Adoption of a Bayesian Network for the Operational Reliability Analysis of Aircraft Systems

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Abstract. To assess and analyze the operational reliability of aircraft systems, an aircraft system Bayesian network (ASBN) method is proposed with the functional and logical coupling relationship of aircraft components, which integrates the characteristics of components related to aircraft operation, is built for analyzing the operational reliability under considering the effect of stochastic features. The aircraft system operating reliability is first assessed by forward inference of ASBN. And the most likely failure component or subsystem under the appearance of different failure condition severity categories are identified. The results show that the aircraft system operating reliability is not as high as the reliability of its components; the most likely failure component or subsystem are those tightly connected to other components or subsystems. The efforts of this paper provide a useful way for deriving operational reliability analysis of complex systems.

1. Introduction

In order to ensure the safety of civil aviation aircraft operation, the aircraft is regulated in relevant laws and regulations in the design and manufacturing, aircraft operation and maintenance. The Federal Aviation Administration (FAA) in the United States and European Aviation Safety Agency (EASA) are the certification authority for airworthiness of civil aircraft. Therefore, the failure probability of each part of the aircraft is not higher than the airworthiness requirement. Aircraft reliability was an important aspect of aircraft safety, its analytical calculation methods have been extensively studied from theory and practice.

There were some classical methods to assess system reliability [1]. The reliability block diagram (RBD) can represent the topology of a system, its blocks represent system components, and links between blocks represent the connections between components. The RBD can model the components of the system and their connections, but it is not sufficient for the complex system reliability analysis. The fault tree (FT) is a top down analysis method, it compute the top event failure thought lower-level events and its relationship between events. FT had been used in aviation industry [2], but its binary event state and complex failure paths caused its application in complex systems would be great limitations. As an inductive method, the event tree can assess the risk of occurrence of different system outcomes by tracing forward through a causal chain. Similarly, while adopting event tree to analyze the complex systems, the size of an event tree can grow rapidly. A Bayesian network is a directed acyclic graph, its node represents a random variable and its link represents the probabilistic dependency between the variables [3]. Each children node is described by a conditional probability table, which describes the conditional probability distribution of the node given the states of its parents. Since node can be defined with multi-state distributions, it can deal with the uncertainty
adequately. What’s more, Bayesian network can use forward and backward inference to analyze the outcomes under collected data information. Thus, Bayesian network is a powerful tool for infrastructure system modeling and reliability analysis.

Iris Tien [1] proposed novel Bayesian network (BN) methodologies to study the reliability assessment of infrastructure systems. To minimize the risk of system failure, both Bayesian forward and backward inference has been used to analyze the infrastructure systems under operating environment and sensor measurements uncertain. The result showed that Bayesian network to be robust to systematic uncertainties, besides, it was an effective way to analyze infrastructure systems reliability.

Achim Washington et al. [4] studied the system safety assessment of remotely piloted aircraft with Bayesian belief network. The subsystems that affect the safety of the aircraft system were interrelated, and the failure laws of each subsystem are different. For example, as a multicomponent structure, the turbine blisk, its failure modes are various while it enduring dynamic workloads, dynamic probabilistic failure analysis could be applied to assess its transient reliability evaluation and structural safety [5-6]. Since traditional system safety analysis can’t adequately take potential uncertainty into consideration, much less the inconstant components failure rate. The Bayesian belief network system safety approach is available to update testing and operational experience data and to deal with the high uncertainty associated with aircraft system scientifically. These analyses can provide a more realistic understanding of the safety characteristics of aircraft systems, which can assist regulators in making more objective and systematic decisions during the stage of designing, manufacturing, operating and maintenance.

Bayesian network had been used for complex system reliability [7]. A complex system, its components may have various performance states and reliability parameters are uncertain, traditional reliability analysis methods cannot handle these issues, but Bayesian networks can perform these tasks well. Besides, the aircraft reliability about the hydraulic system [7] and electrical power system [8], can be analyzed by Bayesian network. The results showed that the Bayesian network can efficiently analyze the reliability of those systems.

Aircraft operational reliability is a measure of the reliability of the aircraft during flight missions, and it reflects the comprehensive influence of factors such as design, manufacturing, operating, maintenance and operational environment. This paper will use the B737NG series aircraft as an example to build an aircraft system Bayesian network (ASBN), its operational reliability will be analyzed based on the failure probability of each component.

