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Publication date
2016

Document Version
Accepted author manuscript

Published in
8th European Workshop on Structural Health Monitoring

Multi-level repair decision-making process for composite structures

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Key words: Composites, Aircraft structures, Decision making, Maintenance repair, Cost benefit analysis, Survivability

Abstract
This paper details the development of a decision-making model that evaluates the multiple repair levels that a composite structure can undergo, each with its inherent achievable survivability and consequence to operations in terms of availability, costs, and scheduling. The goal of this model is to provide the maintainer an integrated approach to all feasible repair solutions within the operational and structural integrity constraints, applicable to any given damage levels found during monitoring. At its core, the model incorporates various stochastic processes to model different types of repairable behavior: the non-homogeneous Poisson process and the renewal process. A case study on the carbon-fiber reinforced polymer flaps of a Boeing 777 has been performed to verify and validate the proposed decision-making model. With the case study providing the means for application of the model in an operational context, a standardized decision making process was delivered that is adaptable to any given failure scenario and implementable in practice.

1 INTRODUCTION

Next generation civil aircraft such as the Boeing 787 and Airbus A350 include more composite materials in their designs as compared to earlier-generation aircraft; approximately 50% of the aircraft by weight and, as a first, including primary load-bearing structures such as the fuselage. Such large-scale adoption of composites for civil transport aircraft design, , is relatively novel. In comparison, aviation has relied on the use of metals for over seventy-plus years, which includes a vast accrued experience in operating, monitoring, repairing and/or replacing metallic structures [1]. The shift to composite components presents a significant challenge for maintenance repair organizations, as relatively limited historical failure data and operational experience with failure behavior is available with respect to composite structures. However, an opportunity can be seized in the maintenance decision-making process after damage detection. This can be in regards to the type and time of repair performed by an inspector, based on the usage and the damage level of the structure of interest.

This paper proposes a novel decision-making model to support the post-damage maintenance decision process. In the development of the proposed decision-making model, two main questions are explored: (1) how can decision factors be used to identify all possible maintenance scenarios with their own inherent repair options, and (2) how can the cost-benefit of available repair options be evaluated with respect to the survivability of the structure? The first step in answering the research questions is to identify the critical decision making factors that lead to possible maintenance actions. The use of deterministic Boolean decision trees results in a list of maintenance scenarios, each with their own possible repair options and times when they can be applied. Survivability of a structure is calculated using Poisson processes as they are fit to be applied on repairable systems [2]. Two processes are used: Non-Homogenous Poisson Process for minimal repairs and Renewal Process for permanent repairs or as-good-as-new assumption. Meanwhile costs are treated on a case by case basis because it is highly dependent on which maintenance scenario is being analyzed. The model is applied in a case study that was performed on an outboard flap of a Boeing 777. This particular structure bears similarity to the Boeing 787 outboard flap which is also carbon-fiber reinforced plastics (CFRP).

The purpose of the model in the realm of structural health monitoring is to provide the maintainer with a decision support tool, which can assist in selection of a repair type which achieves highest survivability for the lowest cost per flight cycle. To facilitate this form of decision support, a novel metric has been developed for the model: the relative survivability-cost (S-C) ratio. The relative S-C ratio informs the maintainers which of the repair options will be most cost-effective at different future monitoring points in time. Based on the inputs for costs from the maintainer and the calculated survivability, for each option the relative survivability-cost ratios are computed for both short term and long term monitoring.

The methodology behind the survivability calculations and how it is combined with the decision making process is detailed in section 2. The consecutive section shows an example of the model application from the case study on Boeing 777. Then the final conclusions of the model development are presented in section 4.

2 METHODOLOGY

Two main areas have been researched for the purposes of building the proposed model: Poisson processes and decision making. One of the main metrics being used to evaluate repair decisions is inherent structural survivability. In order to quantify and forecast the survivability degradation, Poisson processes are implemented into the overall decision support model. This section will also explain how deterministic decision trees are used to identify maintenance scenarios. Due to confidentiality the actual decision tree developed for the case study is omitted, but a representative example is given.

