A Digital Twin Based Framework for Real-time Machine Condition Monitoring

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***Abstract*— Condition Monitoring (CM) is an important approach to extending the life of complex equipment by forecasting the outcome of an event before catastrophic failure occurs. Recent advancements in digital twins (DT) offer additional benefits to machine condition monitoring. In this study, a framework based on DT for real-time condition monitoring of industrial machines is proposed. The multi-layer DT framework consists of a physical entity (PE), virtual equipment (VE), edge device, fidelity service and digital twin services. The virtual equipment is a replica of the physical entity or the monitored machine. It also contains a cloud platform to store data online and an application to interface with the cloud enabling users to check the data remotely. The fidelity service ensures conformity between the PE and the VE. The digital service provides optimal operation and maintenance schedules based on the data from both physical and virtual spaces. The integration of the edge layer enables real-time handling of high-frequency machine data for effective health monitoring. The validity of the proposed framework is demonstrated with a case study based on monitoring a critical component of an industrial drivetrain test rig. The features of the framework allow end-users to visualize the component's real-time health status remotely.**

I. INTRODUCTION

Condition Monitoring (CM) is an important approach to maximize the utilization of complex industrial equipment such as wind turbines, and ships, which normally work in harsh environments for decades [1], [2]. For these complex dynamic systems, failure in one component can lead to a breakdown of entire systems, which causes significant capital and productivity loss. CM plays an important role in alleviating equipment downtime by forecasting the likely outcome of a situation before catastrophic failure occurs [3]. The existing CM technologies mainly rely on historical data from physical assets, making it challenging to achieve the necessary accuracy and adaptability for real-time evaluation of their state. Recent advancement in digital twin (DT), driven by the rapid development of smart sensors and data science, leverages condition monitoring approaches. A DT structure mainly consists of a physical entity and virtual equipment, along with data communication protocols and DT services. The virtual equipment in cyberspace is a representation that depicts the essential characterization of the physical entity in a digital format. DT models possess data from the physical entity and virtual space which can generate real-time hard-to-access data. Thus, DT can provide accurate information and more comprehensive data for system condition monitoring. Moreover, adopting the cloud platform endows DT with high computing and storage capability, which enhances CM performance. Furthermore, digital twins not only establish the virtual mirror of the physical entity, but also help users realize the visualization and transparency of the physical entity. The visibility of the physical process gives the users an intuitive sense.

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Machine condition monitoring generally relies on vast amounts of data collected from various sensors [4]. However, transmitting all the raw and heterogeneous data to the cloud can be inefficient and costly. Storing machine data in the cloud can also pose a challenge for real-time response requirements in some DT applications. In such scenarios, edge computing technology can provide a solution [5]. Using IoT devices, edge computing can effectively process massive time-sensitive data, ensuring real-time responses for DT applications. This approach not only enhances efficiency but also reduces costs associated with cloud storage and data transmission. Therefore, implementing edge computing technology in digital twin applications can significantly improve a condition monitoring system's overall performance and effectiveness. Motivated by this, the present study adopts an existing DT framework for machine health management proposed by Tao et al., [2] by adding an edge computing layer. The proposed DT framework for real-time condition monitoring consists of a physical entity, virtual equipment, edge, fidelity service and digital twin services. The virtual equipment is a replica that can reproduce the physical entity's geometric model, physical properties, and kinematic relationships. It also contains a cloud platform to store data and an application to interface with the cloud enabling users to check the data remotely. The edge devices process the signals collected from sensors and interface with the cloud for data transmission. The fidelity service ensures the synchrony of the physical entity and virtual equipment. The digital service is expected to provide optimal operation and maintenance schedules based on the data from physical and virtual spaces.

The rest of the paper is arranged as follows. Section II presents a literature review of digital twins, condition monitoring, and edge computing. Section III details the proposed framework. A simple case study based on a drivetrain test rig is performed based on the proposed framework in Section IV. Finally, conclusions are presented in Section V.

