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Deployment of Prognostics to Optimize Aircraft Maintenance - A Literature Review

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ABSTRACT

Historic records show that the cost of operating and supporting an aircraft may exceed the initial purchase price as much as ten times. Maintenance, repair and overhaul activities rep- resent around 10-15% of an airlines annual operational costs. Therefore, optimization of maintenance operations to minimize cost is extremely important for airlines in order to stay competitive. Prognostics, a process to predict remaining useful life of systems and/ or components suffering from aging or degradation, has been recognized as one of the revolutionary disciplines that can improve efficiency of aircraft operations and optimize aircraft maintenance. This study focuses on literature that has used prognostics to optimize aircraft maintenance and identifies research gaps for further optimization of aircraft maintenance in commercial aviation. In this paper, the origin and development of prognostics is firstly introduced. Thereafter, the state of art of aircraft maintenance is reviewed. Next, the applicability of prognostics to optimize aircraft maintenance is explained, reviewed, and potential challenges and opportunities are explored. Finally, the state-of-the-art of prognostics in aircraft maintenance is dis- cussed and research gaps are identified in perspective of the deployment of prognostics to optimize aircraft maintenance.

1. Introduction

Aircraft are only profitable when flying, therefore, in order to stay competitive in the competitive global industry that is aviation, airlines try to improve availability as well as flying hours of their aircraft. This availability and thus profitability of aircraft highly relies on adequate maintenance. Maintenance is described by (Swanson, 2001) as a combination of all technical and administrative actions including super- vision, action intended to retain or restore the system into a state in which a system can perform a required function. Optimization of aircraft maintenance operations has been of high interest for both the scientific community as well as the aircraft industry. Not without reason, Maintenance, Repair and Overhaul (MRO) activities represent around 10-15% of an airlines' operational costs with a total of $67.6 billion industry wide in 2016 and is expected to grow to $100.6 billion in 2026 (IATA, 2017). Moreover, historic records show that the cost of operating and supporting a vehicle (aircraft) may exceed the initial purchase price as much as ten times (Asiedu & Gu, 1998). Prognostics aims to make an accurate estimation of the Remaining Useful Life (RUL) and future performance of (aircraft) components. These RUL estimations can be deployed to not only decrease operational disturbances but also improve MRO operations in aircraft maintenance.

Multiple interesting literature reviews on prognostics have been written. (Si, Wang, Hu, & Zhou, 2011) reviewed re- liability based approaches for RUL estimation. (Sun, Zeng, Kang, & Pecht, 2012) reviewed the benefits and challenges of prognostics. (Liao & Kottig, 2014) reviewed hybrid prognostics approaches for RUL prediction of engineered systems in general and an application to battery life prediction. (An, Kim, & Choi, 2015) wrote a review on selecting data-driven or physics-based prognostic algorithms. (Elattar, Elminir, & Riad, 2016) reviewed the origin and evolution of prognostics and different prognostic approaches. We observe that al- though applications in the field of aviation are often considered in these literature reviews, a review solely focused on the use of prognostics in the optimization of aircraft maintenance has yet to be carried out. This is important because efficiency is key in this industry in order to stay competitive, and inadequate maintenance can cause failures which result in delays or cancellations of flights. However, so far no review is available that pools literature on how to use prognostics to optimize aircraft maintenance. On top of that, the ubiquity of sensors (300,000 sensors in the new generations of aircraft) produces a flood of data allowing us to give meaning to information and leads to the need for efficient processing and a relevant interpretation to utilize this data in prognostics (Gouriveau, Medjaher, & Zerhouni, 2016). In recent years, improvements in machine learning and big-data analysis have made it possible to efficiently process this flood of data. This accelerates the development of new prognostic models on components for which no clear degradation pattern or failure mode can be identified. Research shows that 80% of all failures are preventable (Gerdes, Scholz, & Galar, 2016), if prognostics is carried out accurately, one could predict when failures will occur and act accordingly.

The paper is organized as follows. Section 2 elaborates on aircraft maintenance strategies and especially the ones that exploit the benefits of prognostics. Then, Section 3 presents an introduction to prognostics and an overview of prognostic tools and techniques currently available in literature that indicate the RUL of individual aircraft or components. Next, Section 4 shows why the deployment of prognostics is important for aviation industry and how it can improve MRO operations. Section 5 discusses the feasibility of prognostic enabled maintenance systems in current day to day operations. Then, Section 6 concludes the study. Finally, Section 7 identifies possible gaps for further research and proposes possible actions for further improvement of contemporary aircraft MRO operations.

