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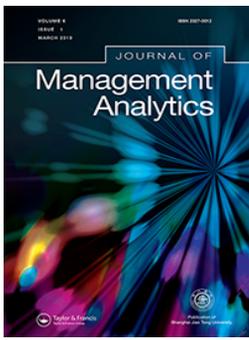
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## Identifying strategic maintenance capacity for accidental damage occurrence in aircraft operations

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Airline operators face accidental damages on their fleet of aircraft as part of operational practice. Individual occurrences are hard to predict; consequently, the approach towards repairing accidental damage is reactive in aircraft maintenance practice. However, by aggregating occurrence data and predicting future occurrence rates, it is possible to predict future long-term (strategic) demand for maintenance capacity. In this paper, a novel approach for integration of reliability modelling and inventory control is presented. Here, the concept of a base stock policy has been translated to the maintenance slot capacity problem to determine long-term cost-optimal capacity. Demand has been modelled using a superposed Non-homogeneous Poisson Process (NHPP). A case study has been performed on damage data from a fleet of Boeing 777 aircraft. The results prove the feasibility of adopting an integrated approach towards strategic capacity identification, using real-life data to predict future damage occurrence and associated maintenance slot requirements.

**Keywords:** aircraft maintenance; strategic capacity identification; stochastic process; inventory control

### Introduction

Aircraft encounter accidental damages during operations, the causes of which 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) (Ren, Chen, & Chen, 2017). Depending on the severity of the damage caused, maintenance actions need to be planned and executed. When safety-critical systems or components are involved, regulatory requirements will drive both the content as well as the urgency of the maintenance action. Besides regulatory aspects, economic considerations play a role. In the highly competitive aviation industry, costly aircraft downtime must be avoided whenever possible (Ren et al., 2017), as aircraft availability is a primary driver of revenue generation capacity.

In operational practice the approach towards repairing accidental damage is reactive. In essence, the response to an accidental damage occurrence is to inspect, diagnose, and perform any ensuing task planning and execution. This process and the

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subsequent decision(s) regarding what action to take and when may lead to additional use of limited resources, for instance manpower, hangar space or materials. If the damage is sufficiently serious and has to be rectified immediately or in very short order, resources may not be available at the right time. This may lead to delays with associated costs for the maintenance organisation as well as the aircraft operator (Cook, Tanner, & Lawes, 2012).

The occurrence of accidental damage can however be characterised as a stochastic process. Such counting processes can be modelled using various representations, for instance as a (non)homogeneous Poisson process. Accidental damage concerns failure modes and mechanisms which act in short time, which is in marked contrast to damage caused by failure mechanisms such as structural aging, fatigue and wear, where the underlying physical failure process(es) generate deteriorating behaviour over a larger timespan (Pleumpirom & Amornsawadwatana, 2012; Pogacnik, Duhovnik, & Tavčar, 2017).

Individual occurrences of accidental damages may be hard to predict and proactively account for, but in aggregate form using stochastic process representations, it is possible to predict future long-term (strategic) demand for maintenance resources associated with accidental damages and compare this with available resource capacity. Herein, strategic demand is related to maintenance resources associated with accidental damages, covering multi-year periods. This may influence maintenance planning policies, as the required capacity (and its variation over time) to address accidental damage occurrences can be ensured. This implies the possibility to fine-tune planned buffer capacity – a usual practice in aircraft maintenance planning – or even adjust available capacity over time. In this research, a novel integrated approach towards accidental damage occurrence prediction and strategic maintenance capacity planning is proposed. Existing models for reliability analysis and inventory control are combined in a new way. In addition, existing studies into capacity determination typically use simulated demand. In contrast, this study presents results for a case study which incorporates actual accidental damage data to generate representative demand behaviour.

The theoretical context of the problem at hand is discussed in the next section. 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 and 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.

### **Theoretical context**

As highlighted previously, 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 process with its own probability distribution. 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 modelling and analysis in aircraft maintenance is discussed first. 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 and long-term inventory control are discussed subsequently, which is followed by a brief synthesis and identification of research gaps.

