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A hybrid approach of machine learning and expert knowledge for projection of aircraft operability

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Abstract. Aircraft operational performance is a key driving factor to flight punctuality and airline profitability. The ability of a system to meet its operational requirements in terms of reliability, availability and costs is termed as ‘Operability’. It is of high importance for aircraft manufacturers to project operability during the early stages of development of an aircraft in order to make trade-off studies. This paper proposes a hybrid approach of using machine learning and expert knowledge to aid the projection of aircraft operational performance during the early design stages. This approach aims to benefit from the huge amount of in-service data available from the current and past fleet of aircraft. Hence, machine learning techniques are used to learn how different technical issues and their associated maintenance activities impact aircraft operations. Expert knowledge is used to establish the default rules of the simulation model used for the operability projection. Results from machine learning are used to improve these rules allowing one to make holistic projections of the operational performance of future aircraft. This approach allows one to estimate the elapsed time in different operational states of an aircraft like flying, turn-around, *etc.* which can then be used to calculate different operability Key Performance Indicators (KPIs) like aircraft reliability and maintenance unavailability.

1. Introduction

In recent years, huge progress has been made towards achieving on-time flights and minimal interruptions to the flight schedule. However, airline operations can still be disrupted due to both technical and non-technical factors arising from the inherent complexity involved in air travel [1]. The ability of an aircraft to meet its operational requirements in terms of reliability, availability and costs is termed as ‘Operability’. It is of high importance to consider aircraft operability during early stages of development of aircraft so that aircraft manufacturers can develop an aircraft that can best fulfill the operational demands of airlines. This can be achieved by projection of aircraft operability which refers to the estimation of aircraft operability during the design of an aircraft by the aircraft manufacturers.

A common way of classifying the major systems and structures of an aircraft is through the Air Transport Association (ATA) standard which specifies 100 numbered categories [2]. *E.g.*, ATA 27 corresponds to the ‘Flight controls’ of an aircraft. Currently, quantitative operability projection is performed at an advanced aircraft design stage when a well defined systems architecture and knowledge of failure modes is available. But, at this stage the architecture of major systems of the aircraft is already determined and any big design changes to improve the operability



performance are very expensive with significant impacts on the aircraft development program [3]. In this paper, it is proposed to address operability at a higher level *i.e.* ATA 2D (2-Digit) level corresponding to major aircraft systems and structures. This can help in making operability trade-offs during early aircraft architecting phases.

Operability is measured by different Key Performance indicators (KPIs) which help to assess the impact of design on the operational performance [4]. The main operability KPIs are Operational Reliability (OR), Maintenance Unavailability (MU), Operational Availability (OA) and Direct Maintenance Cost (DMC).

The objective of this paper is to propose a method to holistically project the operability of major aircraft systems and structures during early aircraft design. This paper aims to develop a hybrid approach of combining expert knowledge and machine learning to benefit from both the domain knowledge of operability experts and in-service data available from the current and past fleet of aircraft. The proposed framework of the hybrid approach is presented in this paper.

The rest of the paper is organized as follows: Section 2 surveys the related work in the domain of operability projection, machine learning and hybrid techniques. Section 3 describes the hybrid approach proposed in the paper. Section 4 discusses some preliminary results obtained through this approach. Section 5 concludes the paper by summarizing the main advantages and limitations of the hybrid approach along with the envisaged future work.

2. Related Work

The prediction of different attributes of aircraft operability like reliability and maintenance cost have been targeted by some previous studies. But as per authors' knowledge, the use of quantitative methods using in-service data to address operability projection during early design stages have been very limited. The related works have been divided into two sub-sections: (i) Operability evaluation and (ii) Machine learning and hybrid techniques.

