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Ordering decision-making methods on spare parts for a new aircraft fleet based on a two-sample prediction

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ABSTRACT

Ordering decision-making on spare parts is crucial in maximizing aircraft utilization and minimizing total operating cost. Extensive researches on spare parts inventory management and optimal allocation could be found based on the amount of historical operation data or condition-monitoring data. However, it is challengeable to make an ordering decision on spare parts under the case of establishment of a fleet by introducing new aircraft with little historical data. In this paper, spare parts supporting policy and ordering decision-making policy for new aircraft fleet are analyzed firstly. Then two-sample predictions for a Weibull distribution and a Weibull process are incorporated into forecast of the first failure time and failure number during certain time period using Bayesian and classical method respectively, according to which the ordering time and ordering quantity for spare parts are identified. Finally, a case study is presented to illustrate the methods of identifying the ordering time and ordering number of engine-driven pumps through forecasting the failure time and failure number, followed by a discussion on the impact of various fleet sizes on prediction results. This method has the potential to decide the ordering time and quantity of spare parts when a new aircraft fleet is established.

1. Introduction

Spare parts inventory of civil aircraft typically accounts for more than 10% of operating cost [1]. An excess of spare parts inventory leads to a high holding cost and impedes cash flows, whereas inadequate spare parts result in costly flight delays or cancellations, causing a negative impact on airline performance. Therefore, appropriate spare parts storage is crucial in maximizing the utilization of aircraft fleet, and minimizing total operating cost. Comprehensive researches on spare parts inventory management and optimal allocation aiming at balancing the material cost and utilization can be found in many literatures, while most of them are based on the amount of historical operational data or condition-monitoring data [2]. When a fleet is established by introducing a number of new developed aircraft, there is little field data or maintenance record. It is challengeable to propose an ordering decision-making method to secure the spare parts management performance under this special situation. This study is motivated to address this problem.

Product life cycle was discerned into initial phase, maturity phase, and end-of-life phase by Dekker [3], and spare parts demand in the end-of-life phase was estimated after the cease of production. In terms of passenger aircraft, its life cycle can also be similarly divided into three phases, which embrace different spare parts supporting polices. In the initial phase, a recommended spare parts list is provided by Original Equipment Manufacturers (OEMs) before aircraft's delivery under the airworthiness and airlines requirements. Because of high reliability and long life of aviation products, certain number of Line Replaceable Units (LRUs) would not fail in a relatively short time after new aircraft entry-into-service, hence, there is no need to store this kind of spare parts at the beginning of new aircraft operation in order to save cost [4]. Airlines expect that an appropriate number of spare parts are well prepared just before failure appears. Thus, the prediction of ordering time and quantity should be proposed to both airlines and OEMs. A theoretical solution named two-sample prediction for lifetime and failure number comes up to address the above problem when a new aircraft fleet is established.

Two-sample prediction can be traced back to Mann and Saunders [5] with the definition: Suppose we have observations $t_{(1)}, t_{(2)}, \cdots, t_{(r)}$ $(r<n)$ as the results of lifetime testing conducted on the items, also, there are m items of the same kind to be put into future use, with lifetimes $x_{(1)}, x_{(2)}, \cdots, x_{(m)}$. We want to

