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OPERABILITY PROJECTION OF MAJOR AIRCRAFT COMPONENTS DURING EARLY AIRCRAFT DESIGN

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Abstract

Aircraft operational performance is a key factor to achieve airline profitability and meet passenger expectations. It is determined by the 'operability' of major aircraft components along with the operational context in which the aircraft operates. Operability is the ability of a system to meet its operational requirements in terms of reliability, availability and costs. This paper proposes a approach to take into account the type of technology employed in a major aircraft component to perform operability projections. An operability model is developed using Bayesian networks that helps project the influence of different input parameters on the operational performance of the major aircraft components. An approach combining engineering and in-service data is used to instantiate the different parameters and train the Bayesian network model. The trained model can be used by system designers to perform operability projections of different design solutions through Bayesian inference and make trade-off studies from an operability point of view. Clustering of the data using unsupervised learning is also addressed in this paper to identify the best combinations of input parameters that can produce the desirable operational performance.

Keywords: Operability projection, Aircraft operations, Early aircraft design, Bayesian networks, Clustering

1. Introduction

Modern day aircraft are some of the most complex systems that have been created by humans. They consist of a huge number of parts that need to work coherently to achieve the different aircraft functions. These different parts of an aircraft are usually categorised into high-level systems which are referred to as major aircraft components in this paper. A classification that is commonly used in the aviation industry is the Air Transportation Association (ATA) 100 specification [1] which defines about 100 categories of high-level systems and structural components. For instance, ATA 27 corresponds to the flight controls system and ATA 53 represents the fuselage of an aircraft.

Aircraft operational performance is a key factor to achieve airline profitability and passenger satisfaction. The overall operational performance of an aircraft is determined by the operability of all its major components. Operability of a system is its ability to achieve its operational requirements in terms of reliability, availability and maintenance costs. Hence, operability of major aircraft components is an important criterion that is taken into account during early aircraft design. Therefore, techniques are required which can perform operability projections of major aircraft components using a few high-level input parameters that are available during early design from the designers. The architecture of such a method called 'Holistic Operability Projection' (HOP) was proposed by the authors of this paper previously [2].

This paper addresses some key input parameters for a major aircraft component that are required to perform operability projections. One such parameter is the type of technology employed in a major aircraft component. Different classes of technology are defined like mechanical, electronic, *etc.*, and a major aircraft component is represented by a probability distribution of these technologies using engineering and in-service data. A Bayesian network model is developed which allows designers to evaluate the operability impact of employing a particular kind of technology for a major aircraft component. Clustering of the different input parameters using machine learning techniques is also addressed in this paper. Clustering can help the designers to identify the desirable values of input parameters that lead to good operational performance.

The remainder of this paper is organized as follows: Section 2 surveys related works. Section 3 discusses the methodology of the study and Section 4 presents the results. Finally, section 5 concludes the paper with some directions for future work.

2. Related work

There have been previous studies in the aviation domain that have addressed the estimation of some of the operability metrics like system reliability and maintenance cost. Conventional techniques for reliability evaluation are fault trees, petri-nets, reliability block diagrams, *etc.* [3] but these require detailed design specifications that are not necessary available during early design. A method for estimating in-service aircraft reliability during preliminary design was proposed in [4], where an algorithm was presented for computing the reliability bounds for a component. Even though this approach could incorporate uncertainties, it was mostly aimed towards the reliability estimation of an individual system whose failure modes are known. On the other hand, our study is aimed at a higher level *i.e.* towards major aircraft components during very early design phases of aircraft development.

In the recent years, there has been an increasing trend towards the utilization of Bayesian networks for reliability and safety applications [5]. This can be attributed to the power of Bayesian networks in incorporating both domain knowledge and in-service data in the models. The advantage of bi-directional inferencing in Bayesian networks helps designers to make both predictive as well as diagnosis studies [6]. Delay propagation in airline networks has been modeled using Bayesian networks [7] which could help identify the major delay-causing factors for airlines. Another study [8] has explored the delay propagation at an airport based on the arrival delay. Bayesian networks have also been used for prognostics and maintenance planning applications [9, 10]. But to the best of authors' knowledge, none of these studies have mapped the relationships between the high-level design properties and type of technology used in major aircraft components to their operational performance, which is the focus of our paper.

Clustering of observations from engineering and in-service data is also addressed in this paper to identify the most desirable combinations of input parameters to produce good operational performance. Clustering techniques have been used in aviation domain in several previous works for different purposes. One of the main applications of clustering algorithms has been towards analysing flight data for safety applications [11–13]. A review of flight data mining techniques has been presented in [14]. Another application of clustering has been to analyse the fuel consumption of commercial aircraft with respect to different flight factors [15], which uses an extension of the widely used K-means algorithm. A data-driven framework is introduced in [16] for analysing airline performance and clustering airport capacity impacts. Even though this study addresses airline operational performance, it mainly focuses on clustering airport capacity impacts, delays and cancellations *i.e.* from an airline point of view. On the contrary, our study addresses the operational performance of an aircraft from a design point of view. As per authors' knowledge, there has been very little work in the literature that addresses the topic of clustering the design properties of major aircraft components with respect to the aircraft operational performance.

3. Operability projection of major aircraft components

There are two main aspects that are considered during operability projections of major aircraft components: aircraft and operational context as shown in Fig. 1. Aircraft major components are initially described using some high-level operability metrics called as Consolidated Operability Metrics (COMs). An additional attribute characterizing the technology of the sub-components is defined using expert knowledge. Operational environment parameters are defined to characterize the operational context in which the aircraft operates. All these parameters are taken into account for projecting the operational performance of the aircraft.

Clustering of the technical issues generated by a major aircraft component is performed using unsupervised machine learning. The learnt clusters are analysed with respect to the 'technology' classes that were tagged manually. Finally, the effect of changing the technology of a major aircraft component is emulated and the resulting operational performance is compared to the reference baseline.

