

System Level RUL Estimation for Multiple-Component Systems

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ABSTRACT

Aircraft are highly valuable assets and large budgets are spent in predictive maintenance programs in order to maximize fleet availability. The application of PHM (Prognostics and Health Monitoring) technologies can be a powerful decision support tool to help maintenance planners. The estimated RUL (Remaining Useful Life) for each monitored component, obtained from a PHM system, can be used to plan in advance for the repair of components before a failure occurs. However, when system architecture is not taken into account, the use of PHM information may lead the operator to replace a component that would not immediately affect the availability of the system under consideration. In this paper, a methodology that combines fault tree information and individual components RUL estimations into a system level RUL (S-RUL) estimation is applied in a real life case study. The results showed that the methodology could have been successfully used in order to anticipate the failure of an aircraft ECS (Environmental Control System) and prevent an AOG (Aircraft on Ground) event from happening.

1. INTRODUCTION

PHM has been recognized by the members of the aeronautical sector such as aircraft operators, MRO (Maintenance, Repair and Overhaul) service providers and aircraft manufacturers as a technology that may lead to important competitive advantages such as reduction in operational cost and increase in fleet reliability (Rodrigues & Yoneyama, 2012).

The main goal of a PHM system is to estimate the remaining useful life (RUL) and the health state of components and systems. It comprises a set of techniques

which use analysis of measurements to assess health state and predict impending failures of monitored equipments. Many works proposed PHM solutions for a high diversity of aeronautical components such as valves (Moreira & Nascimento Jr, 2012), pumps (Gomes, Leão, Vianna, Galvão & Yoneyama, 2012), engines (Babbar, Ortiz, Syrmos & Arita, 2009) and electronic components (Sandborn, 2005).

Methods for decision support using RUL estimations can be found in literature. Sandborn & Wilkinson (2007) and Rodrigues, Gomes, Bizarria, Galvão & Yoneyama (2010) presented examples of decision support methods using PHM information to improve maintenance planning. However, these works focused on the maintenance of one component, without considering that it is part of a system.

Modern aircraft are a good example of a complex system. They comprise multiple subsystems, each of them composed by multiple components. For safety analysis purposes, aircraft system architecture is often represented by a fault tree. When multiple components in a system are monitored by a PHM method, multiple RUL distributions are available for the decision maker. Although this seems to be positive, dealing with this amount of information could turn maintenance planning into a challenging task.

A possible solution for this problem is to calculate a system level RUL distribution based on the RUL distribution of each component. In this new framework, the decision maker does not have to deal with a set of component level RUL estimations. Instead, the S-RUL provides information related to the time when the whole system will stop working (i.e. when the combined failures of individual components will lead to a system failure).

In this work, a methodology to calculate the S-RUL distribution using component level RULs and system architecture information embedded in fault tree representation is applied. This methodology was proposed by Ferri et al. (2013). A case study is presented to illustrate

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the application of the methodology. In this case study, a subsystem of an aircraft ECS (Environmental Control System) is considered.

2. FAULT TREE REPRESENTATION

Fault Tree Analysis (FTA) is a failure analysis technique that, due to its ease of use and effectiveness in discovering and representing the interaction of component failures in a system, was widely adopted since the seventies in industries such as nuclear power generation, aviation and automotive (SAE, 1996).

During the FTA process, graphical diagrams called “fault trees” are produced in order to investigate what are the possible causes for a specific system failure, called the “top event”. Fault trees represent sequences of events that may lead to the undesired top event under consideration. These sequences usually start from faults originated in system components, which combine with other component faults in order to cause failures that will propagate through the system.

The basic elements of a fault tree are the top event, the intermediate events and the basic events. Intermediate events represent failures propagated through the system and can be represented as a logical combination of basic events and other intermediate events. Basic events in a fault tree usually represent component faults. It is possible to attribute a probability of occurrence to each of the basic events in a given operating scenario. If the probabilities of all the basic events are known, it is possible to calculate the probability of the top event to occur using fault tree topology. Figure 1 shows an example of a simple fault tree.

