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Auxiliary power unit failure prediction using quantified generalized renewal process

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ABSTRACT

Auxiliary Power Unit (APU) is an essential component utilized in modern civil aircraft. In order to meet APU availability requirements, failure prediction should be performed in an effective way. To this end, APU performance deterioration can be modeled by a Generalized Renewal Process (GRP). In this paper, aircraft APU failure prediction is implemented using a Weibull-based GRP (WGRP). However, the effect of maintenance activities on aircraft APU required in WGRP is difficult to be quantified. To solve this problem, a new model named Quantified Generalized Renewal Process (QGRP) is developed in this paper. In this model, APU performance-related test parameters after repairs are utilized to quantify the maintenance effect. Based on the proposed QGRP model, the conditional failure rate and hazard rate of each aircraft APU at a future point in time can be calculated based on the APU's virtual age and be combined to predict the number of failures of a fleet of APUs. The performance of the proposed QGRP model is validated using a three-year data set provided by China Southern Airlines. The results show that the QGRP model is effective in aircraft APU failure prediction.

1. Introduction

An Auxiliary Power Unit (APU) is a small gas turbine engine used for producing pneumatic and electrical power rather than for propulsion purposes [1]. Many engineering systems use APUs, such as aircraft, ships, and large ground vehicles. APU is indeed an essential part of today's civil aircraft, which enables an aircraft free from ground power supplies. Another important APU function is to provide the power for main engine starts [2]. Furthermore, for some aircrafts, APU can also provide compressed air and backup electric power to compensate for the effect of dead engines. As a result, high reliability of APU is critical for aircraft operation and safety.

Maintenance is one of the most important means keeping APU reliable and ensuring aircraft safety. When performed effectively, it restores system performance, reduces the failure frequency and prolongs the system's remaining life [3]. In commercial aviation, maintenance strategies mainly include three categories: corrective maintenance, preventive maintenance and condition-based maintenance (CBM) [4]. Corrective maintenance is a basic maintenance strategy. Under corrective maintenance, target equipment is repaired only when a failure occurs. It is uneconomic and unsuitable for aircraft because such failures may lead to some catastrophic consequences. Under preventive maintenance, maintenance operations are often carried out periodically. However, to ensure the reliability of target equipment, maintenance intervals are usually made shorter than required. In other words, the actual health status of the target equipment is ignored and many maintenance actions are indeed unnecessary. In addition, unexpected failures between two maintenance actions may also lead to catastrophic consequences. Unlike the two time-based maintenance strategies, CBM is relatively new. Under CBM, the time when the target equipment should be repaired can be determined using condition monitoring data and failure prognostic models. If CBM is properly realized, unnecessary maintenance operations can be avoided, and maintenance cost can be significantly reduced. Meanwhile, catastrophic consequences can be reduced. Apparently, CBM is a suitable maintenance strategy for aircraft APU as it will remain the aircraft APU

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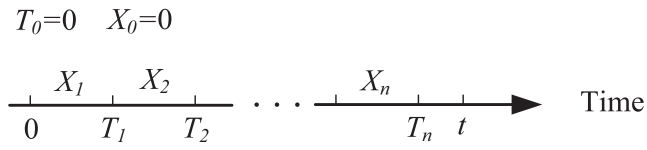

Fig. 1. Schematic diagram of the relationship between X and T.

performance at a high level. One of the challenges for APU CBM is to predict health status of an APU in the future or its time-to-failure (TTF).

Effective failure prediction can provide an alarm before a failure occurs, so that significant system deterioration, malfunction, or even catastrophic failures can be prevented [5]. In [6], the goal is to improve the accuracy of APU TTF prediction. Several machine learning algorithms, including knowledge discovery in databases (KDD) and support vector machine (SVM), are used. Other machine learning-based methods are also utilized to predict TTF or remaining useful life (RUL) [2,7–11]. In [12], APU fault isolation is performed based on FMEA and data mining algorithms. In [13,14], statistical and data analytics methods are utilized for failure prognostics and health monitoring of APU. Moreover, prediction of health status or system reliability also attracts much attention nowadays. Predicting health status and providing feedback are quite important for highly reliable products [15–17]. Wu et al. [18] use Weibull analysis to determine the failure rates of automotive components. In [19], failure prediction of printed circuit board is performed using part stress method.

