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Diagnosis of Equipment Failures by Pattern Recognition

L. F. PAU

ABSTRACT—The main problems in relation to automatic fault finding and diagnosis in equipments or production systems are discussed:
1) compression of the syndrome and observation spaces for better discrimination between failure modes;
2) simultaneous display of the failure patterns and the failure instants, for maintenance control and review of the reliability design;
3) automatic production of a final set of diagnosis assumptions classified according to their probabilities.
4) sequencing of the inspections in accordance with the failure rates and inspection costs.

READER AIDS:
Purpose: Widen state of the art
Special math needed for explanations: Probability
Special math needed for results: Same
Results useful to: Reliability and systems engineers

INTRODUCTION

The paper is concerned with automated diagnosis of generic systems which cannot be modeled by a logical network, and have only a small number of identifiable failure modes, given only the input and output evolutions. In other words, the analysis is based on representations of causality relations between the failure causes and the corresponding operating performances. This kind of approach is therefore specifically useful, for example, for electromechanical equipments, engines, and simple mechanical parts.

The purpose of any diagnostic searching procedure is to recognize a failure mode, or a set of failures (also called syndrome), on the basis of numerical information about the circumstances of the failure, results of non-destructive tests, and information about the past history of the system (including maintenance and operational utilization); all these data determine the failure pattern vector.

The actual diagnosis will be made by comparing this failure pattern vector with known pattern vectors found to characterize the failure modes considered, and called learning patterns. The learning patterns originate from systems for which the failure modes were found by maintenance personnel, and we assume that they are all stored in a frequently updated reliability and maintenance data bank. Comparing the observed symptoms (described by the failure pattern vector) with the learning data, and classifying the ill-working system into one of few classes of possible failure modes, can therefore be formalized as a pattern recognition problem. Some research about this has been reported since 1968 by Becker [1], Cortina [2], Hankley and Merrill [3], Page [4], and Pau [5].

In this paper, we treat some major problems in relation to automatic diagnosis. First, we discuss a compression method of the observations about each system, for better discrimination between failure modes and to eliminate all redundant tests and observations; this is the so-called feature extraction problem. In Section 2, we explain how to display simultaneously the failure patterns and the failure instants, for maintenance control or review of the reliability design of the system. Section 3 deals with the production of a satisfactory list of a few most-relevant diagnostic assumptions, classified according to their probabilities. Lastly, in Section 4, we give some rules for sequencing the inspections by the element-by-element method, in accordance with the diagnostic assumptions, failure rates, and inspection costs.
1. COMPRESSION OF THE LEARNING DATA AND MEASUREMENT SELECTION

1.1 Definition of the Learning Data \( k(I,J) \)

We basically assume that it has been possible to initiate a
good data collection system, monitoring the systems con-
sidered over time, and also their main operating parameters
in service until some observable functional-failure happens.
The implementation of such a data bank is a difficult prob-
lem, extensively discussed in Pau [6]. Let \( I,J \) respectively be
(at a given date) the set of measurements and the set of
pattern vectors describing the failures of all systems of the
same type. The learning data \( k(I,J) = \{k(i,j) \geq 0 \ i \in I \ j \in J\} \)
are either qualitative or quantitative; and can then be
defined as follows: \( k(i,j) \) is the value of measurement \( i \) con-
cerning the system \( j \); i.e., time since last overhaul \( TBO_j \),
voltage at some point, or any binary parameter indicating
that a given subsystem was switched on. Some measure-
ments \( i \) may also be made binary if their intervals of varia-
tion have been sampled into smaller intervals.