2.1 Poisson Process

Non-Homogenous Poisson Process (NHPP)

Non-Homogenous Poisson Process (NHPP) is a Poisson process characterized by a non-constant intensity function *λ(t)*, satisfying the following three conditions:

1. $N = 0$
2. For any $a < b, N(a,b] \sim POI(\int_a^b \lambda(t)dt)$
3. The process has the independent increments property, i.e., for any non-overlapping intervals $(t, t+\Delta t), (s, s+\Delta s)$, $\Delta N_{(t,t+\Delta t)}$ and $\Delta N_{(s,s+\Delta s)}$ are independent

Where,

λ	Intensity function
t, s	Time or Flight Cycles
N	Number of failures in an interval

Equation 1 gives a particular form of the intensity function, known as the power law process or the Weibull intensity function [2].

$$\lambda(t) = \frac{\beta}{\theta}\left(\frac{t}{\theta}\right)^{\beta-1} \tag{1}$$

Where,

β	Weibull shape parameter
θ	Weibull scale parameter

The Weibull intensity function is flexible in its ability to demonstrate various skews and spreads in the data with the shape and scale parameter. This flexibility allows the NHPP to represent structural life models for a wide variety of components. NHPP also adopts an as-bad-as-old repair philosophy, which means that any repair done assumes that the survivability of structure has not been changed and will not improve the lifetime [2]. Rather as-bad-as-old type repairs only corrects the current fault so that it continues to function but also the survival probability continues to degrade at after the repair. NHPP can assume to be an independently and identically distributed (iid) model, and in fact homogeneous Poisson process (HPP) is just a special case of NHPP where the intensity function happens to be constant [2]. Probability of failure occurrence is characterized by Equation 2.

$$P(N) = \frac{e^{t\lambda(t)}\left(t\lambda(t)\right)^{N}}{N!} \tag{2}$$

Renewal Process (RP)

Renewal Process is an as-good-as-new repair process, where the intensity function is also assumed to be non-constant. RP is preferred over HPP because of its ability to illustrate deteriorating and improving systems [2]. Once again the Weibull distribution is used to characterize the process. First the expected and variance of time-to-failure must be calculated as shown by Equation 3.

$$\eta = \theta\Gamma\left(1+\frac{1}{\beta}\right) \tag{3}$$

$$\sigma^2 = \theta^2\left[\Gamma\left(1+\frac{2}{\beta}\right) - \left(\Gamma\left(1+\frac{1}{\beta}\right)\right)^2\right]$$

Where,

η	Expected Time or Flight Cycles to failure
σ^2	Variance of Time or Flight Cycles to failure
Γ	Gamma operator

To calculate the probability of failure occurrence using the renewal process is shown by Equation 4 [2].

$$\lim_{t\to\infty} P\left(N(t) < a(t)\right) = \Phi(y) \tag{4}$$

$$a(t) = \frac{t}{\eta} + y\sigma\sqrt{\frac{t}{\eta^3}}$$

Where,

Φ	Cumulative distribution function of Normal
a	Expected failures in an interval
y	Normal distribution test value for probability of failure
t	Time or Flight Cycles, since as-good-as-new state

2.2 Sequential maintenance events survivability

In section 2.1 the cumulative distribution functions of Poisson processes are detailed but they are valid for only one type of repair event. There are maintenance options for the considered component in this study (the B777 outboard flap) that are characterized by multiple types of repair events. In such cases, sequential event survivability needs to be calculated.

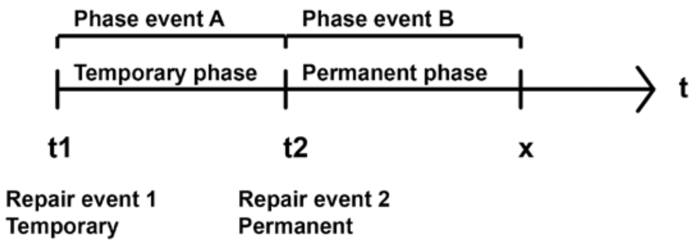

Figure 1: Multiple repair event maintenance scenario

Take for example a maintenance scenario shown in Figure 1. A damage is found and undergoes the first repair event at t_1, a temporary repair which is assumed to be minimal repair and hence follows NHPP during the temporary phase. A certain amount of time later the temporary repair is followed up with a permanent repair at t_2. The second repair event renews the structure to as-good-as-new, and the survivability past t_2 is demonstrated by renewal process for the permanent phase.

