An Analysis of Predictive Aircraft Maintenance Models

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Abstract:

For decades aircraft maintenance has been done on a rigorous and regular basis. This leaves room for unexpected events to cause significant losses for airlines and customers alike. Predictive maintenance aims to provide a dynamic maintenance schedule such that unexpected maintenance events can be minimized. Work has been done to prove the effectiveness of predictive maintenance on a limited selection of aircraft components. Models created have been rigorously tested to prove predictive maintenance can provide significant efficiency and cost-savings to airlines. Due to the limited scale of current implementations, the airline industry has struggled to see the value in predictive maintenance. The work that has been done in these unique models has proved the merit behind predictive maintenance and will support the journey toward realizing the full potential of predictive maintenance in aviation.

Introduction:

A question that was impossible to address until recent times has been: When will an aircraft component fail? With recent advancements in mathematical models, machine learning, and artificial intelligence this is now a question that may have an answer soon. Why even ask this in the first place? One of the most significant expenses for aircraft operators is maintenance. Keeping each plane operating for as long as possible is in the best interest of the operator as they are millions of dollars as an investment. Maintaining aircraft is a great way to extend aircraft lifetimes, and thus an important factor for aircraft operators to consider.

Currently, aircraft maintenance is done on a regular basis. Aircraft are taken in for maintenance at a fixed or changing interval, one that ensures no component will be at risk for failure. Though this procedure is effective at keeping aircraft regularly taken care of, unpredictable and unexpected maintenance events can cause a major disruption in these pre-determined plans. These unexpected maintenance events lead to significant expenses for aircraft operators, especially commercial ones, and often require a complete refactoring of the original maintenance plan. This significant setback has served as a catalyst for devising a more effective solution, one example being predictive maintenance.

Predictive maintenance is the idea of using past data to predict when certain components will need maintenance. For example, given 50 years of aircraft engine maintenance data, when is the most likely time it will need maintenance in the future? With an estimate of this value, the aircraft engines can be serviced to attempt to prevent a possible failure. This approach can be incredibly beneficial to extending aircraft lifetime and uptime, two important factors for aircraft operators.

Any implementation of this approach is incredibly complex for numerous factors such as real-world factors (weather, accidents, etc.), the number of unique components per aircraft, and aircraft usage. Creating a solution to model all these factors and more is an extreme challenge. Because of this, current predictive models are developed for a specific instance with a subset of data. For example, creating predictive models only for aircraft engines based on historical aircraft engine maintenance data. Even though these smaller models cannot address every component on the plane, for now, they do have the opportunity to provide insight into the effectiveness of the idea of predictive maintenance. This survey will discuss three existing predictive models, how they compare, and their overall effectiveness.

Existing Work:

Of the existing work, the three models that will be discussed are predictive maintenance models for aircraft structural airframe maintenance (Wang et al.), aircraft engines (Hermawan et al.), and landing gear (Korvesis et al.).

Cost-Driven Predictive Maintenance Policy:

Wang et al. were able to create a model to predict when maintenance should be taken on the aircraft's structural airframe. Their work was meant to build on fixed interval schedules typically found with aircraft maintenance. Furthermore, existing aircraft predictive maintenance work, according to Wang et al., did not take into consideration the price ratio between different forms of maintenance. This specific model was focused on being a cost-driven predictive maintenance model on aircraft fuselage panels. Overall, this work provides a comprehensive model that yields significant cost savings compared to scheduled maintenance policies.

This work is built on structural health monitoring systems (SHM). These are systems that are within aircraft structures to provide continuous data on their health. One limitation of this work is that SHMs are very uncommon in the field and have been in the testing phase for a significant amount of time (MODIC 2014). Airlines have yet to see a motivation to implement SHMs relative to their cost. In turn, this makes this model, though effective, in a similar category of speculative. SHMs have not won over the industry, meaning this model may not have the potential to be implemented.

However, the complexity of the model is impressive. Real-world data was used to test, and multiple different, practical scenarios were tested showing positive results (see Figure 1). The simulated cost-savings were significant, suggesting the idea of continuously monitoring aircraft health is an effective strategy for making dynamic, predictive maintenance plans. This idea can be extended beyond structural airframe maintenance, thus making this work an important step toward implementing real-world predictive maintenance strategies.

Predictive Maintenance of Aircraft Engines:

Hermawan et al. conducted research to create a model to estimate the remaining useful life of aircraft engines. This work was motivated by the low fault tolerance of aircraft engines. The proposed model was a combination of a convolutional neural network and a long short-term memory neural network that was used to pair the necessity of extracting meaningful features and the time nature of aircraft engine data, respectively. Results from the simulated tests show an improvement in accuracy and computing time compared to previous works that estimated the remaining engine life.

This work is beneficial to the field of predictive aircraft maintenance because of its practical nature. The data was used from engine sensors, which already exist in the field for safety and informational reasons. The work was directly applied to real-world data, proving better results in estimated life and computational time, making this immediately useful (see Figure 3). Furthermore, these aircraft engines are clearly a critical aspect of aircraft, leading to this model having a significant influence on maintenance considerations.

The simplicity of the proposed model yields a limited impact on predictive maintenance strategies, which is a drawback. Estimating the remaining engine life is vital for safety reasons, but the result of the model is binary: The engine will fail at a set time, or it won’t. When developing maintenance plans, this information will be helpful in determining the end of an aircraft’s life span, but for routine checks, the output of this model will not be as effective as others.

Failure Prediction from Post-Flight Reports:

Korvesis et al. aim to create a system that can notify aviation engineers well in advance of when an aircraft component will fail, to allow for time to schedule necessary maintenance to prevent component failures. The system is a regression model to predict the next maintenance event given previous, real-world maintenance events. The model implemented in their work was specifically focused on post-flight report data regarding the landing gear. For this specific component there are still significant costs associated with mismanaged maintenance and the work of Korvesis et al. noted a potential 20% savings in costs to airlines.

