DECOMPOSITION-BASED FAILURE MODE IDENTIFICATION METHOD FOR RISK-FREE DESIGN IN LARGE SYSTEMS

Irem Y. Tumer, Ph.D. *
Research Scientist
Computational Sciences Division
NASA Ames Research Center
Moffett Field, CA 94035-1000
Email: itumer@mail.arc.nasa.gov
Phone: 650-604-2976

Robert B. Stone, Ph.D.
Assistant Professor
Department of Basic Engineering
University of Missouri-Rolla
Rolla, MO 65409-0210
Email: rstone@umr.edu
Phone: 573 341 4086

Rory A. Roberts
Graduate Research Assistant
Department of Mechanical Engineering
University of Missouri-Rolla
Rolla, MO 65409-0210

ABSTRACT

When designing products, it is crucial to assure failure and risk-free operation in the intended operating environment. Failures are typically studied and eliminated as much as possible during the early stages of design. The few failures that go undetected result in unacceptable damage and losses in high-risk applications where public safety is of concern. Published NASA and NTSB accident reports point to a variety of components identified as sources of failures in the reported cases. In previous work, data from these reports were processed and placed in matrix form for all the system components and failure modes encountered, and then manipulated using matrix methods to determine similarities between the different components and failure modes. In this paper, these matrices are represented in the form of a linear combination of failures modes, mathematically formed using Principal Components Analysis (PCA) decomposition. The PCA decomposition results in a low-dimensionality representation of all failure modes and components of interest, represented in a transformed coordinate system. Such a representation opens the way for efficient pattern analysis and prediction of failure modes with highest potential risks on the final product, rather than making decisions based on the large space of component and failure mode data. The mathematics of the proposed method are explained first using a simple example problem. The method is then applied to component failure data gathered from helicopter accident reports to demonstrate its potential.

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KEYWORDS

Failure-free product development; Failure prevention; Function-failure similarity analysis; Principal components analysis; Risk-based design; Failure mode identification.

PRELIMINARIES

Prevention of potential failure modes during product development is especially crucial in high-risk aerospace applications, where failures are unacceptable at any frequency. Failures modes are analyzed thoroughly during the early stages of design to prevent occurrence during operation. In our work, component, failure, and functionality information is derived from engineering drawings and specifications, accident reports, and functional bases, to establish a link between functionality of components and the potential failure modes (Collins and Hagan, 1976; Harris et al., 2000; NTSB, 2001; Stone and Wood, 2000; Shafer, 1980). This information has been used by the authors to draw similarities between different designs (Tumer and Stone, 2001; Roberts et al., 2002; Tumer et al., 2002) using matrix manipulations of the component, failure, and functionality data. The overall goal of our work is to address the failure modes early in conceptual design: to achieve this goal, functions are mapped to failure modes that are experienced by a component that performs the particular functions (Tumer and Stone, 2001; Roberts et al., 2002; Tumer et al., 2002).

In the current paper, we present a means of decomposing large design problems for failure analysis and prevention purposes. In the case of complex engineering systems, the number of components and their interactions with each other, as well as their interactions with the operating environment, can be overwhelmingly large. Working from the original component-failure, component-function, and failure-function matrices can be especially difficult when predictions need to be made to determine safety, performance, and the associated risks. To address this problem, we present an insightful approach to decompose the initial matrices (derived for the function-failure similarity analysis) and derive a low-dimensional representation of the large space of components, failure modes, and functions of relevance. Specifically, this paper proposes a decomposition method which reduces the dimensionality of the function-component-failure space by means of an orthogonal transformation. The current focus is on components and their failure modes, where each component is related to the potential failure modes. The orthogonal decomposition provides a method of determining the failure modes that have the most impact, as well as the failure modes that are redundant in the information that they provide. During the early design stages, the failure modes with more potential may be concentrated on in order to reduce risk, as well as reduce design time and cost. Using such a decomposition approach, the designer can focus on the failure modes that have the potential of becoming a risk factor during the lifecycle of the complex system under investigation.