2.1. Operability evaluation

Operability of a system of interest is its ability to meet its operational requirements in terms of reliability, availability and costs. Operability is also closely related to 'Dependability' and 'Supportability' which are commonly used by some research communities. Classical techniques for dependability evaluation are fault trees, reliability block diagrams, Markov processes and Petri-nets [5]. More recently, in the last couple of decades, there has been a growing interest towards the use of Bayesian networks and its extensions for reliability modeling [6]. Different techniques have been used in the past in the aerospace domain to estimate some characteristics of aircraft operability like reliability of aircraft and its systems. Most of these studies have been focused on evaluating the operational performance at equipment or system level [7, 8] which require detailed definition of the system and knowledge of its failure modes. This kind of information is usually not available during early stages of aircraft development. There have been some studies which have addressed computing the aircraft reliability during in-service operations in order to assist airline operations and mission planning [9, 10]. Unlike these studies, the focus of this paper is to develop a methodology to predict the operational performance of aircraft at major systems and structures level during early design stages, which is sparsely addressed in the literature.

2.2. Machine learning and hybrid techniques

There has been an increasing trend in the use of machine learning and artificial intelligence techniques in the aviation industry owing to the availability of a growing in-service database. Machine learning techniques have been researched previously for aeronautics in the field of prognostics of aircraft systems [11]. But in the case of operability projection at ATA 2D level, pure data-driven solutions might be limiting in terms of data availability and accuracy as there

could be new systems which have never been used before in aeronautics. *E.g.*, hydrogen tanks in commercial aviation. Hence, there is a need to adopt an hybrid approach of expert knowledge and machine learning. These kind of hybrid approaches have been investigated recently in other domains like medicine and biology where they seem to deliver promising results [12]. There exist different types of hybrid approaches depending on the method of coupling between machine learning and simulation [13]. A type of hybrid approach called ‘machine-learning assisted simulation’ where machine learning is used to support the simulation process has been used in the approach proposed in this paper.

3. Hybrid approach

There are several factors that influence aircraft operability like aircraft design, maintenance, operational context, human factors, *etc.* Uncertainty and variability is also inherent in aviation due to the large diversity of airlines and randomness of phenomena like weather, system failures, *etc.* Therefore, projection of aircraft operability is characterized by heterogeneity and multi-disciplinary nature which necessitates a hybrid approach of machine learning and expert knowledge. The proposed methodology to project aircraft operability is shown in Fig. 1.

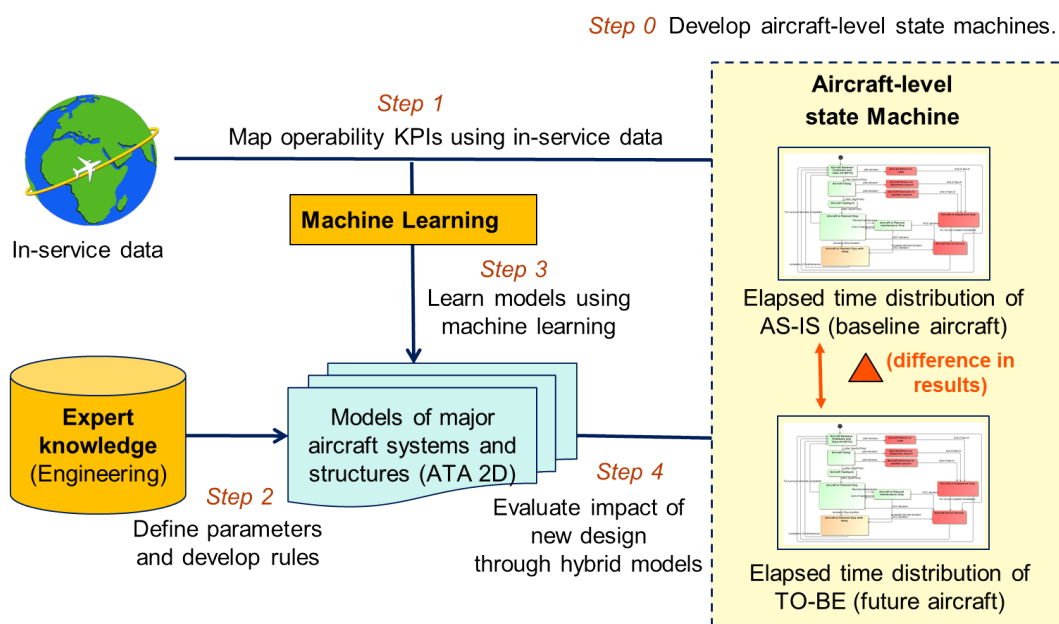


Figure 1. High-level overview of the proposed methodology.

