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# Bayesian Network Education Method to Produce a Condition-Based Maintenance Strategy in Aviation Maintenance Programs

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With an understanding of the current industry and organization orientation, the aviation maintenance industry is preparing a new paradigm shift toward a CBM (Condition-Based Maintenance) strategy. However, one challenge the aviation maintenance industry faces is the lack of CBM training support in the current education setting. This study aims to fill the gap in the CBM strategy training in current aviation maintenance programs. The authors propose Condition-Based Maintenance Bayesian Network (CBM-BN) training materials. The BN has a different principal approach than other frequentist principles, which can generate a prediction model concerning all heterogeneous information. In this paper, the authors describe a framework to develop CBM-BN training material that can be performed in aviation maintenance education. The proposed CBM-BN framework has probability concepts and ten steps; each step has three sections, including materials, activities, and examples for instructors and students. The case study demonstrates that the developed CBM-BN framework and training materials could facilitate CBM strategy training in aviation maintenance programs. A mechanic who can do CBM analysis will be more beneficial and demandable in the job market and contribute to full CBM implementation. Moreover, other CBM educational materials would be needed to compensate for the limitations of BN and increase the maturity level of CBM.

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## Introduction

Aviation maintenance is critical for the continued operation of any asset, system, or aircraft. As the aircraft ages, structures and instruments that are fatigued by friction and vibrations eventually reach their failure point. To prevent a part failure during the aircraft's operation time and to continuously operate in safe conditions, the aviation industry has adopted and implemented a time-based maintenance strategy (Oikonomou et al., 2022). However, these traditional time-based maintenance programs have efficiency issues that increase operational costs and downtime (Prajapati et al., 2012; Oikonomou et al., 2022).

The Advisory Council for Aviation Research and Innovation in Europe (ACARE) (2017) addresses Flightpath 2050, which aims to maximize aviation safety and operational efficiency. Of many plans, ACARE (2017) aims to complete a paradigm change to condition-based maintenance (CBM) from time-based maintenance (TBM) by 2035. In addition, Boeing's outlook (2022) also highlights the need to implement CBM in line with changes in the new-generation fleet.

With an understanding of the current industry and organization orientation, the aviation maintenance industry is preparing a new paradigm shift towards a CBM strategy. However, one challenge the aviation maintenance industry faces is the lack of CBM training support in the current education setting. One methodology for generating the prediction models needed for CBM is the Bayesian Network (BN) principle. It can create an uncertainty prediction model that includes all current heterogeneous information from diagnosis and continuously updates it instead of relying on fixed reliability or frequentist stochastics. Therefore, the authors propose that CBM-BN training materials would assist aviation maintenance institutions in aligning their curriculum with the industry's trend toward CBM practices. This CBM-BN comprises prognosis and diagnosis practices that enable students to predict failure points based on an understanding of the aircraft's condition. The proposed CBM-BN training practice is expected to ease the hurdle of CBM implementation for collegiate aviation institutions.

The problem of this study is the lack of CBM modeling instruction in aviation maintenance programs.

## Literature Review

### Issues of Current Aviation Maintenance Program Education

The requirements for becoming an Aircraft Maintenance Technician (AMT) have been laid out by the Federal Aviation Administration (FAA) in 14 CFR part 65 subpart D. There are two ways to meet eligibility requirements referred to in 14 CFR part 65.77, and this study is focused on section (a); at least 18 months of practical experience related to powerplant and airframe in FAA approved institutional settings (FAA, 2022).

During the 18 months of hands-on experience, the prospective technician should be trained in concepts of maintenance in FAA-approved schools (Code of Federal Regulations, 2022a). The prospective aviation technicians are expected to attain 'critical thinking' skills that enable them to understand current aircraft conditions and decide whether to 'return to service' an asset based on the technician's judgment (Michmerhuizen, 2014). To develop the prospective technicians' critical thinking skills, the U.S. Federal Aviation Administration (FAA) previously set instructional hours in the curriculum (FAA, 2007). However, changes in the regulations as of September 2022 have allowed for competency-based instruction (Aviation Technician Education Council, 2022). However, White et al. (2000) pointed out an issue of this curriculum that it still educates old-fashioned techniques and does not align with industry development and needs. Kraus and Gramopadhye (1999) stated that there is a lack of preparation in the industry setting, such as interpersonal and socio-technical competence in the current aircraft maintenance technician's education setting. Moreover, Kraus and Gramopadhye's (1999) study highlighted the importance of using computer-based training, which enables prospective technicians to expand their insights for in-depth systems in fault diagnosis and repair.

This study will use the aviation maintenance program at Purdue University, Aeronautical Engineering Technology (AET), as the exemplar for building the training materials. The current maintenance program is ABET-ETAC (The Accreditation Board for Engineering and Technology – Engineering Technology Accreditation Commission) 2022-2023 accredited and aligns with FAA CFAR Part 147 requirements (ABET, 2021; Code of Federal Regulations, 2022b; Purdue University, n.d). The AET program is focused on educating students on the proper techniques of using tools and developing troubleshooting skills in preparation for their aeronautical careers (Yother & Johnson, 2021). The more specific course objectives to AET each course level proposed (Ropp et al., 2012) (Refer to Table 1):

**Table 1**
*AET Course-Level Objectives (Ropp et al., 2012)*

| AET Course Level | Learning Objectives |
|---|---|
| 100 Level | Knowledge/Remembering<br>Define-list-recall-remember |
| 200 Level | Comprehension/Understanding<br>Describe-discuss-explain-identify |
| 300 Level | Application/Applying<br>Employ-demonstrate-explain-illustrate |
| 400 Level | Analysis/Analyzing<br>Compare-contrast-differentiate-experiment |
| Capstone and applied projects level | Synthesis/Creating<br>Assemble-construct-design-develop |

For instance, Yother and Johnson (2021) proposed essential aeronautical industry career skills in a 300-level logistics class: Failure Modes and Effects Analysis (FMEA), life cycle cost calculation, and fault trees. The FEMA has significant knowledge of constructing CBM, which enables it to produce equipment failure modes at an early stage (Teixeira et al., 2020). However, the concept is not associated with CBM.