### *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 (Tinga, 2010). 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 accuracy of estimation and subsequent extension towards prediction of future events. In addition, parameter estimation and goodness-of-fit evaluation procedures are dependent on the selected reliability model. To properly address the full modelling and application chain, several systematic approaches have been proposed (H. E. Ascher & Hansen, 1998; V. S. Viswanath Dhanisetty, Verhagen, & Curran, 2015; Garmabaki, Ahmadi, Mahmood, & Barabadi, 2016; Louit, Pascual, & Jardine, 2009). 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. These data can be used to develop models incorporating the influence of operational and/or environmental covariates (Verhagen & De Boer, 2018) or to represent damage occurrence as a multi-state phenomenon (Baruah & Chinnam, 2005; Christer, Wang, & Sharp, 1997; Dong & He, 2007; Hontelez, Burger, & Wijnmalen, 1996).
- *Homogenisation 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 homogenise 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 (Louit et al., 2009). In case of data pooling, superposed or super-imposed systems are the result (H. Ascher & Feingold, 1984). Homogenisation may also include the decision to combine occurrences associated with similar yet non-identical failure modes, which increases the risk of fitting inappropriate distributions to the given data.
- *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). For a monotonic trend the system is said to be either improving

(decreasing number of failures) or deteriorating (with an increasing number of failures). Non-monotonic trends occur when the trends change in time or repeat in cycles (Louit et al., 2009). There are various methods by which trends can be analysed, including graphical and analytical methods.

Common graphical methods include cumulative failure versus time plots, Duane plots, and total-time-of-test (TTT) plots. TTT plots can be modified specifically to test for a Non-Homogenous Poisson Process (NHPP) power law process (Klefsjo & Kumar, 1992), and for a multiple-system configuration (Louit et al., 2009). The major drawback of graphical methods is that the interpretation of the results can be subjective and imprecise.

To address the shortcomings of graphical methods, it is typical to employ analytical methods for trend testing. The characteristics of different analytical tests and their classification based on the null hypothesis (for renewal processes (RP), Homogeneous Poisson Processes (HPP) and Non-Homogenous Poisson Processes (NHPP)) are mentioned in H. Ascher and Feingold (1984). Widely used statistical tests are the Mann test, Laplace test, Military Handbook (MH) test and Anderson-Darling (AD) test (Garmabaki et al., 2016; Louit et al., 2009). The Mann test has a null hypothesis of RP and an alternate hypothesis of monotonic trend. The Laplace test has a null hypothesis of HPP and an alternate hypothesis of NHPP with monotonic trend. This test is more suitable for NHPP with log-linear intensity function. Similar to the Laplace test the MH test also has HPP as its null hypothesis and NHPP with monotonic intensity as an alternative hypothesis. This test is suitable for NHPP with power law process.

- *Reliability model selection:* the most commonly used models for reliability analysis of repairable components are the aforementioned homogeneous Poisson process (HPP), renewal process (RP), non-homogenous Poisson process (NHPP) and generalised renewal process (GRP) (Yañez, Joglar, & Modarres, 2002). Every model is based on certain assumptions relating to the real-world situation. The RP is a counting process where it is assumed that the time between failures are independent and identically distributed with an arbitrary life distribution. At each failure occurrence, the repair performed is a perfect one and hence restores the system to the 'as good as new' (AGAN) condition. The HPP is a special case of the RP where an exponential distribution applies for the time between failures. For the NHPP, the assumption of a minimal repair restores the system to a functional state same as the one just before its failure, i.e. 'as bad as old' (ABAO) condition. Imperfect repair models attempt to incorporate the possibility of repair to intermediate states. These models are much more complicated to implement but can be suitable for real operating conditions (Rai & Bolia, 2014). The General Renewal Process (GRP) is one of the options available to model imperfect repairs. Two variants have been proposed by Kijima (2016), where one model variant assumes that repair is effective only for the last repair, and the other variant assumes that repairs can restore cumulative wear out and damage up to the present time.

Although the imperfect repair models are assumed to model conditions close to reality, Mettas and Zhao (2005) have shown no considerable difference in the estimates from an NHPP models and a GRP. Also, as these models are used for single systems, using a GRP for multiple systems would be difficult when considering pooling of data from multiple systems, as discussed above. Superposed or

super-imposed systems are typically modelled using an HPP or NHPP model (H. Ascher & Feingold, 1984; Crow, 1990).

