A Digital Twin Framework for Enhancing Predictive Maintenance of Pumps in Wastewater Treatment Plants

Seyed Mostafa Hallaji [a], Yihai Fang [a] and Brandon K. Winfrey [a]

[a] Department of Civil Engineering, Monash University, Australia.
E-mail: Mostafa.Hallaji@monash.edu; Yihai.Fang@monash.edu; Brandon.Winfrey@monash.edu

Abstract

Wastewater treatment plants (WWTPs) are a type of critical civil infrastructure that play an integral role in maintaining the standard of living and protecting the environment. The sustainable operation of WWTPs requires maintaining the optimal performance of their critical assets (e.g., pumps) at minimum cost. Effective maintenance of critical assets in WWTPs is essential to ensure efficient and uninterrupted treatment services, while ineffective maintenance strategies can incur high costs and catastrophic incidents. Predictive maintenance (PdM) is an emerging facility maintenance technique that predicts the performance of critical equipment based on condition monitoring data and thus estimates when maintenance should be performed. PdM has been proven effective in optimising the maintenance of individual equipment, but its potential in predicting system-level maintenance demands is yet to be explored. This study proposes a digital twin framework to extend the scope of PdM by leveraging Building Information Modelling and Deep Learning.

Keywords

Digital twin, Building information modelling, Deep learning, Predictive maintenance, Wastewater treatment plants

1 Introduction

Wastewater treatment plants (WWTPs) are a critical civil infrastructure, which plays an important role in protecting the environment and public health by reducing wastewater pollutant loads discharged into waterways [1]. However, the successful operation of WWTPs relies on the effective maintenance of critical assets to ensure efficient and uninterrupted treatment [2]. Among the critical assets in WWTPs, pumping facilities account for 25% of total energy consumption and 10% of total operating costs [3]. In addition to WWTPs, pumps are integral assets in many other industries, such as the petrochemical [4], [5], mining [6] and building sectors [7].

Operating nearly continuously in WWTPs, pumps are subjected to severe degradation. Adopting effective maintenance approaches can ensure their performance quality [8], energy efficiency [9], and reliability [10]. Predictive maintenance (PdM) is regarded as a promising method to address these issues through continuous monitoring of the asset's condition. PdM assesses the asset performance and predicts the asset's future variations in performance and failures. PdM has started to gain significant attention in research and industry recently due to the advances in the Internet of Things (IoT) and machine learning. PdM offers the opportunity to reduce the energy consumption of poor-performing pumps and the cost of maintenance in WWTPs, where this approach has not been applied. Despite successful and wide applications of PdM in the manufacturing and oil and gas industries, PdM practices are yet to be leveraged in the building and civil infrastructure sector [11]. Furthermore, the current PdM of pumping assets still requires extensive expert knowledge, which not only is a barrier to automating the PdM process but may also lead to human errors stemming from operators' subjective influence. This study critically reviews emerging technologies under the Digital Twin (DT) paradigm and investigates their potentials and challenges in integrating with the current PdM practices of pumps in civil infrastructure. The remainder of this paper is organised as follows: Section 2 reviews the literature in Building Information Modelling (BIM) and Deep Learning (DL) in the context of asset maintenance with a focus on pumping facilities. Section 3 analyses the findings from the review and propose a DL-enabled PdM framework, followed by the conclusion in Section 4.

2 Literature review

2.1 DT frameworks for pumps maintenance

A digital twin is a virtual representation of real-world entities and processes, synchronised at a specified frequency and fidelity [12]. Collecting data from the physical system, a DT aims to replicate the behaviour of the system to offer insights into the condition and performance of the system. A DT generally consists of five components: 1) the physical asset, which refers to the facilities whose behaviour is planned to be modelled based on the data collected; 2) IoT to communicate the generated data from the physical asset; 3) Aggregation of data, which refers to data management and storage in a data repository; 4) Analytics, which conducts data analysis and generates information for enhancing the decision-making process; and 5) Actuators, which return the modified decisions to the physical object to reflect the latest strategy of the system.

