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OPTIMAL TROUBLESHOOTING FOR ELECTRO-MECHANICAL SYSTEMS

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ABSTRACT
When a complex electromechanical system fails, the troubleshooting procedure adopted is often complex and tedious. No standard methods currently exist to optimize the sequence of steps in a troubleshooting process. The ad hoc methods generally followed are less than optimal methods and can result in high maintenance costs. This paper describes the use of behavioral models and multistage decision-making models in Bayesian networks for representing the troubleshooting process. It discusses advantages in using these methods and the difficulties in implementing them. An *approximate method* to obtain optimal decision sequence for a troubleshooting process on a complex electromechanical system is also described.

1. INTRODUCTION
When a complex electromechanical system fails, the troubleshooting procedure that is adopted is often complex and tedious. Diagnosis is done in a series of tests and component replacement actions until enough information is obtained to isolate the fault and to bring the system back into operating condition. As the number of components increases, the costs incurred and the time spent fixing the system also increases. In troubleshooting a complex electromechanical system, it would be helpful to have a tool that suggests the most appropriate test to be carried out or the component to be replaced at each stage of the diagnostic process.

This research uses the bleed air control system of the Boeing 737NG airplane as an example application and investigates the possibility of developing such a tool using Bayesian Networks. The bleed air control system has a history of high repair costs and is considered to be fairly complex, having several critical components that may have to be tested or replaced in the event of a failure.

Most often the primary objective will be to repair the device, not just to determine what has gone wrong. At each stage of this process there may be many possible observations, tests and repairs that can be performed. In addition we may also have the option of calling a service: promoting the problem to a higher level of expertise that is guaranteed to be able to repair the device. Because these operations are expensive in terms of time and/or money, we wish to generate a sequence of actions that minimizes costs and results in a functioning device. This is known as an optimal troubleshooting plan.

If there exists a methodology or tool that can suggest the optimal trouble shooting decision sequence, the costs involved can be reduced considerably. The need for such a tool has been the motivation for our research.

2. BACKGROUND AND MOTIVATION
[Raiffa, 1968] describes the use of decision theory for solving problems involving decision making under uncertainty. Decision theory can be difficult to apply for complex diagnosis problems due to computational complexity.

The application of Bayesian networks to diagnostic modeling can be more practicable than decision theory because of inherent assumptions about conditional independence. [Breese, et al. 1992] developed an expert system using probabilistic causal model for diagnosis of efficiency problems in a gas turbine. [D'Ambrosio, 1992] explained the application of Bayesian Networks for real-time decision-making. [Heckerman, et al.1995, 1996] introduced decision theoretic troubleshooting for making cost effective decisions. They used Bayesian networks for belief updating and diagnosis, generated a large set of problem instances, and developed a Monte-Carlo technique for estimating the troubleshooting costs for a given planer and domain. [Jensen.1996, Cowell, R.G., et al. 1999] describe the use of influence diagrams and Bayesian networks for optimal decision-making.

3. DESCRIPTION OF THE 737NG BLEED AIR CONTROL SYSTEM

The 737NG bleed air control system (BACS) provides high-pressure air for use in cabin air conditioning, engine starting, lower cargo compartment heating and anti-icing systems. It bleeds air from the eighth and fourteenth stages of compressor on each side of the 737’s two jet engines. This air is routed through a heat exchanger called the pre-cooler where the bleed air is cooled with air from the engine’s fan. From the pre-cooler, the air continues to the pneumatic manifold.

The bleed air must be delivered to the manifold within specific temperature and pressure ranges. If the air was allowed to flow unrestricted, the manifold could be overheated and/or over pressurized. It is also important to be able to isolate the BACS on one engine from the other side if that system fails. A number of valves are used to regulate the air temperature and pressure and to insure that pressure is not lost through the BACS.

The High Pressure Shut Off Valve (HPSOV) restricts flow from the fourteenth compressor stage when the pressure in the eighth stage is adequate. There is a low pressure Check valve (check) to prevent airflow into the eighth compressor stage. The pressure Relief Valve (PRV) located before the pre-cooler, vents air to ambient if the system becomes over pressurized. The Fan Air Modulating Valve (FAMV) controls the rate of cooling airflow through the pre-cooler (Pclr.). The pressure Reducing and Shut Off Valve (PRSOV), which is after the pre-cooler, limits the air pressure supplied to the pneumatic manifold (man.). The PRSOV also provides over temperature protection for the manifold by reducing flow if the bleed air temperature is too high, and provides a checking function to prevent manifold pressure loss through the BACS. These components are interconnected with a series of ducts.

The BACS has several sensors that are used to diagnose system failures. These sensors include analog readings of temperature and pressure at the pneumatic manifold. There are also switches that indicate when the PRSOV is closed, when the PRV is open, and when the HPSOV is open.

4. BAYESIAN NETWORKS

A Bayesian network is a compact, expressive representation of uncertain relationships among parameters in a domain. It is a graphical model for probabilistic relationships among a set of variables. A Bayesian network consists of a set of variables called nodes and a set of directed arcs connecting them. The variables are connected based on their causal relationships.

Bayesian networks can be used to obtain the information about some variables given the information on others. Each variable has a finite set of mutually exclusive states. The variables together with the directed arcs, forms a directed acyclic graph (A directed graph is acyclic if there is no directed path $A_1 \rightarrow A_2 \rightarrow \ldots A_n$, such that $A_1 = A_n$.).