Let's denote temporary phase and permanent phase as phase event A and phase event B respectively. Phase event A is for the time interval of $t_1 < t \leq t_2$, whereas phase event B is for $t > t_2$. These two phase events are assumed to be independent, meaning that the survivability in phase A doesn't affect phase B survivability [3]. In this scenario P(A) is the survivability of during phase A which is simply Equation 3 from NHPP for $t = t_2$. Then let's explore the probability of surviving till t = x, which means surviving both phase events. The probability of surviving just phase event B, P(B) is given by Equation 5 following the renewal process where N(t) is actually $N(x - t_2)$ because a new process has begun with repair event 2 at t_2. Now that P(A) and P(B) have been established, the probability of surviving two independent phase events is given by conventional statistical methods where [3]:

$$P(A \cap B) = P(A)P(B) \tag{5}$$

Equation 5 is what is referred to as sequential event survivability. Using this equation, the probability of surviving multiple sequence of independent repair events and phases can be quantified.

2.3 Survivability-cost (S-C) ratio

To be able to quantify the cost-effectiveness of a repair option the survivability-cost ratio is used as a metric. Let's denote *S* as the sequential survivability of the structure, whether it be associated with a single repair event or multiple, and cost for a repair option is denoted as *C*. Then the S-C ratio denoted as R_{sc} is simply calculated using Equation 6.

$$R_{SC}\left(t\right) = \frac{S(t)}{C(t)} \tag{6}$$

Though this parameter can be used to compare the cost-effectiveness of different repair options in a scenario, it would be more user-friendly to have a non-dimensional parameter. The proposed non-dimensional parameter is the relative survivability cost ratio. This parameter would be evaluated at the times the maintainer can inspect the structure, most likely at one or multiple planned monitoring maintenance slots. Let's assume that the maintainer is considering three maintenance slots and there are three repair options in this scenario. The model first calculates the S-C ratio for the earliest slot for all repair options. The repair option with the highest S-C ratio at that slot is selected to be the benchmark against which all other S-C ratios at all other slots are compared. Equation 7 shows the relative S-C ratio for a given repair option *r* at a given maintenance slot *m*. The benchmarking S-C ratio is maximum ratio of any repair option at the first maintenance slot $\max R_{SCr1}$.

$$\mathrm{Re}\,l_{SCrm} = \frac{R_{SCrm}}{\max R_{SCr1}} \tag{7}$$

Where,

$\mathrm{Re}\,l_{SCrm}$	Relative S-C ratio
r	Repair option
m	Maintenance slot

This is a non-dimensional scale from 0 to 1 where the comparative cost-effectiveness of different repair options are quantified using their respective sequential event survivability and cost. In this scale 1 is the most cost-effective and the lower the value, the less cost-effective the option is.

2.4 Deterministic scenario tree

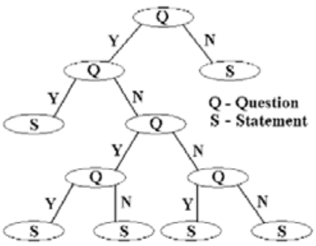

Figure 2: Generic Boolean decision tree[4]

Given that a fault has occurred a maintainer has to understand the current scenario and how that affects his or her options to correct for the fault. There can be multiple decision factors that affect the possible decisions the maintainer can choose. The combination of how these decision factors are set leads to a certain maintenance scenario. The higher the number of factors and the links between them, the higher the permutations of possible scenarios. To be able to understand the complexity of maintenance scenarios that can occur as a result of decision factors, a decision tree approach has been adopted.

There is literature on how on decision tree complexity can be reduced through a learning algorithm such as the study by Freund et al [5]. Although the concern for the proposed model is not reducing complexity of the decision but rather to use decision trees to identify all possible scenarios. This is where the work by Aitkenhead [4] was found to be most applicable. Their work delved into combining decision tree paradigm with evolutionary concepts in order to identify new classification or categories. This can range from identifying which car best suits your criteria, to identifying the type of glass based on chemical composition. A generic example of which is depicted in Figure 2. For the purposes of the proposed model, this form of decision tree classification is used to identify different maintenance scenarios. Five decision factors are considered and prioritized (high to low) as follows:

1. **Station**: Is the aircraft currently stationed at home base airport? Yes or No
2. **Temporary repair limit**: Does the severity of the damage exceed the upper limits of a temporary repair? Yes or No
3. **Aircraft swap availability**: Is there an another aircraft available to be swapped in for avoiding flight cancellation? Yes or No
4. **Spare flap availability**: Is there a spare flap available for installation? Yes or No
5. **Lease flap availability**: Is there a flap available for loan? Yes or No

As can be seen, all five decision factors are deterministic Boolean conditions. This is intentional. Decision tree models that use probabilistic conditions for the decision factors exist and used as demonstrated by Buhrman et al [6] and Ehrenfeucht et al [7]. However, typical applications of such probabilistic decision trees tend to be for forecasting or simulation purposes. In the proposed model the conditions are already known at the moment of damage, so there is no need for probabilistic decision trees.