A DT promises to predict system behaviour using real-time condition monitoring [13]. Fault diagnosis is transformed from a data analysis practice to an immersive and context-relevant platform. A DT is capable of enhancing the PdM of pumping facilities by adding context-awareness to the predictions, which allows automated and accurate decisions. Despite the extended application of DT in recent years, only a few studies were found relevant to the application of DTs in PdM of pumping facilities. For example, Cheng et al. proposed a DT for predicting the condition of mechanical, electrical, and plumbing (MEP) components [11]. The proposed DT consisted of 1) BIM for integrating the facility maintenance information and IoT data, 2) Machine learning for analysing the information and predicting the asset condition. It should be noted that although the term DT was not explicitly used in their research, their framework's components complied with the framework of a DT. Lu et al. proposed a DT framework to facilitate anomaly detection of pumping facilities using machine learning methods [14]. They extended industrial foundation classes (IFC) entities and attributes to accommodate the datasets from different sources, such as asset management systems, space management systems, and building management systems. The data were further analysed for anomaly detection using machine learning methods. These studies demonstrated the use cases of a DT for pumping facilities. It should be noted that the proposed DT in these studies was only limited to anomaly detection of asset conditions and did not include more sophisticated fault diagnosis, such as severity classification.

2.2 BIM for pumping facilities maintenance

BIM is used for the management, integration, exchange and visualisation of data with the intent of facilitating effective collaboration of different stakeholders during different phases of a construction project [15]. In the BIM environment, data interoperability plays an important role in managing and exchanging data in complex projects. To address this issue, IFC and Construction Operation Building information exchange (COBie) were employed to enhance data exchange and interoperability in asset management applications [16]. IFC is a non-proprietary exchange format of building information between architecture, engineering & construction software [17]. COBie captures and delivers the required information in a BIM model to facility management systems [18].

Although BIM is well-established in the building sector, its application to facility maintenance and civil infrastructure is still developing [19]. Chen et al. proposed a BIM-based facility maintenance framework for data integration and automatic scheduling of facility maintenance work orders [20]. In their proposed framework, they leveraged the BIM capability to visualise building facility components and employed IFC to map the data between BIM and facility management systems. Furthermore, BIM is expected to be a comprehensive database, capturing essential information of all building components, which can be efficiently retrieved in a BIM environment. Cheng et al. employed this feature of BIM for managing condition monitoring data of the MEP system in an academic building [11]. They showed that, in addition to interoperability enhancement, BIM could visualise real-time sensor data and analysis result. Finally, they used the proposed framework for evaluating the condition of the facilities at present and in the future, whereby the work orders were rescheduled dynamically.

2.3 DL for pumping facilities maintenance

Significant advances in IoT and Information and Communication Technology (ICT) have enhanced the quantity and quality of data collection. This has been an essential step towards using machine learning models in PdM of pumping facilities [21]. However, traditional machine learning methods are not fully capable of analysing big data (i.e., large volume, velocity, variety, and veracity) due to shallow architecture, which is a barrier to learn complex data scenarios [22]. On the other hand, contemporary methods such as DL are capable of accommodating and analysing big data scenarios. DL algorithms are constructed by deep hierarchical architectures of neural networks, which are able to incorporate feature selection and feature extraction in neural network classifiers [21]. This approach eliminates the need for separate pre-processing, reduces operators' subjective influence and experience requirement.

Applications of DL methods in pumping facilities are discussed in this section. According to our literature review, the use of DL in PdM of pumping facilities is in the primary stage of development, which dates back to 2015, when Zhu et al. employed the Stacked AutoEncoders (SAE) method for diagnosing faults in the cylinder, valve plate, ball bearings, and piston of an axial piston pump [23]. They showed that even in small data scenario problems, DL outperformed traditional methods such as support vector machine (SVM) and backpropagation neural networks (BPNNs). Another DL method that has been employed for fault diagnosis of pumping facilities is Convolutional Neural Networks

(CNNs). CNN focuses on shifts in different properties of data sets, which can accelerate the convergence rate and reduces overfitting in training and validation stages [21]. CNN is a promising method for image and it has been recently shown that it performs robustly in processing time-series data as well. Wen et al. illustrated that this method outperformed SAE, SVM, and BPNNs in processing time-series data when the data is converted to 2-dimensional images [22]. They employed the CNN method for diagnosing six types of fault in an axial piston pump and a self-priming centrifugal pump, using vibration signals with a 10 kHz sampling frequency.

