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Enhanced FMECA: Integrating Health Management Design and Traditional Failure Analysis

<u>Greg Kacprzynski</u> Michael J. Roemer

Impact Technologies, LLC 125 Tech Park Drive Rochester, NY 14623 Carl Byington Rob Campbell Pennsylvania State University Applied Research Laboratory P.O. Box 30 (North Atherton Street) State College, PA 16804-0030

Abstract: DOD acquisition programs have recognized that operating and support costs dominate the total life cycle costs of complex military systems, and therefore should be considered up front in the design process. In order to estimate operating costs, which are predominately related to maintenance costs, a 'view' of the conceptual design must exist that can be used to evaluate the effects of system design variables upon maintenance requirements. This view is currently best embodied in the Failure Modes, Effects, and Criticality Analyses (FMECA).

Additionally, many DOD acquisition programs are interested in designing health management systems through the optimal application of system diagnostic and prognostic techniques to produce substantial safety and life cycle cost benefits. To achieve these benefits, a more systematic and accurate method to evaluate candidate health monitoring approaches during the design process must be incorporated. While the FMECA is a keystone of the maintenance planning process, it has limitations in estimating the impact of Condition-Based Maintenance (CBM) implementation on life cycle costs. CBM technology deals not just with failures, but also with monitoring the progression towards failure through detection, diagnosis, and prognosis. If we are to evaluate maintenance efforts and diagnostic/prognostic technology design choices, then the failure modes must be defined in a way that deals with incipient and evolving failures. Hence, the current paper discusses these issues and helps to collaboratively design the optimal health management solutions for complex machinery from a cost benefit and/or availability standpoint.

We discuss the processing concept of the FMECA++ $^{\circ}$ and introduce methods to optimize the expanded failure mode analysis, health management metrics, and maintainability/availability considerations. A detailed example of a health management analysis is also provided.

Key Words: FMECA, diagnostics, prognostics, health management, cost/benefit, availability

Introduction: The application of health monitoring systems serves to increase the overall reliability of a system through judicious application of intelligent condition monitoring technologies. A consistent health management philosophy integrates the results from the health monitoring system for the purposes of optimizing operations and maintenance practices through, 1.) Prediction, with confidence bounds, of the Remaining Useful Life (RUL) of critical components, and 2.) Isolating the root cause of failures after the failure effects have been observed. If RUL predictions can be made, the allocation of replacement parts or refurbishment

maintenance logistic footprints. Fault isolation is a critical component to maximizing system availability and minimizing downtime through more efficient troubleshooting efforts.

Because of its potential impact, health monitoring and management solutions should be considered during the initial design of a system. For example, implementing a health monitoring technology (defined here as the combination of sensors and algorithms) that is capable of detecting a crack in a rotating part before it gets to a critical size, <u>may</u> allow for a less conservative factor of safety resulting in a cheaper and lighter design that would be too risky if health monitoring was not utilized. This link between the health management system design and the overall system design is shown in Figure 1.

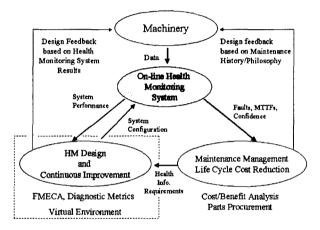


Figure 1 - Health Management with System Design

In this figure, health management system design is shown within the dotted line depicted as a "Virtual Environment". The concept illustrated allows the health management system designer to influence the "top level" system design (shown as "machinery") and assess the downstream availability and life cycle costs associated with the "whole" system including its health management. The final availability and overall life cycle cost relationships must be estimated based on the potential designs offered and an optimization performed based on the design tradeoffs.

Because an initial system FMECA is performed during the design stage, it is a perfect link the critical overall system failure modes and the health management system that is designed to help mitigate these failure modes. Hence, a process will be demonstrated that links this traditional FMECA analysis with health management system design optimization based on failure mode coverage, availability, and life cycle cost analyses.

