AIRCRAFT MAINTENANCE

Wireman (1) in his book entitled *World Class Maintenance Management* refers to maintenance planning as the last frontier for organizations. Many firms are realizing a critical need for effective maintenance of production facilities and operating systems. It is vital that maintenance management becomes integrated with corporate strategy to ensure equipment availability, quality products, on-time deliveries, and competitive pricing. The changing needs of modern organizations necessitate a reexamination of the role that improved maintenance management plays in achieving key cost and service advantages.

The *common trends* from Scandinavian (2) and US (1) benchmarking studies for maintenance suggest that there exists a need to develop clear maintenance objectives and goals, to define key variables for measuring and controlling maintenance activities, to ensure better linkages between maintenance and production, to move toward computer-based maintenance systems, to decentralize some maintenance activities, to instill better training, and to investigate modern maintenance methods.

Effective and efficient maintenance management is essential not only for production systems but for large-scale service systems, such as air and surface transport systems. These repairable systems are subject to aging mechanisms, such as wear, fatigue, creep, and stress corrosion. Inspection and diagnostic activities are integral components of an effective maintenance strategy in an attempt to ensure aircraft system safety, reliability, and availability.

In the United States, the number of domestic passengers for all airlines increased from 250 million to 450 million annually between 1977 and 1987 (3). The Federal Aviation Administration (FAA) anticipates that the number of domestic passengers will reach 800 million in the year 2000, and exceed a billion by 2010 for a 128% and 272% increase (3). This steady growth of air transport and air traffic density places increasing pressure on airlines and their maintenance inspection activities. Recently, the FAA established a fourth national aviation research center called the Air Transportation Center of Excellence for Airworthiness Assurance, which consists of 31 universities, 68 industry partners, and 12 government laboratories.

Efficient inspection activities will facilitate timely aircraft maintenance and minimize the cost of aircraft unavailability. One of the critical issues identified by the aviation industry is the need to examine the effects of repairs on the structural integrity of aircraft. During the past five years, the US Air Force and the FAA have jointly developed the Repair Assessment Procedure and Integrated Design (RAPID) to address this issue. RAPID is a repair tool to perform static strength and damage tolerance analyses of aircraft structural skin repairs. The damage tolerance analysis module in RAPID can calculate fastener loads, perform simplified crack growth computations, determine residual strength, and estimate an inspection schedule (4).

The inspection of aircraft involves a number of complex technical, social, political, economic, and human issues. The main purpose of inspection activity is to determine the state of the equipment, system, etc. This diagnostic activity may uncover faults which will lead to corrective maintenance action. Inspection frequencies, procedures, and criteria may vary for alternative types of aircraft. Alternative safety equipment and measurement accuracies are required for different components. During an inspection, once the state values of the system, equipment, etc. have been identified by the inspector, then an appropriate maintenance action, such as repair, replacement, and overhaul can be recommended. There may be delays in inspections due to coordination and scheduling conflicts. Expertise is required in diagnosing potential safety problems and in making probability assessments. There is increased emphasis on the capturing and systematizing of existing aircraft inspection and maintenance knowledge.

Replacement inspections focus on a specific component or components that have been scheduled for replacement at specific intervals. The component that was in service may undergo further testing in the supply area and repaired if necessary and returned as a usable spare. If it is determined that it is not cost effective to repair the worn component, it will be discarded. Also, a replacement inspection may result in the maintenance inspector making a decision to defer replacement of the inspected component.

For modern aircraft systems, there is a high degree of reliability built in which means that there are infrequent failures. When failures are infrequent, it becomes difficult to quickly detect and isolate the problem. The development of a knowledge base for fault detection and isolation for aircraft will enable the codification of existing inspection expertise before this expertise leaves the organization. Once captured, this knowledge can be efficiently applied on a continuous basis via an expert system to enhance the decision making productivity and consistency of both novice and experienced aircraft maintenance inspectors.

Technological advances in engine performance and reliability, materials, air traffic control, cockpit automation, and training have contributed significantly to the current safety levels of the aviation industry. As technological advances have fostered aviation product development, new advances in information management and decision support technologies have made possible improvements in aviation safety monitoring, analyzing, and alerting. Such advances in information management will lead to more proactive aviation safety actions. This article reports on the development of an advanced decision support system to assist inspectors with aircraft inspection and maintenance diagnostics.

The next section of this article provides a brief, general overview of the evolutionary nature of maintenance management and modeling. This article focuses on presenting new diagnostic methods that use an artificial intelligence (AI) approach for aircraft inspection and maintenance. An expert system is described that is based on a model of Bayesian networks that may be helpful in uncertainty resolution for problem diagnostics. The model is demonstrated with three examples from aircraft inspection and maintenance that illustrate diagnostic procedures for troubleshooting aircraft tire condition, navigation, and hydraulic problems.

Trends in Maintenance Knowledge

Maintenance modeling is inherently evolutionary in nature. As equipment complexity increases, and as the need for high equipment availability becomes paramount in today's complex, dynamic systems, there has been a corresponding increase in maintenance modeling sophistication. The idea of reactionary corrective maintenance progressed to predetermined preventive maintenance, then to large scale industrial maintenance, to condition-based maintenance determined by inspection, to expert maintenance systems, and now towards a futuristic view of intelligent or self maintenance.

Blanchard (5) and Lyonnet (6) provide overviews of the evolving maintenance categories. *Corrective maintenance* involves all unscheduled maintenance actions performed as a result of system/product failure to restore the system to a specified condition. Corrective maintenance includes failure identification, localization and isolation, disassembly, item removal, and replacement or repair in place, reassembly, checkout, and condition verification. *Preventive maintenance* includes all scheduled maintenance actions performed to retain a system or product in a specified condition. These actions involve periodic inspections, condition monitoring, critical item replacements, and calibration.

Predictive maintenance is a relatively new concept in maintenance planning. This category of maintenance occurs in advance of the time a failure would occur if the maintenance were not performed. The time when this maintenance is scheduled is based upon data that can be used to predict approximately when failure will occur if certain maintenance is not undertaken. Data such as vibration, temperature, sound, and color have usually been collected off-line and analyzed for trends.

With the emergence and use of programmable logic controllers (PLCs) in production systems, equipment and process parameters can now be continually monitored. With *condition-based maintenance,* the PLCs are wired directly to an online computer to monitor the equipment condition in a real time mode. Any deviation from the standard normal range of tolerances will cause an alarm (or a repair order) to be automatically generated. Installation costs for such a maintenance system can be high, but equipment service levels can be significantly improved.

Intelligent maintenance or self-maintenance involves automatic diagnosis of electronic systems and modular replacement units (7). Sensor data from remote facilities or machines would be provided on a continuous basis to a centralized workstation. From this workstation, the maintenance specialist could receive intelligent support from expert systems and neural networks for decision making tasks. Commands would then be released to the remote sites to begin a maintenance routine that may involve adjusting alarm parameter values, initiating built-in testing diagnostics, or powering stand-by or subsystems, for instance. The FAA in the United States is developing the Remote Maintenance Monitoring System (RMMS) that is an example of the future direction in maintenance automation (8). In some cases, robotics may be used for remote modular replacements.

