	5.00E-06	5.00E-06	*1.00E-05*	5.00E-06
Effectiveness		0.5	0.95	*0.999995*	0.9999
False Alarm Rate		1.00E-05	1.00E-05	*2.00E-05*	1.00E-05
Unmitigated Failure Cost	$16,000,000.00	$16,000,000.00	$16,000,000.00	$16,000,000.00	$16,000,000.00
Mitigated Fault Cost	$0.00	$300.00	$400.00	$900.00	$100,000.00
False Alarm Cost		$300.00	$400.00	$900.00	$100,000.00
Unmitigated Failure Rate	*5.00E-06*	*2.50E-06*	*2.50E-07*	*2.50E-11*	*5.00E-10*
Mitigated Fault Rate		*2.50E-06*	*4.75E-06*	*1.00E-05*	*5.00E-06*
Lifecycle Unmitigated	*1.25E-01*	*6.25E-02*	*6.25E-03*	*6.25E-07*	*1.25E-05*
Lifecycle Mitigated	*0*	*6.25E-02*	*1.19E-01*	*2.50E-01*	*1.25E-01*
Lifecycle False Alarms	*0*	*2.50E-01*	*2.50E-01*	*5.00E-01*	*2.50E-01*
Unmitigated Failure Costs	*$2,000,000.00*	*$1,000,000.00*	*$100,000.00*	*$10.00*	*$200.00*
Mitigated Fault Costs	*$0.00*	*$18.75*	*$47.50*	*$225.00*	*$12,498.75*
False Alarm Costs	*$0.00*	*$75.00*	*$100.00*	*$450.00*	*$25,000.00*
Total Fault Costs	*$2,000,000.00*	*$1,000,093.75*	*$100,147.50*	*$685.00*	*$37,698.75*
Total Fault Costs (NPV)	***$1,322,923.19***	***$661,523.61***	***$66,243.72***	***$453.10***	***$24,936.28***
Operational Costs					
Maintenance Interval (hrs)		100	1000	400	500
Per-interval cost		$100.00	$120.00	$200.00	$200.00
Usage Cost ($/hr)	$400.00	$400.00	$400.01	$402.00	$400.01
Usage Revenue ($/hr)	$500.00	$500.00	$500.00	$499.00	$500.00
Usage Profig ($/hr)	*$100.00*	*$100.00*	*$99.99*	*$97.00*	*$99.99*
Total Operations		*250.00*	*25.00*	*62.50*	*50.00*
Total Maintenance Cost	*$0.00*	*$25,000.00*	*$3,000.00*	*$12,500.00*	*$10,000.00*
Total Usage Profit	*$2,500,000.00*	*$2,500,000.00*	*$2,499,750.00*	*$2,425,000.00*	*$2,499,750.00*
Total Operational Profit	*$2,500,000.00*	*$2,475,000.00*	*$2,496,750.00*	*$2,412,500.00*	*$2,489,750.00*
NPV Operational Profit	***$1,653,653.99***	***$1,637,117.45***	***$1,651,504.24***	***$1,595,776.10***	***$1,646,874.00***
Design and Manu. Costs					
Baseline Development Costs	$100,000,000.00	$100,000,000.00	$100,000,000.00	$100,000,000.00	$100,000,000.00
Feature Development Costs	$0.00	$10,000.00	$3,000,000.00	$500,000.00	$3,000,000.00
Baseline Manu. Costs	$80,000.00	$80,000.00	$80,000.00	$80,000.00	$80,000.00
Feature Manufacturing Costs	$0.00	$0.00	$800.00	$4,000.00	$800.00
Single-System Dev. Costs	*$500,000.00*	*$500,050.00*	*$515,000.00*	*$502,500.00*	*$515,000.00*
Total Manufacturing Costs	*$80,000.00*	*$80,000.00*	*$80,800.00*	*$84,000.00*	*$80,800.00*
Total Design and Manu.Costs	*$580,000.00*	*$580,050.00*	*$595,800.00*	*$586,500.00*	*$595,800.00*
Totals					
Total Value	-$80,000.00	$894,856.25	$1,800,802.50	$1,825,315.00	$1,856,251.25
Total NPV	***-$249,269.20***	***$395,543.84***	***$989,460.51***	***$1,008,823.00***	***$1,026,137.73***
KEY:	Input	*Response*	**NPV**		