2. Aircraft safety regulations
The aircraft specific equipment or subsystems are required to meet prescriptive standards. From intended missions to operational environments, its components safety features have been satisfied minimum objectives. Regulations about aircraft safety can refer to FAA [9] or Civil Aviation Administration of China (CAAC) [10], the comparative of these safety objectives, failure probability (Average probability of failure per flight hour) objectives as follow:

| Accident probability (hrs⁻¹) | FAA          | CAAC         |
|-----------------------------|--------------|--------------|
| Probable                    | >10⁻⁵        | >10⁻⁵        |
| Remote                      | 10⁻⁵ to 10⁻⁷ | 10⁻⁴ to 10⁻⁷ |
| Extremely Remote            | 10⁻⁷ to 10⁻⁹ | 10⁻⁷ to 10⁻⁹ |
| Extremely Improbable        | <10⁻⁹        | <10⁻⁹        |

Every commercial transport aircraft meets the corresponding specifications, but this does not mean that the aircraft is absolutely safe. For the complexity of the aircraft operating environment and the
uncertainty of aircraft failure, there are still different levels of failure impact. By refer to FAA and CAAC, the different failure condition severity categories are interpreted as follow:

- **Minor.** Failure conditions that would not significantly reduce the aircraft and that cause a series of subsequent adverse effects. Minor failure conditions may include a slight reduction in safety margins or functional capabilities, a slight increase in flight crew workload.

- **Major.** Failure conditions that would reduce the capability of the aircraft, its safety margins, functional capabilities or separation assurance would be a significant reduction in these conditions. The flight crew would cope with adverse operating conditions. In addition, the failure condition has a significant increase in flight crew workload or impairs flight crew efficiency.

- **Hazardous.** Failure conditions that would reduce the capability of the aircraft significantly, a large reduction in safety margins, functional capabilities or separation assurance. The flight crew workload could be excessive, their flight tasks could not be completed accurately or completely.

- **Catastrophic.** Failure conditions that is expected to result in losing the ability to control the aircraft, or causing the uncontrolled crash.

These four failure effect categories would be occur in the case of different component failures. Analysis of different probability ranges and failure effect categories is necessary to study aircraft system operational reliability.

### 3. Aircraft system Bayesian Network

Since the different components have their own different failure laws, the failure rules of aircraft systems composed of these different components are more complex and random. As mentioned before, the system that composed by different components and their failure rules are unclear can be analyzed by Bayesian network. In this chapter, the subsystems of B737NG and its components would be stated; the link relationship of each component and the dependencies between subsystems will be analyzed in detail.

#### 3.1. Aircraft components and subsystems

In this part, the components and subsystems about B737NG would be presented and the connections between components would be focused more on analyzing.

**Power plant system.** There are two CFM56-7B engines providing thrust for B737NG. Besides, it incorporates engine powers electric, hydraulic, pneumatic. Engine is controlled by electronic engine control (EEC); integral drive generator (IDG) and engine driven pump (EDP) are provided power by engine, they are important part of electric system and hydraulic system respectively; the engine also supplies air to the air conditioning system. Auxiliary Power Unit (APU) could supply air and electric for the aircraft if necessary. EDP fuel is a pump that boosted fuel for engine.

**Electrical power system.** Direct current bus (DC bus), alternating current bus (AC bus), main battery (MBAT), auxiliary battery (ABAT) are the four main parts of electrical power system, from which all electrical appliances on the aircraft will get their energy.

**Hydraulic system.** B737NG had three hydraulic systems, hydraulic system A, hydraulic system B, standby hydraulic. Hydraulic system A or B is provided pressure by electric motor driven pump (EMDP) or EDP, an EMDP provides pressure for standby hydraulic. Hydraulic system provides hydraulic power for the action mechanism of the aircraft.

**Fuel system.** Fuel system provides fuel for engine and APU. A center tank and two main tanks in B737NG, fuel system had three pumps on each side: AFT pump, FWD pump and center pump. Those pumps are driven by AC bus.

**Air-cond system.** Bleed air systems get fresh air from engine or APU, the air would be cooled or heated, and then boosted, sent to target cabin finally.