Role of FMECA in Health Management: Traditional Failure Modes, Effects and Criticality Analysis (FMECA) is typically performed in conjunction with the design process¹. FMECA's historically contain 3 main pieces of information as described below:

¹ In this case, "Design" refers to all aspects of the system (components, control, etc.) with the exception of sensors and software used for condition monitoring.

- A list of failure modes for a particular component
- The effects of if the failure mode occurred ranging from a local level to the end effect
- The criticality of the Failure mode (I IV), where (I) is the most critical

While this type of failure mode analysis is beneficial in getting an initial measure of system reliability and identifying candidates for redundancy, there are several areas where fundamental improvements can be made so that FMECA's can assist in health monitoring design. Four important FMECA improvements are described next.

1) Traditional FMECA does not address the precursors or symptoms to failure modes.

To move maintenance from reactive to proactive, it is important to focus on both system and component level indications that the likelihood of a failure mode has increased. Failure mode symptoms that occur prior to failure are these indications. An example of failure mode symptoms associated with a bearing would be an increase in spike energy or an increase in the oil particulate count.

 Traditional FMECA does not address the sensors and sensor placement requirements to observe failure mode symptoms or effects.

The right data is essential to a health monitoring system. It is also important to have an optimal level of failure mode coverage so that enough collaborative information is available to detect and isolate failures. However, the authors' experiences have reinforced the fact that simply adding more sensors is impractical and ultimately reduces system reliability. By including sensors and sensor placement into the FMECA analysis, the location of a particular sensor for the optimum observational quality becomes more apparent. A simple example of this sensor placement issue might be the use of a downstream pressure sensor, necessary for a control function, which can also be used to monitor performance characteristics of upstream components. Moreover, in some cases, a simple change in the specifications of the sensor may provide monitoring capability in addition to the desired basic control function. Increasing the dynamic range or bandwidth of an accelerometer or pressure sensor are typical examples.

 Traditional FMECA does not address health management technologies for diagnosing and prognosing faults.

The natural extension of including sensors in the FMECA is inclusion of diagnostic and prognostic technologies for observing or predicting failure modes and effects. Because several different diagnostic and/or prognostic technologies can be used for detecting a common failure mode, acquisition and implementation considerations must also be examined.

4) Traditional FMECA typically focuses on subsystems independently.

System level symptoms or system level effects are not fully realizable because subsystem interactions are typically not considered. This is a natural result of the communications barrier between the numerous teams and venders responsible for the development of a piece of complex machinery. As a result, unnecessary sensors or Health Management (HM) algorithms may be implemented or possibly overlooked entirely.

With these shortcomings in mind, a new approach has been developed as an extension to a traditional FMECA that can be used in the design of health monitoring and management systems.

Approach to Health Management Design: Figure 2 provides an overview of the approach to health management system design optimization. A basic description of each block will be given here, while details associated with each block will follow. First, a function block diagram of the system must be created that models the energy flow relationships between components. This functional block diagram provides a clear vision of how components interact with each other across subsystems. On a parallel path, a tabular FMECA is created that corresponds to a traditional FMECA except it contains failure mode symptoms, as well as sensors and diagnostic/prognostic technologies.

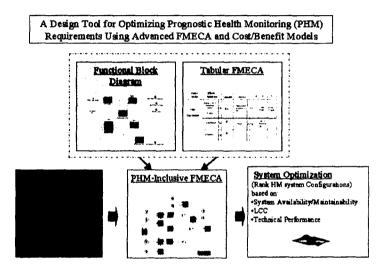


Figure 2 - Organization of the FMECA++ tool

The information from the functional block diagram and the tabular FMECA is automatically combined to create a graphical health management environment that contains all of the failure mode attributes as well as health management technologies. Once the graphical health management system has been developed, attributes are assigned to the failure modes, connections, sensors and diagnostic/prognostic technologies. The attributes are information like historical failure rates, replacement costs, false alarm rates etc., which are used to generate a fitness function for assessing the benefits of the health management system configuration. The "fitness" function criteria includes system availability, reliability, and cost. Some of these attributes must be manually determined if known, while others are related to the attributes of the diagnostic/prognostic technologies which can be determined from independent measures of performance and effectiveness tests. Finally, the health management configuration is automatically optimized from a cost/benefit and/or availability standpoint using a genetic algorithm approach. The net result is a configuration that maintains the highest system reliability to cost/benefit ratio.