Emergence of New Maintenance Methods

Developments in the area of AI have led to the emergence of expert systems and neural networks. These solution techniques have found numerous applications in maintenance planning. Milacic and Majstorovic (7) report on a survey that identified a list of 60 different expert maintenance systems as of 1987. Frequently, the reasons for the use of expert systems in maintenance are the increasing complexity of equipment, the interdisciplinary nature of modern maintenance problems, the departure of maintenance expertise from an organization due to retirements, the reduced training time of novice technicians, and consistently good decisions (9). Spur et al. (10) discuss two general categories of expert maintenance systems: associative diagnosis and model-based diagnosis. In the former, conclusions are reached based on an analysis of fault possibilities that are verified by testing. The search tree uses coded knowledge from domain experts. In the latter, the real performance of equipment is compared with the simulated performance of a computer model, and faults are inferred from the differences between the two.

The applications of expert systems in maintenance are quite diverse. Representative industries include automotive, aerospace, electronics, process, computers, and telecommunications. CATS is an expert maintenance system developed by General Electric Company with a knowledge base of 550 rules to detect sudden failures in diesel-electric locomotive systems. IN-ATE is an expert system used for electronic circuit diagnosis. FSM is an expert system Boeing uses for continuous condition monitoring of aircraft alarms. Lockheed developed RLA, an expert system for repair level analysis for major parts in an aerospace system (11). Bajpal (12) uses an expert system architecture to troubleshoot general problems with machine tools in manufacturing industries. Bao (13) develops an expert system to assist in the manufacturing and maintainability of surface mount technology (SMT) printed circuit board (PCB) assembly. Khan et al. (14) discuss GEMS-TTS, an expert system used by AT&T maintenance specialists to isolate faults in communication links. Corn et al. (15) describe TOPAS, an expert system that diagnoses transmission and signaling problems in real time that may arise on switched circuits. One of the most successful expert systems is CHARLEY, which was developed by General Motors and based on the knowledge of Charley Amble, an experienced maintenance engineer (16). This expert system is used to diagnose problems with broken machine tools and to instruct less experienced individuals by providing explanations. It is reported by GM that CHARLEY has reduced training costs by as much as $500,000 per year per plant.

Although the idea of utilizing expert systems in maintenance held early promise, the use of rule-based programming has led to practical problems in implementation. For example, XCON, an expert system developed by Digital Equipment Corporation for product configuration has over 10,000 rules. Issues such as maintainability of the knowledge base, testability of the program, and reliability of the advice have limited the practical use of most expert systems in maintenance (17). Other approaches, such as constraint-based reasoning, are being developed as alternatives to rule-based systems (18). Also, the reconsideration of Bayesian theory to support probabilistic reasoning and maintenance diagnostics is being reexamined (19).

Neural networks are computing systems that incorporate a simplified model of the human neuron, organized into networks similar to those found in the human brain (20). Instead of programming the neural network, it is *taught* to give acceptable results. The ability of artificial neural networks to capture complex trends has been researched and documented in a significant number of research papers since 1982, when researchers rediscovered their important characteristics (21–23). The large number of research papers available on these characteristics prohibits their documentation here, but as an indication of their diverse cognitive powers, there have been applications of neural networks in varied areas from stock market price prediction and credit rating approval to engineering applications such as pattern/image recognition, digital signal processing, and automated vehicle guidance (24).

Luxhøj and Shyur (25), Luxhøj et al. (26), and Shyur et al. (27) report on the use of artificial neural networks to capture and retain complex underlying relationships and nonlinearities that exist between an aircraft's maintenance data and safety inspection reporting profiles. Neural networks will be used to implement condition-based maintenance because real time sensor data can be trended to predict out-of-tolerance conditions for critical equipment parameters. Maintenance actions can then be initiated for an adaptive response to these anticipated system perturbations. An oil and gas company in Denmark is examining the use of artificial neural networks to predict the meter factor (pulses/unit volume) or k factor for turbine flow meters. By predicting the k factor in future time periods, significant deviations from the usable flow range can be anticipated so that maintenance technicians can make adjustments and prevent the expensive shutdown of a turbine for pumping oil or gas. Although the use of neural networks in maintenance will undoubtedly increase in the future, their solution potential is constrained by our current understanding of human reasoning capabilities and the limits of available computing power.

DEVELOPMENT OF A BAYESIAN MODEL FOR AIRCRAFT FAULT DIAGNOSTICS

As noted in the previous section, there have been numerous expert systems developed in the maintenance and fault diagnosis problem area. Maintenance of complex equipment involves a number of diagnostic procedures that utilize rules and judgments. The large number of rule-based expert systems developed for fault diagnosis prohibit their documentation here, but a survey of applications is provided in Badiru (16). However, classical rule-based expert systems for diagnostics have been recently criticized since the large number of rules for commercial applications results in knowledge bases that frequently are unmaintainable, untestable, and unreliable (17).

With the increased computational power of modern computers, the use of Bayesian probability theory to construct expert systems has been revived. As reported in Kumara et al. (28), current expert systems for fault diagnosis suffer from an inability to handle new faults, an inability to recognize when a fault is beyond the consultation system's scope, inadequate explanation of the final diagnosis, excessive requests for new information, and difficulties in construction.

Bayesian Belief Networks

A Bayesian belief network is used to model a problem domain that contains uncertainty. Bayesian learning views the problem of constructing hypotheses from data as a subproblem of the prediction problem. Essentially, the idea is to use the hypotheses as intermediate steps between data and predictions. However, the hypotheses are made in the context of uncertainty. This uncertainty may be due to an imperfect understanding of the problem domain, incomplete knowledge of the state of the domain at the time when a given task is to be performed, randomness in the system, or a combination of the foregoing factors. Bayesian networks are used to make inferences about the beliefs of users in response to observations. Hence, the terminology of belief network, Bayesian network, and causal probabilistic network have also been used in the past.

A Bayesian belief network is a directed acyclic graph formed by a set of variables and directed links between variables (29). Each variable represents an event and has countable or continuous states. Formally, a Bayesian belief network has the following properties:

- Each node in the directed acyclic graph represents a random variable.
- Each node representing a variable A with parent nodes representing variables $B_1, B_2, \ldots, B_n$ is assigned a conditional probability table:

$$P(A|B_1, B_2, \ldots, B_n)$$

An essential concept for Bayesian belief networks is conditional independence. Two sets of variables, A and B, are considered to be conditionally independent given a third set C of variables if when the values of the variable C are known, then knowledge of the values of B provides no further information about the values of the variables of A:

$$P(A|B, C) = P(A|C)$$

Inference in a Bayesian belief network involves computing the conditional probability for some variables given information (evidence) on other variables. When all available evidence is on variables that are ancestors of the variables of interest, this computation becomes easy. However, when evidence is available on a descendant of the variable(s) of interest, then inference must be performed against the direction of the probabilistic dependencies. In this case, Bayes' Theorem is used:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

A Bayesian belief network is analogous to an influence diagram in which the causal impacts between events are connected by arrows. An influence diagram is used instead of a Bayesian belief network when dealing with decision making, since a Bayesian belief network does not explicitly treat the concepts of utility (probabilistic value assessment) and decisions. An influence diagram is simply a Bayesian belief network extended with utility and decision nodes. The certainty of each state is described by its probability of occurrence, and the relations between events are described by conditional probabilities. The change of the certainty of an event affects the certainty of other events. When evidence enters into the network, the certainty of events, that is, the probabilities of the states of events, can be obtained by propagating the evidence. Therefore, Bayesian networks create a very useful language in building models of domains with inherent uncertainty. The probabilities of events provided by the network model are used to support the decision making. In this article, Bayesian networks are modeled as decision support tools for aviation safety diagnostics.

