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ANALYTICAL METHODS TO EVALUATE FAILURE POTENTIAL DURING HIGH-RISK COMPONENT DEVELOPMENT

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ABSTRACT

Communicating failure mode information during design and manufacturing is a crucial task for failure prevention. Most processes use Failure Modes and Effects types of analyses, as well as prior knowledge and experience, to determine the potential modes of failures a product might encounter during its lifetime. When new products are being considered and designed, this knowledge and information is expanded upon to help designers extrapolate based on the similarity with existing products. This paper makes use of similarities that exist between different failure modes based on the functionality of each component/product. In this light, a function-failure method is developed to help the design of new products with solutions for functions that eliminate or reduce the potential of a failure mode. The method is applied to rotating machinery components and is proposed as a means to account for helicopter failure modes, addressing stringent safety and performance requirements for NASA applications.

KEYWORDS

Failure prevention in design, quality improvement, failure-function commonality, functional basis, analytical methods for design feedback.

FAILURE INFORMATION FOR DESIGN

Feedback of crucial failure information into the design stage is essential in producing high-quality parts that must satisfy stringent performance and safety requirements. Such is the case with high-risk aerospace components. As shown in Figure 1, a typical feedback loop into design must consider all phases where failures and variations can be introduced, including design, manufacturing and assembly, tooling and fixture, and operational considerations. In this paper, the focus is on operational considerations that lead to unacceptable failure modes when these components are placed in operation. Specifically, the paper concentrates on the feedback of failure modes and defects that potentially degrade performance and present safety hazards.

Mechanical Failures in Design

The potential of mechanical failures is a crucial concern in design. Reliability, maintenance, and satisfactory performance of machines and systems depend heavily upon understanding, recognizing, and preventing/eliminating mechanical failures (Collins and Hagan, 1976; Mitchell, 1993; Smith, 1999). Mechanical failure may be defined as any change in size, shape, or material properties of a structure, machine, or machine component that renders it incapable of satisfactorily performing its intended function (Collins, 1993). Success in designing competitive products while preventing premature mechanical failures can be achieved only by recognizing and evaluating all potential failure modes. To this end, the designer must be acquainted with an array of failure modes observed in the field, and with the conditions leading to these failures.

In this work, failures are defined in terms of a basic set of standard mechanical failure modes that all components will be

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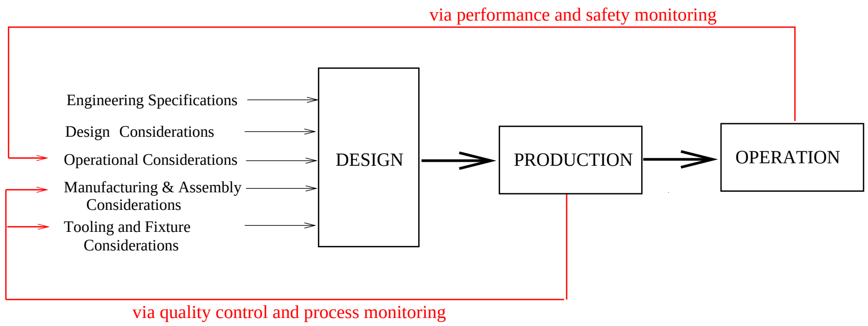

Figure 1. Information Feedback from Design, to Production, to Operation.

Table 1. ELEMENTAL FAILURE MODES.

Main Category	Sub	Main Category	Sub
Elastic Deformation	force induced	Impact	fracture
	temperature induced		deformation
Yielding			wear
Brinnelling			fretting
Ductile rupture			fatigue
Brittle fracture		Fretting	fatigue
Fatigue	high-cycle		wear
	low-cycle		corrosion
	thermal	Creep	
	surface	Thermal relaxation	
	impact	Stress rupture	
	corrosion	Thermal shock	
	fretting	Galling and seizure	
Corrosion	direct chemical attack	Spalling	
	galvanic	Radiation damage	
	pitting	Buckling	
	intergranular	Creep buckling	
	selective leaching	Stress corrosion	
	erosion	Corrosion wear	
	cavitation	Corrosion fatigue	
	hydrogen damage	Creep and fatigue	
	biological		
	stress		
Wear	adhesive		
	abrasive		
	corrosive		
	surface fatigue		
	deformation		
	impact		
	fretting		

subject to during their lifetime. To define this vector of failures, failure modes presented in Collins (Collins, 1993) are used. This list, summarized in Table 1, is accepted as standard; all new systems must be mapped to match these standard modes.

Failure Prevention

To help with feedback from operation and production into design, it is crucial to provide designers and manufacturing engineers with techniques they can use to effectively account for the existing and potential failure modes and mechanisms. At the design and development stages, standard reliability tools are used for a thorough coverage and understanding of all possible and potential failure modes, lengthening the development time of such components considerably. At the manufacturing stage, quality control techniques are used to inspect components (some at a 100% rate) to assure satisfactory and safe operation, making the manufacturing of such components costly and time-consuming (Carter, 1997; Henley and Kumamoto, 1992; Phadke, 1989). Despite these lengthy and costly steps during production, failures still occur at an unacceptable rate when components are placed in their operational states. The increasing pressure in the aerospace industry to reduce the production and development cycle and increase the life cycle of crucial aircraft components, while keeping safety the number one priority, requires more stringent steps during the development of high-risk components.

