This literature review explores Digital Twin technology for predictive maintenance, focusing on Remaining Useful Life predictions. Motivated by my experience in the aviation industry and its need for accurate spare parts forecasting, this study evaluates recent advancements in deep learning, especially Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN).

Literature Reviw of Digital Twins and Remaining Useful life

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# Introduction:

Digital Twins (DT) are virtual representations of physical systems bridging the digital and physical worlds, playing a crucial role in predictive maintenance. As a demand planner in aviation, I forecast spare part requirements for airlines and maintenance facilities, motivating my keen interest in accurately predicting the Remaining Useful Life (RUL) of parts. Predicting failures proactively is essential, as it allows maintenance actions to be scheduled efficiently, reducing unexpected downtime and costs.

This literature review will explore the best way to use Digital Twins in predictive maintenance, specifically focusing on the integration of deep learning techniques such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN). Using Python for data preprocessing and Power BI for visualisation, my project intends to establish a clear analytical pipeline using the NASA C-MAPSS turbofan dataset. By examining current methodologies to see which is best, industry implementations, and visualisation strategies, this review aims to provide comprehensive insights into how predictive analytics, powered by Digital Twins, can effectively forecast remaining useful life.

# Literature Review and Discussion:

On the literature review, I first started by researching digital twins as we must establish what they are and what they are not, as in knowing what it is will allow us to better understand in establishing what algorithms or machine learning techniques are best suited in predicting remaining useful life.

## What is a Digital Twin

It took me a long time to fully grasp the concept of a digital twin, but the IBM video on digital twins on YouTube (*What is a Digital Twin*, IBM, 2021) helped point me in the right direction. In my own words, I would describe a digital twin as a dynamic system that continuously ingests real-world data, interprets its implications, and applies various computational models—ranging from physics-based simulations to data-driven machine learning approaches—to predict and optimise future performance (Horn, 2023). By integrating historical and real-time data, digital twins enable organisations to anticipate potential failures, improve efficiency, and test operational strategies without directly impacting the physical asset (AIAA & AIA, 2021). Furthermore, once real-world data is entered into the digital twin, several options become available. We can optimise current performance using predictive analytics or leverage simulation capabilities to explore different future scenarios.

One essential characteristic of a digital twin is that it must continuously receive data from the physical product it is replicating. This ongoing synchronisation ensures that the digital twin accurately reflects the state of its physical counterpart, allowing for reliable monitoring, diagnostics, and forecasting. The frequency of these updates depends on the nature of the product and its application, with high-precision industrial and aerospace twins often requiring real-time data integration (Hehman, 2023).

Throughout my readings on digital twins, I frequently encountered the name Dr Michael Grieves, who is credited with pioneering much of what we now recognise as digital twin technology. His work primarily focused on product lifecycle management, highlighting how digital twins could be used to optimise an asset from design to decommissioning (Durgut, 2024). This made me realise that while the foundational idea existed earlier—as seen in NASA's use of similar concepts during the Apollo missions (*FoundTech: Legacy of Apollo*)—it was Dr Michael Grieves who formally structured and standardised the digital twin concept into a practical framework that industries could adopt. His contributions provided a foundation for modern applications, ranging from manufacturing to aerospace, solidifying the role of digital twins as essential tools for innovation and operational efficiency (Digital Twin Consortium, 2023).

## Prognostic and Health Management

Prognostics and Health Management (PHM) is a data-driven and model-based approach designed to monitor, assess, and predict the health condition of an asset or system. The primary goal of PHM is to detect early signs of failure, estimate Remaining Useful Life (RUL), and support decision-making for maintenance and operations. By leveraging sensor data, machine learning, and physics-based models, PHM helps organisations implement predictive maintenance (Pd.M.), thereby minimising downtime, reducing costs, and improving safety (Kalgren et al., 2007).

* PHM typically consists of six key functions:
  + Sensing and Data Acquisition – Collecting real-time operational data from sensors.
  + Feature Extraction – Identifying meaningful indicators of degradation.
  + Health Assessment – Evaluating the current condition of the system.
  + Prognostics – Predicting future states and estimating RUL.
  + Decision Support – Providing recommendations for maintenance and operations.
  + System Adaptation – Refining the PHM model based on new data (Vachtsevanos et al., 2006).

