ESTIMATION OF DAILY UNSCHEDULED LINE MAINTENANCE EVENTS IN CIVIL AVIATION

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Abstract

Reducing maintenance cost in today's aviation industry is a necessary step to participate in a market under excessive cost pressure. Airlines as well as maintenance, repair and overhaul companies have to cut costs wherever possible.

An improved MH planning for unscheduled maintenance events could help avoiding expensive overcapacities in certain time slots. A statistical model expressing the occurrence of failures as a stochastic process is developed. Unscheduled maintenance events of a homogeneous modern fleet are analysed to determine representative failure rates for each aircraft system.
The model allows daily MH demand estimates for small aircraft fleets of 15 or 20 aicraft with accuracy of around 75 %.

1 Introduction

With an ever increasing cost pressure in today's aviation industry maintenance, repair and overhaul (MRO) companies have to react on the demand for less expensive services.
In past years, airlines (operators) as well as MRO companies outsourced parts of their business. The big legacy carriers concentrate on their core business of flight operation. Former in-house MRO departments were spinned off and started offering services to other operators as well.
MRO companies themselves began outsourcing work packages that can be conducted anywhere in the world. This includes aircraft overhaul and other heavy maintenance items which are performed in countries with lower labour costs. Therefore maintenance costs are reduced even when ferry flights to the related MRO stations are necessary.

Work induced by unscheduled maintenance events during operation can not be outsourced. Those line maintenace events, which consist of failures or pilot reports, occur during operation and must be fixed prior to the next departure. Here, the only way to reduce costs can be achieved through an advanced man hour (MH) planning which focuses on providing enough MH for necessary work without producing overcapacities in a certain time slot.
Thus MH planning of tomorrow's MRO companies has to be more demand-orientated. That leads to the necessity of means to estimate MH demand in advance. As MH are produced by unscheduled maintenance events (in the following failures) the occurrence of those failures has to be examined.
With onboard monitoring systems like Airman from Airbus Industries exact treatment of failure messages is already possible today. Thus MH or spare part planning can be adapted even before the aircraft arrives at a certain station.
One step beyond this, MRO providers are interested in an estimate of next day's MH

demand. Here onboard monitoring systems are less helpful.
On the other hand, it is obvious that MH demand planning with the purpose described above, can never be as exact as monitoring systems. Demand planning will not be used to predict a certain system failure or a certain part to be replaced (in contrast to condition monitoring).
Therefore the intended kind of planning model will be of great advantage as a rough estimate for MH demand.

This study introduces an approach to estimate the MH demand necessary to handle unscheduled maintenance events on a certain fleet during line maintenance. A modern short and medium-range aircraft type is selected for this study.

2 Literature Review

Severval approaches dealing with MH planning have been presented in the past. [1], [2] and others concentrate on planning of scheduled maintenance events making the problem a scheduling problem. One major assumption in these works is the negligence of stochastically occuring maintenance events.
Focusing on unscheduled events rather than optimizing MH planning can be found in [3], [4], [5] as well as [6].
The background of [3], [4] and [5] are Service Difficulty Reports (SDRs) collected by the Federal Aviation Administration (FAA) which document severe occurrences of events leading to unplanned flight interruptions. [3] and [4] try to estimate the amount of those events in certain time intervals like one year or three months. As this should be used to support fleet supervision by the FAA instead of MH planning this approach is less helpful for short-term MH demand estimation.
[5] do not concentrate on the quantitative estimation of SDRs but qualitatively investigate the influence of aircraft age on the technical performance expressed through SDR occurrences.
[6] treat the problem of condition monitoring-based predictions of engine system failures. Using monitoring data, classification algorithms allow pro-active prediction of most likely engine failures. Thus enabling maintenance personal to replace expensive parts prior to destructive failure occurrence.
The first and today still often cited work on aircraft failures is [7] investigating air conditoning systems. Qualitative results on the degradation status of investigated Boeing 720 are concluded. The usage of aircraft failure rates to estimate the amount of failures in a certain period of time is not regarded.

Other works like [8] investigate the reliability of certain aircraft systems or parts. [8] build a reliability model for Boeing 737 aircraft brakes which purpose is to enhance the planning of preventive maintenance work. The basic idea is very helpful for this study although the work focuses on a certain aircraft system only.