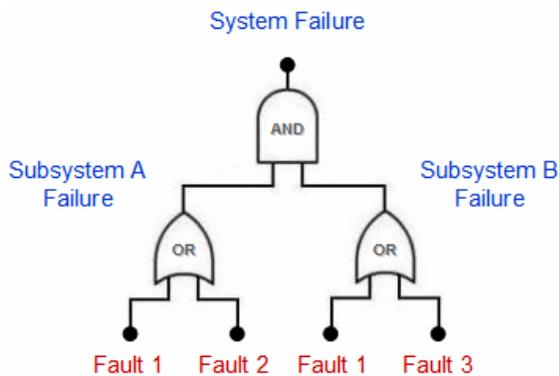


Figure 1. Fault tree example

Assuming that all basic events are independent, a convenient form of calculating the top event probability is by transforming the fault tree into its cut sets form. A cut set is a combination of basic events which, if they all occur simultaneously, will cause the occurrence of the top event.

In the cut sets form, each cut set is represented by an AND logical gate containing in its inputs all basic events forming the cut set under consideration. An OR logical gate is then used, and the output of each AND logical gate is connected to one of its inputs. Figure 2 shows the same fault tree as in Figure 1 transformed to its cut sets form representation. In this example, one cut set is composed by only one basic event (Fault 1). In such a situation, the AND logical gate can be omitted for this cut set and the basic event can be directly connected to the OR logical gate.

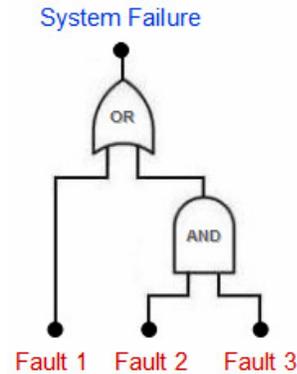


Figure 2. Fault tree in the cut sets form

Each input of the top OR gate is by itself a sufficient cause for the top event. The probability of the top event can then be obtained by calculating the union probability of all cut sets. On the other hand, if the basic events are mutually independent, the probability of each cut set can be obtained by calculating the joint probability of the basic events that compose the cut set. If all the basic events are mutually independent, the joint probability of a cut set is just the product of all its basic events.

3. SYSTEM LEVEL RUL

The System Level RUL (S-RUL) is calculated using the system architecture represented by the system fault tree and the RUL distributions for each component obtained from a PHM system. The procedure to calculate the S-RUL is summarized in Figure 3 (Ferri et al., 2013).

In step 1, the fault tree that represents the system under study is obtained. This information is commonly available for aircraft systems since fault trees are widely used in safety analysis. In step 2, system minimum cut sets representation is obtained based on the system fault tree. In step 3, the RUL estimation of each component is obtained from the PHM system. These estimations are commonly given as probability density functions. In step 4, the probability of each component to fail before instant k is calculated using the RUL predictions for each component.

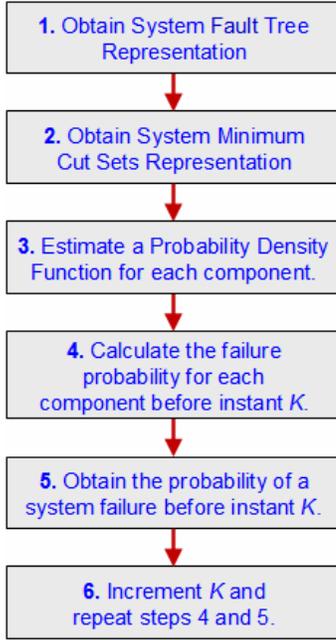


Figure 3. SRUL calculation procedure

Using the minimal cut sets representation, the probability of each cut set to occur before instant k can be calculated by Eq. (1):

$$P(c_i) = \prod_{j=1}^n P(e_j) \quad (1)$$

where $P(c_i)$ is the probability of the i -th cut set, $P(e_j)$ is the probability of the e_j basic event and n is the number of basic events in the i -th cut set. After calculating the probability of each cut set, the probability of the top event to occur before instant k can be calculated using Eq. (2):

$$P_T = 1 - \prod_{i=1}^m (1 - P(c_i)) \quad (2)$$

where P_T is the probability of the top event and m is the number of cut sets. It represents the probability of at least one cut set to occur, which is numerically equal to one minus the probability of no cut set to occur.

Steps 5 and 6 are repeated for subsequent instants. This procedure will result in a CDF (Cumulative Distribution Function) representing the probability of a system failure to occur over time.