2. Aircraft Maintenance

As mentioned, (Swanson, 2001) described maintenance as a combination of all technical and administrative actions to retain or restore the system into a state in which a system can perform a required function. Technical actions can include overhaul, inspection, replacement, defect rectification, and the embodiment of a modification or a repair. Management actions include supervision, classifications as to service- ability, and the supply of spare parts, accessories, raw materials, adhesives, sealants, coatings and consumables. Focusing on aircraft maintenance, not all airlines operate their own maintenance departments, most of them actually out- source their maintenance operations as shown by (Bazargan, 2016). In this way, MRO activities of dozens of airlines are carried out at a single location, where expensive equipment, spare parts, and skilled personnel is located. These maintenance providers are extensively trying to optimize their operations, but still are obliged to schedule maintenance according to maintenance plans provided by authorities as shown by (Gerdes et al., 2016; Air Transport Association of America, 2007). This scheduling of maintenance based on time intervals is part of the Preventive Maintenance (P.M.) strategy. P.M. is the standard maintenance strategy used in aviation and three types of P.M. are identified (Federal Aviation Administration, 1978; Gerdes et al., 2016).

- Hard-time: scheduled removal of a component in accordance with the maintenance manual.
- On-condition: This requires the component to be periodically inspected or checked against some appropriate physical standard to determine whether it can continue service.
- Condition-monitoring: The component can be used until it breaks and will then be replaced. This maintenance strategy is often referred to as Corrective Maintenance (C.M.).

Scheduled maintenance checks are most often referred to as letter checks (A, B, C, D), where A and B are lighter checks and C and D are considered heavy checks (Air Transport Association of America, 2007). The problem with scheduling based on predefined intervals is that these time intervals are not accurate at all, just as the life span of an individual person may vary greatly from the average of the population life expectancy (Uckun, Goebel, & Lucas, 2008). When the time interval between maintenance checks is too short, a lot of time and money get wasted for performing maintenance on equipment which does not need maintenance yet. When the interval is too long, the aircraft component will fail with all the consequences that will entail.

Therefore, if the periods between two different maintenance checks could be accurately determined, maintenance could take place just in time. Condition Based Maintenance (CBM) is a maintenance strategy that aims to only perform maintenance according to the actual component condition and trend of the component condition while still complying with regulations as shown by (Niu and Pecht, 2009). The goal of CBM is to prevent failure and retain the system operational condition with the help of advanced (intelligent) technology that continuously tracks the condition and the trend of the condition of the component. To be able to not only act on actual condition but also on the future condition of the system, maintenance providers are trying to extend CBM to Predictive Maintenance (PdM). (Peng, Dong, and Zuo, 2010) show that PdM not only uses the real-time diagnosis of the actual condition of a system, but also employs prognosis to predict the future system health in order to avoid unnecessary maintenance tasks. PdM thus deploys prognostics, which can be applied to greatly improve estimations of the RUL and therewith is a useful tool for improving maintenance operations as shown by (Zhao, Bin Liang, Wang, and Lu, 2017). (Tchakoua et al., 2014) shows the differences between maintenance strategies mentioned above, where PdM is considered optimal as is shown in Fig. 1, although individual components might have other optimal maintenance strategies depending on their characteristics (Tam, Chan, & Price, 2006; Vandawaker, Jacques, & Freels, 2015; Vianna & Yoneyama, 2018).

Maintenance providers are looking into possibilities to make their maintenance operations more efficient in terms of time and cost. Increasing efficiency in maintenance is as old as maintenance itself and a lot of research has been conducted into increasing the efficiency. From a management perspective we observe that increasing efficiency of maintenance operations by effectively scheduling of personnel is very relevant in every industry, especially because a shortage of skilled mechanics is anticipated. Optimally scheduling the maintenance of the aircraft also is very relevant, especially because unscheduled ground time, which may cause delays and cancellations, is very costly for airlines.

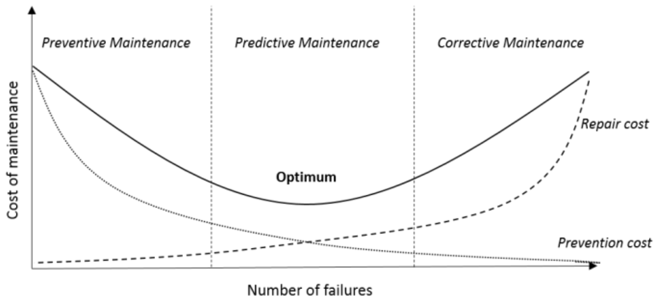

Figure 1: Comparison of different maintenance strategies, adapted from (Tchakoua et al., 2014).

Making the tasks these maintenance personnel needs to carry out more effective is the focus of relatively new optimization methods such as reducing waste using the lean method. Research by (Pogacˇnik, Duhovnik, and Tavcˇar, 2017) for instance shows the use of a lean approach together with prognostics to schedule maintenance services. They show that this lean method could re- duce a seven-day aircraft check, which consists of 300 jobs, to 6 days. Profitability of an aircraft highly relies on its avail- ability, which in turn is particularly influenced by adequate maintenance. On top of that, it still remains very difficult to accurately diagnose which components have failed or predict which components are about to fail. This causes maintenance providers to have a lot of spare parts in stock, because of the large number of aircraft they provide with maintenance, and delays and cancellations are very costly. However, because of the high cost related to the storage of these spare parts together with a degrading quality during this storage, maintenance providers try to decrease the number of spare parts as much as possible. Besides optimizing service and personnel scheduling and decreasing the number of spare parts, maintenance operations can be optimized by improving the:

- supply chain of spare parts
- service life of aircraft
- troubleshooting of failures
- quality of component repairs
- phase-out and replacement of aircraft

As can be observed, aircraft maintenance can be improved by moving from the current P.M. strategy to CBM. In CBM, diagnostics is used to perform maintenance according to the actual condition of the component instead of on predefined time intervals. When prognostics can be used to estimate the RUL of components, maintenance providers could move from CBM to PdM in which this RUL predictions of components can be used optimize MRO activities as (Sun et al., 2012) shows.