Bayesian Belief Network Technology in the HUGIN System

The calculations for the propagation of probabilities in a Bayesian belief network are usually tedious (30). We used HUGIN (29) as a Bayesian network programming environment for modeling and calculations.

HUGIN is a software for the construction of knowledge based systems based on causal probabilistic networks (CPNs). The software was developed as part of an European ESPRIT project on diagnosing neuromuscular diseases. The software incorporates new, efficient algorithms to support Bayesian probability calculations and offers an alternative to traditional rule-based programming (31). As noted previously, these CPNs, also known as belief networks or influence diagrams, represent a possible means to efficiently model the uncertain relationships among components of a system. Moreover, model-based expert systems incorporate causal knowledge by including a representation of a system's structure, function, and behavior. The HUGIN algorithm, a simplification of the Lauritizen–Spieglehalter (32) algorithm, is a novel application of Bayes' Theorem that reduces the probability computations to a series of local calculations using only variables obtainable from one object and its neighbors in a graph structure, thus avoiding a calculation of the global joint probability distribution (31).

The HUGIN model uses a number of statements about the problem domain (e.g., "The patient has lung cancer") and a number of causal relationships between such statements. Each statement is assigned a number of states (e.g., "yes" and "no"), and each state is assigned a probability. Causal dependencies are given as conditional probabilities for a state given the states of the parent node.

In a safety diagnostics model, for example, the knowledge embedded in the cause-effect links between nodes in the CPN will be answers to questions such as "If the direct cause represented by node X is known to have a given value, what is the probability that the effects, given in node Y, will have a certain outcome?" With a CPN, one could ask "If the engine in the car gets hot, what is the probability that the carburetor will stop working?" In normal rule-based systems, the question would probably be "If the carburetor stops working, will the engine then get hot (yes/no)?" With HUGIN, the inference engine allows evidence to be entered into nodes and the effect of such evidence to be propagated to other nodes, which provides for a very efficient reasoning process, thus confirming or refuting beliefs. The model could be used in either moving from observed symptoms to causes (i.e., a diagnostic/analysis mode) or from causes to symptoms (i.e., a design mode). Data for the probabilities of the states at each node is typically obtained from historical information and/or expert judgments.

Horvitz et al. (19) describe an application of HUGIN to develop a probabilistic diagnostic model for NASA's space shuttle propulsion-system engines. The belief network shows how the values of helium pressure affect the pressure readings as reported by the two independent pressure sensors on the space shuttle's orbital maneuvering system (OMS) helium tank. However, these pressure readings can also be affected, with uncertainty, by the errors in the sensor mechanisms themselves. An experienced user in sensor failures can code a belief about the relative rate of failure of alternative critical sensors in the system.

The use of such a model-based expert system is being investigated as a possible computerized technique to support aircraft safety inspectors. Such a system would provide the ability to consider alternative hypotheses under uncertainty when diagnosing aircraft systems. The use of a Bayesian model could provide two types of assistance to the safety inspector. First, information related to the status of the aircraft could be presented, and safety alert information could be displayed. Second, the conditional reasoning properties of the Bayesian network will enable the safety inspector to formulate "What if?" questions on the current condition of the aircraft and experiment with possible causes for the observed symptoms.

The creation of a complete HUGIN model requires three steps. Initially, the nodes of the belief network or the influence diagram must be mapped out. Second, the states of the nodes must be defined. Third, the probabilities of each state must be determined. Each of these phases requires ample planning, or else the model will be compromised during a subsequent point of development. While developing the influence diagram is only the first step, it is the basis for all future algorithmic computations.

The computerized diagnostics model is not intended to replace the expertise of the inspector, but it is designed to provide advanced decision support. A decision support system that uses Bayesian probability computations will not only retain the human in the decision making process but also provide systematic guidance in identifying causal factors for aircraft maintenance problems, evaluating likelihoods of these factors, and decomposing complex combinations of causal factors based upon historical data and/or expert judgments.

Three prototype Bayesian belief networks are presented for safety diagnostics of aircraft subsystems. Since the actual initial probabilities for events and the conditional probabilities between events are not provided in this study, a session with a domain expert on aviation safety was conducted. However, the model structures are based upon fault reporting and maintenance manuals from a major aircraft manufacturer.

HUGIN PROTOTYPE: AIRCRAFT TIRE CONDITION ASSESSMENT

Luxhøj and Williams (33) model aircraft tire condition assessment as an example of a Bayesian belief network application to aviation. This topic was selected because it is reasonably complex and has a direct link to aircraft safety. Many factors affect the performance of an aircraft tire, including weather and pavement conditions. Often, a tire is serviceable even if it has several cuts or a bald patch. Each airline has defined tolerances for when a tire must be replaced. The Federal Aviation Administration (FAA) approves the airlines' maintenance tolerances and procedures. The FAA inspector must be able to identify when a tire has deviated from the airline's requirements and must inform airline maintenance personnel.

The criteria for removing tires are complex. Tires can fail in several different modes. The inspector must be able to rapidly assess the condition of the tires on an aircraft during a ramp inspection. Uncertainties may exist as to the causal factors of an aircraft tire problem. Since the actual initial probabilities for events and the conditional probabilities between events are not provided in this study, a session with a domain expert on aviation safety was conducted. However, the tire condition model structure is based upon the maintenance manual from a major aircraft manufacturer.

Reasons for Tire Replacement

There are many different types of tire damage. Some common problems include deep cuts, long shallow cuts, multiple small cuts in a small area of the tire, Chevron cuts, tread wear, bulges, flat spots, tread separation, and ozone checking. The foregoing problems, depending on their severity, may require immediate removal of the tire. Other problems may allow the plane to continue flight, but maintenance must be scheduled for the next maintenance base or programmed for tire replacement at the next scheduled maintenance. The maintenance procedures of an airline set the following criteria for tire replacement.

Some general guidelines for aircraft tire service and damage limits of a typical airline are provided below. For this typical airline, tire cuts can be classified as shallow, deep, sidewall, and multiple cuts. A cut exceeds the shallow cut criteria if the cut is more then two inches long, and its depth goes through more then two tread breakers. The deep tread cut removal criteria is satisfied if the cut is greater then 1.5 inches long, and its depth exceeds two tread breakers and one cord ply. A shallow tread cut requires replacement if the cut depth is through two breakers, and the cut length exceeds two inches. If a sidewall cut extends into the cord ply, removal of the tire is required. If more then six cuts extend through two breakers and are greater then 1 inch in length, then the tire requires replacement. Additionally, the tire must be replaced if any three cuts are grouped into one quarter of the tire's surface area.

Chevron cutting is caused by operation on grooved runway pavements. Some of the reasons for replacement are chunking of the tire down to the fabric of the tire and chunking that affects wheel assembly balance.

Tires must be replaced when their tread has worn to $\frac{1}{16}$ inch or less at any single spot. In some instances involving tread wear, tire changes may be scheduled for maintenance if a flight will be delayed.