**Landing gear system.** B737NG include main landing gear and nose landing gear. For studying the operation of aircraft, its breaking, up and down would be focused more on this paper.

**Anti-ice system.** Wings, engines, pitots, windshield are key parts of anti-icing. Anti-icing of wing and engine relies on bleed air system, others rely on electrical power system.
Flight management system. The paper summarizes all airborne automation systems into flight management system. Flight management system (FMS) integrates all flight operational related automation subsystems on board, including flight management computer (FMC), very high frequency omnidirectional range (VOR), distance measuring equipment (DME), traffic alert and collision avoidance system (TCAS), air traffic control (ATC), Global Positioning System (GPS), ground proximity warning system (GPWS), radio altimeter (RA), weather radar (WXR), atmospheric data inertial reference system (ADIRS) and autopilot flight director system (AFDS).

Secondary flight control system. Leading edge flap, trailing edge flap, stabilizer, spoilers and speed brake constitute the secondary control system and improve the performance characteristics of the aircraft.

Primary flight control system. Aileron, elevator and rudder constitute the primary control system, they control the aircraft movements roll, pitch and yaw respectively.

3.2. The constitution of ASBN

The key systems in the operation of the aircraft have been briefly described above. This section will state the construction of ASBN. Each part of the aircraft can complete some expected functions by cooperating with other parts. For example, for GPWS to implement ground proximity warning, it needs to obtain altitude information from RA, meteorological information from WXR, navigation information from GPS, and atmospheric data from ADIRS. So when constructing a Bayesian network, the nodes of these information-providing components are the parent nodes of GPWS. In the constitution of ASBN, nodes represent aircraft components or systems, and directed arcs directed acyclic represent functional dependencies between components. Finally, the nodes of several key systems point to four failure condition severity categories: minor, major, hazardous, catastrophic.

The constitution of ASBN is shown in Figure 1.
In order to increase the safety margin of B737NG, many parts are backed up. Generally speaking, there are two sets of main systems, and the parent nodes that they depend on are generally different. This can prevent the rapid propagation of failures caused by excessive system association. Two sets of components between the same subsystem can work with each other. For example, the fuel system can provide fuel from the left fuel tank to the right engine through crossfeed valve. Similarly, the power system can also realize the power supply of different power sources by selecting the conversion of different bus bars.

### 3.3. Components failure law and CPD

The reliability of aircraft systems is complicated because each component not only has its own failure laws, but also is affected by the failure laws of its associated components. Therefore, in ASBN, not only the failure probability of each node must be scientifically described, but also the probability relationship between the nodes must be accurately described. This part first discusses the failure probability of the components, and then analyzes the Bayesian model conditional probability distribution (CPD) among components.

As an excellent commercial aircraft, B737NG has been born for more than two decades. Therefore, the probability of aircraft component failure is at a stable level during the life of the aircraft. This paper studies the operational reliability of the aircraft, it can be assumed that the failure mode of the aircraft components is stable at a certain level during a flight mission. $\lambda_i(t)$ is the component $i$ failure rate, $t$ represents the time, $R_i(t)$ is the component $i$ reliability, and can be expressed as

$$R_i(t) = e^{-\lambda_i(t) t}$$  \hspace{1cm} (1)

The probability that a component performs a specified function under specified conditions and within a specified time is called reliability. The normal operational probability of the component $i$ can be stated as $p_0(i)$, during the study time $t$, it can be expressed as

$$p_0(i) = R_i(t)$$  \hspace{1cm} (2)

Obviously, it is very important to determine the failure rate $\lambda_i(t)$ of each component. Obtaining the failure rate of each component of B737NG is a huge task, which is difficult to achieve in practice due to commercial competition and other issues. So far, the paper only collected the failure rate of the engine is less than 0.003% (hr$^{-1}$). The failure rates of other components are determined according to relevant airworthiness requirements. Specifically, it can be determined by referring to the range of values in Table 1.

However, the range of values in Table 1 is still too large for a component. According to statistics from some airlines [11], the probability of failure of more than 89% of components is a constant during normal use. Therefore, the failure rate of the component is defined as a uniform distribution within a certain range.

$$\lambda_i(t) \sim U[a, b]$$  \hspace{1cm} (3)

For each component, according to the extent of impact on the flight in the event of its failure, determine the value of the $a$ and $b$ parameters of the uniform distribution of each component by refer to Table 1.