4. CASE STUDY

The system under study is a subsystem of an environmental control system (ECS) in an aircraft. This subsystem comprises two monitored components, a pressure control valve and a temperature control valve. A schematic view is presented in Figure 4.

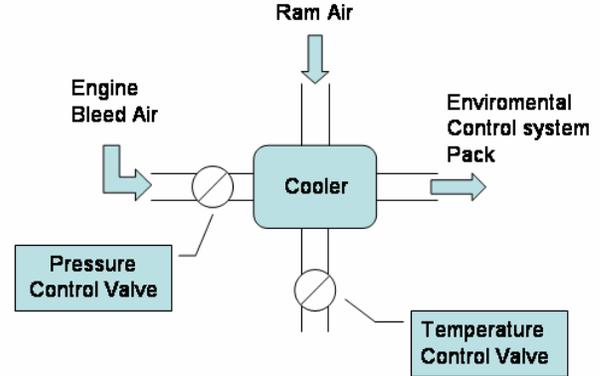


Figure 4. Aircraft environmental control system

The pressure control valve (PCV) is a pneumatic valve that regulates the engine bleed air flow so that a desired set point of pressure is reached. This air is sent to a heat exchanger and cooled until a temperature set point is achieved. The flow of ram air that passes through the cooler is controlled by the temperature control valve (TCV). This flow influences directly the heat exchanged between ram air and engine bleed air.

The aircraft used in this example has two of the subsystems presented (comprising PCV1, TCV1 and PCV2, TCV2), each of them located near one of the engines. For the correct operation of the ECS it is necessary that at least one of these subsystems is working properly and for that, both PCV and TCV need to be working.

The fault tree presented in Figure 5 is used to represent the ECS architecture.

The top event represented in the fault tree is related to the loss of the ECS. It is possible to see that this event only happens when both subsystems are defective. Each subsystem is considered defective if one of its components (PCV or TCV) is not working. The system in Figure 5 is presented in the minimal cut sets representation in Figure 6.

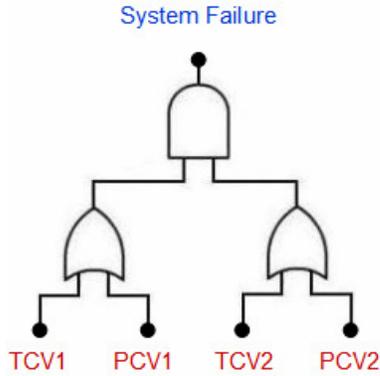


Figure 5. Environment system fault tree

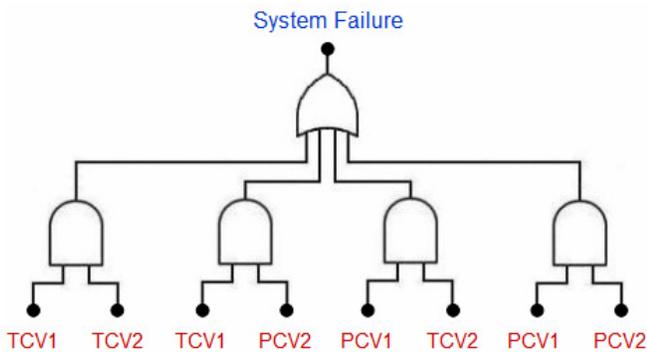


Figure 6. Minimum cut sets representation

4.1 PHM System

In the ECS system under consideration, the PCV and the TCV are the components with the highest failure rates observed on field, and this high number of failures leads to a high number of unscheduled component removals. For the purpose of reducing the number of unscheduled removals, PHM systems were developed for both the PCV and the TCV.

4.1.1. Pressure Control Valve

The pressure control valve is a pneumatic actuated valve. Its purpose is to keep the downstream pressure at a controlled set point value. The most common failure modes of this valve are related to wear of the spring or an increase in friction caused by the wear of the bearings. These failure modes affect the dynamic behavior of the valve. The performance of the pressure controller is also affected.

Field observations indicate that pressure signals exhibit variation in amplitude before a failure event. Such variations motivated the PHM methodology proposed in this work. Figure 7 shows an example of data collected from both a healthy valve and a degraded one. In Figure 7(A) a typical pressure signal for a healthy valve is shown. Figure 7(B) shows the pressure signal collected from a degraded valve just before a failure event.