Flat spots are a reason for tire replacement if the cord is exposed. Other, less severe flat spots may cause the tire to be scheduled for maintenance at the next base. Tread separation, defined as any condition where the tread separates from the tire, can occur in both new and recapped tires. Ozone cracks, caused by environmental conditions, require replacement only if the cracks enter the fabric.

Bayesian Belief Network Development

The first step in developing the maintenance diagnostics expert system is to formulate the problem in the form of a Bayesian belief network. Figure 1 shows the tire replacement network. The network is composed of three layers. The top layer nodes are the tire problems that can be observed during aircraft inspection. These are the problems described above. The bottom layer consists of one node that provides as an output the action required for the tire problems identified. The intermediate layer represents additional information necessary to make a specific diagnosis.

Nodal States. The second step in developing the decision support system is to determine the possible states for each

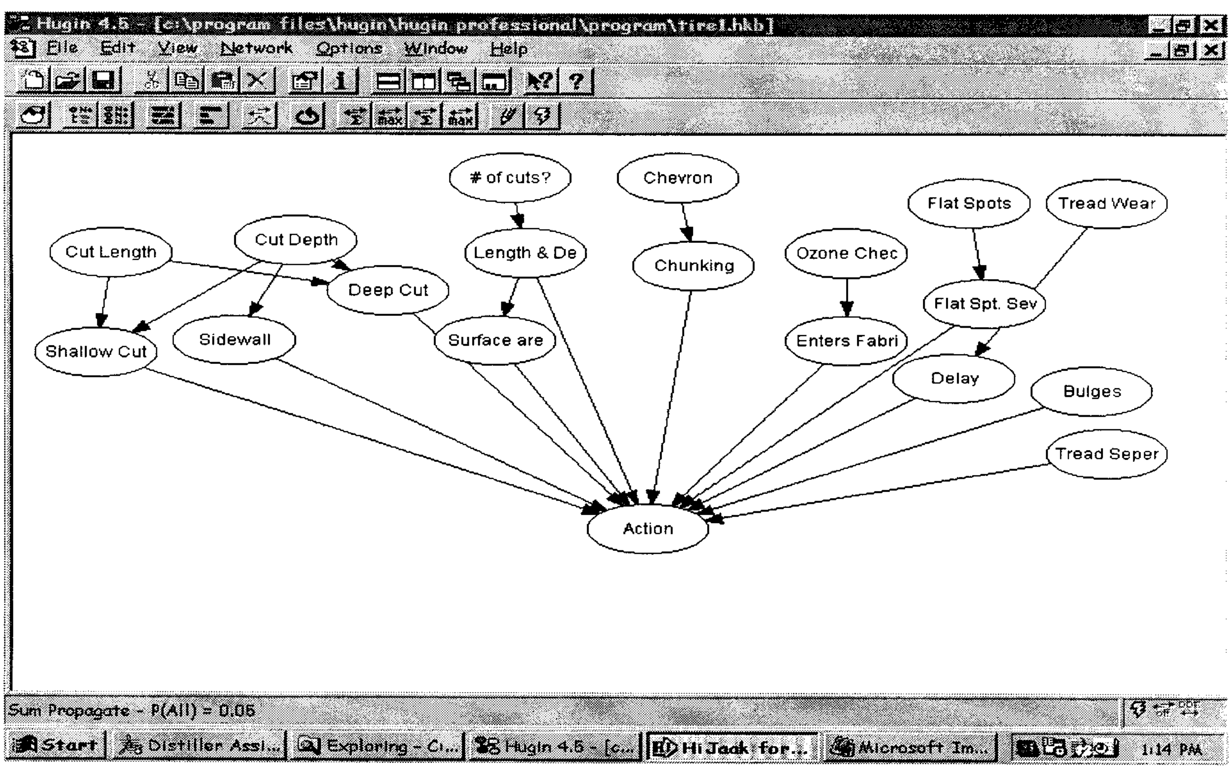

Figure 1. Influence diagram showing causal relationships for aircraft tire condition assessment. [Source: Luxhøj and Williams (33)].

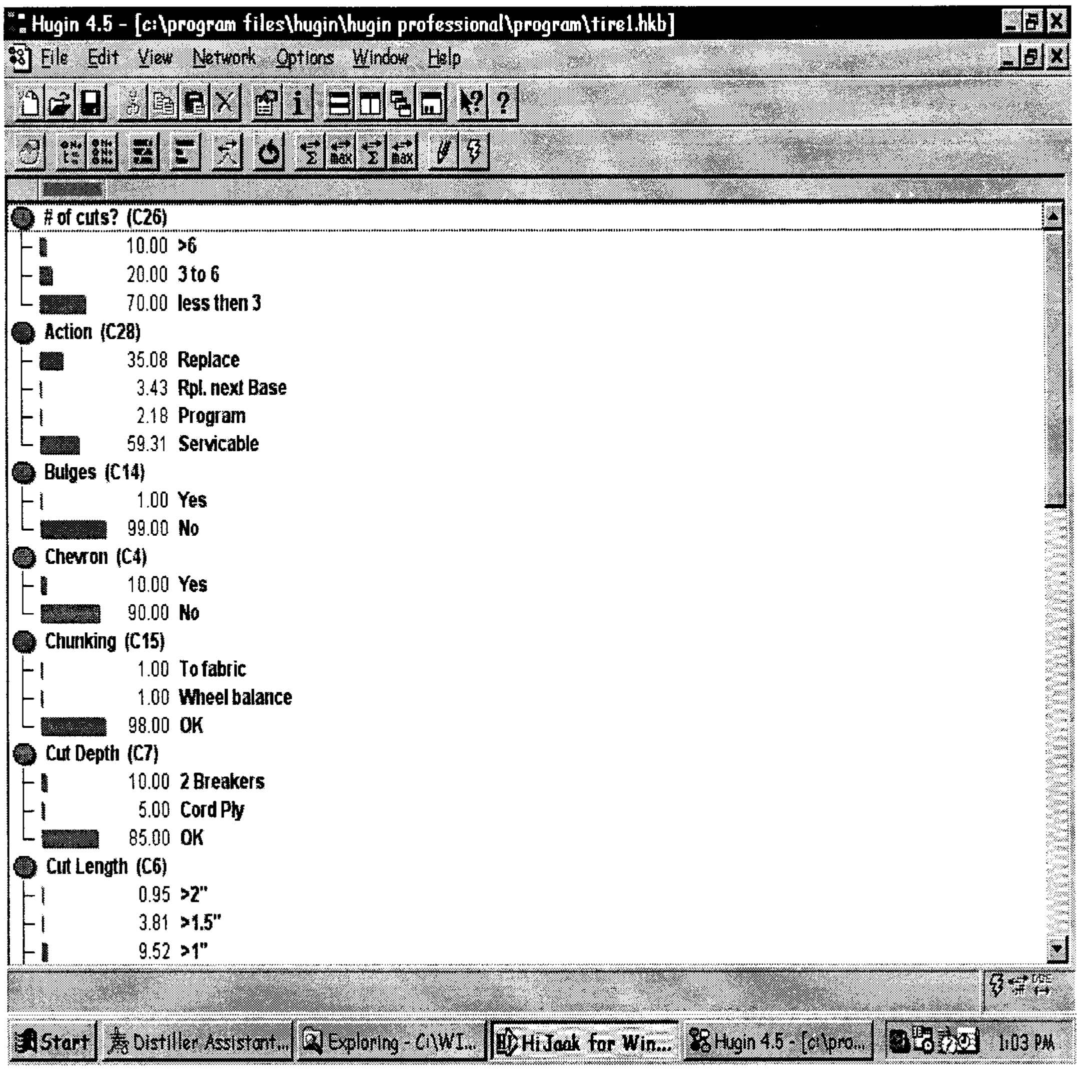

Figure 2. Possible states of several nodes. [Source: Luxhøj and Williams (33)]

node in the Bayesian belief network. For example, the "Cut Depth" node has three possible states. The cut can be through two breakers and the cord ply, it can extend through two breakers, or the cut depth could be acceptable. If the cut is less the two breakers deep, cut depth is not deep enough to require maintenance. Figure 2 provides a listing of the possible states of several nodes.