3 A DT framework for PdM of pumps in WWTPs

With recent advances in machine learning and information modelling technologies, it becomes possible to enhance the PdM and sustainability of critical facilities in civil infrastructures. Based on the literature review of the applications of DL and BIM in DT, this section presents the challenges and opportunities in a DT framework that incorporates BIM and DL for improving the PdM of pumping facilities.

3.1 Data management

An effective DT system is expected to facilitate context-aware decision-making in the pumping facilities of complex infrastructure such as WWTPs. However, designing and deploying a DT system for such complex infrastructure is not straightforward, as the unique operation and maintenance requirements need to be incorporated. Data management is a critical step in a DT system, particularly with the recent development of IoT and ICT, which significantly increased the quality and quantity of data that describes the performance and condition of assets. BIM is a promising data management technology, having a high potential for managing big data and being integrated with the DT framework [24]. BIM has been mainly employed in the architecture, engineering and construction (AEC) industry to integrate the data and formulate parallel offline and online simulations for structural integrity, energy, safety, human comfort and well-being [25]. However, the BIM application in WWTPs is expected to be with the intent of integrating sensor data, maintenance management data and wastewater treatment process data for the corresponding simulations and optimisations in WWTPs. In order to employ BIM in WWTPs successfully, the IoT network data and the computerised maintenance management systems (CMMS) data must be integrated within the BIM environment. The IFC schema facilitates the integration of IoT data with the BIM environment, whereby BIM would be able to visualise the corresponding entities and attributes of WWTPs' facilities, particularly pumps.

3.2 Simulation and optimisation

Simulation and optimisation are critical components of a DT in different applications such as the AEC industry [26], smart cities [27] and manufacturing [28]. Similar to the AEC industry, the WWTP's applications of DT are expected to incorporate simulation and optimisation as critical components. However, the simulation methods and optimisation aims of these components differ significantly in WWTPs. For example, in the application of DT in infrastructure such as bridges [26], finite-element analyses are the core of the simulations to investigate the structural integrity of the infrastructure. Nevertheless, in WWTPs applications, it is expected that a DT supports multiple simulations such as facilities performance simulation and wastewater treatment process simulation. Furthermore, the optimisation in WWTPs focuses on environmental aspects such as carbon emission, energy conservation and water quality. Aggregation and integration of the results obtained from the multiple simulations in WWTPs for automating the system-level decision-making can be regarded as one of the prospective challenges in this field.

3.3 System architecture

Integrating BIM and DL in the DT framework can potentially provide significant opportunities in the PdM of critical pumping facilities in complex environments such as WWTPs. To guide future research works in this direction, this study presents a DT framework that incorporates BIM and DL with the intent of implementing PdM practices of pumping facilities in WWTPs. As shown in Figure 1, the proposed framework consists of three major components, namely physical asset, digital twin, and decision making. In this framework, the pumping system acts as a physical asset. Sensors act as IoT for conveying real-time condition monitoring data. The DT comprises the data/model integration layer and analytics layer. The data/model layer collects the pumping facilities data from the IoT system and CMMS database, then integrates the collected data in the BIM environment via IFC and COBie. In the next step, the data is employed to conduct the data analytics, with the intent of providing an insight into current and prospective conditions of pumping facilities.