The standard deviation of the pressure signal was then chosen as a degradation index (DI) for the PCV, as it can be related to a loss in regulation performance that may evolve to a failure, as described above. Figure 8 shows an example of how this degradation index changes over time. In this figure, the DI is normalized. Each cycle corresponds to one flight.

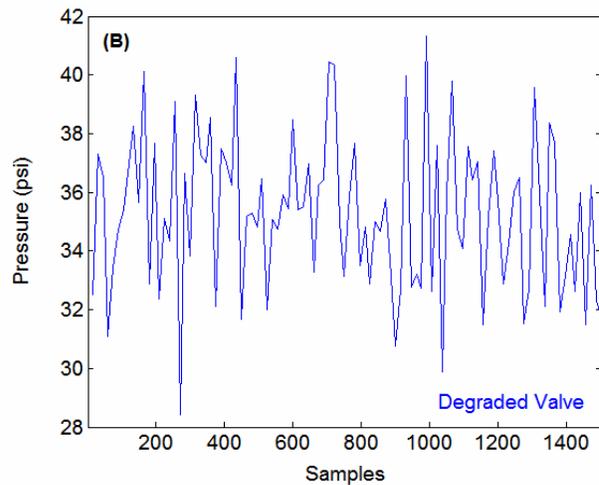
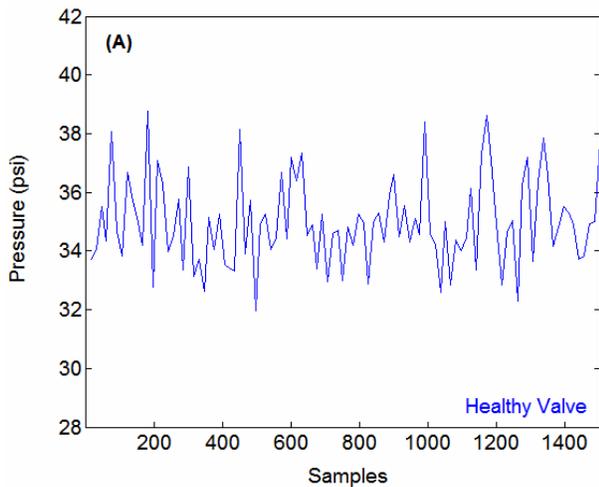


Figure 7. Pressure signals collected from a healthy and a degraded valve

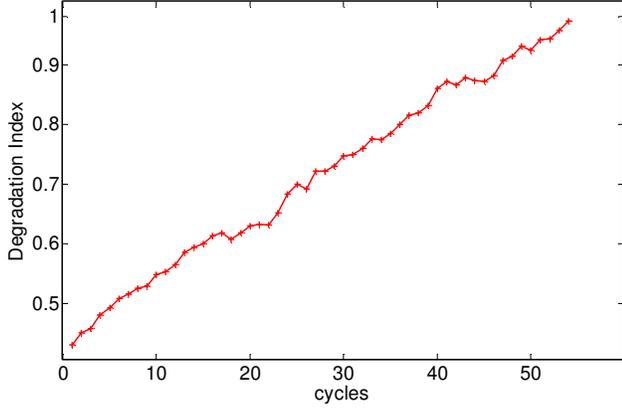


Figure 8. DI evolution for a pressure control valve

For failure prognostics implementation, a Kalman filter was employed. Concerning the dynamic model necessary for filtering and extrapolation, no first principles model was used. The state space representation of a linear degradation evolution with unknown slope was used for this purpose. This model was empirically chosen based on the aspect of the DI evolution. An example of this aspect can be observed in Figure 8. The slope and the degradation were estimated, resulting in the following model:

$$\begin{aligned} d_{k+1} &= a_k + d_k + v_k^1 \\ a_{k+1} &= a_k + v_k^2 \\ DI_k &= d_k + w_k \end{aligned} \quad (3)$$

where d is the estimated degradation, a is the slope, v^1 , v^2 and w are gaussian noises, DI is the degradation index and k is the discrete time instant. In this case, k represents aircraft cycles. State noise v^1 and observation noise w represent, respectively, the actual state and the observation noises present in the data, while v^2 is an artificial noise added for the estimation of the fixed parameter a .