Generic state machine models of aircraft operations were created by the authors in previous works [4] to represent the different states an aircraft can occupy in operation (*e.g.*, in flight, in planned stop) and their dynamic behaviour. All the possible transitions between different aircraft states were specified using the domain knowledge of operability experts.

3.1. Step 1: Establishing reference baseline using in-service data

In step 1 of the proposed methodology shown in Fig. 1, in-service data of existing aircraft is used to populate the different states of the aircraft state machine. Different data sets regarding scheduled flight timings, actual flight timings, operational interruptions, *etc.* are analysed to compute the elapsed time of the aircraft in each of these states. This mapping of elapsed time distribution on the aircraft-level state machine allows calculating the different operability KPIs. In step 1, elapsed time distribution for a reference baseline *i.e.* ‘AS-IS’ aircraft is established.

3.2. Step 2: Developing operability model using expert knowledge

In step 2, major aircraft systems and structures (ATA 2D level) are modeled from an operability point of view using expert knowledge. These models are composed of a list of high-level operability properties as shown in Fig. 2. These operability properties have an impact on the operational performance of the aircraft and were selected by operability experts. Such properties have also been identified in previous works concerning maintainability [14]. The operability properties are grouped into two categories: ‘technical issue’ and ‘maintenance’. Technical issue properties of a system of interest help to characterize the operational impact caused by just the occurrence of technical issues like system failure, structural damage, *etc.* On the other hand, maintenance properties characterize the operational impact caused due to the maintenance actions performed to resolve the technical issues.

These operability properties are defined as probabilistic distributions over a range of discrete values like ‘low’, ‘medium’ and ‘high’. E.g., ‘Performance impact’ of an ATA 2D is a technical issue parameter that characterizes the ability of technical issues of an ATA 2D to degrade the technical, commercial or operational performance. As shown in Fig. 3, the performance impact is ‘high’ 15% of the times, ‘medium’ 60% of the times and ‘low’ 25% of the times. These distributions for different properties have to be manually specified by the operability engineers by experience or by referring to in-service data.

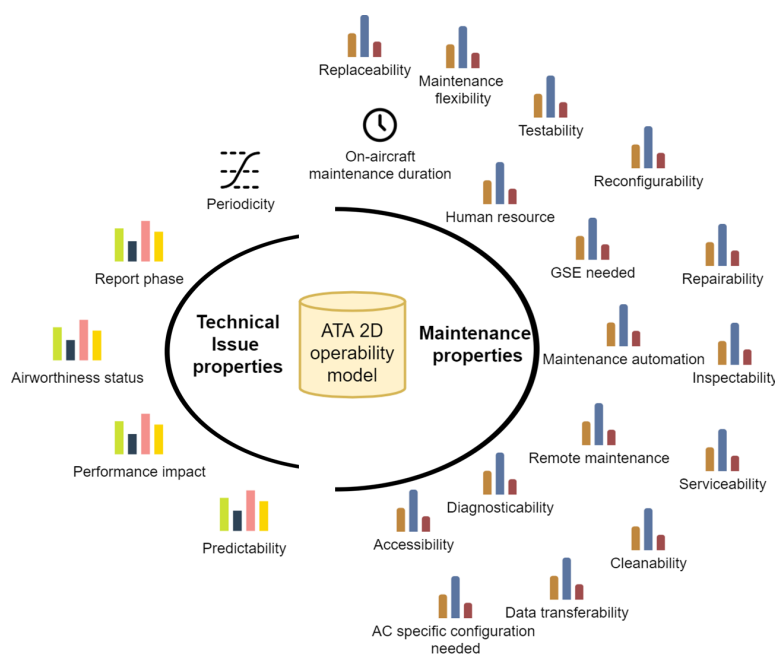


Figure 2. Representation of Operability model framework for major aircraft systems and structures