## Challenges of CBM Implementation

The Advisory Council for Aviation Research (ACARE) (2017) aims to achieve the implementation of CBM by developing predictive maintenance. Boeing (2022) also implicitly highlights the need for the skills required for technicians who can analyze and interpret collected data from sensors and flight information. Therefore, educational institutions have to teach students both predictive and traditional maintenance skills (Boeing, 2022).

A deep body of literature concentrates on CBM approaches using various modeling techniques; meanwhile, only a few studies have defined the implementation of CBM (Texieria et al., 2020). Focusing on the implementation plan, Texieria et al. (2020) stated that an adequate level of 'training support' is required to prepare for a successful CBM implementation. Therefore, this training support would be crucial to implementing the CBM strategy. Teixeira et al. (2020) pointed out that technicians' experience and knowledge are crucial to their careers and help build critical thinking systems. Hence, they require solid insight into different methodologies, skills, and principles that compose CBM. Furthermore, during training, technicians are required to understand the objectives and justification of CBM principles (Texieria et al., 2020). To maximize CBM effectiveness, it is essential to understand asset criticalities such as safety, failure behavior, and operational cost benefit. (Ellis, 2009).

## Bayesian Network (BN) Applications

Bayesian network applications have been widely adopted in predictive modeling. It is also a significant tool to guide a person to a proper decision in uncertain conditions (Chen & Pollino, 2012; Farinha, 2018). BN is defined as a process where

> … variables are represented by nodes linked by arcs that symbolize dependent relationships between variables. The strength of these relationships is defined in the Conditional Probability Tables (CPTs) attached to each node. CPTs specify the degree of belief (expressed as probabilities) that the node will be in a particular state, given the states of the parent nodes. Evidence is entered into the BN by substituting the a *priori beliefs* of one or more nodes with observation or scenario values. Through belief propagation using Bayes Theorem, the a priori probabilities of the other nodes are updated. This belief propagation enables BNs to be used for diagnostic or explanation purposes (Chen & Pollino, 2012, p. 134).

Moreover, it enables a combination of all heterogeneous information, such as performance data, technician perspectives, testing data, and mathematical approaches (Li et al., 2017). Farinha (2018) stated that the Bayesian theorem differs from typical frequentist probabilistic approaches, and it can consider various disciplines to achieve direct and intuitive answers to real-world examples. To be specific, several papers have conducted studies using BN to analyze human factors related to general aviation accidents (Yang & Mott, 2020), human factors related to maintenance accidents (Chen & Haung, 2014; Luxhoj et al., 2003), human safety assessment of accidents (Zhang & Mahadevan, 2021), and human safety analysis of unmanned aircraft systems (Washington et al., 2019). Understanding that the BN can be applied to different domains in aviation, the researchers focused on the application of BN in CBM in the next section.

## Theoretical Reasonings for CBM-BN in Collegiate Aviation Institutions

Researchers understand the need to update old-fashion curricula from discrepancies between collegiate institutions and industry direction. The CBM is approached by big data (Zhang et al., 2019). For example, Airbus A350 produces 2.5Tb of data from 6,000 sensors daily in operation (Rolls-Royce, 2018). In other words, collegiate students will be dealing with big data in their jobs and will be required to have skills in data acquisition, handling big data (pre-processing), diagnosis, and prognosis (Xu et al., 2019).

In addition, BN is a fundamental knowledge that can be applied to various CBM models. The CBM-BN is a new educational material that enables students to understand stochastic future failures by considering heterogeneous information (Dinis et al., 2019), not just relying on pre-determined failure rates given by manufacturers. Once collegiate students understand the practical understanding of CBM-BN, they can develop further advanced CBM models by applying fundamental Bayesian theorems such as Bayesian linear regression (BLR) (Oikonomou et al., 2022) and Naïve Bayes (Saeidi et al., 2019).

## Aviation-Related CBM-BN Studies

Many researchers have studied CBM-BN; the authors review other studies on CBM-BN validity approaches applied to aircraft components. These studies show the ability of BN models to be used in predictive modeling for aviation maintenance.

Sun et al. (2019) studied the aircraft condition system (ACS), built-in sensors were installed to monitor and collect data such as Static Air Temperature (SAT), Total Air Temperature (TAT), Static Air pressure (SAP), Mach number (Ma), Altitude (ALT), Engine Anti-ice (V1) Ram Air Temperature (RAMT), Pack Temperature (PKT), Wing Anti-ice (V2), Low-pressure rotor speed (N1), High-pressure rotor speed (N2), Bleed air temperature (BAT), Bleed air pressure (BAP), Cabin Pressure (CP), Mix Manifold Temperature (MFDT). Based on these ACS behavioral history data, the Bayesian method was used to predict ACS failure.

Ferreiro and Arnaiz (2010) provided a diagnosis and prognosis of aircraft break degradation using Bayesian networks; they designed a ‘condition view’ that estimates the remaining life of components based on break wear drive factors such as aircraft weight, landing velocity, brake operation, flight distance, runway length, weather, and runway condition.

Przytula and Choi (2007) studied the avionics diagnosis and prognosis model using a BN concerning various factors such as system usage, health condition changes, and operation conditions.