The regression model presented by Korvesis et al. is an extensive solution utilizing real-world post-flight data, which is common in the field. This adds the potential for this model to be incorporated directly into existing maintenance scheduling operations. Furthermore, the process in which the prediction function was created is general. Given any series of events over time, the function developed can evaluate the risk of an event occurring within a given period, and dynamically update given new events (see Figure 2). This method is applicable to any case with a time-based history of events, and with the necessary data processing, can be applied to a wide range of different aircraft components for predictive maintenance.

A notable drawback of this model is the ability to get false positives, or incorrectly accessed risks and therefore alerts. This is an important factor in considering its effectiveness in practice, as these false positives can lead to similar performance to the traditional fixed maintenance schedule. Similarly, there are no parameters for the degree of cost savings, such as in other models. This model will require deep analysis and comparison between existing maintenance strategies to successfully evaluate its real-world effectiveness.

Survey Results:

The impact of the previously mentioned related work proves predictive maintenance is an important consideration for future aircraft maintenance policies. When testing with real-world data, these models have the potential to provide significant cost savings to existing maintenance policies. The difficulty of implementing any of the models, however, is the scale of the aviation industry. Proving the value of predictive maintenance to airlines is still an ongoing challenge (Canaday 2023). Additionally, the scale of the related work is a limitation to industry adoption. Ideally, an all-encompassing maintenance policy creation model should be developed to provide seamless integration for aircraft operators. The previously mentioned work, however, will serve as the building blocks for that to become a reality.

With each model, the reported results were very accurate and proved there is value to be had in predictive maintenance. There were different approaches taken, from neural networks to regression functions to full-scale policy creation systems, and each was able to provide significantly effective results. Furthermore, there was a large variation in the data used per model, but the data was on a similar scale. The components with ample data took precedence in the analysis of predictive maintenance. This is an important consideration, as these components are all vital to everyday aircraft operations, thus these works are especially important. By the nature of the overarching question, time-continuous data was virtually required to be able to make accurate predictions, and that was illustrated by the similar properties of all data used. This reliance on time data implied an added reliance on the system to provide that data. As it has been noted in Wang et al.'s work, the reliance on uncommon systems is a drawback in this method of maintenance planning. Overall, each model was highly effective, but the scale of the solution proved to be a challenge for industry adoption.

Conclusion:

Predictive maintenance is an obvious way for airlines to improve their efficiency and save on costs. It provides the opportunity to plan for unexpected component failures, saving themselves money and increasing customer satisfaction. However, the scale of the solution needed is a major factor in the development of these models. Existing work proves that for a specialized group of components models can be developed to be highly accurate and efficient. Furthermore, these models have been tested and validated using real-world data, speaking to the dynamic and effective performance of each one. The complexity of future work in this field is tied to the bigger picture of predictive maintenance. The concept is still in a testing phase in the industry and has yet to prove its value to airline operators. There is merit to the concept, though, and these works have proved that. Each implementation was completed in a unique way using unique data to reach a sufficiently tested and effective product. As the field evolves, increased integration and further refinements can be built on these works. This will lead to improvements in aircraft maintenance and efficiency. The groundwork has been laid by these models to help realize the full potential of predictive maintenance in the airline industry.

References:

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Figure 1:

Cost-Driven Predictive Maintenance Policy test results

Scenario	Cost ratio (c_s/c_{us})	Maintenance policy	Avg. No. of M.S.[a] /aircraft	Avg. No. of U.M.S.[b] /aircraft	Avg. No. of R.P.[c] /aircraft	Avg. M.C.[d] /aircraft
		Scheduled	10	-	14.2	17.9
		Threshold-based	3.6	0	14.2	8.2
r_{un}=0.9	0.16	CDPM	2.9	0.36	7.3	5.7
r_{un}=3	0.05	CDPM	3.0	0.02	7.4	5.8
r_{un}=5	0.03	CDPM	3.1	0	7.5	5.9
r_{un}=10	0.01	CDPM	3.1	0	7.5	5.9

a

M.S. is Maintenance Stop.

b

U.M.S. is Unscheduled Maintenance Stop.

c

R.P. is Repaired Panels.

d

M.C. is structural Maintenance Cost.

Figure 2:

Failure Prediction from Post-Flight Reports risk function output

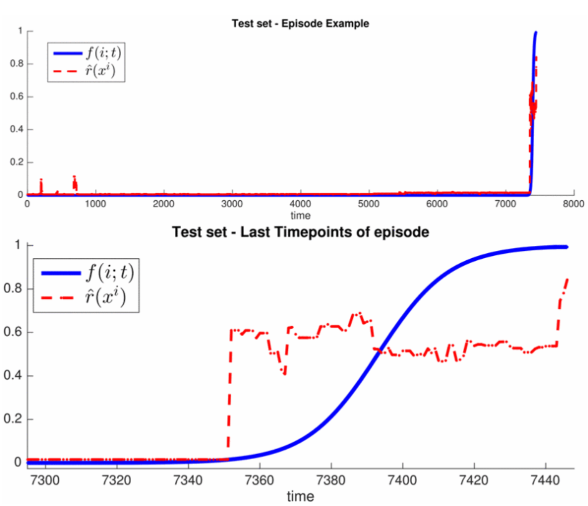

Figure 3:

Predictive Maintenance of Aircraft Engines proposed CLSTM performance against existing models.

Metrics	CNN	LSTM	Proposed CLSTM
Accuracy Rate	89.33%	97.32%	99.60%