ARTICLE FEATURED ON:
INNOVATIE NU | DECEMBER 2020

PREDICT THE UNPREDICTABLE

Authors:

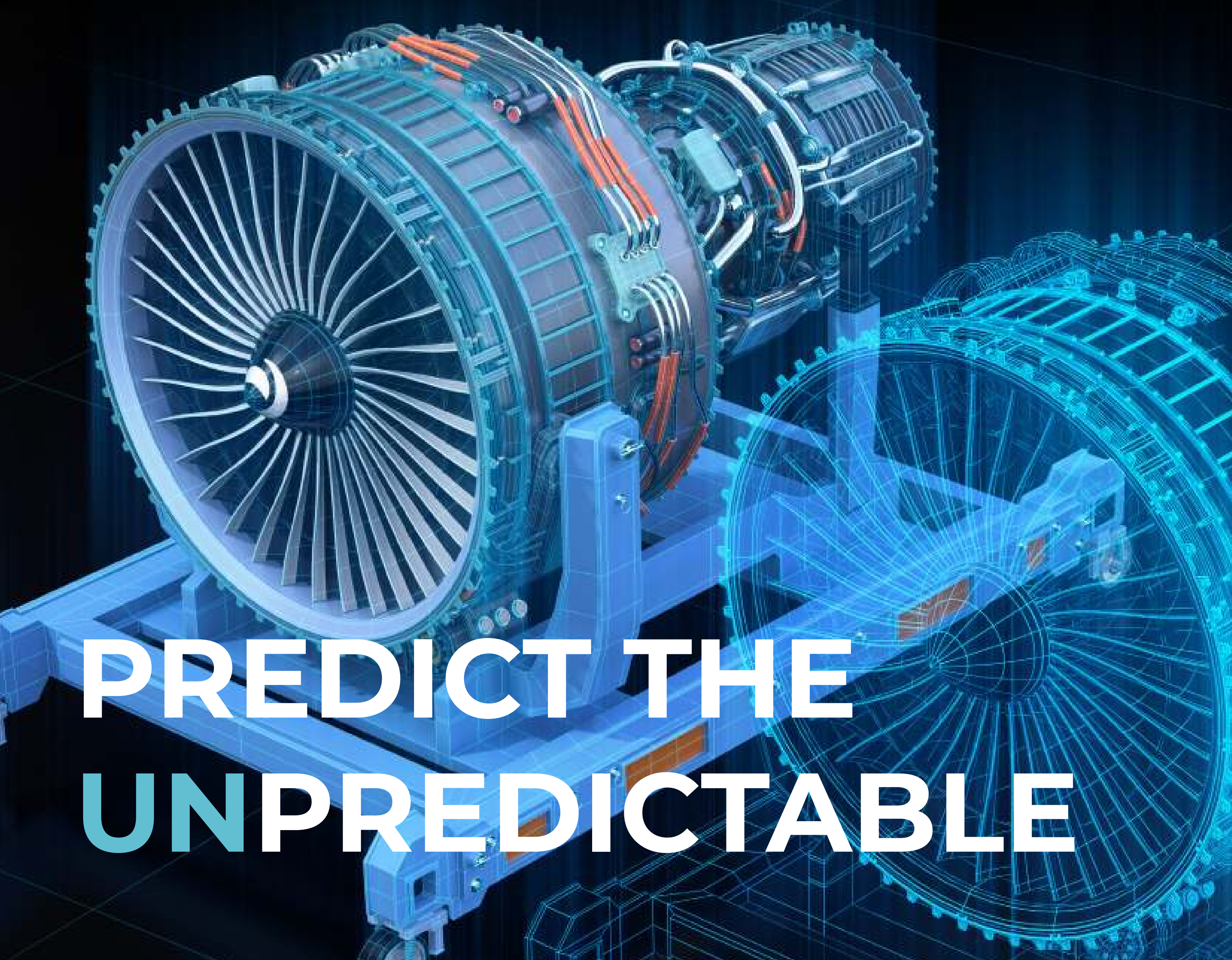
Maaike Slot

Research Engineer
Fraunhofer Project Center at
the University of Twente

Gijs Beumkes

Research Engineer
Fraunhofer Project Center at
the University of Twente

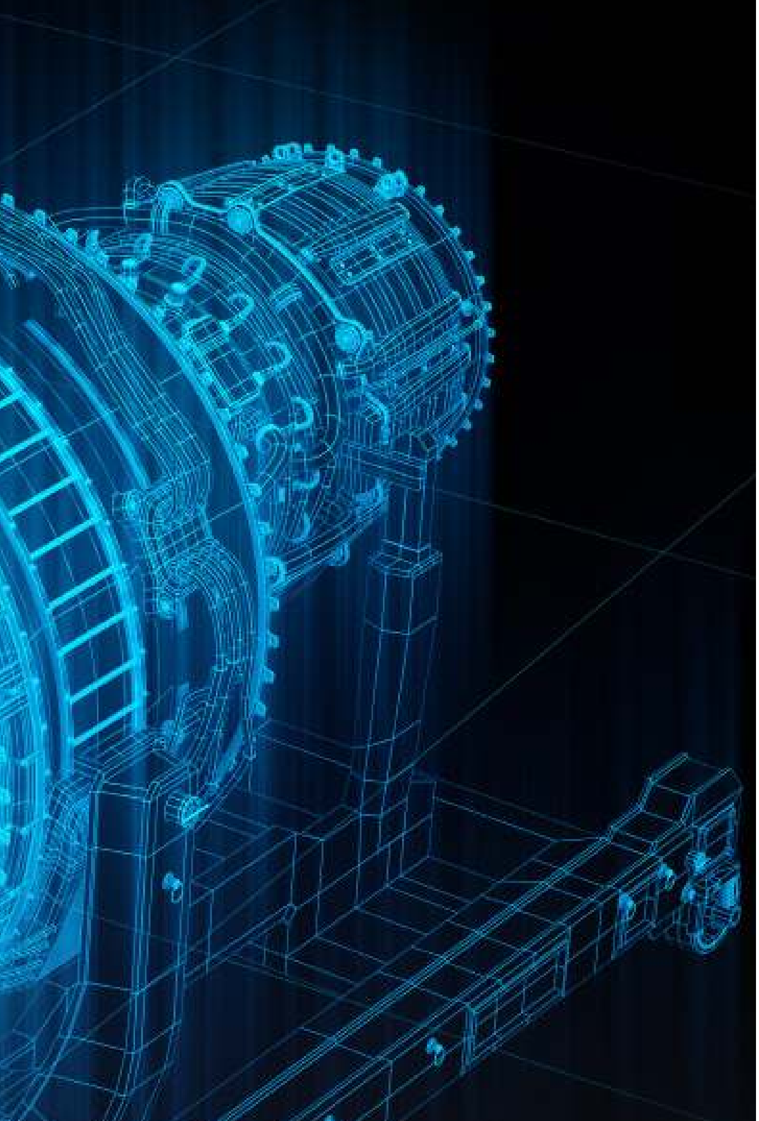
ADVANCED
MANUFACTURING
CENTER



PREDICT THE UNPREDICTABLE

Industries are relying more and more on machines and tools of high complexity. When relying on high complex machines the unexpected failures and downtime costs can have a high impact and result in high costs. Therefore, these machines and their components should be maintained properly to avoid unexpected failures and reduce downtime costs.

Nowadays, sophisticated diagnostic methodologies are available to improve the maintenance. The use of methodologies, such as the commonly known Failure Mode and Effect (and Criticality) Analysis (FME(C) A), enables the identification of the potential failures and prioritize them such that corrective actions can be taken. However, most of the maintenance actions performed today are on a reactive basis: The maintenance actions are performed when the fault has already occurred; therefore, downtime is not prevented. To perform maintenance actions in a **proactive** way, a shift from the traditional fix-it-when-broken (diagnostics) to a predict-and-prevent (prognostics) methodology is required (e.g. predictive maintenance). This allows industry to be more aware of the health status of their machines, components, and tools.



> **DIGITAL TWINNING CAN IMPROVE THE UTILISATION OF PREDICTIVE MAINTENANCE THROUGH MEANINGFUL TARGETED INFORMATION EXTRACTION.**

Prognostic and Health Monitoring is a methodology focused on predicting the time a component will no longer fulfil its intended function. Within this discipline the Remaining Useful Life (RUL) is an important measure in decision-making for maintenance actions. The RUL assesses information on the health of the machine or component at stake. It is estimated by comparing sensor data with historical data by a prediction algorithm, to predict the future state of the component of the machine.

To implement a prediction algorithm a large amount of historical sensor data is required, including data on known previous failures. However, acquiring this data will take time and requires an enormous storage capacity. Additionally, it will be infeasible to measure all aspects of each component (e.g. pressure, temperature or vibrations), which means that a prediction system based on these sensors can rarely capture the complete overview of all possible correlations among the failure modes. Therefore, often the focus is put on specific components without taking the whole environment of the machine into account.

