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# A Multi-Criteria Decision Making Framework for Aircraft Dispatch Assessment

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**Abstract.** The aircraft dispatch decision is a complex analysis based on many factors related to airworthiness regulations, aircraft health status, resource availability at current and future stop(s) and operational preferences of the operator. Within the turnaround time (TAT) a decision has to be made whether the aircraft can return to service, defects have to be deferred, operational restrictions apply, maintenance has to be performed, or if the aircraft is unable to safely perform the next flight. This paper presents a framework for automated dispatch decision support and, as a first step of implementation of the framework, a proof of concept for automated root cause identification by means of a case study on a Airbus A320 wing anti-ice valve. A decision tree algorithm has been applied to a synthetic dataset, representing historical failure data with associated root causes and observed symptoms, achieving correct classification of the root cause for 40% of the cases. Analysis of the results show that the accuracy of the method increases with an increasing number of symptoms associated to a root cause. Furthermore, the method cannot distinguish between root causes with similar symptoms. Although the use of synthetic data restricts conclusions that can be drawn from the results, the work shows a proof of concept for automated root cause identification and leads to initial findings that are essential for future implementation and optimisation of the method. Eventually, the framework will be operationalised in the form of a mobile tool to assist stakeholders in on-site aircraft dispatch decision support.

**Keywords.** Aircraft maintenance, aircraft dispatch, decision support, multi-criteria decision making, root cause analysis

## Introduction

AoG, or aircraft on ground, is terminology used in aviation to indicate that a defect prevents the aircraft to continue scheduled flight operations. While AoG, the aircraft will not be generating revenue by transporting passengers or cargo. Therefore, airline operators aim to minimise AoG by carefully planning flight schedules and maintenance intervals. Because the regulated maintenance intervals are far from efficient with respect to remaining useful life (RUL), and because of the exponential growth of available data and computational power, the aviation industry is now moving towards more data-driven maintenance methods, like prognostics and health monitoring [1, 2]. Instead of performing maintenance at fixed time intervals, these methods use historical data and current health state to only perform maintenance when failure is expected in

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the near future, thereby exploiting more of the RUL. These methods aim to prevent unexpected failures that lead to AoG, but are unlikely to entirely avoid unexpected failures for highly complex systems such as aircraft.

In current airline operations, unexpected failures remain a frequent cause for flight disruptions and should be resolved swiftly to minimise AoG and operational impact. Line maintenance deals with resolving unexpected failures and other maintenance activities within the flight schedule. To avoid delays, all maintenance should preferably be completed within the turn-around time (TAT), which is the time required to complete all ground handling and have the aircraft ready for the next departure [3]. While most line maintenance activities are planned and thus are prepared for, unscheduled tasks following from unexpected failures often disrupt the flight operation, because they require troubleshooting followed by an assessment of the aircraft's capability to perform the next flight. This process is known as aircraft dispatch assessment. Based on the defect information an assessment has to be made if the aircraft can be 1) dispatched without restrictions; 2) dispatched with a component or system inoperative; 3) maintenance is required before dispatch, or that 4) the aircraft is incapable to perform the next flight. The aircraft dispatch assessment is a typical example of a Multi-Criteria Decision Making (MCDM) problem, having multiple alternatives and assessment criteria. In the MCDM domain many methods have been developed to assist the stakeholder to rank alternatives, and in general three main steps have to be performed [4]:

1. Determine relevant decision criteria and alternatives.
2. Attaching numerical measures to the relative importance (i.e., weights) of the criteria and to the impacts (i.e., the measures of performance) of the alternatives in terms of these criteria.
3. Process the numerical values in order to rank the alternatives.