There are several supporting techniques that are often used by designers to account for potential failures (Carter, 1997). Examples (commonly used at NASA) are checklists, FMEA/FMECAs, and FTAs. Checklists are listings of all relevant failure modes and mechanisms. They act as reminders to ensure that the design has been assessed as adequate to meet all possible circumstances. Although often the only source of such information, checklists are typically incomplete and do not provide the complete picture of the mechanisms for failure. A systematic method for drawing up an exhaustive list is lacking from the literature (Carter, 1997). In other words, there is no “algorithm” that enables one to draw up a comprehensive checklist for a specified part. This results in checklists being unreliable design tools.

FMEA (failure modes and effects analysis) and FMECA (failure modes effects and criticality analysis) are tools used to first identify each failure mode at some designated level (e.g., component, sub-assembly, machine), and then trace the effect of the failure through all the higher levels of the hierarchy in turn (Carter, 1997). It is used to establish whether each failure mode has unacceptable consequences on the system as a whole. The problem with this method is that, contrary to what the name implies, FMEA does not tell the designers what to do at the lowest level, if the consequences are unacceptable. While these traditionally-used methods are effective for identifying failure modes related to components, a common complaint is the difficulty in identifying system-wide failure modes (Bowles, 1998; Eubanks et al., 1997; Henning and Paasch, 2000). Traditional FMEA needs a systematic approach capable of capturing a wider range of failure modes, applicable early in the design stage (Eubanks et al., 1997).

FTA (fault tree analysis) performs the reverse. It starts with an undesirable top event and isolates possible causes at each successive lower level of the hierarchy in order to establish the prime cause(s). FTA is more powerful in the sense that it forces the designers to consider all the causes of unacceptable top events. However, the analysis is not pursued far enough, and the prime causes are not revealed (Carter, 1997). Although a well-accepted technique, large system-level fault trees are often difficult to understand, and difficult to build due to the complex logic involved (Henley and Kumamoto, 1992). The weakness of both FMEA and FTA is that the basic sources of unacceptable behavior cannot be identified (Carter, 1997).

Current Research Direction

An important part in these commonly used design-aid techniques is information feedback about all potential failure modes and their causes. These are commonly gathered from experience and previous designs; their significance is typically re-evaluated for each application, depending on the design, manufacturing and assembly, and operational considerations. When designing a new product, or modifying existing products for new environments, it is often up to the designers to assess and draw conclusions about the similarity between different designs, components, and failure modes. To help with this daunting task, general analytical tools are needed for design and manufacturing engineers to understand, predict, and potentially prevent or eliminate failures that might occur during operation, in an effective and timely manner during the design and manufacturing phases. In this work, such tools are sought, making use of known failure modes and the required functionality of the components, across components and systems. It is the authors' view that components have a "commonality" they share at some basic level in terms of their functionality and failure modes. This basic level of commonality is explored by decomposing the knowledge about functionality and failures via matrix manipulations. Once the common modes of failures at the basic levels are determined, a larger family of components/systems can be considered. Using this generalization, this work proposes to formalize the process of feeding failure and reliability information into the design and manufacturing phases, by transforming the information into a form that can be used effectively by engineers in practice (Stone et al., 1999; Stone et al., 2000; Tumer et al., 2000a; Tumer and Huff, 2000).

FUNCTIONAL MODELING IN DESIGN

Functional modeling is a key step in the product design process, whether original or redesign. By developing a formal theory of functional modeling, the intent is to push functional modeling into the realm of repeatable, and even computable, engineering analysis. Stone et al. have had substantial success with their functional model derivation and common functional language as demonstrated by inter-institutional experimental results (Stone and Wood, 2000; Stone et al., 2000).

From Value Engineering to Functional Basis

All functional modeling begins by formulating the overall product function. By breaking the overall function of the device into small, easily solved sub-functions, the form of the device follows from the assembly of all sub-function solutions. The lack of a precise definition for small, easily solved sub-functions casts doubt on the effectiveness of prescriptive design methodologies (Pahl and Beitz, 1988; Ullman, 1997; Ulrich and Eppinger, 1995) among engineers in more analytical fields. For instance, within a given methodology how does one reconcile different functional models of a product generated by different designers? Typically, such differences arise from semantics or poor identification of product function. The development of a standard set of functions and flows, referred to here as a functional basis, and a systematic approach to functional modeling offer the best case to erase remaining doubt.

Much of the recent work on a functional basis stems from the results of value engineering research that began in the 1940s (Akiyama, 1991; Miles, 1972). Value analysis seeks to express the sub-functions of a product as an action verb-object pair and assign a fraction of a product's cost to each sub-function. Sub-function costs then direct the design effort (specifically, the goal is to reduce the cost of high value sub-functions). However, there is no standard list of action verbs and objects. Recognizing that a common vocabulary for design was necessary to accurately communicate helicopter failure information, Collins et al. (Collins and Hagan, 1976) develop a list of 105 unique mechanical functions. Here, the mechanical functions are limited to helicopter systems and do not utilize any classification scheme.

Function-based design methodologies have also pushed the development of functional languages in order to provide a clear stopping point in the functional modeling process and a consistent level of detail. Pahl and Beitz (Pahl and Beitz, 1988) list five generally valid functions and three types of flows, but they are at a very high level of abstraction. Hundal (Hundal, 1990) formulates six function classes complete with more specific functions in each class in order to make function-based design computable. Another approach uses the 20 subsystem representations from living systems theory to represent mechanical design functions (Koch et al., 1994). Malmqvist et al. (Malmqvist et al., 1996) compare the Soviet Union era design methodology known as the

Table 2. CLASSES, FLOW TYPES, AND COMPLEMENTS.

