Digital Twins for PEMFC Diagnostics and Prognostics – Status and Challenges

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ABSTRACT

Fuel cell technology, especially Proton Exchange Membrane Fuel Cells (PEMFC), can be used for achieving zero-emission energy conversion when integrated with renewable sources. However, improvements in cost, durability and reliability remain essential where durability can be improved through Prognostic and Health Management (PHM). Current research in PHM of fuel cells often lacks a robust connection to the physical systems, limiting accurate real-time insights which can be solved using a digital twin. By synchronizing real-time data through sensors, the digital twin can accurately reflect the physical system's performance, which is vital for analyzing complex systems such as fuel cells. This study reviews the digital twin technology of the PEMFC systems for PHM. More specifically, this review discusses advancements in digital twin applications for PHM, challenges in data management and their potential for improving fuel cell durability. Typical applications of digital twins for fuel cell systems are highlighted with a focus on diagnostic and prognostic techniques.

Keywords— **PEMFC, digital twin, PHM, diagnosis, prognosis**

I. INTRODUCTION

In the current industrial trends, the fuel cell technology plays a vital role in zero emission energy conversion and can be emissions free upon integration to renewables wherein the Proton Exchange Membrane Fuel Cell (PEMFC) is the majorly used type of fuel cell for various applications. However, there are scopes of improvements and developments in the technology that are needed to reduce the cost, improve the durability and enhance the reliability of the fuel cell system as a whole. Though there is a lot of research in improving the durability through Prognostic and Health Management (PHM), most of the cases use data-driven, model-based or even hybrid approaches where there is a lack of connection between the physical system and the proposed systems that lacks the real time insights. Hence, a digital twin can be proposed for the PEM fuel cell system to fulfill this lack of connection and performing PHM in real-time. Digital twin technology is growing up as one of the promising solutions for predictive maintenance, real-time monitoring, diagnosis, prognosis and optimization in the industry. This is because of the real-time synchronization of data from the physical system to the proposed system through sensors so that the proposed model is constantly updating and mirroring the performance of the physical system which is crucial to study the complex systems like fuel cells.

In this study, the different methodologies for PEMFC diagnosis and prognosis using digital twins are reviewed taking into account the challenges, drawbacks and future work.

II. DIGITAL TWINS

A digital twin is a virtual representation of a system in real-time which is being constantly updated with the help of sensors from the physical system to mirror its performance. This concept was first established by M. Grieves in 2003 for his study in Product Life Cycle Assessment [1] which was further refined by NASA in 2010 to predict the best maintenance time for the aircraft [2]. With time, this technology has been developed and currently, it is identified as a key component in the industry 4.0 [3]. Different studies proposed their own digital twin structures, but the base architecture of digital twin consists of three parts as physical system, virtual model and their connectivity. A service or application layer is added to the virtual model to facilitate the digital twin achieving different applications. According to all the evolved structure of digital twins from the literature, a 5D model description of digital twin was proposed in [4] as shown in the figure 1 to provide guidance for understanding and implementing a digital twin model.

Digital twin is a promising technology which lately has been extended to different fields covering a wide range of applications such as performance monitoring providing real-time tracking and anomaly detection, Predictive maintenance enabling prediction and resolving problems to reduce downtime, Design and Simulation enabling virtual testing for safe and better decisions, cost and resource optimization through real-time data insights and innovation for product development. Hence, these applications can be utilised in the context of fuel cells to improve the system durability.

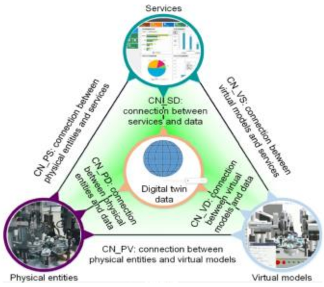

Fig. 1 Digital twin structure proposed in [4]

III. DIGITAL TWINS IN PEMFC PHM

Digital twins of PEMFC can be extended to several applications and this article primarily focuses on the PHM of PEMFC systems.

