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Digital twin driven prognostics and health management for complex equipment

Fei Tao [a], Meng Zhang [a], Yushan Liu [a], A.Y.C. Nee (1)[b,*]

[a] *School of Automation Science and Electrical Engineering, Beihang University, Beijing 100191, PR China*
[b] *Department of Mechanical Engineering, National University of Singapore, Singapore 117576, Singapore*

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ABSTRACT

Prognostics and health management (PHM) is crucial in the lifecycle monitoring of a product, especially for complex equipment working in a harsh environment. In order to improve the accuracy and efficiency of PHM, digital twin (DT), an emerging technology to achieve physical–virtual convergence, is proposed for complex equipment. A general DT for complex equipment is first constructed, then a new method using DT driven PHM is proposed, making effective use of the interaction mechanism and fused data of DT. A case study of a wind turbine is used to illustrate the effectiveness of the proposed method.

1. Introduction

Complex equipment such as aircrafts, ships, wind turbines are designed to work over decades in harsh environment. Thus, performance degradation is inevitable during its operation, which can lead to malfunctioning, resulting in high maintenance costs. Prognostics and health management (PHM) has been introduced for the reliable operation of complex equipment. It is used to monitor the equipment condition, perform the diagnosis and prognosis, and provide design rules for maintenance [1].

However, most current works on PHM are primarily driven by the equipment in its physical space, with little connection to its virtual model. Currently, with the development of cyber-physical system (CPS), it is critical to attach importance to the virtual space and implement the seamless convergence of physical and virtual spaces, to improve the PHM for complex equipment. In this context, in the virtual space, a digital mirror of the equipment and its data are introduced to depict the behaviour of the real entity. Some potential applications have been explored in Ref. [2], however, to implement PHM driven by both physical and virtual spaces, some outstanding common issues still exist. They include (1) building the high-fidelity digital mirror to describe the equipment thoroughly; (2) establishing the interaction between the equipment and its digital mirror to make them support PHM seamlessly; (3) converging the data from physical space and virtual space to generate accurate information for PHM.

In this paper, digital twin (DT), a reference model for the physical–virtual convergence, is applied to address the above three issues. *Firstly*, based on DT, a high-fidelity digital mirror model for the equipment is built in different levels of geometry, physics, behaviour and rule. It provides access to the equipment even out of physical proximity. *Secondly*, the interaction mechanism of DT can detect the disturbances from the environment, potential faults in the equipment and defects in the models. It is a coupled optimization to make the equipment and digital model evolve continuously. *Thirdly*, since DT includes data from the equipment, the digital model, and the fused data, data for PHM can be enriched greatly to provide accurate information.

In this study, a five-dimension DT for complex equipment is first established, then a new approach for PHM driven by DT for complex equipment is proposed, and its framework and workflow are explored in detail. A case study of a wind turbine is presented to show the effectiveness of the proposed new method.

2. Five-dimension DT model

A general and standard architecture for DT model was first built by Grieves [3]. In this architecture, the DT is modelled in three dimensions, i.e. the physical entity, virtual model and connection, and is characterized by the physical–virtual interaction. It has been applied to product design and production [4,5]. Based on this, an extended five-dimension architecture DT is proposed in this paper, adding DT data and services. Compared with Grieves' architecture, besides the physical–virtual interaction, the proposed model fuses data from both the physical and virtual aspects using DT data for more comprehensive and accurate information capture. It can also encapsulate the functions of DT (e.g. detection, judgement and prediction) from the services for unified management and on-demand usage [6].

According to the proposed five-dimension architecture, Fig. 1 shows the proposed DT for complex equipment, which can be depicted as in the following expression,

$$M_{DT} = (PE, VE, Ss, DD, CN) \quad (1)$$

* Corresponding author.
E-mail address: mpeneeyc@nus.edu.sg (A.Y.C. Nee).

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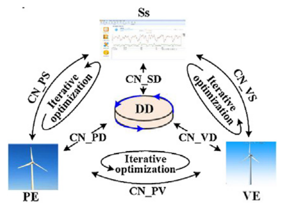

Fig. 1. Five-dimension DT model for complex equipment.

where *PE* refers to the physical entity, *VE* is the virtual equipment, *Ss* stands for services for *PE* and *VE*, *DD* refers to DT data, and *CN* is the connection among *PE*, *VE*, *Ss* and *DD*. To illustrate the proposed DT for complex equipment, a wind turbine (WT) is considered in a case study.

2.1. Physical entity model (PE)

Generally, *PE* consists of the various functional subsystems and sensory devices. Subsystems perform the predefined tasks during operation and sensors collect the states of the subsystems and working conditions. Malfunctioning of any part may cause the *PE* to fail. In Fig. 2, the functional subsystems of a WT consist of the blade, generator, gearbox, yaw system, etc. for transforming wind energy into mechanical and electrical energy. Sensors are deployed to collect the generator temperature, gearbox vibration, power output, etc.