Other similar approaches can be found in the literature. Although some studys have similar intention or methodical background, a short-term estimation of MH demand like intended in the present study could not be identified by the authors.

3 Methodology and Model

3.1 Deduction of the Applied Methodology

[3] apply the basic statistic methodology of regression analysis to forecast amounts of SDRs. Regression analysis is a widely used modeling method to determine a dependend metric variable through multiple metric independent variables. Thus weights for each independent variable are calculated to assure the best explanation of variance.
To estimate annual demand of unscheduled MH throughout a range of different aircraft types [9] use a multiple regression model with promising results. Reducing the estimation interval from one year down to a week or even less, soon reveals bad results in MH demand

estimation caused by too much noise within the data. For the purpose intended, a regression approach estimating the amount of MH in a certain short-time interval is not feasible.

Coping with noisy data leads to the formulation of a representative aircraft of a certain type.

Reliability theory introduces posibilities to model system failures of repairable systems as well as non-repairable systems [10]. Repairable systems or subsystems are those which can be put back into operation after the occurrence of a failure and its repair. In comparison to this, non-repairable systems (often parts or components) cannot be repaired and by this cannot be put back into operation after failure.

With repairable systems one major point of interest is the rate of occurrence of failure (ROCOF). This represents the amount of failure per time unit (e.g. Flight Hours FH, Flight Cycles FC, km or calender time). In reliability theory ROCOF is measured relative to the system age representing the behaviour of the system performance over time. The most known diagram in reliabilty theory is the bathtub curve as can be found in almost every book on reliability like [10] illustrating burn-in failures as well as a constant failure rate and finally a wear-out state. Thus especially mechanical systems' ROCOF tend to change with age.

Repairable system often fail due to single elements failure. As a consequence the certain failure is fixed and the complete system is repaired. Repairs that do not renew the complete system are called mimimal repair, bringing the system back in a bad-as-old state [10].

The sequence of those events can be modeled as a stochastic point process which has an expected value representing the amount of failures in a certain time interval [10]. This expected value can be expressed as follows.

$$N_{12} = E(x_2) - E(x_1) = \int_{t_1}^{t_2} \lambda(x) dx \qquad (1)$$

With N_{12} the amount of failures between the two arbitrary time points t_1 and t_2 ($t_2 > t_1$) and $\lambda(x)$ the related ROCOF of the process.

Identifiying the ROCOF is the most important step in modeling the whole process. [11] as well as [10] and others introduce a ROCOF that is a feasible model for technical systems which show deterioration as well as systems that improve or have constant failure rates. This ROCOF, based on the Weibull distribution, is known as the Power Law Model [11].

$$\lambda(t) = \alpha\beta t^{\beta-1} \qquad (2)$$

The flexibility to model the three different behaviours is possible through identification of the scale parameter α and shape parameter β. [12] underlines the wide range of applications and its positive results. [12] further emphasises that only systems that are equivalent can be modeled together enabling the identification of a representative ROCOF of the related systems.

The parameter identification is conducted with a maximum likelihood estimation for censored data [10][11].

3.2 System Model

Failures occuring during operation of an aircraft can be divided into two classes. The first one consists of failures that have to be fixed prior to the next departure. This can be caused by their importance on airworthiness as well as airline related levels of safety or passenger comfort.
The second class of failures can be deferred and thus do not have to be fixed prior to the next departure.
For the intended estimation model of the MH demand only the first kind of failures are taken into account.
Failures can have multiple causes and each individual cause may occur less frequently. For

this reason failures affecting one certain aircraft system will be treated as one failure type. For example the real failure “right hand main landing gear” and “nose wheel steering” are grouped together into the failure group “Landing Gear”. Aircraft systems are categorised according to Air Transport Associaiton Specification ATA. With systems that are very similar and show only little occurrences, failures are further grouped. Thus “Structures” (“ATA 51”) consist of ATA chapters for structures (ATA 51), fuselage (ATA 53), nacelles (ATA54), stabilizer (ATA 55) and wing (ATA 57). Engine systems are grouped together and called “ATA 71”.