Failure Prevention and Reliability for Design

Reliability, maintainability, and effectiveness of machines and systems depend heavily upon the understanding, recognition, and prevention or elimination of mechanical failures (Collins and Hagan, 1976). The quality of a particular design depends heavily on the ability of the product to function in the given lifecycle, as defined by the customer or user of the product (Ruff and Paasch, 1993). As products become more complex, prevention of failure modes through analysis in the early stages of design becomes very complex and cumbersome.

For applications such as aircraft, the risks associated with missed failures is very high: not only is safety a major issue due to high probability of fatalities (Harris et al., 2000), but the costs involved in repairs and downtimes can become a major burden. A study by Boeing Company showed that, for a fleet of 100 aircraft, the costs generated from delays due to aircraft failure is about \$2*M* per year. (This accounts for revenue loss, increased handling of passengers and cargo, and extra crew wages.) The cost of maintenance alone adds another \$4*M* per year (Stander, 1982; Ruff and

Paasch, 1993). In order to eliminate or reduce the possibility of failure, designers and manufacturing engineers need to be aware of all of the potentially significant failure modes in the systems being designed.

There are several techniques of identifying failure modes, commonly used during conceptual design. Some examples of these techniques are checklists, FMEA (failure modes and effects analysis) and FMECAs (failure modes effects and criticality analysis), and FTAs (fault tree analysis) (Carter, 1997; Henley and Kumamoto, 1992). The details of these methods are explained in (Tumer and Stone, 2001) for reference. In our work, we make use of the information gathered for such techniques, and combine it with information from NTSB and NASA accident reports, maintenance guides, and engineering specifications. This information is then presented to the designer in a form that is easy to analyze and use during the early stages of design. The methods developed in this work are meant to augment the information derived from the more traditional approaches (Tumer and Stone, 2001; Roberts et al., 2002; Tumer et al., 2002).

Orthogonal Decomposition for Dimensionality Reduction

The orthogonal decomposition method proposed in this work is based on previous work reported by Tumer et al. (Tumer et al., 2000) to extract high-variance modes from product surface profiles. This method is extended here to isolate the failure modes with the highest variance, to determine tradeoffs during component development and provide a low-dimensional representation of the significant failure modes for potential classification and prediction purposes (Tumer and Stone, 2001).

Consider 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 $\overline{\mathbf{X}}$, removing the mean vector from each of the m observations, and computing $\Sigma_X = \mathbf{X_0}^T \mathbf{X_0}/(m-1)$ ($m-1$ 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) (Fukunaga, 1990).

The semi-positive definite symmetric covariance 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 $\Sigma_Y = \mathbf{V}^T \times \Sigma_X \times \mathbf{V} = \mathbf{D}$).

This final observation leads to several important conclusions: 1) The orthogonal transformation may be broken down to r separate equations $y_i = V_i^T \times \mathbf{X}$; 2) $\mathbf{Y}$ represents $\mathbf{X}$ in the new coordinate system spanned by $V_1, \ldots, V_n$, and hence is a coordinate transformation; 3) The transformation matrix is the eigenvector matrix of Σ_X. Since the eigenvectors are the ones that maximize the distance function $d_X^2(X)$, we are in effect selecting the principal components of the distribution as the new coordinate axes; 4) The eigenvalues are the variances of the transformed variables y_i; 5)

Figure 1. A Desktop Rotating Machinery Testrig.

Since the transformation is orthogonal, Euclidian distances are preserved, i.e., $||\mathbf{Y}||^2 = ||\mathbf{X}||^2$. When the eigenvalues are listed in ascending order, the resulting eigenvectors correspond to the principal components starting with the highest variance, indicated by the amplitude of the corresponding eigenvalues. The input matrix can be then represented in this new coordinate system using the orthogonal transformation (Fukunaga, 1990).

DECOMPOSITION-BASED FAILURE MODE IDENTIFICATION METHOD

The orthogonal decomposition method described above is used in this work to decompose the space of failure modes and component functions for large complex systems. It is intended as a means to focus designers' attention on the significant failure modes based on the maximum variance criterion. To explain the derivation of the eigenvectors, eigenvalues, and corresponding weights, a simple example problem using a rotating machinery simulator model is used next.