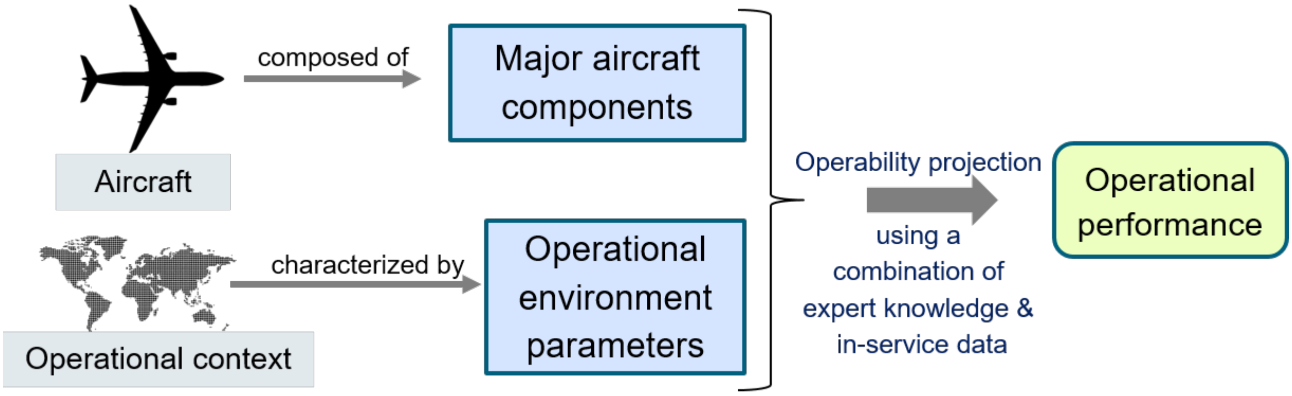

Figure 1 – Main blocks considered for operability projection of major aircraft components.

3.1 Technology tagging of sub-components of major aircraft components

An aircraft major component comprises several sub-components. For instance, if a flight controls system which is an aircraft major component is considered, it consists of several sub-components like aileron actuation, rudder control, flight computers, *etc.* Each sub-component can employ different kinds of technologies to achieve the required function. For example, an actuation system can be realized using hydraulic, pneumatic or electric technology. In modern systems, a combination of technologies is usually observed due to the increasing presence of electronic components like sensors, fly-by-wire systems, *etc.* But, in most cases, it is still possible to identify one or two major technologies employed by a sub-component.

The identification of technology used in a system is important as it can have an impact on the number and severity of Technical Issues (TIs) generated by a system, eventually contributing to the aircraft operational performance. It is assumed that each sub-component of an aircraft major component can be assigned to one of the 10 technology classes defined in Table 1. This list of 10 technology classes was created by the authors relying on domain knowledge from operability experts. The list is not exhaustive and there could be additional classes added when required. The first 5 classes are associated with sub-components which employ primarily any one type of technology like mechanical, hydraulic, *etc.* The classes from 6 to 9 are associated with sub-components which are implemented using dual technologies like mechanical/electronic, *etc.* Finally, when it is not possible to associate a sub-component with any of these 9 classes, it is assigned to class 10 'Other' which signifies that the sub-component uses a technology or a combination of technologies not listed in the table.

A major aircraft component is usually considered at the ATA-2D level. *E.g.*, ATA 27 refers to the Flight controls system. A sub-component of major aircraft component is considered at the ATA-4D level. *E.g.*, ATA 2721 refers to the Rudder control system. First, all the sub-components of a given major aircraft component are identified through engineering design data. The next step is to assign each of these sub-components to one of the technology classes defined in Table 1 to create a dictionary. This assignment of the technology class has to be performed by operability and system experts of the given major aircraft component. Usually, it is relatively straightforward to identify the technology of the sub-component from the system description available in technical manuals published by the aircraft manufacturer. The final step is to associate each technical issue observed in the in-service data with the technology of the sub-component that generated the technical issue using the dictionary that was created earlier. The distribution of technology classes for a major aircraft component forms one of the main input parameters for the operability projections.

Table 1 – List of Technology classes that can be assigned to a sub-component of an aircraft major component.

Class No.	Technology class
1	Mechanical
2	Hydraulic
3	Electrical
4	Pneumatic
5	Electronic
6	Mechanical/Electronic
7	Hydraulic/Electronic
8	Pneumatic/Electronic
9	Electrical/ Electronic
10	Other

3.2 Operability and Operational Environment input parameters

There are other input parameters that are required for operability projections of an aircraft major component which are the Consolidated Operability Metrics (COMs) and Operational Environment Parameters (OEPs) defined in authors' previous work [2].

3.2.1 Consolidated Operability Metrics (COMs)

Consolidated Operability Metrics (COMs) are high-level metrics that can be defined for a major aircraft component from an operational point of view. These COMs drive the operational performance of major aircraft components.

The list of COMs identified for aircraft operability projection is shown in Table 2. These COMs represent different dimensions of operability characteristics of an aircraft major component which can be influenced by design.

Table 2 – List of Consolidated Operability Metrics (COMs) defined for aircraft major components in HOP [2].

No.	Name of COM (N)	Definition	Values (V)
1	Reliability	The number of Technical Issues (TI) per aircraft per year	(continuous value)
2	Detectability	The flight phase of detection of TI	Between Pushback and Take-Off (BPTO), Flying, Planned stop
3	Diagnosability	The need for troubleshooting to diagnose the TI	Troubleshooting, No troubleshooting
4	Dispatchability	The operational and maintenance procedures required to dispatch the aircraft after occurrence of TI	Rectification, No rectification
5	Deferrability	The maximum number of days upto which the TI can be deferred for rectification	Not deferrable, Upto 1 day, From 1 to 3 days, From 3 to 10 days, From 10 days to 120 days, Above 120 days
6	Repairability	The maintenance duration required to rectify the TI	(continuous value)
7	Resourceability	The type of facility and human resources required to rectify the TI	Standard, Non-standard
8	Predictability	The ability to predict the occurrence and type of TI	Predictable, Not predictable

3.2.2 Operational Environment Parameters (OEPs)

The operational context in which an aircraft is operated also has a big influence on its operational performance. Hence, it is important to characterize the operational context in terms of few Operational Environment Parameters (OEPs).

The list of OEPs identified for operability projection of major aircraft components is shown in Table 3.

Table 3 – List of Operational Environment Parameters (OEPs) identified in HOP [2].

