SANDIA REPORT

SAND99-2461
Unlimited Release
Printed September 1999

Markov Modeling with Soft Aggregation for Safety and Decision Analysis

J. Arlin Cooper

Prepared by
Sandia National Laboratories
Albuquerque, New Mexico 87185 and Livermore, California 94550

Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin Company, for the United States Department of Energy under Contract DE-AC04-94AL85000.

Approved for public release; further dissemination unlimited.

Sandia National Laboratories

Issued by Sandia National Laboratories, operated for the United States Department of Energy by Sandia Corporation.

Available to DOE and DOE contractors from
Office of Scientific and Technical Information
P.O. Box 62
Oak Ridge, TN 37831

Prices available from (703) 605-6000
Web site: http://www.ntis.gov/ordering.htm

Available to the public from
National Technical Information Service
U.S. Department of Commerce
5285 Port Royal Rd
Springfield, VA 22161

NTIS price codes
Printed copy: A02
Microfiche copy: A01

SAND99-2461
Unlimited Release
Printed September 1999

Markov Modeling with Soft Aggregation for Safety and Decision Analysis

J. Arlin Cooper
High Consequence Surety Engineering Department
Sandia National Laboratories
P.O. Box 8500
Albuquerque, NM 87185-0490

Abstract

The methodology in this report improves on some of the limitations of many conventional safety assessment and decision analysis methods. A top-down mathematical approach is developed for decomposing systems and for expressing imprecise individual metrics as possibilistic or fuzzy numbers. A "Markov-like" model is developed that facilitates combining (aggregating) inputs into overall metrics and decision aids, also portraying the inherent uncertainty. A major goal of Markov modeling is to help convey the top-down system perspective. One of the constituent methodologies allows metrics to be weighted according to significance of the attribute and aggregated nonlinearly as to contribution. This aggregation is performed using exponential combination of the metrics, since the accumulating effect of such factors responds less and less to additional factors. This is termed "soft" mathematical aggregation. Dependence among the contributing factors is accounted for by incorporating subjective metrics on "overlap" of the factors as well as by correspondingly reducing the overall contribution of these combinations to the overall aggregation. Decisions corresponding to the meaningfulness of the results are facilitated in several ways. First, the results are compared to a soft threshold provided by a sigmoid function. Second, information is provided on input "Importance" and "Sensitivity," in order to know where to place emphasis on considering new controls that may be necessary. Third, trends in inputs and outputs are tracked in order to obtain significant information, including cyclic information, for the decision process.

A practical example from the air transportation industry is used to demonstrate application of the methodology. Illustrations are given for developing a structure (along with recommended inputs and weights) for air transportation oversight at three different levels, for developing and using cycle information, for developing Importance and Sensitivity measures for soft aggregation, for developing dependence methodology, for constructing early alert logic, for tracking trends, for relating the Markov model to other (e.g., Reason) models, for developing and demonstrating rudimentary laptop software, and for developing an input/output display methodology.

Acknowledgment

There were a number of people who made direct contributions to this report through detailed discussions on various aspects, and by reviewing the document. Of particular note are Perry D'Antonio, Paul Werner, John Covan, Roger Hartman, and Casey Jones, all of Sandia National Laboratories. Funding was furnished by the U. S. Department of Energy (through a Laboratory Directed Research and Development award) and by the Federal Aviation Administration (FAA/AAR-424).

Contents

Introduction

There are important situations in decision analysis and safety assessment that must be judged by weighing a variety of diverse factors that are uncertain and do not accumulate contributions linearly or independently. Conventional mathematical models that can combine factors directly or through propositional logic to derive metrics (e.g., probabilistic risk) are insufficient for these classes of problems. For example, determining the safety status of an airline operation might depend on measuring factors such as accident/incident statistics, maintenance personnel/pilot competence and experience, scheduling pressures, and safety "culture" of the organization. Many of the potential metrics on such individual parameters are difficult (and generally uncertain) to determine. Also, there may be ill-defined interrelations among the contributors. A top-down analytical approach requires more than summation of individual parameter assessments, which is used in some tabular schemes. Furthermore, aggregation of the parameters into an overall metric requires a mathematical methodology that can account for nonlinearities and dependence. For example, twice as many attributes is unlikely to be twice as beneficial. Methodology is needed to address this problem, accumulating information nonlinearly and combining it in order to measure an attribute of a system (e.g., safety) or to test hypotheses (e.g., for forensic deduction or decisions about various system design options). The approach should also be capable of being combined seamlessly with conventional approaches. In other words, an overall system might be decomposed into constituent subsystems, some of which are treated by linear mathematics, some by propositional logic, and some by non-traditional methods. Outcome metrics require hybrid combination of the constituents. The strategy extends naturally to decision analysis, where decision aids must be developed concerning acceptability of system safety or concerning the need for operational restrictions; and also to selection among alternative approaches or forensic hypotheses.

In summary, our objectives include:

- deriving safety performance metrics
- facilitating decision analysis
- prioritizing safety hazards
- prioritizing hazard controls
- helping determine proper response actions

Conventional systems surety analysis and the associated decision analysis are basically applicable to only experience-measurable or physical-model-derived data. However, most practical analyses, including high-consequence system surety analysis, must also utilize subjectivity. There has been considerable effort on analytically incorporating engineering judgment. For example, Dempster-Shafer theory establishes a framework in which frequentist probability and Bayesian incorporation of new data are subsets. Although Bayesian and Dempster-Shafer methodology both allow judgment, neither derives results that can explicitly indicate the relative amounts of subjective judgment and measurable data in the results.

Also, most high consequence systems have difficult-to-analyze features under conventional approaches. For example, in our nuclear weapons program, we must determine the probability that a weapon responds safely when exposed to an abnormal environment. There are also non-probabilistic DOE and DoD requirements (e.g., for determining the adequacy of positive measures). The type of processing required for these and similar situations transcends conventional probabilistic and human factors methodology. We intend to demonstrate how our results can apply to these types of situations, and in general to the surety of high consequence systems. We also intend to show how the results can improve the information currently provided to decision-makers. Objective inputs can be derived in a conventional manner; the subjective inputs must be derived from the combined engineering judgment of experts in the field. Both should be processed mathematically in a hybrid structure, and their individual importance to the result uncertainty should be determined and reported.

It is a challenging task to systematically (preferably mathematically) assess such organizational factors as culture, training, policies, regulatory compliance, and business health as to their effects on system operation. Furthermore, these are generally latent factors in influencing critical system operation. Noting this, we have tailored our development toward a Markov-like process.[1] This Markov process can contribute to surety assessment as shown in Fig. 1.

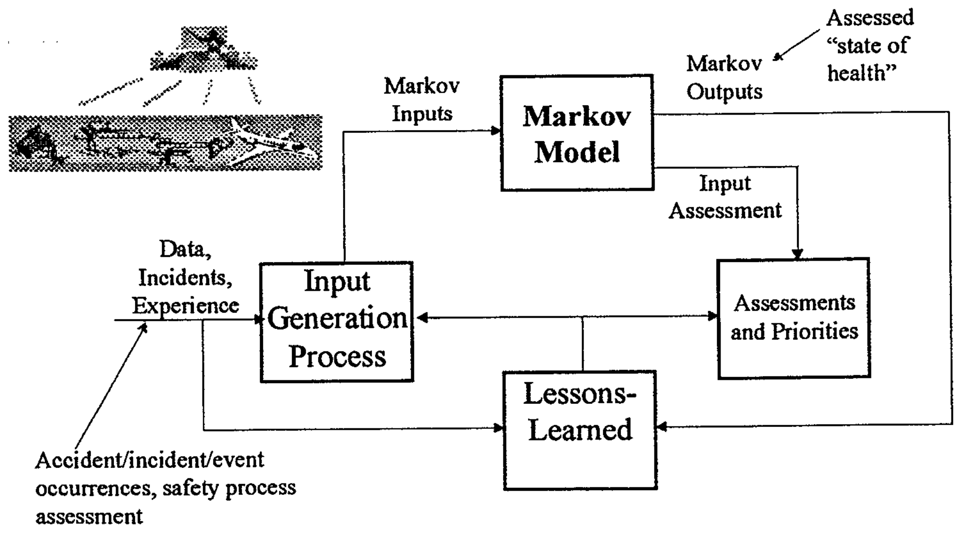


Figure 1. Potential Role of Markov Process in the Oversight Process

The Markov model processes inputs and derives both outputs and processed information about the inputs. The outputs relate to the "state of health" or safety of the system. They also become part of a database intended to track trends and cycles for inputs and outputs. All of this information becomes available for a "lessons learned" (including root cause analysis) process. The information about the inputs includes "Importance" (contribution

[1] Conventional Markov modeling uses probabilistic transitions at discrete times to discrete "next states" depending on the history of one or more previous states. Our treatment is non-probabilistic (soft aggregation mathematics), aimed at latent effects over a continuum of time and state space.

to safety, or "best practices") and "Sensitivity" (areas where improvement can be most significant). Basic guidance on priorities and changes indicated in the oversight assessment process is derived from the lessons learned process and from the input assessment. This is an important benefit of using the coupled processes.

The inputs to the Markov process require interpretive skills and/or job aids (possibly aided by other Markov processing). Contributors are data on accident/incident/event occurrences, Markov and other process assessments, statistical data and analysis, and experience. These also contribute to and derive information from the lessons learned process.

System Decomposition

The application of the process to a system requires a system functional decomposition. The beginning of an aid in performing a useful decomposition is shown in Fig. 2.