Concept of the Functional Block Diagram: The Function Block Diagram (FBD) contains an integrated representation of how components, subsystems and systems interact with one another. It is not a simulation, only a hierarchical map of physical energy flows (i.e. torque transfer, current,

pressure). This energy flow map serves as the backbone for the health management design environment because it contains the failure mode symptoms and effects as well as captures their temporal paths. Figure 3 shows an example of a functional flow diagram at a "system" level. One could select any of the components to reveal specific interactions between its associated subsystem components. This FBD was created with a DARPA owned program called GME developed by ISIS Inc. at Vanderbilt University [7]. Other generic modeling software can also be used to build a FBD.

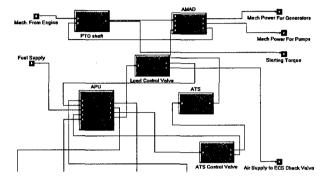


Figure 3 – Functional Block Diagram

As previously mentioned, with this approach, traditional FMECA analyses were enhanced with the addition of sensors, health monitoring technologies and failure symptoms. Figure 4 shows an example of an enhanced FMECA performed on a portion of a fuel system for a F-100 engine.

In this example, as with traditional FMECA, the failure mode is provided along with its effects (ranked from top to bottom as primary, secondary, tertiary, etc.). The Criticality or Frequency of Occurrence of the failure mode is ranked from A to E where:

A = Frequent, B = Probable, C = Occasional, D = Remote, E = Improbable

In practice, this Criticality letter would be associated with a specific probability of failure range.

The Severity of the failure mode is ranked from I-IV where:

I-Catastrophic, II-Critical, III-Marginal, IV - Negligible

The Criticality and Severity are symptoms of a failure mode used in optimizing the health management design discussed later.

In Figure 4, the first FMECA enhancement is that failure mode symptoms have been added to the "effects" column and are shaded in blue (or light gray). Failure mode symptoms are events that can be observed prior to the failure mode occurring or when the failure mode is in a very early stage of development. The effects that are shown in yellow (or dark gray) are downstream failure modes. In the case where an effect is a downstream failure mode, the failure mode of focus could be considered a failure mode precursor.

DEAL			1		= Symptoms				
Module:		Engine Fuel System			= When an effect is a failure mode	s a failure mode			
Component	_	FuelManifold	Blue Sensor		= Existing Sensor				
Faikure Mode Sev.	Sev. Crit.	Symptoms/Effects	Module	Component	Seasors	S Module	S_Component	Diagnostics Prognostics	Prognosties
*******		Increased fuel pressure in fuel supply lines	Engine Fuel System	Fuel Lines	Fuel Pressure	Fuel Pressure Engine Fuel System Fuel Control Unit BIT - Fuel Blockage	Fuel Control Unit	BiT - Fuel Blockage	
		Uneven fuel flow to the combustor	Engine	Combustor	EGT	Engine	Combustor	BIT-EGT	.
Faulty check	L		Engine	Combustor					
valve					EGT	Engine	Combustor	1) Compressor Fault	- Leite
		Decrease in engine performance	Engine	Engine Power Section	Fuel Flowrate Enque Speed	Fuel Flowrate Engine Fuel System Engine Speed Engine	Fuel Control Unit Rotor	Detector 2) Turbine Fault	Performance
					Inlet Temp	Engine	Compressor	Detector	
		Increased fuel pressure in fuel supply lines	Engine Fuel System	FuelLines	Fuel Pressure	Engine Fuel System	Fuel Control Unit	BIT - Fuel Blockage	•
		Uneven fuel flow to the combustor	Engine	Combustor	EGT	Engine	Combustor	BIT EGT	
Plugged 4	LL.		Engine	Combustor		•	•	•	
Strainer	I 				: EGT	Engine	Combustor	1) Compressor Fault	
		Dava ve in anoire neform vero		Engine Power	Fuel Flowrate	Engine Fuel System Fuel Control Unit	1	Detector	Engine
				Section	Engine Speed	Engine	Rotor	2) Turbine Fault	Decompanie
*					Inlet Temp	Engine	Compressor	Detector	Logiosics
Damage, Incorrect, or 2	•	External fuel leak	Engine Fuel System	Engine Fuel System	•			·	
Missing Seals		Fire	Enqine	Engine	•	•			

