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An Industry Scale Digital-Twin for Machine Fault Diagnosis and Prognostics

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Digital Twins promise a new capability for machine monitoring through a virtual real-time replica of a real physical system that can be used to improve operational efficiencies, identify faults and quantify the effects of different operating scenarios. However, few examples exist of true Digital Twins that have been deployed in real world, full-scale industrial operations, where these cyber-physical systems adopt standardized and recognized software platforms and sensing technologies. This paper describes the practicalities developed to manage an industry-scale digital twin for machine condition monitoring through the integration of intelligent algorithms for automated fault diagnostics and future fault state prognostics. Built in collaboration between Ailsa Reliability Solution Ltd and The University of Strathclyde, The Fan Skid Digital Twin system integrates an industry scale electro-mechanical fan assembly with statistical fault models through the use of commercially available cloud-based infrastructure. A standardized sensing and telemetry philosophy have been adopted alongside the implementation of generic control and actuation systems to provide a robust approach to bi-directional interactions. Automated fault diagnosis is performed using an Expert Bayesian Network approach elicited from domain knowledge. Subsequently, a statistical approach to modeling the fault and degradation pathway is adopted, which is constrained by well understood mechanical engineering principles. Furthermore, a rudimentary approach to prognosis uncertainty quantification is introduced, based upon extrapolation of industry standard sensor equipment error margins, to provide best- and worst-case future fault scenario characteristics. Finally, the architecture demonstrates close-to real-time feedback control capability to prevent the onset of worsening faults.

Keywords: Digital Twin, Fan, Condition Monitoring, Diagnostics, Prognostics, Uncertainty.

1. Introduction and Motivation

Time-based maintenance strategies continue to be the most common means of conducting condition monitoring in many engineering disciplines. However, to maximize plant up-time, there is a desire to change maintenance strategies to be more condition- or data-driven, if appropriate and trustworthy approaches can be demonstrated to be robust and reliable in real operational environments. This requires considering the use of, most likely, imperfect operational data and the limited availability of machine or process data.

To support this data-driven condition monitoring evolution, the Digital Twin (DT) concept has been proposed and developed over approximately the past ten years Jung et al. (2023) . DTs can be used to improve operational efficiencies and identify faults through quantifying the effects of different operating scenarios in (close to) real-time and ahead of maintenance interventions. However, few examples exist of 'true' real-time DTs operating in industrial scenarios that adopt standardized and recognized software platforms and sensing technologies.

This paper describes the development and operation of an industry-scale DT meeting the requirement stated above and making the following contributions:

- The presentation of a DT design that adopts standardized, industry-recognized sensing and telemetry infrastructure, and data architecture, providing a blueprint for widespread DT adoption
- An approach to on-line real-time machine condition monitoring through the integration of intelligent algorithms for automated fault diagnostics and future fault state prognostics
- A method that embeds both a well understood mechanical engineering principles derived digital model for fault degradation pathway analysis and prediction, and a well-documented statistical approach to prognosis uncertainty quantification
- Results from experiments using DT system for fault transient scenarios with associated validation

The paper is structured as follows: section two provides background and a literature review of associated technologies and state-of-the-art; section three describes the DT cyber-physical architecture; section four covers technologies demonstration and validation; and, finally, section five concludes and proposes future work.

2. Machine Condition Monitoring with Digital Twins

For the purposes of this work, the authors adopt the definition of a DT from the UK's National Digital Twin Programme NDTP (2025), i.e. the DT system exhibits specific characteristics:

- both a physical and digital representations of the machine, system or process
- two-way relational interaction between the physical and digital systems
- connects with relevant time data to ensure the two systems temporally match

Using DTs for condition monitoring and fault diagnosis has been extensively documented Liu et al. (2022) Bofill et al. (2023). However, in both these review papers it is noted that no single definition of DT exists, varying different approaches to creating DTs exist and there still exists a number of challenges to realizing true industry benefit for the creation and deployment of DTs. These include a limitation associated with installing sensors in specific areas or components of the machine being monitored, alongside the scarcity of fault data in many cases in order to create representative digital models.

Many DT studies in areas related to this paper built on the work of Wang Wang et al. (2019), where a multi-physics model of a rotating machine in a manufacturing process demonstrates the ability to accurately diagnosis machine unbalance faults. However, the approach assumes a fully observable machine and access to sophisticated modeling software.