No.	Name of OEP (N)	Definition	Values (V)
1	Airport type	The type of airport based upon the airline's capacity to perform maintenance activities at this location	Mainbase, Outstation
2	Scheduled stop time	The time duration between the scheduled departure time of next flight and previous flight's arrival time	(continuous value)
3	Mission type	The type of aircraft mission based upon if it is Extended Range Operations (ETOPS) or not	ETOPS, non-ETOPS
4	Aircraft utilization hours	The annual utilization of aircraft in terms of Flight Hours (FH)	(continuous value)
5	Aircraft utilization cycles	The annual utilization of aircraft in terms of Flight Cycles (FC)	(continuous value)

3.3 Main steps of operability projection

Initially, Finite State Machine (FSM) models of aircraft operations were created by the authors in previous work [17] to represent the different states an aircraft can occupy in operation, (*e.g.*, flying, taxiing-in, and planned stop). These models were created using the domain knowledge of operability experts. In these FSM models, all possible transitions between different aircraft states were defined. There are two kinds of FSM parameters that are required to simulate a FSM: transition probabilities and time durations. FSM transition probabilities signify the distribution of probabilities among the different transitions possible from each state. FSM time durations refers to the probabilistic distribution of time that an aircraft spends in each state. Given these two parameters for each state of the FSM, it is possible to simulate it for a given amount of time and compute some useful operability results.

The current paper proposes an extension to HOP by introducing the additional block 'Technology of sub-components' which is a major driver to aircraft operational performance along with COMs and OEPs. Also, some additional COMs and OEPs have been addressed in this paper which are incorporated in the operability model. The major blocks of the projection method employed in this paper are shown in Fig. 2.

As seen from Fig. 2, there are two main parts which are separated by a dotted line: 'Operability projection' and 'New design evaluation'. Operability projection deals with populating the different input parameters from expert knowledge or in-service data and projecting the operational performance using these input parameters. On the other hand, the upper part of the Fig. 2 deals with the assessment of a new design in terms of design properties which can later be used to populate the input parameters required for operability projection, which is out of scope of this paper.

The main steps involved in operability projection are listed below:

- *Step 1*: Instantiate the outputs (aircraft operations FSM parameters) for a reference baseline using in-service data.
- *Step 2*: Instantiate the input parameters for a reference baseline using both expert knowledge and in-service data.
- *Step 3*: Develop the operability model to map the different input parameters to the output parameters.
- *Step 4*: Compute the different operability Key Performance Indicators (KPIs).

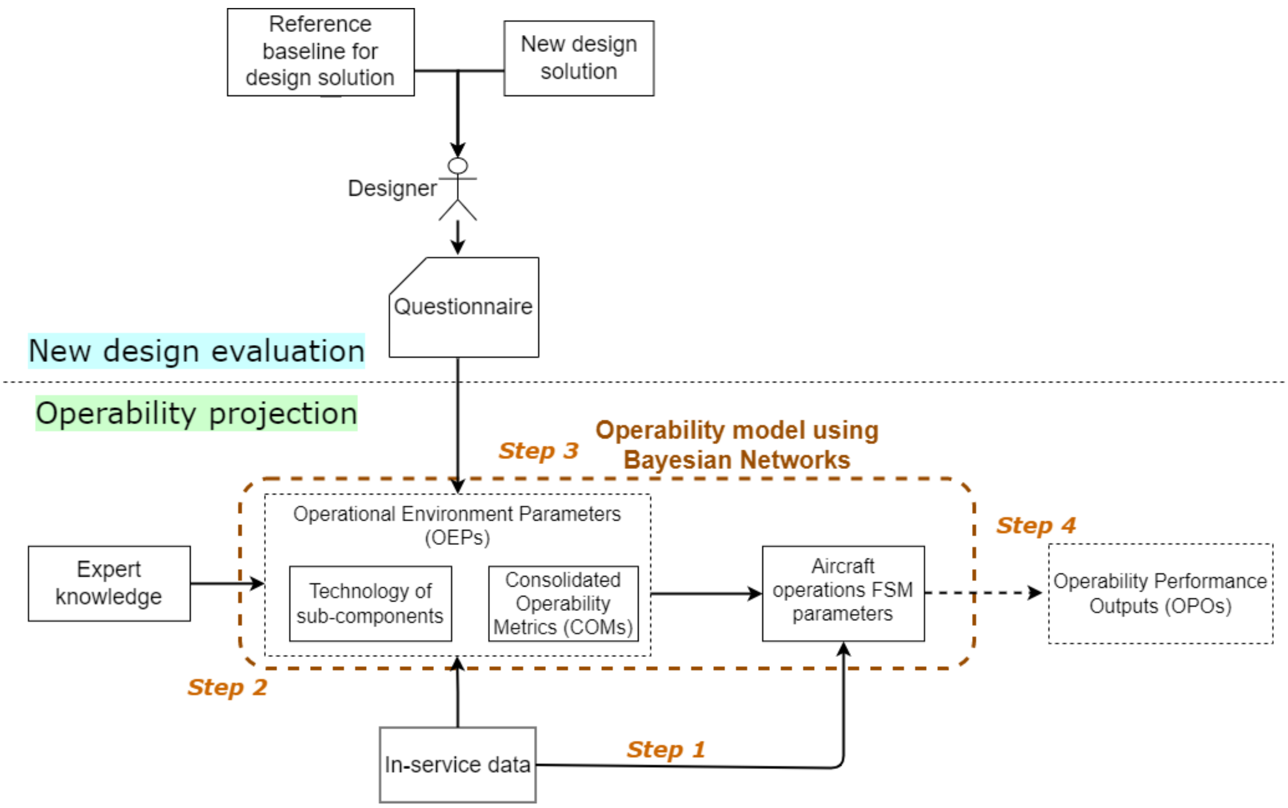

Figure 2 – Different steps involved in the operability projection of major aircraft components.

3.3.1 Operability model

The *Step 3*, *i.e.* the operability model, is realized using Bayesian networks [2] to perform the mapping between the different input and output parameters. Bayesian networks were chosen to create this model owing to their strengths in predictive modeling and performing omni-directional inferences. The parameters (conditional probability tables) of the Bayesian network model need to be specified to perform inferencing. First, the values for all the nodes of the model were populated from engineering data and in-service data as explained in section 3.3.2. These values were in turn used to estimate the conditional probability tables of the nodes using maximum likelihood estimation. The fully specified models could then be used to perform inferences.