3. Prognostics

Prognostics usually means the prediction of the time at which a system or component can no longer perform its intended function. The word prognostics originates from the Greek word ’progignskein’ that means ’to know in advance’. In engineering, prognostics can be defined as the process of RUL estimation of systems or components that are degrading due to either normal operation (no fault symptoms) or detected fault and can be seen as a revolutionary discipline that can change the whole world of complex engineering system life cycle management (Elattar et al., 2016). The engineering discipline that links studies of failure mechanisms to sys- tem life-cycle management is Prognostics and Health Management (PHM). PHM includes fault detection, diagnostics, health management, and prognostics and is used to preserve safe and reliable operation of complex engineering systems in general (Sun et al., 2012). The first important step in PHM is the monitoring and diagnostics process. In this process, sensor data from the functional modules such as communications, navigation, and identification is first monitored, after which the data is preprocessed to extract the feature parameters needed for further diagnostics (Xu, Sun, & Xu, 2015). When data is acquired, preprocessed and the diagnostic health assessment has been carried out, the next step is prognostics. Prognostics is highly reliant upon diagnostics, and cannot be done in isolation. Where diagnostics involves identifying and quantifying damage that has already occurred, prognostics tries to predict damage that is yet to occur (Sikorska, Hodkiewicz, & Ma, 2011). (Sun et al., 2012) shows this information can be used to improve:

- system operations
- system design and development
- production of components
- logistics support and maintenance
- phase-out and disposal of systems
- life cycle cost of systems

3.1 Approaches

Prognostics can be classified into three different approaches:

1. statistics-based approach
2. data-driven approach
3. physics-based approach

The different approaches and their main advantages and disadvantages are shown in Table 1. The se- lection of the right approach for a certain problem is a difficult task because approaches used in the estimation of the RUL do not only differ in accuracy and cost, but also need to consider noise and interference in the data from sensors. The statistics-based approach is the most used approach and depends on massive historical data about the same, mostly uncritical, mass produced components. Advantages of this approach include that it is simple and can easily be adapted to be applicable to other components for which extensive data is available. Many drawbacks of this approach include that the calculated Mean Time Between Failure (MTBF) is of- ten not accurate and components can thus fail before being replaced, also it is hard to apply the models to new components because historic data is not available. The data-driven approach is very popular in the scientific community, due to its quick implementation and deployment, and the increasing interest in machine learning techniques. Moreover, it can be used even when it is impossible to obtain a mathematical degradation model. The approach mainly relies on machine learning techniques that can be used at low cost and without knowledge of the system physics. The drawback of this approach is that is often difficult to let the model learn when no or insufficient data about failure modes exists (Elattar et al., 2016; Sheppard et al., 2009). The physics-based approach is the most effective in terms of predicting the system degradation. In this approach a physical model for the system or component is developed. This physical model is a mathematical representation of degradation in the form of material deformation, fracture, fatigue, and material loss (Elattar et al., 2016; Sheppard et al., 2009). Physical models define relation- ships between degradation of a component and environmental and operational conditions under which the component operates. Combining these physical models with expert knowledge and actual failure modes makes it so effective. (Elattar et al., 2016) show the drawbacks of this approach in that it is very costly, time consuming and data of failure cases is needed. Finally, hybrid approaches combine two or more of the previous described approaches to get the best from each. For example, a combination of the physics-based approach and the data-driven approach makes it so that the physical model can compensate the lack of data and the machine learning compensates the lack of knowledge about system physics. This approach will, however, still carry the disadvantages of used approaches to a certain extent.

NASA considers prognostics the most important in improving system safety, reliability, and availability of aircraft. As mentioned in Section 2, the PdM strategy exploits the bene- fits of prognostics and can be used by maintenance providers to improve their maintenance operations. The challenges that still need to be considered when prognostics is used to predict the future health of systems are presented in Section 7.