- **Situation 12: Low Usage**
  ($T = 2000$)
  When the the product is not used much, the effect on operational and failure costs are also less of a factor, making the development costs a more significant factor. This does not change the preferability in this case.
- **Situation 13: High Discount Rate**
  ($i = 0.2$)
  Similar to the other organizational situations, a high discount factor increases the effect of up-front development costs on the preferability of design options.

4.3. Discussion

The effect of various design scenarios on design choice in Figure 3 shows how a value model can adapt the fault mitigation approach to the individual market and technological situation for a given design problem. For the model to be valid, it would be expected that a situation in which a given PHM approach has the highest value would have the greatest opportunity for that approach, as well as some industry adoption. As a check that this model gives appropriate recommendations, the insights provided by this model are discussed and compared with known industries where PHM systems are adopted.

If safety is the primary consideration, the effect of the feature on mitigating risk (effectiveness E, mitigated fault scenario, false alarm rate, false alarm cost) become the dominant requirements in developing the PHM feature. In these cases (all situations except 7), there is less of a case for PHM systems compared to a traditional redundancy system unless the fault itself is difficult to mitigate or mask and must be prevented instead (Situation 4), the redundancy system is overly prone to common mode errors (Situation 3), the recovery state has a low cost (Situation 5), or some other concern becomes more dominant (Situations 8, 9, and 10). This is characteristic of general aviation, where PHM systems are still not generally used as safety features when a redundancy or fault-reducing design is a viable option, despite weight being a concern.

Operational costs become the primary consideration when there is a high cost to performance or performing maintenance. When performance is a primary consideration (Situation 8), the increased weight, volume, and resource consumption of a redundancy system can become untenable, making PHM systems–which only require increased sensors and computing–preferable. This is characteristic of applications in military aerospace, such as rocketry and fighters or civilian infrastructure such as bridges where PHM has been implemented. When maintenance is the primary consideration (Situation 9), PHM systems also become preferable since they have the ability to reduce the amount of maintenance per-