3.3.2 Data used in the models

In-service data and engineering data were used to populate the Bayesian network models. Engineering data were captured by assessing aircraft technical manuals like Master Minimum Equipment List (MMEL), Aircraft Maintenance Manual (AMM), *etc.* In-service data were analysed from different datasets like flight schedules, actual flight timings, logbook entries, operational interruptions, *etc.* to populate the values of the nodes.

The principal data set used was the aircraft technical logbooks reported by airlines. Aircraft technical logbook is a health record of an aircraft which contains all the reported technical issues along with the corresponding maintenance actions. Each entry in the technical logbook is then enriched with other information from engineering and in-service data sets. Information regarding scheduled and actual flight timings is added using flight timings data sets. It is correlated with the operational interruptions data set to check if there was a delay with the flight corresponding to the technical issue. Several information from engineering data like the type of Ground Support Equipments (GSE), maximum time of deferral of the allowed maintenance action, etc. are used to enrich the original technical logbook dataset. This helps to create a consolidated database that can then be used to compute the different input parameters of the Bayesian network model like COMs and OEPs.

3.4 Use-case

The methodology is demonstrated on a use-case of Flight Controls system (ATA 27) which is a major aircraft component. This use-case was defined on a set of 8 input and 9 output parameters as shown in Fig. 3. In this exercise, 5 COMs were used to describe the major aircraft component from an operability point of view: *Detectability*, *Dispatchability*, *Diagnosability*, *Deferrability* and *Resourceability*. The 'technology of sub-components' is represented by an input node along with two operational environment parameters which are also modelled as input nodes. The output nodes comprise 3 FSM transition probabilities and 6 FSM time durations. The most important output node is 'Planned stop transitions' as it depicts the probability of having a delay which is a key consideration during analysis of a system's operability performance. The node 'Planned stop with delay time' represents the distribution of time spent by the aircraft in a delayed state during operations.

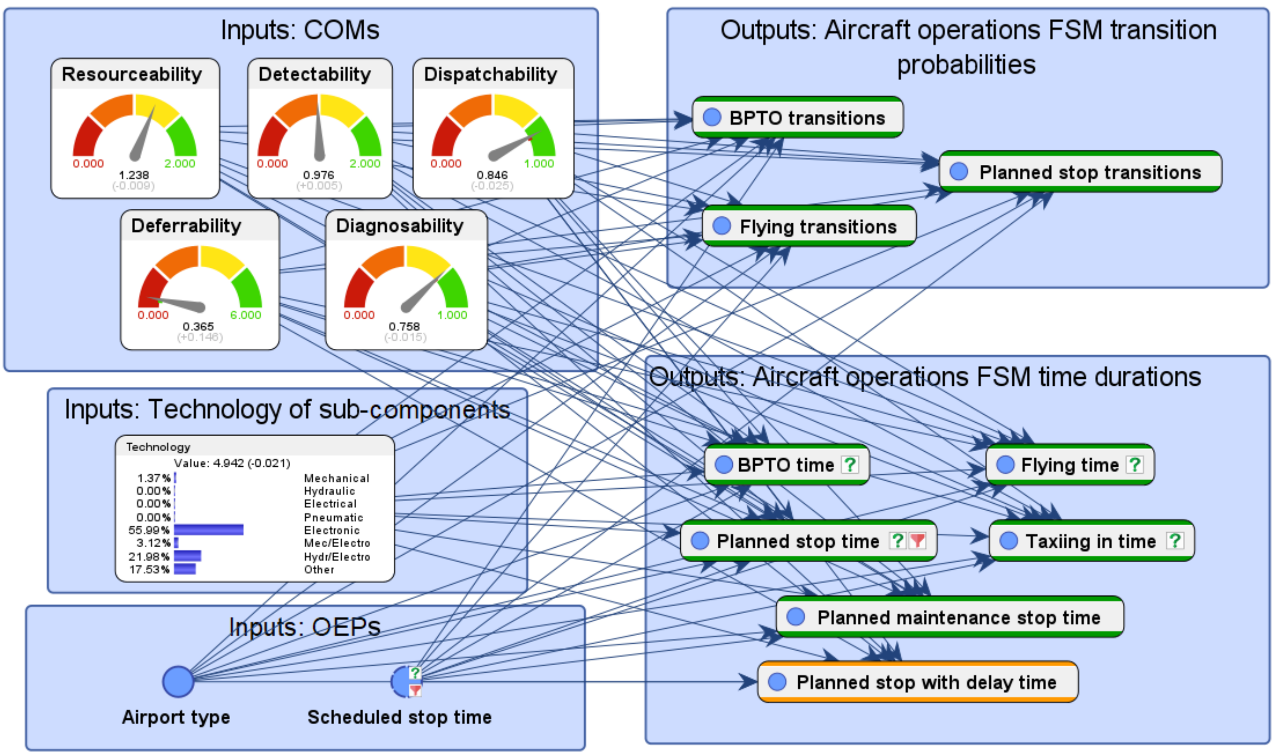

Figure 3 – Bayesian network model of the use-case.

The Bayesian network model for the use-case was built using BayesiaLab software [18]. The database consisted of 2850 entries that corresponds to the technical issues recorded during 4 years of operations of an aircraft fleet.

3.5 Clustering using unsupervised learning

A study was conducted to identify some clusters in the data using unsupervised machine learning to group the technical issues that behave in a similar fashion. One of the objectives was to also check if the clusters obtained through machine learning correspond with the 'technology of sub-components' classes that were identified for each technical issue, as explained in section 3.1

The clustering was performed on 6 parameters of the operability model: 5 COMs and 1 output FSM parameter 'Planned stop transitions'. The operational environment parameters were not taken into account for clustering as the objective was to perform clusters based on the design properties of the major aircraft component that were reflected in the COMs. The FSM parameter 'Planned stop transitions' was considered as it is one of the most important output parameters that depicts the probability of having a delay during aircraft operations. The probability of having an operational interruption like a delay is a key consideration during system design and trade-off studies.

There are several approaches to perform clustering using machine learning techniques. The most popular clustering algorithm for partitioning is K-means [19] owing to its simplicity and ease of implementation. Hence, the clustering in this paper was performed using K-means algorithm which partitions the observations into 'k' clusters in which each observation is assigned to one of the clusters. K-means clustering works only with numerical values, but since our data are categorical in nature, it needs some pre-processing before it can be fed to the K-means algorithm. One-Hot Encoding was used to convert the categorical variables into numerical ones. The K-means algorithm also requires the number of clusters 'k' as an input to perform the clustering. In many cases, it might be hard to guess the number of optimal clusters. Hence, clustering is usually performed for a range of 'k' values and the optimal number of clusters is chosen based on the clustering performance.