The overcome the mentioned pitfalls of the estimation of the RUL, a model-drive discipline can be used where the prediction is based on mathematical equations rather than historical (big) data. This approach allows the online adaption of a virtual representation of the machine based on real behaviour. However, prognostics and health management considered above are used solely on typical components like bearings and gearboxes. The utilisation for all the components of the machine is still very much restricted by the lack of solutions to collect, connect, control and combine the obtained information for predictive maintenance.

Digital Twin

Recent research and implementations of the model-driven approach shows that, with the use of physics based mathematical models, the lack of measuring solutions and information can be solved. In the proposed model-driven approach, gathered data by embedded sensors is analysed using the mathematical representation of the machine to gain insight in the actual behaviour of the machine. Using this technique, data can be obtained which was not accessible before (e.g. temperature flows in combustion engines). This method is also known as virtual sensing.

The detailed mathematical models of components of machines and their interaction allows the user to monitor and gather data from each individual virtual component of the machine. To ensure that the simulated data is accurate and can be used to accurately estimate the RUL, the physics based virtual model is updated using real-time data from the machine. Tuning the simulation and prognosis

algorithm based on feedback from real-time measurements will ensure the simulated functionalities approximate the functionalities of the real machine.

Just like the physics based mathematical model, the digital representation of the physical asset, also called digital twin, is a continuous evolving digital model. Digital twinning technology will not only support in better prognosis of the RUL, but by representing the machine in a virtual and visual manner, it can improve the understanding of the machine and its complex mechanisms inside.

Implementation

So how does this work in reality? And what are the steps that need to be taken? The following steps are required for the implementation of this strategy:

Start with the advanced model of the machine. Besides kinematic and dynamic modelling of

the machine, virtual sensing should be defined to update the simulation model the moment the functionality of the machine changes.. The second phase focuses on the tuning of the physics-based model. As the model is used for the RUL, the model should be as accurate as possible to prevent incorrect interpretations of the machine's health status. Actual sensor data is used as an input in the physics-based model. This step is of high importance since it determines how the change of the machine's functionality will be influenced in the simulation model. The third phase includes the RUL calculation based on the simulation outcome. The fourth and last phase focuses on the identification of the optimal time for the next maintenance action based on the RUL of the components of the machine.

Step 1. Physics-Based Model

The physics-based model is the first aspect of the development of a digital twin based prognostic maintenance strategy. The model is based on the modelling of the mechanical-, electrical- and all other functions of the machine. To reduce the computation time, some components may be modelled as black boxes (the component is modelled without any knowledge of its internal working), grey boxes (theoretical data is used to complete the internal working) and white boxes (the complete functionality is modelled).

Additionally, virtual sensors are defined in the machine to monitor and gather data from the physics-based model. It is important to define which parameters are important to monitor, to calculate the RUL beforehand. Lastly, modelling parameters are defined to update the model. These parameters are based on actual controller and sensor data from the machine with the aim to adjust the behaviour of the machine's model with respect to the actual machine.

