Utilising Digital Twins for Smart Maintenance Planning of Fuel Cell in Electric Vehicles

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Abstract. This paper presents a framework utilising digital twins for predictive maintenance planning of fuel cells in electric vehicles, focusing on real-time condition monitoring and Remaining Useful Lifetime (RUL) prediction. By integrating advanced algorithms, it optimises maintenance schedules to reduce downtime and extend fuel cell lifetime. Despite relying on simulated data, the findings highlight the potential of digital twins to improve fuel cell reliability, and sustainability, illustrating their transformative impact on smart urban transportation systems.

Introduction

In today's rapidly evolving technologies, digital twins (DTs) have emerged as essential tools for linking physical and digital systems. This innovative technology allows for the creation of virtual replicas of physical entities, which can range from individual components to entire urban infrastructures [1]. The adoption of digital twin technology by cities represents a significant advancement towards becoming more intelligent and interconnected. Digital twins contribute to the development of smarter cities by offering dynamic simulations and predictive models that can anticipate potential issues and optimise urban systems. An example of this advancement is seen in projects like DIATOMIC [2], which showcases the applications of digital twins in various sectors within the city for fostering and driving digital innovation.

This paper introduces a framework utilising digital twin in enhancing and optimising future urban transportation systems, specifically through enabling predictive maintenance for fuel cells in electric vehicles. By utilising the capabilities of digital twins, it is possible to monitor the health and performance of fuel cells in real-time, predict potential failures, and schedule maintenance activities proactively. This approach not only extends the lifetime of fuel cells but also ensures the reliability of electric vehicles, contributing to a more sustainable and efficient urban transport system.

Fuel Cell Electric Vehicles

Fuel Cell Electric Vehicles (FCEVs) have gained increasing attention in recent years due to their potential to offer a clean and sustainable alternative to traditional internal combustion engine vehicles. Unlike Battery Electric Vehicles (BEVs), which rely solely on rechargeable

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batteries for power, FCEVs utilise fuel cells to generate electricity, typically through a reaction between hydrogen and oxygen. This process produces only water vapor and heat as byproducts, making FCEVs zero-emission vehicles [3,4]. Figure 1 shows the concept of the hydrogen fuel cell. Despite its several advantages over Battery Electric Vehicles (BEVs), such as energy density, faster refuelling times, longer driving ranges, etc, the complex nature of fuel cell systems necessitates careful monitoring and maintenance to prevent performance degradation and to address any emerging issues promptly. This is where digital twin technology plays a crucial role [4,5].

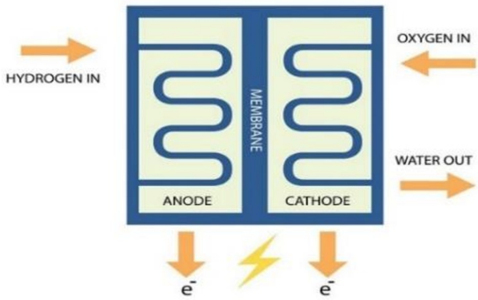

Fig. 1. Fuel cell operation concept.

The integration of digital twin technology in the management of FCEVs allows real-time monitoring of the operational parameters and health status, which highlights the transformative potential of advanced digital tools in paving the way towards more reliable and sustainable urban transport systems [6,7].

Digital Twin Framework

1.1 Introduction

The digital twin technology in FCEV operations offers numerous benefits. These include enhancing performance and reliability, improve maintenance practices, and optimise operational sustainability. Digital twins allow for real-time monitoring of critical parameters of the fuel cell such as temperature, pressure, voltage, and fuel cell health [6,7]. By continuously collecting and analysing data from FCEVs in operation, digital twins can detect anomalies, predict potential failures, and optimise life cycle usage/operation [8,9]. For example, anomalies in fuel cell voltage or temperature could indicate potential issues that require attention, allowing for proactive maintenance and minimising downtime [5]. In addition to operational benefits, digital twins contribute to sustainability efforts by optimising energy usage, reducing waste, and supporting circular economy practices. For instance, by monitoring fuel cell degradation and performance over time, digital twins can inform decisions regarding remanufacturing, reuse, and end-of-life disposal of fuel cell components.