Class	*Basic*	*Subbasic*	*Complements*
Material	Human		Hand, foot, head ,etc.
	Gas		
	Liquid		
	Solid		
Signal	Status	Auditory	Tone, Verbal
		Olfactory	
		Tactile	Temp, Pressure, Roughness
		Taste	
		Visual	Position, Displacement
	Control		

Table 3. CLASSES, FLOW TYPES, AND COMPLEMENTS.

Class	*Basic*	*Subbasic*	*Bond Graph Complements*	
			Effort analogy	*Flow analogy*
Energy	Human		Force	Motion
	Acoustic		Pressure	Particle velocity
	Biological		Pressure	Volumetric flow
	Chemical		Affinity	Reaction rate
	Electrical		Electromotive force	Current
	Electromagnetic	Optical	Intensity	Velocity
		Solar	Intensity	Velocity
	Hydraulic		Pressure	Volumetric flow
	Magnetic		Magnetomotive force	Magnetic flux rate
	Mechanical	Rotational	Torque	Angular velocity
		Translational	Force	Linear velocity
		Vibrational	Amplitude	Frequency
	Pneumatic		Pressure	Mass flow
	Radioactive		Intensity	Decay rate
	Thermal		Temperature	Heat flow

Theory of Inventive Problem Solving (TIPS) with the Pahl and Beitz methodology. TIPS uses a set of 30 functional descriptions to describe all mechanical design functions (Altshhuller, 1984). Malmqvist et al. note that the detailed vocabulary of TIPS would benefit from a more carefully structured class hierarchy using the Pahl and Beitz functions at the highest level. Kirschman and Fadel (Kirschman and Fadel, 1998) propose four basic mechanical functions groups, but vary from the standard verb-object sub-function description popular with most methodologies. However, this work appears to be the first attempt at creating a common vocabulary of design that leads to common functional models of products.

A Functional Basis for Design

Building on the above work, the concept of a functional basis is developed by Stone and Wood (Stone and Wood, 2000; Stone et al., 2000) which significantly extends previous research (Little et al., 1997; Otto and Wood, 1997). A functional basis is a standard set of functions and flows capable of describing the mechanical design space. The work expands the set of functions and groups them into eight classes. Also, for the first time, a definition for each function is given. This initial functional basis subsumes all other classification schemes discussed above along with the 30 basic sub-functions found in TIPS. The standard list of functional descriptions is needed such that the matrices can be shared among different engineers. Summarized in Tables 2, 3, and 4, the functional basis is a vocabulary of function and flow words which may be combined to form a functional description (Stone et al., 2000). A functional description has a verb-object format where the verb is selected from the function list in Table 4, and the object is selected from the flow lists in Tables 2 and 3. The function and flow sets are divided into different categorizations, i.e., class, basic, sub-basic (or flow-restricted). Each successive categorization allows greater levels of detail to be captured in the functional description. Typically, the basic level is sufficient to convey the elemental functions at the basic level.

THEORETICAL BACKGROUND

The methods proposed in this work are based on two methods previously presented by the authors. The first method was presented by Tumer et al. (Tumer et al., 2000a; Tumer et al., 2000b) to extract high-variance modes from product surface profiles. This method is extended in this work to isolate the failure modes with the highest variance in the similarity matrices derived from the information at hand. The second method was presented by Stone et al. (Stone and Wood, 2000; Stone et al., 2000) to derive the similarity between different designs based on functionality, and used to provide a repository for designers. This method is extended in this work to the domain of failure detection, to capture failure-function similarity in high-risk components.

High-Variance Mode Separation

Tumer et al. (Tumer et al., 2000a; Tumer et al., 2000b) present a methodology to extract variation and defect features from machine component surfaces, providing manufacturing and design engineers with a mathematical tool to understand the various components of product surfaces and improve quality. The Karhunen-Loève (KL) transformation uses a covariance matrix and decomposes it into eigenvalues and eigenvectors, and weights to extract major modes and their significance, similar to Principal Components Analysis. For manufacturing surfaces, the modes (eigenvectors) correspond to the major components of the surface variation, decomposed into form, waviness, and roughness errors. The variation pattern of these individual modes can then be monitored by means of the coefficient vectors. The following is a brief presentation of the theory used for this method.

For an $m \times n$ input matrix $\mathbf{X}$,whose columns consist of the variables under study, and whose rows correspond to each observation, the $n \times n$ covariance matrix is computed by first computing the $1 \times n$ mean vector $\overline{\mathbf{X}}$, then removing the mean vector from each of the m observations, and forming the covariance matrix

Table 4. FUNCTIONS CLASSES, BASIC FUNCTIONS AND SYNONYMS.