However, determining the importance of a specific decision criterion for a given problem is hard, because the criterion itself can be difficult to assess due to lack of quantitative and reliable information (e.g., maintenance cost). Hence, to assess the stability of an optimal solution a sensitivity analysis of the decision criteria has to be performed in order for the MCDM method to be effective [5]. A stakeholder can make better decisions by knowing which criteria affect the solution the most. With many MCDM methods available, it is not straightforward to determine which method is most suitable for a specific problem. To assist in selecting the right MCDM method for a given problem the 11 most commonly used methods were analysed by Velasquez and Hester [6], listing their advantages and disadvantages. Multi-Attribute Utility Theory (MAUT) as an extension of Multi-Attribute Value Theory (MAVT), the Analytical Hierarchy Process (AHP) and Simple Additive Weighting (SAW) are frequently used methods, of which the latter is widely used because of its simplicity. The general trend in recent years is to combine multiple methods to overcome specific weaknesses of a particular method. The exponential growth in computational power over the last decades has significantly accelerated this trend and also provides the opportunity to exploit large amounts of data for better decision making.

However, before any MCDM method can be applied to the aircraft dispatch assessment problem, the root cause of the defect needs to be identified first in order to determine the appropriate corrective maintenance action. Only then the different dispatch scenarios can be properly assessed. Current research on the aircraft dispatch problem assumes that the root cause for the defect is known [7], but for most cases the

root cause still needs to be determined during the TAT. In some cases of unscheduled maintenance, when the defect is communicated in-flight, the troubleshooting department can try to determine the root cause beforehand. The troubleshooting procedure for aircraft maintenance is described in the Troubleshooting Manual (TSM) and entails multiple tasks with increasing complexity, ranging from simple tests and resets up until replacement of the defective component. Quick, accurate and automated root cause identification saves valuable time in the TAT that can be used for dispatch decision assessment and maintenance execution, reducing the risk of delay. With the root cause known, the right corrective maintenance task can be determined, the requirements and resources to perform that task can be established and then the alternative dispatch scenarios can be assessed. To this end, the objective of this paper is to 1) introduce a framework for automated dispatch assessment; 2) present a root cause identification approach which fits into this automated dispatch assessment framework and addresses the functionality mentioned above.

Given this focus, this paper first discusses the state of the art in aircraft dispatch decision making, followed by introducing the developed framework for automated dispatch assessment, including the definition of the alternative dispatch scenarios and a definition of the stakeholders involved. A case study for root cause identification using a synthetic dataset, representing a historical database of reported defects, is discussed next and the paper ends with the conclusions.

## **1. Aircraft dispatch state of the art**

While research in the broader domains of operations research and decision support systems has progressed significantly in recent years, research focussing on the aircraft dispatch problem remains scarce [7]. Most studies focus on long-term operations, do not support dispatch decisions directly, do not assess relevant information simultaneously or do not take into consideration the limited time available within the TAT, and are thus not addressing the issues that line maintenance technicians face. Papakostas et al. [7] describe a short-term planning methodology for the line maintenance activities of an airline to increase fleet operability and reduce maintenance cost. Based on four criteria, being cost, operational risk, flight delay and remaining useful life (RUL), dispatch alternatives are calculated and ranked on utility by assigning weights to each criterion. The research introduces a novel method to support the aircraft dispatch decision, including a significant number of relevant criteria, but also has some limitations. Firstly, it is assumed that the root cause of a problem is known, while this is usually not the case. The process of troubleshooting and pinpointing the root cause can be a very time-consuming processes, time that is not available during the TAT. Secondly, the method only considers condition-monitored components, i.e., components for which the condition is assessed (near-)continuously on the basis of direct or indirect information, for instance from sensors. Based on the RUL of these components an assessment is made, but even in recently introduced aircraft many components that could lead to AoG are not condition-monitored. Finally, the research aims to reduce the number of unscheduled maintenance events by using data of condition monitored components and plan corrective maintenance before failure of the component occurs. This, however, does not provide a solution for truly unscheduled failures of (non-monitored) components that require reactive maintenance. In any case, even condition-monitored components can fail unexpectedly. More recent