## Summary

Based on the literature review, training has been demonstrated as a substantial element of successful CBM implementation. The authors identify gaps in the current exemplar AET program in teaching the CBM concept to prospective students; even more, the curriculum focuses on traditional skills and knowledge that are not in line with evolving industry needs and techniques. Research shows that CBM will be implemented in the aviation maintenance industry, and the technicians will be required to do predictive maintenance for coming next-generation aircraft. The BN has a different principal approach than other frequentist principles, which can generate a prediction model concerning all heterogeneous information.

In the next section, the authors propose a new CBM-BN training procedure that is expected to contribute to filling the gap between CBM implementation and providing new training material to aviation maintenance programs in line with new industry needs.

# Methodology

## Theoretical Foundations

### *Fundamental Principles of CBM*

The main goal of implementing CBM is to minimize operating costs. Specifically, by understanding current asset components ‘live condition,’ the operator can minimize redundancy maintenance tasks, which reduce asset downtime and optimize replacements of pointless parts that still have a useful life. This is a new paradigm in the aviation maintenance industry; the CBM strategy enables maintenance based on an aircraft’s health condition, not the traditional TBM strategy, which is reliability-based. Therefore, the operator could achieve a situation known as lean maintenance.

*Fundamental Principles of BN*

BN is structured by inputting all current component conditions or the operator's perspectives/evaluation. For example, suppose an operator wants to know a component's failure point or current degradation level. In that case, the operator must understand the failed component's interconnection systems and quantify each system variable. The outcome guides the component's current health condition. This method differs from the reliability approach, which does not consider the specific asset's current condition.

*Probability concepts*

Conditional probability:

The probability of A occurs in the given probability of B (Triola, n.d.):

$$P(A|B) = \frac{P(A \cap B)}{P\ (B)} \tag{1}$$

*Bayes' theorem*

Bayes' theorem is another way to calculate conditional probability by concerning the prior probability, likelihood, and evidence. To be specific, $P\ (B)$ refers to evidence; $P(A)$ refers to prior probability; $P(B|A)$ refers to likelihood; and $P(A|B)$ refers to posterior probability (also known as updated probability) (Triola, n.d.):

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B) = [P(A) \cdot P(B|A)] + \left[P\left(\overline{A}\right) \cdot P\left(B\middle|\overline{A}\right)\right]} \tag{2}$$

**CBM-BN Framework**

The CBM-BN framework is created based on Chen & Pollino's (2012) steps of BN practice. The following are the author's proposed steps for the CBM-BN structure:

1. Select a component.
2. Troubleshooting methods.
3. Analyze probable causes.
4. Determine each variable collection method.
5. Determine conditional probability table methods.
6. Conditional probability diagram and table.
7. Construct a CBM-BN model.
8. Diagnose and determine engine running condition.
9. Prognosis.
10. Evaluate the framework and discuss limitations.

These framework steps guide constructing a solid practice of the CBM-BN prediction model. Since their problem-solving approaches will show operators how their proposed modeling is reasonable and credible, evaluation and discussion can significantly enhance the maturity of targeted CBM-BN modeling by reflecting others' insights.

To construct the CBM-BN framework and calculate network correlation, the authors propose a *Genie Model*. This model helps to structure the BN model by solving complicated calculations and providing visual support through graph and chart analysis. One requirement is that operators need insight into the principle of the Bayesian theorem concept to generate the modeling, such as setting an observation target, identification of variables, and the data value of each variable.

## Education Material Development

In this section, the authors describe how they used Chen and Pollino's (2012) framework to develop CBM-BN training material that can be performed in the aviation maintenance education setting. In line with the course level objective, this CBM-BN training material can be used in multiple aviation maintenance courses. Using this material, students will collect the data, quantify them, and input them into variables to construct the BN; in other words, students will create various variables of their targeted component and then input the quantified experiments and observations into the conditional probability table (CPT). From the generated BN outcome, students can diagnose and prognosis their targeted aircraft component.

For each step of the process, there are three sections. The first section is for the instructor. It will include any materials the instructor needs to provide the students. The second section is for the students. It will include the activities the students should complete. The final section is an author-developed example of how to complete the task.

### Step 1. Select a Component

The first step in the process is to select a system component to evaluate for condition-based maintenance. There are no real limitations on what the component should be. Only that there is supporting material and knowledge to support the activity.

*Instructors.* The instructors should provide students with troubleshooting charts where students can choose components. The troubleshooting charts will also be used in future steps.

*Students.* Using the material provided by the instructors, the students will select a component they wish to evaluate.

*Example*. To provide an example of proposing a teaching method, the authors selected an opposed reciprocating engine.

### Step 2. Troubleshooting Methods and Step 3. Analyze Probable Causes

*Instructors.* No new material is needed.

*Students.* Using the material provided by the instructor in step 1, the students shall identify failure modes and causes of their system. For this assignment, one failure mode is selected.

*Example.* The focus of this example is on the rough running of the engine. Refer to Table 2 for a section of the troubleshooting table from the FAA.

**Table 2**
*Opposed Engine Troubleshooting Directives (FAA, 2018)*

| Trouble | Probable Causes | Remedy |
|---|---|---|
| Rough running engine | Cracked engine mount(s) | Repair or replace engine mount(s) |
| | Unbalanced propeller | Remove the propeller and have it checked for balance |
| | Defective mounting bushings | Install new mounting bushings |
| | Lead deposit on spark plugs | Clean or replace plugs |
| | Primer unlocked | Lock primer |

**Step 4. Determine Each Variable Collection Method**

*Instructors.* The instructors provide students with raw data on target component variables. The variables can be found in various references. For example,

- Logbook
- Consult with experts and technicians
- Publications
    - Advisor Circular (AC)
    - Airworthiness Directives (AD)
    - Type Certificate Data Sheet (TCDS)
    - Service Bulletins (SBs)
- Reliability level from manufacturer’s standards
    - Mean Time between failures (MTBF)
    - Mean time to failures (MTTF)

*Students.* The students analyze the given raw data and convert it to probability/reliability.