Class	*Basic*	*Flow restricted*	*Synonyms*
Branch	Separate		Switch, Divide, Release, Detach, Disconnect, Disassemble, Subtract
		Remove	Cut, Polish, Sand, Drill, Lathe
	Refine		Purify, Strain, Filter, Percolate, Clear
	Distribute		Diverge, Scatter, Disperse, Diffuse, Empty, Absorb, Dampen, Dispel, Resist, Dissipate
Channel	Import		Input, Receive, Allow, Form Entrance, Capture
	Export		Discharge, Eject, Dispose, Remove
	Transfer	Transport	Lift, Move
		Transmit	Conduct, Convey
	Guide	Translate	Direct, Straighten, Steer
		Rotate	Turn, Spin
		Allow DOF	Constrain, Unlock
Connect	Couple		Join, Assemble, Attach
	Mix		Combine, Blend, Add, Pack, Coalesce
Control	Actuate		Start, Initiate
Magnitude	Regulate		Control, Allow, Prevent, Enable/Disable, Limit, Interrupt, Valve
	Change	Condition	Increase, Decrease, Amplify, Reduce, Magnify, Normalize, Multiply, Scale, Rectify, Adjust
		Form	Compact, Crush, Shape, Compress, Pierce
Convert	Convert		Transform, Liquefy, Solidify, Evaporate, Condense, Integrate, Differentiate, Process
Provision	Store		Contain, Collect, Reserve, Capture
	Supply		Fill, Provide, Replenish, Expose
	Extract		
Signal	Sense		Perceive, Recognize, Discern, Check, Locate
	Indicate		Mark, Display
	Measure		Calculate
Support	Stop		Insulate, Protect, Prevent, Shield, Inhibit
	Stabilize		Steady
	Secure		Attach, Mount, Lock, Fasten, Hold
	Position		Orient, Align, Locate

$\Sigma_X = \mathbf{X_0}^T\mathbf{X_0}/(m-1)$ ($m-1$ is the rank of the $n \times n$ symmetric covariance matrix if $m < n$, losing one additional degree of freedom due to the removal of the mean vector) (Bendat and Piersol, 1986; Fukunaga, 1990).

Assuming the covariance matrix is positive definite ($det \neq 0$), it will result in n nonnegative eigenvalues, and n corresponding eigenvectors. A semi-positive definite symmetric matrix will result in k nonnegative eigenvalues, where k is the rank of the matrix, determined by the number of independent rows. In this case, if $m < n$, and losing one degree of freedom by removing the mean vector, the rank k of the covariance matrix equals $m-1$.

The eigenvalues and eigenvectors of the covariance matrix are computed using the characteristic equation of the Σ_X matrix, namely $|\Sigma_X - \lambda\mathbf{I}| = 0$, with the eigenvectors corresponding to two different eigenvalues λ_i and λ_j being orthogonal. This equation can be rewritten in matrix form as $\Sigma_X \times \mathbf{V} = \mathbf{V} \times \mathbf{D}$, subject to the orthornormality constraint $\mathbf{V}^T \times \mathbf{V} = \mathbf{I}$, with the following eigenvalue (diagonal) and eigenvector matrices:

$$\mathbf{D} = \begin{bmatrix} \lambda_1 & & 0 \\ & \ldots & \\ 0 & & \lambda_n \end{bmatrix}; \quad \mathbf{V} = [V_1 V_2 \ldots V_n].$$

The eigenvector $\mathbf{V}$ can be used as the transformation matrix to transform the n-dimensional $\mathbf{X_0}$ to another vector $\mathbf{Y}$ using the orthogonal transformation $\mathbf{Y} = \mathbf{V}^T \times \mathbf{X_0}$, where the covariance matrix of $\mathbf{Y}$ is $\mathbf{D}$ (from $\Sigma_Y = \mathbf{V}^T \times \Sigma_X \times \mathbf{V} = \mathbf{D}$).

Product-Functionality Similarity Derivation

Stone et al. (Stone and Wood, 2000; Stone et al., 2000) present a methodology for transforming customer need rankings and function structures into quantitative models, offering designers a novel way to archive and communicate product design knowledge. Specifically, they use matrix manipulations to extract product similarity using a product repository which groups products together based on functionality and customer needs. Scaled customer need rankings are first mapped to sub-functions of the product function structure in the form of a product vector ϕ. An $m \times n$ product-function matrix $\mathbf{\Phi}$ is then formed to create a product repository to archive product design knowledge. Each element of the product-function matrix, ϕ_{ij} is the cumulative customer need rating for the ith function of the jth product. To compensate for variations due to different sources of information, the product-function matrix is normalized across the entire product space. The normalized product-function matrix $\mathbf{N}$, has elements $\nu_{ij} = \phi_{ij}\frac{\bar{\eta}}{\eta_j}\frac{\mu_j}{\bar{\mu}}$. Here, $\bar{\eta}$ is the average customer need rating, η_j is the customer rating for the jth product, $\mu_j = \sum_{i=1}^{m} H(\phi_{ij})$ is the number of functions in the jth product (H is the Heaviside function), and $\bar{\mu}$ is the average number of functions (n is the number of products and m is the total number of sub-functions for all products.) The product repository can then be manipulated to

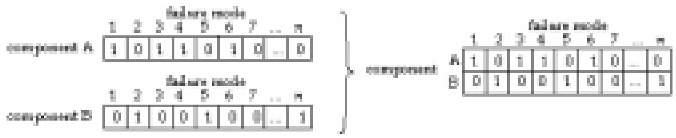

Figure 2. Forming a component-failure matrix.

identify groups of products sharing similar functions and customer needs (product families). Using such a method, a new product's functional model can be used to find similarities so that existing knowledge can guide its development. This is accomplished by computing the product-product matrix using the renormalized matrix $\hat{\mathbf{N}}$ (so that the norm is equal to 1), defined as $\hat{\Lambda} = \hat{\mathbf{N}}^T \hat{\mathbf{N}}$.