More recently, in terms of integrating Artificial Intelligence (AI), Machine Learning (ML) and physics-based models (represented as a DT) to estimate unbalance in rotating systems Tselios and Nikolakopoulos (2025) proposed a sophisticated approach using artificial neural networks (ANNs) to identify the mass and location of an unbalance fault then update/calibrate the digital model parameters using genetic algorithms (GAs). However, this approach depends on significant fault data being available, in a structured manner, to train the ANN. Also Shang et al. (2026) proposes a physics-informed DT approach that accounts for the scarcity of fault samples (for training labels), which is a common scenario when developing machine learning models for fault diagnosis in process-critical applications. In this study the DT is used to resample and augment synthetically created data to make fault features more physically meaningful.

All the above approaches are only applicable

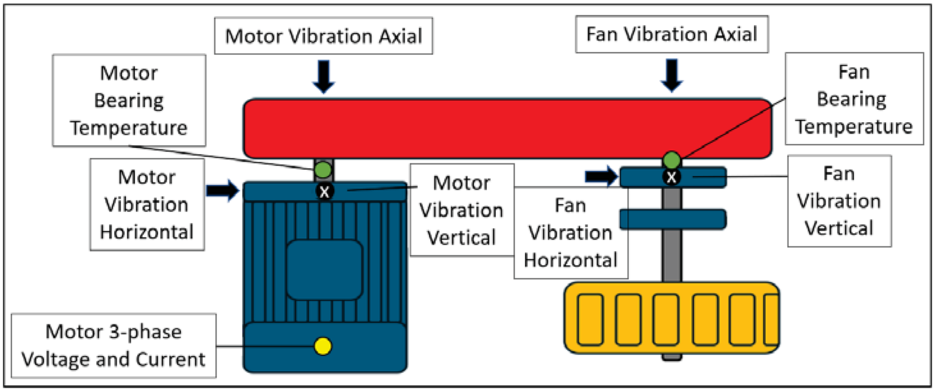

Fig. 1. Fan skid schematic with sensor placement

to the single fault type digitally modeled and/or where an ANN has been trained to identify the same fault type. In the following section, the design and implementation of a more general (both technologically and application oriented) approach to using DTs for rotating machine fault diagnosis and prognostics is proposed.

3. Digital Twin Design and Implementation

The DT presented in this work was designed following the principles laid out in Section 2 and implemented in a manner that can be represented by six discrete stages:

Stage 1 – Sensing for data acquisition. The physical skid is a 22kW motor driving an overhung fan. The full drive-train has many different sensors attached to monitor its condition using various sensing technologies (e.g. voltage, current, temperature) - see Figure 1. However, for the purpose of the DT system demonstration, the main sensing technology required was a fixed-wired vibration system. The system is multi-channel and used stud-mounted sensors on the motor drive-end (single axis on the vertical and single axis on the horizontal), a sensor on the fan drive-end (tri-axis sensor) and a tachometer on the fan shaft to provide angular velocity data. The raw vibration data was captured every 10 seconds and processed locally in the device to provide scalar floating-point values for the data acquisition system, which is accessed via an API for transfer to the DT's cloud architecture.

Stage 2 - Data transfer and cloud Infrastructure. Sensor data is first stored on the local vibration acquisition device. It is then sent to a cloud service, where it is cleaned and stored in time-series-optimized databases. All diagnostic and prognostic models, which are all deployed on the cloud service, access the cloud-hosted data for the purposes of their own computation, with model output related data again stored in the same cloud architecture. Multiple services on the cloud server work together to provide the full functionality of the DT, ensuring it operates in real-time and automatically. This can be seen diagrammatically in Figure 2.

Stage 3 - Continuous fault diagnosis. When the digital twin is in operation, an Expert Bayesian Network (section 3.1) continuously evaluates the current vibration level and machine fault condition to provide real-time fault diagnosis.

Stage 4 - Conditional prognostic model(s). In the event the diagnostic model identifies the existence of a machine fault, this 'triggers' the compute of the related prognostic model (section 3.2), which is used to regulate the speed of the machine.