The past experiments have shown that misleading con-
clusions may be drawn from once-compressed learning data,
either because of too-small learning samples, or because of
careless reports. Methods to account for these phenomena
have been thoroughly tested in practice and justified theo-
retically [5]. Other transformations may be made, in order
to study the learning data from specific viewpoints:

a) the learning data \( k(I,J) \) are called explicit if one of
the sets \( I,J \) designates equipments, and the other, observations
about these equipments as previously defined.

b) the learning data \( k(I,J) \) are called implicit if both sets
\( I,J \) are observations; such a tableau is deduced from an
explicit tableau by aggregating some observations with
respect to all equipments, or by classifying all equipments
with respect to some observations. For example, if \( J \) has
become the set of \( TBO \) intervals, we may define: \( k(i,j) \)
the number of learning equipments having had a failure in the
\( TBO\)-interval \( j \), and on which the symptom \( i \) was present.
Design review generally uses learning data in the implicit
form, while automated diagnosis uses the explicit form.

1.2 Feature Extraction by the Means of
Correspondence Analysis

Assume that the tableau \( k(I,J) \) of non-negative numbers
is given. The feature extraction procedure used herein is a
special form of principal component analysis, characterized
by the following additional properties demonstrated in
Benzecri [7], Pau [8], Lebart and Felenon [9]:

- no prior hypothesis is made about the nature of the ele-
ments in the sets \( I \) (failures) and \( J \) (observations or equip-
ments), and all interactions are considered; in other words,
we do not care for the labels in the sets \( I \) and \( J \).

- all elements in both sets \( I \) and \( J \) can be displayed
simultaneously in the same reduced feature space, because
they play symmetric roles in a tableau; in this reduced pat-
tern space, the Euclidean distance between any two elements
of \( I-J, J-I \), or \( J-J \), is an overall statistical measure of the cor-
respondence between these elements, independently of all scale
effects.

the “varimax” principle used to find orthogonal factors is
not applied to the raw data in \( k(I,J) \), but to quantities
deduced from a contingency table \( p(I,J) \):

\[
p(i,j) = k(i,j) \left( \sum_{n \in J} k(ln) \right)\]

with estimated marginal probability density functions (pdf):

\[
P_i = p(i,.) = \sum_{j \in J} p(i,j) \quad \text{Pr} \{J|i\} = p(i,j)/p(i,.)
\]

\[
P_j = p(.,j) = \sum_{i \in I} p(i,j) \quad \text{Pr} \{I|j\} = p(i,j)/p(.,j)
\]

Correspondence analysis may then be summarized as
follows:

a) The metric on \( I \) is the distance function \( d_i \), while the
metric on \( J \) is the distance function \( d_j \):

\[
d_i^2(i_1,i_2) = \sum_{j \in J} [\text{Pr} \{J|i_1\} - \text{Pr} \{J|i_2\}]^2/p(.,j)
\]

\[
d_j^2(j_1,j_2) = \sum_{i \in I} [\text{Pr} \{I|j_1\} - \text{Pr} \{I|j_2\}]^2/p(i,.)
\]

The weighing factors, such as \( 1/p(.,.) \) are introduced in
order to compensate for cases like the following: an obser-
vation \( i \) may always be related to large conditional proba-
bilities \( \text{Pr} \{j|i\} \) mainly because \( p(i,.) \) is large, and the differ-
ences between \( \text{Pr} \{j|i\} \) values will have an excessive im-
portance when comparing a system \( j_1 \) with a system \( j_2 \).

b) The element \( i \) has Card \( (J) \) coordinates \( \{\text{Pr} \{j|i\}, j = 1, \text{Card} \ (J)\} \); the element \( j \) has Card \( (I) \) coordinates \( \{\text{Pr}
\{i|j\}, i = 1, \text{Card} \ (I)\} \). These coordinates are called profiles
of \( i \) and \( j \) resp. The element \( i \) has the weight \( p(i,.) \), while \( j \)
has the weight \( p(.,j) \).