- *Parameter estimation and goodness-of-fit testing:* In terms of parameter estimation, least-squares estimation or maximum likelihood 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. Depending on the underlying distribution, closed-form or numerical solutions are available to estimate parameters (Rigdon & Basu, 2000).

### ***Integrating maintenance demand occurrences 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 (Aghezzaf, Jamali, & Ait-Kadi, 2007; Groenevelt, Pintelon, & Seidmann, 1992; Kobbacy & Murthy, 2008).

(Dekker & Smeitink, 1994) describe 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. (Bengü & Ortiz, 1994)) in combination with capacity determination and/or optimisation (Bengü & Ortiz, 1994; Dijkstra, Kroon, Salomon, Nunen, & Wassenhove, 1994; Yan, Yang, & Chen, 2004). However, these research efforts focus on operational planning, i.e. describing a short-term time horizon, and often focus on manpower capacity determination. In contrast, Duffuaa et al. (Duffuaa, Raouf, & Campbell, 1999) 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 (Zorgdrager, Verhagen, & Curran, 2014).

In short, the existing state-of-the-art tends to focus on short-term planning, frequently in conjunction with capacity optimisation from a manpower perspective. The availability of maintenance slots (e.g. hangar capacity) is often not taken into account. Some research takes failure / demand rates as a given input, whereas other literature does take into account the stochastic nature of demand through various modelling approaches.

In a maintenance intensive industry like the airline industry, with a significant amount of unscheduled maintenance events, estimation of required maintenance slot capacity needed to fulfil 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 for maintenance slots.

## Method

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

### 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 the following subsections. 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. The following considerations apply and have been adopted in this study:

- 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.

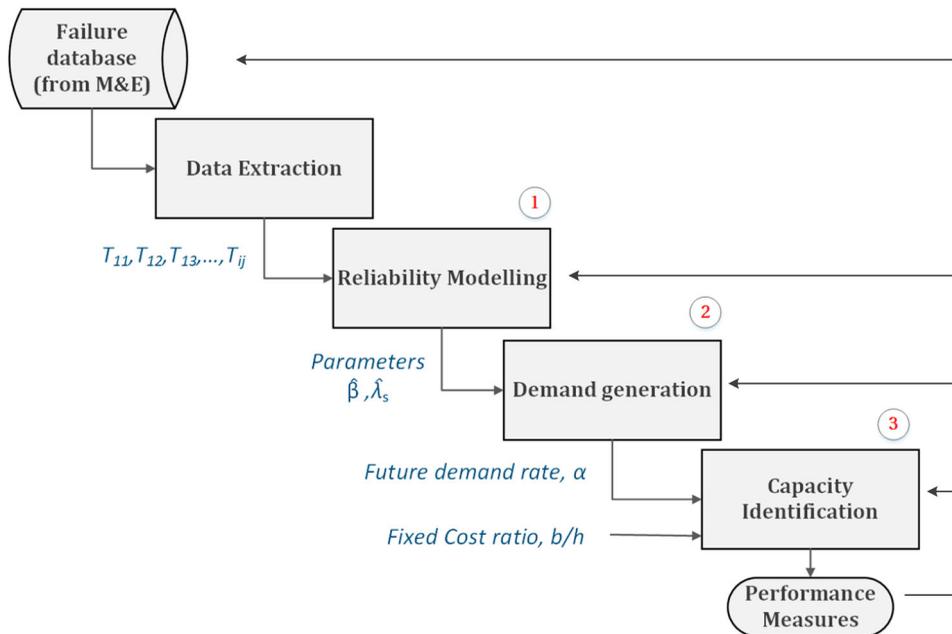


Figure 1. Integrated modelling approach for strategic maintenance capacity identification.

- The reliability model does not explicitly consider repair effectiveness.
- Capacity is evaluated in terms of costs and facilities; material support and manpower 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.
- Maintenance occurrences (as in accidental damage occurrences) do not happen simultaneously; demand occurs in a batch size of one.
- The followed approach allows for backorders, i.e. delayed fulfilment of demand, which in practical terms indicates that an accidental damage occurrence is rectified with some delay.