Defining Probabilities. The third phase in developing the HUGIN model is determining the numerical part of each link. This is accomplished through the use of conditional probability tables. For each node, a conditional probability is input for each node given the state of its parent nodes. The sum of the probabilities of the states of a node must equal one. Figure 3 shows an example of the conditional probabilities entered for the "Length and Depth" node (the node is highlighted in bold). In reviewing the conditional probability table for this node, note that if the number of cuts from the previous node is between 3 and 6, then the probability that the length and depth exceeds requirements is 0.3, and the probability that the requirements are satisfactory is 0.7. In Bayesian terminology, P(length and depth exceeds requirements|3 through 6 cuts) = 0.3, and P(OK|3 through 6 cuts) = 0.7. The next node, surface area, is used to determine the probability of any three cuts being grouped into more than one-fourth of the tire's surface area conditioned on the length and depth requirements and the number of cuts [or P(3 cuts in one-fourth surface area|length and depth exceeds requirements and the number of cuts is between 3 and 6)].

These probabilities were defined through the available literature (34) and in consultation with an aviation safety expert. The safety expert was shown an initial version of the probabilities and suggested revisions based on his prior experience.

Interactive Problem Solving. The HUGIN program allows the model user to adjust the probabilities of states of nodes based on observed information. The software propagates this change through the network and updates the conditional probabilities at each node based on the new information.

Figure 4, a computer screen snapshot from the HUGIN program, shows the unperturbed conditional probabilities. If we observe a deep, long cut in the tire (i.e., we have found

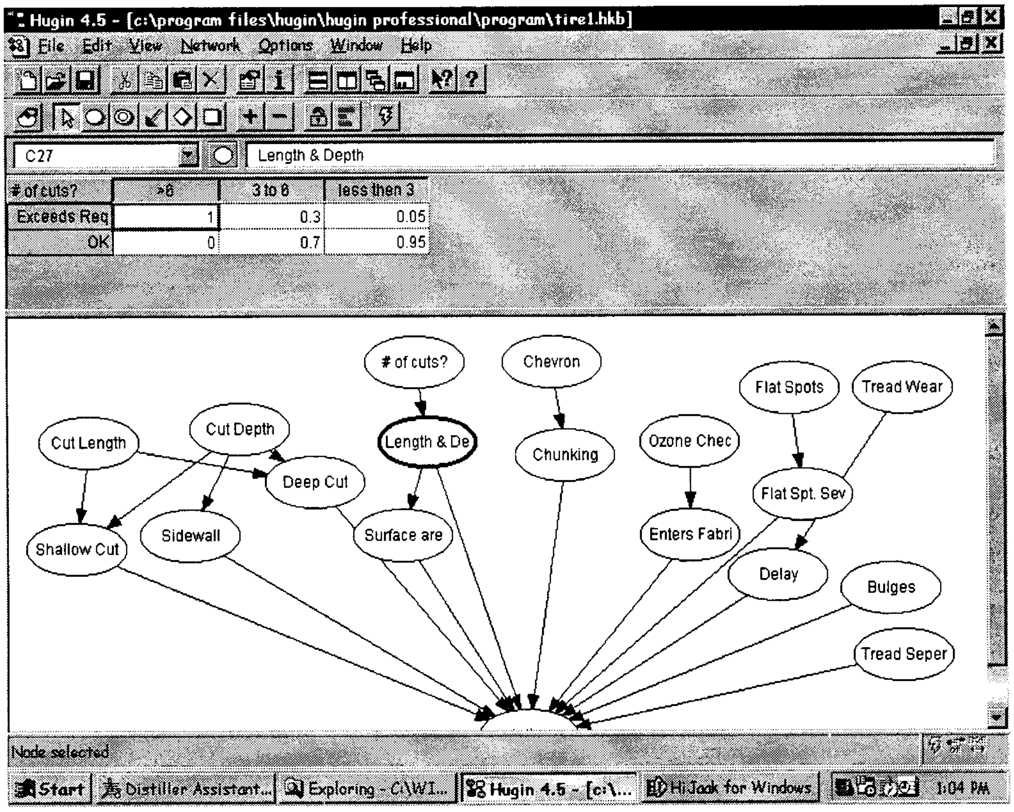

Figure 3. Conditional probability table for "Length and Depth" node. [Source: Luxhøj and Williams (33)]

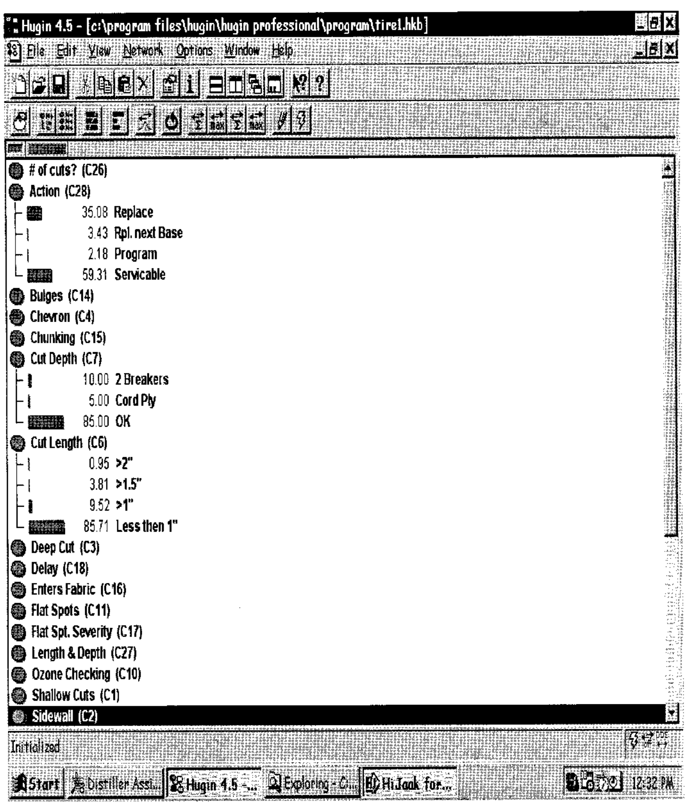

Figure 4. Unperturbed conditional probabilities. [Source: Luxhøj and Williams (33)]

evidence of a cut), the software can propagate the effects of this new knowledge through the network.

