# A Preliminary Study for Aircraft Engine Health Management based on Multi-Scale Kalman Filters

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## ABSTRACT

Aircraft engine is directly associated with flight safety. Its unpredicted failures lead to catastrophic accident and down-time. To prevent these problems, prediction of the accurate remaining useful life of engine is essential. With the rapid development of sensor technology, engine health condition can be monitored with multiple sensors. Therefore, it is important to develop suitable methodologies of integrating various data to improve the accuracy of remaining useful life. This paper attempts to establish fusion methods after examining the existing model based and data driven methods used for the remaining useful life estimation of gas turbine engine. The developed methods are evaluated using the simulated data set C-MAPSS, which includes the parameters associated with degradation in the fan, compressor and turbine during a series of flights.

## 1. INTRODUCTION

Aircraft engine system is highly complex integrated system and its condition degradation is directly related with flight safety and operational cost. In order to address these issues, engine health management (EHM) system has been developed over the past decades in the aircraft industry. Several review literatures are available, e.g., in Tumer (1999), Jaw (2005) and Volponi (2005). The EHM deals with the monitoring, detection, isolation, predictive trending and accommodation of engine degradation and failures. The key drivers in the implementation of the EHM are the total cost minimization, increased asset availability, and mission readiness while maintaining or increasing safety margin.

In general, there have been four functional areas in the advancement of the EHM: oil and debris monitoring, vibration monitoring, usage and life monitoring and gas path analysis and performance trending. In order to make the most "educated" decision, monitoring or information fusion from more than one functional areas are studied. In view of algorithm, the EHM consists of two subsystems: on-board or embedded and off-board or ground-based subsystem. The on-board system collects data, performs built-in-test(BITs) and in-flight monitoring functions, such as detection, assessment, prediction and recommendation/alert. The off-board system uses the in-flight data and reports transferred to the ground for further analysis and decision-making. The overall picture is illustrated in Figure 1 (Kobayashi, 2007).

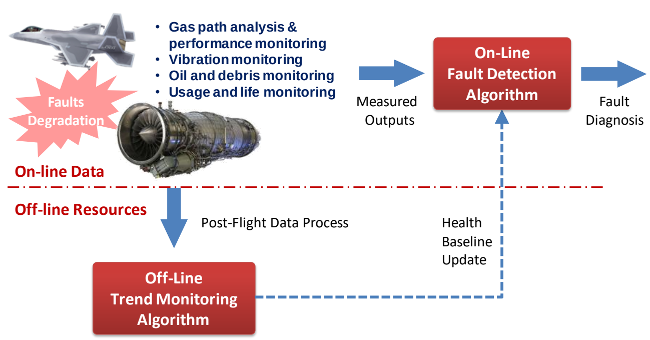



Figure 1. Engine health management system architecture

## 2. CHALLENGES

Although aircraft engines are highly reliable, they encounter many unexpected faults during flight including sensor faults that should be detected. Fault detection is made by monitoring the deviation from reference values of sensor data. This is however challenging since the shifts are made not only by faults but also by degradation. Engine degradation over long period is the result of usage which is not considered as fault. Figure 2 shows the gradual deviation of the engine output from the reference due to the health degradation. The discrete jump from point "a" to "b" indicates fault occurrence. Thus, the total shift $\Delta_k + \delta\Delta$ is observed through a sensor. An on-line diagnostic algorithm, in general, has to process this total shift in order to detect the fault. If the algorithm does not have the capability to handle this shift in the analysis, it may either miss the fault or generate a false alarm, which will eventually lose its diagnostic effectiveness.

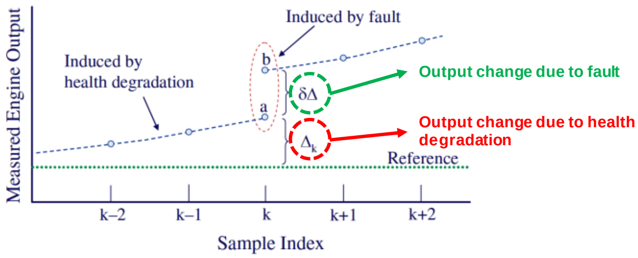
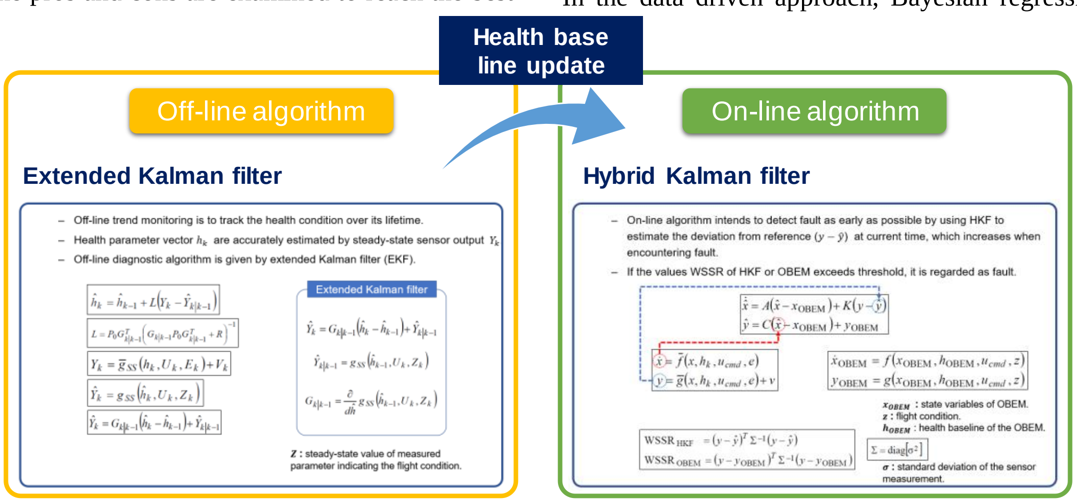