Stage 5 – Machine Feedback Control. If the prognostic model predicts excessive machine impact, then machine speed is regulated and constrained to maintain operation within acceptable operational parameters and avoid excessive degra-

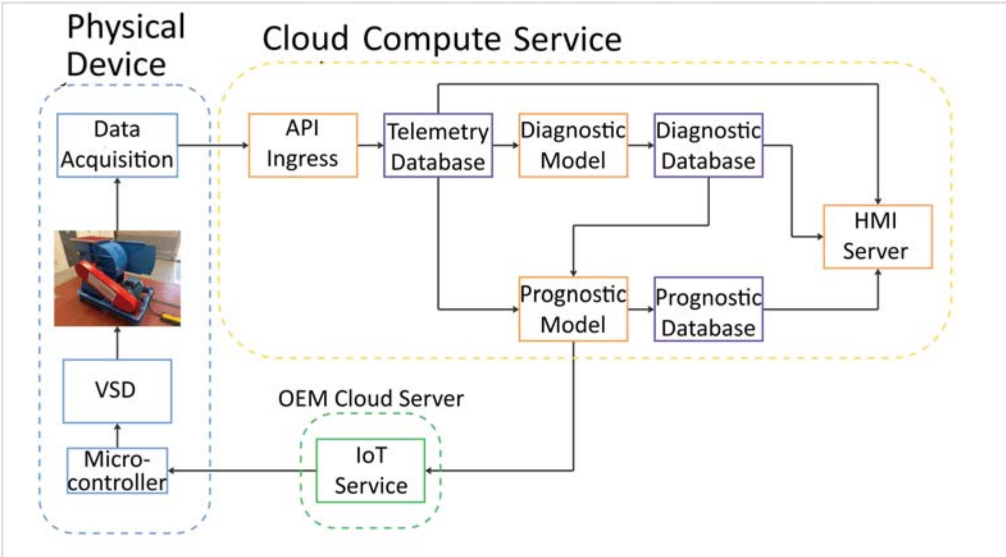

Fig. 2. Cyber-physical architecture for DT system depicting data flows and subsystem integration.

dation. This feedback process in conducted in real-time through a compute engine API call to a third-party Cloud Server which sends a signal to a local micro-controller. The micro-controller outputs a 0-10V DC signal to control the motor's Variable Speed Drive (VSD) via the drive's analogue input terminals.

Stage 6 - Visualization and Human-Machine-Interface (HMI). The HMI for the DT includes visualizations to monitor and review the DTs outputs in real-time. These visualizations use data from the timeseries databases and plot the most recent output along with machine operating parameters such as speed and vibration scalar values enable easy end-user interpretation of machine condition.

The adoption of Commercial Off-The-Shelf (COTS) products for both sensing technologies and digital products and services both provides a standardized approach to DT implementation and a means of rapidly scaling the system for increased numbers of machines and computation. For example, the vibration sensors are readily available and the cloud compute services adopted are 'elastic' meaning they can dynamically and automatically expand as required by the DT system.

3.1. *Expert Bayesian Network*

The intelligent diagnostic model implemented in the digital twin system has previously been described by the authors Gibson et al. (2025). The high-level approach combines and Expert System approach to identify specific vibration fault characteristics in the data, alongside a Bayesian Network approach to determine the relative probability of the range of faults being present in the system at the time of analysis. The Expert Bayesian Network approach to intelligence fault diagnosis is shown diagrammatically in figure 3.

3.2. *Machine Unbalance Fault Prognostic Model*

The DT system is designed to support various fault scenarios. The work presented in this paper solely focuses on a widely recognized common machine fault scenario - unbalance. Additional fault scenarios, including machine misalignment and lubrication faults, will be presented in future work.

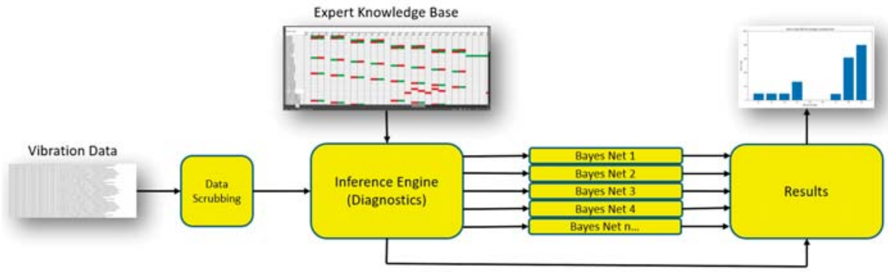

Fig. 3. Expert Bayesian Network approach to intelligent machine fault diagnosis Gibson et al. (2025)

3.2.1. *Analytical Model for Machine Unbalance*

In Matsushita et al. (2021), the unbalance force F (N) is given by:

$$F = m.e.\omega^2 \tag{1}$$

where, m is the unbalance mass (kg), e is the eccentricity (m), i.e. the distance of the unbalance mass from the rotational axis, and ω is the angular velocity (rad/s).