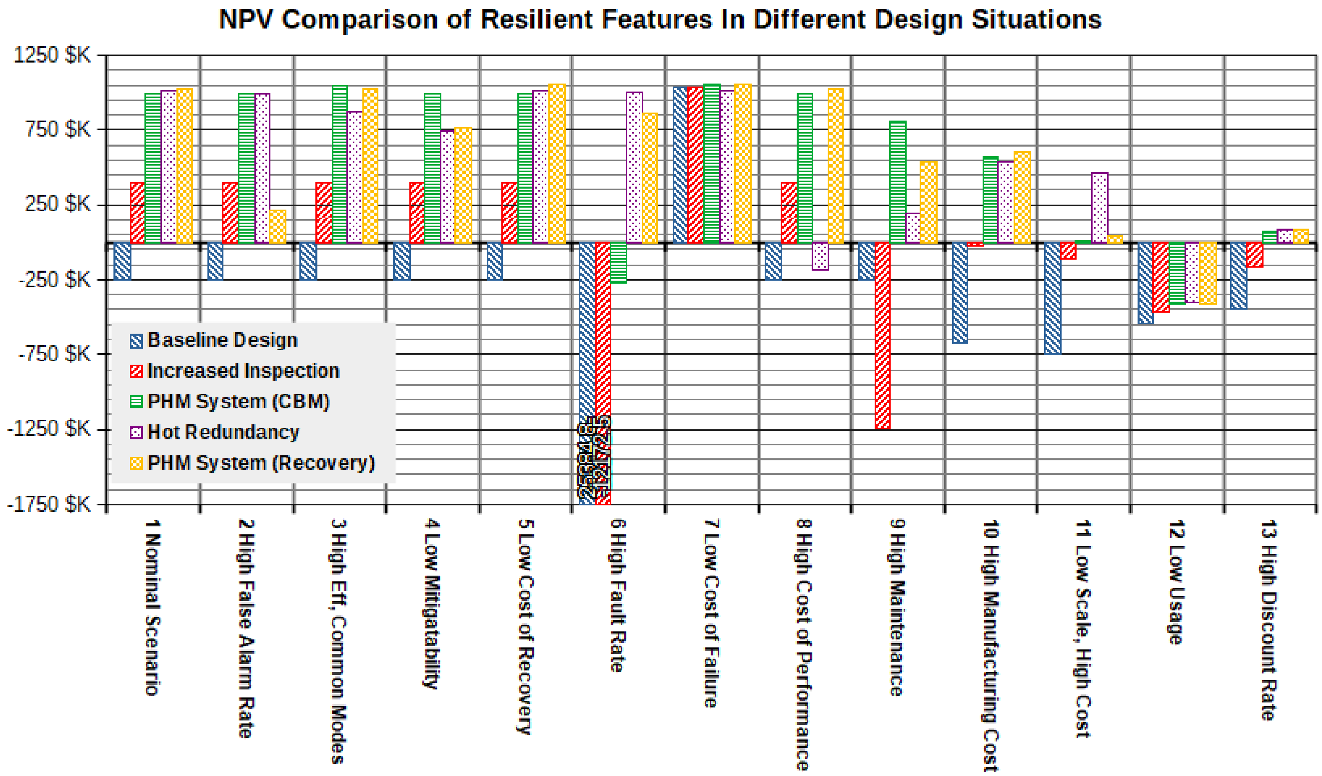

Figure 3. Comparing the value of fault mitigation features under different design situations.

formed while focusing on maintenance that is preventative, which raises the average time between operations as well as the cost of each operation. This is characteristic of current system use in industrial manufacturing, wind farms, nuclear energy production, and railways.

Design cost becomes a primary consideration when the system has low scale, low usage, or a high discount factor (Situation 11, 12, and 13, respectively). While there is some case to implementing a PHM system in these instances when the manufacturing cost of a redundancy is high (such as the nuclear industry), the up-front costs of developing the prognostic system can otherwise become a barrier to preferability. Today, most development of PHM systems is by large, established companies, rather than start-ups which have a much higher internal discount factor since these organizations have more limited funds and a variety of investments that will nominally yield higher returns on the dollar (such as the initial design of a new product, scaling manufacturing operations, etc.).

This shows that the recommendations of a cost model that determines value of different fault-mitigating approaches can give recommendations consistent with where those approaches are actually economical in industry,

5. CONCLUSION

This paper provides framework for developing early PHM system benchmarks based on high-level requirements using a value-driven framework. In this framework, a model is developed of overall cost based on system criteria, including resilience, productivity, and implementability. Using this model, a number of design options can be compared against each other in a systematic, coherent process. A demonstration of this process is provided comparing prevention and recovery-based PHM systems with traditional redundancy and increased inspections with a simple cost model. To show how cost models can adapt design choices to the overall design situation, a variety of design cases are shown with different parameter values for each of those situations. Results from the cost models appear to be consistent with known instances where PHM systems are adopted (and are therefore practical) in industry.

5.1. Future Work

As shown in Figure 3, the relative preferability of fault-mitigating approaches depends heavily on the situation considered. Typically, when practitioners develop value models, they only consider a single situation (e.g. the Nominal Scenario) which relies on a number of uncertain assumptions about the technical and product environment. Early in the design process, however, there may be uncertainties about which situation the product will be used in, and there may be some ability to change the situation to accommodate a particular solution, which should be taken into account in design processes. Methods need to incorporate uncertainty into value models to provide the optimal choice over the range of possible scenarios and provide means of determining how certain the given recommendations are, which can help determine whether a value assessment is conclusive or whether more information is needed. Additionally, methods need to be provided for PHM practitioners that support decision-making not just in a top-down market-driven context (i.e. finding the best technology for a given problem) but in a bottom-up technology-driven context (i.e. finding the best market for a given technology).