c) Let the constant \( r \) be given such that \( r \leq \text{Inf} \{\text{Card} \ (I), \text{Card} \ (J)\} \). We want to minimize, in the sense of the \( d_i \) or
\( d_j \) metric, the dependence between \( I,J \) defined as the norm-
value \( \|p(I,J) - P^I \otimes P^J\| \). If this quantity had been zero,
then the sets \( \{I\} \) and \( \{J\} \) would have been independent in
the probabilistic sense and the observations about each
system would have been independent of the system con-
sidered. But our goal is here to eliminate all redundance in
the data, and to find as many aggregate observations as
possible (also called features) for which this independence
holds, and \( r \) features for which dependence holds so that
discrimination can be done using only these. It can be
shown that the \( r \)-dimensional vector basis of basic features
which minimizes this dependence after transforming Card \( (I) \)–or Card \( (J) \)–dimensional patterns in \( k(I,J) \), into \( r-
dimensional \) vectors, can be constructed as follows [10].

for \( \{I\} \), the \( r \) base vectors \( f_r, l = \{1, r\} \) are the \( r \) first
principal axes of inertia of the solid body made of the discrete
Card \( (J) \) dimensional elements \( i \in I \) having the weights \( p(i,.) \);
this inertia is computed for the $d_1$ distance; let $\lambda(f_i)$ be the inertia of axis $f_i$, $l = (1, r)$ ordered by $\lambda(f_1) \geq \lambda(f_2) \geq \ldots \geq \lambda(f_l)$; the $f_i$’s are normed to the unit length with respect to $d_1$. And $f_i(j)$ is the $l$’s eigenvector (resp. eigenvalue) of the $S = [s_{i,j}]$ matrix:

$$s_{i,j} = \sum_{i=1}^{\text{Card}(I)} p(i,j_1)p(i,j_2)/p(i,.)[p(.,j_1)p(.,j_2)]^{1/2}$$

for $J$, we have definitions and relations for the $r$ basis vectors $g_i, l = (1, r), f_i, d_1, l = (1, r)$ are here row vectors, i.e., linear mappings.

d) The coordinates of the learning patterns projected into the $r$-dimensional feature space, are computed as follows:

for $\{I\}$, the feature $l = (1, r)$ of learning pattern $i \in I$ on the axis $f_i$, originated in the center of inertia of all elements in $\{I\}$, is

$$G(i,l) = f_i \cdot [\Pr{j|l}], j = 1, \text{Card}(J) \text{ vector}$$

for $\{J\}$, the feature $l$ of learning pattern $j \in J$ on the axis $g_i$, originated in the center of inertia of all elements in $J$, is

$$F(j,l) = g_i \cdot [\Pr{j|l}], j = 1, \text{Card}(I) \text{ vector}$$

e) It can be shown that $\lambda(f_i) = \lambda(g_i), l = (1, r)$, and that it is sufficient to compute either the $f_i$’s or the $g_i$’s because:

$$g_i = \frac{1}{\sqrt{\lambda(f_i)}} f_i \cdot [\Pr{j|l}] \quad i = \text{column} \quad \text{J} = \text{row}$$

$$G(i,l) = \sum_{j=1}^{\text{Card}(J)} F(j,l) \Pr{j|l} / \sqrt{\lambda(f_i)}$$

Consequently, it is equivalent to display simultaneously all elements of $I$ and $J$ in either the $f_i$ space or the $g_i$ space, $l = (1, r)$

f) $p(i,j) = p(i,.)p(.,j)[1 + \Sigma_i F(j,l)G(i,l)/\sqrt{\lambda(f_i)}]$
for electronic components, in order to relate the failure modes with technological design parameters; the main application of this is in component selection for specific environments [10, 13, 14].

2.2 Example

As an example, we will interpret some associations between observations and/or time intervals in Fig. 1 relative to an airborne fuel pump. The compressed learning data were initially of the implicit type explained in Section 1.1.