4. Prognostics in Aircraft Maintenance

More and more aircraft maintenance providers are looking to change their operations from P.M. to CBM and some even into PdM, which exploits the benefits of prognostics. As mentioned in Section 2, P.M. does not effectively use prognostics because maintenance takes place at specified time intervals while in PdM, prognostics is used to identify the RUL and the actual real-time condition of the system to schedule maintenance. A lot of literature interchanges definitions of CBM and PdM and thus considers CBM to also exploit the benefits of prognostics, just as PdM does. (Peng et al., 2010) show that being able to perform precise and reliable prognostics is the key of PdM for an engineering system and it is also critical for improving safety, planning missions, scheduling maintenance, reducing maintenance costs, and down time. Aircraft maintenance can be optimized in various areas as described in Section 2, however, prognostics might not be able to increase efficiency in all of these mentioned areas. For example, prognostics will not directly increase efficiency of tasks maintenance personnel needs to carry out, although it can be used for better troubleshooting. Prognostics neither is very useful in making personnel scheduling more efficient. However, personnel scheduling is highly reliant upon service scheduling of aircraft, which could benefit from prognostics. The number of maintenance checks could also be reduced, if these checks are made more efficient. Prognostics contributes to better trouble shooting if a component has broken down, and reduces so called ’No Faults Found’ (NFFs) in maintenance departments, false alarms that cost a lot of money (Ho¨lzel & Gollnick, 2015).

On top of that, research shows human errors are a primary contributor in up to 80% of all aviation accidents and incidents (Rankin, 2007). This could be reduced if the number of maintenance activities is decreased, which in turn reduces the occurrence of accidental damage during these maintenance activities (Sun et al., 2012). Prognostics can be used to schedule more efficiently, identify bro- ken components more efficiently, decrease the frequency of maintenance checks and therewith reduce the amount of col- lateral damage. Prognostics could also be used to minimize the number of spare parts, which is very relevant because re- search shows inventories sum op to above 50 billion dollars in airlines business which results in excessive storage costs (Cai et al., 2017). The following sections will chronologically present literature on the use of PdM in aircraft maintenance, optimization of service scheduling, spare parts management, and the reduction of maintenance and repair-induced failures. Scopus is used as main search engine. Literature focused on maintenance of aircraft in commercial aviation is considered, published later than 2012. Table 2 shows an overview of the presented literature per section. Literature solely focused on the development of prognostic models is reviewed by (Elattar et al., 2016).

4.1 Deployment of Predictive Maintenance

Contemporary maintenance providers are extensively trying to optimize their operations using prognostics and PdM, of which literature will be shown in this section. Most airlines own many more aircraft of the same type, where the information of older aircraft of the same type can eventually be used to optimize maintenance of a fleet of aircraft of this type. Ideally, prognostics is implemented in multiple levels such as shown in Fig. 2. As an example, at the lowest level cracks in every single fuselage panel are identified, after which the impact of this one crack on the total fuselage is evaluated. The fuselage is a part of the total aircraft, and an aircraft is eventually part of a fleet of aircraft. Proof that PdM can optimize maintenance operations is developed by (Kraft et al., 2014). They present research on a fleet of about 100 aircraft engines on long-haul aircraft. A performance improvement program was launched in 2007 in which engine models were developed. These models indicate the effect that the actual condition of a specific part of the engine has on the future operation of the engine. The models use data of actual in- service engines operated at typical conditions of the specific engine fleet. The models were tested in order to optimize the engine maintenance costs per flight hour and the specific fuel consumption. Before their research, engine main- tenance was carried out based on general experience of the OEM. Now the engine maintenance is primarily based on the health monitoring and predictions generated by this research. Results show improvements on many levels, of which an improvement of the engine life span of 30 to 40% probably is the most recognizable. (Feng, Chen, et al., 2014) propose a modeling method based on CBM for a fleet of aircraft. The health status of the aircraft is defined, after which the maintenance optimization program is used to minimize maintenance time, costs, and risk. The research considers prognostic un- certainty, constrained resources and presents results for a case study of a fleet containing 10 aircraft with 4 components that can fail. A different model is shown by (Lin et al., 2017), as they proposed a maintenance decision-making support sys- tem based on a CBM multi-objective decision-making model. This model both minimizes maintenance costs as well as maximizes the availability of the aircraft. They assume aircraft send real-time information about strains of the wing boxes which indicate the real-time condition of the aircraft. This data can then be processed and decisions about required maintenance can be made. (Yang et al., 2018) show how prognostics can be exploited to optimize aircraft maintenance. They use the RUL estimation of all key subsystems of an aircraft to optimize fleet-wide CBM. A heuristic sequential game frame- work is proposed that can help managers determine the best combination of maintenance activities and therewith reduce maintenance time and cost of equipment. This research is a perfect example of what is possible if the RUL of all key sub- systems is estimated. Fig. 2 shows how prognostics on sub- systems can be extended to the RUL estimation of the entire aircraft and from there to fleet-wide maintenance optimization. It is key to couple aircraft of the same type in order to estimate the future performance of the entire fleet of aircraft.

4.2 Service Scheduling

The aviation industry still mostly uses P.M. with periodic maintenance checks which are referred to as A, B, C, or D checks. Each of these checks is very costly and thus it is extremely important to efficiently plan these checks (Bazargan, 2016). The scheduling of all these checks has been extensively ad- dressed in literature, although fewer literature about the scheduling of maintenance checks that exploits the benefits of prognostics exists. (Pattabhiraman et al., 2012) propose skipping some maintenance checks using CBM in service scheduling. They focus on cracks in the fuselage panel which occur due to the repeated pressurization cycles of airplanes. They show that skipping some structural airframe maintenance could re- duce costs while safety is maintained with the use of an on- board structural health monitoring system. Skipping maintenance tasks currently is, however, not allowed by regulations. (Bazargan, 2016) shows an optimization approach of in-house vs. outsourced maintenance strategies.