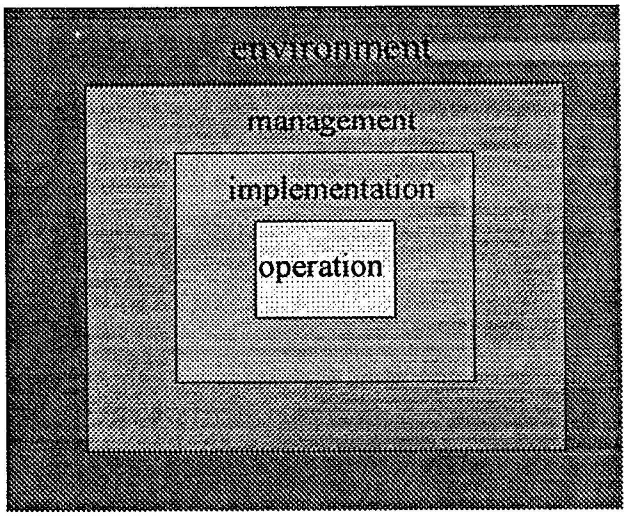


Figure 2. Building A System Within An Environment To Accomplish An Operation

We start with an environment under which safety is to be assessed. For a system such as an air carrier, the environment includes business conditions (competition, financial atmosphere, and regulations) as well as the physical environments in which employees work and aircraft fly.

Next, a management structure (organization, responsibilities, policies) is built within the environment. Implementation takes place within the management structure, which includes carrying out basic responsibilities (e.g., design, analysis, procurement, decision-making). Then operation, the ultimate objective, takes place (e.g., maintenance, air transportation of goods and personnel).

As shown in Fig. 3, this can also be viewed as building a pyramid. Most conventional scrutiny in such an organization focuses on the actual operation (e.g., humans maintaining and flying aircraft). This is certainly necessary where critical operations, such as landing a disabled aircraft, must be studied. But the importance of the contribution of the lower part of the pyramid is frequently neglected.

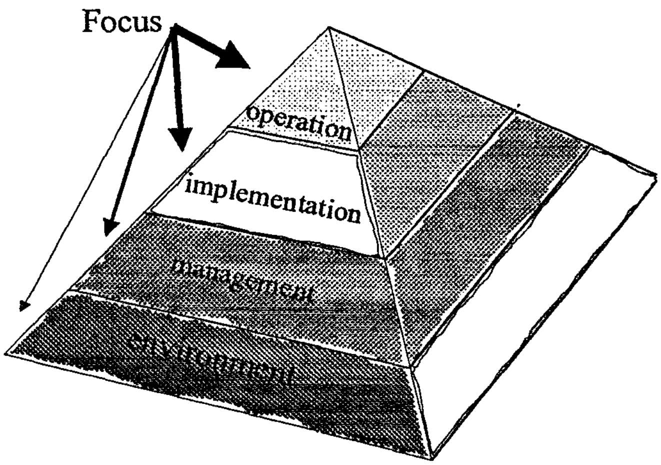
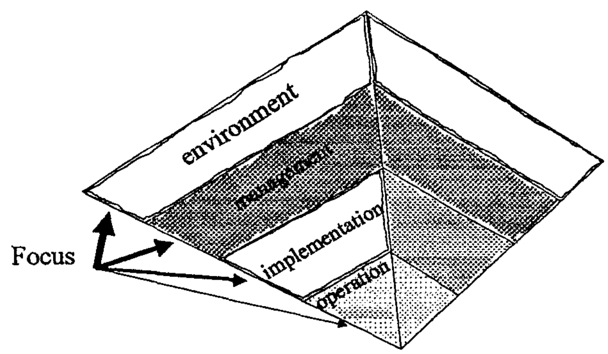


Figure 3. Bottom-Up Organizational System View

One of the contributions of models such as the Markov and Reason [Ref.1] models is to assure that the important role of the rest of the pyramid (which experience shows to have a paramount role in safety) is not minimized. Focussing on this aspect is sometimes called a "top-down" view, as shown in Fig. 4.



Useful in studying subtle latent factors that can be critical to operations

Figure 4. Top-Down Organizational View

In addition to the emphasis shown in the figure, it is important to recognize (as do the Markov and Reason models) influences between subsystem segments, some of which are latent influences. Additional contributions of the Markov model are to recognize cyclic and other trend information, as well as to provide a quantitative means of measuring assessment. The structure for doing this is shown in Fig. 5.

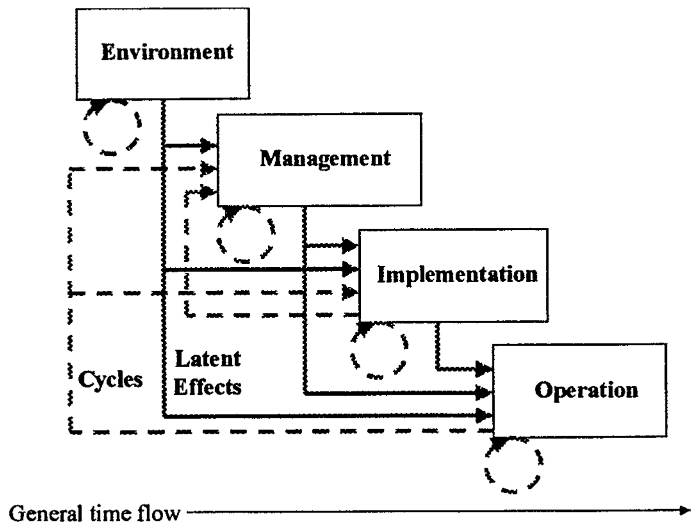


Figure 5. Influences (Latent Effects and Cycles) in a Markov model

Note in the figure that time flows in general from left to right, and the assessment is in general from top to bottom.

Hybrid Analysis

Now consider what types of analyses might be appropriate to quantitatively assess the operation of such a system. A general indication is shown in Fig. 6, simplified to portray three types of analyses.

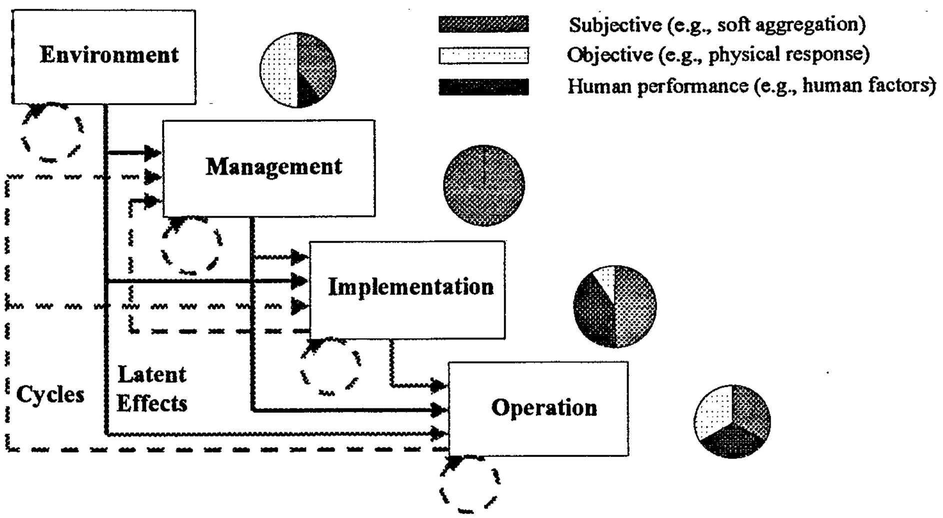


Figure 6. Types of Analyses Matched Generally to Parts of System

Here we indicate that while much is known about environmental analysis, the objective data are generally incomplete without human factors analysis (particularly with regard to adversarial personnel) and subjective analysis. The effects of management structure are essentially totally subjective. Implementation is mostly subjective and human-factorsoriented. The actual system critical operations generally involve all three types of analyses.

Although a complete system assessment might require all three, an oversight function would be mostly described by subjective analysis. In order to show this, first consider how the three types of analyses indicated might interact with each other in a hybrid analysis (see Fig. 7).

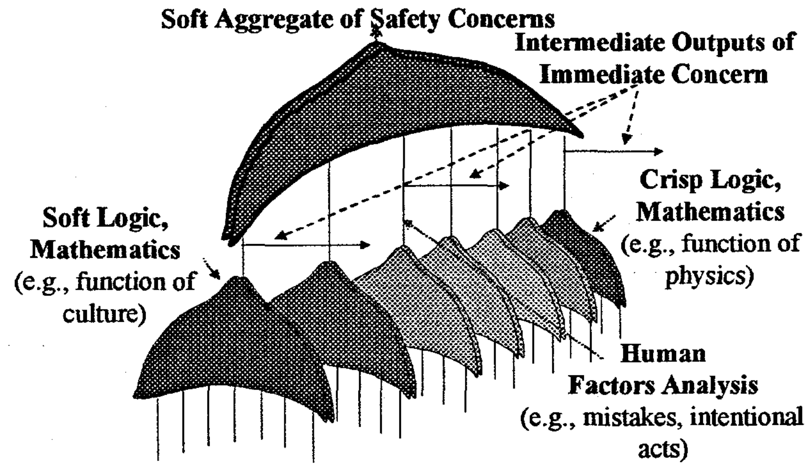


Figure 7. Hybrid Combination of Analysis Types

The inputs from the bottom of the figure are shown being processed across a spectrum of methodologies, ranging from objective, crisp logic, and linear mathematics at the right bottom to subjective, soft logic, and nonlinear mathematics at the left bottom. Human factors analysis is somewhere in between the two extremes. Combining these various forms of analysis can give an overall assessment of safety for any particular situation or subset of situations. This is indicated toward the top of the diagram. Also shown are early alerts that can be derived from the analysis package. The oversight process is most consistent with the lower left part of the diagram, although other forms of analysis can be important in deriving early alerts. For these reasons, soft aggregation mathematics was chosen as the basic analysis engine in the Markov model as applied to oversight, and propositional logic with soft thresholds was chosen for the early alerts.