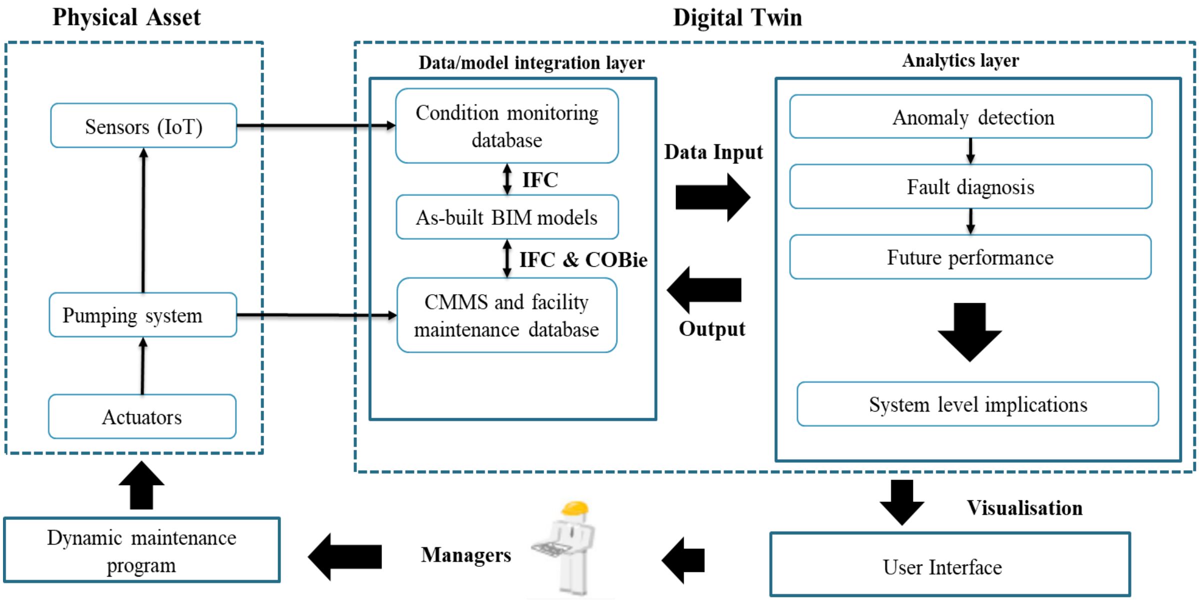

Figure 1. Proposed DT-enabled pumps maintenance framework in WWTPs

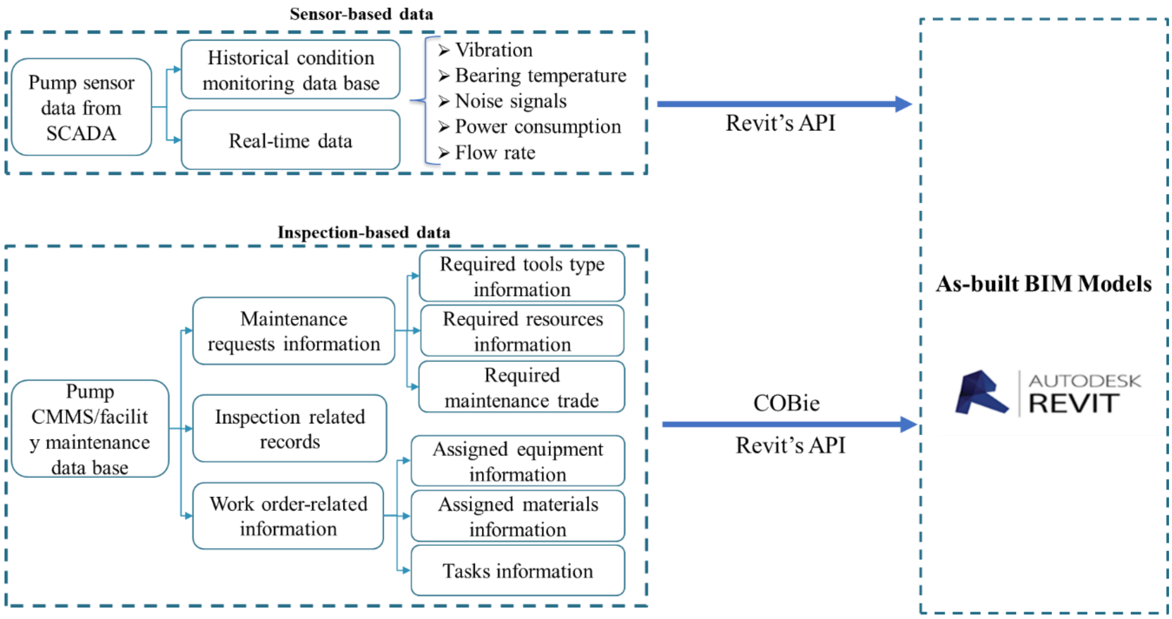

Figure 2. Illustration of data/model integration layer for big data management

Figure 2 illustrates how pump condition data and maintenance information are acquired and integrated into a BIM model using IFC, COBie and Revit's Application Programming Interface (API). Pump condition data can be collected by sensors in real-time or by querying a database, while pump maintenance information, including maintenance requests, inspection records, and work orders can be retrieved from the CMMS. In the proposed framework, sensor data are integrated into the BIM model, by developing corresponding IFC entities. The CMMS data was mapped into the BIM model by leveraging COBie. In this architecture, DL serves a functional role in the analytics layer, where the integrated data from the BIM model are employed to detect faults and predict the future performance of pumping facilities. Next, leveraging the high visualisation capabilities of BIM, the results of the simulations above are delivered to managers to make context-aware decisions for ongoing and future maintenance of pumping facilities.

