Data Pipeline Considerations for Aviation Maintenance

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Abstract—**In the aviation space, maintenance is the main driver in the push for Internet of Things (IoT) device management systems, artificial intelligence (AI)/machine learning (ML) research, and cloud infrastructure. The potential for this approach to reduce downtime, maximize component lifetime, reduce man-hours on diagnosis and repair, and optimize supply chains and scheduling has driven massive investments across the industry. And yet, the challenges in delivering on these promises with the available data and technology should also not be minimized. To reach its full potential, maintenance program implementers must understand what predictions can be derived from the available data, what maintenance actions may be driven by those predictions, and how the predictions should be presented to the appropriate decision makers in ground operations and the logistics chain. This report examines the current state of data within the aviation maintenance space, variations in component level coverage, and how that translates to the type, volume, and timeliness of data and computational infrastructure necessary to provide *right time* predictions and analytics to maintainers, supply chain managers, and operators. This report also addresses some of the specific challenges in the aviation space with respect to data availability, equipment variability, use variability, and maintenance action coding that can affect the ability of operators to derive value from a data science program.**

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1. INTRODUCTION

To maximize equipment reliability, maintenance programs have long utilized data to predict and identify failures, estimate useful life, intelligently order parts, and select the correct timing for maintenance activities. In aviation, maintainers also rely on a combination of line checks, time- and usage-based maintenance strategies, and pilot reports to determine the appropriate actions to maximize time-on-wing. Modern computing capacity and onboard sensor capabilities permit anomaly detection and crew awareness of issues both in-flight and upon landing. The current capability to collect machine data from aviation equipment is vast with an engine capable of producing terabytes of data per flight hour. At the same time, many other types of data, both legacy and modern, exist in various forms across the aviation maintenance domain, and the extent to which data is utilized is inconsistent across the industry. The path of effective maintenance, as described in [1], suggests an alignment of ”increasingly efficient maintenance effort, realistic resources, and doing the right thing.” This paper will examine the current state of available data resources and how they are being used in the effort to do the right thing at the right time.

2. MAINTENANCE STRATEGIES AND THE AVIATION MAINTENANCE CHECK SYSTEM

Every aircraft undergoes aircraft maintenance checks to be cleared to fly, as shown in Table 1. In civil aviation, operators and airworthiness authorities such as the FAA and EASA review boards together determine an operator's Continuous Airworthiness Maintenance Program. The maintenance inspection programs are derived from a combination of original equipment manufacturer (OEM) recommendations as well as operator and authority experience.

Aviation Maintenance Check System

In addition to the pre- and post-flight inspections, also known as line checks, there are checks that take place at regular calendar or usage intervals known as *ABCD checks* that are described in Table 1. These checks are typically defined by the manufacturer initially but can be modified by the operator in a process with the governing regulatory body. A-checks are the most frequent and can take an aircraft out of service for several hours while D-checks are a full refit of the aircraft that may take an aircraft out of service for weeks.

Table 1. Aviation Maintenance Checks

Check	Frequency	Description
Line	typically pre-flight	Minimal tools, performed at gate, visual inspection.
A	100-1000 hours or 200-300 flights	General inspection for damage or corrosion. Includes service checks. Can take a few days.
B	6-8 months	Usually takes several days. Often incorporated into A checks.
C	20-24 months	Most components inspected. Usually takes a couple weeks.
D	6-10 years	Heavy Maintenance Visit (HMV). Deep inspection and overhaul. Can take a few months.