The performance of clustering is evaluated using a metric called Silhouette score [20] which measures how similar the observations are to the other observations in their own cluster compared to the observations from the other clusters. The Silhouette score s_i for a given observation i is computed according to the equation 1.

$$s_i = \frac{b_i - a_i}{max(b_i, a_i)} \tag{1}$$

where:

$s_i =$ silhouette score of the observation i
$a_i =$ intra-cluster distance that is defined as the average distance of i to all the other observations in its own cluster
$b_i =$ inter-cluster distance that is defined as the average distance of i to all the observations from the closest cluster of i

The overall Silhouette score is calculated as the mean of Silhouette scores of all the observations. Its value ranges from -1 to 1. A positive value close to 1 indicates that clusters are compact and well separated. Values close to 0 indicate that the clusters are overlapping with each other. A negative value indicates that the observations have been misclassified. So, the optimal number of clusters is usually the one that produces the highest Silhouette score.

For the use-case, the clustering was performed by varying the number of clusters from 2 to 9 and the Silhouette score was computed in each case. A plot of Silhouette score versus number of clusters is shown in Fig. 4. It can be observed that the highest Silhouette score is obtained when the number of clusters is equal to 8. Hence, the number of clusters 'k' was assigned to 8 for performing clustering.

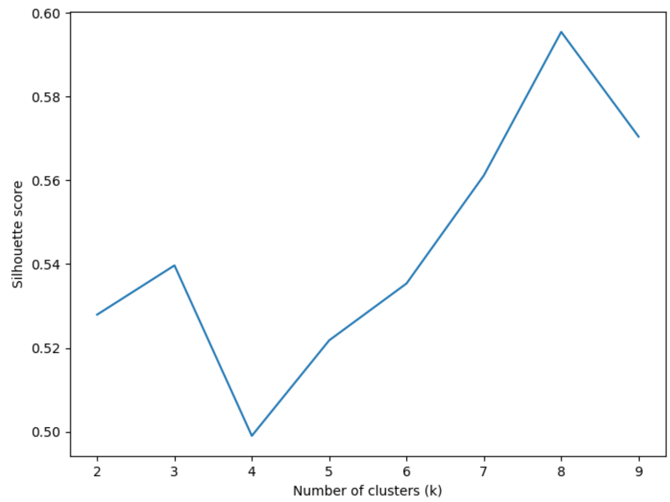

Figure 4 – Plot of Silhouette score versus number of clusters.

The learnt clusters were analysed with respect to the 'Technology classes' that were tagged manually. Also, each learnt cluster was analysed with respect to its operational performance.

4. Results

For the use-case, the different nodes of the Bayesian network model were populated using engineering and in-service data for an aircraft type. In-service data for a fleet of this aircraft type was collected and analysed over a time period of 4 years. The fully specified Bayesian network model was used to perform inferences.

The clustering exercise was performed in PySpark as it is very efficient when working with large datasets. It uses data parallelism by partitioning the dataset into smaller partitions, thereby reducing the time of computation.

4.1 Technology classes

The initial probability distribution obtained for the 'Technology of sub-components' is shown in Fig. 5. It can be seen that about 56% of the technical issues generated by the use-case (flight controls system) were due to *Electronic* sub-components. The next major technology that generated technical issues was *Hydraulic/Electronic* which accounted for 22% of the total technical issues. This can be explained by the fact that flight controls system majorly consist of flight computers, controllers and hydraulic actuators. Apart from electronic and hydraulic sub-components, there were a smaller amount of technical issues generated by *Mechanical* (1%) and *Mechanical/Electronic* (3%) sub-components, which accounts for the mechanical linkages and connectors. There were about 18% of technical issues that could not be categorised into one of the defined technology classes due to lack of sufficient information from in-service data. The 'Value' of 4.942 indicated in the Fig. 5 depicts the mean of the distribution when classes are numbered from the top starting from 0.

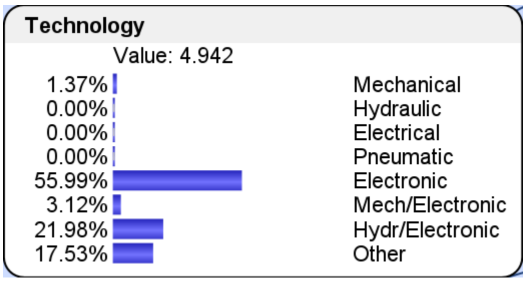

Figure 5 – Initial probability distribution for the technology classes for the use-case.

The fully specified Bayesian network can be used to perform inferences when evidence is set on any of the nodes. The evidence propagates in all directions in a Bayesian network. There are different kinds of evidence which can be set on nodes depending on the objective of the analysis. It is called 'Hard evidence' when a particular state of a node is set to 100% probability. This is useful to see the individual impact of a particular state on the output nodes of the model. Probabilistic evidence can be set on a node when the probability distribution of a node is altered between the different states. This type of evidence can be useful to compare a new design with respect to an existing baseline.

For the reference flight control system, about 56% of the technical issues are generated by *Electronic* sub-components. Let a hypothetical system be assumed to have technical issues that are generated only by electronic components *i.e.* hard evidence is set on 'Technology' node to 100% *Electronic*. This is just to illustrate the individual impact of a technology and may not be representative of real systems as it might not be feasible to have 100% of any one kind of technology. Through Bayesian inference, the impact on the output FSM parameters can be observed which is shown in Fig. 6. It can be seen from the 'Planned stop transitions' node that there is a reduction in probability of having a delay from 12.7% to 11.9 %. From the 'Planned stop with delay time' node, it can be seen that the mean of delay time reduces by about 4 minutes. These results show that technical issues generated by *Electronic* sub-components in the flight control system have a lower tendency to cause operational interruptions. This could probably be due to the fact that technical issues related to electronic systems can be diagnosed more easily than other kinds of systems like mechanical, pneumatic, *etc*.

