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# Identification of Strategic Maintenance Resource Demand - A Reliability Based Approach

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**Abstract.** Airline Maintenance and Engineering (M&E) organizations face accidental damages on their fleet of aircraft as part of daily practice. As this type of damage is stochastic in nature, the approach towards repairing accidental damage is reactive in practice. However, it is possible to predict future long-term (strategic) demand for maintenance resources associated with accidental damages and use this to identify required capacity. To achieve the mutually related goals of prediction of future repairs and determination of capacity, a novel approach for integration of reliability modelling and inventory control is presented in this paper. Here, the concept of inventory control has been specifically applied to determine the maintenance capacity by taking into account the stochastic demand related to unscheduled repairs following from accidental damages. To predict demand, a Non-homogeneous Poisson Process (NHPP) reliability model has been adopted. The reliability model includes superpositioning, through which failure behaviour at aircraft fleet-level can be estimated and subsequently simulated. The resulting demand is fed into a single-system, single location base-stock inventory model. This allows for determination of strategic capacity based on optimum costs as well as service level requirements. A case study has been performed on a fleet of Boeing 777 aircraft of a major European airline. The results prove the feasibility of adopting an integrated approach towards strategic capacity identification, using real-life data to predict future demand occurrence.

**Keywords.** Aircraft maintenance, strategic resource scheduling, reliability

## Introduction

When operating aircraft, there is a clear, present but minor risk of incurring accidental damage. Causes of accidental damage include collisions with ground and cargo handling equipment, erosion from rain, hail, lightning or runway debris, and damages resulting from human error during aircraft operations and maintenance (e.g., tool-drops) [1]. The resulting damage typically needs to be repaired quickly to adhere to regulatory requirements, given possible safety implications. Furthermore, from an economic perspective, there is a major incentive to repair quickly: prevent costly aircraft downtime [1]. At an individual level, accidental damages are highly stochastic in nature compared to damage caused by structural aging, fatigue and deterioration. Note that fault forecasting related to these latter causes, as for instance described by

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Pogacnik et al. [2] and Pleumpirom et al. [3], are not incorporated from this perspective. The approach towards repairing accidental damage is reactive in operational practice. This may lead to additional use of limited resources, for instance manpower, hangar space or materials. If resources are not available at the right time, delays may ensue, leading to very high costs for the maintenance organisation as well as the operator.

However, at a fleet level, it is possible to predict future long-term (strategic) demand for maintenance resources associated with accidental damages and compare this with available resource capacity. This may influence maintenance planning policies, by identifying the required capacity (and its deviations over time), with the possibility to fine-tune planned buffer capacity or even adjust available capacity over time. To achieve the mutually related goals of prediction of future repairs and determination of resource capacity requirements, a novel approach for integration of reliability modelling and inventory control is presented in this paper. While the constituent elements are part of well-established research fields, limited work has been done towards integrating these elements towards capacity identification purposes in maintenance applications. In addition, existing studies typically use simulated demand. In contrast, this study presents results for a case study which incorporates actual accidental damage data.

The theoretical context of the problem at hand is discussed in Section 1. This is followed by introduction of the method followed, comprising integration of reliability modelling and analysis, stochastic demand generation and capacity planning through an inventory control method. The method is applied in a case study, which uses actual Boeing 777 damage data from a European airline / maintenance operator. The case study explores capacity planning through sensitivity analysis for a range of parameters. Finally, conclusions are given and future research directions are indicated.

## 1. Theoretical context

The occurrence of accidental damage is a stochastic process: a counting variable can be used to enumerate the number of occurrences resulting from an underlying random process. Given the availability of sufficient occurrence data, stochastic process models can be used to characterise the process of damage occurrence. From a maintenance perspective, these models have been studied in-depth as part of reliability modelling and application. The most relevant theory regarding reliability in aircraft maintenance is briefly discussed in Section 1.1. The reliability models can subsequently be used to predict future occurrences of accidental damage, which opens up a path towards determination of long-term capacity requirements. Existing models towards planning of maintenance capacity are discussed in Section 1.2.