Figure 4 - Tabular FMECA of a F-100 Fuel System

The "Component" column identifies the component immediately affected by the failure mode while "Module" is the subsystem in which the component resides. This functional relationship is cross-referenced with the functional block diagram. In a similar fashion, the "Sensor" column lists the sensor that can <u>observe</u> the symptom or effect while "S_Module" is the subsystem in which the sensor resides and "S_Component" is the component it is linked to. All sensors in this example are required for control or safety purposes. Finally, "Diagnostics" and "Prognostic" column have been added. The "Diagnostics" column describes any discrete diagnostic (Built in Test (BIT)) or algorithms that can observe the symptom or effect. The "Prognostics" column describes any prognostic algorithms that can be used to obtain a RUL prediction on the failure mode.

Graphical Health Management Environement

The FBD and the tabular FMECA contain enough information to generate a graphical health management design and testing environment without any further human intervention. Figure 5 provides a simple representation of the graphical health management system model and will be used to illustrate the use of collaborative information to predict and isolate faults. In this figure, the "S's" represent sensors local to a component. Failure modes (FM's) are shown that originate in this component and their associated local effects. Downstream effects will propagate up to the next higher level. Diagnostic monitors and prognostic monitors are also present in this model. Consider the following example.

The diagnostic monitor (D1) could identify that the symptoms of either Failure Mode 1 (FM1) or Failure Mode 2 (FM2) have developed. If, in addition to this observation, the prognostic monitor (P) linked to "FM1" determines that "FM1" has a high probability of failure, "FM1" can be assigned more risk than "FM2". Now consider if "P" and "D1" did not exist. In this scenario, there is nothing in this health management configuration that can predict "FM1" or "FM2" before they occur. However, the effect of "FM1" is a symptom of "FM3" and, in this case, there is potential that the fault path could be prevented with "D2" before higher level effects develop. Therefore, if "FM3" is found to have occurred and "D2" did not alarm, "FM2" would be the more likely root cause (accounting for the false-negative potential of the "S4"/"D2" combination) and fault isolation potential is improved.

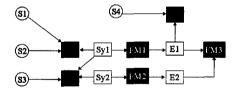


Figure 6 – Generic Graphical FMECA Representation

Health Management Attributes: To autonomously evaluate the cost/benefit of a HM system configuration, all aspects of the system must ultimately be assigned, or modify, a dollar value. Some of these "attributes" are more easily derived that others. All attributes can be grouped into "Cost Related" or "Technical Related". Cost related attributes relate to true dollar values such as hardware cost or component replacement cost while some technical related attributes are complexity factor or sensor observational quality. The FMECA^{++®} aspects that are assigned attributes within a HM system include:

- 1. Failure modes (FM)
- 2. Sensors (S)
- 3. Connections (Sy/E)
- 4. Diagnostics (D)
- 5. Prognostic (P)

Each of these health management system "building blocks" that make up the Integrated HM model have "attributes" that contribute to the overall health management system configuration cost function. A description of each of these "building block" attributes is provided next.

Failure Modes - Failure Modes have been assigned a minimum of 5 attributes. These are:

- 1. Criticality (A-E) or Failure Rate (0-1) (Pf)
- 2. Severity level (I IV) (S)
- 3. Consequential Cost of Failure Mode occurring (CC)
- 4. Cost of a False Detection (CF)
- 5. Cost saved with Planned Maintenance (M)

The "Severity" (S) is a multiplier in the cost function that may represent the safety factor of a particular failure mode. The "Consequential Cost" (CC) is the sum of replacement, refurbishment, maintenance etc. costs for a particular failure mode as well. The downstream effects of a failure mode are naturally accounted for in the integrated FMECA++^C model. The "Cost of False Detection" (CF) represents the cost of an inspection maintenance event, reduced availability etc. Finally, the "Cost Saved with Planned Maintenance" (M) is the benefit realized by being able to predict when (with confidence bounds) a failure will occur.

