sparkcognition™
Maintenance Advisor

Why Machine Learning is the Future of Predictive Maintenance in Aviation

There's no arguing that preventing failures and accidents is critical for the aviation industry. Minor incidents can ground planes for extended periods of time and necessitate expensive repairs; a single day of grounding for a plane costs roughly $4-$5 million. Major incidents put pilots and passengers at risk.

Because of these disruptions, the industry is always on the lookout for newer, better maintenance methods, and the approach on everyone's radar screen at the moment is predictive maintenance. While everyone agrees on the name, there is less consensus on what it means or how to implement it. But to truly unlock the potential of predictive maintenance, it needs to be paired with artificial intelligence (AI) and machine learning (ML).

DEFINING PREDICTIVE MAINTENANCE

Different sources often use the phrase "predictive maintenance" to describe a wide range of processes, so it's important to clarify precisely what is meant by this term. Generally speaking, there are three maintenance approaches referred to as predictive maintenance: reactive maintenance, prognostics, and true predictive maintenance. However, only one of these is genuinely predictive.

Reactive Maintenance

The simplest of these maintenance approaches is reactive maintenance. This is no more than the most basic model of maintenance—an asset breaks and then is repaired. There are more streamlined methods of reactive maintenance that allow process and logistical needs to be more quickly communicated—for example, arranging for a replacement part to be ready as soon as the plane touches down—but this is still reactive rather than predictive in nature.

Prognostics

Prognostics is a type of maintenance that constructs physics-based models using engineering expertise. Those models are then used to monitor causal factors to failure, analyzing certain predefined variables and identifying patterns or correlations for a potential problem in the system. This evaluation is similar to how a medical checkup works—a trained doctor takes the measure of your heart rate, blood pressure, and other variables, combined with your descriptions, and tells you if you're at risk of any given medical condition based on certain patterns in those variables.

This approach to maintenance offers a great deal of value, but there are things prognostics just can't catch. The models it uses are too rigid, rendering them unable to function well under extreme or unusual conditions. They also can't always predict exactly when a component will fail, any more than a doctor can tell you exactly when you can expect to have a heart attack.

True Predictive Maintenance

True predictive maintenance expands on physics-based models and causal failures. It trains on historical data and then examines patterns of data across sensors, looking for indicators of impending failure.

An airline in eastern Asia implemented this technology and reduced their average maintenance interval by twenty minutes, saving roughly $40M/year.

This method is more difficult to implement than reactive maintenance or prognostics, but it's more sophisticated and flexible in the failures it's able to detect and predict. Rather than simply warning that a component is at risk, true predictive maintenance specifies exactly when and how a failure will take place. It isn't hampered by edge cases, or by changes in the components of the system, since it can learn and adapt over time.

To refer back to the medical checkup example, predictive maintenance would be akin to a doctor putting a patient in a full-body scanner that examines every aspect of the patient and can then predict, for instance, that they'll have a heart attack on June 8th. Predictive maintenance can take a far wider range of variables into account than prognostics, and deliver far more specific, accurate predictions.

THE ROLE OF ARTIFICIAL INTELLIGENCE

Predictive maintenance can be (and has been) done without the use of artificial intelligence, but AI alleviates—or even eliminates—many of the difficulties associated with the approach.

Speed and Scale

Predictive maintenance requires large amounts of data. This includes data being collected by aircraft sensors, as well as information created and collected around the aircraft, such as maintenance logs and tech notes. Contained in all this data is the knowledge operators need to understand to avoid dangerous mishaps, but analyzing it all can be daunting. Data analysis at this scale is cumbersome, requiring time and staff resources that maintainers don't have. For these same reasons, predictive maintenance done by human analysts alone also can't scale to large operations.

Artificial intelligence—and more specifically, machine learning—can unlock the insights in this data quickly, efficiently, and accurately. ML platforms analyze large volumes of data, identify anomalous behavior, and understand causal relationships using advanced unsupervised learning techniques. This system provides operators with faster insights into mishap prevention for any size of operation.

Model Upkeep

Another problem machine learning addresses is maintaining the models over time. Traditional predictive models that don't employ AI differ for individual asset types, such as aircraft classes, and even between individual aircraft of the same type. A change in even a single variable, such as a replaced part, necessitates reworking the entire model. This also applies to the normal changes a plane goes through over time as it is used; an aircraft that has been flown a number of times is not going to run the same as when it was brand new. Models will degrade in accuracy unless they're maintained.

Consider the variety and variability that exists within and between individual aircraft and classes of aircraft. A model must be created per component per configuration per aircraft type, and then these models must be constantly updated. This adds up to an unmanageable number of models and an untenable workload for operators and analysts, making these predictive models a cost drain rather than a benefit.

Machine learning models avert these problems because they dynamically learn and maintain themselves by adjusting to any component or aircraft and adapting to changes over time. This allows ML-powered predictive maintenance to overcome what is otherwise a near-insurmountable hurdle to implementing predictive maintenance for operators.

Insufficient Data

Predictive maintenance, and even prognostics, requires large amounts of data to work properly, but not all systems or subsystems have the sensors to provide that data. In fact, it's often only the newest aircraft that are outfitted with the sensors that traditional predictive maintenance and prognostics need, leaving a significant percentage of planes without access to advanced monitoring and maintenance techniques. An aircraft can be retrofitted with sensors, but this is an expensive process—often prohibitively so—and may compromise privacy of data.

Machine learning alone can't solve this dilemma, but ML-powered natural language processing (NLP) can. Most software is only able to analyze structured data, or data containing numbers or categories, which is estimated to be no more than 20% of the data produced by organizations. NLP can decipher and use unstructured data as well—be it PDFs, books, journals, audio, video, images, notes, analog data, or any other source imaginable.

This capability is valuable for aviation operators because with NLP, predictive maintenance models can use sources of data beyond sensors. This includes all manner of associated data about an aircraft, e.g., maintenance records. By extracting facts, figures, entities, and contextual data from an aircraft's maintenance history, predictive maintenance solutions outfitted with NLP find causal patterns that indicate potential failures, even in so-called dark subsystems that lack sensors.

Prescriptive Maintenance

Predictive analytics, while invaluable, is only part of the value that machine learning delivers. After all, predictive maintenance doesn't absolve operators from having to perform maintenance. Prescriptive maintenance goes beyond simply identifying impending failures by also recommending optimal courses of action. This feature allows operators to better plan maintenance in places and times where it will cause the least disruption, and where the needed parts will be available. Prescriptive maintenance also allows operators to better plan optimal distribution of parts.

The value of this capability is enormous. An airline in eastern Asia has implemented this technology, reducing their average maintenance interval by 20 minutes. In doing so, along with fewer false positives and other benefits of predictive maintenance, they've saved roughly $40 million a year.

The aviation industry is often full of uncertainty—but it doesn't have to be. Machine learning technologies are already allowing major operators to truly harness the potential of their data, enabling safer and more predictable operations.

ABOUT SPARKCOGNITION

SparkCognition's award-winning AI solutions allow organizations to predict future outcomes, optimize processes, and prevent cyberattacks. We partner with the world's industry leaders to analyze, optimize, and learn from data, augment human intelligence, drive profitable growth, and achieve operational excellence. Our patented AI, machine learning, and natural language technologies lead the industry in innovation and accelerate digital transformation. Our solutions allow organizations to solve critical challenges—prevent unexpected downtime, maximize asset performance, optimize prices, and ensure worker safety while avoiding zero-day cyberattacks on essential IT and OT infrastructure. To learn more about how SparkCognition's AI solutions can unlock the power in your data, visit www.sparkcognition.com.