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

### *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.

#### *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 (providing an aircraft breakdown structure). This is used to generate a breakdown of damage occurrences per primary aircraft structure (systems are not considered in the current research, as the vast majority of impact occurrences are related to aircraft structures). 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 ? 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, and is furthermore necessitated by relatively low sample sizes per single system. Using a superposed system is the driving factor behind the aggregation assumption mentioned previously. The principle behind superposition is illustrated in [Figure 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,

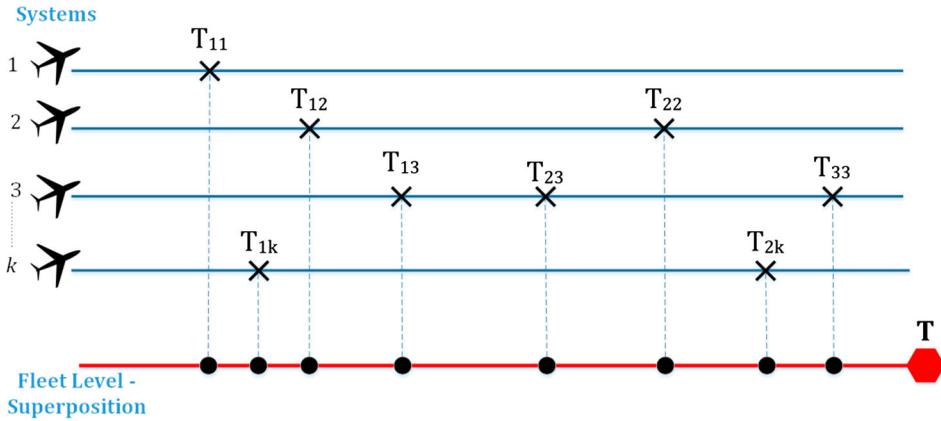


Figure 2. Superpositioning of  $k$  independent systems.

the NHPP process is adopted, with a power law process (PLP) to represent the intensity function. The NHPP is a stochastic point process that assumes the as bad as old (ABAO) repair assumption. 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 NHPP is characterised by a non-constant intensity function and satisfies the following three conditions (Rigdon & Basu, 2000), where  $N$  denotes the number of failures and  $t$  denotes time:

1.  $N(0) = 0$
2. For any  $a < b$ ,  $N(a, b] \sim POI(\int_a^b u(t)dt)$
3. The process has the independent increments property, indicating that for any non-overlapping intervals  $(t, t + \delta t)$  and  $(s, s + \delta s)$ , the number of failures  $N$  in those intervals are independent.

The intensity function for the PLP is given by Crow (1990):

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

With  $\lambda$  and  $\beta$  denoting the scale and shape parameters respectively. In the case of superpositioning with  $K$  systems, the power law intensity function is given by the equation below (Crow, 1990):

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

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), as described by Rigdon and Basu (2000)

and using the equations given below:

$$\hat{\lambda} = \frac{\sum_{j=1}^k N_j}{kT^{\beta}} \quad (3)$$

$$\hat{\beta} = \frac{\sum_{j=1}^k N_j}{\sum_{j=1}^k \sum_{i=1}^{N_j} \ln\left(\frac{T}{T_{ij}}\right)} \quad (4)$$

For a superposed system as discussed here,

$$\hat{\lambda}_s = k\hat{\lambda} \quad (5)$$

Goodness-of-fit testing is performed by the Cramer–von Mises test, adapted from Crow (Crow, 1990), which is specifically used to test the data for a PLP model. The following equation gives the associated test statistic.

$$C_m^2 = \frac{1}{12M} + \sum_{j=1}^M \left( Z_j^{\bar{\beta}} - \frac{2j-1}{2M} \right)^2, \quad (6)$$

where  $M$  is the total number of failures for a time-truncated case, and  $\bar{\beta}$  is the unbiased estimate of the shape factor. The test statistic obtained is checked for the appropriate significance level by correlating with the standard critical value table provided for the Cramer–von Mises test. According to Rigdon and Basu (2000), a significance level of 95% satisfies the case for the PLP model.

### 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  $T_i$  (Tobias & Trindade, 2011). The distribution function derived from a PLP with superpositioned intensity function is given by

$$F_{T_{ij}}(t) = 1 - \exp(-\lambda_s[(y+t)^{\beta} - y^{\beta}]) \quad (7)$$

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

$$T_1 = \left[ -\frac{1}{\hat{\lambda}_s} \ln U_1 \right]^{1/\beta} \quad (8)$$

$$T_q = \left[ T_{q-1}^{\beta} - \frac{1}{\hat{\lambda}_s} \ln U_q \right]^{1/\beta}, \quad q \geq 2 \quad (9)$$

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. Note that this approach is only valid if the shape parameter  $\beta$  of the NHPP power law is equal to or close to 1. For power law processes showing stronger deteriorating or improving behaviour (i.e. with  $\beta$  being substantially larger or smaller than 1), a time-dependent demand rate should be determined.