Figure 5 shows the changes in conditional probabilities. Note that the probability for a diagnosis of tire replacement at the "action" node increases to one. Figure 6 shows a situation where a flat spot has been observed that does not require immediate replacement, and the new information has been propagated through the system. The diagnosis at the bottom level action node now indicates that the tire should be replaced at the next maintenance base. An inspector observing aircraft on the ramp could use this model to get a better understanding of the severity of a maintenance problem. A diagnosis of this type can assist the inspector in determining whether the carrier is adhering to its maintenance procedures.

HUGIN PROTOTYPE: AIRCRAFT NAVIGATION SYSTEM

Luxhøj (35) develops a HUGIN prototype to diagnose problems with an aircraft's navigation system. An accurate navigation system in an aircraft is important to aviation safety in autopilot, communications, and navigation. The inspection of the navigation system for a large aircraft is performed by comparing the readings of the altimeters on the pilot's panel and on the flight officer's (F/O) panel. The navigation system is normal when both altimeters are operative. That is, the readings from two altimeters are identical. Otherwise, a search for the faulty component is initiated. A typical altimeter consists of a meter system, a barometer indicator, and an alternative air data. The meter displays the flight altitude. The barometer indicator signals when the barometer has

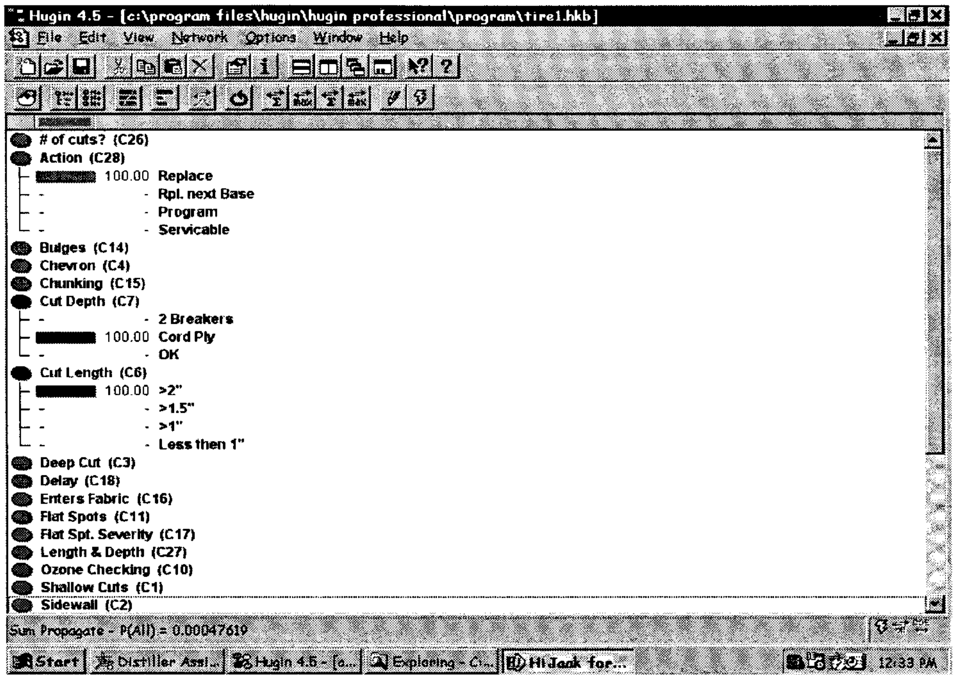

Figure 5. Propagation of "Evidence" of cut depth and cut length. [Source: Luxhøj and Williams (33)]

failed. If the barometer has failed, the altimeter is inoperative. An influence diagram displaying these causal relationships is presented in Figure 7. However, it is possible that the altimeter is inoperative when the barometer is normal. Some of these types of altimeter errors can be corrected if the alternative air data is selected. The alternative air data can also correct some of fluctuating meter problems. The influence diagram with probabilities is shown in Fig. 8. The conditions of components which affect the altimeter's reading are shown in the left. Each component is subject to one

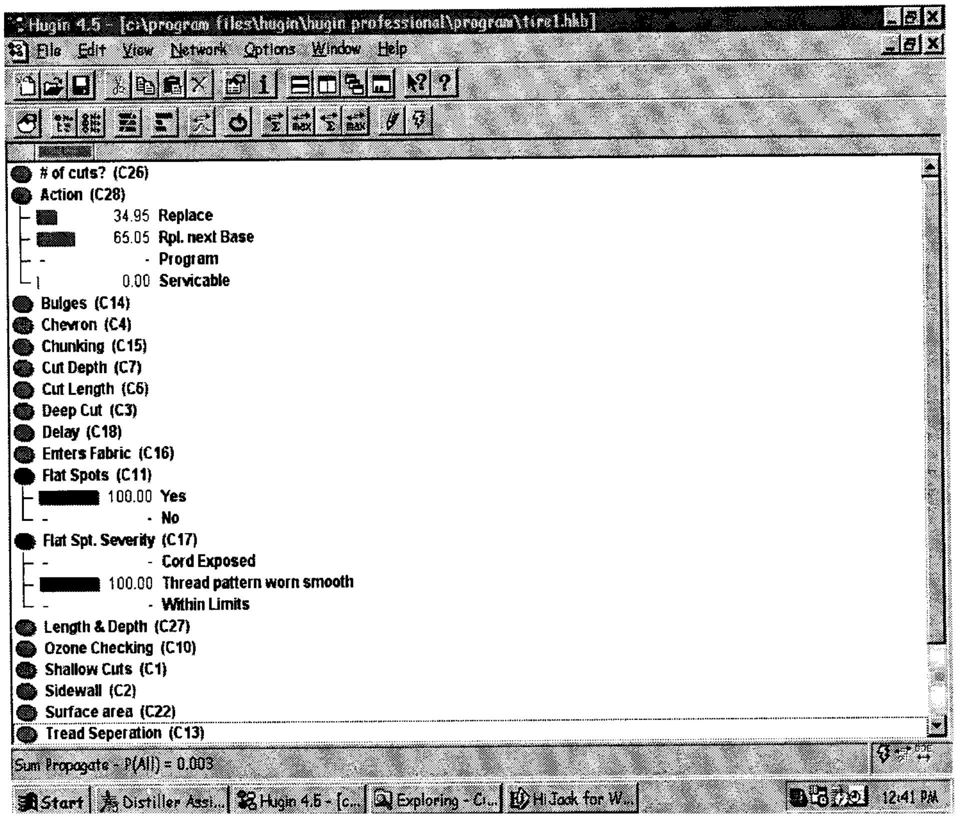

Figure 6. Observation of flat spot and maintenance recommendation. [Source: Luxhøj and Williams (33)]

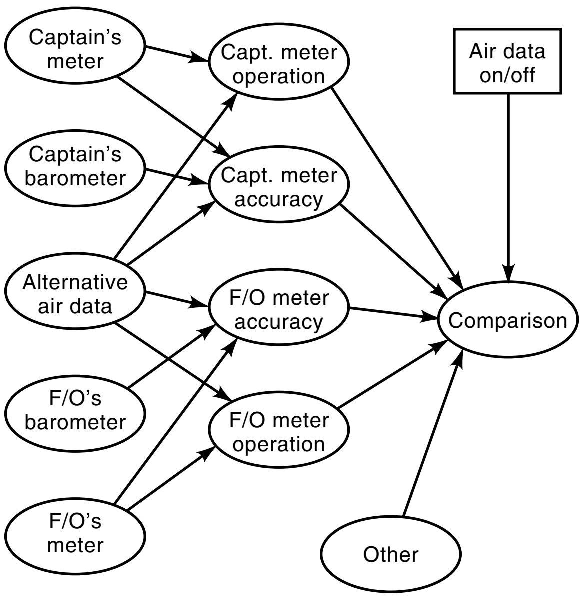

Figure 7. Influence diagram showing causal relationships for aircraft navigation system. [Source: Luxhøj (35)]