The scheduling of maintenance activities beyond the post-flight line check requires the coordination of maintainers, aircraft, flight crews, hangars, and supply chains. This is typically a highly manual task, pulling in representatives across

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Table 2. Common Maintenance Strategies

Strategy	Description	When it is used
Reactive	Assets and Components are replaced upon failure	When it makes far more sense to replace than repair the asset and the replacement parts are easy to acquire and install.
Preventative	Perform regular checks and repairs, usually as defined by the OEM	When an asset can cause unacceptable operational disturbance when it fails or when the repair/replacement is not easy to execute due to downtime, expense, or availability. Checks must have adequate coverage of failure modes to avoid unplanned outages.
Condition-Based	Use testing and sensors to assess the current condition of the asset and make decisions about repair and replacement	High priority assets that can be tracked or sensored/monitored that have clear guidelines for technician intervention.
Predictive	Use statistics and machine learning to predict when a part is likely to fail or reached the end of its' useful life and intervene when appropriate	Critical assets that can be monitored and supported with CBM but that also possess large and well curated amounts of data suitable for model training.
Prescriptive	Predictions are used to directly drive technician action	Critical assets with mature PMx systems that have enough historical performance data and well understood connections between observed asset behavior and appropriate technician action.

all of the aforementioned groups. It is generally not optimized [2], cannot be done far in advance, and does not typically take into account condition-based or predictive alerts. Those alerts will often be addressed in an unscheduled maintenance event. Alternative approaches to manual scheduling such as one outlined in [3] exist, but have not yet found industry-wide application.

Maintenance Strategies

These types of checks are a form of preventative maintenance (PM). Several commonly employed maintenance strategies are described in Table 2 These regular inspections may be supplemented with condition-based maintenance (CBM) and predictive maintenance (PMx), which use sensor devices on subsystems of the aircraft to determine maintenance requirements or to give an estimate of remaining useful life (RUL) of a component [4]. Predictive maintenance strategies can also incorporate pieces of data outside the component in question such as data from maintenance logs, information from flight acquisition units, and fleet-wide analysis to determine if an action needs to be taken by the maintainers. Ideally, the computing required to do these tasks would be handled during the flight or in the time it takes to prepare the aircraft for the next flight to maximize on-time departures and minimize downtime.

3. Data from Wing to Hangar and Back

Today, many modern computing technologies have been incorporated into aviation maintenance. Sensor networks, mobile ”smart” devices, and ERP systems were outlined as highly suited for aircraft maintenance by [5], and are now commonly seen across many commercial operators. This newer, highly structured data can exist alongside data available from older methods of reporting such as manually-entered sensor observations as well as legacy data such as handwritten maintenance logs and inspection reports. A comprehensive approach to the data must take into account availability as well as the quality, quantity, and utility when driving a maintenance action.

Data flows through an aircraft maintenance hangar from onboard sensors, maintenance logbooks, inspection drones, ”smart” toolboxes, imagery from structural inspection reports, handheld Bluetooth-enabled sensors that commercial carriers are beginning to adopt, and the ERP systems for managing part supply chains. Much of this data could be used to augment a maintenance program and has been applied to varying degrees. In addition, data systems in the aviation space typically accommodate vast quantities of historical information from past inspections, but it can be challenging to get it out in a useful format from legacy systems and often requires extensive conditioning to be usable.

4. Data Challenges: Availability, Quality, Usability

When considering the strategies that are available to the data science team for an aviation maintenance system, a major consideration will be the availability, quality, and usability of the data. There are many situations in which potentially available and useful data is either not collected in a usable way or is not appropriately connected to other data sources. One simple example is data from handheld sensors such as tire pressure gauges. Typically, data taken from these sensors are not consistently entered into any system of record as it is often meant to be a very quick check. It is left to the individual maintainers to decide if a reading is necessary and relevant to record as is shown in Table 3. There are efforts to convert some of those sensors into smart sensors that can automatically enter readings into a database, but currently, tire pressures in commercial aviation are using the more traditional approach and tire pressure is often not recorded.