Test Rig Example

The simple example hypothesizes that the design of a rotating machinery test rig goes through detailed analysis by design engineers to assure failure and risk-free performance (Tumer and Stone, 2001). The test rig design includes 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, shown in Figure 1. This system is located at NASA Ames Research Center, whose purpose is to simulate vibrational fault situations (Tumer and Huff, 2002). The same example was used in demonstrating the mechanics of the function-failure similarity method developed by Tumer and Stone in (Tumer and Stone, 2001). Some duplication of the explanation of initial matrices is allowed in this paper for clarity.

Initial Matrices

Three components considered in this example are: the shaft, gears, and bearings (Tumer and Stone, 2001). Let $\mathbf{C}$ be an $m \times 1$ vector of subsystems and/or components for the application domain under study (e.g., rotorcraft, aircraft, space spation, mars rover, mars polar lander, etc.) Let $\mathbf{F}$ be an $n \times 1$ vector of failures commonly found in that application domain. Selecting a subset from elementary failure modes, these components are assumed to be subject to wear, fatigue, corrosion, fretting, and impact failure modes (Collins and Hagan, 1976). 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 matrix has n failure modes in its columns (representing the variables), and m components in its rows (representing the various observations). Table 1 presents the aggregated component-failure matrix, with 1's representing an occurrence of a failure for a given component, and 0's representing non-occurrence.

Table 1. Component-Failure Matrix **CF**.

1	1	0	1	1
1	0	1	1	0
0	1	0	0	1

Table 2. PC Matrix for **CF**.

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

Table 3. SC Matrix for **CF**.

-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

Table 4. LAT Vector (Eigenvalues) for **CF**.

1.2743
0.3924
0.0000

Note that the columns correspond to the failure modes ($F1$ is wear, $F2$ is fatigue, $F3$ is corrosion, $F4$ is fretting, and $F5$ is impact), and the rows correspond to the components under study ($C1$ is a gear, $C2$ is a bearing, and $C3$ is the shaft.)

Principal Axes of Variation for Design

Let $\Sigma_{CF} = \mathbf{CF}^T \times \mathbf{CF}/(m-1)$ be the covariance matrix of the component-failure matrix **CF**, an $n \times n$ symmetric matrix (n is the number of elemental failure modes). In this work, Principal Components Analysis (PCA) is used to compute the transformed variables, eigenvectors, and eigenvalues, described in the previous section. In the following, the *PC* matrix corresponds to the eigenvector matrix **V**, the *SC* matrix corresponds to the transformed vector **Y**, and the *LAT* vector contains the diagonal elements of the eigenvalue matrix **D**, which represent the eigenvalues of the covariance matrix of the input data.

The input matrix **CF**, with $m = 3$ and $n = 5$, is defined in Table 1. Using the centered input vector $\mathbf{CF_0} = \mathbf{CF} - \overline{\mathbf{CF}}$, the PCA script in Matlab results in the principal components, scores, and latent values, shown in Tables 2, 3, 4. The *PC* matrix provides the eigenvectors of the 5×5 covariance matrix, providing the coefficients of the new coordinate system described by the principal axes, with respect to the old coordinate system described by the variables $F1$, $F2$, 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 Fi. The principal axes correspond to the directions with maximum variability, and provide a simpler and more parsimonious (low-dimensional) description of the covariance structure (Johnson and Wichern, 1992). The coordinate transformation is shown schematically in Figure 2 for a case with three variables $F1$, $F2$, and $F3$ only.