Oversight Levels

The specific application of the Markov model to oversight depends on additional decompositions. In Fig. 8, the U.S. Air Transportation System is decomposed into 11 subsystems, of which the four in the middle of the figure are appropriate constituents of the ATOS (Air Transportation Oversight System) process. One of these (Pre-Flight Operations) is shown further decomposed (as an illustration), and this process can continue until an arbitrary level of usefulness is obtained. No interactions between the subsystems are indicated at this point. The environment is not included, since it is not directly affected by the oversight system.

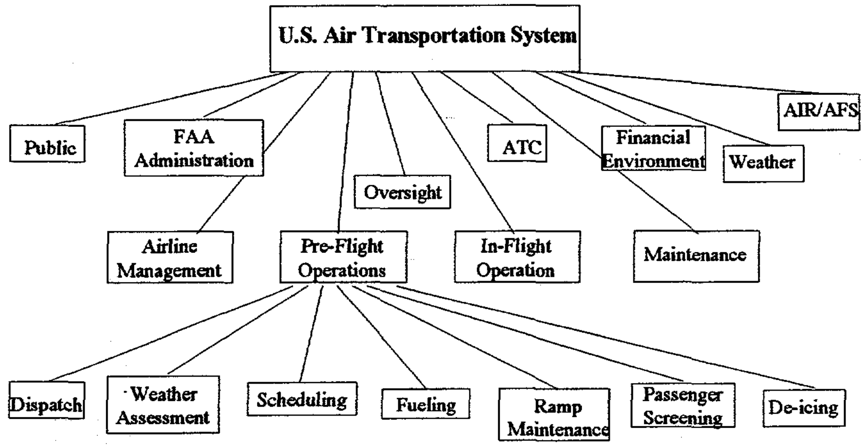


Figure 8. Illustrative Decomposition of the U.S. Air Transportation System

Next, the four chosen subsystems are to be portrayed in a Markov structure. Note that however important the top-down influences may be to the overall system safety, we also must recognize that immediate criticality increases as we move from left to right in Markov diagrams. In order to capture both the importance of early influences and the immediate criticality of later influences, we have elected to portray Markov modeling for the oversight activity generally from lower left to upper right, where time generally increases from left to right and immediate criticality generally increases from bottom to top. The structure shown in Fig. 9 is termed a "second-level" Markov structure, because it is one step decomposed beyond the top (first) level (no decomposition).

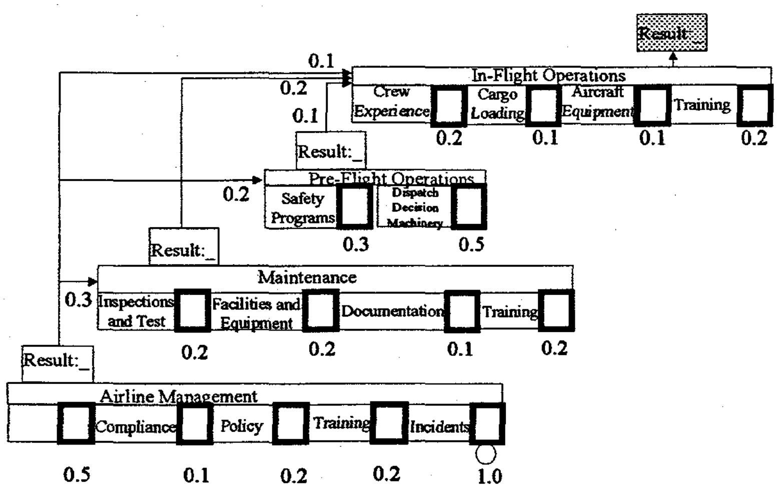


Figure 9. Second-Level Markov Model

Each of the four subsystems has associated inputs for user entry, which are indicated by the 15 open boxes. Inputs can range from low (zero) to high (one), where the higher values contribute more to safety, except for boxes with an attached circle—for these, lower values contribute more to safety. This is intended to be consistent with the implication of the names associated with the inputs. The weights necessary for the soft aggregation process are shown in the figure associated with each input. Although considerable care was taken in selecting the subsystems, the interconnections, the inputs, and the weights, it is expected that users who are more familiar with the FAA oversight system would make their own choices as they become familiar with using the Markov tool. Methodology to facilitate this "insight" is included with the tool.

The second-level Markov structure was introduced first, because it is most consistent with initial illustration of the tool properties. Two other levels are also of interest. The first level, shown in Fig. 10, is useful for a "quick look" at a system.

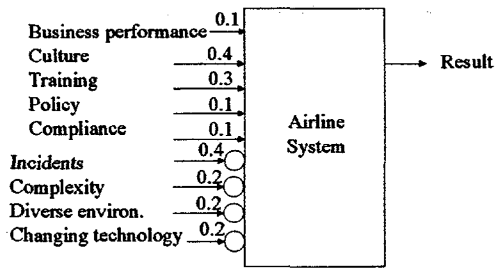


Figure 10. First-Level Markov Tool

The third level architecture involves further decomposition of the second level. It is shown in Fig. 11 for FAA oversight, with 20 subsystems and 45 inputs. This is expected to be the most useful level for a comprehensive assessment function use. While more detailed decompositions could be made, the user would begin to lose sight of the top-down view, and preventing this loss of perspective is a paramount objective of the Markov project. When opening the third-level option on the Markov software tool, the user will see a display of the architecture similar to that shown in the figure. The four dashed rectangles (corresponding to the four level-two boxes) indicate regions for which a more detailed view can be selected, and through which inputs can be entered.

Figures 12-15 provide the input and weight details for each of these regions. Figure 12 shows the Management region and its 11 available inputs. The multiple outputs indicate that the intermediate results are used in various other parts of the system. Similarly, the Maintenance view selection enables entry of 14 additional inputs, the Pre-Flight Operations view enables the entry of 12 additional inputs, and the In-Flight operations view enables the entry of the final eight inputs for this example application.

Levels one, two, and three can be selected individually after opening the Markov tool. They provide three separate ways to look at the system. There is no "roll-up" of results from lower levels to higher levels. The complete mathematical description (soft aggregation mathematics) is detailed in the appendix for the example application.