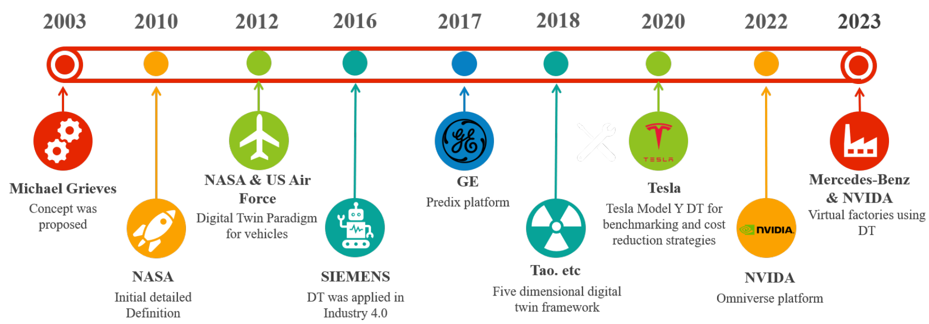

Fig. 1. Timeline of the evolution of digital twin.

II. Related Work

This section overviews the history of the digital twin evolution and summarizes its research and development progress in condition monitoring. Edge computing techniques in digital twins are also reviewed in this section.

A. The Evolution of Digital Twin

The concept of digital twin technology can be traced back to the early 2000s. Grieves [6] used the term "digital twin" to describe a virtual replica of a physical asset that could be used to simulate its behavior in real time. The idea was to create a digital twin allowing engineers to test and optimize designs before they were built in the physical world [6]. In 2010, the initial detailed definition of Digital Twin was given by the National Aeronautics and Space Administration (NASA) as "an integrated multi-physics, multi-scale, probabilistic models, sensor updates, fleet history, and so forth, to mirror the life of its flying twin [7]. Tao et al., [8], [9] proposed a five-dimensional DT model for prognostics and health management for a wind turbine system. The proposed model included physical part, virtual part, connection, data, and service [8], [9]. Figure 1 shows a timeline of some major milestones in the evolution of digital twins.

B. Digital Twin in CM

Condition monitoring is a process of monitoring the state of a system or equipment to identify any deviations from its normal operating condition. CM aims to detect any potential issues before they result in equipment failure, downtime, or safety hazards [10], [11]. Early detection of defects can enable timely maintenance, which can effectively reduce the occurrence of unplanned downtime, costly repairs, and safety-critical incidents. Introducing digital twins in CM can overcome limitations in existing monitoring approaches (lack of qualitative data) and offer additional benefits [12]. By creating digital twin models using sensor data, engineers can predict equipment failures, optimize maintenance schedules, and reduce downtime [13], [14], [2]. It enables proactive maintenance and improves overall efficiency, making it an essential technology for modern engineering practices [15]. Digital twin technology can also be integrated with other monitoring technologies, such as vibration analysis and thermography to provide a comprehensive view of equipment performance [16]. Moreover, remote access to digital twin models enables remote diagnosis and support, which is critical during travel restrictions [17]. It also supports condition-based maintenance and real-time decision-making, improving efficiency and cost-effectiveness by providing engineers and technicians with real-time insights into the performance of equipment and systems [18].

C. Edge Computing in Digital Twin

Edge computing is a distributed computing paradigm gaining popularity due to the rise of Internet of Things (IoT) devices, which generate massive data that need to be analyzed and processed in real-time [19], [20]. Edge computing makes computation and storage closer to the source of data, reducing the latency and bandwidth requirements of the centralized cloud computing model [21]. These advantages of edge computing have the potential to benefit digital twins in CM. Edge computing enables digital twins to leverage the power of distributed computing and real-time data processing close to its source, thereby enabling better insights and decision-making capabilities [22]. This is particularly important in applications having a large number of assets that require real-time data processing, such as manufacturing and transportation [23], [24].