1.2 Integration of Digital Twin Technology in Fuel Cell

The integration of digital twin technology in fuel cell of electric vehicles, shown in Figure 2, involves a layered system connecting hardware, data transmission, cloud-based applications, and end-users. Hardware components such as sensors, the fuel cell, and data acquisition (DAQ) devices are deployed within the FCEV to capture real-time data on parameters like temperature, pressure, and voltage. Data is transmitted to cloud-based applications for analysis, which include a database for data storage and analysis, and a dashboard interface for data visualisation and user interaction. End-users access the digital twin platform via the

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internet, including stakeholders such as operators and service providers, who use the insights provided by the digital twin for performance optimisation and decision-making. This integrated system enables continuous monitoring, analysis, and optimisation of fuel cell operations, enhancing reliability, efficiency, and sustainability.

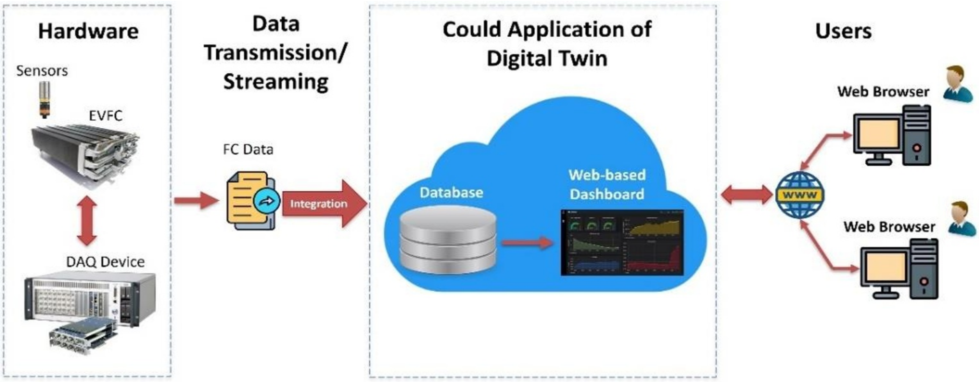

Fig. 2. Architecture of digital twin for fuel cell.

The proposed digital twin framework incorporates two core functionalities aimed at monitoring, analysing, and optimising the performance of the fuel cell. These functionalities include:

• *Condition Monitoring:* This includes observing various parameters and behaviours of the fuel cell in real-time (e.g. temperature, pressure, flowrate, humidity), detecting deviations from expected performance and allowing proactive adjustments to enhance overall performance and ensure optimal operation.

• *Remaining Useful Lifetime (RUL) Prediction:* RUL prediction is a crucial aspect of the digital twin framework, particularly for optimising maintenance schedules and extending the lifetime of fuel cell components. By employing monitoring data from digital twin, the reliability and degradation process are analysed to estimate the RUL of fuel cell components.

Building on the insights provided by condition monitoring and RUL prediction of digital twin, Predictive Maintenance (PdM) planning utilises these outputs to schedule maintenance activities in a proactive manner. Although not a direct function of the digital twin, predictive maintenance planning employs the real-time monitoring data and RUL estimates to optimise maintenance schedules, minimise downtime, and ensure the efficient allocation of resources, thereby enhancing the overall reliability and lifetime of the fuel cell system.

This paper focuses on presenting the methodology and initial implementation of the predictive maintenance planning model for fuel cell utilising outputs from the digital twin model. The following section elaborates on the approach and findings.

Predictive Maintenance Model for Fuel Cell

In this section, we present the methodology, development, and implementation of the predictive maintenance model for fuel cell system based on integrated approach of RUL-based reliability and cost analysis.

1.3 Methodology

The proposed predictive maintenance method of fuel cell utilises inputs from digital twin to optimise maintenance scheduling. The predictive maintenance model integrates four sub-models: RUL Model, which utilises Weibull reliability function to predict the RUL of the fuel cell and its components. The Repair Impact Model, which assesses the improvement in

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component condition after repair or replacement. The Maintenance Cost Model, which provides cost estimates for different repair strategies applied to each component. Finally, the Core Scheduling Model, which utilises a Genetic Algorithm (GA) to develop maintenance plans that minimise maintenance costs while maximising component condition. Figure 3 illustrates the predictive maintenance scheduling approach based on GAs, while Figure 4 presents the mathematical formulation of the core scheduling model.