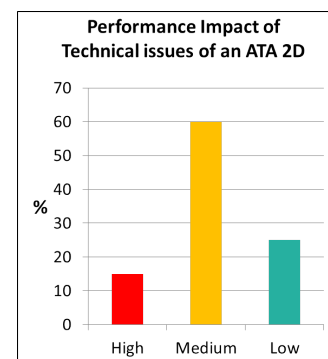


Figure 3. Example of probabilistic distribution of an operability property ‘Performance impact’

3.3. Step 3: Machine Learning

In step 3, machine learning techniques are used to learn the holistic models (*e.g.*, information related to aircraft technical issues) from the results previously obtained in step 1. For a use-case of flight control computer (part of ATA 27), neural networks were used to predict which aircraft states were impacted by different technical issues and their associated maintenance. It was modelled as a multi-class classification problem. These learned models can then be used by operability engineers to predict the values for new designs and the results can be used to calibrate the simulation model developed in step 4.

3.4. Step 4: Simulation framework

A simulation framework is used to make operability projections for new designs *i.e.* ‘TO-BE’ aircraft using both expert knowledge and machine learning. The simulation framework was built using Simpy which is an open-source python framework for Discrete-Event Simulation (DES) shown in Fig. 4. DES is well suited for simulating a series of events [15] and since technical issues can be represented as a series of events, DES was selected as the modeling technique.

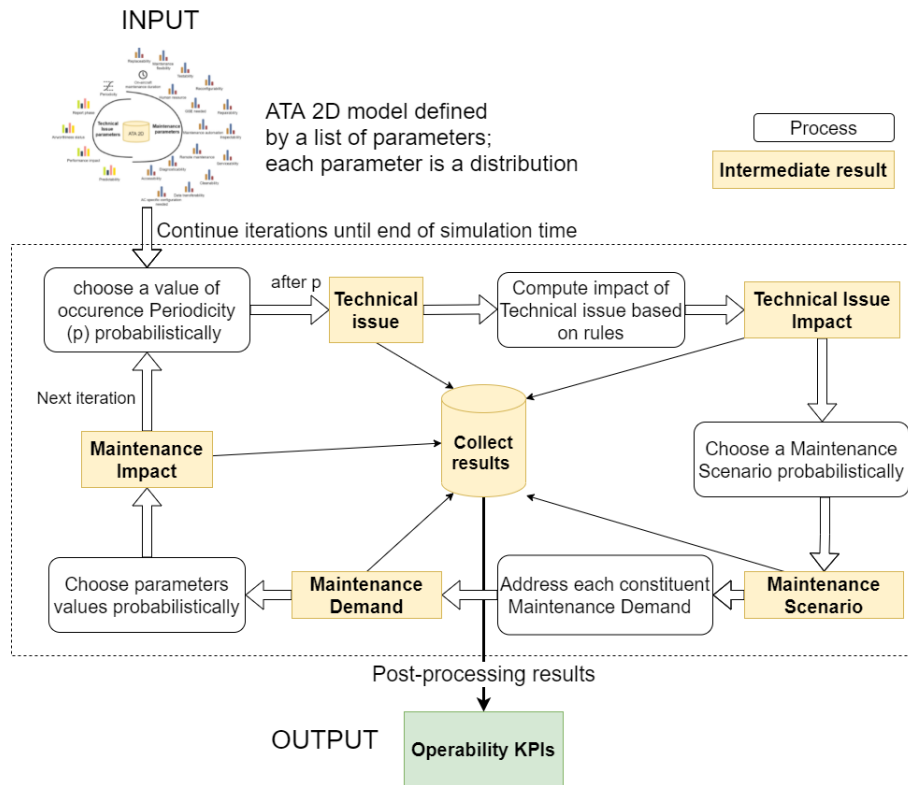


Figure 4. Workflow of the simulation framework (step 4) for evaluating impact of new designs.