FUNCTION-FAILURE METHOD: A DESIGN TOOL

In this paper, the ideas of extracting "high-variance modes" and "product similarity" are extended to failure detection for a family of aerospace components and products. The method is based on the idea that there is a commonality or similarity to all failure modes based on the functionality of the features/components/systems under study. An example problem using a rotating machinery simulator model is used in this paper. Future work will extend this idea to the domain of helicopter failures and functions. The following presents the theory behind the approach and its application to a rotating machinery example.

Function and Failure Information for Components

Let $\mathbf{C}$ be an $m \times 1$ vector of subsystems and/or components for the application domain under study (e.g., helicopter, aircraft, spacecraft). Let $\mathbf{F}$ be an $n \times 1$ vector of failures commonly found in that application domain. Let $\mathbf{E}$ be the $r \times 1$ vector containing all elemental functions for the components under study. To represent failure information, such individual vectors (containing information on failure modes, functionality and components) are weaved together into a matrix of information. To begin, consider failure information which is typically recorded with respect to components or subsystems. This information can be arranged succinctly using a component vector $\mathbf{C}$ and a failure vector $\mathbf{F}$ with elements indicating the failure modes that can occur for the component. The m component vectors are aggregated together to form $\mathbf{CF}$, the $m \times n$ component-failure matrix, where n is the total number of failure modes occuring across all m components. The formation of a sample component-failure matrix is shown in Figure 2.

Similarly, components can be described in terms of their functionality. Here, an elemental function vector $\mathbf{E}$ is constructed

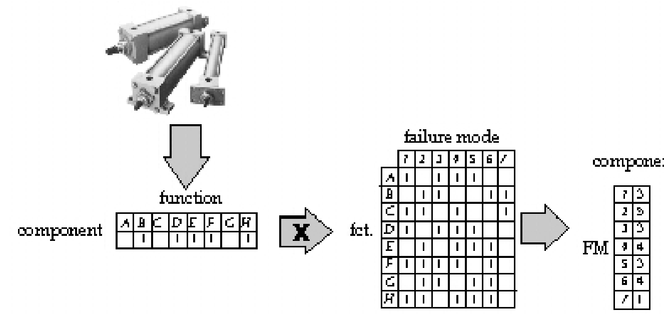

Figure 3. Using a functional model to identify potential failure modes during a component's conceptual design phase.

for each component with elements that indicate the functionality of the component. Aggregating each vector of r functions, together for the m components (represented in the columns), creates the $r \times m$ function-component matrix $\mathbf{EC}$, where r is the total number of functions necessary to describe all of the m components. The function-component matrix is closely related to the product-function matrix Φ, reviewed above, though this time functionality of components rather than that of the entire product, is considered. Thus, the $\mathbf{EC}$ matrix may be constructed as a binary matrix with a 1 indicating the component solves a certain function and a 0 indicating the opposite, or the elements of $\mathbf{EC}$ may be weighted to include additional information.

Linking Failure Mode to Function

Once the component-failure and function-component matrices are computed, the relationship between function and failure can be computed as: $\mathbf{EF} = \mathbf{EC} \times \mathbf{CF}$. This $r \times n$ matrix, called the function-failure matrix, relates the failure modes to the elemental functions. Each element ij indicates whether any component solving function i has ever failed by failure mode j. This information is useful when designing or redesigning components, offering failure modes to guard against during the design phase. For example, a new design or redesign of an existing component might proceed as follows. A component's functional model is specified as a vector. That vector is multiplied by the function-failure matrix, $\mathbf{EF}$, to produce a component-failure mode vector. This vector then indicates potential failure modes the component could experience and the likelihood of occurrence for each failure mode (the larger the failure mode value, the mode likely). The designer is then able to design out the identified failure modes during the conceptual design stage. This approach is shown schematically in Figure 3.

Figure 4. A Desktop Rotating Machinery Testrig.

Table 5. COMPONENT-FAILURE MATRIX EXAMPLE.

	$F1$	$F2$	$F3$	$F4$	$F5$
$C1: gear$	1	1	0	1	1
$C2: bearing$	1	0	1	1	0
$C3: shaft$	0	1	0	0	1

Application Example: Rotating Machinery

Consider the design of a simple rotating machinery system, consisting of a shaft attached to a motor by means of a coupling, supported by two sets of ball bearings, which drives a gear box via two belts, which in turn drives a load. A picture of a simple rotating machinery system is shown in Figure 4. This system represents the Machinery Fault Simulator located at NASA Ames Research Center, whose purpose is to simulate vibrational fault situations (Tumer and Huff, 2000). In the case of a helicopter, the load would be equivalent to driving the rotor blades with an epicyclic transmission gearbox (Huff et al., 2000a; Huff et al., 2000b). The input to the tranmission would be a shaft, supported by bearings, driven by the helicopter engine.

To present a simple example, three types of components are considered: namely, the shaft, gears, and bearings. These components can be subject to elementary failure modes, described in Table 1, that need to be considered at the early design stages. Selecting a subset from these failure modes, these components are assumed to be subject to wear, fatigue, corrosion, fretting, and impact failure modes. Table 5 presents an aggregated matrix of failures and components, with 1's representing an occurrence of a failure for a given component, and 0's representing non-occurrence. The failure modes are labeled as follows: F_1 is wear, F_2 is fatigue, F_3 is corrosion, F_4 is fretting, and F_5 is impact. The components are labeled as follows: C_1 is a gear, C_2 is a bearing, and C_3 is the shaft. The failure modes represent the variables (columns) and the components represent the various observations (rows).