1. Prognosis

The first digital twin model for PEMFC [5], was developed in 2020, and integrated a 3D multi-physics model with data-driven surrogate models for real-time monitoring of key parameters like temperature, oxygen, relative humidity, and liquid saturation in the fuel cell. Using Artificial Neural Network (ANN) for hydrogen distribution prediction and a Support Vector Machine (SVM) for other parameters, it achieved prediction accuracy with RMSE values between 3.88% and 24.8%. While efficient, it had limitations due to simplifying assumptions, suggesting future improvements with optimization algorithms to better represent physical PEMFC conditions. A study in [6] improved PEMFC digital twin models by using 20 selected operating conditions and a 3D multi-physics PEMFC model with Proper Orthogonal Decomposition (POD) to create a reduced order model and singular value decomposition (SVD) extracting key modes from experimental data for real-time predictions. The model was validated with minimal deviation (0.11%-24.04%) and sub-second prediction times, being well suited for on-site use. This was later adapted in [7] to upscale multi-physics predictions for a commercial PEMFC stack. A 3D multi-physics digital twin model for single-cell predictions that was validated against a high-fidelity CFD model, attaining prediction times under a second per cell, though the assumptions still impact accuracy. In [8], a data-driven digital twin was developed for predicting Remaining Useful Life (RUL) using a deep transfer learning model based on a stack denoising autoencoder (SDA) and feedforward neural networks (NN) as shown in the figure 2. The model operates in two phases: an offline phase mirroring PEMFC behaviour with historical data and an online phase that updates with real-time measurements, using stack voltage as the performance indicator. A case study demonstrated prediction accuracy of 0.9 to 0.95 despite limited data, but the model has limitations, such as the lack of physical phenomena in modelling and the need for complete degradation data, which can be costly for large systems. To address the limitations of previous studies, a digital twin architecture for online RUL prediction was proposed in [9], employing Long Short-Term Memory (LSTM) networks and Quantile Huber Loss (QH-Loss). This architecture utilized LSTM for feature mapping to capture long-term dependencies in time series data, while QH-Loss enhanced accuracy by combining Huber and quantile regression losses. Results demonstrated effective prediction capabilities, although accuracy declined towards the end of the fuel cell's lifespan. Future work is suggested to explore advanced machine learning algorithms to improve the capture of degradation patterns. An early-stage degradation prediction digital twin for PEMFC was developed in [10], monitoring degradation through stack voltage drop and temperature. The model employs a hybrid approach that combines Convolutional Neural Networks (CNN) for spatial features and LSTM networks for temporal features, enhancing multi-step-ahead prediction performance, particularly in early-stage assessments with limited data. Validation through a case study on two fuel stacks under varying loads showed that the CNN-LSTM model achieved low RMSE and MAE values, confirming the effectiveness of the transfer learning approach, although it may struggle to fully capture the complexities of real-world degradation patterns. In [11], a digital twin for non-intrusive condition monitoring of a FCEV was developed using the Energetic Macroscopic Representation (EMR) method to model multi-physical interactions. The Echo State Network (ESN) algorithm was employed to predict the long-term degradation of the fuel cell, and the model was implemented on the Opal-RT platform for real-time simulations. The approach accurately predicted hydrogen consumption, output voltage, and current, enhancing overall prediction accuracy by incorporating new data points. In [12], a digital twin model for predictive maintenance of fuel cells in electric vehicles was proposed, focusing on condition monitoring and RUL prediction. The model optimized maintenance scheduling through four stages: predicting RUL using a Weibull reliability function, verifying component conditions post-repair, estimating maintenance costs through mathematical models, and developing maintenance plans using Genetic Algorithm (GA). Although this methodology was implemented using Visual Basic, it did not include an established digital twin architecture or validation of the predictive model. In [13], a digital twin approach using a Long Short-Term Memory Neural Network (LSTM-NN) and clustering methods is introduced to track test bench conditions and detect accelerated degradation rates in the test scenarios.

Fig. 2 Digital twin architecture proposed in [8]

During validation, the LSTM model successfully identified anomalies in the data, though it faced limitations in monitoring the fuel cell completely due to an inability to process raw data. However, it effectively flagged abnormal data points and demonstrated sensitivity in anomaly detection.