*Example.* The authors developed a CBM model of the condition of the engine running, and various conditional data can be applied to each variable (Refers to Table 3). Each variable is required to measure the probability/reliability in certain periods, such as operation hours, flight cycles, and calendar months. For example,

- The reliability level of parts by manufacturers.
- Frequency of defect found during the observation period.
- Components failure likelihood rates by technicians and experts.

- Historical data of aircraft accidents/incidents associated with components.

**Table 3**
*Probability of Engine Operation Variables*

| | Variable | Condition | Percentage |
|---|---|---|---|
| (a) | Spark Plugs | Clean: | 80 % |
| | | Dirty: | 20 % |
| (b) | Primer Inspection | Pass: | 80 % |
| | | Fail: | 20 % |
| (c) | Propeller | Balanced: | 90 % |
| | | Unbalanced: | 10 % |
| (d) | Engine Mount(s) | Pass: | 99 % |
| | | Fail: | 1 % |
| (e) | Mounting Bushing(s) | Pass: | 90 % |
| | | Fail: | 10% |

**Step 5. Determine Conditional Probability Table (CPT) Methods**

*Instructors.* The instructors inform CPT and collection methods per step 5 *Example*.

*Students.* Understand CPT concepts and collection methods.

*Example.* The CPT is an essential part of constructing the BN model. This step is a process of how parent nodes correlate to a child node. In other words, the probability of a child node occurs when the parent node already occurred. A combination method is selected to determine the correlation between the two nodes: observational data and expert knowledge.

- Observational data: This is a simple data collection method by observations. i.e., count the probability that an event (child node) occurs when events (parent node) occur.

- Expert knowledge: Consult with industry experts. i.e., ask how frequently an event (child node) occurs when an event (parent node) occurred in a certain period.

**Step 6. Conditional Probability Diagram and Table**

*Instructors.* The instructors provide students with conditional probability diagrams and table guides. It was developed by the authors to show an example of a conditional probability diagram and table guide (Refer to Table 4).

**Table 4**
*Conditional Probability Diagram and Table Guide*

| | |
|---|---|
| 1. | How many parent nodes (Variables) does your component have?<br>Answer: i.e., 5 parent nodes: Mounting Bushing(s), Engine Mount(s), Propeller, Spark Plugs, and Premier Inspection |
| 2. | What is your child node?<br>Answer: i.e., 1 child node: Running Engine |
| 3. | Decide the order of parent nodes<br>Answer: i.e., the parent node order is 1. Spark Plug; 2. Primer Inspection; 3. Propeller; 4. Engine Mount(s); 5. Mounting Bushing(s)<br><br>Note. The actual order is subject to change by students |
| 4. | Determine the probability of the target component for each conditional branch |
| 5. | Construct a conditional probability diagram |
| 6. | Construct CPT in Excel or manually input the value based on the conditional probability diagram |

*Students.* The students follow the conditional probability diagram and table guide and structure the conditional probability diagram. The completed students' conditional probability example refers to Figures 1, 2, and Table 5. Once students complete filling out each conditional probability diagram, they will convert it to an Excel file and import it to the *Genie model* or manually input the value into the *Genie model*. The Excel file example is represented in Table 5.