The D maintenance check includes all categories of the A, B, and C checks and a lot of non-routine maintenance tasks and thus is by far the most expensive. Airlines have the opportunity to out- source this maintenance, and (Bazargan, 2016) actually shows that it is sometimes optimal to outsource the more expensive checks (D checks), while less expensive checks should be per- formed in-house. However, this is highly dependent on the age of aircraft because older aircraft will require more frequent maintenance. (Feng, Bi, Zhao, et al., 2017) implicitly use prognostics in their game theory approach to optimize a CBM service scheduling problem of a fleet of aircraft. The game first looks for a local optimal strategy for different sets, after which the cooperative game tries to find the global optimum for all sets. The characteristics of the fleet reliability model and maintenance problem are still very basic though. (Feng, Bi, Chen, et al., 2017) extend this research by means of agent learning which uses the health data of the aircraft more effectively. (Lin, Luo, & Zhong, 2018) developed a multi- objective decision-making model for the maintenance of air- craft. They propose a CBM approach based on RUL predictions that minimizes fleet maintenance cost and maximizes fleet availability. Moreover, a case study regarding a fleet of 10 aircraft is conducted which shows the approach meets the scheduling requirements. The paper addresses the negative influence caused by uncertainty, but is still just a start for research in this direction. Finally, another research that de- ploys prognostics to optimize service scheduling is presented by (Vianna & Yoneyama, 2018). They use a Kalman filter to predict the wear of some aeronautical redundant systems. A Kalman filter is useful because it can deal with noisy or even incomplete measurements to estimate the RUL. The method is used to optimize a maintenance scheduling problem.

4.3 Spare Parts Management

Many airlines order excessive spare parts in the first several years while in these years the demand of spare parts is limited, which contributes to the huge inventories of spare parts which sum up to above 50 billion dollars (Cai et al., 2017). Prognostics is relevant in spare parts management because of the fact that it can predict the RUL and thus it helps to or- der spare parts only when the components are just about to fail. Although relatively outdated, (Muckstadt, 2005) wrote a book about spare parts in supply chains. The book is not focused on aircraft, but on supply chains in general. Nevertheless, it includes a lot of mathematical models and optimization techniques for spare parts management. Focusing on spare parts in aircraft industry, (Fritzsche & Lasch, 2012) present a paper on a faster and more efficient supply of spare parts by trying to minimize unscheduled maintenance using prognostics. When aircraft need unscheduled maintenance, there is a high possibility of inefficient spare part deliveries. They present a model based on the actual condition of components and their predicted future performance to be able to accurately schedule maintenance. This information is then used to optimize the stock and delivery of spare parts while at the same time decreasing the number of flight cancellations drastically. Although their model minimizes cost, it does not consider the implementation costs of the advanced technology that is needed to accurately estimate the RUL of components. (Rodrigues & Yoneyama, 2013) present a paper that shows how PHM information can improve fleet availability.

The authors consider the failure of components of a fleet of 10 aircraft and the repairs and replacement of these components. The number of spare parts in stock can be reduced because spare parts can now be ordered just-in-time. Interesting is the fact that the authors consider uncertainties in the estimation of the RUL. (Cai et al., 2016) very clearly shows how prognostics can improve spare parts management. They optimize aircraft engine maintenance service based on RUL and stochastic repair times. The goal of the research is to carry out maintenance just-in-time, based on the real-time condition of the engines. The results show it is possible to accurately estimate the RUL which can reduce the number of spare engines needed. A different paper by the same authors,

(Cai et al., 2017), present a joint inventory management strategy together with an optimization of maintenance inspection and spare parts provisioning. Physical degradation models are considered that describe the RUL of critical spare parts. The interesting thing about this paper is that the authors con- sider different phases in the spare part provisioning, if an air- craft is new, no or very little spare parts are needed in the first years. Moreover, the authors consider different inspection intervals, which is consistent with the actual situation in industry. Research by (Vandawaker et al., 2017) does consider the costs of implementing a condition aware system that uses prognostics. They present how PdM can improve operations, especially the supply of spare parts for a fleet of Joint Strike Fighter (JSF) fighter jets. Each aircraft has 20 unique components with different failure times, and the impact of ordering spare parts on basis of predicted failure of these components is inspected. The developed model also changes the supply ordering frequency, taking costs for holding spare parts into consideration. The authors show that the overall annual sup- ply costs can be decreased while at the same time the aircraft availability is increased if prognostics is used. (Mofokeng & Marnewick, 2017) present a case study at an aircraft maintenance company to find factors contributing to the delays of A-checks. Maintenance reports were analyzed for half a year in 2016 and the authors identified causes for delay. A poor logistics process related to spare parts was found to be the cause of delay most of the times. Also, poor planning, lack of communication, lack of human resources, lack of capability, and defects were identified as causes of delay. With the help of prognostics these delays could be mitigated or even resolved.