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Nomenclature

Notations

n_{CS}, n_{HS} Size of current sample and historical sample
r_{CS}, r_{HS} Failure number of current sample and historical sample
$t_{CS(g)}$, $\tau_{CS(h)}$ Complete and censored lifetime of current sample, $g=1, 2, \ldots, r_{CS}$, $h=1, 2, \ldots, n_{CS}-r_{CS}$
$t_{HS(g)}$, $\tau_{HS(h)}$ Complete and censored lifetime of historical sample, $g=1, 2, \ldots, r_{CS}$, $h=1, 2, \ldots, n_{CS}-r_{CS}$
m Future sample size
$t_{FS(j)}$ The jth complete lifetime observation of future sample, $j=1, 2, \ldots, m$
$t_{j,1}$ The first failure time of the jth LRU in future sample, $j=1,\ldots,m$
t_{LD} Lead time in calendar time
t_{UR} Aircraft utilization rate
t_{OR} Ordering time
$t_{FS(1),L}$, $t_{FS(1),L,C}$,$t_{FS(1),L,B}$ Lower confidence bound of the first failure time $t_{FS(1)}$ and its classical and Bayesian estimate
γ Confidence level
$f(t)$ Probability Density Function (PDF) of Weibull distribution
β, η, $\hat{\beta}$, $\hat{\eta}$ Scale parameter and shape parameter of Weibull distribution, and their Maximum Likelihood Estimate (MLE)
$F(t)$, $R(t)$ Cumulative distribution function (CDF) and reliability function (RF)
$[t_{PL1}, t_{PL2}]$ Planned period
$\{N(t), t>0\}$ Power intensity function
$\lambda(t)$ Power intensity function
ξ, α Shape parameter and scale parameter of a Weibull process
$P[N(t)=k]$ Probability that k failures occurring in the time interval $(0,t]$
k Failure number, $k=1,2,\ldots.$
$E[N(t)] = (t/\alpha)^{\xi}$ Mean function of $\{N(t), t>0\}$
$f_m(t_{FS(j)}|\beta, \eta)$, $f_m(t_{FS(1)}|\beta, \eta)$ Conditional PDF for $t_{FS(j)}$ and $t_{FS(1)}$
$\hat{t}_{FS(j),C}$, $\hat{t}_{FS(1),C}$ Classical predictor of failure time $t_{FS(j)}$ and $t_{FS(1)}$
y Random variable $y = t^{\hat{\beta}}$
$f(y|\lambda)$ PDF of y
λ Distribution parameter, $\lambda = 1/\eta^{\hat{\beta}}$
$\pi_0(\lambda)$ Gamma prior distribution for λ
(n_0, τ_0) Parameters of the Gamma distribution
$L(\lambda|Data)$ Likelihood function
$\pi(\lambda|Data)$ Posterior PDF of random variable λ
$f_m(t_{FS(j)}|\lambda)$ Conditional PDF of the jth failure time $t_{FS(j)}$
$f_m(t_{FS(j)})$, $f_m(t_{FS(1)})$ PDF for $t_{FS(j)}$ and $t_{FS(1)}$
$\hat{t}_{FS(j),B}$, $\hat{t}_{FS(1),B}$ Bayesian predictor of $t_{FS(j)}$ and $t_{FS(1)}$
$E[N(t_{PL1}, t_{PL2})]$ Failure number of the LRUs occurring in the time interval $[t_{PL1}, t_{PL2}]$
k_U The upper limit for $N(t_{PL1}, t_{PL2})$
$P\{N(t_{PL1}, t_{PL2}) = k|\xi, \alpha\}$ Probability that k failures occurring in the time interval $(t_{PL1}, t_{PL2}]$
$P\{N(t_{PL1}, t_{PL2}) \le k_U|\xi, \alpha\}$ Probability that no more than k_U failures occurring in the time interval $(t_{PL1}, t_{PL2}]$
α_B Bayesian estimate of α

predict the jth lifetime $x_{(j)}$ $(1 \le j \le m)$ among the new items. From the OEMs' point of view, the LRUs' first failure is of basic interest, which can be used for decision-making for a new aircraft fleet. This study is motivated to create a simplified prediction model to forecast the lifetime and failure number, which can be applied to determine spare parts ordering time and ordering quantity for new aircraft.

In this model, Weibull distribution of the installed parts is introduced. Considering certain number of LRUs are newly developed for a new type of aircraft, reliability testing is the main source of reliability data with little operational information. A classical two-sample prediction method for lifetime and failure number is given based on reliability testing data. On the other hand, the suppliers of aircraft equipment point out that there are many LRUs inherited from existing mature products with minor modification. It is feasible to incorporate historical reliability data of similar products into spare parts prediction. Therefore, aircraft operation/maintenance records were collected from domestic airlines, and were applied to predict the materials demand for a new aircraft fleet as a kind of prior information from the Bayesian point of view.

This paper is organized as follows. A brief literature review is given in the next section. Section 3 details the modeling background and spare parts ordering policy for new aircraft. Section 4 presents failure time prediction model, classical and Bayesian prediction bounds for lifetime are given. Section 5 illustrates failure number prediction based on a Weibull process. In Section 6, identification of ordering time and number of aircraft Engine Driven Pump (EDP) are computed. Section 7 investigates the influence of the fleet size on the prediction results. Finally, a concluding mark is made in Section 8.

2. Literature review

2.1. Civil aircraft spare parts prediction models

Traditionally, spare parts are classified into four groups: rotables, repairables, expendables and consumables by Gu [6]. Different replenishment policies are planned as different spare parts categories. For instance, rotables and repairables are mainly based on predicted failures estimated by manufacturers, while as to expendables and consumables, the reorder point system is used to control and manage inventory, which is insufficient because it is subjective and imprecise according to a survey conducted by Ghobbar and Friend [7]. Considering the feature of intermittent, aircraft spare parts demand was classified into four categories [8], including slow moving demand, strictly intermittent demand, erratic demand, and lumpy demand, which complicates the challenge of inventory management as balancing of component inventories with their holding costs. In addition, Godoy [9] focused on condition managed critical spares (CMS) which were expensive, highly reliable, with higher lead times, not available in store, and were under condition monitoring. The spare parts investigated in this paper are similar to CMS, but condition monitoring is not necessary.

Many studies about spare parts inventory has been completed considering initial phase, maturity phase, and end-of-life phase of product life cycle. Behfard [10] investigated the final order aiming at the situation when the spare parts has ceased at the end-of-life phase, and developed a heuristic method to find the near-optimal last time buy (LTB) quantity in presence of an imperfect repair option of the failed parts that can be returned from the field. Li [11] provided a methodology for corporations purchasing spare