**Figure 1**
*Completed Example: Conditional Probability Diagram – Clean Spark Plug*

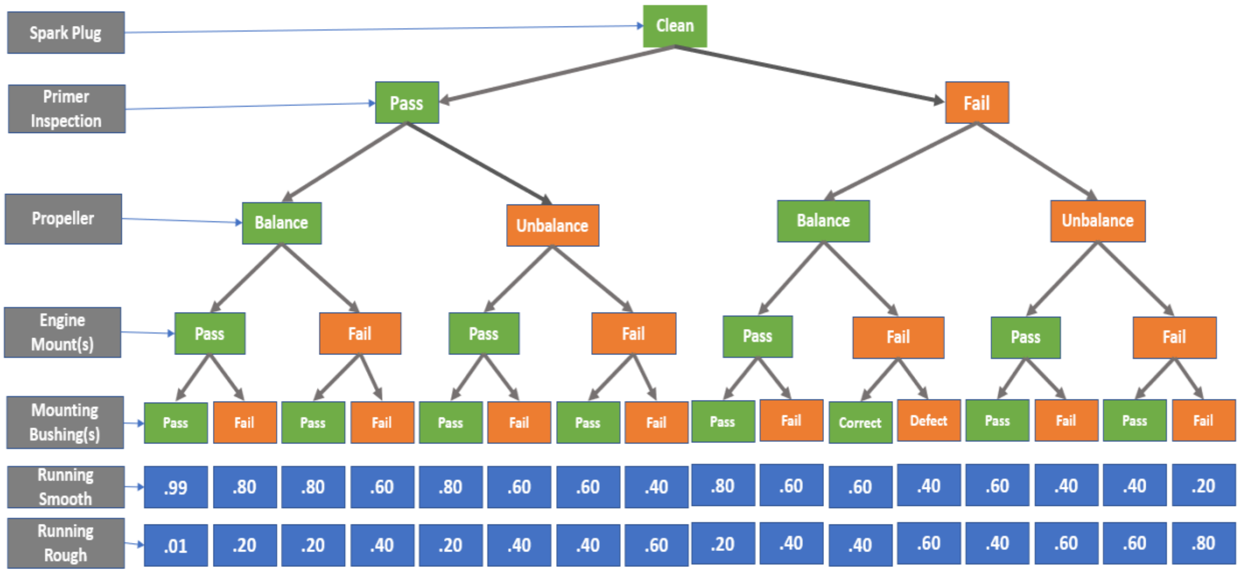



**Figure 2**
*Completed Example: Conditional Probability Diagram – Dirty Spark Plug*

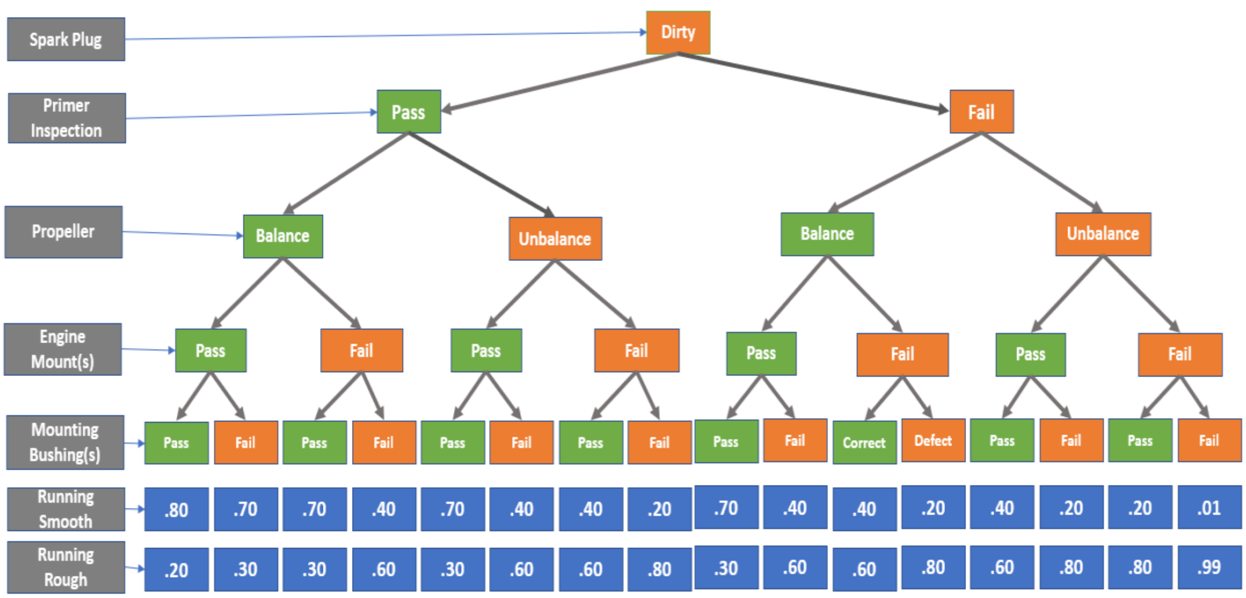


**Table 5**

*Completed Example: CPT of Running Engine Condition*

| Spark Plugs | Clean | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Primer Inspection | Pass | | | | | | | | Fail | | | | | | | |
| Propeller | Balanced | | | | Un-Balanced | | | | Balanced | | | | Un-Balanced | | | |
| Engine Mount(s) | Pass | | Pass | | Pass | | Fail | | Pass | | Fail | | Pass | | Fail | |
| Mounting Bushing(s) | Pass | Fail | Pass | Fail | Pass | Fail | Pass | Fail | Pass | Fail | Pass | Fail | Pass | Fail | Pass | Fail |
| Running Smooth | .99 | .80 | .80 | .60 | .80 | .60 | .60 | .40 | .80 | .60 | .60 | .40 | .60 | .40 | .40 | .20 |
| Running Rough | .01 | .20 | .20 | .40 | .20 | .40. | .40 | .60 | .20 | .40 | .40 | .60 | .40 | .60 | .60 | .80 |

| Spark Plugs | Dirty | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Primer Inspection | Pass | | | | | | | | Fail | | | | | | | |
| Propeller | Balanced | | | | Un-Balanced | | | | Balanced | | | | Un-Balanced | | | |
| Engine Mount(s) | Pass | | Fail | | Pass | | Fail | | Pass | | Fail | | Pass | | Fail | |
| Mounting Bushing(s) | Pass | Fail | Pass | Fail | Pass | Fail | Pass | Fail | Pass | Fail | Pass | Fail | Pass | Fail | Pass | Fail |
| Running Smooth | .80 | .70 | .70 | .40 | .70 | .40 | .40 | .20 | .70 | .40 | .40 | .20 | .40 | .20 | .20 | .01 |
| Running Rough | .20 | .30 | .30 | .60 | .30 | .60 | .60 | .80 | .30 | .60 | .60 | .80 | .60 | .80 | .80 | .99 |

*Example.* Because of the complexity of understanding the CPT, the students are required to generate a conditional probability diagram first. This will help students to understand each conditional probability (Refer to Figures 3 and 4). To fill out the conditional probability diagrams, the students need to identify the probabilities of each conditional branch.

**Condition**: What is the probability of the engine running either (smooth) or (rough) in the given five conditions (Refer to Figures 4 and 5)?

(a) Spark plug = (clean) or (dirty);
(b) Primer inspection = (pass) or (fail);
(c) Propeller = (balanced) or (unbalanced);
(d) Engine mount(s) = (pass) or (fail);
(e) Mounting bushing(s) = (pass) or (fail).

For example, referring to the first left branch of Figure 3., to identify the probability of an engine running smooth (A= child node), students need to be concerned with 1 through 5 conditions (parent nodes). The probability value will fill '**A**.'

**Condition**: The engine is running smooth

(a) Spark plugs are clean and;
(b) Primer inspection pass and;
(c) Propeller is balanced and;
(d) Engine mount(s) pass and;
(e) Mounting bushing(s) pass.