Some of the variables are identified as the *cause* nodes i.e., those whose state can affect the state of other nodes. They are also called *parent* nodes and often their state cannot be directly known. Other nodes represent the end result produced because of the state of the *cause* nodes; they are called the *effect* nodes and normally can be readily observed and help in obtaining some kind of information regarding the status of the *cause* nodes, so they are also called *information* nodes. These *information* or *effect* nodes do not have any child nodes connected to them. The directed arcs indicated the causal influence from the parent node to the child node. For each variable v with parents $p_1,\ldots,p_n$ there is specified a conditional probability table P ($v/ p_1, \ldots, p_n$). This conditional probability table gives the information or decides what state the variable v takes for a given set of states taken by it's *parent* nodes.

Figure 1 shows a very simple Bayesian network. The node A is called the *Parent* or the *cause* node and the node B is called the *child* or the *effect* node. The directed arc connecting them represents the causal relationship between them. The node *A* has two states; *True/False* and *B* have three states *above normal, below normal, Normal.* The associated probability tables look like those shown in Fig 2. Figure 2(a) shows the associated prior probabilities of variable *A* in states true /false. Figure 2(b) shows the table associated with variable *B*.

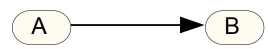


Figure 1. A Simple Bayesian Network

(a)

	P (A)
True	0.65
False	0.35

(b)

A	P (B= Above Normal /A)	P (B= Normal/A)	P (B= Below Normal/ A)
True	0.18	0.8	0.02
False	0.75	0.1	0.15

Figure 2. A model of probability tables associated with the nodes in a Bayesian network.

The values of the data points in table (b) of the Fig. 2 decide the probabilistic relationship between the node it is associated with and its parents. If the information regarding the state taken by variable B is known with certainty, then the probabilities associated with variable A are changed accordingly. Thus the relations between nodes are updated based on the information that is fed into the network.

To make a decision using *decision theory* we require the entire joint probability distribution table for the n components, which is often exponentially large in size as the value of n increases. In Bayesian networks, because of the conditional independence assumption, only the immediate parents of a node are considered to have an effect. Thus it requires only the local joint probability tables at each node.

In the conditional probability tables most of the data points take the probability values that are normalized over specific set of states taken by its parents and are easy to predict. Most of them take values of 0 or 1. In a joint probability table used in decision analysis (for switching back the links) each value has to be calculated using Baye's rule, which can require a large amount of computational time. Because of these two reasons Bayesian Networks are much easier to apply than Decision Theory. For a more detailed explanation of Bayesian Networks and causal relationships refer to [Jensen 1996], [Charniak 1991], [Pearl 1988].

A troubleshooting process starts with taking some indications from a domain that represents the machine or system of interest. These indications are an effect produced by a specific functional configuration of all the components involved. The objective in a troubleshooting process is to fix the cause of failure that is responsible for the indication observed. A decision maker observes all the indications and based on the information obtained updates his/her beliefs regarding the cause of failure. This is a backward approach to the cause-effect relationship and is similar to belief updating in Bayesian networks. Because of this similarity between a trouble-shooting process and the belief updating in Bayesian networks, Bayes nets seemed to be a potential tool to obtain an optimal troubleshooting plan. This motivated us to test the applicability of Bayesian networks to the 737 Bleed air control system.

4.1 Building A Bayesian Model For The 737-Bleed Air Control System

For building a Bayesian model that effectively represents the system of interest, a through understanding of the working of the system and the various possible indications, their interrelations, the associated ambiguity groups, the data that can be accessed, etc is required. This is necessary for choosing the variables that represent nodes, their possible states and their interdependencies. We also needed to understand how Bayes nets could be applied to obtain an optimal repair policy. Most of the existing work concentrates on the diagnosis phase only and very little information was available on how Bayesian networks can be applied to real systems to make multi stage decision-making in the troubleshooting and repair process.

A trouble shooting session is started by observing the problem-defining node to be abnormal. The 737 bleed air control system was found to have sixteen critical components. Several Bayesian networks were constructed to represent the system logically. Two of them were promising and we named them the *behavior model* and the *general model*.

4.1.1. The Behavior Model:

The behavioral model approach takes into consideration the behavior of the system and its dependence on the performance of the components. From the clustering of the components found in the schematic diagram, the airflow path is divided into four sections. In each section the air is considered to be in a specific air state, this state is described by temperature and pressure of air in that section.

Air state 1: (Compressor to Intermediate check valve or high stage valve.) In this zone the state of air i.e., the temperature and the pressure of the bleed air depends on the stage of the compressor being used to feed the Bleed Air Control System (for the 737NG it is either the 5^{th} or 9^{th} stage). If the 5^{th} stage of the compressor is used, then the node *Air State 1* refers to the air in flow path connecting the compressor and the intermediate check valve. If the feed is from 9^{th} stage then *Air state 1* refers to the air contained between the inlet from the 9^{th} stage of the compressor and the high stage valve. The temperature and pressure of the air in *Air state 1* depends on the compressor stage responsible and the condition of the ducting in this zone (a leak in the duct may result in the drop of temperature and pressure).

Air state 2: (Intermediate check valve or high stage valve to PRSOV.) The state of air in this zone depends on the state of air supplied to this zone from the preceding zone in the flow path, the check valve or high stage valve and the ducting in this zone (represented by duct 2). The two nodes, temperature at 2 and pressure at 2, give the information about air state 2.