Clearly, the failure mode attributes do not specifically address a number of maintenance related and availability issues. A number of these issues are introduced in a companion paper.

Sensors - Sensors were defined in the model as components for measuring physical quantities such as temperatures, pressures and currents. The attributes assigned to the sensors include:

- 1. Acquisition and Implementation Cost (AIC)
- 2. Criticality (A-E) or Failure Rate (SPf)
- 3. Weight Cost (W) (for aerospace applications)
- 4. Observational Quality (0-1) (OQ)

The total "cost" of a particular sensor is a function of its utility in a variety of diagnostic and prognostic tools as well as its role in control system functionality.

The "Observational Quality" attribute of a particular sensor is a function of its type and placement with respect to the failure mode being observed. The identification of a parsimonious suite of sensors and their placement is a necessary step in the design of a health management system in order to optimize the detection and prognostic capability of the available sensors. A number of different approaches have been investigated by the authors [1] to help in the optimum sensor and placement in terms of health management. One method was via a system test and sensitivity study, wherein the observability of the identified failure mode symptoms at each potential sensor location was determined. Locations within the system with the largest overlapping of failure modes and the highest observability are used to select

potential locations for sensor placement. A key part of this process is a sensitivity matrix that quantifies the observability of different variables throughout the system for a set of failure modes.

Symptom and Effect Connection Attributes - Symptom and Effect connections within the graphical FMECA environment represent the causal and temporal links between failure modes and their effects. The only connection attribute is "Propagation Probability" – (Pp) which is the likelihood of an effect propagating downstream.

Diagnostic and Prognostic Attributes - Diagnostics can be either discrete or continuous. Discrete diagnostics are traditionally algorithms that produce 0 or 1 depending on if a threshold has been exceeded. Many types of Built In Tests (BITs) can be classified as Discrete Diagnostics. An example of discrete diagnostics is an Exhaust Gas Temperature (EGT) reading that has exceeded a predetermined level.

Continuous diagnostics are algorithms designed to observe transitional effects and diagnose a failure mode based on the method and rate in which the effect is changing. Continuous diagnostics are usually associated with observing the severity of failure mode symptoms. Examples of continuous diagnostics would be a spike energy monitor for identifying low levels of bearing race spalling or an A.I. classifier for diagnosing that a valve is sticking.

The attributes identified for Diagnostics have been broken up into Technical and Cost related. The Technical attributes include:

1) Detection Confidence score (0-1) - (DC) 2) % false positive score (0-1) - (FP)

The "Detection Confidence score" can be used to simultaneously account for true-negative and true-positive characteristics.

The Cost Attribute of Diagnostics include:

1. Development, Implementation and Tech. Maintenance Cost (DAIC)

Finally, Prognostic algorithms can use a combination of sensor data, a-priori knowledge of a failure mode and diagnostic information to predict the time to a failure or degraded condition with confidence bounds. Prognostic algorithms are linked directly to failure modes in the graphical FMECA model. Like diagnostic algorithms, both technical and cost related attributes have been identified for prognostic algorithms.

Technical Attribute:

1. Prognostic Accuracy (0-1) – (PA)

Prognostics do not have an attribute associated with false alarms. The "Prognostic Accuracy" accounts for the early detection quality of the technology. A physical prognostic model (i.e. based on an FE model) would ideally have a higher prognostic accuracy than an experienced-based model (i.e. Weibull distributions of historical failure rates).

The Cost Attribute for Prognostics is:

1. Development, Implementation and Tech. Maintenance Cost - (PAIC)

A valid concern is how the technical attributes of diagnostic and prognostics technologies can be determined. One method is addressed in [1] whereby algorithms are tested objectively from performance and effectiveness standpoints using transitional run to failure data. Of course in the absence of this type of information, and with a new sensor/algorithm combination, an educated guess may be the only option.