Variations in Component Coverage

The differences in data type and collection result in different kinds of challenges between components all the way to fleet level. Certain components, such as the power plant, can be highly sensored and capable of producing many terabytes of data per flight hour. This data is usually edge processed with only event data captured and recorded. Other components in the system may be generating large quantities of data. However, this data may not be captured or used in any record or, even if fully captured, may never be analyzed. This could be viewed as a potential investigation area for data analysis or as a waste of system resources. Many components in the aircraft such as structural components or consumable components such as tires may not generate any data from sensors but are monitored through regular inspection. The inspection reports may be stored as a structured form, a scanned report, or in some cases, a paper form stored in the hangar. The onboard Flight Data Acquisition Unit (FDAU) is required by regulation to capture certain aspects of aircraft flight such as time, position, heading, attitude, and critical

Table 3. Example Analysis of Tire Data Availability for Maintenance, from [6]

Stream	Type of Data	Data Feed	Completeness	Reliability
Handheld Sensors	PSI, Temp, Tread Depth	Human Recorded	Inconsistent	Low Reliability
On board Sensors	Automated warnings for low pressure	Automatic	Available in Database	Reliable
Configuration	Serial Number, Position, Hours used, Number of Cycles	Human Recorded	Available in Database	Semi Reliable
Asset/Inventory	Number in Stock, Location, Usage, Purchase logs	Software processed and recertified during inspection/inventory	Available in Database	Semi Reliable
Operational Data	Pilot assignment, Technician servicing tire	Automatic/Sensor	Available in Database	Reliable
Schedule	Airport locations and dates	Automatic	Available in Database	Reliable
Maintenance History	Maintenance shop data, Installation dates, Maintenance records, Purchase logs	Human Recorded	Available in Database Position of tire change not consistently recorded	Semi Reliable

control parameters. These are required by law to only be kept for a limited amount of time; the retention of these artifacts after that time period is not guaranteed to be consistent.

Issues Within Sensor Data

A typical commercial airliner contains sensors for fuel, oil, hydraulics, air and vertical speed, engine status, torque, flow, proximity, lift and load, navigation, and position both of the aircraft and components. The number of sensors keeps increasing, with many modern aircraft possessing thousands of sensors, sometimes within a single component. While this may represent the purest form of data to use to analyze RUL on aircraft components, there can be issues within the sensor data that can complicate its use.

Sensors on aircraft exist in a highly dynamic environment, where exposure to the elements and damage from routine operation may go unchecked, especially if the sensor failure on its own does not generate alerts. In addition, failed or corrupted sensors may be so difficult to repair/replace that they may either be left on the aircraft and understood to be flawed, or initiate the removal and possible replacement of many other components due to how difficult it can be to access the sensor on the aircraft.

One example of corrupted sensor data is described in [7], where issues with sensor dropout on the 4G accelerometers that feed the Integrated Vehicle Health Monitoring System (IVHMS) they use may result in unnecessary major component replacement. They identify a method of using the remaining sensor signals to reconstruct the missing signal using deep neural networks. However, this solution cannot necessarily be extended to all IVHMS sensors and is limited by both the size of the training set and the lack of even distribution of flight regimes in the training set.

For obvious safety reasons, aviation sensor data will overwhelmingly consist of data in routine operation and in particular flight regimes (straight and level) rather than in anomalous behavior. This is bias that may also cause issues in models due to the dearth of abnormal, but important behavior as well as infrequent, but normal activities that may not be properly addressed within models trained against it. In these cases, synthetic data may be required to enrich the training set.

Sensor data may seem straightforward and obvious at the outset, but in many cases the interpretation of the sensors, how degradation and damage affects the overall data profile, and operational use cases missing due to dataset bias is often best interpreted by the combination of the data science team, maintainers, pilots, and other subject matter experts.

Data from Maintenance and Support Teams

The maintenance and hangar support teams generate many data streams on their own. The hangar will have orders and invoices for parts and consumables. Maintenance teams will keep time sheets, logs, inspection reports, and compliance documents and reports, some of which only exist in paper form. Some operators have also begun using smart tool and tool management systems that send data and tool usage information straight to a database.