### *1.1. Applications of reliability modelling in aircraft maintenance*

A sizeable body of work discusses reliability modelling and analysis, using experience-based, statistical, evolutionary or physical model-based methods [4]. From the perspective of accidental damage occurrences on aircraft, methods should be suitable to address the repairable nature of the structures and components that typically face these type of damages. Selecting a suitable reliability model that provides the best match with the underlying failure process as well as the available data is of utmost importance for estimation accuracy and subsequent extension towards prediction of future events.

Several systematic approaches towards reliability model selection and application have been proposed [5-8]. These approaches typically address the methodology, data, information and assumptions needed for model building, the properties of different models, and tools and techniques to determine whether a particular model is appropriate for a given data set. The following aspects are particularly relevant towards the modelling of incidental damage:

- **Data collection:** to model repairable components, a key parameter to collect is the time between failures, or in this case, damage occurrences. Technical information concerning occurrences, description of occurrences and their characteristics, as well as environmental conditions, repair times and root causes are data of interest as well.
- **Homogenization process:** Many models assume independence and identically distributed occurrence times, despite possible differences in extraneous factors (e.g., operational and environmental conditions). In particular cases, it is necessary to homogenize the available data, leading to a set of identical components with comparable operational and environmental conditions. This can be even more important given the infrequent nature of failure / damage occurrence, which may lead to adoption of data pooling to generate sufficiently large sample sizes for subsequent analysis [7].
- **Trend analysis:** Before committing to a specific model, it is usual to test the available data for trends, as behaviour can be monotonic or nonmonotonic (or trend free). There are various methods by which trends can be analysed, including graphical and analytical methods.
- **Reliability model selection and parameter estimates:** the most commonly used models for reliability analysis are the homogeneous Poisson process (HPP), renewal process (RP), non-homogenous Poisson process (NHPP) and generalised renewal process (GRP) [9]. In case of data pooling, superposed or super-imposed systems result [10], which can be modelled using a HPP or NHPP model. In terms of parameter estimation, least-squares estimation or maximum likehood estimation are typically used to estimate model parameters, followed by goodness-of-fit testing to establish whether the model estimates are sufficiently close to observed reality.

### *1.2. Integrating maintenance demand and capacity planning*

Product reliability over time drives future demand for repair or replacement activity. As such, if sufficiently accurate estimates of product reliability are available, it becomes feasible to predict future demand for different time horizons. This information can subsequently be used to identify and plan maintenance activity and the supporting capacity.

There has been significant interest in models seeking to integrate the aspects of production, quality and maintenance for planning purposes within various industries. Within the production industry, planning refers to determination of lot sizes (the units of products manufactured) and computing the capacity needs in the case of changing demand. Economic production quantity (EPQ) models, which can be classified as a type of inventory control model, have been used extensively to incorporate fluctuating demand due to maintenance events [11-13].

Dekker [14] describes existing models to determine the required capacity to carry out maintenance, but restrict efforts to planned maintenance. When considering unplanned (or unscheduled) maintenance, the demand behaviour becomes stochastic. Several research efforts describe maintenance demand generation using stochastic processes (e.g. an NHPP model in Bengu et al. [15]) in combination with capacity determination and/or optimization [15-17]. However, these research efforts focus on operational planning, i.e., describing a short-term time horizon. In contrast, Duffuaa et al. [18] aim to integrate maintenance demand forecasting with strategic planning. However, time series techniques are employed to perform forecasting, which has drawbacks in terms of identifying and responding to trends as well as stochastic behaviour [19].

In a maintenance intensive industry like the airline industry, with a significant amount of unscheduled maintenance events, estimation of required capacity needed to fulfill any future unscheduled repairs becomes important from a strategic planning point of view. To the best of the authors' knowledge, there has been no work that directly addresses the stochastic nature of unscheduled maintenance induced by accidental damages in combination with strategic capacity identification.