This proposed framework is expected to address the technical challenges in the current PdM of pumping assets in WWTPs. However, the following potential issues should also be noted in the implementation of such a framework:

- WWPTs are operated by multiple teams from different backgrounds, such as mechanical engineers, process engineers, and chemical engineers, who utilise different software for their analyses. Teaching staff how to maximise collaboration via using the developed BIM and DL-based applications under the paradigm of DT can be challenging. Leveraging augmented reality can be helpful to address this challenge since WWTPs are a very critical infrastructure, and trial and error strategies on real-world plants can compromise the efficiency of the plant.
- The vast majority of WWTPs have already been constructed decades ago and deploying multiple sensors to the constructed facilities might be time-consuming, cost-intensive and technically difficult. To address these challenges, it is essential to develop DL methods performing well with the sensors available in WWTPs.
- Moving toward automation of asset maintenance and treatment processes in WWTPs, cyber security might be raised as another challenge. Therefore, relevant risk assessments should be carried out before the implementation of the DT framework to construct proper risk mitigation strategies.

4 Conclusions and Future Work

This paper presents a review of emerging technologies including Building Information Modelling (BIM) and Deep Learning (DL) under the Digital Twin (DT) paradigm for their potentials and challenges in strengthening PdM practices of pumps in civil infrastructure. Based on the review, this Hoppe study envisions a digital twin framework with the aim to extend the effectiveness of PdM in WWTPs. It was shown that in order to enhance data interoperability and collaboration in WWTPs, it is indispensable to expand the data schemas (e.g., IFC and COBie) that link different operation databases and platforms. It was also shown that DL could offer significant opportunities, such as enhancement of automation and precision in PdM of pumping assets. Implementing such a framework has the potential to improve sustainability and facilitate informed decision making in the operation and maintenance of WWTPs.

References

[1] L. Ho and G. Ho, “Mitigating ammonia inhibition of thermophilic anaerobic treatment of digested piggery wastewater: use of pH reduction, zeolite, biomass and humic acid,” *Water Res.*, vol. 46, no. 14, pp. 4339–4350, 2012.

[2] V. Hernández-Chover, L. Castellet-Viciano, and F. Hernández-Sancho, “Cost analysis of the facilities deterioration in wastewater treatment plants: A dynamic approach,” *Sustain. Cities Soc.*, vol. 49, no. January, p. 101613, 2019.

[3] G. Hoppe and A. Kihn, “Energy Efficiency in Water and Wastewater Facilities a Guide to Developing and Implementing Greenhouse Gas Reduction Programs,” *U.S. Environ. Prot. AGENCY*, 2013.

[4] C. Xie, Q. Wu, H. Wu, and G. Liu, “Vibration signal acquisition and processing system design in the oil field water-injection station pump,” *International Conference on Intelligent Computing, Communication and Devices*, *ICCD 2017*, vol. 752. Springer Verlag, pp. 1255–1262, 2019.

[5] M. R. Etminanfar, M. S. Safavi, and N. Abbasian-Vardin, “An analysis of magnetic pumps failure used in the oil refinery industry: Metallurgical point of view,” *Eng. Fail. Anal.*, vol. 112, 2020.

[6] H. L. Xu, W. Chen, and C. Xu, “Cavitation performance of multistage slurry pump in deep-sea mining,” *AIP Adv.*, 2019.

[7] X. Xu, Y. Lei, and Z. Li, “An Incorrect Data Detection Method for Big Data Cleaning of Machinery Condition Monitoring,” *IEEE Trans. Ind. Electron.*, vol. 67, no. 3, pp. 2326–2336, 2020.

[8] R. K. Mobley, *An Introduction to Predictive Maintenance (Second Edition)*. 2002.

[9] L. Castellet-Viciano, V. Hernández-Chover, and F. Hernández-Sancho, “Modelling the energy costs of the wastewater treatment process: The influence of the aging factor,” *Sci. Total Environ.*, vol. 625, pp. 363–372, 2018.

[10] J. Wang, L. Zhang, Y. Zheng, and K. Wang, “Adaptive prognosis of centrifugal pump under variable operating conditions,” *Mech. Syst. Signal Process.*, vol. 131, pp. 576–591, 2019.