As an example, the first principal component can be used to describe the original variables in the transformed coor-

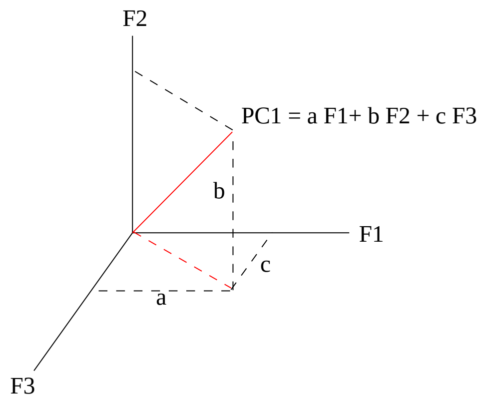

Figure 2. Coordinate Transformation Using PCA.

dinate system as a linear combination of all five 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 $F2$ & $F3$ have an equal but contrasting effect on the first principal component, and so on. The eigenvalues of the covariance matrix are represented in the *LAT* vector, shown in Table 4. 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 (more parsimonious) manner, and can be considered as a model of the sample data. The second principal component has an eigenvalue of 0.39, and accounts for the remaining 23.54% of the variance. (There are only two eigenvalues in this case since the rank of the covariance matrix is $m-1=2$. The rest of the eigenvalues belong to the null space.)

The scores in the *SC* matrix provide the relative weight for the eigenvectors on each of the observations (components), and are computed as $\mathbf{CF_0} \times PC$. The scores are then interpreted as corresponding to the pattern of the variation for each eigenvector over the different machinery components (C_i) under study. The first column of the *SC* matrix corresponds to 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 ($\lambda_2 = 0.39$). Using this example, for the first component $C1$ (gear), the first principal mode has a weight of -0.21, whereas for the second component $C2$ (bearing), the same principal mode has a weight of 1.22, 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 $F5$ may 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. Based on this information, 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.

APPLICATION TO THE RISK-FREE DESIGN OF LARGE SYSTEMS

To assure a failure and risk-free product, designers make use of any information and previous knowledge about potential failure modes that might occur during a system's lifecycle. In this work, we propose to reduce the load on

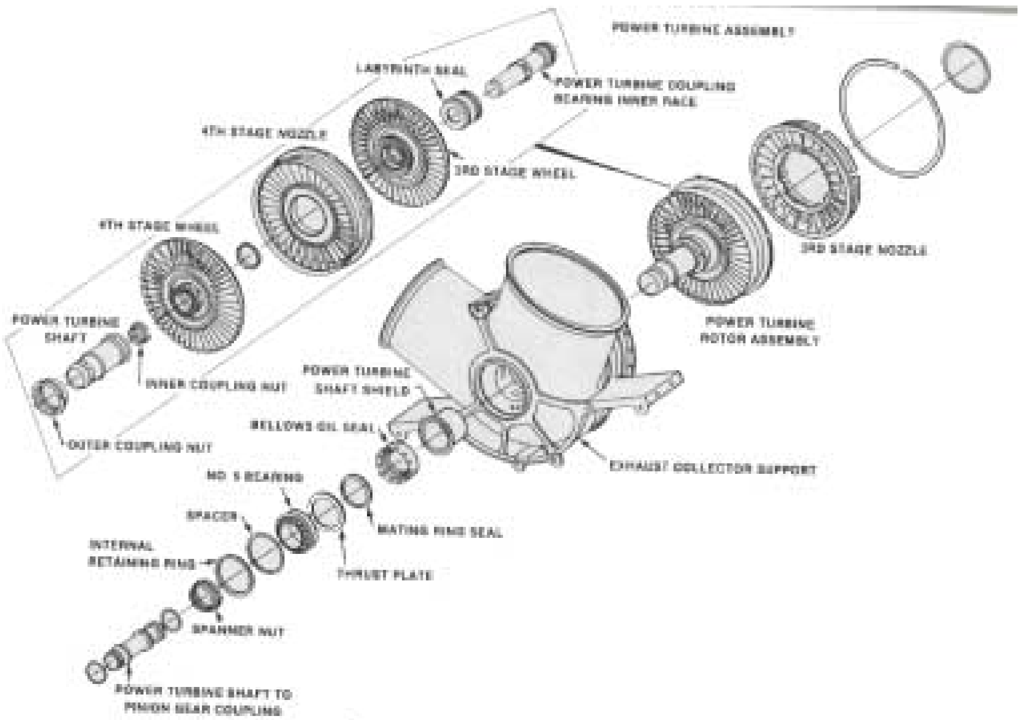

Figure 3. Turbine Subsystem for an OH58 Helicopter.

the designer by concentrating on a linear transformation of failure and component data gathered from real accident reports, eliminating the need to sort through large amounts of data. A feasibility study is presented in this section using a rotorcraft system as an example, first introduced in (Roberts et al., 2002).