Step 2. Tuning of the Physics-Based Model and Data Acquisition

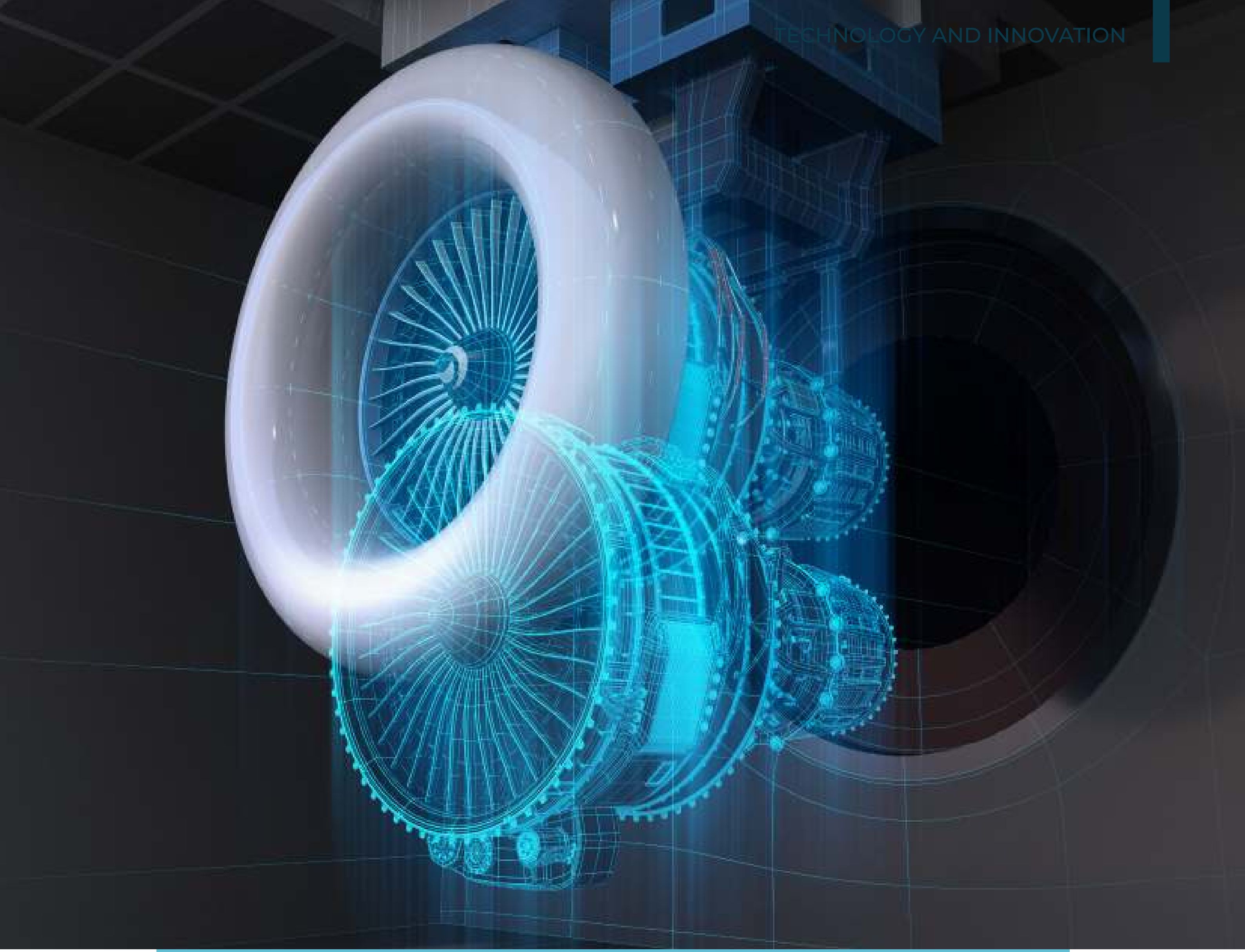
The second step is the tuning of the physics-based model. The tuning requires actual data from the machine. It is necessary to define the data that should be gathered and monitored with sensors and controllers on the machine or its components. Not all data is relevant and can be used as an input in the physics-based model. The obtained data should therefore be analysed and processed such that large amounts of unnecessary data are avoided.

The processed data is used as an input in the physics-based model and the results are compared to those of the actual machine. To eliminate the error of the comparison, an estimation of the modelling parameters should take place periodically and updated in the digital model. This tuning procedure is based on the comparison of the actual machine's component behaviour and the predicted simulation outcome. Critical components have to be updated more frequently than others that have less impact on functionality.

After the modelling of the machine and tuning during operation, the main objective is to utilize the Digital Twin. Simulations of the outcome of the performed tasks are compared to the output of the real machine in operation. A comparison is made, and the results are used to calculate the RUL. Next to that a validation of the usefulness of the information and the representation of the information for the user should be reviewed.

Step 3. Remaining Useful Life Calculation

The RUL of the machine or its components is calculated by considering the data gathered from the controllers and sensors on the machine as well as from the outcome of the simulation of the physics-based model. The necessity of the Digital Twin arises from the fact that the collected sensor data are not always adequate for the estimation of the RUL since the functionality of the machine can change over time. The virtual sensors are therefore used to capturing abnormalities in the behaviour of the real machine. Calculating the RUL the factors such as future operation plan and the model of physical degradation are checked and the simulation outcome is compared with nominal output of the machine.



Step 4. Maintenance Decision Making

The final step in the development of a prognostic maintenance planning is the time to perform maintenance actions. Financially valuable considerations should be made on whether and when to perform maintenance actions based on the RUL.

In Conclusion

Adoption of the proposed digital twin based prognostic maintenance strategy can change end-to-end business, optimizing maintenance actions and considering predictive maintenance tools to reduce downtime, improve safety, and increase profit.

With the physics-based model the ability arises to implement prognostic maintenance strategies using little data and almost no historical data. The calculation of the RUL can help to instantly check the condition of a machine as well as the future prediction of the condition of its components.

Authors:

Maaike Slot

Research Engineer
Fraunhofer Project Center
at the University of Twente

Gijs Beumkes

Research Engineer
Fraunhofer Project Center
at the University of Twente