Table 1. Descriptions of Fault Codes for Aircraft Navigation System

Fault Codes	Descriptions
34-12-01-01	Inoperative barometer on captain's altimeter
34-12-02-01	Rectifiable nonbarometer related error on captain's altimeter
34-12-03-31	Not rectifiable nonbarometer related error on captain's altimeter
34-12-07-01	Captain's meter is sticking
34-12-70-01	Rectifiable fluctuation on captain's meter
34-12-71-01	Not rectifiable fluctuation on captain's meter
34-12-04-02	Inoperative barometer on flight officer's altimeter
34-12-05-02	Rectifiable nonbarometer related error on flight officer's altimeter
34-12-06-02	Not rectifiable nonbarometer related error on flight officer's altimeter
34-12-07-02	Flight officer's meter is sticking
34-12-70-02	Rectifiable fluctuation on flight officer's meter
34-12-71-02	Not rectifiable fluctuation on flight officer's meter

Source: Luxhøj (35).

or more failure modes. The status of the altimeters is indicated by the fault codes in the middle. The descriptions of the fault codes are listed in Table 1. The comparison result and the selection of the alternative air data is displayed in the right.

Note that there are three observations for the inspection: the condition of the metering system (normal, sticky, or fluctuating), the barometer indicator, and the comparison result. In addition, the selection of the alternative air data is an action. By propagating the evidence of the observations, the network would provide the possible fault codes of the navigation system. As illustrated in Fig. 8, if an inspection shows that

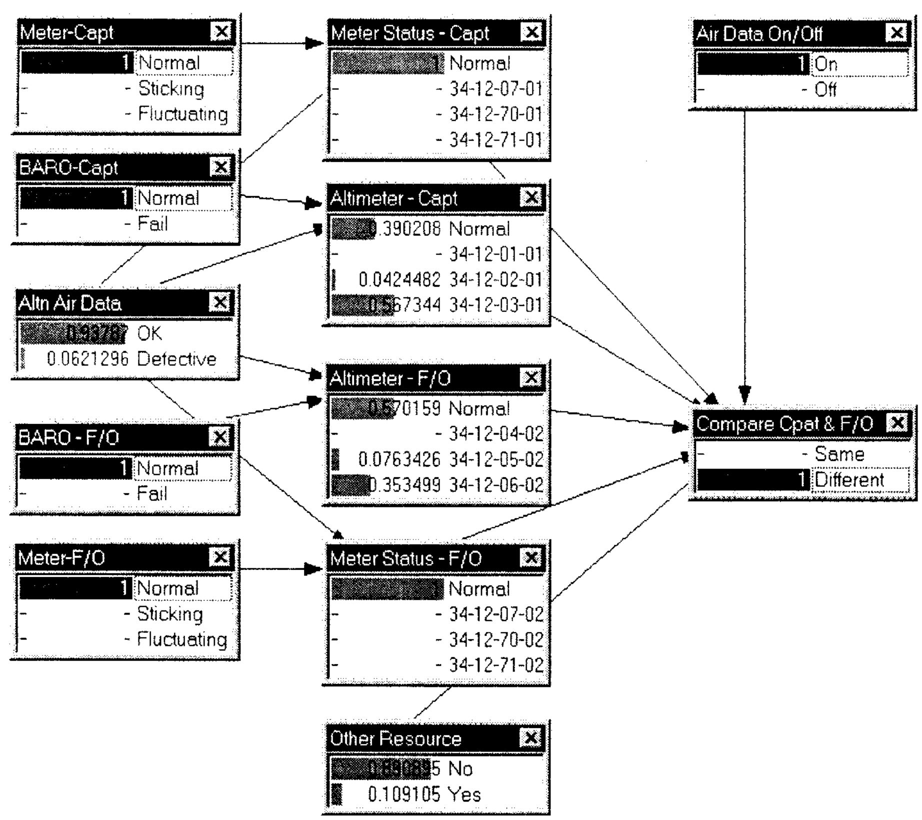

Figure 8. Navigation system model with probabilities given that all observations are known. (HUGIN Result). [Source: Luxhøj (35)]

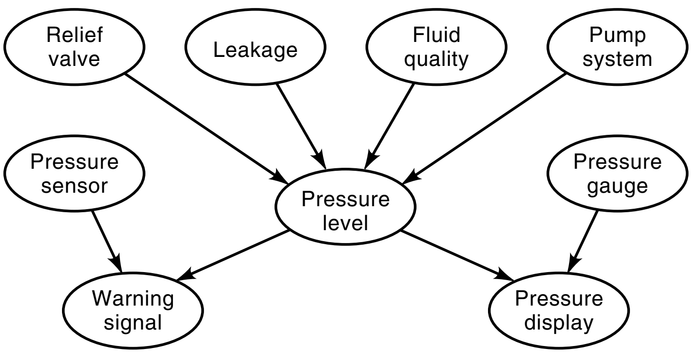

Figure 9. Influence diagram showing causal relationships for aircraft hydraulic system. [Source: Luxhøj (35)]

the readings from two altimeters are different with the alternative air data selected, but both meters are normal and none of the barometer indicators is on, the inspector would know the most possible fault is a not rectifiable altimeter error on the pilot's panel from the information provided by the network.

HUGIN PROTOTYPE: AIRCRAFT HYDRAULIC SYSTEM

Luxhøj (35) also reports on a HUGIN prototype to diagnose technical problems with an aircraft's hydraulic system. The hydraulic system of an aircraft should maintain its pressure in a normal range, that is, a working level, in order to support the control surface to function. A hypothetical example in Fig. 9 shows that the pressure level in the hydraulic system is affected by the presence of leakage, the fluid quality, and the conditions of the relief valve and the pump system. The pressure is monitored by a dual system: the pressure gauge displays the pressure level, and a sensor lights up a warning signal when the pressure is out of the normal range. However, the monitoring results will be in error if the sensor or the pressure gauge has failed. An influence diagram with probabilities or a causal probabilistic network is shown in Fig. 10.

Usually, the only information for the hydraulic system is obtained from the pressure display and the state of the warning signal. If the information suggests that the hydraulic system is in error, knowing the most possible factor that causes the error would facilitate the identification of the problem efficiently. A case in Fig. 10 shows that we can almost ensure that the actual pressure level is lower than the normal range when the pressure gauge displays low pressure level and the warning signal is on. The network also shows several candidates to cause the malfunction: the relief valve fails in opening, the quality of the fluid has degraded, or the system has leaks. Since both the relief valve and the fluid quality have the highest probabilities to fail, the most efficient inspection or maintenance is to start the diagnosis with these two causes.

An inspector who found that the fluid of the hydraulic system was just serviced so that the fluid quality should be good can enter this evidence into the network and obtain the new findings from the network as in Fig. 11. Now, the probability of the leakage increases, but the relief valve that fails in opening is even more evident. The inspector should check the relief valve first and probably would identify it as the cause for the low hydraulic pressure.