Each failure is a single stochastic process with its own ROCOF. In this study the following aircraft system are modeled.

Tab. 1. Failure categories according to ATA

ATA	System
21	Air Conditioning
23	Communications
24	Electrical Power
25	Equipment & Furnishing
27	Flight Controls
28	Fuel
29	Hydraulic Power
32	Landing Gear
33	Lights
36	Pneumatic
38	Water & Waste
49	Auxilliary Power Unit
“51” - 51,53,54,55,57	“Structures”
“71” - 71 to 80	“Engines”

As an appropriate assumption to cope with individual exact repair times each failure has the same average repair time of 0.5 MH. This is confirmed by experts from MRO industries and is a major point in reducing the model’s complexitiy. Thus the estimation of MH demand is equivalent to the estimation of numbers of failures. Instead of 0.5 MH the demand for each failure can be adjusted and in general set to say, *d* MH.

Beside unscheduled maintenance events aircraft have to undergo regular inspections, so called checks which are also known as scheduled maintenance events.
During those checks unscheduled maintenance can occur as well. Here, often a lot of failures are identified because systems are inspected in depth. These failures are not taken into consideration for the intended model due to the fact, that only failures occuring during normal operation are of interest for a MH demand model.

With these assumptions the model for the MH demand caused by unscheduled maintenance events in a certain time can be expressed by:

$$MH_{t_1 t_2} = d \sum_{i=1}^{n_{AC}} \sum_{i=1}^{n_{ATA}} \int_{t_1}^{t_2} \lambda_i(x)dx \qquad (3)$$

n_{AC} is the number of aircraft in the fleet of estimation, n_{ATA} is the number of aircraft systems and thus the number of failure types. *d* represents the MH demand for a single repair.

To determine the accuracy of the model the magnitude of error relative to the estimate (MER) is calculated [13].

$$MER = \frac{|empiry - estimate|}{estimate} \qquad (4)$$

Another measure of the model’s accuracy is the difference between empirical values and model values, so called residuals. The standard deviation of the residuals is used to build confidence bounds for the estimation.

4 Data of this Study

4.1 Original Data

To assure modeling only equivalent aircraft [12] one single type of aircraft is selected for this study. This aircraft is a modern short- and medium-range aircraft being in operation at several fleets worldwide.

For this study data from one operator with legacy carrier profile and continental climatic operation conditions are analysed.
Data contain maintenance-logfiles, daily FH and FC as well as aircraft age measured in FH ever flown (Total FH) and scheduled maintenance check dates. Reported failures can be identified by their ATA code with additional information about the deferal status. Written information on the individual failures are not available. All data mentioned are reported for three subsequent years and contain all failures within this time for more than 60 aircraft.

4.2 Preparation of Data

Modeling representative ROCOFs for the related aircraft type requires a wide range of different aged aircraft. Sorting the aircraft by their age in Total FH leads to a range between 4000 FH and 34000 FH. Thus an age span of almost 10 years is available.
The more aircraft examined simultaniously the more representative the modeled ROCOFs will be. At each point of age as much aircraft as possible should be available avoiding noise through single outliers. Thus the data are additionally censored to the time span between 8000 FH and 32000 FH to assure at least 10 aircraft at each point of age.

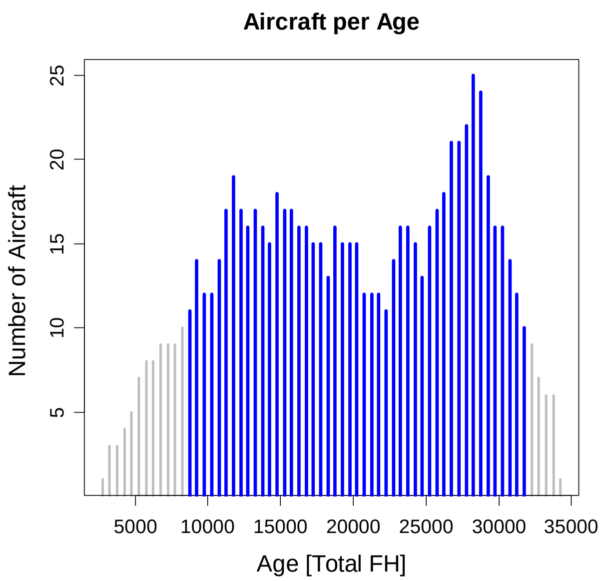

Fig. 1. Availabe number of aircraft per age

In today's aeronautical industry empirical data are difficult to obtain. Especially, sensible data containing failure information of aircraft are only accessible with rarity and under restrictions. Thus for reasons of anonymity no values will be added to failure rate diagrams.