For a new design solution, the operability impact of changing the technology of sub-components can be emulated and analysed by setting probabilistic evidence on the 'Technology' node. A hypothet-

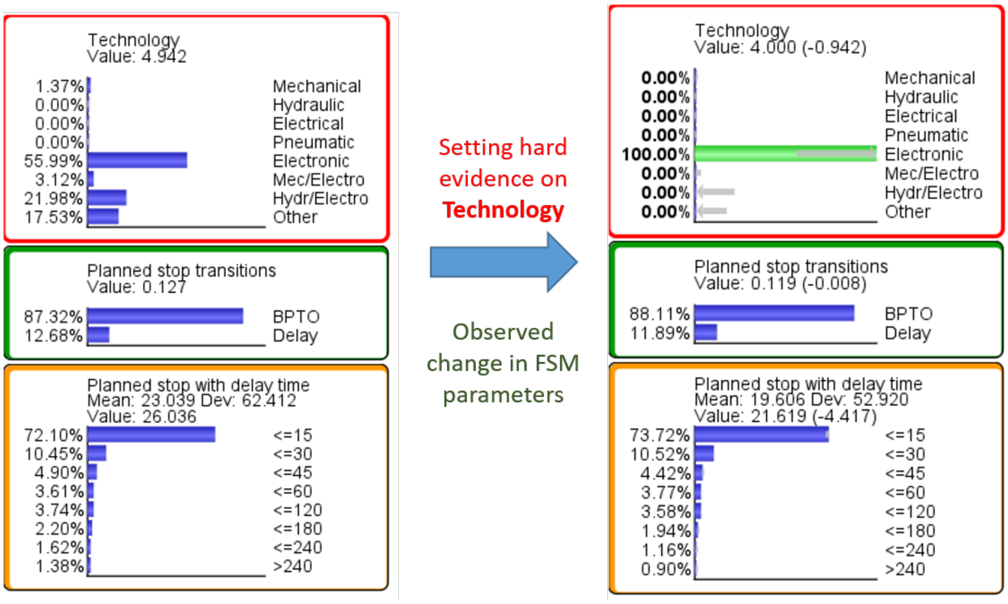

Figure 6 – Results of setting hard evidence on 'Technology' to 100% *Electronic* in the Bayesian network model.

ical new design of the flight controls system is considered where some of the hydraulic/electronic actuators are replaced by mechanical/electronic actuators. In this study, it is assumed that the number of technical issues produced by a certain kind of technology is proportional to the number of sub-components employing that technology. Hence, an increase of mechanical/electronic actuators causes a corresponding increase in the number of technical issues produced by the mechanical/electronic sub-components and vice-versa. Thus, the resulting probability distribution of the 'Technology' node is assumed to have changed such that the probability of technical issues generated by *Hydraulic/Electronic* state reduces by 10% and the probability of technical issues generated by *Mechanical/Electronic* state increases by 10% as shown in Fig. 7. But, in reality, the number of technical issues produced by sub-components depends on many factors like technology employed, reliability of technology, failure modes of the sub-component, *etc*.

Through Bayesian inference, the impact of changing the probability distribution of the 'Technology' node on the FSM parameters can be observed as shown in Fig. 7. It is seen that there is an increase in the probability of having a delay by 1.5% and the mean value of delay time increases by 1 minute. This small degradation in performance could possibly be attributed to the relatively lower maturity of mechanical/electronic actuators in aviation compared to hydraulic/electronic actuators. It has to be also noted that the current operability model was trained on a limited dataset of one major aircraft component that looked at only unscheduled maintenance. As and when a bigger and wider dataset covering several major aircraft components is used to train the model, results that are more representative of reality could be achieved.

These kind of quantitative results regarding technology of sub-components can help system designers to evaluate the operability impact of a major aircraft component during early design. It can thus help architects in conducting trade-off studies between different candidate systems from an operability point of view.

4.2 Clustering

Clustering was performed using the K-means algorithm as explained in section 3.5. As the optimal number of clusters was 8 corresponding to the highest Silhouette score, the observations were split into 8 clusters. The probability of causing a delay for the different clusters is shown in Fig. 8.

In Fig. 8, the numbering of clustering starts from *0* and hence ends at *7*. It can be seen that some clusters have a higher tendency to cause delays like clusters *2* and *7* whereas other clusters like *1*, *4* and *5* have negligible probabilities of causing delay. The clusters *3* and *6* have 15% and 6%

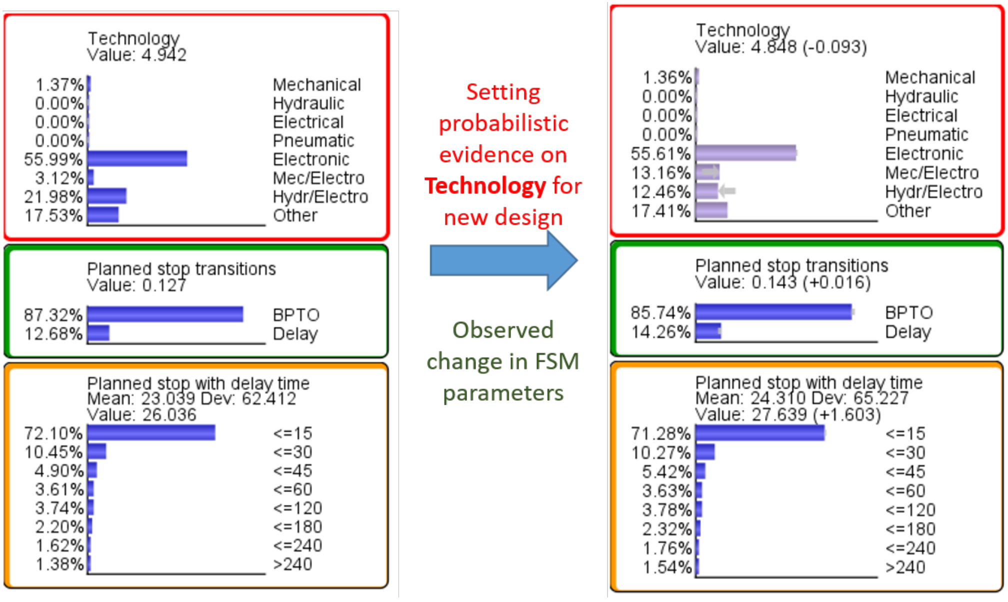

Figure 7 – Results of setting probabilistic evidence on 'Technology' for a hypothetical new design in the Bayesian network model.