Actually, equipment health status is dynamic over time. For a repairable system such as APU, its health status trend can be represented by a deterioration process. There are many available methods for modeling deterioration processes [20]. The use of hazard function is one of them [21]. Hazard function has many forms such as power law, s-shaped, log-linear function. Generally, for a degrading system, its hazard function (hazard rate) is increasing over time. However, as a typical repairable system, APU deterioration process is affected by maintenance. Therefore, maintenance effect should also be considered in APU failure prediction. Generalized Renewal Process (GRP) considering "virtual age" is a well-known method for modeling deterioration process with maintenance [22–24]. In addition to the parameters of a given probability distribution, a rejuvenation parameter q representing maintenance effect is introduced in GRP. This idea was firstly proposed in [25]. When $q = 0$ and $q = 1$, GRP model becomes Renewal Process (RP) model and Non-Homogeneous Poisson Process (NHPP) model, respectively [26–28]. When the given probability distribution is Weibull distribution, GRP is called Weibull-based GRP [29–31]. However, it is difficult to determine the value of virtual age in GPR. In order to address this problem, this paper proposes a Quantified Generalized Renewal Process (QGRP) model and uses this model for APU failure prediction. Under the QGRP model, a new virtual age function is proposed based on monitoring data in order to quantify the effect of each maintenance action. A series of experiments are presented to illustrate the superiority of the proposed QGRP model. This work contributes to the construction of APU CBM framework and can be used to support civil aviation maintenance programs. Furthermore, such QGRP models can also be applied to model other repairable systems.

The remainder of this paper is organized as follows. Section 2 introduces the basic methodology of WGRP model. Section 3 introduces the proposed QGRP model and a failure prediction framework based on QGRP model. Section 4 shows experiment data sets and failure prediction results. Section 5 concludes this paper and discusses future work.

2. Weibull-based generalized renewal process

2.1. Definition of generalized renewal process

GRP is a stochastic model that can be utilized to describe the deterioration process of a system subject to maintenance by introducing the concept of virtual age [32]. In GRP, the real time of the system is substituted by virtual age [33]. There are two types of GRP model: Kijima Model I and Kijima Model II [34]. The definition of GRP is described as follows.

Let T_i be the actual cumulative time until the i^{th} repair and X_i be the time interval between the $(i-1)^{th}$ and the i^{th} repairs as shown in Fig. 1. It can be seen that $T_i = \sum_{j=1}^{i} X_j$is the age of the system before the ith repair occurs. Generally, T_0 and X_0 are assumed to be zero. Under the GRP model, T_i and X_i can be considered as random variables, and the random vectors $T = (T_1, T_2, \cdots, T_n)$ and $X = (X_1, X_2, \cdots, X_n)$ can be considered as stochastic time series.

Let $F(t)$ and $f(t)$ be the cumulative distribution function (CDF) and probability density function (PDF) of TTF for a new system, respectively. Virtual age represented by V_i reflects the cumulative maintenance effect. Under Kijima Model I, maintenance effect on each repair is only related to the last time between repairs. There is an assumption that the damage between the $(i-1)^{th}$ and the i^{th} repair can be partially removed by the i^{th} repair. Let q be the effect of the i^{th} repair. Then, after the i^{th} repair, V_i can be calculated as:

$$V_i = V_{i-1} + qX_i \tag{1}$$

and equivalently,

$$V_i = q\sum_{j=1}^{i} X_j = qT_i \tag{2}$$

Under Kijima Model II, the effect of each repair is related to the whole history of repairs. Suppose that all historical cumulative damage of the system can be partially removed by the i^{th} repair. Virtue age V_i after the i^{th} repair can be calculated as follows:

$$V_i = q(V_{i-1} + X_i) \tag{3}$$

and equivalently,

$$V_i = q(q^{i-1}x_1 + q^{i-2}x_2 + \cdots + x_i) \tag{4}$$

Then, the CDF of X_i can be expressed as:

$$F(X_i \mid V_{i-1}) = \frac{F(X_i + V_{i-1}) - F(V_{i-1})}{1 - F(V_{i-1})} \tag{5}$$

GRP involves a concept that virtual age is related to statistical characteristics of repairs. The quality of repairs is reflected by parameter q. The drawback is that the value of q is constant and the differences between various repairs are ignored.

2.2. The methodology of WGRP

WGRP model is first presented in [31]. In WGRP model, X_i represents the time between the $(i-1)^{th}$ and the i^{th} repairs, which is assumed to follow a Weibull distribution under the condition of virtual age V_i. Let α and β be the shape and scale parameters of Weibull