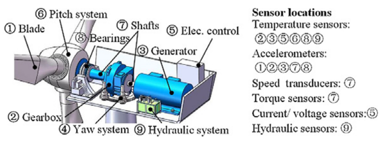

Fig. 2. Physical WT model.

2.2. Virtual equipment model (VE)

VE is a high fidelity digital model of the *PE*, which integrates multiple variables, scales and abilities of the *PE* to reproduce its geometries, physical properties, behaviours and rules in the virtual world. *VE* is modelled as follows,

$$VE = (Gv, Pv, Bv, Rv) \tag{2}$$

where G_v, P_v, B_v and R_v, stand for the geometry model, physics model, behaviour model and rule model, respectively. The modelling of *VE* is interpreted as follows, combining with the construction of the virtual WT model in Fig. 3.

G_v is constructed as a 3D solid model. The WT components (e.g. gearbox, blade and shaft) are assembled using a commercial CAD modelling software.

P_v simulates the physical properties of the *PE*. For the WT, blade deformation, gear tooth stress and bearing temperature, etc. can be simulated in this level using the finite element method (FEM).

B_v describes the behaviour of the *PE* governed by the driving factors (e.g. control orders) or disturbing factors (e.g. human interferences). Behaviour of the WT includes power generation, yawing, pitching, untwisting, etc. Power generation is a function of the wind speed and power transmission efficiency, while yawing is expressed as the relation among the yaw angel (φ_y), yaw rate (ω_y), and yaw error (*err*) [7].

R_v includes rules of constraints, associations and deductions. The rules work as the 'brain' to make the *VE* judge, evaluate, optimize and/or predict. For the WT, constraints for the wind speed can be simulated through force analysis and associations of parameters can be mined from cloud data using neural network.

By the constructed *VE*, G_v, P_v, B_v and R_v are coupled in functions and structures to form a complete mirror image of the *PE*.

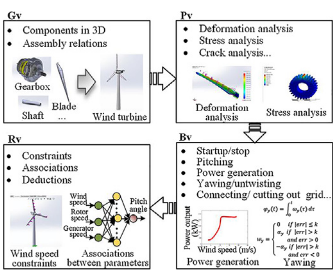

Fig. 3. Virtual WT model.

2.3. Services model (Ss)

Ss includes services for *PE* and *VE*. It optimizes the operations of the *PE*, and ensures the high fidelity of the *VE* through calibrating the *VE* parameters during its running to sustain its performance with the *PE*. *Ss* consists of elements as in (3), which describes the function, input, output, quality and state of services. *Ss* can be scheduled to meet the demands of the *PE* and *VE*.

$$Ss = (Function, Input, Output, Quality, State) \tag{3}$$

Take the power output monitoring service for the physical WT model as an example. It can be represented as Ss_monitor = (Power output monitoring, (wind speed, power output of physical WT, power output of virtual WT), power condition, (time, cost, reliability), (work, idle, failure)).

2.4. DT data model (DD)

DD includes five parts as denoted in (4),

$$DD = (Dp, Dv, Ds, Dk, Df) \tag{4}$$

where D_p is the data from the *PE*, D_v is the data from the *VE*, D_s is the data from the *Ss*, D_k represents the domain knowledge, and D_f denotes the fused data of D_p, D_v, D_s and D_k. *DD* includes data from both physical and virtual aspects as well as their fusion, which enriches the data greatly. Fig. 4 shows the *DD* of the WT.

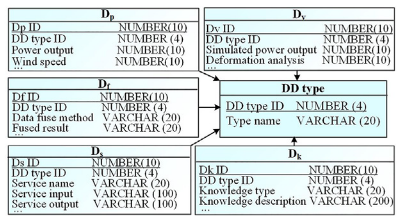

Fig. 4. *DD* of the WT.

2.5. Connection model (CN)

CN includes six parts as expressed in (5),

$$CN = (CN\_SD, CN\_PD, CN\_VD, CN\_PS, CN\_VS, CN\_PV) \tag{5}$$

where *CN_SD*, *CN_PD*, *CN_VD*, *CN_PS*, *CN_VS*, and *CN_PV* denote the connection between *Ss* and *DD*, *PE* and *DD*, *VE* and *DD*, *PE* and *Ss*, *VE* and Ss, *PE* and *VE*, respectively. Each connection (denoted as *CN_XX*) is bidirectional and the delivered data is modelled in (6).

$$CN_XX = (Datasource, Unit, Value, Scope, Sampling\ interval) \tag{6}$$

Take *CN_PV* for the WT as an example. Data from the physical WT (e.g. yaw angle) is expressed as CN_PV_yaw_angle = (Physical WT, degree, 10, 0-1080, 10s). Order from the virtual WT (e.g. yaw rate) is denoted as CN_PV_yaw_order = (Virtual WT, rad/s, 8.7e-3, 0-(1.7e-2), 10s).

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