Conversely, the probability of an engine running rough with the same conditions will be a complementary value of the engine running smooth. This probability value will fill '**B.'**

**Figure 3**

*Conditional Probability Diagram – Clean Spark Plug*

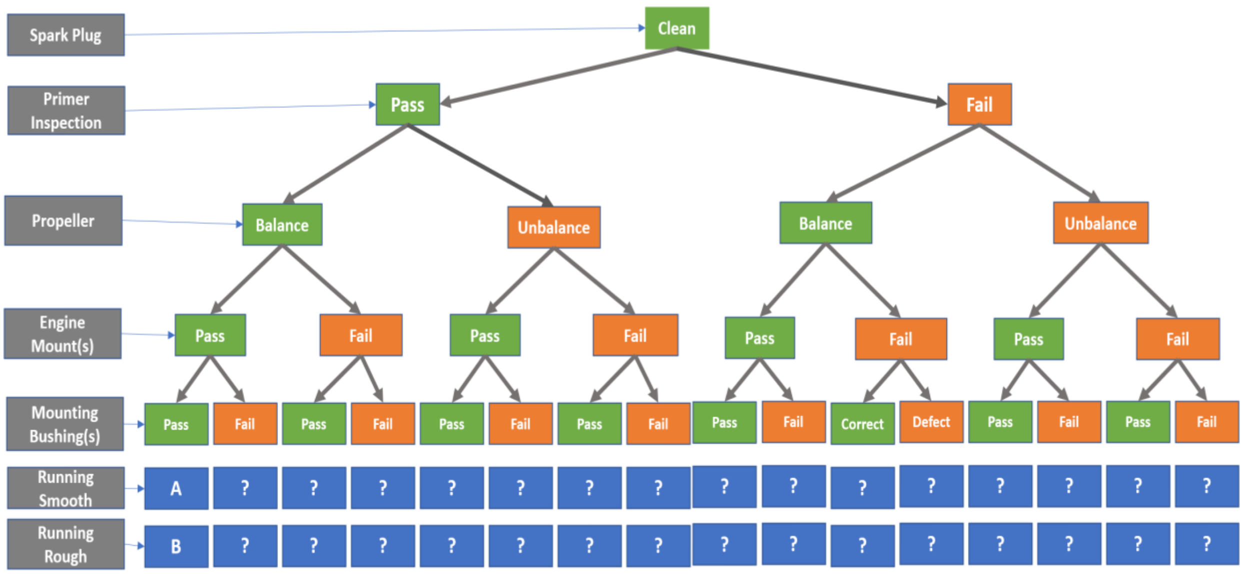
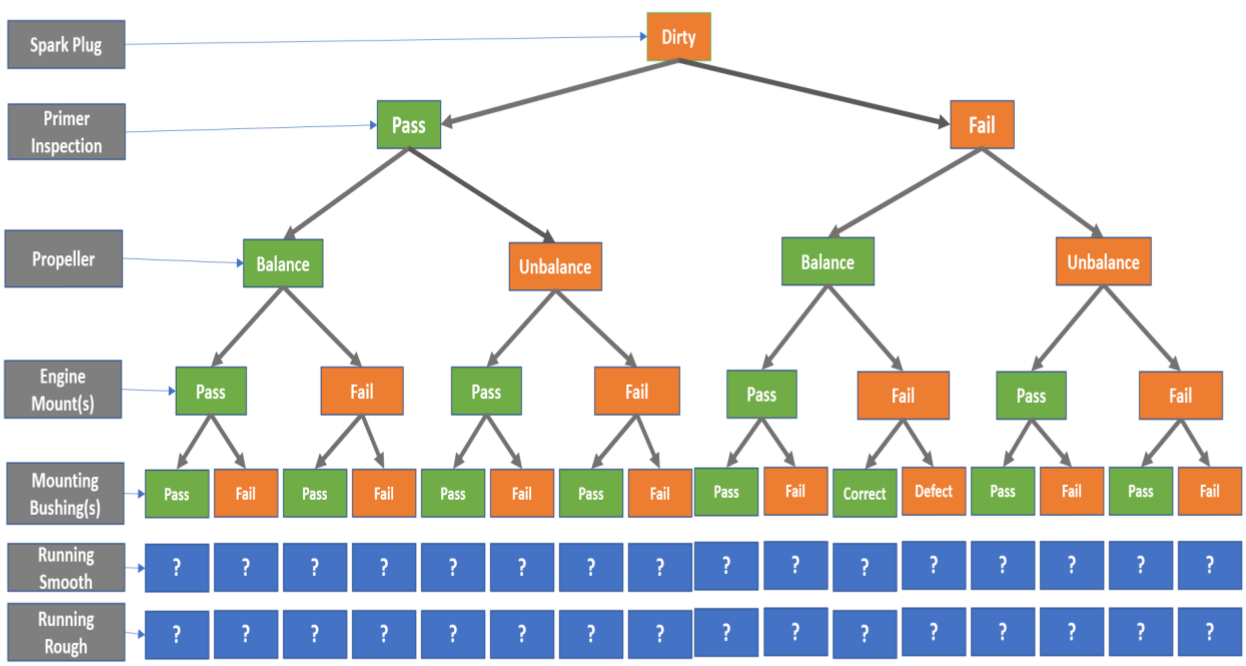