During the simulation, an ATA 2D generates a series of Technical Issues (TI) according to the specified distribution for frequency of TI. Each TI then assumes a value for each of the TI properties according to the specified probability distributions for the ATA 2D. The impact of a TI is calculated based on three criteria: ‘airworthiness impact’, ‘performance impact’ and ‘report phase impact’ with weights of 0.5, 0.25 and 0.25 respectively and an overall score is assigned. The technical issue parameters used in the simulation are listed in Table 1.

Table 1. Technical Issue parameters used in the simulation.

Parameter	Expression
Frequency of TI	probabilistic distribution (e.g., Lognormal)
Report phase	distribution over discrete values : Taxi-out / Flying / Stop
Airworthiness impact	distribution over discrete values : Low / Medium / High
Performance impact	distribution over discrete values : Low / Medium / High
Predictability	distribution over discrete values : Low / Medium / High

Based upon the calculated overall score of the technical issue, a maintenance scenario is selected probabilistically based on the predefined distribution of maintenance scenarios for each score. A maintenance scenario is a sequence of maintenance actions that are required to fully resolve a technical issue. The impact of each individual maintenance action constituting the maintenance scenario is computed. Simulation is executed for a given amount of time and the aggregated impact of all the technical issues and their associated maintenance is used for calculating the operability KPIs.

Initially, simulation rules have to be defined by experts regarding how different operability properties of the operability model created in step 2 impact the operational performance and how the scores for different technical issues are to be calculated. The input values for the distributions of the operability properties should also be defined by operability experts. But wherever sufficient in-service data is available, in-service figures for the properties can be analysed using data processing to replace the input values given by experts. For instance, distribution pattern for the frequency of occurrence of technical issues was computed from in-service data and updated in the simulation model.

Similarly, insights from machine learning obtained in step 3 were used to revise the simulation rules in order to achieve more realistic projections. A current limitation is that the process of analysing machine learning results and improving the simulation rules has to be performed manually by expert judgement. In future models, the simulation framework is expected to be automatically updated using results of machine learning through a tighter coupling of simulation and machine learning models.

The results obtained for the new design in terms of elapsed time distribution and operability KPIs can be then compared to the results obtained for the reference baseline in step 1 *i.e.* comparison of TO-BE versus AS-IS aircraft. This allows to see the change in operational performance of the new design versus the reference aircraft, and also make trade-off studies between different candidate designs.

4. Preliminary results

The feasibility of the proposed approach was tested by instantiating the simulation framework for ATA 27 (Flight controls system) with sample input values. Nine different maintenance scenarios (MS1 to MS9) were identified which could be used to resolve the different technical issues. For instance, MS1 corresponds to immediate full rectification of the technical issue whereas MS4 corresponds to deferred rectification meaning the flight operations can continue without having fully rectified the technical issue.

Technical issue properties like frequency, report phase, etc. were instantiated using sample values for the flight controls system commonly observed in operations. The probabilistic distributions of maintenance scenarios were also defined for all the different scores of technical issues. Results from machine learning performed on flight control computer allowed better calibration of the distributions of maintenance scenarios. The discrete-event simulation was executed for a time period of 30 years. Results for each technical issue that was generated during the simulation were recorded along with their corresponding maintenance scenarios and maintenance actions used to resolve them. Post-processing of the data yielded useful insights like the global distribution of maintenance scenarios employed for ATA 27 shown in Fig. 5 and the distribution of maintenance actions' durations shown in Fig. 6.