CONCLUSIONS

After observing a problem, the aircraft inspector begins to identify the causes for the problem quickly. Therefore, the

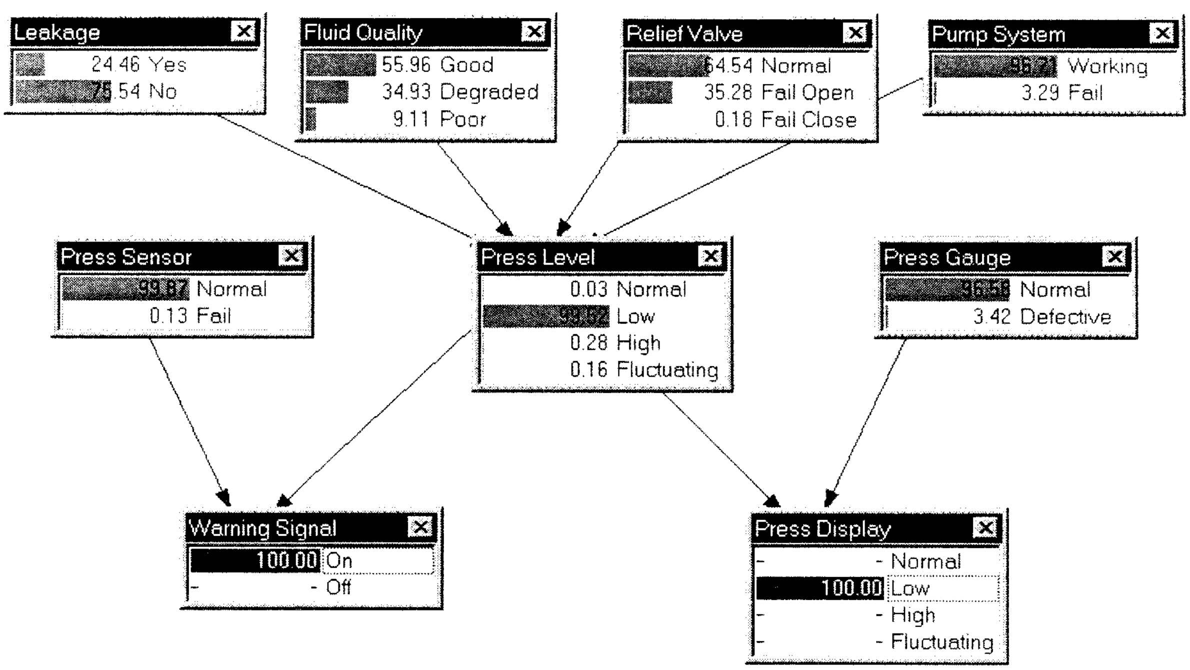

Figure 10. Hydraulic system model with probabilities given that the pressure display shows low level and warning signal is on. (HUGIN Result). [Source: Luxhøj (35)]

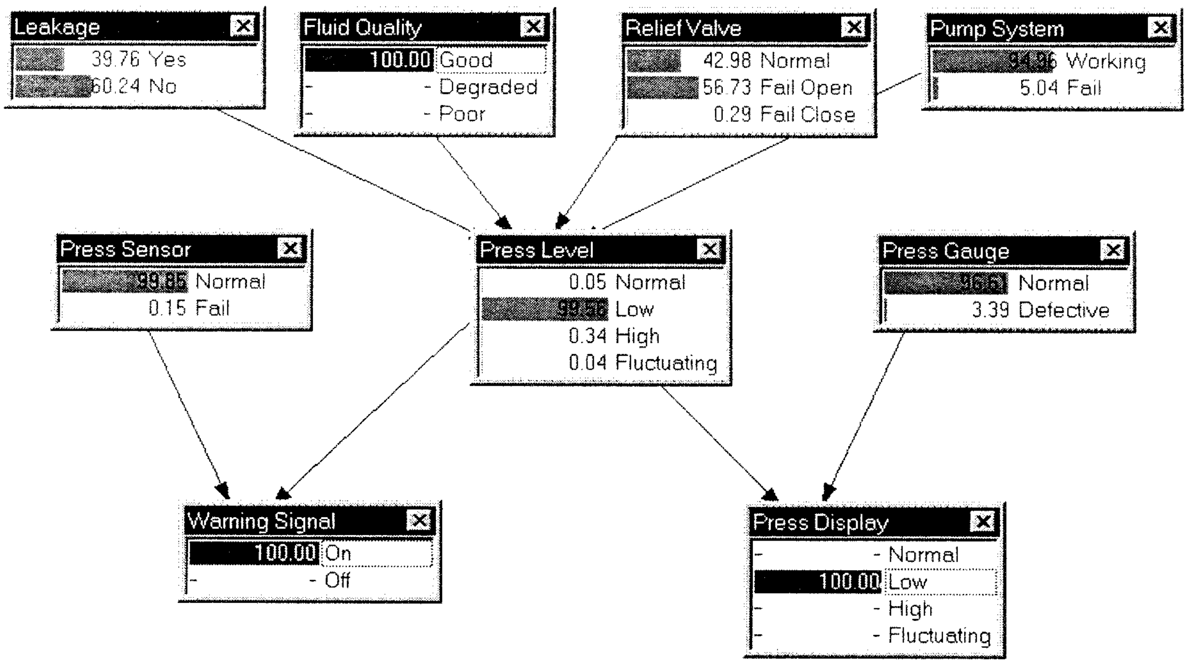

Figure 11. Hydraulic system model with probabilities given that the pressure displays low level, warning signal is on, and fluid quality is good. (HUGIN Result). [Source: Luxhøj (35)]

probabilities of the possible causes are important references to prioritize the search and to identify the causes precisely and efficiently. Such probabilities can be provided by a Bayesian network, as described in the previous examples. The influence diagram that identifies causes in a malfunctioning system is modeled by a Bayesian network. When any problem is detected, the posterior probabilities of possible causes can be determined after the observations are entered into the network.

The calculations of propagating the evidence are based on probability theories. Although the calculations are usually tedious, several software tools are available and can propagate the evidence quickly. The Bayesian network model then serves as a convenient decision support device for aviation safety inspectors. Probability theory enables the development of qualitative relationships among beliefs and the ability to process the relationships between these beliefs so that plausible conclusions can be obtained. Once the user inputs his or her beliefs, the Bayesian network can then be used to make inferences about the beliefs in response to observations.

In this study, a domain expert in aircraft safety with 15 years of aviation experience was consulted to verify the structure of the Bayesian networks for each example and to assess the probabilistic relationships in the belief networks. The belief network representation allows an expert to structure relationships about a system qualitatively, and then to quantify those relationships with conditional probabilities. Belief networks thus form the basis of a diagnostic reasoning system. Our domain expert certified that the models provide accurate inferences about an inspector's beliefs as a function of evidence.

In conclusion, a Bayesian network can be modeled for aviation safety scenarios to provide probabilities of possible causes for safety-related problems. The probabilities of the causes support the inspector's decision in assigning priorities to the search to identify the safety problems. Knowledge elicitation is less than in rule-based systems, since the knowledge is embedded in the structure of the Bayesian belief network. Such a network also has potential to function as an intelligent tutoring system for novice aviation safety inspectors who are learning about inspection diagnostic procedures.

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