Rotorcraft Failures and Functions

The application is a Bell 206 helicopter whose army counterpart, an OH58 helicopter, is located at NASA Ames for flight research purposes (Huff et al., 2002). Helicopter accident reports published by the National Transportation and Safety Board and NASA were carefully studied to determine the common failure modes and the components and subsystems affected by these failures (Harris et al., 2000; NTSB, 2001; Roberts et al., 2002). Maintenance guides, engineering schematics, and design specifications for this type of rotorcraft were studied thoroughly to determine the components and subsystems of relevance (Shafer, 1980).

The engine and power train subsystems were identified as the primary systems where failures occurred. As an example, a schematic of the turbine system contained inside the engine of a Bell 206 helicopter is shown in Figure 3, along with a detailed description of the components contained in the assembly (Roberts et al., 2002). 29 components and subsystems were identified as potentially causing failures. These components had a total of 10 failure modes reported in the accident reports. There were 1000 accident reports involving the Bell 206 helicopters, and 69 of these corresponded to component failures for the engine and power train. Tables 5 and 6 present the components and failure modes extracted from the reports (Roberts et al., 2002).

Table 5. Components from Helicopter Accident Reports (**C**).

Element	Description
C1	air discharge tubes
C2	bearing
C3	bleed valve
C4	bolt
C5	compressor case
C6	compressor mount
C7	compressor wheel
C8	coupling
C9	diffuser scroll
C10	exhaust collector
C11	fire wall
C12	front diffuser
C13	front support
C14	governor
C15	housing
C16	impeller
C17	mount
C18	nozzle
C19	nozzle shield
C20	O ring
C21	P3 line
C22	plasting lining
C23	pressure control line
C24	pylon isolator mount
C25	rear diffuser
C26	rotor
C27	shaft
C28	spur adapter gearshaft
C29	turbine wheel

Table 6. Failure Modes from Helicopter Accident Reports (**F**).

Element	Description
F1	bond failure
F2	corrosion
F3	fatigue
F4	fracture
F5	fretting
F6	galling and seizure
F7	human
F8	stress rupture
F9	thermal shock
F10	wear

Reduction of the Component-Failure Space for Design Use

Using the vectors from Tables 5 and 6, the input matrix **CF**, with $m = 29$ and $n = 10$, is defined as in Table 7. With the mean vector removed, the PCA decomposition results in the principal components, scores, and latent values shown in Table 8.

From the *PC* matrix in Table 8, the first principal component can be used to describe the original variables in the

Table 7. **CF** matrix from helicopter failure and component data.

0	0	0	0	0	0	0	0	0	0
0	0	4	0	0	1	0	0	1	1
0	0	0	0	0	0	0	0	0	0
0	0	1	0	1	0	0	0	0	1
0	1	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
0	0	2	0	0	0	0	1	2	0
0	0	2	0	0	0	0	0	0	2
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	2	1	0	0	0	0	0	1
0	0	0	0	0	0	0	0	1	1
0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	1
0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0
0	0	2	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	2
0	0	0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0	0	0
1	2	0	0	0	0	0	0	1	0
0	0	5	0	0	0	0	0	0	0
0	0	4	0	0	0	0	1	5	0

new (transformed) coordinate system as a linear combination of all 10 potential failure modes as follows:

$$\begin{aligned} pc1 = & -0.0079F1 - 0.0438F2 + \mathbf{0.8786}F3 + 0.0134F4 \\ & + 0.0132F5 + 0.0467F6 - 0.0131F7 + \mathbf{0.1023}F8 \\ & + \mathbf{0.4604}F9 + 0.0308F10. \end{aligned} \quad (1)$$