## 2. Method

To address the identified research gap, an approach is proposed which is defined in Section 2.1., followed by more in-depth discussion of the contributing elements of reliability, demand and capacity modelling..

### *2.1. Approach and assumptions*

The followed approach to integrate the modelling elements is given in Figure 1. It highlights the main elements of the integrated approach, including three main steps which are described in more detail in Sections 2.2 – 2.4. In addition, the main input and output parameters are included, as well as a feedback loop to incorporate the periodic updates to the input data, reliability model output, demand generation and subsequent capacity identification.

In terms of assumptions and scope, the integrated approach has been developed with an eye towards application for accidental damage occurrences. As such, the following aspects should be taken into account:

- All accidental damages are aggregated; no individual types are considered.
- The type of repair is not specifically considered as part of the reliability model. Repair time is considered negligible in comparison to the time between events.
- The reliability model does not explicitly consider repair effectiveness.
- Capacity is evaluated in terms of costs and facilities; material support required to fulfil a maintenance action is not taken into account.
- It is assumed that all aircraft are to undergo maintenance at a single location.

Having introduced the integrated approach, the following sections will consider the main elements in more detail, starting with the followed approach towards reliability modelling.

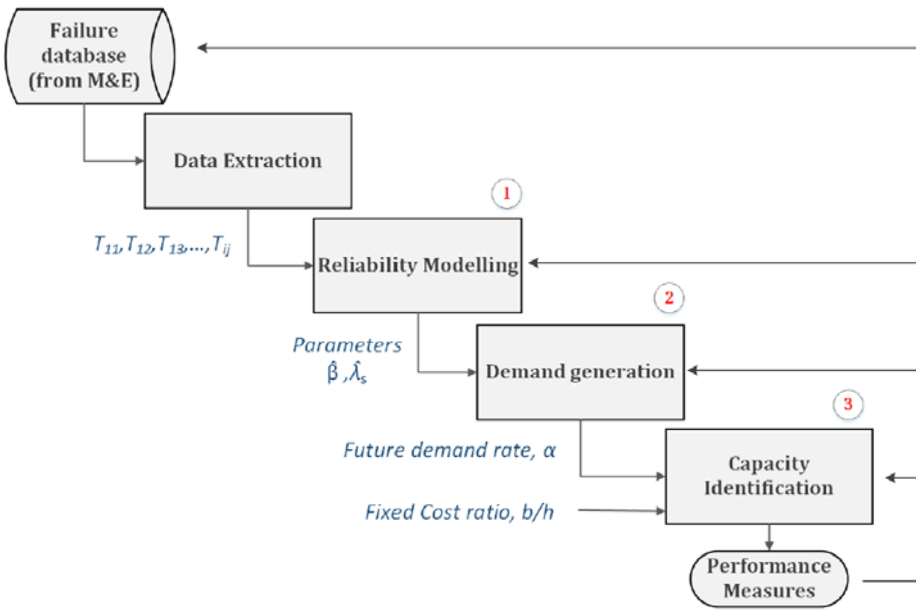


**Figure 1.** Integrated modelling approach for strategic maintenance capacity identification

### *2.2. Step 1 - Reliability modelling*

In terms of reliability modelling, in principle it is possible to adopt a variety of stochastic process models. Model selection and parameter estimation is dependent on the (type of) data considered. As such, data extraction is first considered, followed by model selection and parameter estimation.

#### *2.2.1. Step 1.a - Data extraction*

For the problem at hand – i.e., incidental damage occurrences on a fleet of aircraft, a step by step approach is taken to extract relevant data:

1. Data classification in terms of number of damage occurrences into the main ATA-100 chapters, leading to a breakdown of damage occurrences per primary aircraft structure. This is followed by a further classification up to component level.
2. Damage occurrences classification for each system (aircraft).
3. Extraction of occurrence characteristics (type; time of occurrence).