Air state 3: (PRSOV to precooler.) This zone is affected by the ducting in this zone and the PRSOV, which in turn can be affected by Bleed air regulator.

Air state 4: The fourth and the final stage accounts for the zone of the airflow path that falls after the Precooler. The air in this zone can be affected by the FAMV (fan air modulating valve), APU check valve, duct pressure transmitter, ground check valve, precooler, over temperature switch and the ducting in this zone. The parameters of this air are the same as those given by the cabin temperature and pressure.

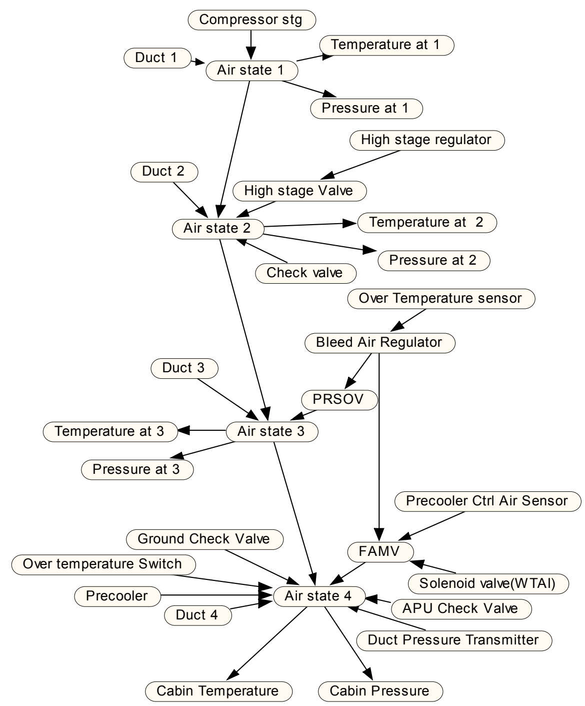


Figure 3. Bayesian network for the *Behavior* model of 737 BACS

The states taken by various nodes in the network are shown in the Table 1.

This model needs the information regarding all possible modes of failure for each component and the corresponding probability values. This information can be obtained from the FMEA and FIM. The FMEA and FIM do not provide information regarding the various possible sub states into which each air state can be divided. This model also needed some pressure and temperature related data, which was not readily available at the time of research. This approach assumes that air pressure and temperature can be observed for each air state. This model requires additional system information on the affects of failure of any specific ducting on the resulting indication set. Because of these constraints we did not investigate this model further.

Table 1. List of nodes used in the Behavior model and their corresponding states.

S.No.	Node	States of the node
1	Compressor stage	5^{th} or 9^{th}
2	High stage valve	Failed closed, failed open, Normal
3	High stage regulator	Shutoff valve failed closed, Shutoff valve failed open, no control air, high 'control' air, Normal
4	Check valve	Failed closed, failed open, Normal
5	Over temperature sensor	Failed closed, failed open, Normal
6	Bleed air regulator	Over temperature sensor failed, circuitry failure to signal high, no control air, high 'control' air, Normal
7	PRSOV	Failed closed, failed open, Normal
8	Preecoler control air sensor	Failed fully closed, failed fully open, Normal
9	Solenoid valve (WTAI)	Failed closed on ground, Normal
10	APU check valve	Failed closed, failed open, Normal
11	Over temperature switch	Failed with open circuit, failed with closed circuit, Normal
12	Duct pressure transmitter	Signal fails High, signal fails Low, Normal
13	Precooler control valve	Failed closed, failed open, Normal
14	Duct 1,2,3,4	Leak, normal
15	Air state 1,2,3,4	Not known
16	Temperature at 1,2,3	Not known
17	Pressure at 1,2,3	Not known
18	Cabin temperature	Not known
19	Cabin pressure	Not known

4.1.2. The General Model:

Unlike the *Behavior model*, this model considers only the physical components and the indication sets produced by their failure. Figure 4 shows the bayesian network representing the relations between the components and the indications produced. The set of components and indications represented in this model are listed in Appendix 2.

4.2 Building A Bayesian Network For Optimized Troubleshooting

The Bayesian network for a 16 stage trouble shooting process of this model is shown in Fig.5(b). This network is a result of using the basic network shown in Fig.5(a) and then repeating it 16 times. To make the model sensitive and to take maximum advantage of the technology (Bayesian Networks), all the components and indications are taken into consideration simultaneously in this model.