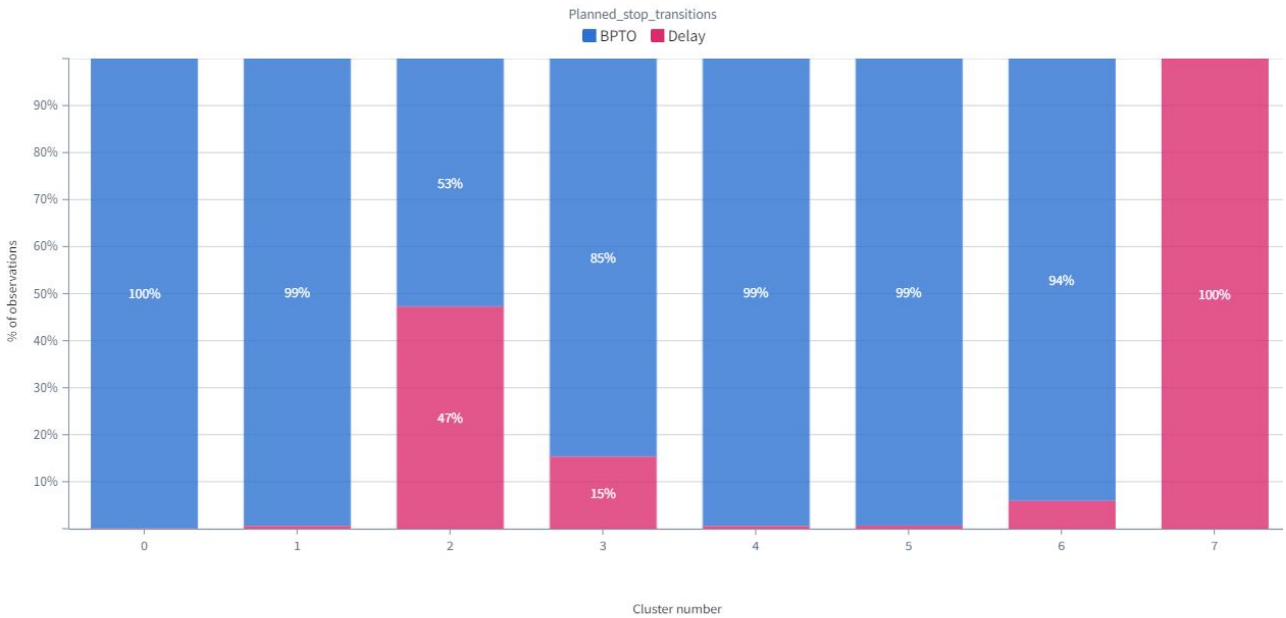

Figure 8 – The probability of having a delay for different learnt clusters.

probabilities of causing delays. The cluster *0* has 0% probability of causing a delay making it the best cluster in terms of operability impact. Hence, the clusters with good operational performance can be identified and they can be analysed to understand what combinations of states of COMs are desirable. The analysis of clusters with respect to one of the COMs 'Detectability' is shown in Fig. 9.

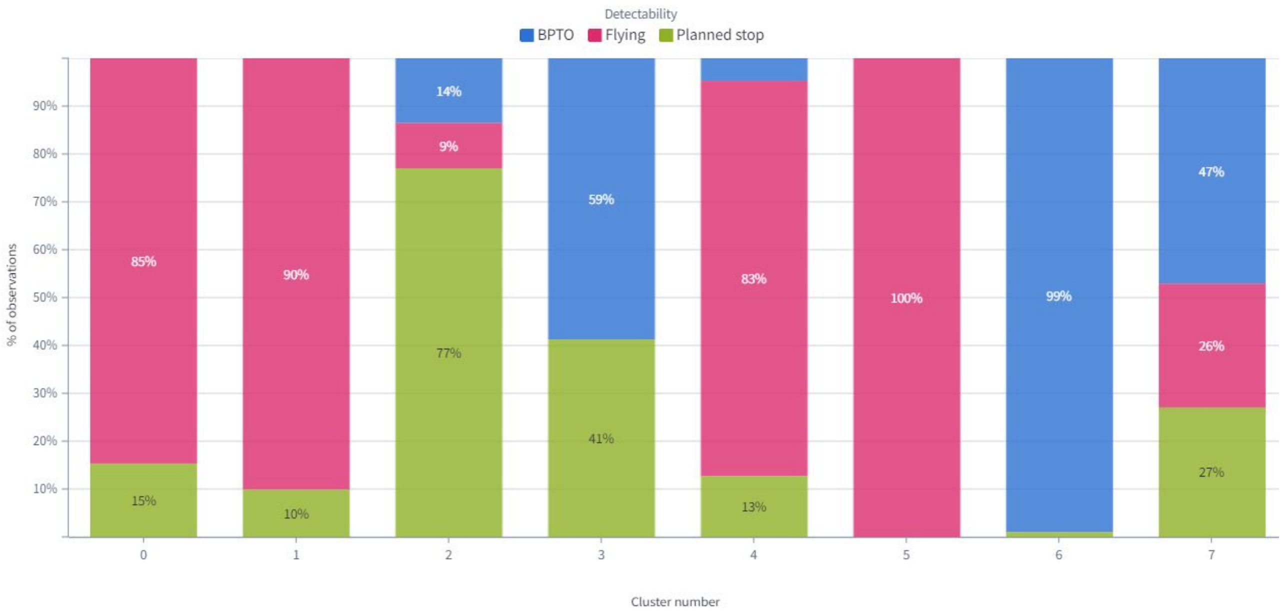

Figure 9 – Distribution of states of COM 'Detectability' for different learnt clusters.

From Fig. 9, the distribution of states of COM 'Detectability' for each of the learnt clusters can be observed. It can be seen that there is a lot of variation between the different clusters. For instance, in the cluster *0*, a majority (85%) of the technical issues were detected during *Flying*, 15% of the technical issues were detected during *Planned stop* and none of the technical issues were detected during Between Pushback and Take-Off (BPTO). Detection of technical issues during BPTO is usually more severe for the airline as it has very little time for rectification before it becomes an operational interruption. On the other hand, when the technical issue is detected during flying or planned stop, it allows the airline more time for rectification, thereby reducing the probability of an operational interruption like a delay. Therefore, the low probability of delay for cluster *0* as seen in Fig. 8 could probably be attributed to the low probability of the *BPTO* state for cluster *0* observed in Fig. 9.