5 Results

5.1 Parameter Identification

Aircraft are split into two groups. The training aircraft are used for parameter identifcation. Remaining aircraft are validation aircraft.
The likelihood functions are formulated and solved in the free Software Package R.

For the air conditioning failure ATA 21 the following parameters where identified and will be shown representatively: $\alpha = 3.6\ 10^{-5}$ $\beta = 1.54$.

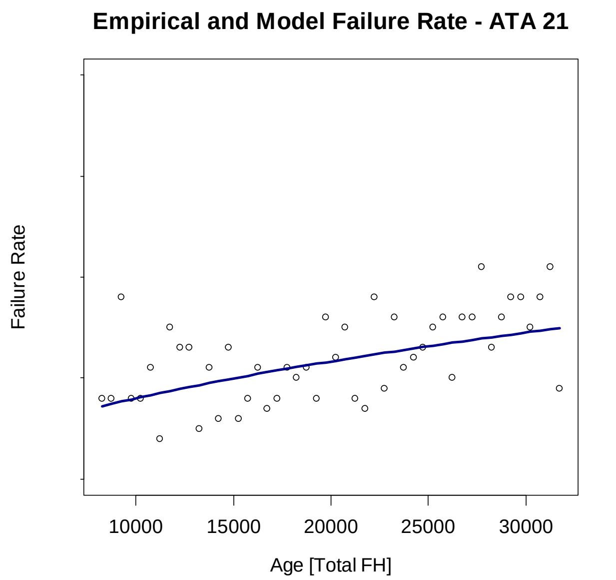

Fig. 2. Empirical and model failure rate for failure type ATA 21 air conditioning

Applying the likelihood function with the Power Law Model ROCOF assumes that the data follow the related rate. Testing whether this assumption is true or not can be conducted with a statistical goodness of fit test (Chi²-Test). With a significance level of 5% test results less than a certain critical value lead to the acceptance of the model for the empirical data in the sample. This means the model is a valid one.

All failure types modeled passed the goodness of fit test.

In the following diagrams the resulting ROCOFs of each failure type are illustrated. For reasons of clarity two diagrams are presented making the illustration less crowded. The failure types in each diagram are not sorted by any logic.