Health Management System Optimization - In order to optimize the core configuration of a health management system (i.e. what sensors and associated algorithms to implement) based on the enhanced FMECA approach previously described, a cost or fitness function that accounts for reliability, technical risk, complexity and overall life cycle costs must be developed. This total "fitness" function will then be minimized to arrive at potential HM system configurations. The plot on the top of Figure 6 shows system dependability as a function of cost in the absence of a health monitoring system. In this scenario, the redundancy and high factors of safety are essential to insure that critical failures maintain a low failure rate. [3] The lower plot illustrates the effect of implementing a HM system. With effective (and dependable) diagnostic and prognostic capabilities, system redundancy can be reduced and the boundaries of the design envelope can be safely extended. With health monitoring capability, the overall system dependability remains high while safety is not compromised.

Cost/Benefit of a Health Management System

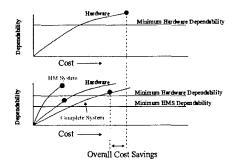


Figure 6 - Using HM to increase overall system reliability

The health management design environment contains a sufficient amount of information to generate and evaluate a fitness function for the configuration. This fitness function is of the form:

For each Failure Mode – FM(i) Step 1) Probability of Failure * Severity *Consequential Cost of FM(i) +(Downstream Failure Mode Consequential Costs) * Probability of Propagation Step 2) *HM risk reduction attributed to FM(i) Step 3) + Cost associated with False Alarms on FM(i) Step 4) + Total Cost of all HM technology

Specifically, the formulation is as follows:

Step 1 and 2 =

$$\sum_{FM_{i}}^{FM_{y}} \left\{ \left[\prod_{D_{FM}} DC \cdot \frac{\sum_{S_{p}} OQ(1 - SPf)}{NsensorsD} \cdot \prod_{P_{FM}} PA \cdot \frac{\sum_{S_{p}} OQ(1 - SPf)}{NsensorP} \right] \cdot \left[(Pf \cdot S(CC - M) \cdot Pp) + \sum_{FM_{i+1}}^{FM_{y}} Rolled _ Up \right] \right\}$$

Where the cost saved with planned maintenance (M) can only be realized if a prognostic algorithm is present on the failure mode.

The "Rolled Up" costs =

$$Pf \cdot S(CC) \cdot Pp \cdot \left(\prod_{D_{FM}} \left(1 - \frac{\sum_{S_{FM}} OQ}{NsensorsD} \right) \cdot DC \cdot \prod_{P_{FM}} \left(1 - \frac{\sum_{S_{PM}} OQ}{NsensorsP} \right) \cdot PA \right)$$

Step 3 =

$$+ (1 - Pf) \cdot S \cdot \left[1 - \left[\prod_{S_{FM}} (1 - SPf) - \prod_{D_{FM}} (1 - FP) \right] \right] \cdot Ch$$

Finally Step 4 =

$$+\sum_{S} (W + AIC) + \sum_{D} DAIC + \sum_{P} PAIC$$

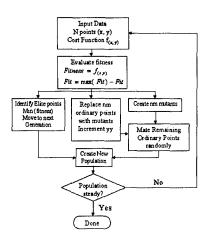
Configuration Optimization: The HM system optimization (optimization of the previously described cost function) will operate between two boundaries; a "maximum" HM system configuration that includes the "wish list" of all potential sensors and associated algorithms that achieve complete failure mode coverage and a "minimum" configuration that is necessary for safety and control. The optimization algorithm will examine random configuration variations and calculate the "fitness" or cost for each.

A genetic algorithm optimization scheme was chosen for the HM optimization because genetic algorithms are better configured to handle optimization problems with little regard for non-linearity, dimensionality or function complexity in general. Potential cost functions generated in the FMECA++ $^{\circ}$ environment can include hundreds of independent variables and thus makes it impractical to utilize traditional optimization techniques such as gradient decent or other derivative-based algorithms.

The genetic algorithm optimization scheme developed capitalizes on the benefits of both the *classic* and *elite* genetic algorithm approaches. In general, the genetic algorithm operates by evaluating the "fitness" of a "gene pool" population within a given environment. New "generations" (potential solutions) are created using a combination of "parent" genes and "mutations". Only the most "fit" genes (best solutions) are ultimately passed through the generations [5]. In terms of health management system design optimization, the "environment" is the FMECA model while the "gene pool" represents the many different health management configurations.