Capturing Modes and Variation Patterns

Using the matrices introduced above, the principal modes of variation in the data are derived for the case of the simple example, providing designers with a means to make tradeoffs at the early stages of design.

Deriving Principal Modes and Variation Patterns Recall that the covariance matrices for the aggregated component-failure, function-component, and function-failure matrices, are referred to as Σ_{CF}, Σ_{EC}, and Σ_{EF} throughout the rest of this discussion. To simplify the discussion, the $m \times n$ component-failure matrix, $\mathbf{CF}$ is selected as an example. The component-failure matrix is composed of n failure modes in its columns (variables), and m components in its rows (observations). Let $\Sigma_{CF} = \mathbf{CF}^T \times \mathbf{CF}/(m-1)$ be the covariance matrix of the component-failure matrix $\mathbf{CF}$. Σ_{CF} is an $n \times n$ symmetric matrix (n is the number of elemental failure modes), where the individual ijth elements are equivalent to the similarity between failures in terms of components. In the following, the principal mode derivation presented above is applied to the rotating machinery example, by running a Principal Components Analysis (PCA) on the input matrix $\mathbf{CF}$.

Application to Rotating Machinery Test Rig For the rotating machinery test rig example, Table 5, the input matrix $\mathbf{CF}$, with $m = 3$ and $n = 5$, is defined as:

$$\mathbf{CF} = \begin{bmatrix} 1\ 1\ 0\ 1\ 1 \\ 1\ 0\ 1\ 1\ 0 \\ 0\ 1\ 0\ 0\ 1 \end{bmatrix},$$

whose mean vector is computed as:

$$\overline{\mathbf{CF}} = \begin{bmatrix} 0.6667\ 0.6667\ 0.3333\ 0.6667\ 0.6667 \end{bmatrix}.$$

The centered input vector is $\mathbf{CF_0} = \mathbf{CF} - \overline{\mathbf{CF}}$. The covariance matrix Σ_{CF} is computed as:

$$\Sigma_{CF} = \begin{bmatrix} 0.3333 & -0.1667 & 0.1667 & 0.3333 & -0.1667 \\ -0.1667 & 0.3333 & -0.3333 & -0.1667 & 0.3333 \\ 0.1667 & -0.3333 & 0.3333 & 0.1667 & -0.3333 \\ 0.3333 & -0.1667 & 0.1667 & 0.3333 & -0.1667 \\ -0.1667 & 0.3333 & -0.3333 & -0.1667 & 0.3333 \end{bmatrix}$$

Note that the elements of the covariance matrix represent the commonality between the $n = 5$ failure modes (variables), and can be used to help with the design. Using Matlab, the PCA script results in the following outpurs:

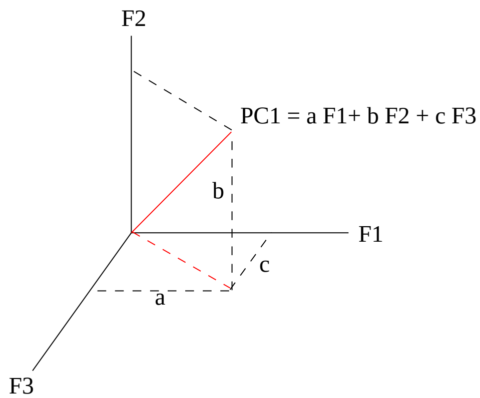

Figure 5. Coordinate transformation using PCA.

$$pc = \begin{bmatrix} 0.3943 & -0.5869 & 0.0425 & 0.7058 & 0.0000 \\ -0.4792 & -0.3220 & -0.5750 & 0.0347 & -0.5787 \\ 0.4792 & 0.3220 & -0.7877 & 0.0475 & 0.2095 \\ 0.3943 & -0.5869 & -0.0425 & -0.7058 & -0.0000 \\ -0.4792 & -0.3220 & -0.2128 & 0.0128 & 0.7882 \end{bmatrix}$$

$$sc = \begin{bmatrix} -0.2163 & -0.7133 & -0.0000 & 0.0000 & -0.0000 \\ 1.2214 & 0.2527 & -0.0000 & -0.0000 & 0.0000 \\ -1.0050 & 0.4606 & -0.0000 & -0.0000 & -0.0000 \end{bmatrix}$$

$$lat = \begin{bmatrix} 1.2743 \\ 0.3924 \\ 0.0000 \end{bmatrix}$$

The pc matrix represents the eigenvectors of the 5×5 covariance matrix, and represents the coefficients of the new coordinate system described by the principal axes, with respect to the old coordinate system described by the variables F_1, F_2, etc. The columns of this matrix correspond to each of the principal components, and the values in each row represent the coordinate based on the original variables F_i. The principal axes give the direction of the new coordinate system defined by the eigenvectors of the covariance matrix, corresponding to the directions with maximum variability, and provide a simpler and more parsimonious description of the covariance structure (Johnson and Wichern, 1992). An illustrative schematic of the coordinate transformation is shown in Figure 5 for a case with 3 variables $F1$, $F2$, and $F3$ only.