The first principal component is a transformed version of the original failure modes, with the coefficients indicating the relative significance of each failure mode. As observed, failure modes $F3$ (fatigue), $F8$ (stress rupture), and $F9$ (thermal shock) have the highest contribution to the first principal component. The variance of the scores for the first principal component (first column of *SC*) equals the first eigenvalue in the *LAT* vector (λ_1 = 2.40, 67.3%), and the variance of the scores for the second principal component equals the second eigenvalue (λ_2=0.73, 18.86%). Using the *SC* matrix in Table 8, a plot of the first score vector is shown in Figure 4, which shows the distribution of the first principal component over the 29 components in the subsystems being studied. In this example, components $C2$ (bearing), $C7$ (compressor wheel), $C28$ (spur adapter for gear shaft), and $C29$ (turbine wheel) have the highest weighting for the first principal component.

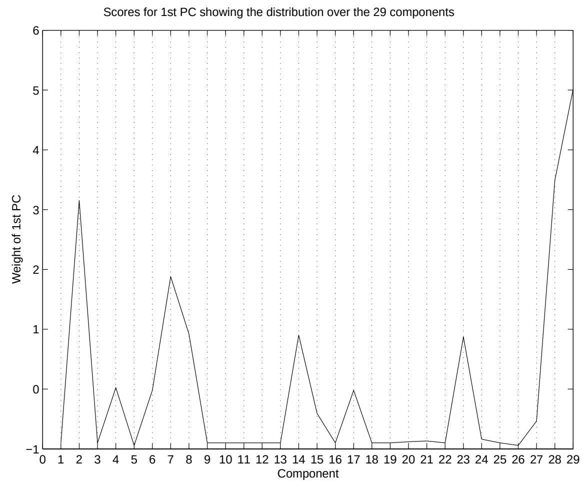

Figure 4. Distribution of Scores for 1st PC over the 29 Components.

Potential Uses and Benefits

In this work, we are proposing the decomposition provided by the PCA transformation as a tool to analyze and predict the effect of potential failure modes on the system being designed. In the helicopter case study above, the first principal component, which is a linear combination of all 10 failure modes obtained from the accident reports, explained 67.3% of the total variance in the **CF** data, followed by the second principal component which explained 18.8% of the total variance, adding up to over 85% of the total variance in the data. The scores corresponding to these two principal components determine the weight of each of the 29 components under study. The principal components with the highest variance and their relative effects on the design components can be studied using the scores, as shown in Figure 4, eliminating the need to go through every component and failure combination. When starting from large component-failure matrices (**CF**) for complex systems, the decomposition provided by this method will enable a study of the most critical failure modes in an efficient way. Using a large database of components, systems, and potential failure modes, the few dominant principal components (high-variance eigenvectors) resulting from the PCA decomposition can be used as a "model" of the component-failure information in the system. Any new component or set of components can be compared with this model to predict the severity of the potential failures.

Consider, for example, a large component-failure matrix **CF** for a complex engineering system, decomposed using the PCA-based approach presented here, and reduced to three principal components $pc1 = \sum_i^n \alpha_i F_i$, $pc2 = \sum_i^n \beta_i F_i$, and $pc3 = \sum_i^n \gamma_i F_i$. These three eigenvectors in the transformed domain are assumed to contain the majority of the total variance in the original data (see derivation above.) The three eigenvectors can be stored as the model of the large component-failure database and used to analyze a new set of components subject to a given failure modes. Let **X** be a $k \times 1$ vector of components under study to determine the effect of a potential failure mode F_i. The projection of the new vector **X** onto the individual eigenvectors represented by **pc1**, **pc2**, and **pc3**, computed as $\mathbf{X} \times \mathbf{pc1}^T$ will provide the relative weighting of the first principal component on the components under investigation. Such an approach will help designers concentrate on the components that have the highest potential of exhibiting the particular failure mode. A similar analysis can be carried out for a single component subject to a number of failure modes contained in the original database of components and failures.