The HM building blocks that contribute most effectively to the minimization of the "fitness" function will be passed on to the "next generation". This process is described in the block diagram in Figure 7.

Figure 8 shows a 2-D contour of a simplified cost function associated with two variables. Normally the dimensionality would be much higher and equal to the number of possible combinations between the max. and min. configurations. This cost function was chosen to illustrate how the genetic algorithms work because it has three clear minimas, with only one as the global minima (the solution we are looking for). An initial population was generated that represents a small fraction of the possible HM configurations. Within the optimization process, aspects of this population are combined, mutated and re-evaluated.



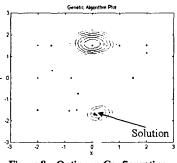


Figure 8 – Optimum Configuration

Figure 7 – Genetic Algorithm Flow Chart

Example of HM design and optimization: Figure 9 shows the Maximum and Minimum HM configuration addressing failure modes for a bearing and bearing housing.

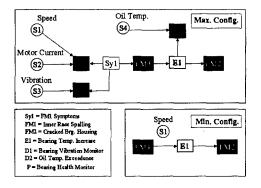
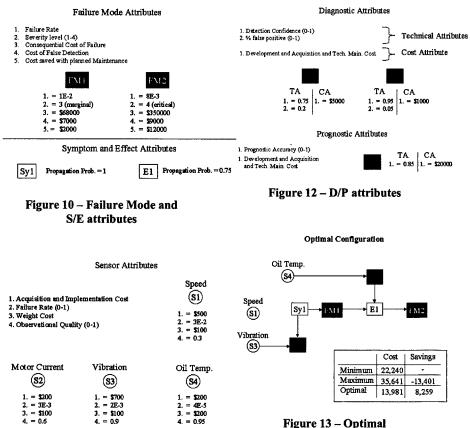


Figure 9 - Max and Min Configurations

Notice that in the Max. configuration, a diagnostic monitor is observing the vibration related symptoms of Inner Race Spalling and a prognostic monitor is predicting when the spalling will occur with a high severity using motor current, and speed. If the spalling were to occur, another diagnostic monitor (D2) will observe if oil temperature is too high and thus potentially prevent cracking of the Bearing Housing (FM2). In the Minimum configuration no health monitor capability exist and the speed sensor is present for control purposes only. If bearing spalling were to occur the risk of the housing cracking would be based entirely on the Propagation Probability between FM1 and FM2. The attributes assigned to each of the HM components in the Max. configuration are given in Figures 10 through 12.



Configuration and Results



The results of a cost/benefit analysis of the Min and Max configurations is shown in Figure 13. In the Minimum configuration there is no benefit in terms of risk reduction from a HM system but there is also no added cost for false alarms and HM hardware. The cost of 22,240 is the dollar value calculated for risk of both FM1 and FM2 occurring. In contrast, the maximum configuration has too much HM capability. The risk reduction of FM1 (calculated at 78%) and FM2 (10%) is not sufficient to offset the higher risk of false alarms and the significant technological development cost of prognostics in this case. The optimal configuration was found to retain both the vibration diagnostic monitor and oil temp monitor. They provided a fair amount of risk reduction (40% and 10% respectively) while maintaining good system reliability. Further optimization approaches that account for maintenance plans and system availability may be found in [11].

Conclusion: An approach has been presented that extends traditional FMECA capabilities to aid in the design of health management solutions that can for reduce total ownership costs and improve availability for complex engineered systems. This approach utilizes a graphical FMECA environment where failure modes, failure mode symptoms/effects, sensors, and diagnostic/prognostic technologies are represented. The health management system configuration can be optimized from an availability and cost/benefit standpoint with a genetic algorithm approach through analysis of the fitness attributes on HM system building blocks. The ultimate objective of this approach was to form a methodology and environment which aids condition based maintenance practices by mitigating or preventing failure modes while still keeping sensor and diagnostic/prognostic technology costs at a minimum.

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