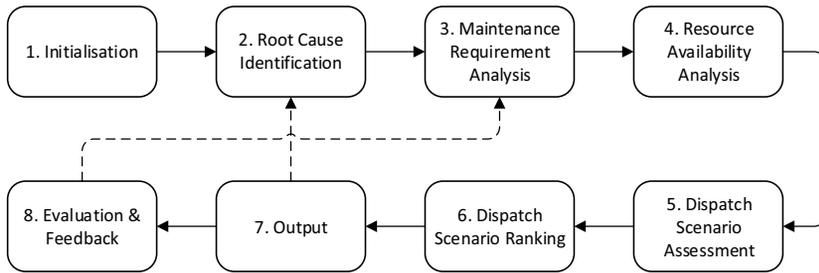
work within the domain also indicates the research gap for operability assessment of the aircraft during its mission. Tiassou et al. [8] aim to develop a model to assess changes in the aircraft health status online to support mission planning, even during flight, and evaluate the probability that an aircraft can continue flight operations for a given period of time using a dependability approach. The model relies on accurate reliability data to assess successful mission completion and to plan maintenance activities, which might not always be available. Moreover, the model provides predictions of component failures and maintenance task durations for operational planning, but does not account for maintenance task execution or determining the root cause of a defect.

For industry, the state of the art is more difficult to analyse due to intellectual property restrictions and the use of generic marketing terminology in the specifications. Solutions provided by manufacturers like Airbus and Boeing are able to include data from many (on-board) sources and, combined with a well-developed user interface, are powerful tools to optimise aircraft operability and maintenance activities [9, 10]. They also offer support in maintenance task execution by providing related documentation, include the aircraft's maintenance history and troubleshooting assistance. The systems aim to reduce unscheduled maintenance activities through continuous real-time health monitoring and provide decision support based on that data, but do not mention direct dispatch decision support in case of an unforeseen event. Another issue is the fact that both new and modernised aircraft are equipped with extensive integrated health monitoring systems, but a significant part of the world fleet still operates with less advanced health monitoring capabilities and therefore is unable to fully benefit from these data-driven support systems. Another drawback of these systems is that they are vendor specific and are designed to work optimally, or even solely, for aircraft of a specific manufacturer, requiring multiple systems for mixed fleet operators. Unfortunately, the fragmentation of different information systems is currently one of the main headaches for operators. Maintenance, Repair and Overhaul (MRO) service providers like Mxi and Lufthansa Technik aim to overcome this problem by offering integrated maintenance support systems to operators that combine different data sources to optimise the maintenance operation from supply chain to prognostics and maintenance planning [11, 12]. Similar to the vendor specific solutions, these solutions focus on data-driven methods to prevent unscheduled maintenance occurrences and are not aimed for short-term unscheduled event resolution; direct dispatch decision support is not featured.

In short, both the academic and industry state of the art show that there is still a need for direct dispatch decision support to assist the stakeholders in aircraft line maintenance and minimise flight disruptions and the associated cost.

## **2. Framework for automated dispatch assessment**

The objective of this project is to provide internal stakeholders with ranked dispatch alternatives in order to support them in decision making and reduce flight disruptions through optimised dispatch decisions. To get from a reported defect to a list of ranked dispatch alternatives a framework was developed to support this functionality. Figure 1 shows a schematic representation.



**Figure 1.** Schematic overview of the dispatch assessment tool.

The functionality of the steps in the framework is as follows:

### 1. Initialisation

During the initialisation step all relevant information about the aircraft and the defect is gathered. The defect information includes data such as the error code, fault message or description of the problem. Based on the defect information the related troubleshooting procedure (TSM) is determined. The aircraft information includes data such as its registration mark, manufacturer, model, current configuration and location. The flight schedule, and in particular the estimated time of departure (ETD), is also essential information for dispatch option evaluation.

### 2. Root Cause Identification

The TSM provides describes symptoms that are related to a root cause and the Aircraft Maintenance Technician (AMT) will register observed symptoms on a mobile device. Based on historical data of similar symptoms and root causes, the most likely root cause is determined. If the root cause can be determined with a specific predefined level of certainty, the system proceeds to the next step. When this level of certainty can't be obtained either an incorrect TSM task was selected, or insufficient data for classification was available. In the first case the AMT is asked to select the TSM task manually, for the latter case the a manual analysis has to be performed. All results are used to expand the existing historical database for future classification.