An application of edge computing in digital twins can be found in online anomaly detection for automation systems. Edge computing was introduced to improve data transmission efficiency and satisfy real-time response [5]. Wu et al., [16] proposed an edge computing-based digital twin for intelligent transportation systems, which enables traffic management teams to make better decisions regarding traffic flow and congestion. In addition to the above applications, edge computing is also being used in digital twin applications for energy management [25] and smart city planning [26]. Edge computing is rapidly becoming a critical component of digital twin applications, enabling real-time data processing, predictive maintenance, and better decision-making capabilities.

III. Digital Twin Based Condition Monitoring Framework

The proposed DT framework for real-time condition monitoring consists of a physical entity, virtual equipment, edges,

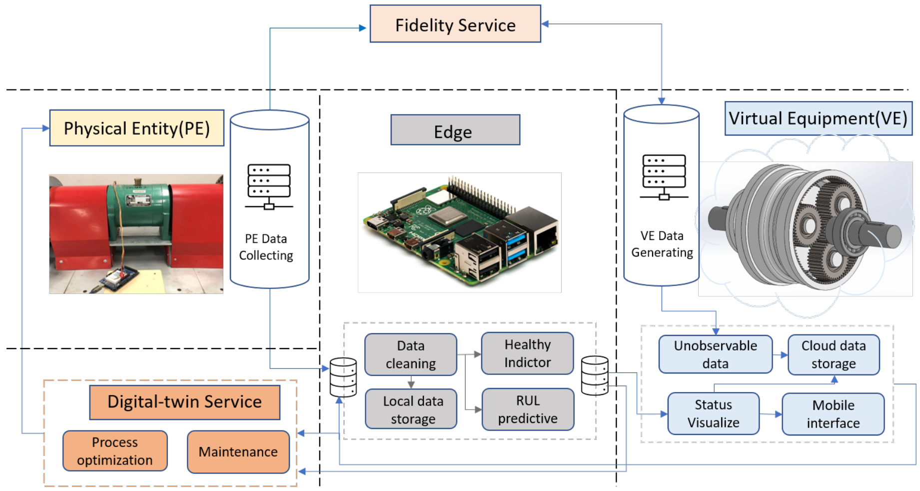

Fig. 2. The proposed digital twin based framework for machine condition monitoring.

fidelity, and digital twins services as shown in Fig. 2. The virtual equipment is a replica that can reproduce the physical entity's geometric model, physical properties, and kinematic relationships. It also contains a cloud platform to store data online and an application to interface with the cloud enabling users to check the data remotely. The fidelity service ensures the synchrony of the physical entity and virtual equipment. The digital service is expected to provide optimal operation and maintenance schedules based on the data from physical and virtual spaces.

A. Physical Entity

The physical entity (PE) consists of all system components and sensory devices. The system runs at various conditions to perform desired tasks and operations, and the sensors collect the working states and the system's operational data. To establish the virtual equipment (VE) for CM, the attributes of the PE need to be obtained from various aspects such as geometrical structures, physical properties, operational and environmental conditions, kinematics and dynamics. Sensory devices could provide machinery measurement data to indicate PE's healthy states, and these data are of great importance for the successful development of the VE. The measurement data could be obtained from built-in devices and add-on sensors. Built-in devices like controllers, drives, encoders or other internal sensors could provide primary operational data like the input voltage, position and speed, etc. Add-on sensing technologies with external sensors offer a non-invasive way to acquire more prominent measurements like vibration, temperature, force, torque, etc. These data greatly enhance edge computing with comprehensive measurements and can also improve the fidelity of the virtual equipment as they can provide more reference indicators.

B. Virtual Equipment

A virtual equipment (VE) is a digital replica of the PE in cyberspace. It is constructed based on physical information and sensing measurements. The VE is expected to reproduce PE in three regards: 1) construct the geometric model of PE in cyberspace; 2) simulate the physical property of PE; 3) describe the behaviours of PE in response to driving and disturbing factors. The VE also contains a cloud platform and interfaces, which allows online data storage and users to visualize components' health status remotely.