### Step 3 – capacity identification

To identify capacity, a single item, single location base stock policy ( $s, s-1$ ) inventory model is adopted (Zipkin, 2000). In essence, this model determines the optimal base stock inventory level  $s$  on the basis of stochastic demand input, as well as considerations with respect to inventory and backorder costs. The primary assumptions of the single item, single location base stock policy are that demand is stochastic in nature, leadtime is constant, orders are placed one-by-one (in other words, a single demand occurrence gives rise to an immediate order of size 1). The base stock policy aims to keep the inventory at a specific level – the base stock, denoted by  $s$ .

The input to the capacity identification model proposed in this research are (1) the demand rate  $\lambda$  (or  $\lambda(t)$ , depending on the demand characteristics) and (2) capacity cost factors related to maintenance slot cost as well as maintenance delay cost. In terms of the capacity identification, a translation has to be made from inventory model parameters to maintenance capacity parameters. The analogy is simple: instead of having available stock to meet demand, there is available slot capacity to meet repair demand caused by accidental damages. The capacity identification model

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 maintenance checks
$\alpha$	Poisson distributed demand rate	Poisson distributed occurrence rate
$\bar{A}$	Stockout frequency: long-term rate in which demand exceeds stock	Long-term rate in which occurrences exceed capacity
$\bar{I}$	Long-term average inventory	Long-term average resolved occurrences
$\bar{B}$	Long-term average backorders	Long-term average non-resolved occurrences
$C(s)$	Cost of operating at a given base stock	Cost of maintenance at a given slot capacity

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.

The rationale for this translation is further specified below:

- *Maintenance slot capacity  $s$* : maintenance slot capacity is determined by the number of maintenance positions at one or more locations. In practical terms, this either means aircraft terminal stands (in the case of line maintenance) or aircraft hangars. Typically, especially for larger operators / MROs, hangars have multiple positions per single hangar, though this depends on the aircraft type(s) being maintained. For instance, many aircraft hangars have space for 3–4 narrow-body aircraft such as the Airbus A320 or Boeing 737 families, or 1–2 positions for wide-body aircraft such as the Boeing 777 or Airbus A330 aircraft types. In line with maintenance station classification, single locations may or may not have hangars: for instance, a maintenance base (usually the primary hub in the operator's network) may have multiple hangars, whereas class I or II stations may not have hangars available. This points to another consideration: operators may have multiple locations in their network with hangars available for maintenance purposes. For small-to-medium size carriers, this is usually restricted to a single location, which is in line with the assumptions used in this research. As a final point, the cost of a maintenance slot is denoted by a cost factor  $h$ .
- *Leadtime  $L$* : the leadtime expresses the time between consecutive maintenance opportunities. In practical terms, for accidental damage occurrences – especially ones associated with large damage sizes which require dedicated maintenance tasks for removal and installation of substructures, to be conducted in the hangar – this indicates the time between consecutive hangar maintenance opportunities. This time is determined in the maintenance schedule. Various factors apply to drive the generation of this schedule: time limits on individual or sets of maintenance tasks associated with particular aircraft, available slots, fleet utilisation and network considerations, as well as resource constraints such as manpower. If there is no opportunity at a particular maintenance opportunity to rectify an accidental damage (for instance due to the fact that the available time has already been fully planned for), the rectification task will have to wait for the next opportunity: this can occur when occupation of the current maintenance slot has ended, or when a maintenance slot at a different position is freed up. In this research, leadtime is measured in flight cycles (FC), though other time-based metrics could also be adopted.
- *Poisson-distributed occurrence rate  $\alpha$* : the occurrence rate  $\alpha$  is an output of the demand generation process as explained in the Method section.
- *Long-term rate in which occurrences exceed capacity  $\bar{A}$* :  $\bar{A}$  denotes the long-term rate in which accidental damage occurrences (or in other words, demand for maintenance slots) exceed the available capacity. It is a measure of the percentage of time in which the system is unavailable to meet demand, which incurs penalty costs associated with maintenance delay, using a penalty cost factor  $b$ .
- *Long-term average resolved occurrences  $\bar{I}$* : this metric indicates how successful the system is in resolving occurrences for a stated maintenance slot capacity  $s$ .