### 3. Maintenance Requirement Analysis

With the root cause known the required maintenance action can be determined and subsequently the required resources for maintenance execution (e.g., man hours, equipment and spare parts).

### 4. Resource Availability Analysis

In this step availability of the required maintenance resources (determined in step 3) at current and future stop(s) is checked. In some cases it is desirable to defer a defect, for example when there are better maintenance facilities at the next stop, or when there is already maintenance planned in the near future. Therefore, the dispatch option "dispatch by MEL" is evaluated, in which case the aircraft is dispatched with certain systems or components inactive. Constraints for flying with systems or components inoperative are detailed in the Minimum Equipment List (MEL). Currently inactive systems or components of the aircraft are listed in the Hold Item List (HIL), which must be compared with the MEL to verify that deferral of the current defect is compliant. Other resources, such as the flight schedule, flight crew limitations and the mission profile are included as well.

## 5. Dispatch Scenario Assessment

All possible dispatch scenarios are evaluated based on the requirements and resources available. Based on the input of industry experts and the dispatch definition by Tiassou et al. [8], a new dispatch scenario definition was developed, shown in Figure 2.

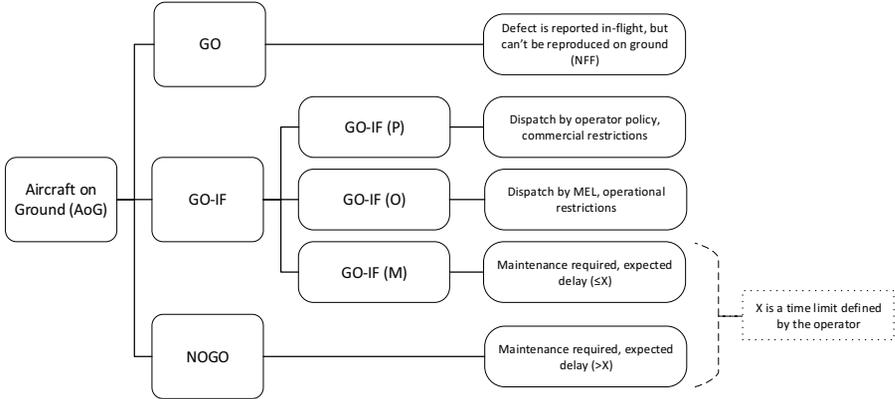


Figure 2. Modified dispatch scenario definition.

When an aircraft is AoG the following dispatch scenarios are defined (in order of operational impact):

- **GO**: the reported defect is not found, either because there is no defect or because the defect can only be observed while flying; known as No Fault Found (NFF). The aircraft is dispatched without additional restrictions.
- **GO-IF**: the aircraft can be dispatched with restrictions, or after a maintenance task is performed. GO-IF has the following subcategories:
  - **(P)**: the defect only leads to commercial restrictions, e.g., an operator can choose not to sell a seat with a defective table. The defective item can be deferred to a preferred maintenance opportunity. The aircraft is dispatched by operator policy.
  - **(O)**: the defect can be deferred in compliance with the MEL and doesn't conflict with the current HIL status. The aircraft is dispatched by MEL and operational restrictions may apply.
  - **(M)**: the defect requires corrective maintenance before dispatch. A delay will follow if the maintenance elapsed time exceeds the ETD. As the delay increases specific limitations can lead a NOGO, for example due to crew flight time limitations. After completion of the maintenance task the aircraft can be dispatched.
- **NOGO**: the reported defect can't be deferred or fixed before the ETD or maximum allowable delay ( $X$  in Figure 2) and the flight has to be cancelled.  $X$  is defined by the operator according to their business model (e.g., low cost, high passenger comfort). The aircraft can't be dispatched and remains AoG.

## 6. Dispatch Scenario Ranking

When the feasible dispatch scenarios are determined they are ranked according to specific criteria set by the operator (e.g., cost, time), integrated by a weight matrix for the decision criteria.