3 CASE STUDY

In this section an example of a maintenance scenario model output from the Boeing 777 outboard flap case study is illustrated and discussed. Firstly the scenario itself is described to place the model outputs into context. The changes in instantaneous survivability of the different options are shown, which is then followed by how sequential event survivability is affected by multiple repair events. While it is possible to plot and analyze the S-C ratio at every flight cycle after the initial damage, it is of more interest to the end-user what he/she can expect the cost benefit will be at different inspections times. This is visualized in the form of relative S-C ratio at short term, medium term, and long term inspection.

3.2 Scenario definition

4. Decision factor	Priority	Setting
Station	1	Home base
Temporary repair upper limits exceeded	2	No
Aircraft swap availability	3	Yes
Spare flap availability	4	No
Lease flap availability	5	No

Table 1: Decision factor settings to define the scenario

The decision factors settings are shown in Table 1. The last two factors being set to 'No' immediately discards the possibility of installing a spare flap or a flap on loan. As the aircraft is currently stationed at home base which has all the facilities for a permanent repair, that becomes a confirmed option. A permanent repair would require that the aircraft be grounded for long period of time, prompting a cancellation of a scheduled flight. Luckily decision factor 3 states that there happens to be an aircraft available to swap in for the planned flight. Costs of swapping an aircraft is lower than cancellation, hence it would be preferable for the permanent repair option [8,9].

On top of the permanent repair, decision factor 2 indicates that temporary repair is still feasible for the damage. The feasibility of temporary repairs is dictated by structural repair manuals provided by original aircraft manufacturers. The manuals state the damage dimension limits (for delamination, dents, nicks, etc.) for which temporary or permanent repair must be applied. These temporary repairs tend to take short time to apply, so if this option were to cause any airline operation disruption, it would be in the form of a delay. Disruption costs for all options are accounted for in the repair costs [8]. Though temporary repair is feasible, regulations stipulate that temporary repair must be followed up by a permanent repair within 400 flight cycles (FC). In this particular case the maintainer has identified that there is a reserve slot for maintenance available in 20FC and an A-Check in 185FC. So if the temporary repair is applied it must either be followed up by a permanent repair at the reserve slot or at the A-Check. As a result of the scenario settings, the decision making model outputs three repair options:

Option	Repair event 1	Repair event 2
(1) Temporary → Permanent	Immediate Temp	Perm at reserve slot (20 FC)
(2) Temporary → Permanent	Immediate Temp	Perm at A-Check (185 FC)
(3) Permanent	Immediate Perm	-

Table 2: Possible repair options for this scenario

3.2 Instantaneous and sequential event survivability

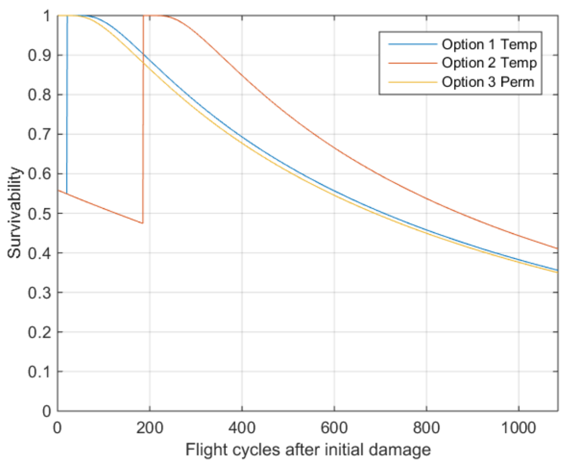

Figure 3: Instantaneous survivability of the structure for each repair option

Figure 3 shows the instantaneous survivability of the structures for the three different options. It should be noted that the moment right before the initial repair, the survivability of the structure is at 0.56 due to its previous use. The temporary repairs is assumed to be as-bad-as-old repair action, therefore the survivability continues to degrade from 0.56 using NHPP. Then when a permanent repair is applied at either reserve slot or A-Check, the survivability goes up to the value of 1 because of the as-good-as-new assumption and follows the renewal process trend to plot rest of the survivability till C-Check at 1085FC. C-Check is another major maintenance check and is executed in long intervals.