The vibrational amplitude A is proportional to the unbalance force (F) and inversely proportional to the system stiffness k, assuming damping is negligible for simplicity:

$$A \propto \frac{F}{k} \propto \frac{m.e.\omega^2}{k} \tag{2}$$

Hence this relationship implies that the vibrational amplitude A is proportional to the square of the rotational speed ω:

$$A \propto \omega^2 \tag{3}$$

Therefore, an approximate for machine unbalance vibrational amplitude can be mathematically modeled as a second order polynomial that is fitted to vibrational data related to a range of machine rotational speeds. This is the model adopted and extrapolated to provide the digital twin with a prognostic capability. A preliminary implementation and validation of this modeling approach is shown in Figure 4, based upon data collected from the fan skid physical asset.

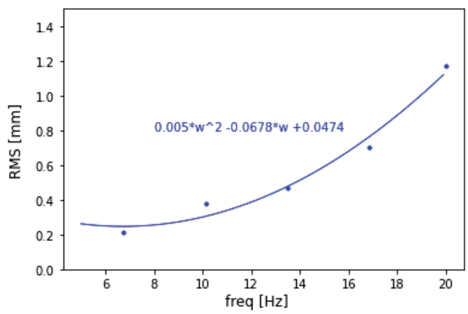

Fig. 4. Example of analytical model fitting

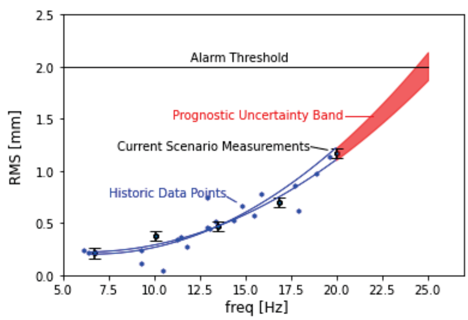

Fig. 5. Demonstration of prognostic methodology

3.2.2. *Prognostic Uncertainty for Unbalance Prediction*

The approach adopted for prognostic uncertainty quantification presented is from Wainer (2021), where a rudimentary uncertainty quantification approach is implemented to capture the best- and worst-case future fault scenario characteristics.

The vibration sensors used for data acquisition

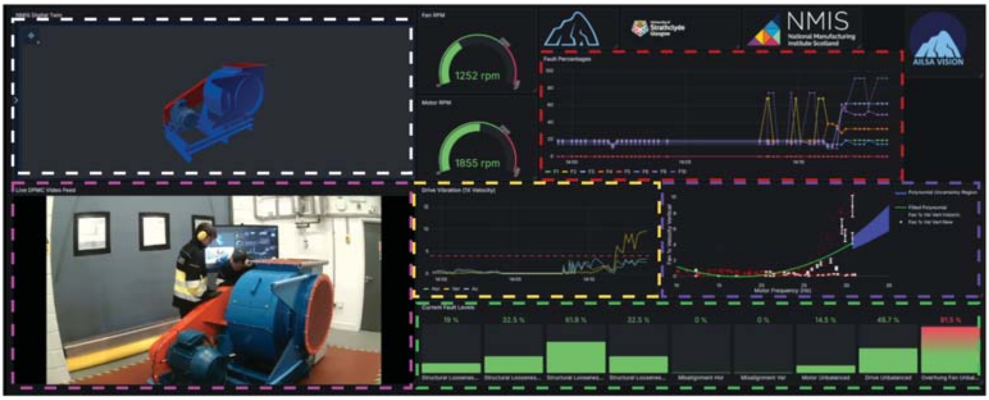

Fig. 6. HMI for unbalance scenario demonstration. White box – 3D model of fan skid; Pink box – Live video feed of the NMIS DPMC facility; Red box – Time-series of fault probability scores; Yellow box – Time-series of Fan 1X velocity vibration data; Purple box – Unbalance prognostic model; Green box – Histogram of probability percentages of diagnostic fault scenarios.

have predetermined manufacturer error margins. These error margins act as the starting point for determining the uncertainty associated with the corresponding predictions of the unbalance prognostic model. Error margins are considered as systemic uncertainty quantification on the measurement system. Extrapolating the prognostic model adopting best- and worst-case scenarios, based upon these sensor error bands, provides a degree of prognostic uncertainty for machine operation at increased or excessive machine rotating speed.