## 7. Output

The output is a list of ranked dispatch scenarios presented to the AMT on a mobile device. The best ranked scenario is proposed to the captain and, when agreed upon, executed. If the captain doesn't accept the proposed scenario, the second best result can be selected, and so on. When the chosen dispatch scenario requires the execution of a maintenance task, the AMT also verifies that the defect is resolved. Results are recorded in the historical database for root cause identification.

## 8. Evaluation and Feedback

In the evaluation and feedback stage the actual outcome of the chosen dispatch scenario is evaluated with respect to the decision criteria, by comparing them to the outcome predicted by the system. This way, it can be verified that the system inputs (e.g., maintenance requirements and resources) were correct or require adjustment. Based on the evaluation the corresponding defect instance in the historical database for root cause identification can be classified to improve future classification.

With the framework explained, the development is initiated at step 2 by means of a case study for automated root cause identification.

## 3. Case study root cause identification

For this case study the wing anti-ice valve (WAIV) of an Airbus A320 is considered. The current troubleshooting procedure is described step-by-step in the TSM and includes execution of several maintenance tasks in the process. The TSM describes 18 possible root causes and 17 symptoms that may be related to a specific root cause for a defective WAIV. Symptoms are either indicated by on-board systems warnings, the flight crew or are identified by the technician.

With no current access to actual maintenance data, a synthetic dataset representing the maintenance history of an Airbus A320 fleet is created. The file contains 10000 entries, each representing a WAIV defect with one of the 18 root causes randomly assigned. Symptoms that are not related to a specific root cause according to the TSM always remain zero. For the symptoms that do relate to a root cause a value of 0 or 1 is randomly assigned using a uniform distribution, 1 representing a symptom that is observed (true) and 0 for the symptoms that are not observed (false). Many machine learning algorithms for root cause analysis (RCA) have been developed over the last decades and based on the work of Solé et al. [13], providing an extensive overview and classification of available RCA models, a decision tree algorithm is used to classify root caused based on the observed symptoms. The decision tree analysis is performed using Weka, a machine learning software tool developed by the University of Waikato in New Zealand [14], and more specifically the J48 algorithm is used. With the current synthetic dataset the algorithm can classify the root causes correctly for only 40% of the time, which is far from sufficient for use in an operational environment.

The confusion matrix in Figure 3 provides a detailed insight on the classification performance, where the root causes are labelled **a-r**. On the diagonal the number of correctly classified root causes is given, marked in green. Root causes **f**, **l**, **m** and **n** (orange columns) are never classified at all, which can be explained by the fact that they all have just one symptom associated. Moreover, the symptom is shared with root causes **o** and **k** (blue columns), which are frequently incorrectly classified as root cause **f**, **l**, **m** or **n**. Root causes that have more symptoms associated to them also show these classification errors, most clearly shown for root causes that have a origin at both the right- and left-hand side of the aircraft. For example, root causes **e** and **i** are the wing anti-ice valve controllers on opposite sides of the aircraft and share exactly the same symptoms, leading to them being mixed up almost equally with their counterpart (red bordered cells). Figure 3 also shows that no other root cause has been classified incorrectly as **e** or **i**. Similar accuracy can be found for root cause **p** (aircraft wiring, green column). These root causes share the characteristic of having a high number of associated symptoms (i.e., 13 for **e** and **i**, 12 for the aircraft wiring).