To build a high-fidelity virtual representation of PE, an accurate geometric model and physical property model that can mirror the physical assets is needed. A geometric model is a mirror image or 3D solid model that can depict all geometry components and describe their kinematic relationship. The geometric model can be created by commercial CAD modelling software, and the assembly constraints of the CAD model can describe the kinematic relationships.

The physical property model conveys these properties that can simulate the response of PE's components in physical principles, such as the strain and stress governed by material properties of the parts and constitutive models. The physical property, such as strain and stress can be described through theoretical analysis using finite element analysis (FEA), while the property without a sound theoretical model can be expressed by the empirical formula.

The behaviour model is another essential factor for constructing accurate VE. The behaviour model defines the dynamic response of the whole system under diverse operating and environmental conditions. For example, the output torque of a gearbox is affected by its control order and health status but is also subject to its loading and the temperature and lubrication conditions of the bearing system.

C. Fidelity Service

Fidelity service aims to integrate physical entity (PE) and virtual equipment (VE). PE is subject to degradation and is affected by operational orders and environmental conditions. VE which serves as the mirror image of PE should be able to reflect its actual performance. To eliminate the discrepancy of PE and VE is the main function of the fidelity service. In order to make the VE be consistent with the response of PE, the fidelity service can be regarded as an optimization control problem. The control aim is to eliminate the error between the dynamic response from VE and the actual response measured from PE.

D. Edge computation

The advancement of information technologies, such as edge computing, IoT and cloud computing, leverages the means of processing the data collected from the field. Cloud computing is a highly flexible computing infrastructure that allows heterogeneous data to be processed remotely. However, it has challenges in massive data transmission and real-time computing requirements. Edge computing pre-processes data before sending it to the cloud, thereby reducing its size and complexity. Edge computing analyzes data using real-time and historical data collected from physical entities. Data is collected through built-in and external sensing devices. There are massive amounts of raw data from the physical entity. The edge devices can be utilised to transform the raw high dimensional sensor data into effective health indicators, which can be utilized to monitor the health status and predict a component's as remaining useful life (RUL).

E. Digital Twin Service

The digital twin service is supposed to output the optimal operating conditions and the best maintenance strategies based on the measurement data from PE and the simulated data from VE. The actual measurement data and the unobservable data simulated from VE are streamed to DT service. Those data are analyzed to perform a more comprehensive diagnostic and prognostic process. DT service could give optimal operating schedules to the system to maximize its life cycle based on the results. In addition, DT service can also provide optimal maintenance strategies according to the results.

IV. Case study

The proposed DT based condition monitoring framework has various technologies working together for integrated utilization, as shown in Fig. 3. This section presents a case study to evaluate the effectiveness of the proposed system. In this case study, the PE and VE were established, and real-time data was collected from PE through vibration sensors. The real-time data was analyzed on edge and stored in a local database. The edge layer would estimate a health indicator (HI) which reflects the real-time health status of the monitored component from the PE. In this work, the VE contains an application allowing users to see the health status of components. The case study chose a bearing in the gearbox as the component to be monitored.

A. PE of a Drivetrain Test Rig

The physical entity of this case study is an electromechanical drivetrain controlled by the variable frequency drive. The drivetrain consists of three main parts: an electrical motor, a generator, and a planetary gearbox. The operational conditions, such as motor speed and output loading, can be dynamically controlled to evaluate the condition monitoring system more practically. The gearbox has a two-stage planetary gear structure with two identical planetary gears consisting of a stationary ring gear, a sun gear and a carrier holding three planet gears. The reduction ratio of the gearbox is 1:1 as its two planetary stages are identical.

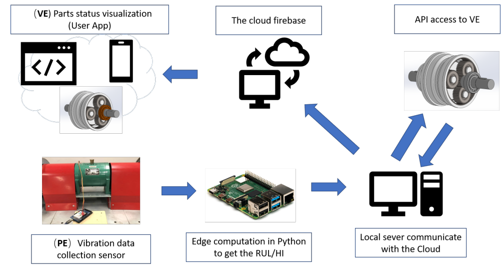

Fig. 3. Establishment of a digital twin for a drivetrain test rig.