In the Kalman filter, the information concerning the variance of the parameter estimates at instant k is contained in the covariance matrix P_k . Using this information, the variance $\sigma_{v_k^2}^2$ can be obtained. An adaptive noise estimation procedure was used. This procedure is described in details in Leão (2011). In this procedure, $\sigma_{v_k^2}^2$ is calculated according to Eq. (4):

$$\sigma_{v_k^2}^2 = \left(-1 + \frac{1}{\lambda} \right) P_k \quad (4)$$

where λ is a fixed positive value in the range [0.5 1).

Using the d and a distributions estimated at a given instant and the model presented in Eq. (3), Monte Carlo simulations were performed until d reaches a failure threshold. Failure thresholds were chosen according to the concept of Hazard Zone (HZ) (Orchard & Vachtsevanos, 2009).

The HZ defines a region, modeled by a bounded distribution, with high probability of failure occurrence. In this work, failure thresholds were sampled according to the chosen HZ distribution. The HZ was defined as a normal distribution with mean of 0.975 and standard deviation of 0.008. The HZ was defined using a set of run-to-failure DI series.

4.1.2. Temperature Control Valve

The temperature control valve is a pneumatic valve designed to control the air flow that passes through the cooler in order to control the temperature of the air sent to the ECS pack.

TCV failure reports showed that cabin temperature often presented variations few days before an event of failure. In an attempt to capture this behavior, the temperature standard deviation was chose as a DI. Figure 9 shows an example of the DI proposed. Each cycle corresponds to one flight.

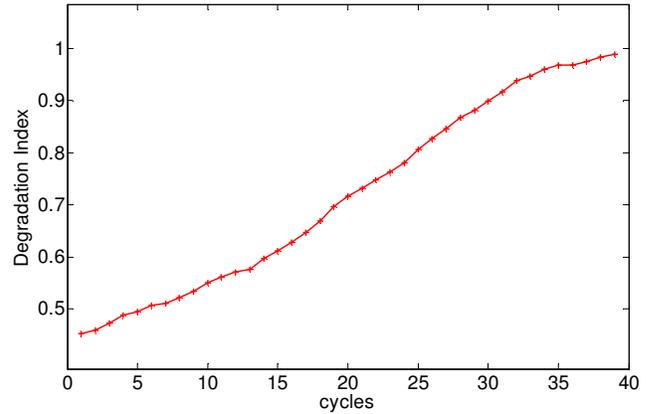


Figure 9. DI evolution for a temperature control valve

For degradation estimation and failure prognostics, a framework comprising a Kalman filter and a linear degradation progression model was used. This framework is similar to the presented for the PCV.

In this application, the HZ was defined as a normal distribution with mean of 0.99 and standard deviation of 0.0034.

4.2. Scenario Description and S-RUL Application

The scenario described in this section consists of the operation of a real aircraft. Although PCVs and TCVs were monitored for systems 1 and 2, no maintenance action was taken using this information. Figure 10 and Figure 11 show the degradation index progressions for PCVs and TCVs. The degradation index increases until a failure occurs at the last data point presented.