[11] J. C. P. P. Cheng, W. Chen, K. Chen, and Q. Wang, “Data-driven predictive maintenance planning framework for MEP components based on BIM and IoT using machine learning algorithms,” *Autom. Constr.*, vol. 112, no. December 2019, p. 103087, 2020.

[12] DTConsortium, “THE DEFINITION OF A DIGITAL TWIN,” 2020. [Online]. Available:

https://www.digitaltwinconsortium.org/hot-topics/the-definition-of-a-digital-twin.htm. [Accessed: 03-Dec-2020].

[13] B. Schleich, N. Anwer, L. Mathieu, and S. Wartzack, “Shaping the digital twin for design and production engineering,” *CIRP Ann.*, vol. 66, no. 1, pp. 141–144, 2017.

[14] Q. Lu, L. Chen, S. Li, and M. Pitt, “Semi-automatic geometric digital twinning for existing buildings based on images and CAD drawings,” *Autom. Constr.*, vol. 115, no. March, p. 103183, 2020.

[15] C. Eastman, T. Paul, S. Rafael, and L. Kathleen, *BIM Handbook BIM Handbook Rafael Sacks*. 2011.

[16] S. Hamil, “What is COBie?,” 2018. [Online]. Available: https://www.thenbs.com/knowledge/what-is-cobie.

[17] R. Volk, J. Stengel, and F. Schultmann, “Building Information Modeling (BIM) for existing buildings - Literature review and future needs,” *Autom. Constr.*, vol. 38, pp. 109–127, 2014.

[18] Q. Sun and Z. Ge, “Probabilistic Sequential Network for Deep Learning of Complex Process Data and Soft Sensor Application,” *IEEE Trans. Ind. Informatics*, 2019.

[19] Q. Lu, X. Xie, A. K. Parlikad, and J. M. Schooling, “Digital twin-enabled anomaly detection for built asset monitoring in operation and maintenance,” *Autom. Constr.*, vol. 118, no. May, p. 103277, 2020.

[20] W. Chen, K. Chen, J. C. P. Cheng, Q. Wang, and V. J. L. Gan, “BIM-based framework for automatic scheduling of facility maintenance work orders,” *Autom. Constr.*, vol. 91, no. March, pp. 15–30, 2018.

[21] Y. Lei, B. Yang, X. Jiang, F. Jia, N. Li, and A. K. Nandi, “Applications of machine learning to machine fault diagnosis: A review and roadmap,” *Mech. Syst. Signal Process.*, vol. 138, p. 106587, 2020.

[22] L. Wen, X. Li, L. Gao, and Y. Zhang, “A New Convolutional Neural Network-Based Data-Driven Fault Diagnosis Method,” *IEEE Trans. Ind. Electron.*, vol. 65, no. 7, pp. 5990–5998, 2018.

[23] Z. Huijie, R. Ting, W. Xinqing, Z. You, and F. Husheng, “Fault diagnosis of hydraulic pump based on stacked autoencoders,” in *2015 12th IEEE International Conference on Electronic Measurement & Instruments (ICEMI)*, 2015, vol. 01, pp. 58–62.

[24] L. Ding, R. Drogemuller, P. Akhurst, R. Hough, S. Bull, and C. Linning, “Towards sustainable facilities management,” *Technol. Des. Process Innov. Built Environ.*, pp. 373–392, 2009.

[25] C. Boje, A. Guerriero, S. Kubicki, and Y. Rezgui, “Towards a semantic Construction Digital Twin: Directions for future research,” *Autom. Constr.*, vol. 114, no. November 2019, p. 103179, 2020.

[26] K. Ding, H. Shi, J. Hui, Y. Liu, and B. Zhu, “Smart steel bridge construction enabled by BIM and Internet of Things in industry 4.0: A framework,” in *ICNSC 2018 - 15th IEEE International Conference on Networking, Sensing and Control*, 2018.

[27] M. Tomko and S. Winter, “Beyond digital twins – A commentary,” *Environment and Planning B: Urban Analytics and City Science*. 2019.

[28] M. Schluse, M. Priggemeyer, L. Atorf, and J. Rossmann, “Experimentable Digital Twins-Streamlining Simulation-Based Systems Engineering for Industry 4.0,” *IEEE Trans. Ind. Informatics*, 2018.