2. Diagnosis

A digital twin model for the dynamic behaviour of a PEMFC air feed system was proposed in [14], focusing on fault diagnosis. This method develops a dynamic model and a model-based digital twin estimator that adjusts parameters in real-time using sensor temperature data. Fault detection relies on analysing residuals which were compared against a fault signature matrix to pinpoint issues like increased resistance due to overheating or flooding. However, this model is limited to the air feed system and utilizes a basic fault library, lacking a comprehensive digital twin for the entire fuel cell. To address the challenge of limited fault data, the study in [15] presented a fault diagnosis method for PEMFC systems using a digital twin, CNN and unsupervised domain adaptive learning. The methodology involves creating a digital model of the fuel cell, simulating fault injections to generate fault data, and using residual signals to train feature extractors and classifiers. The model was validated under different load conditions. Limitations include the assumptions that the digital and real domains share the same fault space and potential inaccuracies in dynamic load conditions, which can lead to misdiagnosis. Overall, the proposed method shows promise, achieving over 80% diagnostic accuracy without real test data. Another study in [16] proposed a digital twin model built on a multi-physics model in MATLAB Simscape to enhance fuel cell efficiency through anomaly detection and performance assessment. Initial results show 60% efficiency under optimal conditions and 45% near maximum current. While promising for real-time monitoring and risk-free experimentation, challenges remain with model complexity and integration with control systems, which requires robust data synchronization methods. In [17], the performance limitations of existing diagnostic models for PEMFCs under varying data distributions were addressed by proposing a cross-domain diagnosis method using digital twins and transfer learning. First, a Temporal Convolutional Network (TCN) extracts time series features in the source domain and then, a Domain Adaptive Transfer Convolutional Network (DATCN) is employed in the target domain. The digital twin was used to generate operational data for several fault types, achieving a diagnostic accuracy of 99.92% with the TCN. When validating the DATCN across various target domains, it adapted successfully and this represented an average accuracy improvement of 30% over traditional models. However, the approach relies heavily on the digital twin's capability to generate source domain data, necessitating customized feature extraction and domain adaptation techniques. The study also notes simplifications made in the modeling assumptions. Future work aims to enhance transfer learning methods and validate this approach across other energy systems. In the study [18], digital twin is used in the virtual testing of fuel cell

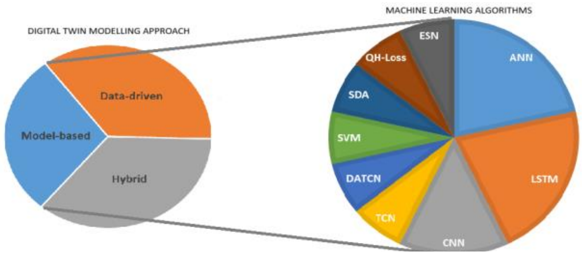

Fig. 3 Digital twin modelling methods with machine learning algorithms

powertrain systems, enabling effective on-board diagnostics where a high-fidelity fuel cell model functions as the digital twin, reproducing failure modes by triggering faults in auxiliary components such as the cathode compressor and cooling loop. Using MATLAB and GT-Suite-RT, a cost-effective Hardware-In-Loop setup tested diagnostic controls on a fuel cell hybrid vehicle, showing improved diagnostic accuracy and consistency. This model effectively simulated real-world scenarios and predicted the component and system faults.

Significant advancements in PEMFC digital twin technology have enhanced PHM by integrating various data-driven methods and more accurate modelling techniques. From model-based methods to data-driven and hybrid methods, digital twin has been employed for different applications but this study is mainly focused on the PHM. Figure 3 shows the modelling approaches used for PEMFC digital twin and the different machine learning algorithms used for the PHM of PEMFC.

IV. Conclusion

Digital twin is a growing and promising technology used in different fields for various applications due to its ability for real-time virtual modelling, enabling predictive maintenance, performance optimization and improved decision-making. Hence, this can be used in the complex systems like fuel cells to have real-time insights. Enhancing the PEMFC system durability relies on effective PHM through diagnosis and prognosis. As traditional methods often lack real-time connectivity and insights, a digital twin can fulfill this by integrating data-driven approaches with physical insights for accurate detections and predictions for PHM, improving system durability. The main focus of this paper was to review the recent advancement in PEMFC digital twins with an emphasis on prognosis and diagnosis approaches. For a high-fidelity digital twin, the main challenges faced in the literature are the need for extensive data in data-driven applications and a highly accurate multi-physics model. By leveraging digital twins, researchers can optimize maintenance schedules and improve overall system durability, addressing the challenges posed by limited operational data and a highly accurate model.

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Please indicate the topic of the paper:

Topic of paper : Production or Storage or Application	Application

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