If an insufficient number of damage occurrences for each individual system is present, it is possible to combine *k* systems into one single system. This principle is known as superposition. While conclusions at individual system level are impossible, the advantage of the superposed system is that it can model reliability for the entire *k* systems, representing a fleet (of aircraft). This matches the strategic orientation of the current research. The principle behind superposition is illustrated in Figure 2.

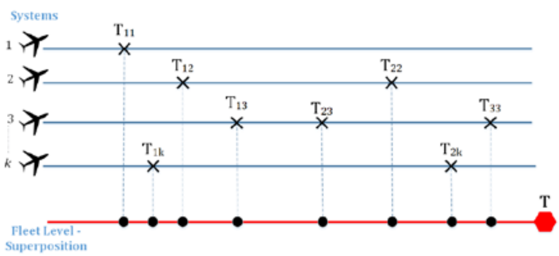


**Figure 2.** Superpositioning of $k$ independent systems

### 2.2.2. Step 1.b - Reliability modelling and analysis

When using superpositioning, available stochastic process models for repairables are typically restricted to HPP and NHPP models. For the case considered in this research, the NHPP process is adopted, with a power law process (PLP) to represent the intensity function. Suppose the observation of a system starts at age 0 and runs until time $T$ (truncation time), the number of failures the system experiences during this time is denoted $N(T)$ and is a random variable with successive times to failure $T_{i,j}$. The intensity function for the PLP is given by [20]:

$$u(t) = \lambda \beta t^{\beta - 1}, \qquad t > 0 \tag{1}$$

In the case of superpositioning with $k$ systems, the power law intensity function is given by the equation below [20]:

$$u_s(t) = k\lambda \beta t^{\beta - 1}, \qquad t > 0 \tag{2}$$

With $\lambda_s = k\lambda$ thus representing the superpositioned scale parameter of the PLP, and with $\beta$ being the shape parameter. Parameter estimation can be performed using Maximum Likelihood Estimation (MLE), accompanied by the Cramer-von Mises test, adapted from Crow [20], which is specifically used to test the data for a PLP model.

## 2.3. Step 2 - Demand generation

The obtained reliability model and its parameters can be used to simulate future demand, which is stochastic in nature. Demand is the number of occurrences in a given unit of time, denoted by $\alpha$. Demand is generated using the inverse transform method to calculate successive damage occurrence times $T_i$ [21]. The distribution function derived from a PLP with superpositioned intensity function is given by:

$$F_{T_{ij}}(t) = 1 - \exp(-\lambda_s[(y+t)^{\beta} - y^{\beta}]) \tag{3}$$

This can be used to derive the equations for the successive occurrence times as given below:

$$T_1 = [-\frac{1}{\hat{\lambda}_s} \ln U_1]^{1/\beta} \tag{4}$$

$$T_q = [T_{q-1}^{\beta} - \frac{1}{\hat{\lambda}_s} \ln U_q]^{1/\beta} \quad , \quad q \geq 2 \tag{5}$$

Here $T_1$ is the time to first occurrence and $T_q$ are the successive occurrence times after $T_1$ (both of them representing fleet level behaviour due to superposition, hence dropping the index *j*), with $U_q$ representing a uniformly distributed random variable for simulation purposes. Due to the random number $U_q$, each generated sequence of occurrence times $T_i$ $(= T_1 + T_q)$ is unique. To capture aggregate behaviour, a Monte Carlo simulation can be performed. The time between occurrences for the generated sequences are analysed to determine the mean time between failures (MTBF). Finally, demand rate $\alpha$ is computed from the MTBF, where the $\alpha$ signifies the number of occurrences per flight cycle.

### *2.4. Step 3 - Capacity identification*

To identify capacity, a base-stock policy inventory model is adopted [22]. The input to the capacity identification model are the demand rate $\alpha$ and several capacity cost ratios. The capacity identification model generates outputs in the form of several performance measures through which the capacity requirements can be identified. Table 1 describes the main model parameters, their inventory control definitions as well as their translation towards the aircraft maintenance domain.