The data acquisition system consists of a micro-electromechanical systems (MEMS) accelerometer, a micro-controller unit, and a single-board computer. The sensing device, LIS3DH is a 3-axis digital MEMS accelerometer. The Arduino Mega 2560 serves as a microcontroller unit to interface with the MEMS accelerometer. Arduino's inherent analog-to-digital converter (ADC) makes the analog sensors readily accessible to the system without additional interfacing electronics. However, because of the communication limitation of Arduino, a portable single-board computer - Raspberry Pi 4B, is chosen to facilitate integrating the sensor and microcontroller into the digital twin framework. Raspberry Pi 4B is a widely used single-board computer with powerful wireless communication capability and is compatible with various operating systems. Moreover, they can handle complex data analytic tasks such as signal processing and machine learning. A host computer serving as a central local server is established to control and manage the edge nodes and interact with a cloud database. At the same time, a local database is also set up to store the data intermediately.

B. Construction of VE

According to the digital twin framework proposed in Section III, the virtual equipment of the drivetrain test-rig gearbox was constructed. With the obtained physical information, the geometric model of all the gearbox components was built up in the commercial CAD modelling software SolidWorks. The physical properties, like materials, were set up simultaneously. The kinematic relations of all the components were realized by setting assembly constraints.

The geometric model, physical properties, and kinematic model were constructed in SolidWorks to have a virtual replica of the real gearbox. To fulfill more complex tasks, such as changing the settings of components, an application programming interface (API) was developed, enabling users to access SolidWorks using programming to manipulate the virtual model. The virtual model interface (VMI) was programmed in C#. The VMI was used to change the subject's colour to indicate its health status according to the data analysis results. The sensor data collected from the

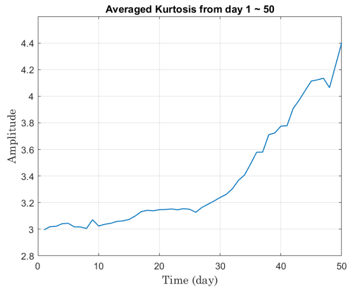

Fig. 4. Kurtosis based healthy indicator.

machine was preprocessed in the edge device and transferred to the local server. The transmitted data, which is the health indicator value calculated from the high dimensional accelerometer data, is analyzed to indicate and predict the health status of the bearing being monitored. With the analysis results, the VMI would access SolidWorks to change the component's colour accordingly, which indicates the real-time health status of the bearing.

Data storage on the cloud was achieved using Firebase powered by Google. The interface between Firebase and the local server was also realized by VMI. The visualized data of the component produced by VMI, such as images, was formatted and uploaded to the cloud. An executive program that allows users to monitor the health status of the component was also developed in C#. It retrieves the data from the cloud and displays the visualized images to the users.

C. Data Analysis in Edge Layer

The PE in this study is a drivetrain test-rig. However, utilizing it to simulate a run-to-failure experiment for a bearing was cumbersome. Therefore, to verify the effectiveness of the proposed digital twin framework, a publicly available bearing run-to-failure dataset was utilized [27], [28]. The data was obtained from a high-speed shaft of a 2 MW wind turbine. Over a 50-day period, the severity of the inner race fault in the high-speed shaft bearing of the turbine was increasing due to harsh operation. Accelerometer signals and tachometer signals are recorded for a duration of 6 seconds every day. The nominal operating speed of the high-speed shaft was 1800 rpm (30 Hz).

In order to mimic a bearing run-to-failure scenario in the drivetrain test-rig, we utilized the accelerometer data of the wind turbine bearing as being the run-to-failure data of one of the bearings of the test-rig gearbox. Instead of the LIS3DH MEMS accelerometer directly collecting data from the test-rig, the available accelerometer data was converted into a health indicator in the edge device. Kurtosis was used to generate the health indicator of the bearing. Kurtosis is a sensitive, non-linear, and robust statistical measure that is often used in condition monitoring to detect changes in a machine's condition over time in machine vibration signals. Figure 4 shows an example of the results.