**Figure 4**

*Conditional Probability Diagram – Dirty Spark Plug*




## Step 7. Construct CBM-BN Model

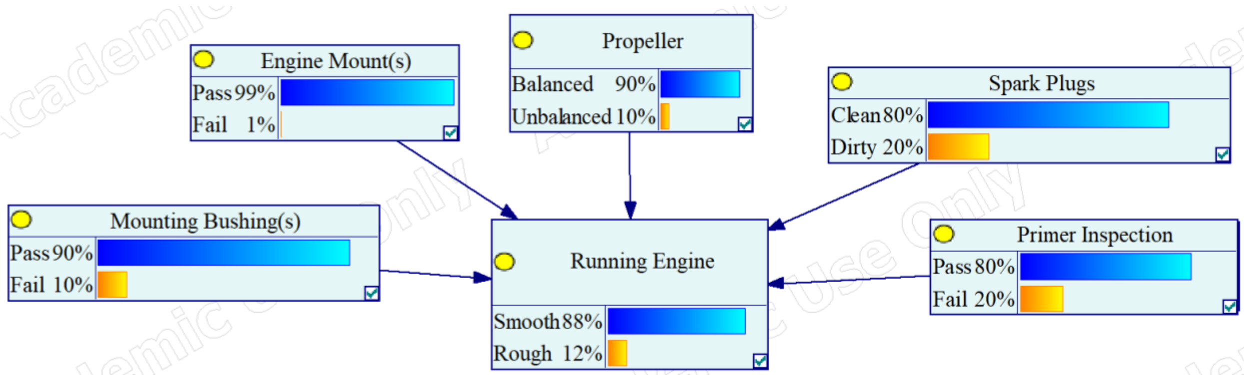
*Instructor*. Demonstration of *Genie software* instructions per *Genie manual* (BayesFusion, 2020). Provide students with the structure of the CBM-BN model.

*Students*. Download the student version of *Genie software* and review the structure of the CBM-BN model from the *Genie software*.

*Example.* The data values in this proposed simulation example assume and substitute verisimilar numbers in the general aviation industry (Refer to Figure 5). This is an outcome of the engine running the CBM model using BN.

**Figure 5**

*Prediction Model of Engine Running Condition using the BN*



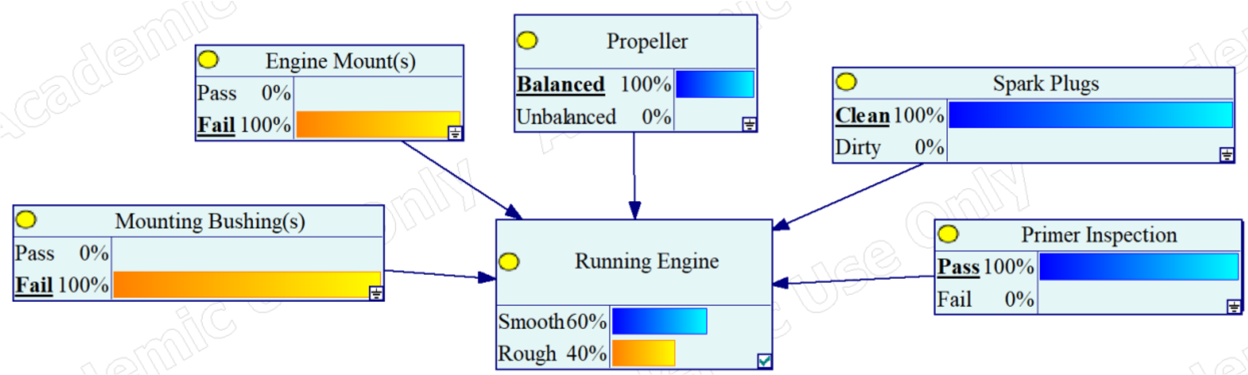

**Step 8. Diagnose and Determine Engine Running Condition and Step 9. Prognosis**

*Instructors.* The instructors provide an acceptable airworthiness level and condition for student models.

*Students.* Based on the given acceptable airworthiness level and condition, update the CBM-BN model; if the updated model has un-airworthy results, then generate a maintenance plan; if the updated model is airworthy, a maintenance plan is not needed.

*Example.* The *Genie model* allows the operator to control evidence; for example, by controlling 100% of the accuracy level of inspection and/or conditions, the operator can understand the updated predictive level of engine running condition (Refer to Figure 6).

**Figure 6**
*Updated Prediction Level of Engine Running Condition*




Each parent node is linked to the child node, which is targeted to determine the condition of the 'Running Engine.' Concerning variables (parent nodes) that are composed of a 'Running Engine,' the operator can predict the level of engine running condition. Referring to Figure 5, if the engine is running smoothly, the value is determined to be 88%. If students want to know the following probability of the engine running smoothly, they will refer to the **Condition** statement. **Condition**: After X-hour operations, students find defective mounting bushings and engine mounts, and the other three variables (propeller, spark plugs, and primer inspection) are in good condition. What is the current probability of the engine running smoothly?

At this point, students selected the two bad variables in failed and selected the other three variables that are good in goods in the *Genie model* (Refer to Figure 6). Then, the CBM-BN model determines the updated chances of running smoothly and roughly for the next operation if maintenance is not performed. In addition, to enhance the validation of this model, the students may be required to declare an acceptable engine running condition. For example, an instructor set 80% as the acceptable airworthiness level for running the engine smoothly. If the outcome is not determined at 80% and only reaches 40% (Refer to Figure 6), then students are required to generate a maintenance plan and perform maintenance concentrated on the issued variables such as 'Engine Mount' and 'Mounting Bushings.' This diagnosis and prognosis practice will provide insights into the understanding of current conditions as well as guide what maintenance practice needs to be done in a current situation.

### Step 10. Evaluate the framework and discuss limitations

*Instructors.* The instructors evaluate students' CBM-BN model per the author's developed assessment items (Refer to Table 6).