CLOSURE

This work aims to provide design methodologies for failure and risk-free product design in complex engineering systems. This paper discussed an approach to reduce the dimensionality of overwhelmingly large component-failure information (required for the function-failure similarity analysis published previously) by means of a mathematical decomposition using Principal Components Analysis. The fundamentals of the method were demonstrated using a simple test rig example, followed by an application of the method to a case study of failures and components extracted from helicopter accident reports. The potential use in design was discussed in terms of providing a low-dimensional model of the component and failure database. The method requires a large database of all possible components and failure modes for a set of subsystems, either from maintenance manuals, FMEA documents, or accident reports. The purpose of the paper was to demonstrate initial feasibility. Further analysis of large complex systems and their failures is necessary to establish the value of taking such a decomposition approach to failure-free product design. A large anomaly/problem reporting database at NASA's Jet Propulsion Laboratory is currently being studied for analysis using the methods discussed in this paper. Future work planned also includes: 1) development of a standard taxonomy with a comprehensive set of failure modes that covers all possible failures at an elemental level, including mechanical, electrical, and software failures; 2) derivation of statistical information such as occurrence rates based on distributions of failure modes from available anomaly and accident databases; 3) development of a complete methodology for function-failure analysis that combines the decomposition-based failure mode identification approach with the function-failure similarity analysis presented in previously published work (with the intent to test the methodology using JPL's design testing and simulation environments.)

REFERENCES

Carter, A. (1997). *Mechanical Reliability and Design*. Wiley.

Collins, J. and Hagan, B. (1976). The failure-experience matrix: a useful design tool. *ASME Journal of Engineering for Industry*.

Fukunaga, K. (1990). *Introduction to Statistical Pattern Recognition*. Academic Press, New York, NY.

Harris, F. D., Kasper, E. F., and Iseler, L. E. (2000). U.S. civil rotorcraft accidents: 1963 through 1997. In *NASA/TM-2000-209597*.

Henley, E. and Kumamoto, H. (1992). *Probabilistic Risk Assessment: Reliability Engineering, Design, and Analysis*. IEEE.

Huff, E., Tumer, I., Barszcz, E., Dzwonczyk, M., and McNames, J. (2002). Analysis of maneuvering effects on transmission vibrations in an AH-1 Cobra helicopter. *Journal of the American Helicopter Society*, 47(1):42–49.

Johnson, R. and Wichern, D. (1992). *Applied Multivariate Statistical Analysis*. Prentice Hall, New York, NY.

NTSB (2001). National transportation safety board. In *http://www.ntsb.gov*.

Roberts, R., Stone, R., and Tumer, I. (2002). Deriving function-failure similarity information for failure-free rotorcraft component design. In *ASME Design for Manufacturing Conference*, volume DETC2002/DFM-34166, Montreal, Canada.

Ruff, D. and Paasch, R. (1993). Consideration of failure diagnosis in conceptual design of mechanical systems. In *ASME Design Engineering Technical Conferences*, volume 53, pages 175–187, Albuquerque, NM.

Shafer, J. (1980). *Fundamentals of Helicopter Maintenance*. Aviation maintenance publishers, Basin, NY.

Stander, C. (1982). *Fault isolation BITE for increased productivity*. IEEE.

Stone, R. and Wood, K. (2000). Development of a functional basis for design. *Journal of Mechanical Design*, 122(4):359–370.

Tumer, I. and Huff, E. (2002). On the effects of production and maintenance variations on machinery performance. *Journal of Quality in Maintenance Engineering*, To appear in September 2002.

Tumer, I. and Stone, R. (2001). Analytical method for mapping function to failure during high-risk component development. In *ASME Design for Manufacturing Conference*, volume DETC2001/DFM-21173, Pittsburgh, PA.

Tumer, I., Stone, R., and Roberts, R. (2002). Towards failure-free design: reducing dimensionality in function-failure similarity analysis for large databases. In *ASME Int'l Mech. Eng. Congress & Exposition*, volume IMECE2002-33473, New Orleans.

Tumer, I., Wood, K., and Busch-Vishniac, I. (2000). A mathematical transform to analyze part surface quality in manufacturing. *ASME Journal of Manufacturing Science and Engineering*, 122(1):273–279.

Table 8. The resulting PC, SC, and LAT for **CF** (helicopter data.)