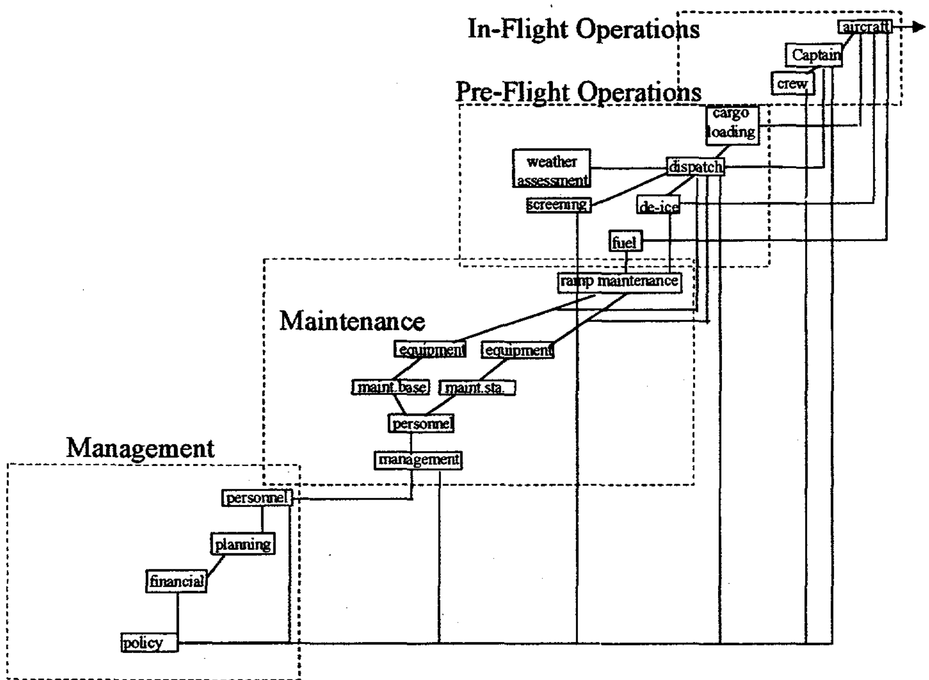


Figure 11. Third-Level Markov Decomposition Architecture

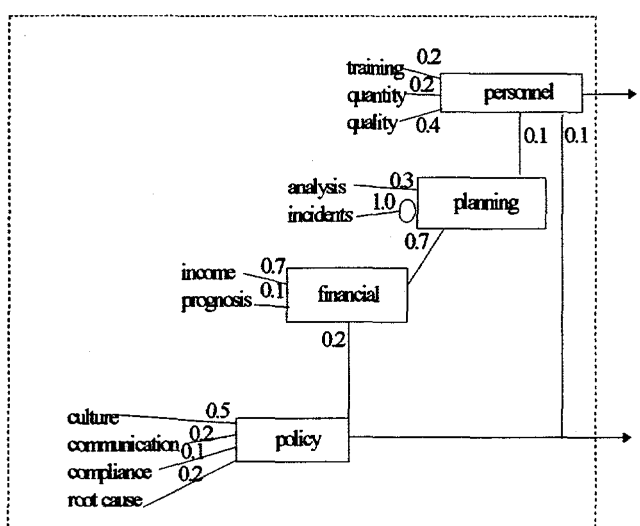


Figure 12. Management Subsystem

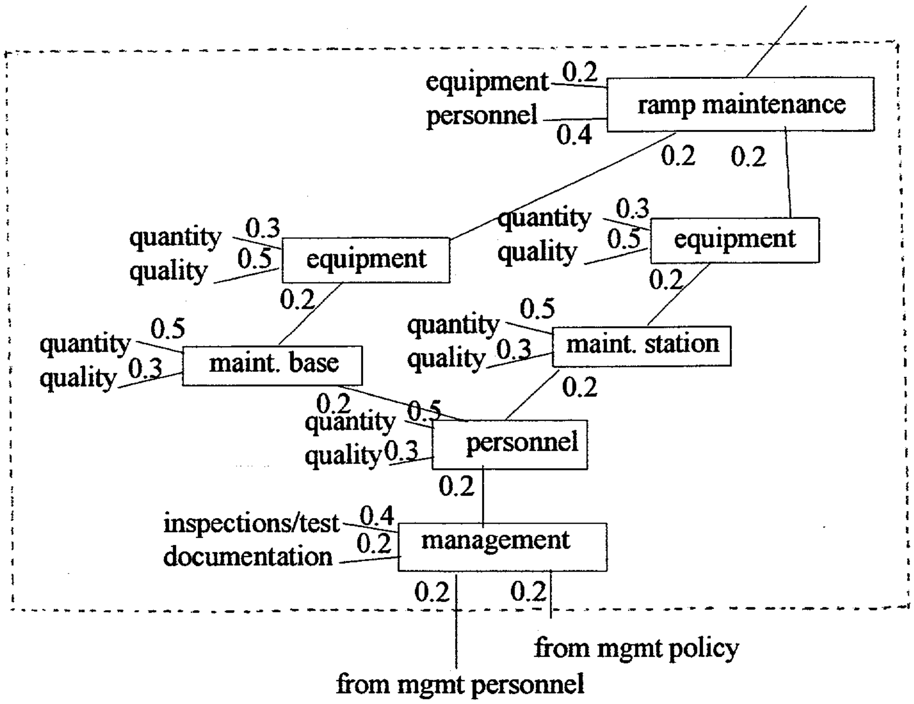


Figure 13. Maintenance Subsystem

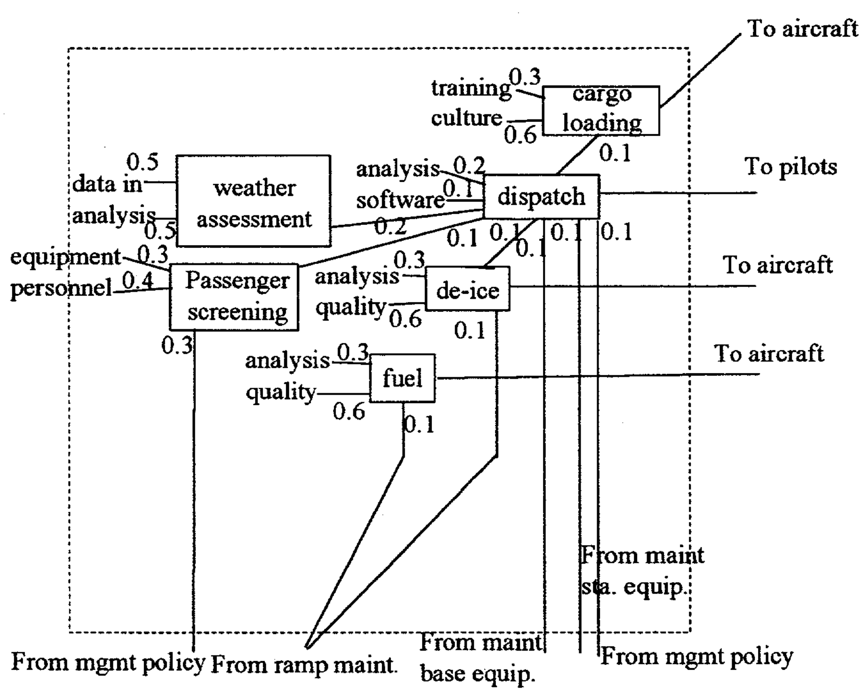


Figure 14. Pre-Flight Operations Subsystem

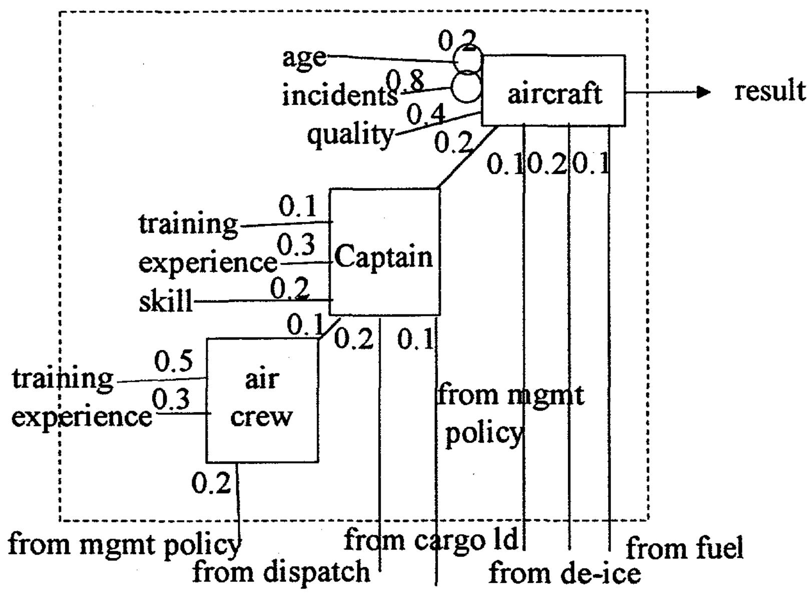


Figure 15. In-Flight Operations Subsystem

Cycle Effects

The presence of cycles (functions with time variation during repetition cycles) was indicated in Figs. 5 and 6. Various forms of cycles are present in most systems. There are a number of cycles that are of interest in air transportation oversight. For example, some of these are flight cycles for aircraft, repair cycles for maintenance shops, life cycles for aircraft, life cycles for air carrier companies, training cycles for employees, hiring cycles for employees, etc. Examples of cycles in the Markov model are shown in Fig. 16, with flight cycles and repair cycles in hours, assessment cycles in weeks, training cycles in months, employee cycles in years, and company cycles in decades (all general indications of periods). System assessment is a function of composites of these factors, where each might contribute more positively to safety for a period of time and more negatively for a period of time. The system assessment can be derived, for example, from the Markov tool software. It is essential to understand this when tracking trends, so that the causes of the effects are identified. An example composite is shown below in Fig. 17, where the overall assessment trend is influenced by company life cycle, training cycle, and employment cycle. Without this cycle information, one wouldn't know how to interpret the composite trend. Also shown in the diagram is the general potential to derive level of inspection intensity as a function of the state-of-health trend.

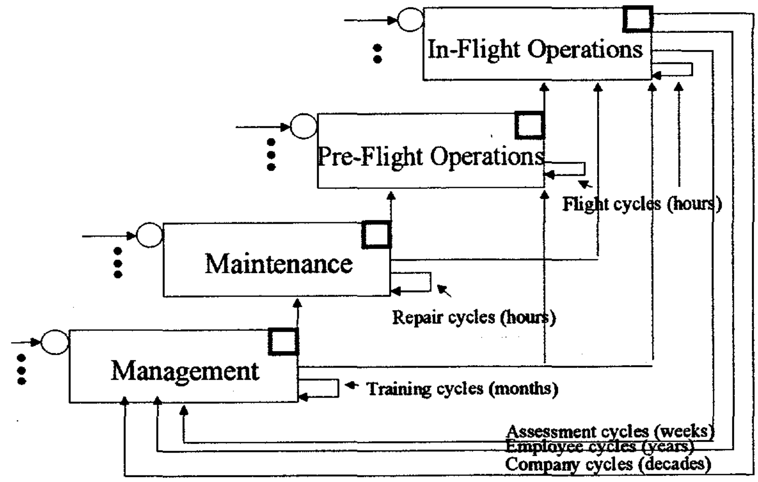


Figure 16. Illustration of Markov Cycles

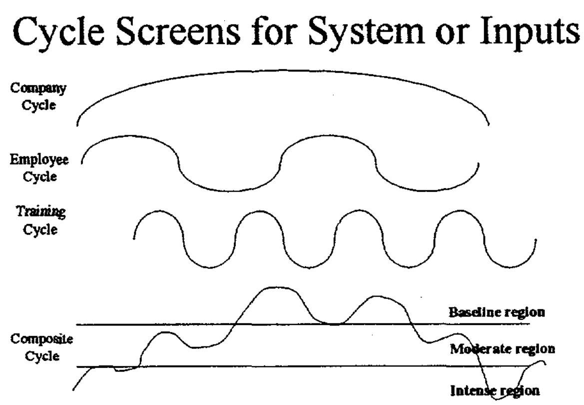


Figure 17. Example of Utilization of Cycle Information

Early Alert Logic

IF organizational surety/maturity is low ➔ THEN Intense Scrutiny

IF operating environment is risky, OR data indicators are serious, ➔ THEN Moderate Scrutiny

IF procedures are falsified ➔ THEN Intense Scrutiny

IF procedures are treated as routine ➔ THEN Moderate Scrutiny

IF significant carelessness noted in cargo loading, OR in maintenance, OR in aircraft operation ➔ THEN Intense Scrutiny

IF any carelessness noted in cargo loading, OR in maintenance, OR in aircraft operation ➔ THEN Moderate Scrutiny

Figure 18. Example of Early Alert Logic

Taken literally, Fig. 18 implies conventional propositional logic expressions for deriving early alert decisions about amount of oversight required for a system. However, we actually use soft inputs rather than crisp (similar to fuzzy sets[2]). Also, decisions such as those indicated in Figs. 17 and 18 are realistically made in a non-abrupt fashion. We frequently might be tempted to treat thresholds of concern, such as probabilistic safety requirements, as firm, whereas their source of derivation is not firm. For example, if we have a requirement that a system must maintain safety from catastrophic failure to a probability of one in a million, the implication is that an analysis that derived a system safety measure of 1×10^{-6} would be indicative of a satisfactory system (meets the requirement) and an analysis that derived a system safety measure of 1.1×10^{-6} would be indicative of an unsatisfactory system (fails to meet the requirement).