Figure 2. Influence of health degradation and faults

## 3. EXISTING APPROACHES

In order to address the problem above, there have been three prognostic approaches: data-driven, model-based and fusion or hybrid approaches. A data-driven approach requires a large amount of historical data for training and lacks generality, while a model based approach takes advantage of merits of both physical knowledge and historical data information (Wang, 2014). However, as the aircraft engine system is complicated, establishing accurate physical model is still challenging, which makes this approach less effective. To overcome these limitations, recent effort is given to the fusion methodologies that have ability to integrate or fuse the various algorithms, achieving the efficient and accurate prognosis. In this study, representative algorithms are chosen and studied from the three approaches. They are applied respectively to the simulated data set (Saxena, 2008) made by C-MAPSS (Frederick, 2007) to predict the RUL, which includes the parameters associated with degradation in the fan, compressor and turbine during a series of flights. From the results, the pros and cons are examined to reach the best solution or develop another new improved approach.

Figure 3 Integrated framework of Kalman filter for EHM




In the model based approach, there have been two major algorithms: Kalman filter and Particle filter. In the former approach, (Kobayashi, 2007) has developed integrated Kalman filter framework to accommodate both the off-line for trend monitoring and on-line for fault detection, in which the on-line is based on the hybrid Kalman filter, and the off-line is based on the extended Kalman filter. A schematic framework is given in Figure 3. Due to the stochastic and nonlinear nature of the engine system performance degradation, a new study was made with Regularized Particle Filtering (RPF) by (Wang, 2014), which can overcome the sample impoverishment problem and track the transient changes in the system state and parameters due to faults. An example result is given in Figure 4.

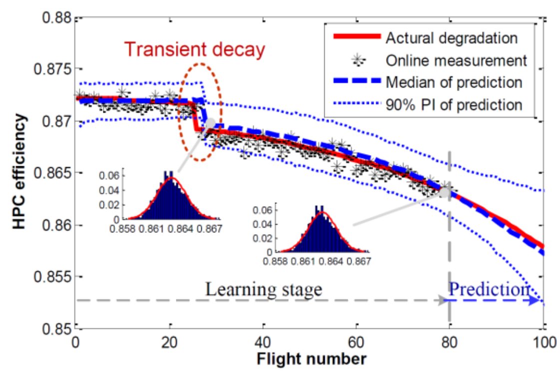



Figure 4. Predicted HPC efficiency with external fault

In the data driven approach, Bayesian regression (Zaidan, 2013) and artificial neural network (Macmann, 2016) are the most representative algorithms. The Bayesian regression combines the two sources of information: historical in service data from the engine fleet population and once-per flight transmitted performance measurements. Using this data, the Bayesian technique presents predictive results within well defined uncertainty bounds. The neural network employes self-organized map algorithm to classify data, which are added as an additional input for a neural network designed to predict remaining usable life. In the fusion approach, the study made by (Xu, 2014) is reviewed, in which the Dempster-Shafer regression (DSR), support vector machines (SVM) and recurrent neural network (RNN) are used individually to predict the remaining useful life of an aircraft gas turbine engine. Then, a new concept called Comentropy-based fusion prognostic model is employed to integrate the three methods in a manner that can take the strengths of each method while overcoming their respective limitations.

Based on the close review and study of the representative algorithms and fusion approaches, they are coded and implemented in practice for the simulated data set C-MAPSS as given in (Saxena, 2008) which deals with the aircraft engine fault occurrence and degradation. This will be addressed in the conference presentation.

## 4. CONCLUSIONS AND FUTURE STUDY

This paper aims to review the current state of the art of the algorithms for the aircraft engine health management. Several algorithms including the model based and data driven approaches are chosen to examine among the many described in the literature. They are applied and implemented for the simulation data set C-MAPSS, from which the pros and cons are evaluated to reach the best solution or develop another new improved approach.

## ACKNOWLEDGEMENT

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