The next part will discuss the determination of the CPD of the ASBN. The CPD of two variables $X_1$ and $X_2$ can be represented as $p(X_1|X_2)$, standing for the probability of $X_1$ given $X_2$ that is the probability of $X_1$ after the event $X_2$ has been happened. Similarly, $p(X_1|X_2,\cdots,X_n)$ representing the probability of $X_1$ after having an observation for $X_2,\cdots,X_n$.

Tabular CPD is the simplest representation of CPD. It can contain all the possible combinations of different states of variables and the probabilities corresponding to these states. In order to explain the construction of CPD, the EEC1, EDP fuel1 and engine1 of ASBN are taken as an example.
The variable EEC1, it can be categorized into two values (normal, failure). So, \( p(EEC1) \) can be represented in the tabular form as follows:

**Table 2.** The tabular CPD of EEC1.

| states | \( p(EEC1) \) |
|--------|----------------|
| normal | \( p_0(EEC1) \) |
| failure| \( 1-p_0(EEC1) \) |

Similarly, variable EDP fuel1 is root node in ASBN, its CPD can be represented as follows:

**Table 3.** The tabular CPD of EDP fuel1.

| states | \( p(EDP \text{ fuel1}) \) |
|--------|----------------------------|
| normal | \( p_0(EDP \text{ fuel1}) \) |
| failure| \( 1-p_0(EDP \text{ fuel1}) \) |

As the engine1 depends on both the normal of EEC1 and EDP fuel1, \( p(\text{engine1}|\text{EEC1,EDP fuel1}) \) will be considered, which is the conditional distribution of engine1, given EEC1 and EDP fuel1. To briefly explain the status of variables, the numbers 0 and 1 indicate the normal and failure states of the component respectively.

**Table 4.** The tabular CPD of engine1.

| states | EEC1_0 | EEC1_0 | EEC1_1 | EEC1_1 | EDP fuel1_0 | EDP fuel1_1 | EDP fuel1_0 | EDP fuel1_1 |
|--------|--------|--------|--------|--------|-------------|-------------|-------------|-------------|
| normal | \( p_0(\text{engine1}) \) | 0 | 0 | 0 | \( p_0(\text{engine1}) \) | 0 | 0 | 0 |
| failure| \( 1-p_0(\text{engine1}) \) | 1 | 1 | 1 | \( 1-p_0(\text{engine1}) \) | 1 | 1 | 1 |

The normal functioning of the engine depends on EEC controlling and EDP fuel pressurizing the fuel. So if either of them fails, the engine will not work. Besides, the CPD of each variable is determined based on its actual function of the aircraft system.

It is worth mentioning that four failure condition severity categories: minor, major, hazardous, catastrophic, their CPD are different form the components in aircraft. For they were used to measure the operational reliability of aircraft system, the impact of changes in their related factors on the value of the CPD probability will not be as clear as other parts. Because the extent of influence is non-linear, this paper assumes that each influencing factor fails, and the extent of failure of the relevant severity category increases by 25%. For example, a severity category, minor, its CPD is shown as Table 5.

**Table 5.** The tabular CPD of engine1.

| Component status | normal | failure |
|------------------|--------|---------|
| Air-cond_0       | 1      | 0       |
| Air-cond_0       | 0.75   | 0.25    |
| Air-cond_1       | 0.75   | 0.25    |
| Air-cond_1       | 0.5    | 0.5     |

4. ASBN operational reliability analysis
This part will use the Bayesian network to analyze the reliability of the aircraft system. Firstly, the Bayesian principle will be introduced, and then the Bayesian network forward and backward inference would be adopted to assess the reliability of the aircraft system.
4.1. Bayesian network principle
The joint probability distribution of Bayesian network \( p(X_1, X_2, \ldots, X_n) \) over all its random variables \( \{X_1, X_2, \ldots, X_n\} \) can be represented as follows:

\[
p(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} p(X_i | \text{Par}_G(X_i))
\]  

(4)

It is known as the chain rule for Bayesian networks.

Here, \( \text{Par}_G(X_i) \) is the parent of \( X \) in the graph \( G \).