These results from simulation allow calculating the different operability KPIs. For instance, certain kinds of maintenance scenarios lead to an operational interruption like 'Immediate rectification'(MS1). There were 65 operational interruptions recorded during the entire simulation time corresponding to an Operational Interruption (OI) rate of 0.12%. The total maintenance unavailability (amount of time that an aircraft is under maintenance) was calculated to be 0.92 days/year due to ATA 27. These kinds of results allow system architects to

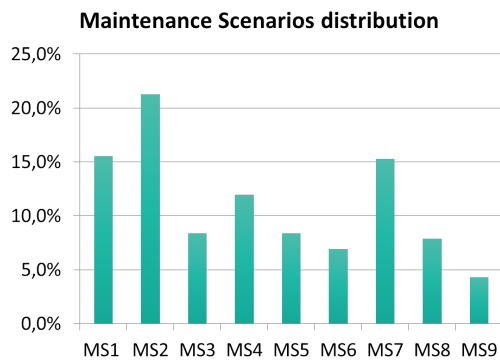


Figure 5. Distribution of maintenance scenarios used to resolve the technical issues for ATA 27

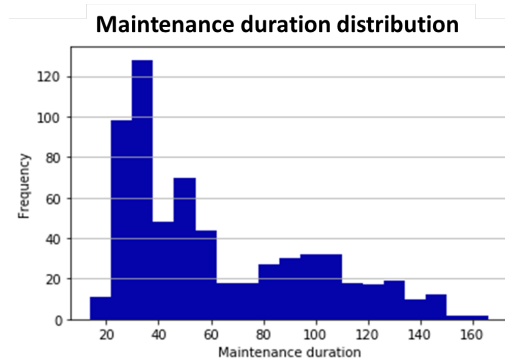


Figure 6. Distribution of maintenance actions' durations for ATA 27

compare different design alternatives during trade-off studies from an operability point of view. It also helps architects to conduct sensitivity studies to check which input parameters have a major impact on the operational performance.

5. Conclusion

Aircraft operability projection during early development stages helps aircraft manufacturers to develop an aircraft that is fully mature and reliable from the entry-into-service. As seen in the literature review, very few quantitative techniques exist today that can project aircraft operability holistically during early design stages. A hybrid methodology of combining machine learning and expert knowledge is proposed in this paper that can help project operability during early design by utilizing both in-service data and expert knowledge. Aircraft-level state machines were populated using in-service data that allowed establishing a reference baseline. Neural network techniques were used to learn how different technical issues can impact the operational performance of aircraft. A discrete-event simulation framework was built using expert knowledge which was later improved using the insights from machine learning. Stochastic simulations of these hybrid models were used to project the operability of future designs.

Combining in-service data along with expert knowledge allows obtaining more realistic operability projections than pure knowledge-based or pure data-driven methods. As aircraft design generally happens in a derivative fashion, there are a majority of aircraft systems that are inspired or re-used from previous designs. The design of these aircraft systems can benefit from in-service data which can yield useful information regarding the occurrence of technical issues and their resolution in operations. During each new aircraft program, there are some new systems which have never been used in any previous aircraft and hence no in-service data is available. For these systems, operability projections have to be performed using inputs from domain experts based on physical or mathematical modelling of system properties. Therefore, employing a hybrid approach will allow one to complement the results available through one method to the other. By default, expert knowledge is used to build the simulation models for projection of future design. Wherever in-service data is available, results from machine learning are used to replace the existing parameter values or rules deployed in the model.

A limitation of the proposed approach is that in-service data is currently given predominance over expert knowledge. But in-service data can sometimes be affected by erroneous and insufficient data which can in turn lead to poor projections. Hence, due care has to be taken during data pre-processing to make sure that results from in-service data are validated by an operability expert before injecting it into the hybrid model. Another issue with stochastic

simulations is that several iterations have to be performed in order to attain sufficient confidence in the results. Also, a large amount of good quality data is required to initialize the simulation model. This limitation can be partially overcome with the careful injection of in-service data wherever available.

In the future, a more synergistic combination of machine learning and expert knowledge is envisaged to overcome the limitations posed by in-service data. Also, the operational representativity of the model can be increased by incorporating airport and maintenance organisation parameters.

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