Inadequate job coding can hinder a predictive maintenance program. Historical maintenance actions can be used for a variety of purposes in both condition-based and predictive maintenance, but in many cases, the classification of such actions can be inconsistent or contain information inadequate to assess condition. One example is that of tire changes. In investigations across multiple maintenance programs, we have observed that the position of the tire change is not always recorded. This makes it impossible to determine the RUL for any individual tire as well as preventing a calculation of mean time between failure (MTBF) in fleet-wide statistics. Many RUL prediction techniques are limited to applications with fixed operating conditions and adequate underlying data structure to capture those conditions may not be present to train a machine learning model. However, there are some techniques that can be used to overcome these deficiencies [8].

Another issue within maintenance data is that in aviation, many components are replaced before failure [9]. This can be due to many factors, such as replacements at convenient times during an inspection or while at a maintenance facility, or replacement due to its removal in the effort to access a different component. These factors may not always be considered in analysis of RUL and can affect the resultant fleet metrics.

Fleet Analysis and Model Development

Fleet analysis is a powerful tool in maintenance. Comparing the operations and maintenance actions of aircraft against one another is critical to understanding the drivers of costs in terms of delays, manpower, repairs and operation across the life cycle of an aircraft. Mofokeng [10] identified that the most dominant factor driving cost was flight hours, but that each aircraft performs or fails differently depending on its inherent design and how it is operated.

Within a particular airframe under a single operator, a uniform fleet becomes heterogeneous due to retrofits and upgrades applied at different times due to differences in usage, wear, or damage. This can complicate efforts to baseline and characterize fleet health due to the variation within the population. Heterogeneity can also cause unforeseen complications in data as replacement components may add new or changes to existing data streams that may not be reflected in the system of record. The system of record may not also be updated to take advantage of sensor data that comes online as newer components replace unsensored legacy components. This misses a monitoring opportunity that could remain overlooked for years.

Large operators of aircraft, both on the commercial and military side, can leverage their institutional datasets for model training and development. One such example is described in [11], where the data science team at FedEx leveraged an intimate understanding of their own fleet to develop predictive models for hundreds of aircraft components on their aging MD-11 and MD-10 fleet. These aircraft do not possess many sensors, so they utilized the data from their maintenance records to develop models using survival analysis that permitted them to estimate RUL on component families without using sensor data, allowing them to schedule maintenance for planned remove/replace instead of experiencing an unscheduled departure delay. Survival analysis has also been used in the development of digital twin models for the estimation of RUL [12]. Another example of leveraging a large historical dataset for predicting failure is described in [13], where post flight reports were used rather than time series data to predict component failure.

For smaller operators, developing such a large, diverse, and well-understood dataset is not possible, and for them some services and datasets have started to emerge that have the potential to be utilized for maintenance analysis. One such example of a training set and study is the NGAFID Maintenance Classification (NGAFID-MC) dataset. This dataset consists of thousands of labeled flights from flight data recorders. Several recent examples of analysis on this dataset include classifying approach type [14], differentiating between pre and post maintenance flights with convolutional transformers [15], and event detection [16].

There are also several commercial vendors that provide flight data monitoring and analysis. These vendors can build up a similar set of flight data as a large provider and offer insights from it to smaller operators, but may not be able to integrate it with the knowledge of the maintenance and operations as a large operator.

Data Curation

For many mid- to large-scale operators, flight maintenance data records can reach back years, sometimes decades, through retrofits and upgrades in both onboard sensing technology and computer systems. This can represent a major curation hurdle for a maintenance data science team, as they will have to negotiate changes in formats, technician coding, and data structures. Over the years, historical data may become degraded due to past efforts to clean and restructure systems and the meanings behind technician actions and codings may become lost. The data science team may either decide to undertake the effort to reconstruct or write the data off as unusable.

5. Applications and Pipelining

Determining an appropriate data pipeline for the quantities and types of data flowing through an aviation maintenance program requires a consideration of the application for which it is to be used and in particular, the timeliness that each application demands. Certain applications, such as making determinations of alerts in flight, must have very fast turnarounds and demand edge computing where other applications, such as maintenance scheduling or procurement optimization, may only require weekly or even quarterly reports.