- *Long-term average non-resolved (delayed) occurrences  $\bar{B}$* : this metric is complementary to the long-term average for resolved occurrences, describing the average number of delayed maintenance occurrences. Together with the long-term rate  $\bar{A}$ , this metric gives an indication of the backlog of the system, which is penalised by a maintenance cost factor as mentioned before.
- *Cost of maintenance at a given slot capacity  $C(s)$* : the slot capacity  $s$  is the variable of interest. A trade-off can be observed between the value of  $s$  and the associated cost for operating  $s$  maintenance slots versus the cost of maintenance delays when  $s$  is insufficiently large to meet demand.

## Results

To test the proposed approach, a case study has been conducted. The case study background and setup are first described in more detail, followed by results and sensitivity analysis.

### 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. The database covers 10+ years of operational use. Following data extraction, the case study has been scoped towards two types of secondary aircraft structures, being the outboard flaps and leading edge slats. The flaps and slats are 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.

### 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 have been established. All estimates are significant at the 95% confidence level, as established by application of the Cramer–von-Mises test.

Table 2. Case study – reliability model input data.

Parameter	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

Table 3. NHPP power law process – parameter estimates.

Symbol	Outboard flaps		Leading edge slats	
	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

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. It can also be noticed that the values of the scale parameter are quite low in absolute terms, which denotes that the occurrence of accidental damage is relatively rare. This is in line with observations from the raw data comprising this case study.

The resulting superimposed intensity functions can be visualised 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 a time-independent demand rate  $\alpha$ , the results of which are given in Table 4.

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  $\bar{A}$ ,  $\bar{B}$  and  $\bar{I}$ : the long-term rate in which demand outstrips capacity, and the average number of delayed repairs and fulfilled repairs respectively. These parameters 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 minimisation of the cost function ( $S$ ); (2) by fixing an adequate service level through  $\bar{A}$ .

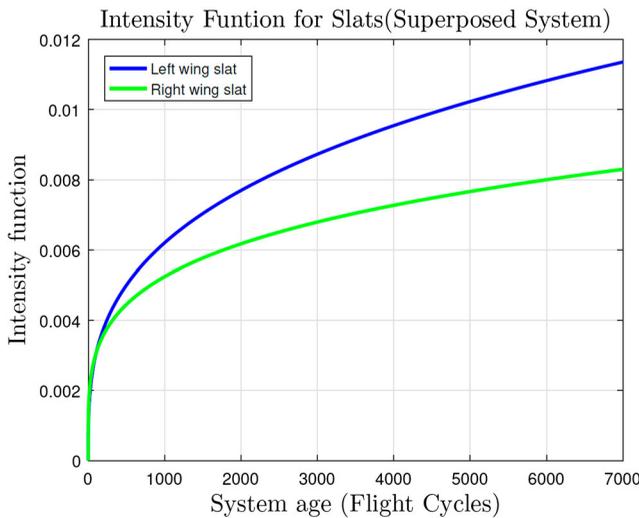


Figure 3. Intensity function plots for slats.

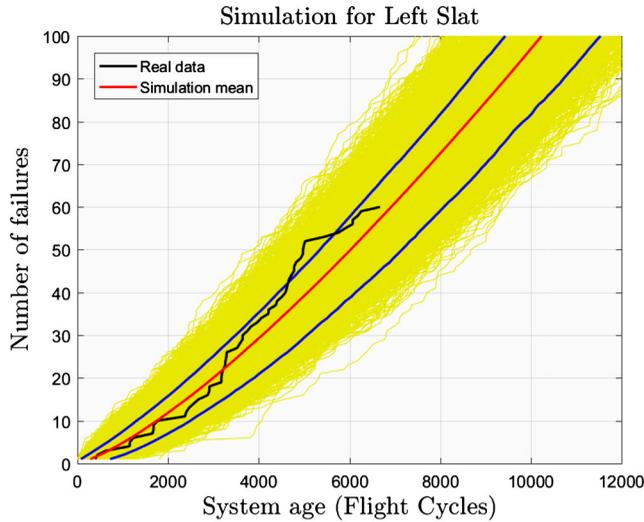


Figure 4. Monte Carlo simulation output – left slat.