It is also be noted that the tachometer rotational speed sensor error is non-zero but of a far smaller order of magnitude when compared to vibration sensor error and hence assumed to be zero for uncertainty modeling purposes.

This methodology is demonstrated in Figure 5. In Figure 5 an arbitrary alarm threshold is denoted. In the scenario where increased speed would lead to an alarm event, this is the control signal that leads to machine speed curtailment and the avoidance of asset degradation and failure.

As associated with Figure 5, it is noted that creation of the prognostic uncertainty band adopts both current scenario data points and historic data points. Current and historic data points are required for model building but also are used as a means of validating the model. When the diagnostic model initially identifies a fault scenario, at that point in time there does not exist enough data to fit a model appropriately. Therefore, data from previous scenarios of the same fault type, which have previously been labeled as such and stored in the system's data-base, are used for initial fitting, with newest data points taking priority over historic points as they become available. Moreover, by comparing current fault scenario data points against data points for historic scenarios of the same fault type, this provides a means of validating the model. This is due to all faults being associated with a common machine, albeit at different times and potentially to different severities of fault.

4. Case-Study Demonstration

The physical elements of the DT system are located at the National Manufacturing Institute Scotland (NMIS), Digital Process Manufacturing Centre (DPMC), in Ayrshire, UK. The facility and the DT system are used to demonstrate research translation and technologies moving from concepts to higher technology readiness level (TRL) products and services.

To demonstrate the concepts described in this work, two related scenarios are now presented: a base-line no-fault scenario; and, an unbalance scenario where significant weight is added to a fan propeller.

For the base-line scenario, the diagnostic system does not identify a fault, no prognostic is conducted, all data visualizations are depicted by stationary time-series signals, and no feedback speed control or constraint is exhibited. To contrast this operational scenario, qualified machine maintenance stopped the machine and added 48g of additional weight to fan four of the ten-fan device. Once the weight was added and the machine operation area was cleared and the machine was then brought back up to speed, all while the digital systems continued to operate in the background.

As there was now a considerable vibration, the diagnostic system now correctly identifies (see Figure 6, red and green boxes) there is a high probability that there was a fault – here diagnosed as an overhung fan unbalance fault. As described in section 3.1, the DT diagnostic model identifying a fault results in the prognostic model be activated. All data is now feed into the unbalance prognostic model and it begins to update in real-time, producing the unbalance prognostic with uncertainty graph that includes current sensor data, as depicted in Figure 6 (purple box). For this demonstration scenario, increasing motor speed results in increased vibration and passing an alarm threshold where subsequently the cloud compute engine sends a signal to the micro-controller to curtail the motor speed below a value which results in the alarm threshold being crossed. The control methodology associated with the speed control continues to assess likely alarm threshold exceedance as more data is acquired and the prognostic model updates in real-time. When the updated prognostic model predicts increased vibration, the motor speed is stepped down to maintain vibration values within acceptable healthy conditions.

5. Conclusions and Future Work

Industrial machines have multiple failure modes which vary in severity and how they manifest. Asset owners will continue to be challenged with maintaining plant up-time unless they adopt new tools to recognize degraded operation from high volumes of monitoring data. This work contributes a practical DT methodology developed for a real industry-scale application and using industry adoptable cyber-physical equipment and cloud-based architecture. The approach has been shown to effectively impact on machine fault diagnosis and prognosis, supporting industry ability to reduce machine degradation and down-time. The modeling approaches implemented require minimal training or representative data and can be adapted for varied machines and fault conditions. It is also scalable due to the use of widely available sensor and actuation technologies and extendable cloud services.

However, there are limitations with the current approach, summarized as follows. Each failure mode may require different and more complex models to physically or empirically represent the phenomenon occurring. The financial costs associated with implementing and maintaining the digital cloud infrastructure are not insignificant. The intelligent system conducting diagnosis suffers from the well documented knowledge bottleneck. Each of these three limitations may all contribute to the challenge of scaling the approach to a large number of machines, each potentially with a large number of unique fault considerations.

Future work will involve extending and incorporating additional prognostic models, incorporating more sophisticated means of feedback control and could potentially include improved machine state visualizations and human-machine interactions, e.g. machine CAD model overlays and augmented reality.

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