Maintenance Programs

The flow of data through a maintenance program for even a midsize operator can involve hundreds of people, including not only the data science team, but the component teams for each airframe, OEMs, replacement part vendors, procurement teams, scheduling, and supply chain. Figure 1 outlines a common organizational flow for a maintenance system.

In this flow, the data science team negotiates with subject matter experts across all the teams to identify the most effective ways to use the available data. Effectiveness in this case can also include factors such as timeliness of data conditioning and output. Some analytics, such as ones dealing with inflight anomaly detection are, by necessity, handled in flight with resulting flags and alerts downloaded at a base station by a technician once on the ground. Other analytics may be required to run in the timespan of how long it takes to turn the aircraft around (i.e. prepare for the next flight), limiting the amount of data that can be moved off the aircraft to a cloud based solution. By contrast, maintenance scheduling analytics may only need to be run daily or weekly, and supply chain and procurement analyses may only require execution every month to every quarter. These factors will help determine where the analysis will take place, be it on an edge device located on the aircraft, in a base station in the hangar, or in a cloud based solution.

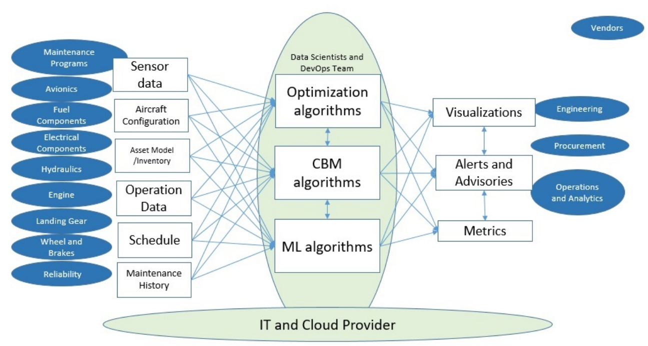

Figure 1. Organizational Flow of Information through Aviation Maintenance system

Connecting Systems

In many cases, the data for a full analysis may not reside within a single system. In this case, connecting systems of varied vintages, levels of sophistication, and curation will provide an additional challenge. These systems may reside within different groups of an organization operating at different levels of technological sophistication. Some of the challenges encountered may be needing to keep up with any format changes made in a legacy system, necessitating multiple imports, and a lack of support if the legacy maintainers are not a part of the new project.

An additional consideration for the integration of multiple systems for a unified data pipeline is the time requirements. Real-time and near real-time task pipelines demand more sophisticated computing capabilities than batch processing run at a less regular cadence. Some legacy systems may be based on technologies that do not support easy or rapid data extraction. Therefore, it may be necessary to consider either excluding data from these systems from the (near) real-time computations or investing in extract, transform, load (ETL) teams to translate the data into a format that can be utilized by the newer pipeline.

Incorporating Analog Data

In the context of aircraft maintenance, there is a fair amount of textual data that may or may not be considered for incorporation into the predictive maintenance pipeline. To incorporate these into a predictive maintenance data pipeline requires additional considerations of the operators abilities. Typically, a transition to an electronic method of capturing traditional logbook data would be ideal for the most seamless avenue of incorporation.

However, if conversion to an electronic process isn't feasible, the operator will need to consider the cost of resources to scan in the handwritten data or the impact excluding this data may have on the system's ability to predict as a whole. As discussed earlier, tires are a good candidate for this type of component that may only have handwritten logs and no sensors. The most practical option in these cases may be to obtain historical data for training where possible for the purposes of survival analysis and developing some heuristic of expected time to failure without expanding to the extent of ongoing incorporation of analog data into the pipeline.

Incorporating Third Party Data

It may be necessary to incorporate data from a third party. In the case of aircraft predictive/prescriptive maintenance, this may take the form of sensor data or vendor data.

For sensor data, the scope of this task will largely depend on how many sensors are included within the system. Every sensor will often have its own application programming interface (API) and means of obtaining data and these will have to be considered and factored into the pipeline's development. Some legacy sensors may have not considered pipeline considerations and it can be anticipated that some APIs will not meet the requirements for incorporation into a modern data pipeline.