Figure 5 shows output when the first approach is applied, using a cost ratio between delay penalty  $b$  and slot cost  $h$  of 1,5 together with a leadtime value of 50 flight cycles. These values have been chosen to represent the model behaviour under close-to-realistic conditions, as the exact cost and schedule figures were confidential and consequently not available from the operator. As mentioned previously, the leadtime of 50FC reflects the period between two consecutive maintenance opportunities.

Figure 5 shows that  $C(s)$  is a convex function in  $s$ . A cost minimum can be observed at  $s = 1$ , indicating that a single slot is most cost-effective for long-term planning under the current input conditions. However, this does imply that an operator should be tolerant to delays in repairs. This can be true for a number of conditions, e.g. when non-safety critical parts are affected, or when repairs are allowed to be temporary in nature for a specific time period until the damage has to be repaired in a more permanent fashion (V. S. Viswanath Dhanisetty, Verhagen, & Curran, 2018).

Given that the leadtime relates to a period of 50 flight cycles, one can extrapolate that 30 slots have to be available over a period of 1500 flight cycles to address incidental damage occurrences, at a cost minimum. Note that this only describes required capacity for incidental damages to the slats – the incorporation of multiple aircraft structures will drive up this number. On the other hand, in real life, a single maintenance slot can be used to accommodate a large variety of tasks, so while the

Table 4. NHPP power law process – parameter estimates.

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

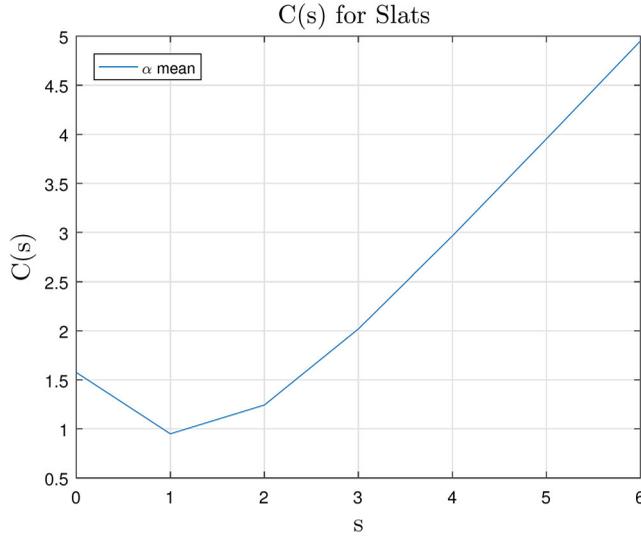


Figure 5. Cost function for slats.

extrapolation given above gives an indication of the problem size, it is not necessarily reflective of real-life implications.

In addition to the results visualised in Figure 5, Table 5 shows the performance measure values for different levels of maintenance slot capacity. It is clear that additional capacity leads to higher fulfilment of demand, but at a significantly higher cost.

Table 5 also provides insight into results for the second approach mentioned previously: fixing a service level through  $\bar{A}$ . For instance, with 3 maintenance slots, a service level of 0.91 can be achieved. As maintenance slots are integer values, maintaining specific service levels (e.g. the industry standard of 0.95) can be achieved by rounding up to the nearest integer, or by incorporating real-life planning implications as mentioned above.

### Sensitivity analysis

To investigate the model behaviour in more detail, various parameters have been varied as part of sensitivity analysis. Figure 6 shows variation of cost when the

Table 5. Performance measures for different levels of  $s$ .