Analyzing the proximities between TBO- (Time Between Overhauls) intervals \( j \in J \) and the failure modes PPR, PHU, we notice that

- the wear-out of the electrical brushes is strong between 200 and 800 hours, small to medium up to 4500 hours if no failure has occurred and exceptionally low after that time.
- oil leakage failures are explicitly discriminated as being the most important early failures between 0 and 50 hours;
- pressure-drop failures happen essentially between 200 and 800 hours and exceptionally around 100 or 1500 hours in relation to an important wear-out of the electrical brushes.

It can readily be inferred from the above, and a more detailed analysis of the same, that the mean time between unscheduled repairs for these pumps could be improved towards the nominal value of 1700 hours, by eliminating the pressure drop failures PPR through an improved design. These are also most strongly associated with the positions \( P_3 \) and \( P_4 \), even \( P_1 \), on the aircraft.

3. REAL TIME DIAGNOSIS BY PATTERN RECOGNITION

The goal of this section is to present a method which, given all observations \( I \) on a system, produces automatically a list of the most probable failure modes of this system. The pattern recognition approach used includes first the learning stage, next the real time feature extraction, and lastly the classification procedures wherein the \( r \) features characterizing the failed system are compared to the compressed learning data.

3.1 Learning Stage

The learning patterns \( \{i, j \} \) are defined as being a large number of systems of the same type for which the failure mode has been determined by the quality control or maintenance personnel. The learning data \( k(I,J) \) are obtained by gathering all information \( i \in I \) (including times between overhauls, etc.) about these learning patterns. We assume that the total number of different failure causes \( d \) is small with respect to the total number of equipments observed. Assume that the probability distribution \( \{\pi(d)|d \in D, \pi(d) > 0, \sum_{d} \pi(d) = 1\} \) of the failure causes has been estimated within the learning data or by other means.

The learning features, which will be used during the recognition phase, are the images of the learning patterns in a reduced feature space having a fixed dimension \( r \). The feature extraction procedure used is the correspondence analysis of paragraph 1.2 applied to the tableau \( k(I,J) \), of the explicit type.

3.2 Real Time Feature Extraction for a Failed Equipment

Assume that troubleshooting has just been observed on an equipment \( j \) of the type investigated in Section 3.1 and it has been possible to gather all information \( \{k(i,j), i \in I\} \) about \( j \). We can consider \( j \) as a supplementary learning pattern belonging to an unknown class \( d(j) \). But since the feature extraction of the learning data \( k(I,J) \) is made without taking care of the knowledge of \( d(J) \), we assume that \( j \) does not perturb the learning features too much, and map the equipment \( j \) into the feature space by (2). Thus the coordinate of equipment \( j \) on the \( l \)-th feature axis \( g_l \) is

\[
F(j,l) = g_l \left[ \sum_{i \in I} k(i,j), i = 1, \text{Card } (I), l = (1, r). \right. \tag{4}
\]

Studying the maps discussed in Section 2, we then look for instructing associations of \( j \) either with the learning equipments \( \{i, j \} \) for which \( d(j) \) is known, and/or with the observations \( i \in I \). These associations help substantially in formulating some precise experimental hypothesis about the mechanism of the failure detected in Section 3.3 on the equipment \( j \).
3.3 Diagnosis and Classification Procedure

We will consider one single classification procedure, placing each equipment $j$ into the most probable failure mode class $d(j) \in D$. Though, if the corresponding probability of correct classification is below some given threshold, then the equipment $j$ is rejected and no diagnosis can be formulated. The generalized nearest neighbor rule is used as indicated (and treated theoretically) in Patrick and Fisher [15], Pau [10].

$j$ has failure mode $d(j) \in D$ if:

$$\varphi_{d(j)} \pi_{d(j)} = \max_{d \in D} \varphi_d \pi_d,$$

and

$$\varphi_{d(j)} \geq \alpha > 0$$

$j$ cannot be diagnosed if:

$$\max_{d \in D} \varphi_d \pi_d < \alpha$$

where

$$\varphi_d \equiv n_d / [(N_d + 1)V_d]$$

$d$ class of failure causes selected in $D$.