In order to more realistically portray the comparison of information aggregation with a threshold of concern, we mathematically construct a non-abrupt transition. This function is termed a "sigmoid," and is expressed with an exponential constituent so that the abscissa value transitions gradually from zero to one as the ordinate value, *f*, increases through a decision threshold, with the transition rate determined by a constant, *q*. Figure 19 shows an application of this approach.

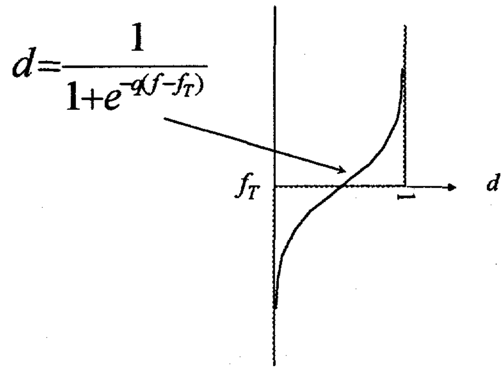


Figure 19. Sigmoid Decision Transition Function

Display Methodology

The general display strategy used [Ref. 2] is indicated in Fig. 20. Here, inputs (0 to 1) are entered through "virtual" (mouse-controlled) knobs, including uncertainty. Outputs include subsystem (or at the top level, system) safety status (0 to 1) on dials (also including uncertainty). Indicators show (by color intensity) recommended surveillance status. "Drill-down" dials show Importance and Sensitivity measures for inputs and trend rate of change and acceleration for outputs as well as inputs. An idle cursor over a knob or intermediate input brings up the assigned weight display.

---

[2] In crisp logic, conditions are either met (1) or not met (0). In fuzzy sets, the degree of match is measured on a continuum between 0 and 1.

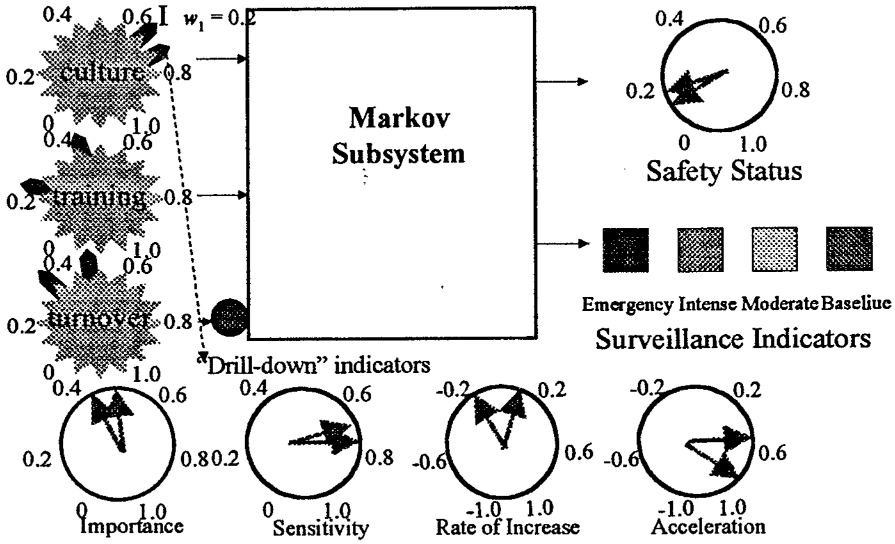


Figure 20. Markov Output Display Methodology

Soft Aggregation

Soft mathematical aggregation is useful in a significant number of applications. Inputs may contribute to the output without being related to linear, Boolean, or possibilistic mathematics. For example, a production line employee who is disgruntled or unmotivated, or a training program that is not done skillfully might not directly cause an accident, but the presence of such situations projects safety concerns and potential contributors to an accident, if other unfavorable events occur.

In an analogous illustration, a medical doctor might accumulate weighted health information combined non-linearly (weight/height, blood pressure, EKG, temperature, pulse rate, blood test parameters, reflexes) to indicate the patient's state of health. Safety indicators are similar in helping contribute toward a status judgment. The potential effectiveness of protective control measures (e.g., medicine) is also weighed. In these and similar applications, there is a particular need for mathematically modeling the manner in which individual contributions accumulate toward a limit (e.g., "unsafe" or "safe") without ever completely achieving the limit. The model chosen for these situations is exponential, as shown in Figure 21. The effects of safety protective measures are aggregated up the ordinate and the effects of threats are aggregated down the ordinate. The abscissa indicates a weighted "rating" function that is subjectively obtained based on expert judgment. The equation used is:

$$f = \left[1 - e^{-\sum_{i=1}^{n} k w_i x_i} \right] e^{-\sum_{j=1}^{m} k v_j y_j} \quad (1)$$

The w_i and v_j indicate "weights" on the significance of the protective measure and threat aggregates, respectively (n and m in number). The weights are normalized so that $\sum_{i=1}^{n} w_i = 1$ and. $\sum_{j=1}^{m} v_j = 1$. The x_i and y_i are ratings of how good the controls are and how bad the hazards are on a scale of 0 to 1. The constant k is a variable dependent on the number of aggregate constituents. The figure shows an example aggregation of threats and controls. The aggregation can be carried out with the parameters combined in any order; or the aggregation can be carried out for the entire system at once.

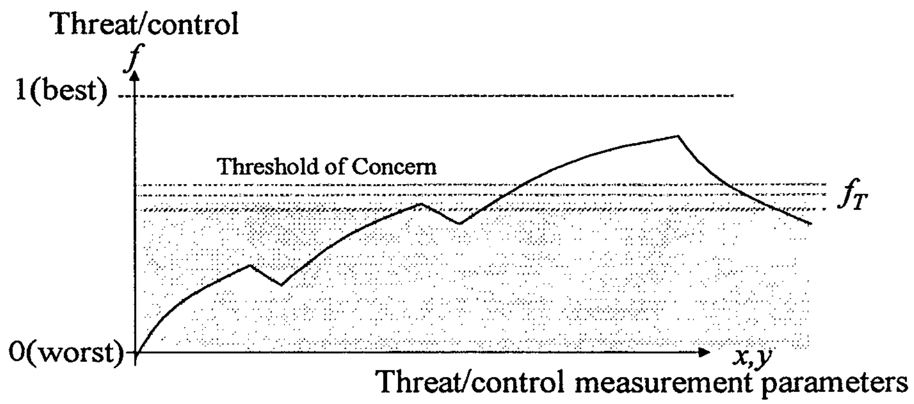


Figure 21. Exponential Aggregation, Including Threshold of Concern

Figure 21 shows an example growth of the aggregate attribute with three contributing controls and decline with three types of concerns. Also shown is an example soft "threshold of concern," which is conceptually a fuzzy threshold (indicated by multiple lines and modeled by a sigmoid function), above which system concern becomes significant.

Importance and Sensitivity

In addition to the information provided by the Markov outputs, information about the inputs is valuable. Two useful measures are: Importance (amount of contribution to the output) and Sensitivity (amount of change in the output that a change in the input could make if improved). For Importance of controls, we use the weighted sums generated by each input to derive the amount of contribution, and for Sensitivity of controls, we use one minus the value multiplied by the weighted sums generated by each input to derive the amount of potential for improvement. For Importance of hazards, we use one minus the weighted sums generated by each input to derive the amount of contribution, and for

Sensitivity of hazards, we use the value multiplied by the weighted sums generated by each input to derive the amount of potential for improvement. All of this is expressed mathematically in the Appendix for an example application.

Trends

Static assessments need to be supplemented by multiple assessments over time, from which trends can be derived. The Markov methodology provides trends information in several ways. The inputs can be stored in a database, so that historic information can be plotted to show trends over time. The process is also used both for the overall result output, and for each subsystem output.

An example trends plot is shown in Figure 22. In the figure, the quantitative representation of a particular input (or output) is tracked over a period of time, during which multiple assessments are made. As is typical of such plots, there is some cyclic response and "noise" on the plot as trends develop. Also indicated (by the vertical spread) is the uncertainty due to subjectively derived evaluations.