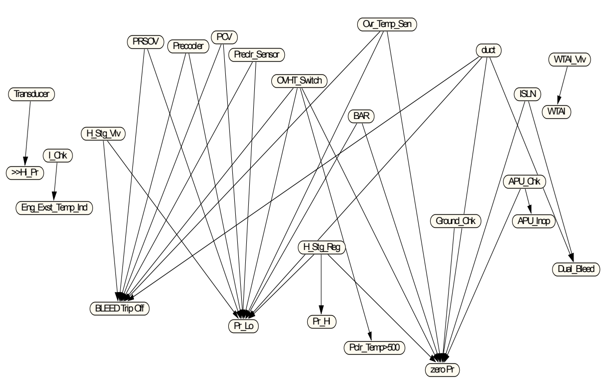
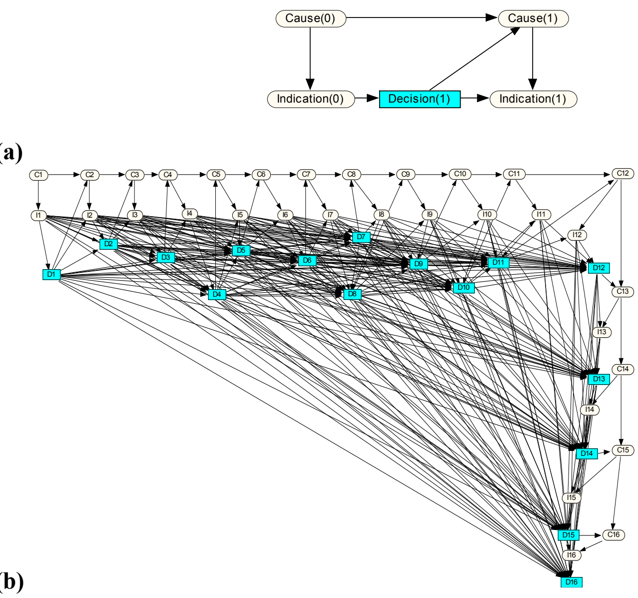


Figure 4. Bayesian network for the *General* model of 737 BACS

The nodes *C1, C2,…, C16* represent cause of failure before decisions *D1,D2,…,D16* are made respectively. The nodes *I1, I2,…, I16* are the indications observed after making the decisions D1,D2,…,D16 respectively. Each cause node C_i has 16 states. Each indication node I_i is given 11 states, except the 1^{st} indication node, which has only 8 states (as no decisions are taken prior to it and the system is assumed to be in failed state), 8 for the indications given in FMEA, two for tests (*component tested is OK, Component tested is defective)* and an additional state *Normal* to accommodate for the case when the working condition of the system is restored. Each decision node D_i has 28 states representing 16 replacement actions and 12 testing actions.

The list of states given to each *Decision, Indication* and *Cause* nodes are listed in Appendix 1.



(a)

(b)

Figure 5. Trouble-Shooting network model for optimal decision making in (a) Single-Stage (b) 16-Stage BACS

This model results in a cumbersome network as can be seen from Figure 5. In this model at the initial cause node we need 16 prior probabilities, which indicate the chance by which each one of the 16 components could be a cause of failure.
The table attached to the indication node (I1) requires 16 × 8 = 128 data points and the table attached to cause node *C2* requires 16 × 16 × 28 = 7168 data points. The remaining cause nodes have probability tables of the same size (7168 data points). All the indication nodes except I1 will have tables with 16 × 11 = 176 data points.

As we expand the network to make it suitable for multi stage decision-making, we need to fill the belief tables for each node in the network. For the decision node, the size of the data table or probability table attached increases exponentially with the stage of decision it represents. At the n^{th} stage of decision-making, the data table attached to the decision node will have $(28)^{n} \times (11)^{n} \times 8$ data points. A trouble shooting sequence for a 737 bleed air control system may extend up to 16 decision stages, hence the value of n = 16. This means that the condition table attached to the decision node will have as many as 5.25×10^{40}data points.

The entire network needs a total of 5.26×10^{40} data points to be filled. Though most of them are 0s or 1s, it is practically impossible to manually feed such huge amount of data.

Because of this practical challenge we attempted to develop a simpler model, even at the cost of compromising sensitivity to some extent. It was thought to attempt this technology by using a single indication at a time and to develop separate networks for each indication and the associated ambiguity group. From Fig.4 it can be seen that most of the indications have a very small ambiguity group and to investigate this approach, the indication *Zero Pressure* is chosen. This indication has an ambiguity group size of 8 components. The cause node in this model had 8 states. The indication node had 4 states and the decision node 14 states (8 replacements and 6 tests). The data table associated with the nth decision node contains $(14)^n \times (4)^n \times 1$. For the probability table associated with 8^{th} stage decision node 9.6×10^{13} data points are to be filled, a figure though considerably less than 5.25×10^{40} but still far beyond the scope of practical possibility.

Finally it was decided that, unless the code behind the software is changed in such a way that it makes it easier to fill the database required it is not possible to apply Bayesian networks to a complex system like Bleed Air Control System for obtaining optimal decision sequence. However with a better understanding of the system they can be used for diagnosis purposes provided the required data is available.

5. THE APPROXIMATE METHOD

This method is based on the decision-theoretic troubleshooting method suggested by [Heckerman et al. 1996]. If decision theory has to be applied to find the optimal decision sequence for the trouble shooting process, the effective cost of repair (ECR) values for all the branches of the decision tree are calculated and then the path with the lowest ECR (effective cost of repair) value is chosen, which gives the optimal decision sequence.

Let C_i^o and C_i^r be the cost of observation and the cost of repair for the component, c_i respectively. It is assumed that an observation or test will definitely be done before taking the repair action for every component. If the $c_1, \dots, c_n$ is the order in which the components are observed and repaired then the expected cost of repair is given by

$$\text{ECR}\,(c_{1,\dots,}\, c_n) =$$
$$(C_1^O + p_1 C_1^r) + (1-p_1)(C_2^O + \frac{p_2}{1-p_1}C_2^r) + (1-p_1-p_2)(C_3^o + \frac{p_3}{1-p_1-p_2}C_3^r) + \dots$$
$$= \sum_{i=1}^{n}[(1-\sum_{j=1}^{i-1} p_j)C_i^O + p_i C_i^r] \qquad (1)$$

It is also assumed that if there is no observation possible for any component then it is considered to be observed at a cost equal to the cost of repair and the cost of repair for that component is taken to be zero as the component is already repaired.