$N_d$ number of learning patterns $j \in J$ belonging to the class $d \in D$.

$\pi_d$ estimated probability of occurrence of a random failure mode $d$ in the set $D$, as introduced in 3.1.

$n_d$ integer parameter, determined for each class $d$.

$V_d$ minimal volume of a neighborhood of the newly observed equipment $j$ in the $r$-dimensional feature space, so that $(n_d - 1)$ learning patterns of the class $d \in D$ are interior to this neighborhood, while one single learning pattern is on the boundary thereof.

$\alpha$ given confidence threshold.

This classification can briefly be explained as follows; it can be shown that $\varphi_d$ is an asymptotically unbiased distribution-free estimator of the pdf for the class $d$ of patterns in the feature space at the location of $j$ found in Section 3.2. $\alpha$ is then the threshold pdf required to formulate a diagnosis. Maximizing the classification gain by a Bayes decision rule introduces the weights $\pi_d$: the equipment $j$ is then classified, if possible, into the class $d$ having the largest $\pi_d \varphi_d$.

An $\varepsilon$-neighborhood of $j$ in the set $\{j\}$ of learning patterns, is defined as follows in the $r$-dimensional feature space:

$$v(\varepsilon, j) = \left\{ j \in J \left| \sum_{i \in T_r} |F(j, i) - F(j, i)| < \varepsilon \right. \right\}$$

These neighborhoods are related to the $L_1$-metric, instead of the classic Euclidean $L^2$-metric; this modification reduces the classification computation time and yields correct classification rates which are at least as good as for the $L^2$-metric [16].

The next best suspected failure mode $d'(j)$ is the one maximizing $\varphi_d \pi_d$ for $d \in D - d(j)$; this process can be repeated, and a ranked list established over the most probable alternate failure modes $d(j), d'(j), \text{etc.}$ Though it is clear that this procedure would be misleading if the actual failure had not been included in the catalog $D$; if the result $d(j)$ happens frequently to be absurd, one has to examine thoroughly the learning data and the set $D$ of alternate failures.

In Pau [10], this procedure is made sequential in order to find a compromise between a short diagnostic computation time, and a high mean true diagnostic probability.

In the next section, we will show how this method can be used for failure localization purposes in a modularized system; meanwhile, an example will be given where the object is to find some well-defined failure modes.

3.4 Example of Automated Testing

We have considered a stationary fabrication process of complex electromechanical systems with very stringent specifications and small dimensional tolerances. The 82 observations on each equipment $j \in J$ in the process were the measurements made by the quality control department at the input of the process, and the operational characteristics of the machine tools when used on each specific system (setting, cumulated time of operations, time since servicing, type of tool, air flow, temperature, oil flow, rotation speeds, workers operating the machines, ...). The 21 classes of failures included the special class $d_0$ of all equipments for sale fulfilling all quality control requirements. In the following, $x = 0$.

a) During the learning phase, data were collected on Card ($J$) = 2000 items (20 days of production), among which 800 non-acceptable items were identified at the final quality control and where each received a diagnosis (chosen among the 20 classes of failures). These learning data were processed on a general purpose IBM 370-65 computer (12 min. CPU). The computation of the $f/j = (1,r)$ ran into some numerical diagonalization difficulties. Through the review process described in Section 2.1, it became possible to pinpoint those systematic aspects of the production process having directly the strongest contributions to the named failures, in this case the oil flows.

b) During the testing phase, a true recognition rate of 92% was achieved for the items classified into the class $d_0$ by the final quality control, still working. The mean true diagnosis rate for the 20 types of actual failures was 81% when $r = 10$; mean unitary diagnostic computing time: 0.46 sec.

c) During the operational phase under final implementation, all 82 observations will be monitored in real time for each equipment in the production line; most nondestructive tests and the final quality control will be suppressed. A few specialists will play a supervisory role for the automatic diagnostic system, including the small online data-logging and computing unit. Considerable economic benefits can be obtained, as evaluated on the basis of the resting phase b). These specialists will perform design reviews, and modify and enlarge the learning data bank.