4.4 Reduce Maintenance and Repair-Induced Failures

When prognostics is used to more efficiently schedule maintenance using RUL estimations, maintenance of different components can be combined which reduces the number of maintenance checks needed (Ho¨lzel, Schilling, & Gollnick, 2014). Prognostics can thus also reduce the amount of ground sup- port equipment and manpower needed. Because the failure modes of the failed components are known, repairs are more efficient and the number of NFFs will reduce as is also shown in Fig. 3. Moreover, mechanics may cause accidental damage to other components while carrying out maintenance. This is most often called collateral damage during repairs, and if this damage stays unnoticed, this can result in additional system downtime or failures. Research shows that of all aviation accidents and incidents, human errors were identified as a cause in up to 80% of times (Rankin, 2007; Daneshjo, Majernik, Danishjoo, & Krivosudska, 2017). Boeing already acknowl- edged this problem in 1992 and offers a human factors tool to all of its airline customers called Maintenance Error Decision Aid since 1995 (Rankin, 2007). Boeing expanded this tool to also include violations in company policies, processes, and procedures that lead to an unwanted outcome. (Feng, Li, & Sun, 2014) present an interesting paper where they simulate human behavior when assigning personnel to specific maintenance tasks. A multi-agent system is used to describe the maintenance process and assign maintenance personnel. Agents in the system can take decisions and can consider all sorts of behavior of maintenance personnel from human error to capability level.

The agents propose bids to the management to find the optimal personnel for a certain task, a case study shows promising results but is still subject to a lot of assumptions and uncertainties. (Rashid et al., 2014) and (Shanmugam & Paul Robert, 2015) show that it is important to make use of prognostics to decrease the number of maintenance activities because human errors occur more often due to increasingly complex human-machine interactions in air- craft maintenance. (Duarte et al., 2016) also show this area of research is relevant as they reviewed multiple case studies in which a component of an aircraft has failed. Different components from engines to aircraft structures and landing gears are considered and an extensive failure analysis has been con- ducted. The authors clarify that the human factor bears a significant role in the failure of aircraft systems and components. More specifically, in most of the investigations, the root cause for the incident was directly or indirectly related to human causes.

5. Discussion

We observe that there are some challenges to overcome be- fore PdM will be the standard in aircraft maintenance. Al- though prognostic models for individual components have received quite some attention in literature, the interaction be- tween these components and the assessment of the health of the entire aircraft still proves to be very difficult. Especially, little research into the health management of entire fleets of aircraft is available. Moreover, (Ma, Zhang, & Meng, 2015) state that if the aircraft design and PHM system are designed separately, the optimal design can never be reached. They thus propose a collaborative PHM development framework in which the PHM and aircraft design are completely integrated, as for instance has been done in the JSF project (Calvello, Olin, Hess, & Frith, 2007; Hess, Calvello, & Dabney, 2004). (Zhang et al., 2014; Nicolai & Dekker, 2008) show another challenge for prognostics in the verification and validation of the techniques used. It is important to acknowledge the degree to which a model and its associated data accurately rep- resent the real-world. Models will remain a representation of reality, and thus these need to be validated thoroughly. When we consider the data-driven approach for prognostics, which is the most widespread in the PHM community, as the name says: data is needed. Especially, it is very important to be able to determine the real-time condition of aircraft and estimate the future performance. Multiple models have been de- scribed in Section 3, most of which show promising results, but in order to be able to estimate the real-time condition of aircraft, real-time data from the aircraft is needed wherever it is located. According to (Gomes, Rodrigues, Leao, Gal- vao, & Yoneyama, 2018), even though in-flight data transmission costs are reducing, we are still far from a reality where streaming of large amounts of data can be performed for the great majority of flights. Besides, smaller aircraft do not have the hardware to gather continuously sampled data.

Considering the use of prognostic maintenance strategies in industry, although a lot of research has been conducted, prognostic models have not been significantly applied to optimize maintenance operations in aviation industry. The state-of- the-art remains to be maintenance at specified time intervals. The length of these intervals is very difficult to determine, but can be determined when the real-time condition of the aircraft is assessed. The future performance is estimated using prognostics and in theory maintenance scheduling would take place just-in-time and components would never cause unexpected, expensive maintenance events. Unfortunately, estimations of RUL and degradation of performance remain subjected to uncertainty. When the RUL estimations used in PdM are not accurate, the use of PdM could have the same drawbacks as P. M. When the RUL is underestimated, main- tenance is planned too often, while unscheduled ground time and system failures could occur when the RUL is overestimated. (Vandawaker et al., 2015; Vianna & Yoneyama, 2018) assess the topic of risk management in prognostics regarding these uncertainties. The use of prognostics can reduce costs and increase safety, if and only if, the estimations of the RUL are accurate enough. (Arahchige & Perinpanayagam, 2018) analyzed and confirmed the significance of uncertainties in prognostics, which include modelling errors, noise, and sensors. They show one of the first detailed statistical analysis on the effect of sensor noise which can be used in uncertainty management. Together with the validation of the models, assessing the uncertainty of the models and therewith addressing the risk of using these models in reality is a must before the use of prognostic maintenance systems will be feasible in aircraft industry. Management has the task to evaluate the prediction of prognostic models and their according uncertainties and take careful decisions (Vandawaker et al., 2015). Experience in taking these decisions is an advantage, but it will take some time before companies will be skilled enough to accurately assess the uncertainties resulting from the prognostic models.