### History of PHM

It is fascinating to see how PHM evolved by integrating traditional maintenance strategies with emerging technologies. Condition-Based Maintenance (CBM), which has been in practice for over 60 years, laid the foundation for PHM. Early discussions on incorporating sensor data into CBM techniques can be traced back to Hess et al. (2003). These discussions emphasised the need for real-time data collection to enhance predictive maintenance capabilities.

From the 2000’s onward, rapid advancements in computing power have further accelerated the adoption of PHM. Industries have leveraged big data analytics, artificial intelligence, and cloud computing to refine maintenance strategies and optimise Remaining Useful Life (RUL) predictions. Additionally, this period marked the rise of industry standards, signalling the field’s growing maturity. Organisations like SAE International and IEEE (ISO 13374, 2012) played a crucial role in developing PHM standards, ensuring consistency and widespread adoption across industries. Researchers such as Lee et al. (2014) have further highlighted how PHM integrates with Industry 4.0, digital twins, and real-time monitoring to improve asset reliability and performance.

The continuous evolution of PHM demonstrates its growing importance in predictive maintenance and asset management, driven by technological advancements and industry-wide collaboration.

## Remaining Useful life

My project focuses on exploring which algorithms or machine learning techniques are most effective in predicting Remaining Useful Life (RUL). Additionally, I aim to present and explain these concepts as I progress, using strong visual aids to enhance clarity. However, before diving into specific methodologies, it is essential to establish what exactly is meant by Remaining Useful Life, as this concept can have multiple interpretations. For instance, an aircraft engine under inspection may have a projected operational lifespan of another year, but economic considerations might dictate an earlier replacement to optimise operational efficiency and cost-effectiveness (Wu et al., 2024). In contrast, some components are designed to be used until complete failure, maximising their full operational life. This variability in RUL application highlights the importance of defining it in context, ensuring its calculation aligns with both engineering reliability and economic feasibility (Thakkar & Chaoui, 2021).

**Definition**: (RUL)

Remaining Useful Life (RUL) is the estimated time span an asset can continue to operate before failure or the need for replacement occurs (Remaining Useful Life Prediction Based on Deep Learning: A Survey). RUL is a concept rooted in predictive maintenance and prognostics, aiming to strike a balance between preventing failures and scheduling maintenance or replacement without wasting useful service life. (Kalgren et al 2007)

I have always found historical perspectives valuable in understanding concepts more clearly. As I explored the literature, it became evident that maintenance strategies originally followed fixed schedules—like how cars in the UK require an MOT check annually, or how aviation regulators mandate overhauls every 10 years. However, these scheduled maintenance intervals did not guarantee the elimination of failures. A car can still break down between MOT periods, and an aircraft component might require replacement before or after an overhaul cycle. This inefficiency led to wasted resources, as failures could sometimes have been anticipated and addressed earlier. This needs to optimise maintenance intervals and reduce unnecessary costs led to the rise of Prognostics and Health Management (PHM)—an approach inspired by the healthcare industry but widely applicable in Industry 4.0 and manufacturing. By the early 2000s, standards and research in PHM began to formalise the term Remaining Useful Life. For instance, Kalgren et al. (2007) introduced standardised PHM terminology, explicitly defining RUL as the predicted time to failure of a component.

### Methods for Calculating RUL

There are several ways to estimate RUL, each depending on the available data and the desired accuracy:

* Using lifetime data: This method relies on historical failure records and time-series analysis to predict an asset’s expected lifespan.
* Using run-to-failure histories: By analysing past degradation trends, models can compare the current state of an asset to previously observed failure patterns.
* Using condition thresholds: If a failure threshold is defined (e.g., vibration exceeding a critical limit), RUL is estimated based on the asset’s current state and the projected time until it crosses that threshold.

### Common Algorithms for RUL Prediction

Different types of models are used for RUL estimation, broadly categorised as follows:

* Physics-based (model-based): These rely on physical degradation models, such as crack growth or wear equations, to estimate remaining life.
* Data-driven models: These include:
  + Regression models – Statistical approaches that use historical trends to predict failure time.
  + Machine Learning – Algorithms such as neural networks, random forests, and support vector machines, which learn from sensor data to estimate RUL.
  + Survival analysis and hazard models – Statistical models that predict failure probability over time.
* Hybrid approaches: These combine physics-based models with data-driven techniques, leveraging both engineering knowledge and machine learning to improve accuracy.