If the component c_1 is observed first incurring an observation cost of C_1^o, then the probability with which it is found defective is p_1. The defective component can be repaired with an additional cost of C_1^r, after which the process is terminated.

Another case would be when the observed/tested component is found to be OK. This can occur with a probability of $(1\text{-}p_1)$. The component is found to be functioning properly and the next component is observed and if found defective then it is repaired and the trouble-shooting action is terminated, otherwise observe the next component. This process continues until the system is brought back to working condition.

Now let us consider a troubleshooting sequence that has the same order of decisions as the sequence in the previous case, except for the terms i=k and i=k+1(which will interchange positions). That means component c_{k+1} is checked prior to checking the component c_k. The ECR value for this sequence is given by ECR ($c_1, \dots c_{k-1}, c_{k+1}, c_k, \dots c_n$).

The path with the lowest ECR value between the two paths, gives the optimal plan. To decide which of these two has the lowest ECR value, the difference between the two values is found. We obtain the difference in the expected costs of repairs of the two sequences as:

$$\text{ECR}(c_1, \dots, c_n) - \text{ECR}(c_1, \dots c_{k-1}, c_{k+1}, c_k, \dots, c_n)$$
$$= p_{k+1}C_k^o - C_{k+1}^o p_k \qquad (2)$$

The ECR ($c_{1,\dots,}c_n$) can be less than ECR ($c_{1,\dots,}c_{k+1,}c_{k,\ \dots,}\ c_n$) if and only if $p_k/C_k^o > p_{k+1}/C_{k+1}^o$. If p_1, p_2 are the probabilities of failure of two components and C_1, C_2 are the costs associated with them respectively for component c_1 and component c_2, then, the decision is made based on the values p_1/C_1^o and p_2/C_2^o. If p_1/C_1^o is greater than p_2/C_2^o, then component c_1 is tested first otherwise component c_2 is given preference. Thus by calculating the values of p_i/C_i^o for all the components and sorting them in descending order the optimal trouble shooting plan can be obtained.

The *decision-theoretic troubleshooting* method takes into consideration only the first stage decision and the results may not be as good as those obtained from decision analysis. Though the results obtained are not fully accurate, a reasonably good approximation of the optimal trouble shooting sequence can be obtained using this method

In the *decision-theoretic troubleshooting* method the assumption had been that any repair action is done only after the concerned observation/test is performed. But in the 737-Bleed Air Control System model at every stage of decision making the decision makers have the choice either to perform the test and then decide the repair action or to directly select a repair action without performing a test. To improve the accuracy of results, in the *approximate method* we relaxed this assumption.

In this case if the effective cost of repair for any component after the observation happens to be greater than the repair cost incurred if a repair action is chosen without making an observation, then it is wise to select a repair action without making an observation. This can be verified by checking if $(C_i^o + p_i C_i^r) - C_i^r > 0$ (3).

If Eq. (3) is true, then perform the replacement action directly, otherwise observe and then replace if needed. For finding out if a test/observation is required in the case of combined replacement and checkout costs we check if $[C_i^o + p_i(C_i^r + C_i^c)] - C_i^r > 0$ (4).

In determining the value of p/C for a decision to *observe and repair*, the cost C_i^o is used and for a decision to *repair without an observation*, the cost C_i^r is used. By sorting the p/C values thus obtained we can determine the optimal troubleshooting plan.

We first attempted to consider a single indication and the associated ambiguity group to find the optimal decision sequence using this method and then a general order for replacement is obtained for the complete list of 16 components. Based on this order an optimal plan for each individual indication can be found.

Thus by considering each indication and the corresponding ambiguity group separately we can obtain an optimal repair or test sequence in the presence of a specific indication. Attempts were made to use the Effective Cost of Repair values calculated in place of the individual costs of repair but the sequence obtained is not much different from that obtained using the direct repair cost.

The cost values required were obtained from estimation provided by experts. The observation and repair costs used are in terms of man-hours. Table 4 shows the costs incurred and the failure probabilities of all the critical components of the 737-Bleed Air Control System.

Table 4. Observation costs; repair costs and the failure probabilities for the critical components of 737-Bleed air Control System

After any component replacement the system is tested

#	Component	Trouble Shooting, failure verification cost (C^o)	Failure rate	Repair & Replacement Cost (C^r)	Check Out Cost (C^c)	Probability (P)	Normalized Probability (p)
1	High Stage Valve	1.2	5.43E-05	3.146	1.07	2.08E-04	0.137
2	High Stage Regulator (Controller)	0.4	4.42E-05	3.047	1.07	1.70E-04	0.111
	Check Valve	-	2.49E-06	0.75	0.25	9.56E-06	
4	PRSOV	0.8	3.44E-05	1.827	2.17	1.32E-04	0.087
5	BAR(Ctlr)	0.4	4.43E-05	3.423	1.775	1.70E-04	0.112
6	Precooler	1	1.91E-05	9.264	2.75	7.33E-05	0.048
7	PCV	0.6	4.34E-05	1.44	2.22	1.67E-04	0.109
	Precooler Ctrl Air Sensor	-	2.61E-05	3.04	1.81	1.00E-04	
9	WTAI	0.6	2.37E-05	2.962	1.55	9.10E-05	0.060
	Over Temperature Switch	-	1.38E-05	1.2	0.75	5.30E-05	
	Bleed Air Over Temp Sensor	-	1.05E-05	3.04	1.81	4.03E-05	
12	Duct Pressure Indication Transmitter	1	1.73E-05	2.5	1.4	6.64E-05	0.044
13	Isolation Valve	1.2	9.10E-06	1.94	0.42	3.49E-05	0.023
14	APU Check valve	0.8	9.56E-06	1.5	0.325	3.67E-05	0.024
15	Ground Air Start Check Valve	0.6	9.56E-06	1.5	0.325	3.67E-05	0.024
16	Duct	0.33	3.54E-05	4	2.5	1.36E-04	0.089