With the move to prognostic maintenance systems, suppliers of aircraft components will now be able to predict future performance and can use this as an advantage to maximize their revenue (Phillips & Diston, 2011). This, however, also brings up difficulties in the fact that information about many of different components will have to be coupled by airlines to be able to schedule maintenance more accurately. With regard to prognostic approaches, the reason the data- driven approach is the most widespread in the PHM community, while the physics-based approach is more accurate, is largely because of the fact that the physics-based approach is time consuming and very costly. Management of airlines needs to consider the fact that maintenance is a very large part of their operation and invest in research and development of more effective prognostics, although one might argue the cheaper data-driven approach is not ineffective. We observe that it might be difficult for management to determine the profitability of mathematical models that describe the degradation of the condition of components of aircraft. Those models will become more profitable when maintenance operations are moved from maintenance at fixed time intervals to PdM based on the actual real-time condition of aircraft. In this, governments can play a role in reconsidering regulations that specify the amount and frequency of maintenance checks, however, their response to new technologies tends to be quite slow (Quinlan, Hampson, & Gregson, 2014). This is interesting because already in 2008, the Department of Defense of the USA released a technical report about the potential of CBM (Department of Defense, 2008). Another difficulty which needs to be considered is the data ownership, airlines own the data which their aircraft generate, but aircraft and air- craft engines are manufactured and maintained by different companies. Data sharing would greatly accelerate research and development, however, especially large airlines are not excited about sharing this data (Uckun et al., 2008). Recently, new initiatives by aircraft manufacturers such as Airbus and Boeing might change this when they provide data capturing and processing.

6. Conclusion

From the reviewed literature we conclude that the deployment of prognostics can optimize operations in aircraft maintenance. The first area of optimization is maintenance scheduling, where prognostics enables service scheduling according to the future condition of the aircraft(components) in- stead of at fixed time intervals. The second area that bene- fits from prognostics is the field of spare parts management, where decreasing the amount of spare parts in stock decreases costs and a just-in-time delivery of spare parts is the main goal of optimization models. The third area of improvement is the reduction of maintenance by more accurate scheduling and fault diagnostics. This will cause a reduction of the amount of collateral damage due to human errors and lower repair cost due to more effective troubleshooting. Moreover, human-machine interactions have become very complex in recent years and the difficulty will keep increasing, which will augment this problem. It is important for management to acknowledge maintenance errors and violations and con- sider that violations, while intentional, are also caused by contributing factors.

7. Further Research

The feasibility of deploying prognostic maintenance systems to optimize maintenance operations is explored in this paper. We observe that although there are some difficulties from both a technical as well as a management perspective, the implementation is certainly feasible. Most of the contemporary difficulties lie in the fact that methods are still relatively new and thus aircraft maintenance companies have little experience using them. Technologies are advancing ever more rapidly, and thus it will only be a matter of time be- fore companies obtain this experience. We observe multiple challenges for further research of which some have been extensively discussed in previous sections.

7.1 Empirical Validation of Prognostic Models

Empirical validation is concerned with the validation of prognostic models with reality based on observation or experience instead of solely on theory. Although most of these models show promising results, they will need to be validated before the models can be used in the real-world.

7.2 Quantification and Risk Assessment of Uncertainties in Prognostic Models

Uncertainties in these models need to be addressed and quantified to be able to make risk assessments and improve maintenance operations. Management of airlines will have to take careful decisions based on these risk-assessments which will become more straightforward with time and experience. Regarding the little amount of research into prognostic models, the development of these models is a difficult and time-consuming task. Moreover: data is needed. As we can observe from for example the competition set up by NASA (Saxena, Goebel, Simon, & Eklund, 2008), the supply of extensive reliable data from aircraft engines causes an impulse to research.

Especially when this data is backed by some sort of competition as has been done by NASA. Airlines and aircraft companies such as Boeing and Airbus should make extensive data available to validate the models presented in literature. In this way, prognostic approaches can be validated and implemented in industry.

7.3 Integrating PHM in the Design of New Aircraft

Aircraft manufacturers have the noble task to integrate PHM in the design of their aircraft, such as has been done in the JSF fighter-jet project. This is especially a difficult task because the aircraft manufacturer does not design and build all parts of the aircraft, on the contrary, thousands of suppliers deliver all sorts of parts from engines to bolts and from fuselage panels to landing gear.

7.4 Interaction between Damaged Components of Aircraft

Because all of these components come from different suppliers, research is needed to evaluate the interaction of damage in one component in relation to the degradation of adjacent components. Data-driven prognostic models based on ma- chine learning could be used to identify relations that cannot be seen by the naked eye.