4. SEARCHING FOR A FAULTY MODULE IN A MODULAR SYSTEM

The subject of this section is the localization of a single faulty module on the basis of the results of the automated diagnostic procedure of Section 3.3. The problem is more precisely to find a search sequence minimizing the expected
cost (or time) to complete the fault localization, given a suspected failure mode \( d(j) \).

It is assumed that systems of the type previously treated are made of \( M \) statistically independent modules, which can be inspected by module-by-module tests. We assume moreover that given a failure mode \( d(j) \), the prior probabilities \( R_m(d(j)), m = 1, M \) of failure of each of the \( M \) modules are known; each system can only have one single faulty module corresponding to the failure mode \( d(j) \). Let \( \tau_m \) be the prior known cost (or time) required to conduct all tests/observations on the module number \( m \).

Define the state of the system by one single faulty module \( m \) included in a subset \( S_m \) of not yet inspected modules, which are all assumed failure-free except \( m \); the probability of this state of the system is then:

\[
R^*_m = \frac{R_m(d(j))}{1 - R_m(d(j))} / \sum_{q \in S_m} \frac{R_q(d(j))}{1 - R_q(d(j))}
\]

The search procedure is then the following, starting with \( m = 1 \):

Step \( m \): * \( (m - 1) \) modules have previously been tested/observed and found not-faulty. \( S_m \) is the subset of all remaining modules not yet tested.

- select, according to one of the rules 1-3, an element of \( S_m \), and perform all tests/observations on this module.
- if this module is faulty, then stop the search; if not, then go to next step \( m + 1 \).

Rule 1 \[
\max_{i \in S_m} \left\{ \frac{R^*_i}{\tau_i} \right\} \quad \text{Gluss [17]}
\]

Rule 2 \[
\max_{i \in S_m} \left\{ \frac{-R^*_i \ln R^*_i - (1 - R^*_i) \ln (1 - R^*_i)}{\tau_i} \right\} \quad \text{Pashkovskiy [18]}
\]

Rule 3 \[
\max_{i \in S_m} \left\{ \frac{R_i(d(j))}{\tau_i} \right\} \quad \text{Pashkovskiy [18]}
\]

The rules 1-3 yield quasi-optimal inspection sequences, the efficiency of which may be compared using statistical decision theory [19]. In the actual cases investigated, the best rules appear to be 1 and 2; more generally the idea of decomposing the diagnostic procedure into first finding the failure mode of highest probability \( d(j) \), and next the faulty module, proves to be very efficient. In those environments where automated diagnosis may be required, it is important only to activate the diagnosis and shift over to some redundant system in parallel, when a functional failure is actually observed on the initial system. It is not always necessary to localize instantly the failure, and the search subprocedure may eventually be postponed; on the basis of the results of this subprocedure, it will only be necessary to put down and repair the faulty module. In those operational applications where the parameter estimation problems were not dominant, savings of 15-20% on the total maintenance and diagnosis times were observed.

5. CONCLUSION

Our pattern recognition techniques can help make maintenance more efficient, and make the designers understand the complex relationships between the operational environment, the production control, and other internal or external factors. They are probably the only approach to diagnosis in mechanical and non-purely electronic equipments. The results are the more realistic and profit-earning if the individual equipments are numerous and have to be monitored during their whole life. But the success relies finally upon the quality of the data records, and upon the reliability of the monitoring sensors used.

REFERENCES

Analyzing the Interface of Reliability and Economics of Unmanned Satellites

H. W. von Guerard

ABSTRACT—This paper deals primarily with the reliability of unmanned scientific or commercial satellites. In the course of reliability analysis an hierarchy of reliability predictions is generated, reaching from preliminary apportionment by subsystems: to figures of merit, usually obtained by Boolean algebra; to results based on failure modes, effects and criticality analysis (FMECA); to data from an elaborate, though still static, fault tree; and eventually to data depicting the dynamics of mission time line and contingency analyses.