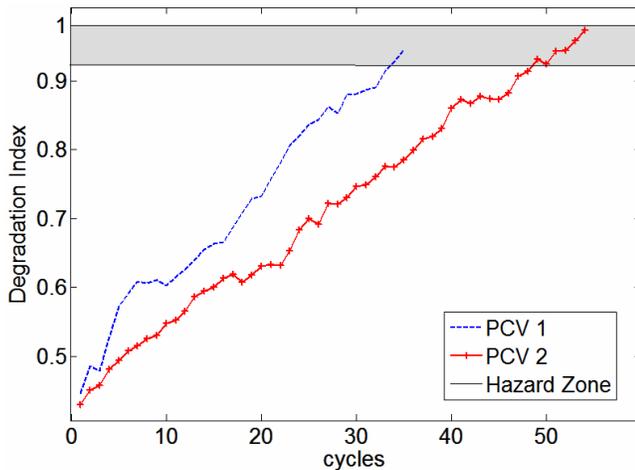


Figure 10. DI evolutions for two pressure control valves

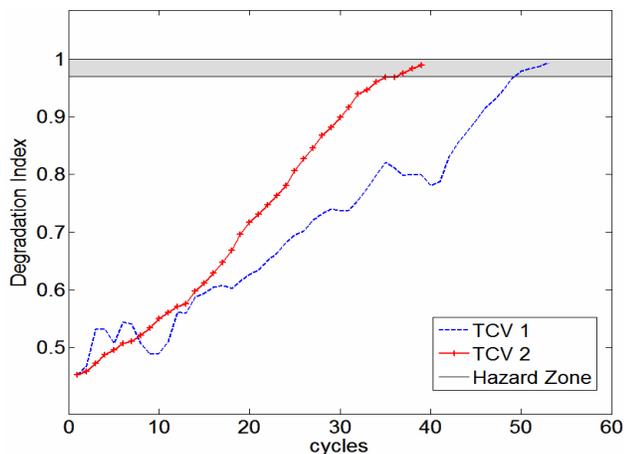


Figure 11. DI evolutions for two temperature control valves

The sequence of events and the consequences of each event of this real life example can be summarized as follows:

- On cycle 35, PCV 1 failed. Maintenance team removed the valve. The aircraft lost subsystem 1 but continued its normal operation.
- On cycle 39, TCV 2 failed. Maintenance team removed the valve. The aircraft lost subsystem 2. With both systems inoperative, the aircraft was grounded. Flights were delayed and the company had to rearrange other aircraft and passengers.
- After this event, both PCV 1 and TCV 2 were replaced and the aircraft continued its normal operation.
- On cycle 53 TCV 1 failed. Maintenance team removed the valve. The aircraft lost subsystem 1 but continued its normal operation.
- On cycle 54, PCV 2 failed. Maintenance team removed the valve. The aircraft lost subsystem 2. With both systems inoperative, the aircraft was grounded. Flights were delayed and the company had to rearrange other aircraft and passengers.

Analyzing the sequence of events presented and observing the degradation indexes in Figure 10 and Figure 11, it is possible to conclude that both AOG (aircraft on ground) events could be avoided by using the monitoring system. A prognostic system could be used to predict, with some degree of confidence, failure instants for all components thus allowing the maintenance plan to be modified to avoid the occurrences.

Although this seems to be a reasonable task, the workload for the decision maker could be reduced by using the concept of S-RUL. In the situation presented herein, the decision maker would have to analyze four RUL predictions (PCV 1, PCV 2, TCV 1 and TCV 2) to take the necessary actions. Using the concept of S-RUL, these four RUL estimations could be transformed in one S-RUL related to the remaining useful life of the whole environmental control system.

To illustrate this concept, consider a situation where the decision maker needs to analyze the data available up to cycle 25. Figure 12 and Figure 13 show, respectively, the RUL predictions for PCVs and TCVs at cycle 25.

The S-RUL was calculated following steps 1-6, presented in section 3. Figure 14 shows the S-RUL thus obtained.