PC =

-0.0079	0.0658	-0.0297	-0.3337	0.0298	-0.0044	-0.0206	-0.0548	-0.5405	-0.7661
-0.0438	0.1611	-0.1372	-0.9087	0.0196	-0.0204	-0.0431	0.0734	0.2579	0.2302
0.8786	-0.4253	-0.1795	-0.0876	-0.0297	-0.0058	-0.0415	0.0641	-0.0222	0.0106
0.0134	-0.0512	0.0366	-0.0254	-0.1267	-0.7826	-0.0617	-0.5976	0.0757	-0.0044
0.0132	-0.0695	-0.0129	0.0113	0.9766	-0.0001	-0.0060	-0.1939	0.0585	0.0002
0.0467	-0.0531	0.0253	-0.0495	-0.1501	0.5310	0.3261	-0.6415	0.3558	-0.2073
-0.0131	-0.0074	0.0769	0.0134	-0.0531	0.2683	-0.9280	-0.2390	0.0077	0.0237
0.1023	0.1862	0.0299	0.1200	0.0316	-0.1796	-0.1427	0.3186	0.6968	-0.5468
0.4604	0.8142	0.2587	0.0663	0.0405	0.0262	0.0459	-0.1126	-0.1383	0.1321
0.0308	-0.2844	0.9339	-0.1818	0.0128	-0.0116	0.0468	0.1002	0.0200	-0.0037

SC =

-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
3.1525	-1.0837	0.2512	-0.2732	-0.2713	0.5369	0.2948	-0.4120	0.1238	-0.0508
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
0.0229	-0.6386	0.4928	-0.0158	0.9040	-0.0029	0.0414	-0.0442	0.0313	-0.0071
-0.9436	0.3016	-0.3859	-0.6665	-0.0361	-0.0058	-0.0008	0.0587	0.2329	0.2160
-0.0212	-0.2847	-0.4282	0.1546	-0.0854	0.0087	0.0007	0.0495	-0.0472	-0.0036
1.8805	1.1047	-0.0604	0.3196	-0.0025	-0.1243	-0.0918	0.2070	0.3508	-0.2757
0.9190	-1.2788	1.2601	-0.2965	-0.0895	-0.0203	0.0527	0.3140	-0.0294	-0.0004
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
0.9016	-1.0456	0.3628	-0.1402	-0.2290	-0.7913	-0.0558	-0.3838	0.0263	-0.0011
-0.4085	0.6704	0.9439	0.1268	-0.0024	0.0292	0.1349	-0.0271	-0.1433	0.1142
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
-0.0212	-0.2847	-0.4282	0.1546	-0.0854	0.0087	0.0007	0.0495	-0.0472	-0.0036
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
-0.8820	-0.1513	0.7621	0.0739	-0.0960	0.2713	-0.8390	-0.1535	0.0027	0.0058
-0.8689	-0.1439	0.6852	0.0605	-0.0429	0.0030	0.0890	0.0855	-0.0050	-0.0179
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
0.8706	-0.7794	-0.6206	0.0783	0.8615	0.0028	-0.0469	-0.0803	-0.0109	0.0072
-0.8381	-0.4283	1.6191	-0.1213	-0.0301	-0.0086	0.1358	0.1857	0.0150	-0.0216
-0.8998	0.1406	-0.2487	0.2422	-0.0557	0.0146	0.0422	-0.0147	-0.0250	-0.0142
-0.9436	0.3016	-0.3859	-0.6665	-0.0361	-0.0058	-0.0008	0.0587	0.2329	0.2160
-0.5349	1.3427	-0.2940	-1.8426	0.0538	-0.0045	-0.0186	-0.0352	-0.1880	-0.1878
3.4931	-1.9857	-1.1463	-0.1959	-0.2042	-0.0145	-0.1655	0.3060	-0.1359	0.0387
5.0190	2.6969	0.3568	0.3432	0.0596	-0.0573	-0.0372	-0.0024	-0.1084	0.1416

LAT =

2.4096
0.7291
0.3540
0.1972
0.0646
0.0361
0.0323
0.0229
0.0124
0.0088