again. The costs incurred in this process are called check out costs, C^c. In such a case the total cost of repair will be the sum of the *repair/replacement cost* alone and the *check out cost*. Table 5 shows the results obtained from two separate investigations for identifying the components that need a test/*observation* before the *repair/replacement* action. In either case the results supported an *observation/test* action before a *repair/replacement* action, wherever it is possible. The rows with gray shade indicate the components that did not have any special observation or test. From the results obtained, all components would be tested before replacement.

Table 5. Is an *observation/test* action required before a *repair/replacement?*

Component	$C_i^o + p_i C_i^r$	$C_i^o + p_i(C_i^r + C_i^c)$	IS $(C_i^o + p_i C_i^r) - C_i^r > 0$?	IS $[C_i^o + p_i(C_i^r + C_i^c)] - C_i^r > 0$?
High Stage Valve	1.63E+00	1.78E+00	Yes	Yes
High Stage Regulator (Controller)	7.39E-01	8.58E-01	Yes	Yes
Intermediate Check Valve	7.50E-01	1.00E+00	-	-
PRSOV	9.58E-01	1.15E+00	Yes	Yes
Bleed Air Regulator (Controller)	7.82E-01	9.80E-01	Yes	Yes
Precooler	1.45E+00	1.58E+00	Yes	Yes
Precooler Control Valve	7.57E-01	1.00E+00	Yes	Yes
Precooler Control Air Sensor	3.04E+00	4.85E+00	-	-
Solenoid Valve (WTAI) (CTAI)	7.77E-01	8.69E-01	Yes	Yes
Over Temp Switch	1.20E+00	1.95E+00	-	-
Bleed Air Over Temp Sensor	3.04E+00	4.85E+00	-	-
Duct Pressure Indication Transmitter	1.11E+00	1.17E+00	Yes	Yes
Isolation Valve	1.24E+00	1.25E+00	Yes	Yes
APU Check valve	8.36E-01	8.44E-01	Yes	Yes
Ground Air Start Check Valve	6.36E-01	6.44E-01	Yes	Yes
Duct	6.86E-01	9.09E-01	Yes	Yes

Table 6. Indication ambiguity Group and Its Size.

#	Indication	Possible Causes	Size of the ambiguity group
1	BLEED TRIP OFF Light On	High Stage valve, Bleed air Regulator, PCV, Over temp Switch	4
2	Bleed Valve will not close when the Bleed switches moved to OFF, Engine is the bleed source	PRSOV, Bleed air Regulator	2
3	Duct Pressure High, engine is the bleed source	PRSOV, Bleed air regulator Duct pressure transducer, Dual duct pressure indicator	4
4	Duct Pressure Low, engine is the bleed source	PRSOV, Bleed air regulator Duct pressure transducer, Dual duct pressure indicator High stage Valve High stage controller, PCV, duct	8
5	Duct Pressure Zero, engine is the bleed source	PRSOV, Bleed air regulator Duct pressure transducer, Dual duct pressure indicator 450 deg F Thermostat PCV, duct	7
6	Isolation Valve does not Open or Close properly	Bleed Air Isolation Valve	1
7	Duct pressure, L and R pointers not the same (split), engine is the bleed source	PRSOV, Bleed air regulator Duct pressure transducer, Dual duct pressure indicator High stage Valve High stage controller, PCV, duct	8
8	Duct pressure, L and R pointers not the same (split), APU is the bleed source	Duct pressure transducer, Dual duct pressure indicator Isolation Valve	3

Table 6 shows the ambiguity group size and the various possible causes for the set of eight indications as given in the FIM.

Table 7 shows the ranking of the components based on p/C values calculated using normal *repair/replacement cost* and the combined *repair/replacement* cost. Based on these rankings the optimal trouble shooting sequence in the presence of any indication given in table 6 can be found. For example, when the BLEED TRIP OFF Light is *On*, the ambiguity group contains high stage valve (5), Bleed air regulator (BAR) (1), PCV (4), over temperature switch (13) (The numbers in braces adjacent to each component indicates its rank according to table 5(b)). Following the priority order indicated by the rank and including the tests an optimal plan is obtained. The optimal troubleshooting (TS) sequence for this indication would be:

1. Test BAR, if defective replace BAR and terminate TS or continue
2. Test PCV, if defective replace PCV and terminate TS or continue
3. Test High Stage Valve, if defective replace High Stage Valve and terminate TS or continue
4. Replace Over Temperature Switch and terminate TS.