Data Transformation

Once all necessary systems are incorporated into the pipeline and data is available, an additional challenge will be determining which data is necessary to the goals of the predictive maintenance system being designed. In the design of the pipeline, considerations must be made with regards to what sensor data is absolutely necessary and the cost/benefits of pursuing resolution of any missing/corrupted data versus removing same from consideration.

Beyond the challenges with the data itself, pragmatic elements must be considered, such as dimensionality reduction and feature transformation so that the pipeline is storing the most salient data for downstream predictive maintenance applications. The techniques for dimensionality reduction and feature selection/transformation vary widely depending on the context and scale of the system being designed. All stakeholders will often need to be consulted to ensure the data is transformed in such a way that the downstream applications run seamlessly without any performance loss.

Data Storage

The final step in most data pipelines is the storage of the data for consumption by the downstream predictive maintenance applications. Here, the choice of technology will oftentimes be driven by the scope of the system being developed.

Some components of an aircraft predictive/prescriptive maintenance system may be in real or near-real time. For example, if the system receives an event from a prior flight and the aircraft is soon to depart on another flight but that event triggers a need for an immediate check. Prior to the aircraft departing, the system must be able to scan the incoming data from the prior flight, determine if there are any critical alerts and if so, communicate these to the maintenance crews for immediate intervention. The data needed for these systems need to be stored in easily accessed "hot storage."

Conversely, there may be some components of the system that only run periodically, such as supply chain/inventory forecasting. Data critical to these systems such as vendor delivery times or typical inventory levels may be stored in "cold storage." This hot vs. cold storage consideration will play a large factor in the determination of where and how to store the data. As discussed in [17], there are significant cost considerations in the types of storage used and careful determinations on this front can have a big impact.

Server Considerations

Once the data pipeline is built, another decision point must be with regards to where the pipeline will be served from. As seen in Table 4, there are a number of capability differences that the operator must consider both within the context of their resources as well as the demands and scale of the predictive maintenance system.

Table 4. On Premises vs. Cloud - Selected Comparisons

Capability	On-Premises	Cloud
Cost	Large initial investment plus power and space.	Pay for resources used but price may change.
Scalability	Requires technology purchases to scale.	Easily scalable but may incur additional charges.
Reliability	Requires infrastructure and team dedicated to support.	SLA often includes 24/7/365 guarantees with history of compliance.

Most aircraft predictive maintenance systems will inherently incorporate edge computing in some capacity. Many of the sensors found on modern-day aircraft have sensors that do not retain all time series data, but rather, just the requisite event logs as designed by the manufacturer.

The main decision here is whether or not the system will be stored on-premises or on a cloud service. Some drivers in this selection will be existing infrastructure, technical workforce capabilities and knowledge based and operating costs.

6. Towards Predictions and Prescriptions

The purpose in pursuing a predictive maintenance program in aviation is primarily to eliminate unscheduled maintenance delays. Sensoring equipment and managing the data pipeline required to support the output of those sensors represents a major capital investment to those companies.

Figure 2 describes some of the most common maintenance questions grouped by level of abstraction from the aircraft. Outlining the major points of inquiry can suggest lines of investigation that may not have been obvious.

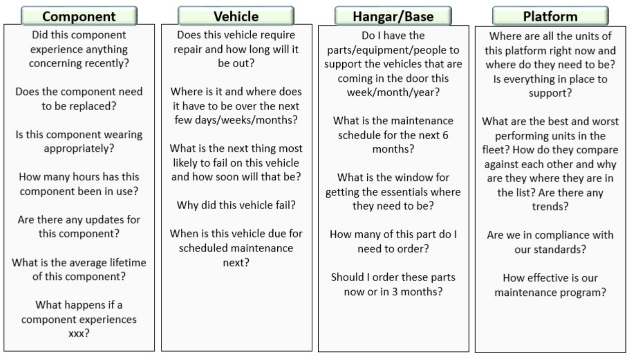

Figure 2. Common Maintenance questions arranged by level of abstraction

Component Questions

The common maintenance questions surrounding the component level of the system often address whether or not there is a benefit in sensoring the component versus allowing it to go unsensored. For example, it would be impractical to place sensors on most of the bolts/nuts/screws that fasten components to the body of the vehicle. Typically, these would be addressed in the course of other maintenance if the maintainer were to notice that they were stripped or somehow not clasping as firmly as might be expected.