The choice of algorithm depends on the context. For well-understood components with consistent failure modes, physics-based models or simple regression may suffice. However, for complex systems with large volumes of sensor data, advanced data-driven techniques are often more effective. Regardless of the approach, ensuring that the model can adapt to different operational conditions and account for uncertainty is a crucial consideration in RUL modelling.

Having established a good grasp of what a digital twin and what RUL life is and seeing a bit of history of how it has come about now we can move on to the meat of our literature review, which is as our stated goal is understand what techniques are best for predicting remaining useful life, so we must see what the literature have about these techniques.

## Time Series Analysis

Since we are predicting Remaining Useful Life (RUL), we are essentially performing a time series analysis, making it an important concept to understand before moving forward.

**Definition:**

Time series analysis is a statistical technique used to analyse sequential data points collected over time to identify patterns, trends, and relationships (Box et al., 2015). It is widely applied in forecasting, anomaly detection, and signal processing.

I find it particularly interesting that, as a demand planner, I routinely perform time series analysis by analysing historical demand, applying different forecasting algorithms, and generating predictions for future trends. The same fundamental principles apply when predicting RUL, as both involve analysing past data to anticipate future outcomes.

To illustrate this in our project, let’s consider a simple example: imagine we have a sensor measuring an engine’s temperature every second. This sensor data forms a time series. By analysing the recorded temperature values over time, we can identify patterns, predict future fluctuations, and detect anomalies that may indicate potential failures. This predictive capability is crucial in maintenance planning and failure prevention, making time series analysis a core element of our approach.

## Machine learning

For predicting the Remaining Useful Life (RUL) of a digital twin, we will be utilising machine learning (ML). Before diving into specific techniques, it is essential to establish what machine learning is. One of the most straightforward definitions comes from W3Schools:

*“Machine Learning is making the computer learn from studying data and statistics. Machine Learning is a step into the direction of artificial intelligence (AI). Machine Learning is a program that analyses data and learns to predict the outcome.” (W3Schools, Machine Learning)*

While this definition provides a strong foundational understanding, at a higher academic level, we require a more systematic and technical definition:

*“Machine learning is a subset of artificial intelligence that focuses on developing algorithms and statistical models that enable computers to learn from data, recognize patterns, and make predictions without being explicitly programmed.” (Goodfellow, Bengio & Courville, 2016)*

The key aspect that stands out to me in both definitions is the idea that machine learning models can uncover insights and make predictions without explicit programming, even identifying patterns that might go unnoticed by human analysts.

***The Shift from Traditional Methods to Deep Learning***

Earlier methods for RUL prediction heavily relied on regression models and decision trees. While effective to some extent, these models required extensive domain expertise to fine-tune parameters and coefficients, and they struggled to handle nonlinear relationships in complex datasets (Thakkar & Chaoui, 2022). As datasets grew and complexity, these traditional approaches became increasingly hard to work with.

This challenge led to the evolution of deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks.

Deep learning has been transformative for digital twins, allowing for hierarchical feature extraction, enabling automatic pattern recognition, and improving predictive capabilities in time-series data (Li et al., 2024). For example, CNNs excel at capturing spatial relationships within sensor data, while LSTMs are highly effective for handling long-term temporal dependencies (Hochreiter & Schmidhuber, 1997). Their combination has proven particularly powerful for RUL estimation in aviation digital twins, such as those leveraging NASA’s C-MAPSS dataset (Wen, Dong & Gao, 2019).

### Key Machine Learning Models for RUL Prediction

* Convolutional Neural Networks (CNNs)
  + Definition: CNNs are deep learning models that process data with a grid-like topology (such as time-series data) using convolutional layers to extract hierarchical features (Li et al., 2024). They have been widely used for image classification, object detection, and pattern recognition, but have also been adapted for time-series analysis and RUL prediction.
* Long Short-Term Memory (LSTM) Networks
  + Definition: LSTMs are a type of recurrent neural network (RNN) specifically designed to learn from sequential data by retaining long-term dependencies. Unlike traditional RNNs, LSTMs mitigate the vanishing gradient problem using gating mechanisms (Hochreiter & Schmidhuber, 1997).
* CNN-LSTM Hybrid Models
  + CNNs and LSTMs can be combined to leverage the strengths of both. CNNs extract meaningful spatial features, while LSTMs capture temporal dependencies. This hybrid approach has demonstrated superior performance for RUL prediction (Muthukumar & Philip, 2024).