**Table 1.** Model parameters – inventory control and aircraft maintenance interpretations

| Symbol | Inventory control | Aircraft maintenance |
|---|---|---|
| $s$ | Base stock inventory level | Slot capacity (number of maintenance positions at a (set of) location(s)) |
| $L$ | Leadtime – time taken for order to arrive | Leadtime – time between two major maintenance checks |
| $\alpha$ | Poisson distributed demand rate | Poisson distributed occurrence rate |
| $\overline{A}$ | Stockout frequency: long-term rate in which demand exceeds stock | Long-term rate in which demand exceeds capacity |
| $\overline{I}$ | Long-term average inventory | Long-term rate for resolved occurrences |
| $\overline{B}$ | Long-term average backorders | Long-term rate for non-resolved occurrences |
| $C(s)$ | Cost of operating at a given base stock | Cost of maintenance at a given slot capacity |

## 3. Results

To test the proposed approach, a case study has been conducted. This is described in more detail in Section 3.1, followed by results, sensitivity analysis and validation.

### *3.1. Case study description*

The case study has been conducted on a fleet of Boeing 777 aircraft from a major European airline, for which a database containing historical incidental damage occurrence data has been made available, covering 10+ years of operational use. Following data extraction, the case study has been scoped towards two types of secondary structures (outboard flaps and leading edge slats), further subdivided into geometric location (left-hand side (LHS) and right-hand side (RHS)) on the aircraft. Table 2 provides an overview of the main input data. For all components, the timeline has been truncated at 7000 flight cycles (FC). $N_q$ represents the total number of accidental damages observed, with $k$ representing the number of individual aircraft on which these damages have been observed. Interpreting the table, one can for instance observe that the LHS flap has had 64 occurrences on 53 individual aircraft, whereas the RHS flap has had 48 occurrences on 30 individual aircraft.

**Table 2.** Case study – reliability model input data

| Symbol | LHS flap | RHS flap | LHS slat | RHS slat |
|---|---|---|---|---|
| $T(FC)$ | 7000 | 7000 | 7000 | 7000 |
| $N_q$ | 64 | 48 | 61 | 47 |
| $k$ | 53 | 30 | 35 | 35 |

### *3.2. Results*

A superpositioned NHPP power law process has been applied to the data presented in Table 3. Using Maximum Likelihood Estimation, the parameter estimates as given in Table 3 were established. It is interesting to note that the outboard flaps show close-to-random occurrence behaviour (as would be expected from incidental damage occurrence), whereas the leading edge slats both show a slight upwards deviation in their respective shape parameter values.

**Table 3.** NHPP power law process – parameter estimates

| | Outboard flaps | | Leading edge slats | |
|---|---|---|---|---|
| Symbol | LHS flap | RHS flap | LHS slat | RHS slat |
| $\hat{\beta}$ | 1.108 | 1.045 | 1.311 | 1.236 |
| $\hat{\lambda}_s$ | 0.003514 | 0.004593 | 0.000553 | 0.000831 |

The resulting superimposed intensity functions can be visualized as shown in Figure 3. Figure 4 shows the output of a Monte Carlo simulation (n = 1000) for the LHS slat, showing the mean demand value as well as the associated quantiles. The mean has been used to generate demand rate $\alpha$, the results of which are given in Table 4.