However, the treatment may change in the course of design of the predictive maintenance system and pipeline if it were to be discovered in the course of data analysis that one particular fastener was complicit in most unplanned failures or flight delays. It might still not be practical to place a sensor on it, but it would be valid to consider how RUL for this piece could be conceived of to mitigate these unplanned and costly delays.

Vehicle Questions

With regards to the vehicle level of the predictive maintenance system design, while aircraft has been the focus, there are often many other vehicles to consider. This may include whether or not fueling operations or other processes need to be considered within the scheme of predictive and prescriptive maintenance.

With the aircraft specifically, fleet-size considerations will often be of practical importance for the operator and choice of heuristic. Whether or not an aircraft is out of service and for how long will be directly related to what other aircraft are available for the operator to continue operations. If it is a smaller operator, it's possible that any amount of downtime may reduce a significant amount of their capacity. Therefore, other operational considerations may need to be considered within the predictive/prescriptive maintenance scheme to accommodate these needs.

Hangar/Base Questions

At the hangar/base level, many of the considerations here are related to supply chain needs. Oftentimes, there are larger forces impacting the predictions and necessities of the system here. Are there data pipeline needs to track performance of vendors and deliveries in order to make appropriate orders for anticipated parts needed?

If it is determined that incorporating vendor data is necessary, collaboration with the vendors will often be necessary in order to seamlessly incorporate the data and obtain it in the format needed for practical applications.

Platform Questions

At the platform level, many of the more strategic and operational concerns must be considered. This is where stakeholder relations will become critical for optimal development of a predictive/prescriptive maintenance system. While most of the data pipeline is contemplated within the context of input, output must also be addressed. What actions should be captured within the system to allow for further improvement and refinements of the system?

This may also be where it is within scope to consider security requirements and standard requirements. Given the stakes of appropriate aircraft maintenance, it must be ensured that any system remains within the confines of safe operation and meeting all regulatory requirements.

7. Conclusion

Having a realistic characterization of the kinds and nature of data available in the aviation maintenance ecosystem is useful to those desiring to develop advanced maintenance programs that rely on extensive amounts of clean and structured data.

Aircraft maintainers are incorporating modern computing technologies into their operations in a drive towards less reactive and more predictive maintenance strategies. While there have been many advances in the collection of data in some highly sensored subsystems such as the engine, subsystems that rely on visual inspection and handheld sensors may not have as much coverage, which can limit options for developing an optimized maintenance strategy. Additionally, organizational limitations such as how maintenance actions are recorded can hinder the calculation of key statistics necessary for a predictive maintenance program. It requires the combined effort of maintainers, subject matter experts, and data scientists and engineers to identify and address these shortcomings in order to maximize the utility of the data.

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References

[1] J. Levitt, *Complete Guide to Preventative and Predictive Maintenance*, 2nd ed. New York, NY: Industrial Press Inc, 2011.

[2] Q. Deng, B. Santos, and R. Curran, “A practical dynamic programming based methodology for aircraft maintenance check scheduling optimization,” *European Journal of Operational Research*, vol. 281, pp. 256–273, 08 2019.

[3] Q. Deng, B. Santos, and W. Verhagen, “A novel decision support system for optimizing aircraft maintenance check schedule and task allocation,” *Decision Support Systems*, vol. 146, 03 2021.