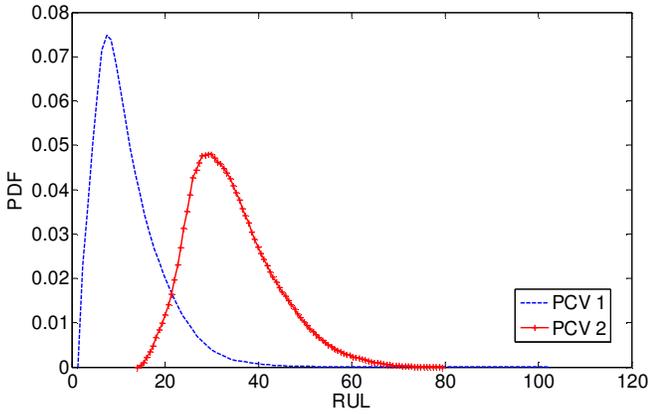


Figure 12. RUL estimations for the pressure control valves

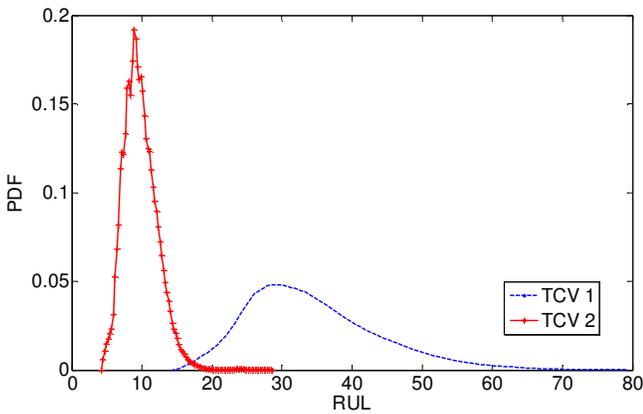


Figure 13. RUL estimations for the temperature control valves

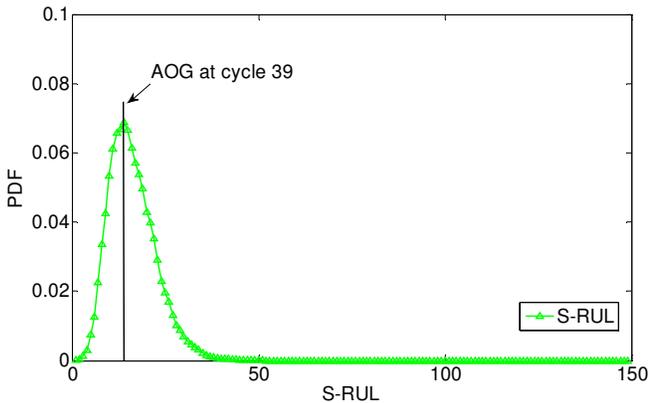


Figure 14. S-RUL estimation before any maintenance action

Observing Figure 14, it can be noticed that the first AOG could be predicted and a maintenance action could be planned. After replacing PCV 1 and TCV 2, the new S-RUL is presented in Figure 15.

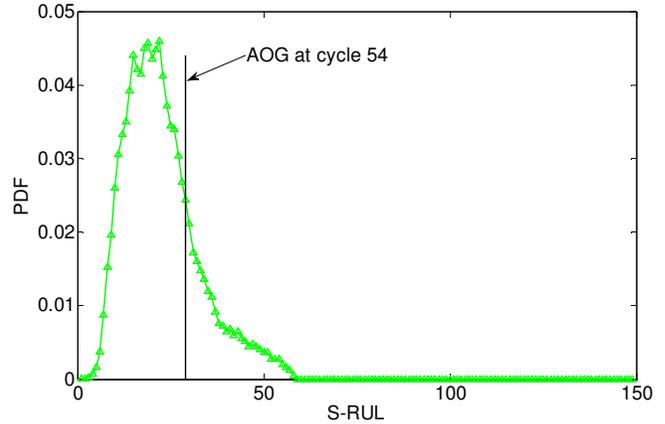


Figure 15. S-RUL estimation after replacing PCV 1 and TCV 2

Figure 15 shows that the second AOG could also be avoided. It is important to notice that the variance of the S-RUL presented in Figure 15 is greater than the variance of the S-RUL presented in Figure 14. This fact is explained by the fact that the second S-RUL prediction has a larger prognostic horizon, which leads to a greater uncertainty.

5. CONCLUSIONS

We found that the methodology discussed in this work could have been successfully used in a real life case study in order to estimate when a failure event would happen. This estimation could have been used to plan a maintenance intervention and prevent an AOG event from happening.

The methodology combines individual components RUL estimations into a single system level RUL (S-RUL) estimation. This characteristic becomes more relevant when the number of components within the system increases.

In complex systems, it may not be obvious to determine which component is the most critical for the system operability in a given scenario, even when RUL estimations for all components are available. The methodology discussed in this work is an alternative to evaluate the impact of each component in system operation by analyzing the changes in the S-RUL distribution.

The results presented in this paper were derived under the assumption that the failure events are independent. This assumption may not be realistic for some engineering systems. In many practical systems, the failure of one component may affect the condition or even cause a failure of other components. One relevant topic for future research is to consider the dependencies among all system components in the estimation of the system level RUL. Moreover, it would be of interest to investigate the computational complexity of the proposed method with respect to the number of components and the level of connectivity within the system.

Future research could also investigate how to adapt the methodology for the situation in which RUL estimations are not available for all components. Combining multiple top events in one single analysis can also be an interesting topic for further research.

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BIOGRAPHIES



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