Table 7. (a) ranking by using normal *replacement/repair* cost

Rank	Component	p/C
1	Bleed Air Regulator (Controller)	0.279
2	High Stage Regulator (Controller)	0.278
3	Duct	0.27
4	Precooler Control Valve	0.182
5	High Stage Valve	0.114
6	PRSOV	0.108
7	Solenoid Valve (WTAI) (CTAI)	0.099
8	Precooler	0.048
9	Duct Pressure Indication Transmitter	0.044
10	Ground Air Start Check Valve	0.04
11	APU Check valve	0.03
12	Over Temp Switch	0.029
13	Precooler Control Air Sensor	0.022
14	Isolation Valve	0.019
15	Bleed Air Over Temp Sensor	0.009
16	Intermediate Check Valve	0.008

(b) ranking by using combined *replacement/repair* cost

Rank	Component	P/C
1	Bleed Air Regulator (Controller)	0.279
2	High Stage Regulator (Controller)	0.278
3	Duct	0.27
4	Precooler Control Valve	0.182
5	High Stage Valve	0.114
6	PRSOV	0.108
7	Solenoid Valve (WTAI) (CTAI)	0.099
8	Precooler	0.048
9	Duct Pressure Indication Transmitter	0.044
10	Ground Air Start Check Valve	0.04
11	APU Check valve	0.03
12	Isolation Valve	0.019
13	Over Temp Switch	0.018
14	Precooler Control Air Sensor	0.014
15	Intermediate Check Valve	0.006
16	Bleed Air Over Temp Sensor	0.005

6. DISCUSSION

Decision Analysis is a well-known tool for making optimal decisions. But the number of branches in a decision tree becomes very large for relatively small number of choices. Even for making an optimal decision in a troubleshooting process of a simple system this number will be exponentially large. When applied with a complex system such as a 737-BACS with sixteen critical components the number of branches to be evaluated will be more than 2.0×10^{17}. Although this method is more potentially accurate than the other methods discussed in this paper, it is impractical to apply in complex real world scenarios. This method is a one-time useful tool. For any small changes in the probability values, cost values and physical configuration of the system under consideration, the entire decision tree has to be re-evaluated.

Bayesian Networks is also a technology that can be a useful tool in decision-making. There are many commercial software tools that can be used for building Bayesian models and are available at reasonable price. A Bayesian network once built can easily accommodate small changes in the data or minor modifications in the physical configuration of the system, thus it is a many-time usable tool. This technology serves very well for diagnosis of a complex electromechanical system, but is found to be too complex for obtaining an optimal multi stage decision sequence using the available software tools. *Bayesian networks* are not as accurate as decision analysis due to the assumption of conditional independence.

The *approximate method* is a very simple procedure compared to the above two methods and found to be the most practical method. Though the results obtained are approximate, they can be of potential help to the decision maker in a troubleshooting process. This method is logically much stronger than *ad hoc decision-making* methods often used in the industry.

All the above methods are based on probability theory, which in itself is a subjective concept and the results they provide may not be hold true in all situations. In such a case the approximate method is a very good tool that provides reasonably good results at a relatively low cost and effort.

In all the above-discussed methods many approximations and assumptions are made to make the system under consideration suitable for applying the theories discussed. Without these assumptions and approximations, it would be impossible to meet all the data requirements and the computation time required in the process. One such assumption is that there exists only a single failed component in the event of a system failure indication. If we relax this assumption and include multiple failures, a system with n components will have (2^n -1) different configurations of failure. This assumption is considered reasonable, given the low failure rates of the components in the 737-BACS.

7. RECOMMENDATIONS

Using the priority order suggested, the manuals that are currently in use like FIMs and FMEAs can be improved. If an integrated Bayesian network is built by combining the Bayesian models for isolated systems, it can improve the efficiency of the *diagnosis* procedure. This is because any specific failure may have connected effects on other systems and thus there will be more indications for any cause of failure and this can help in easy isolation of faults.

Building *Behavior* models for this purpose can enhance the scope of the Bayesian network used. For this purpose it would be more beneficial to use the experience of an expert regarding the indications and failure causes than relying on the standard manuals like FIMs and FMEAs. The manuals often deal with each system in isolation and often does not give enough information regarding the variables that actually describe the behavior of the system under consideration. This limits the sensitivity of the Bayesian models that can be developed.

8. CONCLUSIONS

There are no standard methods to optimize the troubleshooting sequence of a complex electromechanical system. The ad hoc methods followed often result in high maintenance costs. With a 737-Bleed air control system as a model this paper showed building behavior models and multistage decision-making models in Bayesian networks. It discussed advantages in using them and the difficulties in implementing them. An *approximate method* to obtain optimal decision sequence for a troubleshooting process on a complex electromechanical system is demonstrated.

1. The *Bayesian Network* method can be applied to diagnose a complex electro-mechanical system. It cannot be used to obtain the optimal trouble shooting sequence using the existing software tools due to practical constraints on computational time and memory requirements.
2. The *approximate method* can be used to obtain a reasonably good approximation of the optimal troubleshooting sequence. The disadvantage of this approach is that it uses only a one step look ahead.