a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	
408	0	0	0	0	0	88	0	0	0	76	0	0	0	0	0	0	0	a
0	197	0	104	0	0	0	33	0	205	5	0	0	0	0	0	4	11	b
0	0	424	0	0	0	0	0	0	0	125	0	0	0	0	0	0	0	c
0	0	0	283	0	0	0	266	0	0	9	0	0	0	0	0	10	0	d
0	4	2	2	247	0	0	3	270	1	0	0	0	0	0	0	14	5	e
0	0	0	0	0	0	0	0	0	0	432	0	0	0	112	0	0	0	f
360	0	0	0	0	0	95	0	0	0	81	0	0	0	0	0	0	0	g
0	0	0	296	0	0	0	225	0	0	11	0	0	0	0	0	5	0	h
0	5	2	8	280	0	0	2	244	2	0	0	0	0	0	0	13	7	i
0	205	0	97	0	0	0	40	0	187	4	0	0	0	0	0	1	7	j
0	0	0	0	0	0	0	0	0	0	480	0	0	0	131	0	0	0	k
0	0	0	0	0	0	0	0	0	0	487	0	0	0	101	0	0	0	l
0	0	0	0	0	0	0	0	0	0	424	0	0	0	110	0	0	0	m
0	0	0	0	0	0	0	0	0	0	438	0	0	0	99	0	0	0	n
0	0	0	0	0	0	0	0	0	0	474	0	0	0	107	0	0	0	o
11	9	0	6	0	0	2	5	0	7	0	0	0	0	0	482	0	14	p
0	0	32	89	0	0	0	13	0	0	5	0	0	0	0	0	389	0	q
0	112	0	72	0	0	0	55	0	91	3	0	0	0	0	0	3	232	r

Figure 3. Confusion matrix for the decision tree classification

Because a synthetic dataset was used, these initial findings only provide an indication of the performance that can be achieved when authentic data is used. It is expected that authentic data will include stronger and more consistent underlying correlations between symptoms and root causes. However, the applied method shows a proof of concept and has led to the following observations that will be taken into account for future development; 1) root causes with only one or few associated symptoms lead to a low classification accuracy, 2) the method cannot distinguish between root causes with similar associated symptoms, and 3) the accuracy of the method improves with a growing number of associated symptoms.

Based on these observations, some recommendations are determined for the development of the automated root cause identification method. Firstly, root causes having only one or few associated symptoms require additional information for accurate classification. Secondly, for root causes that share the same set of associated

symptoms with other root causes it might be useful to aggregate them for improved accuracy. Both recommendations require intervention of an expert; the AMT. Finally, this initial case study also clarified the following factors:

- Unlike the assumption in the created data file, it is very unlikely that historical data will show evenly distributed root causes. In reality, some root causes will appear more frequently than others.
- Some symptoms will have more influence than others on the root cause classification, which can be incorporated by assigning weight factors to the symptoms.
- Subsequently, some symptoms will show to be irrelevant and can be removed for classification (i.e., apply feature selection).
- In reality it is infeasible to perform the entire troubleshooting procedure during the TAT, which would include replacing the component itself and result in a GO-IF (M) or NOGO without any dispatch assessment. Hence, it needs to be determined to what extent the troubleshooting procedure needs to be completed to provide sufficient information for dispatch assessment.
- With many methods available for RCA [13], it is worthwhile to evaluate the performance of other suitable methods.

#### 4. Conclusions

When an aircraft faces a defect, a decision has to be made whether the aircraft can continue flight operations or not. This aircraft dispatch decision is complex due to the large amount of factors that have to be considered, the multiple stakeholders involved and a limited amount of time available before the next scheduled flight. To avoid costly AoG, current research mainly focuses on prognostics, health monitoring and preventive maintenance, but those methods cannot entirely avoid the occurrence of unexpected failures in a complex system like an aircraft. The need for direct dispatch decision support for unexpected failures and, additionally, the need for automated root cause identification was identified. This paper proposes a framework for automated dispatch decision support and initiates the implementation by the development of a method for automated root cause identification in a case study. The framework aims to automate the dispatch decision, starting from a reported defect up to providing ranked dispatch alternatives, using an eight-step approach. A crucial step in the framework is the capability to automatically determine the root cause of a defect, which is tried to be achieved by comparing observed symptoms with previous instances of that defect. A case study was performed on the Airbus A320 wing anti-ice valve, using a synthetic dataset. The J48 decision tree algorithm was applied using Weka and an overall accuracy of 40% for identifying the correct root cause was achieved. The confusion matrix showed that a root cause with one or few associated symptoms is rarely correctly classified, the accuracy of root cause classification increases with an increasing amount of associated symptoms and that root causes with similar associated symptoms can't be distinguished between. While the use of a synthetic dataset limits the conclusions that can be drawn about the performance, the case study showed a promising method for automated root cause identification and has led to several recommendations for future development.

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