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BIOGRAPHIES

Daniel Hulse is a Mechanical Engineering Ph.D. student at Oregon State University whose work focuses on engineering resilience at the early stages of design. His Masters thesis studied multidisciplinary engineering design using a multi-agent model to show the value of collaborative design behaviors on design performance. He previously did his undergraduate work at Walla Walla University, and has interned at NASA and the Department of Energy. He is broadly interested in the applications of decision theory and novel modelling techniques to engineering design and optimization.
Dr. Christopher Hoyle is currently Associate Professor in the area of Design in the Mechanical Engineering Department at Oregon State University. His current research interests are focused upon decision making in engineering design, with emphasis on the early design phase. His areas of expertise are uncertainty quantification methodologies, Bayesian statistics and modeling, stochastic consumer choice modeling, optimization and design automation. He is coauthor of the book Decision-Based Design: Integrating Consumer Preferences into Engineering Design. He received his PhD from Northwestern University in Mechanical Engineering in 2009 and his Masters degree in Mechanical Engineering from Purdue University in 1994.

Dr. Kai Goebel is a Principal Scientist in the System Sciences Lab (SSL) at PARC. His interest is in prognostics health management, and autonomy for a broad spectrum of cyber-physical systems in the transportation, energy, aerospace, defense, and manufacturing sectors. Prior to joining PARC, Dr. Goebel worked at NASA Ames Research Center and General Electric Corporate Research & Development center. At NASA, he was leading the Discovery and Systems Health tech area which included groups for machine learning, quantum computing, physics modeling, and diagnostics & prognostics. Dr. Goebel has carried out applied research in the areas of machine learning, real time monitoring, diagnostics, and prognostics. He has fielded numerous applications for aircraft engines, transportation systems, energy applications, medical systems, and manufacturing systems. He holds 18 patents and has published more than 350 papers. Dr. Goebel was an adjunct professor at Rensselaer Polytechnic Institute is now adjunct professor at Lulea Technical University. He is a member of IEEE, ASME, AAAI, AIAA, VDI, and SAE. He is a co-founder of the Prognostics and Health Management Society and is associate editor of the International Journal of PHM.

Dr. Irem Y. Tumer is the Interim Vice President for Research at Oregon State University. In her role, she is responsible for developing strategy and advocating for research, and leading and managing the core functions of the research enterprise. This includes Centers and Institutes; the Office of Commercialization and Corporate development; the Office of Research Integrity; and the Office of Sponsored Research and Award Administration. Dr. Tumer also holds a professor position in the School of Mechanical, Industrial, and Manufacturing Engineering and a fellow of the American Society of Mechanical Engineers (ASME). Over a 20+ year career as an internationally recognized researcher, she has secured research funding from diverse sources, including NSF, AFOSR, DARPA, NASA, private foundations, and industry. She served as program and conference chair at major conferences, as associate editor on key journals, and on numerous editorial and advisory boards. She has organized and been invited to multiple cross-agency workshops to chart research directions for federal agencies, including NASA, DARPA, NSF, and AFRL. From 2013-2018, Dr. Tumer served as the Associate Dean for Research in the College of Engineering at Oregon State University. In that role, she built and led the Research Administration Office for the College of Engineering and established a formal faculty development program. The strategies she implemented led to transformative changes for the College of Engineering, including significant increases in proposal submissions, awards, and research expenditures, and record numbers of early career awards. Prior to joining OSUs faculty in 2006, Dr. Tumer was a researcher, group lead, deputy area lead, and program manager at NASA Ames Research Center for over eight years. Dr. Tumer received her undergraduate, master's and doctorate degrees in mechanical engineering from The University of Texas at Austin. Her research interests are in the areas of system design, reliability engineering, and risk analysis, and her work has been applied to spacecraft, aircraft, and nuclear power plant design. She received multiple research awards, including a faculty researcher award in 2010 and a research collaboration award in 2012.