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A cost driven predictive maintenance policy for structural airframe maintenance

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Abstract Airframe maintenance is traditionally performed at scheduled maintenance stops. The decision to repair a fuselage panel is based on a fixed crack size threshold, which allows to ensure the aircraft safety until the next scheduled maintenance stop. With progress in sensor technology and data processing techniques, structural health monitoring (SHM) systems are increasingly being considered in the aviation industry. SHM systems track the aircraft health state continuously, leading to the possibility of planning maintenance based on an actual state of aircraft rather than on a fixed schedule. This paper builds upon a model-based prognostics framework that the authors developed in their previous work, which couples the Extended Kalman filter (EKF) with a first-order perturbation (FOP) method. By using the information given by this prognostics method, a novel cost driven predictive maintenance (CDPM) policy is proposed, which ensures the aircraft safety while minimizing the maintenance cost. The proposed policy is formally derived based on the trade-off between probabilities of occurrence of scheduled and unscheduled maintenance. A numerical case study simulating the maintenance process of an entire fleet of aircrafts is implemented. Under the condition of assuring the same safety level, the CDPM is compared in terms of cost with two other maintenance policies: scheduled maintenance and threshold based SHM maintenance. The comparison results show CDPM could lead to significant cost savings.

1. Introduction

Fatigue damage is one of the major failure modes of airframe structures. Repeated pressurization/depressurization during take-off and landing cause many loading and unloading cycles which could lead to fatigue damage in the fuselage panels. The fuselage structure is designed to withstand small cracks, but if left unattended, the cracks will grow progressively and finally

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cause panel failure. It is important to inspect the aircraft regularly so that all cracks that have the risk of leading to panel fatigue failure should be repaired before the failure occurs.

Traditionally, the maintenance of aircraft is highly regulated through prescribing a fixed schedule. At the time of scheduled maintenance, the aircraft is sent to the maintenance hangar to undergo a series of maintenance activities including both engine and airframe maintenance. Structural airframe maintenance is a subset of airframe maintenance that focuses on detecting the cracks that can possibly threaten the safety of the aircraft. In this paper, maintenance refers to structural airframe maintenance while engine and non-structural airframe maintenance are not considered here. Structural airframe maintenance is often implemented by techniques such as non-destructive inspection (NDI), general visual inspection, detailed visual inspection (DVI), etc. Since the frequency of scheduled maintenance for commercial aircraft is designed for a low probability of failure, it is very likely that no safety threatening cracks exist during earlier life of majority of the aircraft. Even so, the intrusive inspection by NDI or DVI for all panels of all aircraft needs to be performed to guarantee the absence of critical cracks that could cause fatigue failure. Therefore, the inspection process itself is the major driver of maintenance cost.

Structural health monitoring (SHM) systems are increasingly being considered in aviation industry.[1–4] SHM employs a sensor network sealed inside the aircraft structures like fuselage, landing gears, bulkheads, etc., for monitoring the damage state of these structures. Once the health state of the structures can be monitored continuously or as frequently as needed, it is possible to plan the maintenance based on the actual or predicted information of damage state rather than on a fixed schedule. This spurs the research to predictive maintenance.

Prognostic is the prerequisite of the predictive maintenance. Prognostics methods can be generally grouped into two categories: data-driven and model-based. Data-driven approaches use information from previously collected data from the same or similar systems to identify the characteristics of the damage process and predict the future state of the current system. Data-driven prognosis is typically used in the cases where the system dynamic model is unknown or too complicated to derive. Readers can refer to[5,6] that give an overview of data-driven approaches. Model-based prognostics methods assume that a dynamic model describing the behavior of the degradation process is available. For the problem discussed at hand, a model-based prognostics method is adopted since the fatigue damage models for metals have been well researched and are routinely used in the aviation industry for planning the structural maintenance.[7–9]

Predictive maintenance policies that aim to plan the maintenance activities taking into account the predicted information, or the "prognostics index" were proposed recently and attracted researcher's attention in different domains.[10–14] The most common prognostics index is remaining useful life (RUL).[15–18] A large amount of methods on RUL estimation have been proposed such as filter methods (e.g., Bayesian filter,[19] particle filter,[20,21] stochastic filter,[22,23] Kalman filter[24,25]), and machine learning methods (e.g., classification methods,[26,27] support vector regression[28]). In addition to the numerical solutions for RUL prediction, Si et al.[29,30] derived the analytical form of RUL probability density function. Some of the predictive maintenance policies adopting the RUL as a prognostics index to dynamically update the maintenance time can be found in Refs. 12, 14, 31.

In some situations, especially when a fault or failure is catastrophic, inspection and maintenance are implemented regularly to avoid such failures by replacing or repairing the components that are in danger. In these cases, it would be more desirable to predict the probability that a component operates normally before some future time (e.g. next maintenance interval).[32] Take the structural airframe maintenance as an example, the maintenance schedule is recommended by the manufacture in concertation with safety authorities. Arbitrarily triggering maintenance purely based on RUL prediction without considering the maintenance schedule might be disruptive to the traditional scheduled maintenance procedures due to less notification in advance. In addition, planning the structural airframe maintenance as much as possible at the scheduled maintenance stop when the engine and non-structural airframe maintenance are performed could lead to cost saving. To this end, instead of predicting the remaining useful life of fuselage panels, we consider the evolution of damage size distribution for a given time interval, before some future time (e.g. next maintenance interval). In other words, we adopt the "future system reliability" as the prognostics index to support the maintenance decision making. This distinguishes our paper from the majority existing work related to predictive maintenance.

The motivation developing advance maintenance strategies is to reduce the maintenance costs while maintaining safety. Researchers proposed many cost models to facilitate the comparison of maintenance strategies.[10,12,13,33] All these cost analysis and comparison share one thing in common. The maintenance strategy is independent from unit cost (e.g., the set up cost, the corrective maintenance cost, the predictive maintenance cost, etc.) and the interaction between strategy and unit cost has not been considered, which in fact might affect the maintenance strategy in some situations. For example, in aircraft maintenance, it is beneficial to plan the structural airframe maintenance as much as possible at the same time of scheduled maintenance and only trigger unscheduled maintenance when needed. If the cost of unscheduled maintenance is much higher than the scheduled maintenance, the decision maker might prefer to repair as many panels as possible at scheduled maintenance to avoid unscheduled maintenance. That is to say the cost ratio of different maintenance modes could be a factor that affects the maintenance decision-making. In this paper, we take a step further from the existing work to take into account the effect of cost of different maintenance modes on the maintenance strategy, i.e., the cost ratio is taken as an input of maintenance the strategy and partially affects the decision-making. This is our motivation of developing the cost driven predictive maintenance (CDPM) policy for aircraft fuselage panel. By incorporating the information of predicted damage size distribution and the cost ratio between maintenance modes, an optimal panel repair policy is proposed, which selects at each scheduled maintenance stop a group of aircraft panels that should be repaired while fulfilling the mandatory safety requirement.

As for the process of prognosis, we consider four uncertainty sources. The item-to-item uncertainty accounts for the variability among the population, which is considered by using one degradation model to capture the common degradation characteristics in the population, with several model parameters