Permanent repair on the other hand has only one repair event immediately after the initial damage. Hence its survivability starts at the value of 1 and continues to degrade as dictated by the renewal process.

Unlike permanent repair, the temporary options are characterized by two repair events. The first repair event is a temporary repair, followed by a temporary phase. After this phase the second repair event occurs which is a permanent repair, followed by permanent phase. If the maintainer wants to know the probability of surviving temporary phase and a certain amount of flight cycles into permanent phase, surviving both phases, then the corresponding sequential event survivability has to be used. This is plotted for all three options in Figure 4.

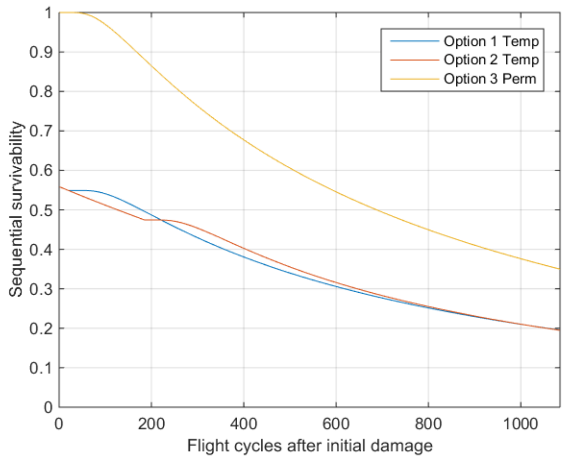

Figure 4: Sequential event survivability of the structure for each repair option

The instantaneous and sequential event survivability are both the same for permanent option because there is only one event and one phase. Similarly for the first phase of the temporary repair options, the instantaneous and sequential event survivability is same. After the second repair event, the sequential survivability stagnates (at .54 for option 1 and 0.47 for option 2) because permanent repair has been applied. These sequential survivability values are then used for the survivability cost ratios and compared for short term and long term monitoring points.

3.3 Relative Survivability-Cost ratios

While the S-C ratio for every flight cycle trend can be plotted, the end-user is more interested in the cost-effectiveness of the flap, with this component surviving till maintenance inspections where the structure can actually be inspected and monitored. That is where the relative S-C ratio as given in Figure 5 is most illustrative. To clarify terminology in Figure 5: surviving until reserve slot will be designated as short term, until A-Check as medium term, until C-Check as long term.

So let’s assume that the maintainer wants to know what is the most cost-effective option to make the structure last in the short term. Looking at Figure 5, the relative S-C ratio is the same value at 1 for both temporary options. This means that the most cost-effective action, is making sure the structure lasts for the short term using just temporary repair, which in this case cost 2,800€. The initial cost of permanent is so high (35,500€) that it is just not rational to spend the amount to make the structure last only 20FC. Hence the permanent option is heavily penalized as a short term option with a relative S-C ratio of 0.14.

Now consider that the maintainer is interested in making sure the structure lasts in the medium term 185FC. Then checking Figure 5 it can be seen that option 1 has drastically reduced relative S-C ratio at 0.08, and the cause for this is twofold. First is the cost increase that occurred for this option at the reserve slot. The temporary repair is followed up by a permanent repair, bringing the total cost of this option from 2800€ to 32,800€, hence lowering the S-C ratio. The second reason is because the sequential event survivability has continued to decay at temporary phase and after repair event 2 (permanent repair) at 20FC. In fact the continued decay of the survivability for longer periods of flight cycles is what reduced the relative S-C ratios of all three options. Option 3 with permanent only, has reduced relative S-C ratio from 0.14 to 0.12 purely because of reduced survivability. So in the end, if the maintainer wants to ensure the structure survives till medium term at 185FC, then they would chose option 2 to run temporary phase out till A-Check and not incur the additional cost of an earlier permanent repair.