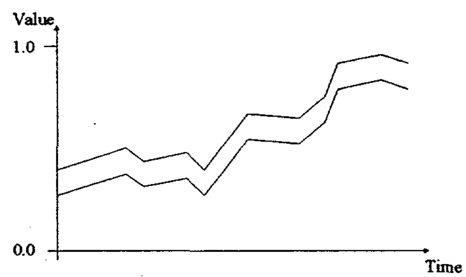


Figure 22. Example Trends Plot with Uncertainty

Dependence

Dependence among inputs requires special treatment. Soft aggregation, by its exponential nature, inherently includes some implicit dependence, but beyond this, there are inputs that can be readily identified as being explicitly dependent. For example, culture and training are separate, but generally related. For this reason, we allow the user of the Markov methodology to signify a measure of dependence for a specified group of inputs. This measure ranges from 0 (complete independence) to 1 (complete dependence). The result is that groups of dependent controls do not contribute as much to safety status as if they were independent. This is described in Eqn. 2:

$$f_d = [1 - e^{-\frac{1}{k}[(w_i x_i)_{\min} + \{\sum_{i=1}^{n} w_i x_i - (w_i x_i)_{\min}\}(1-d)]}] \times [e^{-\frac{1}{k}[(v_j y_j)_{\max} + \{\sum_{j=1}^{m} v_j y_j - (v_j y_j)_{\max}\}(1-d)]}] \qquad (2)$$

Here, the summation limits range over the inputs in the dependent set, tending toward the most conservative assessment. In this manner, the equation can be applied to as many groups as desired.

Conclusions

The non-traditional Markov model described in this report is especially useful in system safety analysis and decision support, because of its top-down perspective; the ability to track latent effects, cycles, and trends; and its soft aggregation capabilities. Other attributes are the ability to mesh information derived about the inputs as well as the outputs with lessons-learned and root-cause-analysis functions. A final benefit is the straightforward software implementation, which has been demonstrated in various forums.

References

1. *Managing the Risks of Organizational Accidents*, James Reason, Ashgate, 1997.
2. Sandia National Laboratories Patent Disclosure: *Organizational Safety and Display*, Paul W. Werner and J. Arlin Cooper, May 27, 1999.

Appendix: Example Mathematical Specifications

Top-Level Computation Specifications

Business performance: x_1
Culture: x_2
Training: x_3
Policy: x_4
Compliance: x_5
Incidents: y_1
Complexity: y_2
Diverse environment: y_3
Changing technology: y_4

$$\text{Result} = (1 - e^{-2(0.1x_1+0.4x_2+0.3x_3+0.1x_4+0.1x_5)})e^{-2(0.4y_1+0.2y_2+0.2y_3+0.2y_4)}$$

Importance Measures:

Business Performance: $0.1x_1$
Culture: $0.4x_2$
Training: $0.3x_3$
Policy: $0.1x_4$
Compliance: $0.1x_5$
Incidents: $0.4(1-y_1)$
Complexity: $0.2(1-y_2)$
Diverse Environment: $0.2(1-y_3)$
Changing Technology: $0.2(1-y_4)$

Sensitivity Measures:

Business Performance: $0.1(1-x_1)$
Culture: $0.4(1-x_2)$
Training: $0.3(1-x_3)$
Policy: $0.1(1-x_4)$
Compliance: $0.1(1-x_5)$
Incidents: $0.4y_1$
Complexity: $0.2y_2$
Diverse Environment: $0.2y_3$
Changing Technology: $0.2y_4$

Second-Level Computation Specifications

Airline Management Subsystem

Safety Culture = x_1 (system constant: $w_1 = 0.5$)

Compliance = x_2 ($w_2 = 0.1$)
Policy = x_3 ($w_3 = 0.2$)
Training = x_4 ($w_4 = 0.2$)
Incidents = y_1 ($v_1 = 1.0$)

Subsystem Result: $x_5 = (1 - e^{-2(w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4)})e^{-2v_1y_1}$

Maintenance Subsystem

x_5 solved for above ($w_{5,1} = 0.3$)
Inspections and Test = x_6 ($w_6 = 0.2$)
Facilities and Equipment = x_7 ($w_7 = 0.2$)
Documentation = x_8 ($w_8 = 0.1$)
Training = x_9 ($w_9 = 0.2$)

Subsystem Result: $x_{10} = 1 - e^{-2(w_{5,1}x_5 + w_6x_6 + w_7x_7 + w_8x_8 + w_9x_9)}$

Pre-Flight Operations Subsystem

x_5 solved for above ($w_{5,2} = 0.2$)
Safety Programs = x_{11} ($w_{11} = 0.3$)
Dispatch Decision Machinery = x_{12} ($w_{12} = 0.5$)

Subsystem Result: $x_{13} = 1 - e^{-2(w_{5,2}x_5 + w_{11}x_{11} + w_{12}x_{12})}$

In-Flight Operations Subsystem

x_5 solved for above ($w_{5,3} = 0.1$)
x_{10} solved for above ($w_{10} = 0.2$)
x_{13} solved for above ($w_{13} = 0.1$)
Crew Experience = x_{14} ($w_{14} = 0.2$)
Cargo Loading = x_{15} ($w_{15} = 0.1$)
Aircraft Equipment = x_{16} ($w_{16} = 0.1$)
Training = x_{17} ($w_{17} = 0.2$)

Subsystem (and Final) Result: $1 - e^{-2(w_{5,3}x_5 + w_{10}x_{10} + w_{13}x_{13} + w_{14}x_{14} + w_{15}x_{15} + w_{16}x_{16} + w_{17}x_{17})}$

Importance Measures:

Management Safety Culture: $0.5x_1(0.3*0.2 + 0.2*0.1 + 0.1) = 0.09x_1$
Management Compliance: $0.1x_2(0.18) = 0.018x_2$
Management Policy: $0.2x_3(0.18) = 0.036x_3$
Management Training: $0.2x_4(0.18) = 0.036x_4$
Management Incidents: $(1-y_1)(0.18)$

Maintenance Inspections and Test: $0.2x_6(0.2) = 0.04x_6$
Maintenance Facilities and Equipment: $0.2x_7(0.2) = 0.04x_7$
Maintenance Documentation: $0.1x_8(0.2) = 0.02x_8$
Maintenance Training: $0.2x_9(0.2) = 0.04x_9$

Pre-Flight Operations Safety Programs: $0.3x_{11}(0.1) = 0.03x_{11}$
Pre-Flight Operations Dispatch Decision Machinery: $0.5x_{12}(0.1) = 0.05x_{12}$

In-Flight Operations Crew Experience: $0.2x_{14}$
In-Flight Operations Cargo Loading: $0.1x_{15}$
In-Flight Operations Equipment: $0.1x_{16}$
In-Flight Operations Training: $0.2x_{17}$

Sensitivity Measures:

Management Safety Culture: $0.5(1-x_1)(0.18)$
Management Compliance: $0.1(1-x_2)(0.18)$
Management Policy: $0.2(1-x_3)(0.18)$
Management Training: $0.2(1-x_4)(0.18)$
Management Incidents: $0.18y_1$

Maintenance Inspections and Test: $0.2(1-x_6)(0.2)$
Maintenance Facilities and Equipment: $0.2(1-x_7)(0.2)$
Maintenance Documentation: $0.1(1-x_8)(0.2)$
Maintenance Training: $0.2(1-x_9)(0.2)$

Pre-Flight Operations Safety Programs: $0.3(1-x_{11})(0.1)$
Pre-Flight Operations Dispatch Decision Machinery: $0.5(1-x_{12})(0.1)$

In-Flight Operations Crew Experience: $0.2(1-x_{14})$
In-Flight Operations Cargo Loading: $0.1(1-x_{15})$
In-Flight Operations Equipment: $0.1(1-x_{16})$
In-Flight Operations Training: $0.2(1-x_{17})$

Third-Level Computation Specifications

Management Subsystem

Culture: x_1, Communication: x_2, Compliance: x_3, Root cause capabilities: x_4.

$$x_5 = 1 - e^{-4(0.5x_1+0.2x_2+0.1x_3+0.2x_4)}$$

Income: x_6, Business prognosis: x_7.

$$x_8 = 1 - e^{-4(0.2x_5+0.7x_6+0.1x_7)}$$

Analysis: x_9, Incidents: y_1.

$$x_{10} = (1 - e^{-4(0.7x_8 + 0.3x_9)})e^{-4y_1}$$

Training: x_{11}, Quantity: x_{12}, Quality: x_{13}.

$$x_{14} = 1 - e^{-4(0.1x_5 + 0.1x_{10} + 0.2x_{11} + 0.2x_{12} + 0.4x_{13})}$$

Maintenance Subsystem

Inspections/test: x_{15}, Documentation: x_{16}.

$$x_{17} = 1 - e^{-4(0.2x_5 + 0.2x_{14} + 0.4x_{15} + 0.2x_{16})}$$

Personnel quantity: x_{18}, Personnel quality: x_{19}.

$$x_{20} = 1 - e^{-4(0.2x_{17} + 0.5x_{18} + 0.3x_{19})}$$

Maintenance base quantity: x_{21}, Maintenance base quality: x_{22}.

$$x_{23} = 1 - e^{-4(0.2x_{20} + 0.5x_{21} + 0.3x_{22})}$$

Maintenance station quantity: x_{24}, Maintenance station quality: x_{25}.

$$x_{26} = 1 - e^{-4(0.2x_{20} + 0.5x_{24} + 0.3x_{25})}$$

Maintenance base equipment quantity: x_{27}, Maintenance base equipment quality: x_{28}.

$$x_{29} = 1 - e^{-4(0.2x_{23} + 0.3x_{27} + 0.5x_{28})}$$

Maintenance station equipment quantity: x_{30}, Maintenance station equipment quality: x_{31}.

$$x_{32} = 1 - e^{-4(0.2x_{26} + 0.3x_{30} + 0.5x_{31})}$$

Ramp maintenance equipment: x_{33}, Ramp maintenance personnel: x_{34}.

$$x_{35} = 1 - e^{-4(0.2x_{29} + 0.2x_{32} + 0.2x_{33} + 0.4x_{34})}$$

Pre-Flight Operations Subsystem

Fuel analysis: x_{36}, fuel quality: x_{37}.