The outlined routine has been developed, mainly in the US, to quite some perfection, but it still leaves unanswered the customer’s most natural concern: how much reliability, within what time, at what price? Therefore, an attempt is made to schedule the above work elements, so that the amount of reliability as well as its allocation become subject to the classical criterion of marginal utility. It is fully realized that there are considerations, such as design freeze partly due to long-lead items, that put a limit to this endeavor.

The postulated analysis consists, in essence, of two models in sequence: first, the fault tree, which exhibits the technical failure modes, their probability of occurrence, and their interdependence. Second, the mission failure model, referring to total and partial deficiencies in performing utility functions, and to their interactions as regards the degree of performance.

Straightforward analysis by the concept of marginal utility has not always proven feasible; there may be prerequisites that are difficult, if not impossible to fulfill, such as true cost allocation to interdependent mission components (e.g., geographical coverage, timing, bandwidth, amplification); or the need for game-theoretic evaluation of the economic risk in a competitive environment. These arguments may be valid if one were considering satellite utility as such; as long, however, as this task is restricted to local allocation of incremental reliability, the problem becomes manageable not only in principle, but with reasonable prospect of fruitful results.

READER AIDS:
Purpose: Widen state of the art
Special math needed for explanations: Probability, utility theory
Special math needed for results: Same
Results useful to: Reliability engineers, system analysts

I. ON THE SIGNIFICANCE OF SATELLITE RELIABILITY ANALYSIS

This paper will focus on the ways the content of a reliability program is shaped by economic factors, superimposed upon technical and operational considerations relating to unmanned satellites. The principal attribute of program utility, i.e., cost effectiveness, is served by selecting for implementation only those elements offering high incremental value return per unit cost.

The topic makes a system analyst’s dream come true: here is the opportunity to tackle various clear-cut problems which in other work areas are usually only vaguely defined, or so ill-structured that no significance can be attached to a quantitative analysis. To be more specific: this refers to the not-so-familiar pattern of asking for optimum reliability vs. cost vs. weight trade-offs, a good question which often suffers from lack of a definite objective function.

Several different features of unmanned spacecraft projects contribute to the more optimistic view of the matter:

The satellite forms a relatively self-contained system with little interference from inside (e.g., from human operators) or from outside (e.g., from the environment).

Furthermore, human life is not at stake; hence reliability becomes realistically negotiable.

The complexity of the system is such as to require a major analytic effort. The challenge is sufficient to justify the attention of the serious minded systems analyst.

Payout of the spacecraft system is a measurable quantity. Benefits and shortcomings can be expressed in a common scale of monetary units. Thus the overall tradeoff analysis becomes feasible.


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Louis-François Pau was born in Copenhagen, Denmark, on May 29, 1948. He received the Master's degree in mathematics from the Paris University in 1969, while studying at the École Nationale Supérieure de l’Aéronautique where he obtained the degree of engineer in avionics. He received the "docteur ingénieur" degree from Paris University in 1972 in the field of statistical pattern recognition.

Dr. Pau is presently Associate Professor of operations research and mathematical statistics at the Technical University of Denmark. He has been a professor of pattern recognition at the École Nationale Supérieure de l’Aéronautique since 1970. From 1969 to 1972 he worked mainly on military research projects, and as a consultant for Air France in the field of diagnosis of failures. His fields of interest are diagnosis of failures, speech recognition, pattern recognition theory, feature extraction, as well as differential games. In 1970, he was called for 3 months by the McDonnell Douglas corporation, working on the DC-10 program.

Dr. Pau has published papers in several scientific and technical journals in France and Scandinavia; he holds several patents. He is a member of the French and Danish operations research societies, and has received two scientific prizes in France.