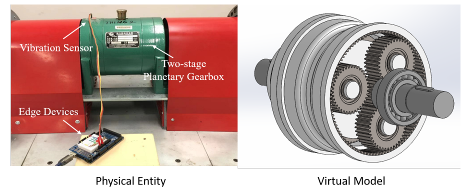

Fig. 5. The physical entity (PE) and virtual equipment (VE) considered in this study.

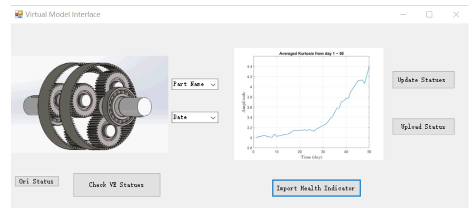

Fig. 6. Virtual Model Interface allowing communication between the edge and cloud.

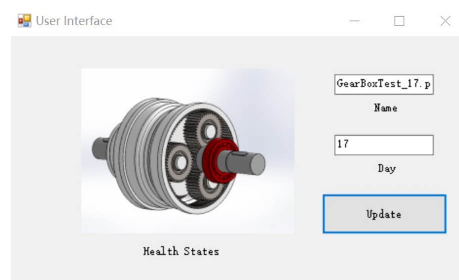

Fig. 7. User interface to monitor health states of components.

D. Results

The DT model for the gearbox of a drivetrain test rig was established. The PE was set up at a vibration lab at the University of Auckland. The virtual model of PE was developed in Solidworks. Figure 5 shows the DT's physical entity and virtual model. The cloud real-time database of VE was built on the Firebase. The edge computing was conducted on a portable single-board computer Raspberry Pi 4B and the local server. The interface between the edge and the VE was developed and run on the local server. The communication in this case study is one-way from PE to VE, and their synchrony is not so demanding. So the fidelity service was not of prime importance, and we just regarded the rotating speed of the shaft as the synchronized indicator. The DT service is not included in this case study and will be taken care of in the extended research of this work. Figure 6 shows the Virtual Model Interface (VMI), which connects the edge and cloud of the DT system. The command button of *Import Health Indicator* allows loading of the processing results in the edge. The results of computing the health indicator in the edge are displayed in the image box. The command button of *update status* triggers the event of getting access to SolidWorks to modify the setting of the virtual model accordingly. The VMI also allows users to check the health status of the component locally. Users can check the health status of a certain component at a specific time by choosing the component and time range from the drop menu. The command button of *Upload Status* activates the communication between the local server and the cloud. After triggering, the data will automatically be formatted and uploaded to the cloud (Firebase). The user interface, Fig. 7, for monitoring is an executive application. Users can run the application and choose a certain date they want to check the health status of the PE, and the application will access the cloud and retrieve the required data to display in the image box. Users can check the PE status anywhere and anytime visually via the application.

V. Conclusion & Future Work

In this paper, we proposed a digital twin based framework for real-time condition monitoring of an industrial gearbox. The proposed DT framework builds on the five-dimensional framework by integrating an edge computing layer. In the case study, the physical entity of a drivetrain test rig gearbox was utilized. The virtual model was constructed in SolidWorks. The in-house edge-cloud interface was developed in C#, enabling the data to be uploaded from the local server to the cloud (Firebase). The interface that allows users to check component's health status was developed in C# to retrieve the data from the cloud. As a result, the DT framework realized the function of enabling users to check their health status remotely. The proposed framework was able to handle high-frequency raw machinery data by converting it into lower dimensional indicators in the edge layer and integrating it with a DT for efficient monitoring of the machine under observation. This aspect can be particularly useful when real-time remote monitoring needs to be achieved by analysing large volumes of machine data.

Some aspects of the framework still need further work like improving the communication functionality between the PE and the VE as in this study we only discussed one-way communication rather than bidirectional communication. Future work will focus on improving this aspect of the framework along with focusing on integrating sophisticated health indicators in the edge layer.

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