$$x_{38} = 1 - e^{-4(0.1x_{35}+0.3x_{36}+0.6x_{37})}$$

Passenger screening equipment: x_{39}, Passenger screening personnel: x_{40}.

$$x_{41} = 1 - e^{-4(0.3x_5+0.3x_{39}+0.4x_{40})}$$

De-ice analysis: x_{42}, De-ice quality: x_{43}.

$$x_{44} = 1 - e^{-4(0.1x_{35}+0.3x_{42}+0.6x_{43})}$$

Weather data input: x_{45}, Weather analysis: x_{46}.

$$x_{47} = 1 - e^{-4(0,5x_{45}+0.5x_{46})}$$

Dispatch analysis: x_{48}, Dispatch software: x_{49}.

$$x_{50} = 1 - e^{-4(0.1x_5+0.1x_{29}+0.1x_{32}+0.1x_{41}+0.1x_{44}+0.2x_{47}+0.2x_{48}+0.1x_{49})}$$

Cargo training: x_{51}, Cargo culture: x_{52}.

$$x_{53} = 1 - e^{-4(0.1x_{50}+0.3x_{51}+0.6x_{52})}$$

In-Flight Operations Subsystem

Aircrew training: x_{54}, Aircrew experience: x_{55}.

$$x_{56} = 1 - e^{-4(0.2x_5+0.5x_{54}+0.3x_{55})}$$

Captain training: x_{57}, Captain experience: x_{58}, Captain skill: x_{59}.

$$x_{60} = 1 - e^{-4(0.1x_5+0.2x_{50}+0.1x_{56}+0.1x_{57}+0.3x_{58}+0.2x_{59})}$$

Aircraft quality: x_{61}, Aircraft age: y_2, Aircraft incidents: y_3.

Final result: $x_{62} = (1 - e^{-4(0.1x_{38}+0.2x_{44}+0.1x_{53}+0.2x_{60}+0.4x_{61})})e^{-0.2y_2-0.8y_3}$

Importance Measures

Management policy culture: $0.5x_1(0.2*0.7*0.1*0.2*0.2*2*(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1) + 0.1*0.2*0.2*2*(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1) + 0.2*0.2*2*(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1) + 0.3*0.1*(0.2*0.2 + 0.1*0.1) + 0.1*(0.2*0.2 + 0.1*0.1) + 0.2*0.2*0.2 + 0.1*0.1) = 0.053\ x_1$
Management policy communication: $0.2\ x_2(0.106) = 0.0212\ x_2$
Management policy compliance: $0.1x_3\ (0.106) = 0.0106\ x_3$
Management policy root cause process: $0.1x_4\ (0.106) = 0.0212\ x_4$

Management finances income: $0.7x_6(\ 0.7*0.1*0.2*0.2*2(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1*0.1)) = 0.00000252x_6$
Management finances prognosis: $0.1x_7(0.0000036) = 0.00000036x_7$

Management planning analysis: $0.3x_9(0.1*0.2*0.2*2(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1*0.1)) = 0.0000015x_9$
Management planning incidents: $(1.0 - y_1)(0.000005)$

Management of personnel training: $0.2x_{11}(0.2*0.2*2(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1*0.1)) = 0.0001x_{11}$
Management of personnel quantity: $0.2x_{12}(0.00005) = 0.0001x_{12}$
Management of personnel quality: $0.4x_{13}(0.00005) = 0.0002x_{13}$

Maintenance management of inspections/test: $0.4x_{15}(0.2*2(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1*0.1)) = 0.0001x_{15}$
Maintenance management documentation: $0.2x_{16}(0.00025)$

Maintenance personnel quantity: $0.5x_{18}(2(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1*0.1)) = 0.00065x_{18}$
Maintenance personnel quality: $0.3x_{19}(0.0013) = 0.00039x_{19}$

Maintenance base quantity: $0.5x_{21}(0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1*0.1) = 0.0016x_{21}$
Maintenance base quality: $0.3x_{22}(0.003) = 0.001x_{22}$

Maintenance station quantity: $0.5x_{24}(0.003) = 0.0016x_{24}$
Maintenance station quality: $0.3x_{25}(0.003) = 0.001x_{25}$

Maintenance base equipment quantity: $0.3x_{27}(0.2*(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1*0.1)) = 0.0048x_{27}$
Maintenance base equipment quality: $0.5x_{28}(0.016) = 0.008x_{28}$

Maintenance station equipment quantity: $0.3x_{30}(0.016) = 0.0048x_{30}$
Maintenance station equipment quality: $0.5x_{31}(0.016) = 0.008x_{31}$

Ramp maintenance equipment: $0.2x_{33}(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1*0.1) = 0.0016x_{33}$
Ramp maintenance personnel: $0.4x_{34}(0.08) = 0.032x_{34}$

Pre-flight operations fuel analysis: $0.3x_{36}(0.06) = 0.018x_{36}$
Pre-flight operations fuel quality: $0.6x_{37}(0.06) = 0.036x_{37}$

Pre-flight operations passenger screening equipment: $0.3x_{39}(0.1(0.2*0.2 + 0.1*0.1)) = 0.0015x_{39}$
Pre-flight operations passenger screening personnel: $0.4x_{40}(0.005) = 0.002x_{40}$

Pre-flight operations de-icing analysis: $0.3x_{42}(0.2 + 0.1(0.2*0.2 + 0.1*0.2)) = 0.0618x_{42}$
Pre-flight operations de-icing quality: $0.6x_{43}(0.206) = 0.1236x_{43}$

Pre-flight operations weather data in: $0.5x_{45}(0.2(0.2*0.2 + 0.1*0.1)) = 0.005x_{45}$
Pre-flight operations weather analysis: $0.5x_{46}(0.01) = 0.005x_{46}$

Pre-flight operations dispatch analysis: $0.2x_{48}(0.2*0.2 + 0.1*0.1) = 0.01x_{48}$
Pre-flight operations dispatch software: $0.1x_{49}(0.05) = 0.005x_{49}$

Pre-flight operations cargo loading training: $0.3x_{51}(0.1) = 0.03x_{51}$
Pre-flight operations cargo loading culture: $0.6x_{52}(0.1) = 0.06x_{52}$

In-flight operations air crew training: $0.5x_{54}(0.1*0.2) = 0.01x_{54}$
In-flight operations air crew experience: $0.3x_{55}(0.02) = 0.006x_{55}$

In-flight operations captain training: $0.1x_{57}(0.2) = 0.02x_{57}$
In-flight operations captain experience: $0.3x_{58}(0.2) = 0.06x_{58}$
In-flight operations captain skill: $0.2x_{59}(0.2) = 0.04x_{59}$

In-flight operations aircraft quality: $0.4x_{61}$
In-flight operations aircraft age: $0.2(1 - y_2)$
In-flight operations aircraft incidents: $0.8(1 - y_2)$

Sensitivity Measures:

Management policy culture:
$0.5(1 - x_1)(0.2*0.7*0.1*0.2*0.2*2*(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1) + 0.1*0.2*0.2*2*(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1) + 0.2*0.2*2*(0.2*0.2*0.2)(0.6*0.1 + 0.1*0.2 + 0.1*0.1*0.2*0.2 + 0.1*0.1*0.1) + 0.3*0.1*(0.2*0.2 + 0.1*0.1) + 0.1*(0.2*0.2 + 0.1*0.1) + 0.2*0.2*0.2 + 0.1*0.1) = 0.053(1 - x_1)$
Management policy communication: $0.2(1 - x_2)(0.106) = 0.0212(1 - x_2)$
Management policy compliance: $0.1(1 - x_3)(0.106) = 0.0106(1 - x_3)$

Management policy root cause process: $0.1(1-x_4)(0.106) = 0.0212(1-x_4)$

Management finances income:
$0.7(1-x_6)(0.7*0.1*0.2*0.2*2(0.2*0.2*0.2)(0.6*0.1+0.1*0.2+0.1*0.1*0.2*0.2+0.1*0.1*0.1*0.1)) = 0.00000252(1-x_6)$
Management finances prognosis: $0.1(1-x_7)(0.0000036) = 0.00000036(1-x_7)$

Management planning analysis: $0.3(1-x_9)(0.1*0.2*0.2*2(0.2*0.2*0.2)(0.6*0.1+0.1*0.2+0.1*0.1*0.2*0.2+0.1*0.1*0.1*0.1)) = 0.0000015(1-x_9)$
Management planning incidents: y_1 (0.000005)

Management of personnel training: $0.2(1-x_{11})(0.2*0.2*2(0.2*0.2*0.2)(0.6*0.1+0.1*0.2+0.1*0.1*0.2*0.2+0.1*0.1*0.1*0.1)) = 0.0001(1-x_{11})$
Management of personnel quantity: $0.2(1-x_{12})(0.00005) = 0.0001(1-x_{12})$
Management of personnel quality: $0.4x_{13}(0.00005) = 0.0002(1-x_{13})$

Maintenance management of inspections/test:
$0.4(1-x_{15})(0.2*2(0.2*0.2*0.2)(0.6*0.1+0.1*0.2+0.1*0.1*0.2*0.2+0.1*0.1*0.1*0.1)) = 0.0001(1-x_{15})$
Maintenance management documentation: $0.2(1-x_{16})(0.00025)$

Maintenance personnel quantity: $0.5(1-x_{18})(2(0.2*0.2*0.2)(0.6*0.1+0.1*0.2+0.1*0.1*0.2*0.2+0.1*0.1*0.1*0.1)) = 0.00065(1-x_{18})$
Maintenance personnel quality: $0.3(1-x_{19})(0.0013) = 0.00039(1-x_{19})$