Based on the pc matrix, the first principal component can be used to describe the original variables in the new (transformed) coordinate system as a linear combination of all 5 failure modes as follows: $pc1 = 0.3943F1 - 0.4792F2 + 0.4792F3 + 0.3943F4 - 0.4792F5$. Using this relationship, the designer can deduce that $F2$, $F3$ and $F5$ have a higher effect than $F1$ and $F4$, and that $F2$-$F3$ and $F2$-$F5$ have an equal but contrasting effect on the first principal component. The eigenvalues of the covariance matrix are represented in the lat vector. Note that with an eigenvalue of 1.27, the first principal component accounts for 76.46% of the total variance in the data, and hence is sufficient to represent the failure information in a simpler manner, and can be considered as a model of the variation in the sample data. The second principal component has an eigenvalue of 0.3924, and accounts for the remaining 23.54% of the variance. (There are only two eigenvalues since the rank of the covariance matrix is $m-1 = 2$. The rest of the eigenvalues belong to the null space.)

While the eigenvectors of the $n \times n$ covariance matrix ($\mathbf{CF_0}^T\mathbf{CF_0}$) are presented in the pc matrix, the scores in the sc matrix represent the weights for the eigenvectors on each of the observations ($\mathbf{CF_0} \times pc$). The scores are then interpreted as corresponding to the pattern of the variation over the different components (C_i) under study, for each principal mode. The first column of the sc matrix represents the first principal component, with each row corresponding to each component $C1$, $C2$, and $C3$ (observations). The second column corresponds to the second principal component. The remaining columns belong to the null space, since the rank of the covariance matrix in this case was $m-1 = 2$. The variance of the scores for the first principal component (first column of sc) equals the first eigenvalue ($\lambda_1 = 1.27$), and the variance of the scores for the second principal component equals the second eigenvalue ($\lambda_2 = 0.3924$). Using this example, for the first component C_1 (gear), the first principal mode has a weight of -0.2163, whereas for the second component C_2 (bearing), the same principal mode has a weight of 1.2214, hence indicating a stronger influence on this component.

The transformed representation of the failure information in terms of a principal mode can be used by designers to decide on tradeoffs in terms of failures. For example, failure modes $F2$, $F3$ and $F5$ have a more significant effect on the overall performance and quality of the product than failure modes $F1$ and $F4$, as indicated by the first column of the pc matrix. Depending on the application of the component and its functionality, the designer might want to pay closer attention to the first three modes, and not be as concerned with the last two modes. For example, in this case, the bearing component $C2$ depends more heavily on these three modes, as indicated by the first column of the sc matrix. Tradeoffs are a common occurrence in design. A means to analytically decide on tradeoffs can result in significant savings in time and cost. Similar conclusions can be drawn by starting with the function-component and the function-failure matrices.

Capturing Similarity Information

The matrices described in this paper represent convenient ways to mathematically capture failure mode and function data for components. Additional useful design information may be obtained through matrix manipulations of the data. The resulting similarity matrices (equivalent to covariance matrices from above) provide tools for designers to assess and design against the impact of potential failure modes.

Deriving Similarity Information Similarity matrices can be derived in several ways, depending on the purpose of the designer. First, taking the transpose of the function-component matrix and post multiplying it by function-component matrix yields an $m \times m$ symmetric component-component matrix. Mathematically, the component-function similarity matrix is given by: $\hat{\Lambda}_{EC} = \overline{\mathbf{EC}}^T \times \overline{\mathbf{EC}}$, where $\overline{\mathbf{EC}}$ is the normalized function-component matrix with each column normalized to unity for convenience. Each element ij of the component-function matrix indicates the similarity between component i and component j based on elemental functions. That is, if component i is functionally similar to component j, then element λ_{ij} will have a value in $(0,1]$. Components that are completely similar with themselves have a similarity value of 1 due to the normalization of the function-component matrix. Likewise, components that share no functions in common will have a similarity value of 0. The component-function similarity matrix gives designers a tool to identify possible replacement components that solve similar functions. It also provides a way to search and rank component solutions that are similar in function and use design by analogy techniques to embody a design.

Alternatively, post multiplying the component-failure matrix by its transpose yields a symmetric matrix with elements that indicate the similarity of components by failure. Mathematically, the component-failure similarity matrix is given by: $\Lambda_{CF} = \mathbf{CF} \times \mathbf{CF}^T$, The elements of the component-failure similarity matrix, λ_{ij}, indicate the number of failure modes that component i has in common with component j. Here, the non-normalized versions of the matrices are used because the interest is in getting an actual count of failure modes. One possible use for the component-function and component-failure similarity matrices is to identify component solutions that prevent certain failure modes. If, between functionally-similar components A and B (as determined by $\hat{\Lambda}_{EC}$), component B does not experience all of the same failure modes as component A (as determined by Λ_{CF}), then there is some characteristic of component B that could be incorporated into A to improve its performance.

Finally, premultiplying the component-failure matrix by its transpose yields a symmetric matrix with elements indicating failure mode combinations which occur across components. A high value in element ij of the failure-component similarity matrix indicates that failure modes i and j affect many components jointly. Mathematically, the matrix is formed by: $\Lambda_{FC} = \mathbf{CF}^T \times \mathbf{CF}$. This similarity matrix yields insight into possible interactions of two or more failure modes. It can be used to direct component remedies that will eliminate more than one failure mode. In terms of current FMEA and FTA techniques, knowledge of failure modes that often occur interactively would give designers a more complete list of possible product failures to investigate.

Table 6. FUNCTION-COMPONENT MATRIX EXAMPLE.