## Discussion and synthesis

the exploration of digital twins, prognostics and health management (PHM), and machine learning has highlighted the evolving landscape of predictive maintenance and Remaining Useful Life (RUL) estimation. This section synthesises key findings, drawing connections between theoretical frameworks, technological advancements, and practical applications.

Digital twins provide a dynamic, data-driven representation of physical assets, facilitating real-time monitoring and predictive insights. One key characteristic of a digital twin is its continuous synchronisation with its physical counterpart, ensuring accurate diagnostics and forecasting. This aligns well with the broader principles of PHM, which aims to enhance asset reliability through sensor integration, predictive modelling, and adaptive maintenance strategies (Kalgren et al., 2007). The synergy between digital twins and PHM has been reinforced by the emergence of Industry 4.0 technologies, such as cloud computing, artificial intelligence, and the Internet of Things (IoT) (Lee et al., 2014).

### Machine Learning and RUL Prediction

As industries transition from traditional maintenance strategies (such as scheduled overhauls) to more adaptive and intelligent maintenance approaches, machine learning has played an increasingly vital role in enhancing digital twin capabilities. The shift from regression models and decision trees to deep learning architectures has enabled greater automation and scalability, particularly in complex time-series environments (Thakkar & Chaoui, 2022). This transition is particularly evident in the aviation industry, where NASA’s C-MAPSS dataset has been widely used to benchmark RUL estimation models (Wen, Dong & Gao, 2019).

Two of the most impactful deep learning techniques used in digital twins for RUL prediction are Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. CNNs, initially designed for image recognition, have proven effective for feature extraction in time-series data, while LSTMs, a form of recurrent neural network (RNN), excel in capturing long-term dependencies within sequential data (Hochreiter & Schmidhuber, 1997). These two approaches, when combined into hybrid CNN-LSTM models, have demonstrated superior performance in predicting degradation patterns and estimating RUL (Muthukumar & Philip, 2024).

### Comparative Insights

* Traditional Models vs. Deep Learning: While regression-based and decision tree models have historically been used for RUL estimation, they require extensive manual feature engineering and struggle with nonlinear relationships in sensor data. In contrast, deep learning models can automatically learn hierarchical features, reducing the need for domain expertise while improving accuracy.
* CNN vs. LSTM: CNNs are particularly strong in detecting spatial relationships across sensor channels, making them effective for pattern recognition in multivariate time-series data. However, CNNs lack an inherent mechanism for capturing long-term dependencies in sequential data. LSTMs, on the other hand, specialise in maintaining historical context, making them better suited for analysing gradual degradation trends over extended time horisons (Li et al., 2024).

# Gaps and Future Direction

Throughout my review, I noticed that despite advancements in deep learning methods, particularly CNNs and LSTMs, several challenges persist. One notable gap is the limited focus on the real-time applicability of these models in operational environments. Many studies I've examined predominantly use historical data with limited consideration of real-time sensor integration and data streaming constraints, critical factors in aviation predictive maintenance.

Additionally, there is insufficient exploration of model interpretability and application in the work environment, crucial for practical implementation in highly regulated industries like aviation, where decisions based on predictions must be transparent and justifiable. Existing literature often emphasises prediction accuracy, overlooking interpretability and explainability, potentially limiting real-world adoption.

Future research should address these gaps by integrating explainable AI (XAI) methods within CNN-LSTM hybrid frameworks. I propose further exploring lightweight model architectures capable of real-time analysis while maintaining high predictive accuracy. Additionally, my practical work will test these methods' robustness under varying operational conditions using the NASA C-MAPSS dataset, ultimately aiming to bridge theoretical research and practical deployment. Addressing these gaps will significantly enhance the reliability and acceptance of digital twins in predictive maintenance applications.

# Conclusion

In conclusion, I believe the research conducted thus far provides a strong foundation for completing my project effectively. This exploration has demonstrated that the topic of digital twins, prognostics and health management, and machine learning is both exciting and rapidly maturing, particularly within the context of Industry 4.0. We have entered a period in which innovative machine learning techniques have the potential to revolutionise predictive maintenance practices significantly.

Through the literature reviewed, we have observed the evolution from traditional maintenance methods toward more sophisticated and predictive approaches that utilise advanced algorithms such as CNN and LSTM. This transition is especially evident in applications aimed at accurately predicting Remaining Useful Life (RUL). Given the insights gathered from this literature review, I am confident we are now well-positioned to advance into the practical application phase of the project, exploring and identifying which machine learning techniques will best predict RUL in digital twins and its interpretability within the work environment.

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