[4] D. Azevedo, A. Cardoso, and B. Ribeiro, “Estimation of health indicators using advanced analytics for prediction of aircraft systems remaining useful lifetime,” *PHM Society European Conference*, vol. 5, no. 1, 07 2020.

[5] M. Lampe, M. Strassner, and E. Fleisch, “A ubiquitous computing environment for aircraft maintenance,” *University of St.Gallen*, 01 2004.

[6] A. Spexet, E. Tilden, S. Conley, E. Klein, K. Blond, J. LaRocco-Olsewski, and D. Alvord, “The connected hangar: Ubiquitous computing and aircraft maintenance,” in *UbiComp ’22: Proceedings of the 2022 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 2022.

[7] A. D. Harper, N. Breen, D. Alvord, D. Pendleton, and T. Hresko, “Sensor-data reconstruction for helicopter structural-health monitoring using deep learning,” ser. Smart Materials, Adaptive Structures and Intelligent Systems, vol. ASME 2020 Conference on Smart Materials, Adaptive Structures and Intelligent Systems, 09 2020.

[8] H. Liao and Z. Tian, “A framework for predicting the remaining useful life of a single unit under time-varying operating conditions,” *IIE Transactions*, vol. 45, no. 9, pp. 964–980, 2013. [Online]. Available: https://doi.org/10.1080/0740817X.2012.705451

[9] W. J.C., Verhagen, and L. W. De Boer, “Predictive maintenance for aircraft components using proportional hazard models,” *Journal of Industrial Information Integration*, vol. 12, pp. 23–30, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2452414X17300845

[10] T. Mofokeng, P. T. Mativenga, and A. Marnewick, “Analysis of aircraft maintenance processes and cost,” *Procedia CIRP*, vol. 90, pp. 467–472, 2020, 27th CIRP Life Cycle Engineering Conference (LCE2020)Advancing Life Cycle Engineering : from technological eco-efficiency to technology that supports a world that meets the development goals and the absolute sustainability. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2212827120302869

[11] R. Provence and D. Taylor. (2022, 07) Applied predictive maintenance in aviation: Without sensor data. Databricks and FedEx. [Online]. Available: https://www.youtube.com/watch?v=82KiWQqmKWU

[12] S. Heim, J. Clemens, J. E. Steck, C. Basic, D. Timmons, and K. Zwiener, “Predictive maintenance on aircraft and applications with digital twin,” in *2020 IEEE International Conference on Big Data (Big Data)*, 2020, pp. 4122–4127.

[13] P. Korvesis, S. Besseau, and M. Vazirgiannis, “Predictive maintenance in aviation: Failure prediction from post-flight reports,” in *2018 IEEE 34th International Conference on Data Engineering (ICDE)*, 2018, pp. 1414–1422.

[14] K. Karboviak, S. Clachar, T. Desell, M. Dusenbury, W. Hedrick, J. Higgins, J. Walberg, and B. Wild, “Classifying aircraft approach type in the national general aviation flight information database.” Berlin, Heidelberg: Springer-Verlag, 2018.

[15] T. D. Hong Yang, Aidan Labella, “Predictive maintenance for general aviation using convolutional transformers,” in *36th AAAI Conference on Artificial Intelligence*, 2022.

[16] A. P. LaBella, J. A. Karns, F. Akhbardeh, T. Desell, A. J. Walton, Z. Morgan, B. Wild, and M. Dusenbury, “Optimized flight safety event detection in the national general aviation flight information database,” in *Proceedings of the 37th ACM/SIGAPP Symposium on Applied Computing*, ser. SAC ’22. New York, NY, USA: Association for Computing Machinery, 2022, p. 1570–1579. [Online]. Available: https://doi.org/10.1145/3477314.3507115

[17] Y.-F. Hsu, R. Irie, S. Murata, and M. Matsuoka, “A novel automated cloud storage tiering system through hot-cold data classification,” in *Proceedings of the 2018 IEEE 11th International Conference on Cloud Computing (CLOUD)*. San Francisco, CA, USA: IEEE, 2018. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8457837

Biography

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