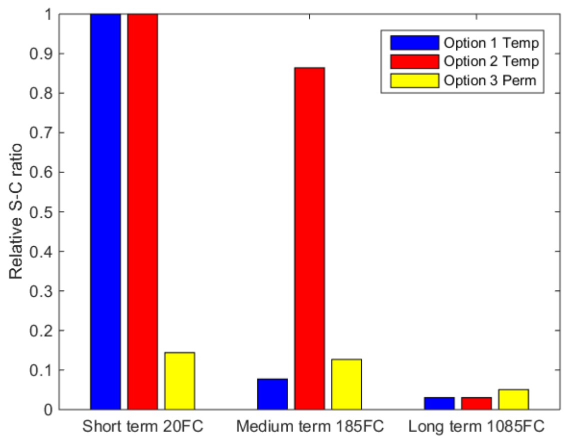

Figure 5: Relative survivability-cost ratios at different monitoring points in time

Lastly, the maintainer may also want to choose an option that is most cost-effective for the long term, looking ahead towards C-Check, which in this scenario will occur at 1085FC. In this case looking back at Figure 5, option 2 has also fallen in relative S-C ratio much like option 1 at medium term because of the cost of a follow-up permanent repair. Both temporary option 1 and 2 now have had a total costs of 32,800€. Yet option 3, immediate permanent repair, with the higher total cost of 35,500€ is indicated as the most cost-effective option for the long term. This a consequence of the fact that option 3 never had a temporary phase dragging down the sequential event survivability. In other words option 3 never took the risk of lower survivability that comes with minimal repair. So under the given scenario, option 3 is the preferred long-term solution, despite higher total cost. Naturally, under different scenarios (e.g. where no aircraft swap is available), different outputs may be expected.

4 CONCLUSIONS

In maintenance, it is common that every damage is a unique scenario influenced by a vast array of decision factors. Each scenario may come with multiple repair options, which is then followed by a maintainer making the most cost-effective repair decision based on his/her criteria. The challenge however, is that the cost-effectiveness is of a repair option may not always be readily apparent. It can change depending on if the maintainer looks in the short term or long term. Hence to facilitate this decision making process, a decision support tool is developed to assist in selection of a repair type which is most cost-effective. The term cost-effectiveness is defined as achieving highest survivability for the lowest cost per flight cycle.

Before repair options can be evaluated, a deterministic Boolean decision tree is used to identify all possible maintenance scenarios. The decision factors are prioritized in the decision tree and based on their individual Boolean setting the maintenance scenario is known. The maintainer is then presented with all possible repair options. Following from the identification of the repair options, each of these are evaluated for the survivability using Poisson process, specifically Non-Homogenous Poisson Process (NHPP) for minimal repair and Renewal Process (RP) for as-good-as-new repairs. Survivability of an option with multiple repair events is also taking into consideration using sequential event survivability. At the core of the proposed decision support tool is a metric that has been designated as relative survivability-cost (S-C) ratio. These ratios are calculated for each repair option at different monitoring points in time both in the short term and long term. The relative S-C ratios quantifies the cost-effectiveness of each options at a point in time, allowing for the maintainer to quantitatively compare the options.

To verify the applicability of such a model a case was conducted on Boeing 777 outboard flap, made of carbon-fiber reinforced plastics (CFRP). The intention is to expand the applicability of the decision support tool to aircraft with heavier use of composite materials such as the Boeing 787 and Airbus A350. In order to do so, more verification and validation tests have to be applied on wider array of structures. This would lead to a more integrated support tool for the whole aircraft that accounts for damages and monitoring of all structures.

REFERENCES

[1] Nicolais, Luigi, Michele Meo, and Eva Milella, eds. Composite materials: a vision for the future. Springer Science & Business Media, 2011.

[2] Rigdon, Steven E., and Asit P. Basu. Statistical methods for the reliability of repairable systems. New York: Wiley, 2000.

[3] Dunyak, James, Ihab W. Saad, and Donald Wunsch. "A theory of independent fuzzy probability for system reliability." Fuzzy Systems, IEEE Transactions on 7.3 (1999): 286-294.

[4] Aitkenhead, M. J. "A co-evolving decision tree classification method." Expert Systems with Applications 34.1 (2008): 18-25.

[5] Freund, Yoav, and Llew Mason. "The alternating decision tree learning algorithm." ICML. Vol. 99. 1999.

[6] Buhrman, Harry, and Ronald De Wolf. "Complexity measures and decision tree complexity: a survey." Theoretical Computer Science 288.1 (2002): 21-43.

[7] Ehrenfeucht, Andrzej, and David Haussler. "Learning decision trees from random examples." Information and Computation 82.3 (1989): 231-246.

[8] Rapajic, Jasenka, ed. "Beyond airline disruptions." Ashgate Publishing Limited. Surrey, England (2009).

[9] Cook, Andrew, and Graham Tanner. "Modelling the airline costs of delay propagation." AGIFORS Airline Operations Conference, London, UK. 2011.