4.2. Bayesian forward inference
The construction of ASBN, the probability value of the variables, and the determination of the CPD have been analyzed above. This section will discuss the assessment of the reliability of ASBN in four failure severity categories under the given component failure probability and CPD. The results are shown in Table 6.

| failure severity categories | normal (hr\(^{-1}\)) | failure (hr\(^{-1}\)) |
|-----------------------------|------------------------|------------------------|
| minor                       | 0.999986               | 0.000014               |
| major                       | 0.999970               | 0.000030               |
| hazardous                   | 0.999966               | 0.000034               |
| catastrophic                | 0.999985               | 0.000015               |

Suppose the failure probability of each part is between 10\(^{-5}\) and 10\(^{-7}\), the reliability failure calculation result of the aircraft system is higher than the failure probability of each part. From the results, the failure severity category of major and hazardous are more likely happen than minor and catastrophic.

The reliability of aircraft systems is lower than the reliability of components, the reasons can be summarized as follows.

1. The association and interdependence of components and subsystems cause that the failure could propagate easily and quickly among components. There is no doubt that this is a disadvantage of most systems. An organic system is formed by the coupling of components, but failures can quickly propagate within the system. Aircraft systems are no exception. Although many systems have two sets, and each system has multiple components backed up, more failures come from the failure propagation of its associated systems. For example, the fuel system and electrical power system are directly related to the engine system, and the engine system also directly affects the electrical power system and hydraulic system. The hydraulic system also directly affects the aircraft primary and secondary flight control system. Therefore, any failure of these systems directly leads to a significant reduction in the aircraft operational reliability.

2. There are too many factors affecting aircraft system operational reliability. The reliability of the aircraft system may be affected by aircraft automation equipment, it may be affected by the failure of components, or it may be the failure of the operating transmission mechanism. The existence of these factors makes the study of aircraft system operational reliability not only focus on the failure probability of components, but more on the realization of the overall performance of the system.

4.3. Bayesian backward inference
Bayesian backward inference is a powerful tool for Bayesian network analysis. As for ASBN, it can analyze the most likely failure components or subsystem that cause the failure severity categories. This section will discuss the likelihood of components or subsystem failure if one of the failure severity categories had happened. The failure probability of the components are counted per flight
hour, then the following inference probability also reflects the possibility of occurrence per flight hour correspondingly.

If the assessment minor category has occurred, which subsystems are most likely reason to cause it happen? Bayesian backward could find the truth. The results are shown in Table 7.

**Table 7.** Probability of subsystems if minor happen.

| subsystems | normal  | failure  |
|------------|---------|----------|
| Air-cond   | 0.3542  | 0.6458   |
| Anti-ice   | 0.6176  | 0.3824   |

Table 7 shows that air-cond system is more likely to failure than anti-ice system, under the condition of minor occurrence. But from the perspective of probability values, the probability of these two subsystems occurring is relatively large. So the air-cond system most likely causes the aircraft system operational reliability assessment into minor category.

Similarly, if the assessment major category has occurred, the subsystems failure probability are shown in Table 8.

**Table 8.** Probability of subsystems if major happen.

| subsystems            | normal  | failure  |
|-----------------------|---------|----------|
| Landing gear          | 0.3713  | 0.6287   |
| Air-cond              | 0.4561  | 0.5439   |
| Secondary flight control | 0.7411  | 0.2589   |
| Anti-ice              | 0.8273  | 0.1727   |

The larger the value of failure, the higher the probability that the system will fail under given conditions. From the data in Table 8, air-cond system and landing gear system are more likely to failure than secondary flight control system and anti-ice system, under the condition of major occurrence.

There are two inferences can be made. One is that once the major category really occurs during the operation of the aircraft, it is most likely caused by the landing gear system. The second is that trying to reduce the fail probability of landing gear system and air-cond system is the most effective way to lower the major fail probability.

Besides, if the assessment hazardous category has occurred, the subsystems failure probability are shown in Table 9.