Hence, through analysis of cluster *0*, it could be inferred that having lower probabilities of the state *BPTO* could lead to better operational performance. This information provides cues to the designers to choose a candidate design solution that has a less proportion of *BPTO* state. Hence, scrutinization of machine-learnt clusters by systems designers can yield valuable insights regarding the desirable states of different COMs for achieving good operational performance, thus leading to relevant design-to-operability choices.

The clusters obtained through unsupervised learning were compared with the different technology classes as shown in Fig. 10. It could be observed that there was no direct correlation between specific clusters and technologies for the use-case of flight controls system. It was seen that each cluster contained a distribution of different technologies. *E.g.*, cluster *0* is composed of 43% *Electronic*, 32% *Hydraulic/Electronic*, 1% *Mechanical*, 2% *Mechanical/Electronic* and 23% of *Other* technologies. Hence, it could be inferred that there are other factors taken into account during the learning process along with the technology class.

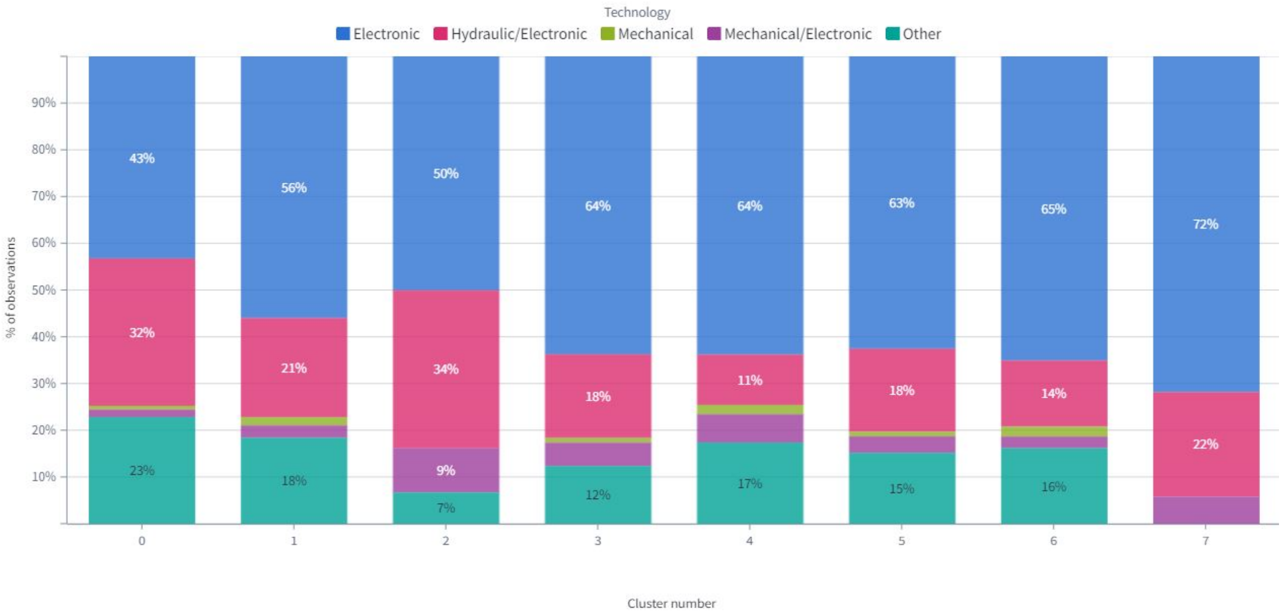

Figure 10 – The composition of different learnt clusters in terms of technology classes.

5. Conclusions

During early aircraft design, it is important for aircraft manufacturers to perform operability projections of major aircraft components in order to produce a mature aircraft that can achieve good operational performance. There are several factors that affect the operational performance of an aircraft. This paper mainly addresses the aspect of technology used in the aircraft major components, and tries to quantify its impact on the operational performance. Clustering of the observations using machine learning is also proposed in this paper.

A Bayesian networks model is used to make the operability projections. Along with technology of sub-components, some other high-level operability metrics (COMs) to characterize a major aircraft component and operational environment parameters are taken into consideration. Results from Bayesian inferencing show the impact of changing the technology of sub-components. It was seen that for the use-case of flight control system, technical issues generated by electronic components had a lesser tendency to cause delays compared to mechanical components. These kind of quantitative results can help the system designer during early design to take high-level decisions regarding the technology of the major aircraft component from an operability point of view.

Clustering of the observations was performed using K-means algorithm. The optimal number of clusters was determined to be 8 based on Silhouette score. Some clusters yielded better operability performance than the others. So, the clusters were analysed with respect to different COMs to understand what states of COMs are desirable to produce good operability performance. For instance, it was seen that for a cluster having good operability performance, it had a very low probability of the state *Between Pushback and Take-Off (BPTO)* for the COM 'Detectability'. It could be explained by the fact that the technical issues detected during BPTO have a high probability of causing operational interruptions as airlines have very limited time to perform maintenance before the scheduled departure time. Consequently, it could be inferred that a lower probability of detecting technical issues in BPTO could contribute towards achieving better operability performance. Hence, these kind of analyses results from the machine learnt clusters can yield valuable insights to the system designers regarding the best combinations of input parameters that can yield good operational performance.

To summarize, the Holistic Operability Projection (HOP) method provides designers and aircraft architects a tool to perform operability projections of major aircraft components during early aircraft design using domain knowledge and in-service data. HOP is intended to address the highly uncertain nature of aircraft operations and cater to different varieties of technical issues that could arise. The modeling of aircraft operations on a Finite State Machine (FSM) is a novel way of representing operability results which can provide a global view of aircraft operational performance to the designers. HOP is also intended to guide designers to focus on improving the most crucial operability parameters that impact operational performance.

The future work consists of expanding the Bayesian network model with more Consolidated Operability Metrics (COMs) and output parameters like Finite State Machine (FSM) transition probabilities and time durations. It might also be interesting to perform clustering analysis on this expanded model for different kinds of major aircraft components like Integrated modular avionics system (ATA 42) and Landing gear system (ATA 32), which might produce different clusters owing to the larger amount of data. Finally, it is planned to develop a simulation of aircraft operations FSM that will compute some operability Key Performance Indicators (KPIs).

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7. Copyright Statement

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