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REFERENCES

1. Breese, J., Horvitz, E. Poet, M., 1992, "Automated Decision-Analytic Diagnosis Of Thermal Performance In Gas Turbines," Proceedings of the International Gas Turbine and Aeroengine Congress and Exposition, ASME 1992.
2. Breese, J.S., Heckerman, D., 1996, "Decision-theoretic Troubleshooting: A Framework for Repair and Experiment," Technical Report MSR-TR-96-06, Microsoft Research, advanced technology division, Microsoft Corporation, Redmond, USA.
3. Breese, J.S., Heckerman, D., 1996, "Decision-theoretic Troubleshooting: A Framework for Repair and Experiment," Technical Report MSR-TR-96-06, Microsoft Research, advanced technology division, Microsoft Corporation, Redmond, USA.
4. Charniak, E., 1991, "Bayesian Networks Without Tears," Artificial Intelligence Magazine, Winter 1991.
5. Clark, G.E., Paasch, R.K., 1996, "Diagnostic Modeling And Diagnosability Evaluation Of Mechanical Systems," Journal of Mechanical Design, September 1996.
6. D'Ambrosio, B., 1992, "Real-time Value-driven Diagnosis". Third Workshop on Principles of Diagnosis, October 1992.
7. D'Ambrosio B., 1999, "Inference in Bayesian Networks," AI Magazine 20(2).
8. Eubanks, C. F., Kmenta, S., Ishii, K., 1996, "System Behavior Modeling As A Basis For Advanced Failure Modes And Effects Analysis," Proceedings of The ASME Design Engineering Technical conference. 1996
9. Jensen, F.V., 1996, "An Introduction to Bayesian Networks," UCL Press, London.
10. Pearl, J., 1988, "Probabilistic Reasoning In Intelligent Systems: Networks Of Plausible Inference," Morgan Kaufman.
11. Raiffa, H., 1968, "Decision Analysis: Introductory Lectures On Choice Under Uncertainty," Random House series.

APPENDIX 1:

List of states in the decision node

D1: Replace High Stage Valve
D2: Replace High Stage Regulator (Controller)
D3: Replace Intermediate Check Valve
D4: Replace PRSOV
D5: Replace Bleed Air Regulator (Controller)
D6: Replace Precooler
D7: Replace Precooler Control Valve
D8: Replace Precooler Control Air Sensor
D9: Replace Solenoid Valve (WTAI) (CTAI)
D10: Replace Over Temp Switch
D11: Replace Bleed Air Over Temp Sensor
D12: Replace Duct Pressure Indication Transmitter
D13: Replace Isolation Valve
D14: Replace APU Check valve
D15: Replace Ground Air Start Check Valve
D16: Replace Duct

D17: Test High Stage Valve
D18: Test High Stage Regulator (Controller)
D19: Test PRSOV
D20: Test Bleed Air Regulator (Controller)
D21: Test Precooler
D22: Test Precooler Control Valve
D23: Test Solenoid Valve (WTAI) (CTAI)
D24: Test Duct Pressure Indication Transmitter
D25: Test Isolation Valve
D26: Test APU Check valve
D27: Test Ground Air Start Check Valve
D28: Test Duct

List of states in the *cause* node

C1: Defective High Stage Valve
C2: Defective High Stage Regulator (Controller)
C3: Defective Intermediate Check Valve
C4: Defective PRSOV
C5: Defective Bleed Air Regulator (Controller)
C6: Defective Precooler
C7: Defective Precooler Control Valve
C8: Defective Precooler Control Air Sensor
C9: Defective Solenoid Valve (WTAI) (CTAI)
C10: Defective Over Temp Switch
C11: Defective Bleed Air Over Temp Sensor
C12: Defective Duct Pressure Indication Transmitter
C13: Defective Isolation Valve
C14: Defective APU Check valve
C15: Defective Ground Air Start Check Valve
C16: Defective Duct

List of states in the *indication* node

I1: BLEED TRIP OFF Light On
I2: Bleed Valve will not close when the Bleed switches moved to OFF, Engine is the bleed source
I3: Duct Pressure High, engine is the bleed source
I4: Duct Pressure Low, engine is the bleed source
I5: Duct Pressure Zero, engine is the bleed source
I6: Isolation Valve does not Open or Close properly
I7: Duct pressure, L and R pointers not the same (split), engine is the bleed source
I8: Duct pressure, L and R pointers not the same (split), APU is the bleed source

I9: Normal
I10: Tested component OK
I11: Tested component defective

APPENDIX 2:

Node	Component / Indication
Transducer	Pressure Transducer
PRSOV	Pressure relief and shutoff valve
PCV	Pressure Control Valve
Preclr_Sensor	Precooler Sensor
H_Stg_Vlv	High stage Valve
OVHT_Switch	Over Heat Switch
Ovr_Temp_Sen	Over Temperature Sensor
Duct	air ducts connecting components
H_Stg_Reg	High Stage Regulator
BAR	Bleed Air Regulator
Ground_Chk	Ground Check Valve
ISLN	Isolation Valve
WTAI_Vlv	Wing Thermal Anti-icing Valve
WTAI	Wing Thermal Anti-icing
APU_Chk	Auxillary Power Unit Check Valve
APU_Incp	Auxillary Power Unit Insufficient Pressure
Dual_Bleed	Bleed air present from both engines
H_Stg_Reg	High Stage Regulator
I_Chk	Intermediate Check Valve
Eng_Exst_Temp_Ind	Engine exhaust Temperature Indicator
BLEED TripOff	Bleed tripOff Light
Pr_Lo	Pressure Low Indication on the Gauge
Pr_Hi	High Pressure Indication
Pclr_Temp>500	Precooler temperature is above 500Deg C
Zero Pr	Pressure gauge indicating zero pressure
>>Hi_Pr	Abnormally high gauge pressure