**Table 9.** Probability of subsystems if hazardous happen.

| subsystems            | normal  | failure  |
|-----------------------|---------|----------|
| Flight management     | 0.3811  | 0.6189   |
| Landing gear          | 0.3969  | 0.6031   |
| Secondary flight control | 0.7567  | 0.2433   |
| Power plant           | 0.8986  | 0.1014   |
| Fuel                  | 0.9985  | 0.0015   |
| Primary flight control | 0.9991  | 0.0009   |

From the data in Table 9, flight management system and landing gear system are more likely to failure than others; the fuel system and primary flight control system are most unlikely happening, under the condition of hazardous occurrence.

Identically, it can be inferred that the flight management system or the landing gear system attribute most for the hazardous category appearance during the operation of the aircraft. The most effective way to lower the hazardous fail probability is trying to reduce the fail probability of flight management system and the landing gear system.
Finally, if the assessment catastrophic category has occurred, the subsystems failure probability are shown in Table 10.

**Table 10.** Probability of subsystems if catastrophic happen.

| subsystems           | normal  | failure |
|----------------------|---------|---------|
| Flight management    | 0.1921  | 0.8079  |
| Power plant          | 0.7893  | 0.2107  |
| Fuel                 | 0.9977  | 0.0023  |
| Primary flight control| 0.9991  | 0.0009  |

From the data in Table 10, under the condition of catastrophic occurrence, flight management system and power plant system are more likely to failure than fuel system and primary flight control system; the fuel system and primary flight control system are more unlikely happening.

The value about the failure probability of flight management system is significantly larger than others. In other words, the flight management system is very likely main cause if the assessment catastrophic or hazardous categories have occurred. Similarly, reducing the failure probability of flight management system can significantly improve the operational reliability of aircraft system.

Since flight management system is so important to the hazardous and catastrophic severity categories, it is necessary to adopt Bayesian backward inference in flight management system to analyze the most likely failure component.

Assuming the flight management system has failed, adopt Bayesian backward inference to analyze the failure probability of each component of the system, the result is shown as Table 11.

**Table 11.** Probability of components if flight management system fail.

| sub-components | normal  | failure |
|----------------|---------|---------|
| TCAS           | 0.1005  | 0.8995  |
| GPWS           | 0.1824  | 0.8176  |
| FMS            | 0.2730  | 0.7270  |
| WXR            | 0.5305  | 0.4695  |
| FMC            | 0.6705  | 0.3295  |
| AFDS           | 0.7664  | 0.2336  |
| VOR            | 0.8383  | 0.1617  |
| DME            | 0.8503  | 0.1497  |
| ADIRS          | 0.8538  | 0.1462  |
| RA             | 0.8699  | 0.1301  |
| ATC            | 0.9163  | 0.0837  |
| GPS            | 0.9703  | 0.0297  |

According to the data in Table 11, TCAS, GPWS, FMS are the most likely failure under the condition of flight management system failure, what’s more, their failure probability values are several times higher than others, which means that the risk of failure in the system is spread to these several subsystems. To improve the reliability of flight management system, the possible solutions include reducing the failure probability of components and changing the component dependencies to reduce the correlation between systems.

A more comprehensive treatment of aircraft operational reliability within Bayesian network has been shown in this part. Specifically, the Bayesian forward inference is used to assess ASBN operational reliability taking into account the aircraft system components with different level of failure scenario and certain CPD among components. The output of the ASBN operational reliability analysis process has associated with each component failure uncertainty in the failure condition severities and objective relationship among components. Given failure condition severity category, the Bayesian backward inference is used to determine which aircraft subsystems could be the key part
attribute to the system failure. If the reliability of those sensitive subsystems can be guaranteed to a high level, the operational reliability of aircraft systems will be improved significantly.

5. Conclusions
With the integrated design and manufacturing of civil aircraft industry, the complexity of aircraft have brought great challenges to the evaluation and analysis of aircraft operational reliability. Traditional reliability analysis approaches do not adequately solve the components uncertainty or interconnected aircraft systems. Based on existing method research, this paper has shown how the aircraft system associated with certain relationship among uncertainty components can be assessed and analyzed their operational reliability by Bayesian network. The aircraft system operational reliability and sensitive components under given failure conditions had been assessed and analyzed through the adoption of ASBN. The research results show that the aircraft system operational reliability is not as high as the reliability of its components; the most likely failure component or subsystem under different failure condition severity categories have been identified. This work could provide a systematic and objective perspective about aircraft operational reliability for stakeholders.

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