**Table 6**
*Assessment Items*

| | |
|---|---|
| BN assessment | 1. In the CPT, the sum of the probability values of each child node must equal 1<br>2. Structure model considering relationships between parent nodes and child node<br>3. Properly identify the probability/reliability of variables<br>4. The conditional probability diagram and table guide match the *Genie model* |
| CBM assessment | 1. Logical understanding of target CBM component<br>2. Model data collection method selections |
| CBM-BN assessment | 1. Corrective model updates based on given conditions by an instructor<br>2. Maintenance plan generation based on diagnosis and prognosis model output<br>3. Model practicability evaluation per industry standards (FAA, AC, AD, Manufacturer's Manual, etc.)<br>4. Analysis of model risks and benefits compared to traditional maintenance strategies<br>5. Model evaluations: discussion, limitations, future improvements, and final decision |

*Students.* The students evaluate their model through three assessment items, then make a final decision and future development in terms of CBM-BN model policies, standards, and limitations.

*Example.* This project is designed to work with a small group of three to four students. This intentionally mimics the use of small groups in the aerospace industry. For example, each detailed part of the Boeing 777 is widely distributed to engineers who designed the parts using simulation tools (Madhavan et al., 2016). There are many engineers, but they do not all work together. The aircraft is broken into smaller sections and divided up. A small group of engineers will work on their section before combining it into a larger section until the entire aircraft is complete.

Therefore, student groups will concentrate on one issue of the aircraft troubleshooting table (e.g., Refer to Table 2). The group is expected to build a prediction model of the intended component by referencing the assessment rubric and collecting parameters using reliable resources and equipment such as maintenance manuals, FAA documents, manufacturer documents, and testing equipment. Then, the group will use the *Genie model* program to build the CPT to find the visual outcome of each variable connection (Figures 2 and 3). All groups will analyze and present their focused components and have a discussion session regarding the proper actions of the component if the predictive outcome is a non-airworthy condition.

## Discussion

The aviation industry is preparing for a new maintenance strategy. Modern aircraft collect performance data through the Airplane Condition Monitoring System (ACMS) (Sun et al., 2019). Oikonomou et al. (2022) state that new-generation aircraft such as Boeing 787 and Airbus 350 are equipped with thousands of sensors for recording and monitoring health conditions. One example is the aircraft's brake system: "…the aircraft itself measures the position of the actuators when clamped to the carbon discs and infers the carbon thickness from this measurement" (Oikonomou et al., 2022, p. 2). Therefore, aligning with the aviation industry's direction, aviation maintenance institutions should teach CBM strategy to prospective students. This proposed CBM-BN material will help instructors teach the CBM concept to students as well as expand student insights into an aircraft component's failure point by analyzing hidden probability. Moreover, this teaching material enhances students' decision-making techniques.

The current aviation industry has aimed to meet the goal of the International Civil Aviation Organization (ICAO)'s 2050 carbon net zero (n.d.). By reviewing Ha et al. (2022) study, the researchers find that this CBM-BN education method can be a way to foster sustainable concepts in students by contributing to operational improvements. Therefore, in the future, a mechanic who can do CBM analysis will be more beneficial and demandable in the job market and contribute to full CBM implementation.

This research requires two future developments to be a step closer to a practical approach and increase model creditability. CPT calculation verification and CBM-BN output validation are required with actual industry data. First, manual coding by subject matter experts (SMEs) is essential to compute CPT and map the original CBM-BN network (Yang & Mott, 2020). Second, it is important to find the relational weights between the child node and the parent node. In other words, find the causality of the failure and evaluate the components' contribution to the failure (Pitchforth & Mengersen, 2013). When students carefully compute the correct probabilities, taking into account the root cause of the failure, and enter them into the correct nodes, then Genie software computes diagnosis and prognosis outputs.

For validation of CBM-BN output, it is a process to validate the CBM-BN model's performance by comparing observed and predicted output. Many researchers use various validation methods such as absolute deviation (MAD) (Dinis et al., 2019), mean absolute percentage error (MAPE), root mean squared error (RMSE) (Oikonomou., 2022), mean squared error (MSE) (Ferreiro & Arnaiz, 2011), and relative error (Sun et al., 2019).

## Limitations

The limitation of this study is that CBM-BN is one approach among various CBM approaches. The disadvantage of the BN is that when multiple factors are considered together, the logic will be complex and require substantial data (Rath et al., 2022). Therefore, future researchers are required to study other analytical CBM skills that can compensate for the disadvantages of the CBM-BN model and increase the maturity level of CBM operation. As discussed in the literature review, Boeing highlighted the importance of analytical skills to the new technicians' generation, so more CBM skills and techniques need to be developed and taught to the next generation of aviation technicians. For example, other CBM techniques include hidden Markov chain modeling, Artificial Neural Networks (ANN), Fuzzy Logic (FL), and Convolutional Neural Networks (CNN).

## Conclusion

This paper aims to provide training materials for instructors to educate prospective aviation technicians on a new strategy for aircraft CBM modeling that can be used in any FAA CFAR Part 147 aviation maintenance program. The authors review the issues and challenges of the industry. To ease the hurdle of the CBM implementation challenge, the authors propose CBM training materials for the aviation maintenance program in line with future industry needs. The authors create CBM models using the BN. The CBM-BN training material is supplemented with an example. Prospective aviation technicians are expected to learn the CBM-BN and apply it to the construction of CBM strategy. CBM-BN analytical skills knowledge will be beneficial to potential technicians and a more important skill set in the future. Moreover, other CBM educational materials would be needed to compensate for the downside of BN and increase the maturity level of CBM.

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The CBM-BN model is developed using the *Genie* model (Refer to Figures 3 and 4), available free of charge for academic research and teaching use from BayesFusion, LLC, https://www.bayesfusion.com/.

## Conflict of Interest Statement

The authors declare no conflict of interest.

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