Maintenance base quantity: $0.5(1-x_{21})(0.2*0.2)(0.6*0.1+0.1*0.2+0.1*0.1*0.2*0.2+0.1*0.1*0.1*0.1) = 0.0016(1-x_{21})$
Maintenance base quality: $0.3(1-x_{22})(0.003) = 0.001(1-x_{22})$

Maintenance station quantity: $0.5(1-x_{24})(0.003) = 0.0016(1-x_{24})$
Maintenance station quality: $0.3(1-x_{25})(0.003) = 0.001(1-x_{25})$

Maintenance base equipment quantity: $0.3(1-x_{27})(0.2*(0.6*0.1+0.1*0.2+0.1*0.1*0.2*0.2+0.1*0.1*0.1*0.1)) = 0.0048(1-x_{27})$
Maintenance base equipment quality: $0.5(1-x_{28})(0.016) = 0.008(1-x_{28})$

Maintenance station equipment quantity: $0.3(1-x_{30})(0.016) = 0.0048(1-x_{30})$
Maintenance station equipment quality: $0.5(1-x_{31})(0.016) = 0.008(1-x_{31})$

Ramp maintenance equipment: $0.2(1-x_{33})(0.6*0.1+0.1*0.2+0.1*0.1*0.2*0.2+0.1*0.1*0.1*0.1) = 0.0016(1-x_{33})$
Ramp maintenance personnel: $0.4(1-x_{34})(0.08) = 0.032(1-x_{34})$

Pre-flight operations fuel analysis: $0.3(1-x_{36})(0.06) = 0.018(1-x_{36})$

Pre-flight operations fuel quality: $0.6(1 - x_{37})(0.06) = 0.036(1 - x_{37})$

Pre-flight operations passenger screening equipment: $0.3(1 - x_{39})(0.1(0.2*0.2 + 0.1*0.1)) = 0.0015(1 - x_{39})$
Pre-flight operations passenger screening personnel:
$0.4(1 - x_{40})(0.005) = 0.002(1 - x_{40})$

Pre-flight operations de-icing analysis: $0.3(1 - x_{42})(0.2 + 0.1(0.2*0.2 + 0.1*0.2)) = 0.0618(1 - x_{42})$
Pre-flight operations de-icing quality: $0.6(1 - x_{43})(0.206) = 0.1236(1 - x_{43})$

Pre-flight operations weather data in: $0.5(1 - x_{45})(0.2(0.2*0.2 + 0.1*0.1)) = 0.005(1 - x_{45})$
Pre-flight operations weather analysis: $0.5(1 - x_{46})(0.01) = 0.005(1 - x_{46})$

Pre-flight operations dispatch analysis:
$0.2(1 - x_{48})(0.2*0.2 + 0.1*0.1) = 0.01(1 - x_{48})$
Pre-flight operations dispatch software: $0.1(1 - x_{49})(0.05) = 0.005(1 - x_{49})$

Pre-flight operations cargo loading training: $0.3(1 - x_{51})(0.1) = 0.03(1 - x_{51})$
Pre-flight operations cargo loading culture: $0.6(1 - x_{52})(0.1) = 0.06(1 - x_{52})$

In-flight operations air crew training: $0.5(1 - x_{54})(0.1*0.2) = 0.01(1 - x_{54})$
In-flight operations air crew experience: $0.3(1 - x_{55})(0.02) = 0.006(1 - x_{55})$

In-flight operations captain training: $0.1(1 - x_{57})(0.2) = 0.02(1 - x_{57})$
In-flight operations captain experience: $0.3(1 - x_{58})(0.2) = 0.06(1 - x_{58})$
In-flight operations captain skill: $0.2(1 - x_{59})(0.2) = 0.04(1 - x_{59})$

In-flight operations aircraft quality: $0.4(1 - x_{61})$
In-flight operations aircraft age: $0.2y_2$
In-flight operations aircraft incidents: $0.8y_2$

DISTRIBUTION:

ANDERSEN,JOHN ANDREW 12300 MS 0428
DRELL,SIDNEY D. 12300 MS 0428
NICKELL,WILLIAM C. 12300 MS 0428
SPRAY,STANLEY DEAN 12300 MS 0491
STEVENS,WILLIAM LOUIS 12300 MS 0491
SAVERINO,EVERETT L. 12300 MS 0637
CARLSON,DAVID D. 12301 MS 0428
SHAW,JOHN D. 12301 MS 0428
TRAUTH JR.,CHARLES A. 12301 MS 0428
SMITH,RICHARD E. 12302 MS 0491
WERNER,CAROLINE L. 12302 MS 0491
NORRIS,WILLIAM L. 12303 MS 0639
OELSNER,RONALD MARTIN 12303 MS 0632
BOHN,MICHAEL P. 12304 MS 0405
BREEDING,ROGER J. 12304 MS 0405
SHIRLEY,CLINTON G. 12304 MS 0405
ABATE,MARCEY L. 12323 MS 0829
DIEGERT,KATHLEEN V. 12323 MS 0829
FORSYTHE,JAMES C. 12323 MS 0829
MARLMAN,KAREN S. 12323 MS 0829
BLACKLEDGE,MICHAEL A. 12326 MS 0638
GENTRY,FLOYD L. 12326 MS 0638
KNIRK,DWAYNE L. 12326 MS 0638
PEERCY,DAVID E. 12326 MS 0638
TRELLUE,PATRICIA A. 12326 MS 0638
COOPER,J. ARLIN 12331 MS 0490 (15)
COVAN,JOHN M. 12331 MS 0490
D'ANTONIO,PERRY E. 12331 MS 0490
DEMMIE,PAUL N. 12331 MS 0820
EKMAN,MARK E. 12331 MS 0490
HERMANSEN,VERN L. 12331 MS 0490
ISBELL,DARYL 12331 MS 0490
MCCULLOCH,WILLIAM H. MS 0490
PREW,ROBERT C. 12331 MS 0490
ROSS,TIMOTHY J. 12331 MS 0490
SCHWOEBEL,RICHARD LYNN 12331 MS 0490
WERNER,PAUL W. 12331 MS 0490 (15)
ZIMMERMAN,DEAN ANTHONY 12331 MS 0490
CATES,JAMES P. 12332 MS 0492
CHEN,KENNETH C. 12332 MS 0492
DVORACK,MICHAEL A. 12332 MS 0492
LEWIS,DONALD ROBERT 12332 MS 0492
LOESCHER,DOUGLAS H. 12332 MS 0492
MAULDIN,WINFORD E. 12332 MS 0492

MCCOLLISTER,DARYL R. 12332 MS 0492
OLSON,DAVID R. 12332 MS 0492
SUMMERS,DANIEL A. 12332 MS 0492
WOLCOTT,JAMES F. 12332 MS 0492
BENNETT III,DAVID E. 12333 MS 0405
BROWN,THOMAS D. 12333 MS 0405
CALDWELL,MICHELE 12333 MS 0405
DHOOGE,NANCY J. 12333 MS 0405
FUENTES,MARTIN K. 12333 MS 0405
HANCOCK,JOHN V. 12333 MS 0405
JONES,TODD R. 12333 MS 0405
KALEMBA,SALLY A. 12333 MS 0434
MALONEY,KEVIN J. 12333 MS 0405
SCHRINER,HEATHER K. 12333 MS 0405
SOBOLIK,KERI B. 12333 MS 0405
YOUNG,MARY LOUISE 12333 MS 0405
EVERETT,JEFFREY J. 12334 MS 0434
FRONCZAK,EDWARD L. 12334 MS 0434
HUMBERT,STEVEN B. 12334 MS 0434
STAYTON,JACK E. 12334 MS 0434
TRUSSELL,FREDRICK G. 12334 MS 0434
HENDERSON,JAMES T. 12335 MS 0830
SJULIN,JANET M. 12335 MS 0830
KONNICK,PAUL J. 12336 MS 0637
HOFFMAN JR.,JOHN P. 12345 MS 0490
KUSWA,GLENN W. 12365 MS 0635
HERNANDEZ,OSCAR R. 12367 MS 0636
HILL,DWIGHT S. 12367 MS 0636
ROGERS,MICHAEL S. 12367 MS 0636
CUMIFORD,LESLIE A. 02567 MS 0521
DALTON,LARRY J. 02615 MS 0535
CRANWELL,ROBERT M. 06411 MS 0746
ROBINSON,DAVID G. 06411 MS 0746
CAMP,ALLEN L. 06412 MS 0747
DANIEL,SHARON LEE 06412 MS 0747
MILLER,LEANN ADAMS 06412 MS 0747
WYSS,GREGORY D. 06412 MS 0747
TRUCANO,TIMOTHY G. 09231 MS 0819
BATY,ROY S. 09115 MS 0825
OBERKAMPF,WILLIAM L. 09115 MS 0825
ROLLSTIN,LARRY R. 09115 MS 0825
BLACKWELL,BENNIE F. 09113 MS 0835
MEYERS,CHARLES E. 04000 MS 0149
CLOER,BRYON K. 04001 MS 0188
KUNSMAN,DAVID M. 05415 MS 0425
PAYNE JR.,ARTHUR C. 05415 MS 0425

GILLIOM,LAURA R. 06232 MS 0455
REXROTH,PAUL E. 05824 MS 0765
RINGLAND,JAMES T. 08112 MS 9201
CASHEN,JERRY J. 08116 MS 9202
EASTERLING,ROBERT G. 09800 MS 0417
CENTRAL TECHNICAL FILES 8940-2 MS 9018
TECHNICAL LIBRARY 4916 MS 899 (2)
REVIEW & APPROVAL DESK (FOR DOE/OSTI) 04912 MS 0612
PATENT & LICENSING OFFICE 11500 MS 0161