7.5 Real-time Health Management of an Entire Fleet

A thing we also observe is the fact that frameworks connecting individual aircraft RUL estimation and real-time condition to fleet-wide RUL estimation and real-time condition is very scarce in literature, more effort is needed before fleet- wide PdM can intensively be used in aircraft industry.

7.6 Optimization of Maintenance Operations Using the Real- time Condition of a Fleet of Aircraft

Monitoring the real-time condition and accurately predicting the future performance of an entire fleet of aircraft enables optimization of maintenance operations as described in this paper. We observe most research has been conducted into the optimization of service scheduling, spare parts management, and the reduction of the amount of maintenance and repair-induced failures. Although research is still limited and the research that has been done often considers only a fraction of the thousands of components of an aircraft. We believe the deployment of prognostics can optimize the entire logistics supply chain of aircraft maintenance, including the phase- out, reuse, and recycling of aircraft and their components. Furthermore, with the accurate estimations of RUL one can extend the service life of an aircraft and avoid unnecessary replacement of components, which contributes to a more sustainable aircraft industry in general. In summary, we observe research gaps in the following areas:

- Empirical validation of prognostic models
- Quantification and risk assessment of uncertainties in prognostic models
- Interaction between damaged components of aircraft
- Integrating PHM in the design of new aircraft
- Real-time health management of an entire fleet
- Optimization of maintenance operations using the real- time condition of a fleet of aircraft

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Appendix

Table 1: Different prognostics approaches and their main advantages and disadvantages.

Approach	Advantages	Disadvantages
Statistics-based	Simple and easily applicable to other components	Not accurate and difficult to apply to new components
Data-driven	Quick implementation, low cost, and useful even if degradation is unknown	Large amounts of (useful) data necessary and thus difficult to apply to new components
Physics-based	Very accurate and specific	Applicability, time consuming and expensive

Table 2: Overview of reviewed literature per topic

Section and topic	Author and year of publication
Deployment of PdM (4.1)	(Kraft, Sethi, & Singh, 2014)
	(Feng, Chen, Sun, & Li, 2014)
	(Lin, Luo, & Zhong, 2017)
	(Yang et al., 2018)
Service scheduling (4.2)	(Pattabhiraman, Gogu, Kim, Haftka, & Bes, 2012)
	(Bazargan, 2016)
	(Feng, Bi, Zhao, Chen, & Sun, 2017)
	(Feng, Bi, Chen, Ren, & Yang, 2017)
	(Vianna & Yoneyama, 2018)
Spare parts management (4.3)	(Fritzsche & Lasch, 2012)
	(Rodrigues & Yoneyama, 2013)
	(Cai, Li, & Chen, 2016)
	(Cai, Xin, & Xi, 2017)
	(Vandawaker, Jacques, Ryan, Huscroft, & Freels, 2017)
	(Mofokeng & Marnewick, 2017)
Reduce maintenance and repair-induced failures (4.4)	(Feng, Li, & Sun, 2014)
	(Rashid, Place, & Braithwaite, 2014)
	(Shanmugam & Paul Robert, 2015)
	(Duarte et al., 2016)

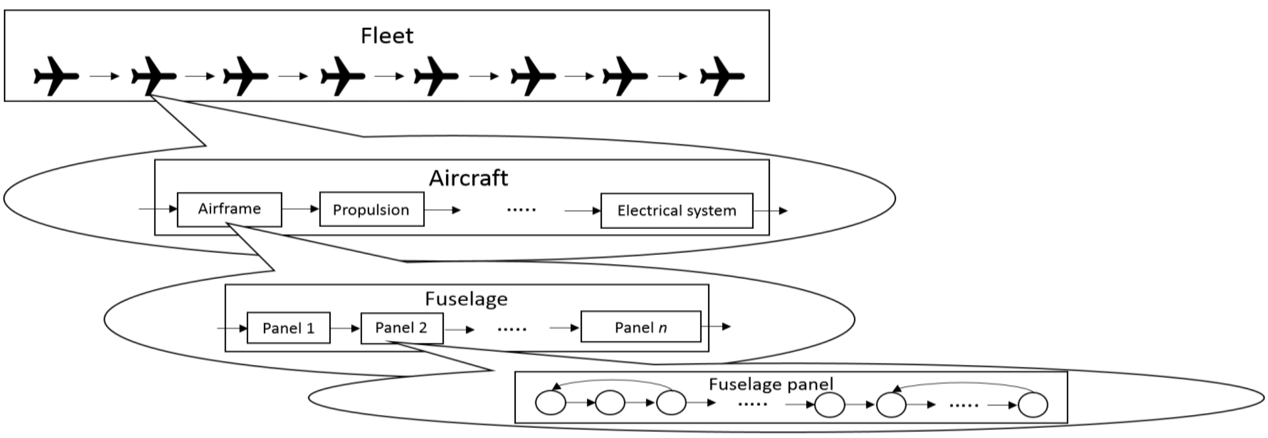

Figure 2: Prognostics on different levels, adapted from (Collins & Huzurbazar, 2012).