$s$	$\bar{A}$	$\bar{B}$	$\bar{I}$	$C(s)$
0	1.00	1.050	0.00	1.575
1	0.65	0.400	0.35	0.950
2	0.28	0.117	1.067	1.243
3	0.09	0.028	1.978	2.019
4	0.02	0.005	2.955	2.963
5	0.00	0.001	3.951	3.952
6	0.00	0.000	4.950	4.950

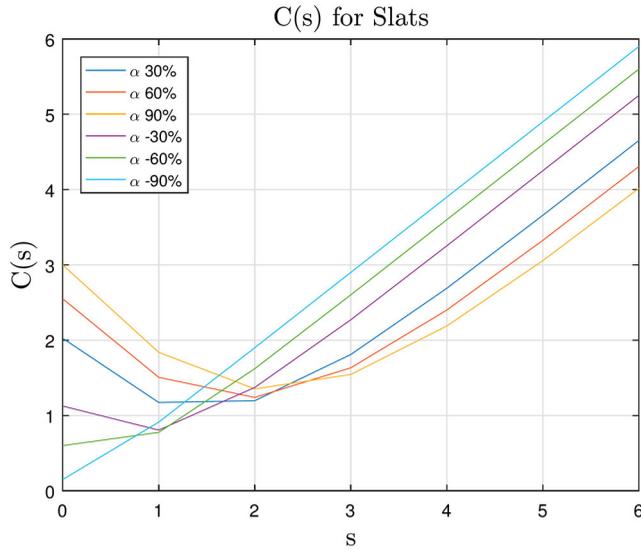


Figure 6. Cost variation with changing demand.

demand is varied from the current rate  $\pm 90\%$ , with step size 30%, showcasing the sensitivity of the cost optimum to changes in demand rate. It can be noted that at extremely low occurrence rates (i.e. demand  $\alpha$  being reduced by 90% and 60% respectively), the cost function is not convex anymore. For these number, the expected demand and the associated costs are almost negligible in comparison to the cost implications of operating one or more maintenance slots. For higher demand rates, the implication of maintenance delay costs drives the optimal slot capacity to a progressively higher value.

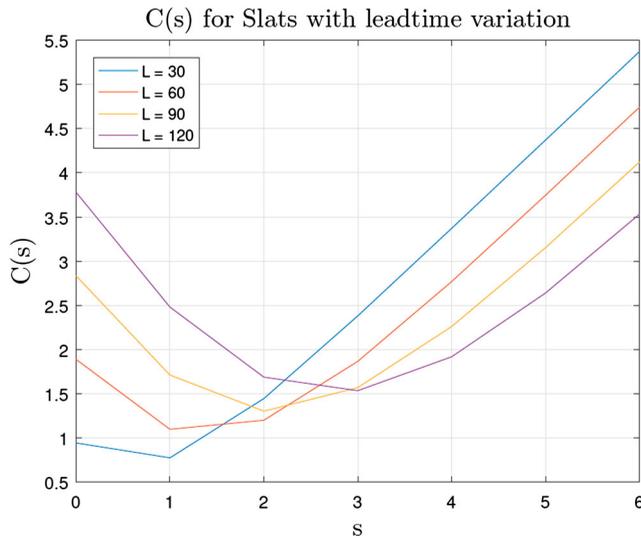


Figure 7. Cost variation with changing leadtime.

Figure 7 shows cost variation when leadtime (i.e. the time between consecutive maintenance opportunities) is varied between 30–120 flight cycles. Clearly, larger periods of time between available opportunities results in higher requirements on the amount of required maintenance slots (as expressed by  $s$ ), but also in higher absolute cost. Both findings are in line with expectations on model behaviour.

### Conclusions and recommendations

This research has presented an adaptation of an inventory control model, specifically the base-stock policy model, towards identifying strategic maintenance capacity for stochastic demand. The base-stock model has been used to identify the capacity required to carry out future unscheduled maintenance to accommodate accidental damage occurrences. The proposed approach has been successfully applied to real-life damage occurrence data, verifying the feasibility of the approach and opening various options with respect to strategic capacity identification and planning. Results show that long-term, strategic maintenance capacity can be optimised relative to cost or determined relative to service level. Sensitivity analysis has been applied to show model behaviour under various conditions.

In future work, several assumptions can be relaxed. For instance, a constant lead-time has been applied to model repair opportunities, which is not necessarily reflective of real-life processes. Follow-up research should focus on the variation in the maintenance schedule, both planned and unplanned (e.g. due to delays in maintenance execution). 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. Next to this, the case study considered in this research does not focus on the addition of maintenance capacity requirements when considering multiple systems and/or components. Finally, a time-varying demand rate may be used to more accurately reflect reliability behaviour for (strongly) improving or deteriorating systems.

### Disclosure statement

No potential conflict of interest was reported by the authors.

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