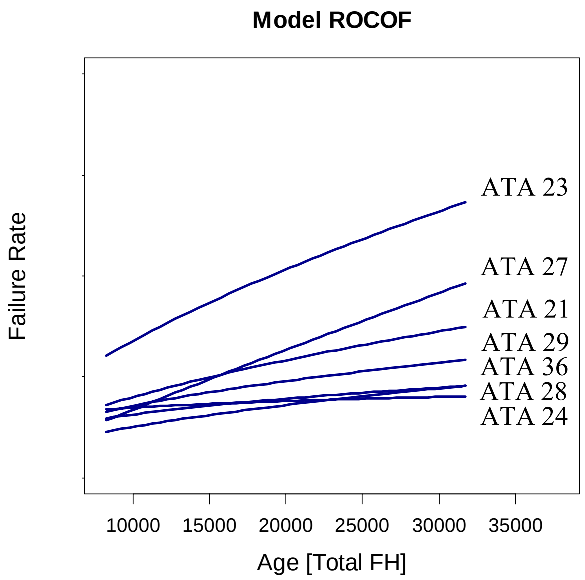

Fig. 3. Model ROCOFs ATA 21,23, 24, 27, 28, 29, 36

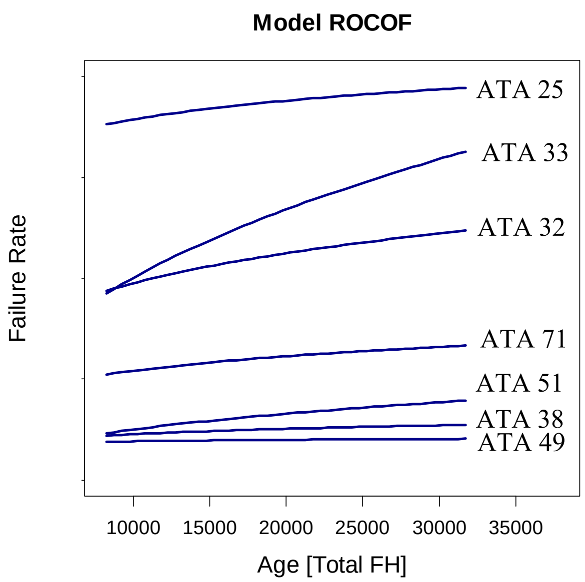

Fig. 4. Model ROCOFs ATA 25, 32, 33, 38, 49, 51, 71

With the aircraft age in the sample between 8000 FH and 32000 FH the model is only applicable to aircraft of the related type and age. Extrapolation beyond this age should be done with great care.

5.2 Model Application

The ROCOFs for each failure type are the overlay of several equivalent aircraft. Thus the model represents an almost average aircarft of the related type. For this reason applying the model to one aircraft only will never lead to any senseful result. To obtain useful results the estimation of the MH demand for a fleet of 15 or 20 aircraft is necessary. For big airlines this is the amount of aircraft which have their station at a certain airport or will be treated simultaniously in one time slot.

To obtain representative results a fleet of 15 and 20 aircraft is randomly chosen from the set of training aircraft as well as the validation aircaft several times. The model (3) is applied for each day in the three years of data. The resulting mean MER (MMER) are the average of each random selection's MER. The residuals are those of all random selections together.

Table 2. MMER Model application for a one day estimation interval

Fleet size	Training Data MMER	Validation Data MMER
15	25 %	25 %
20	22 %	22 %

Table 3. Standard deviation of residuals

Fleet size	Training Std. deviation	Validation Std. deviation
15	8.3	8.4
20	10.3	9.8

The residuals almost follow a normal distribution allowing to build 95%-confidence bounds as ±1.96 standard deviations of the residuals.
With these confidence intervals the maximum of the MH demand can be estimated with 95%.

Table 4. 95%-Confidence bounds for daily estimation

Fleet size	Confidence bound
15	± 16.4
20	± 19.6

Estimates for three or seven days are possible as well and for the reason of statistics lead to even better accuracy.

6 Conclusion and Further Research

6.1 Conclusion

The presented approach illustrates that reliability theory methods are applicable to the problem of aircraft unscheduled maintenance. The flexible Weibull-based ROCOF of the Power Law Model allows the formulation of representative failure rates for almost every aircraft system. Thus short-time estimations of MH demand for fleets of 15 or 20 aircraft are possible. The model accuracy following simple statistics is between 75% and almost 80% for daily estimations.
The model in this simple form is applicable to the estimation of MH demand as only ATA 24 (Electrical Power) needs a different qualification. Every other failure type can be treated by one class of qualification. Therefore mixing the failure types to calculcate an overall demand can be done without loss of vital information.

The investigated aircraft age is between 8000 FH and 32000 FH. Extrapolation of ROCOFs should be done with great care.

One limitation can not be clarified with complete confidence. Aircraft are continiously maintained and technically improved following manufacturer advises. New aircraft of the same type already have those improvements as standard delivery condition. Thus new and older aircraft even of the same type may show slight differences which can, at the time being, not completely be analysed as no information about the aging of new aircraft is availabe.

6.2 Further Research

Using the aircraft age and the individual flight hours in the interval of estimation allows valid and useful results.
To enhance the model accuracy further research will focus on the use of other variables. After the fundamental ROCOF approach presented the use of ROCOF with so called covariates may further improve the accuracy.
Assuring the correct use of the ROCOF model the failure rate prior and after maintenance checks were investigated prior to formulation of likelihood functions. No significant influence by those checks is present for 13 out of 14 failure types. For the reason of this simple model the negligence of the slight improvement for one failure type is acceptable. Further research will deal with the proper improvement factor for that failure.

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