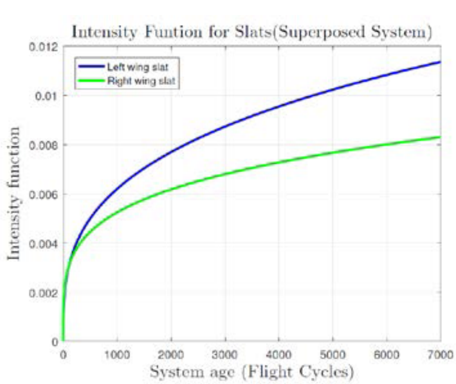


**Figure 3.** Intensity function plots for slats

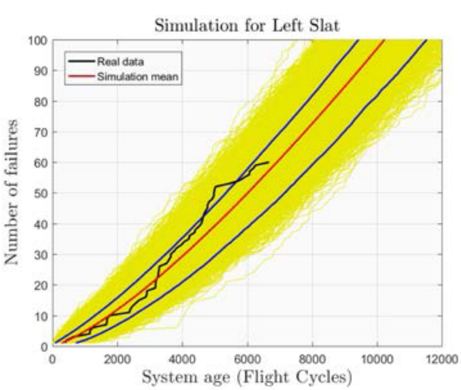


**Figure 4.** Monte Carlo simulation output – left slat

The demand rates generated from the Monte Carlo simulations are used as the input for the planning model. The three measures that help in understanding the effects of the demand are $\overline{A}$ , $\overline{B}$ and $\overline{I}$ . These are functions of $s$, where $s$ is the number of slots available in a hangar to carry out repair for a given component. There are two ways by which the desired slot capacity can be identified: 1) by fixing an adequate service level through $A$; 2) by minimisation of the cost function $C(s)$.

**Table 4.** NHPP power law process – parameter estimates

| | Outboard flaps | | | Leading edge slats | | |
|---|---|---|---|---|---|---|
| **Demand** | **LHS flap** | **RHS flap** | **Combined** | **LHS slat** | **RHS slat** | **Combined** |
| $\alpha_{mean}$ | 0.0103 | 0.0073 | 0.0176 | 0.0121 | 0.009 | 0.021 |

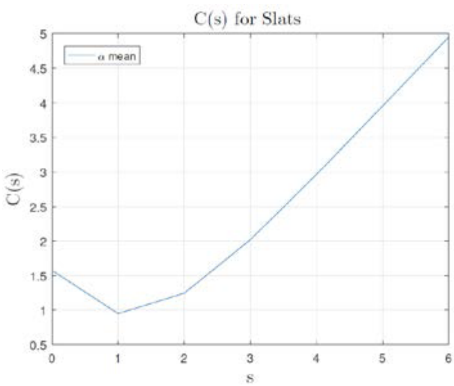


**Figure 5.** Cost function for slats

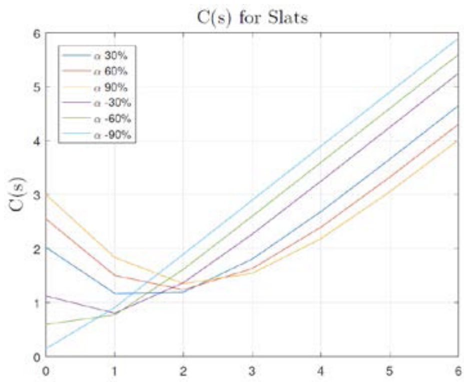


**Figure 6.** Cost variation with changing demand

Figures 5 and 6 show output when the second approach is applied, using a cost ratio between penalty and holding cost of 1,5 together with a leadtime value of 50 flight cycles. Figure 5 shows a cost minimum at $s$ = 1, indicating that a single slot is most cost-effective for long-term planning under the current input conditions. This indicates that 30 slots have to be available over a period of 1500 flight cycles to address incidental damage occurrences, at a cost minimum. Figure 6 shows variation of cost when the demand is varied from the current rate ± 90%, with step size 30%, showcasing the sensitivity of the cost optimum to changes in demand rate.

## 4. Conclusions and Recommendations

This research has presented a successful adaptation of an inventory control model, specifically the base-stock policy model, towards identifying strategic maintenance capacity resource demand. The base-stock model was used to identify the average capacity required to carry out future unscheduled maintenance for slats and flaps, on the basis of real-life damage occurrence data. The results show that it is possible to apply an integrated approach towards strategic capacity identification, using real-life data to predict future demand occurrence.

In future work, several assumptions can be relaxed. For instance, a constant leadtime has been applied to repair fulfilment, which is not necessarily reflective of real-life processes. Furthermore, the presented model assumes a superimposed system repaired at a single location with a certain slot capacity. However, in real life conditions, several locations may be available in the maintenance network.

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