	$C1: gear$	$C2: bearing$	$C3: shaft$
$E1$: *change m.e.*	1	0	0
$E2$: *guide m.e.*	1	0	1
$E3$: *transfer m.e.*	1	0	1
$E4$: *position m.e.*	0	1	0
$E5$: *stabilize m.e.*	0	1	0

Application to Rotating Machinery Test Rig For the components of the Machinery Fault Simulator considered, functional descriptions are found using the functional basis of Tables 2, 3, 4. The function vectors for each component are aggregated together to form the function-component matrix **EC** (with $r = 5$ and $m = 3$) shown in Table 6.

Calculating function-failure matrix as $\mathbf{EF} = \mathbf{EC} \times \mathbf{CF}$ gives:

$$\mathbf{EF} = \begin{bmatrix} 1 & 1 & 0 & 1 & 1 \\ 1 & 2 & 0 & 1 & 2 \\ 1 & 2 & 0 & 1 & 2 \\ 1 & 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 & 0 \end{bmatrix},$$

where the rows represent the elemental functions E_i and the columns represent the failure modes F_j. (Recall the component-function matrix **CF**, Table 5). Observing the function-failure matrix, one sees that function pairs *guide m.e.-transfer m.e.* and *position m.e.-stabilize m.e.* experience the same failure modes. Also, the failure modes *fatigue* and *impact* occur more frequently for the functions *guide m.e.* and *transfer m.e.*. Though this is a limited example, the function-failure data can be used to identify traditionally occurring failure modes when only a component's function is known and use that knowledge to design out the potential failure.

Additional design observations can be made by computing the similarity matrices. First, the component-function similarity $\hat{\Lambda}_{EC}$ is calculated from the function-component matrix after normalizing each column to unity as follows:

$$\overline{\mathbf{EC}} = \begin{bmatrix} \frac{\sqrt{3}}{3} & 0 & 0 \\ \frac{\sqrt{3}}{3} & 0 & \frac{\sqrt{2}}{2} \\ \frac{\sqrt{3}}{3} & 0 & \frac{\sqrt{2}}{2} \\ 0 & \frac{\sqrt{2}}{2} & 0 \\ 0 & \frac{\sqrt{2}}{2} & 0 \end{bmatrix},$$

and,

$$\hat{\Lambda}_{EC} = \overline{\mathbf{EC}}^T \times \overline{\mathbf{EC}} = \begin{bmatrix} 1.000 & 0.000 & 0.816 \\ 0.000 & 1.000 & 0.000 \\ 0.816 & 0.000 & 1.000 \end{bmatrix}.$$

The component-function similarity matrix identifies that components 1 and 3 (i.e., the gear and the shaft) are similar in function when one is projected onto the other. This indicates that the gear could possibly be used as a replacement for the shaft (or vice versa) and that solution principles used in the gear could be used in a redesign of the shaft (again, the converse is also true).

Next, the component-failure similarity matrix is calculated from the component-failure matrix (non-normalized) as:

$$\Lambda_{CF} = \mathbf{CF} \times \mathbf{CF}^T = \begin{bmatrix} 4 & 2 & 2 \\ 2 & 3 & 0 \\ 2 & 0 & 2 \end{bmatrix}.$$

Note that the diagonal simply returns the count of failure modes each component experiences. Component 1 (the gear) shares two failure modes in common with each of the other components, while components 2 and 3 (bearing and shaft) have no common failure modes. Consider components 1 and 3 which are functionally similar (with a similarity index of 0.816) and share two failure modes in common (from the component-failure matrix). If a design solution for one component is found that eliminates the common failure modes, then that solution will most likely be applicable to the remaining component as well.

Finally, the failure-component similarity matrix is calculated as:

$$\Lambda_{FC} = \mathbf{CF}^T \times \mathbf{CF} = \begin{bmatrix} 2 & 1 & 1 & 2 & 1 \\ 1 & 2 & 0 & 1 & 2 \\ 1 & 0 & 1 & 1 & 0 \\ 2 & 1 & 1 & 2 & 1 \\ 1 & 2 & 0 & 1 & 2 \end{bmatrix}.$$

For this set of components and recorded failures, the failure modes F1-F4 (wear and fretting) and F2-F5 (fatigue and impact) tend to occur on the same component most frequently. Other combinations of failure modes are possible, but not as likely. Failure modes F2-F3 (fatigue and corrosion) and F3-F5 (corrosion and impact) have no incidence of occurring on the same component. This information provides useful information for FMEA and FTA techniques.

CONCLUSIONS AND FUTURE WORK

In this paper, a function-failure method was introduced to take advantage of the commonality between failure modes and functionality of components. The method is meant to provide designers with an analytical means to make tradeoffs and design decisions to avoid potential failure modes. A crucial piece of the work is the inherent link between functionality and failure modes. The method is applied to a simple example using a rotating machinery test rig, to illustrate its potential. The purpose of developing such analytical methods is to meet the tight performance and safety requirements imposed on designers for critical NASA applications. Future work includes applications in helicopters, and shuttle subsystems (Huff et al., 2000a; Huff et al., 2000b; Tumer and Huff, 2000).

As an ongoing collaborative project between NASA Ames and The University of Missouri-Rolla, the function-failure method will be applied to helicopter failure data presented by Collins, et al in (Collins and Hagan, 1976). This initial investigation of helicopter failures will be followed by a thorough analysis of actual failures collected from accident data, which will be provided to the authors in terms of a survey. A mapping of the assigned functions onto the basic set of functions presented in this work has been completed. This mapping, accompanied by the standard failure modes described in Table 1, will be used to start analyzing the helicopter failure data using the function-failure method presented in this paper.

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