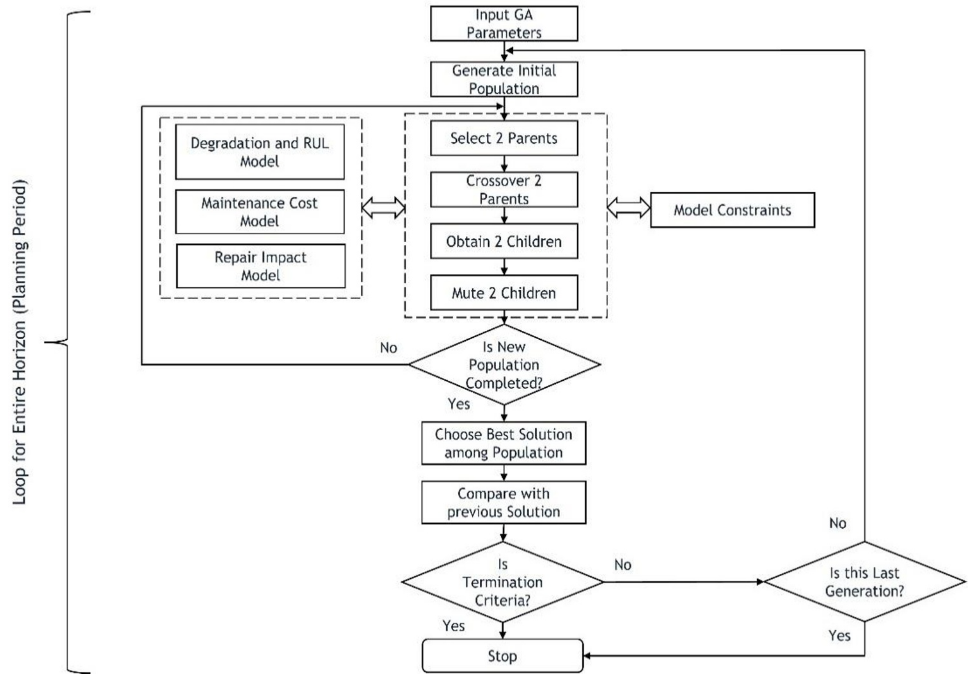


Fig. 3. Predictive maintenance methodology.

✓ **Objective Function:**

$$Maximize\ RT_S/MC_S$$

✓ **Subject to:**

$$RT_S \geq Threshold_S\ (predefined\ minimum\ reliability\ for\ Fuel\ Cell\ System)$$

$$RT_c \geq Threshold_c\ (predefined\ minimum\ reliability\ for\ component)$$

$$\sum_{t=1}^{T}\sum_{c=1}^{C} MC_c \leq Threshold_t\ (predefined\ maximum\ repair\ budget\ per\ intervension)$$

$$RT_c = \begin{cases} RT_c^{new} & if\ c\ is\ selected\ for\ repair \\ RT_c & otherwise \end{cases}$$

$$RT_S = \prod_{c=1}^{C} RT_c$$

where:

RT_S is the overall reliability of the fuel cell system at the end of time interval t

RT_c is the reliability of the component at the end of time interval t

MC_S is the total maintenance cost of the fuel cell at the end of time interval t

RT_c^{new} is the new reliability of component after maintenance

Fig. 4. Mathematical formulation of the core scheduling model.

1.4 Predictive Maintenance Model Development

1.4.1 Data and Assumptions

Due to unavailability of data from a digital twin at this stage of development, we adopt a simulation-based approach for model development. We use expert judgment supported by literature to decompose the fuel cell stack system into five components: Proton Exchange Membrane (PEM) Assembly, Gas Distribution System (GDS), Cooling System (CS), Electrical Connections (EC), and Housing Cover (HC) [10-13]. Then, we estimate the model parameters, as summarised in Table 1, to experiment our approach. These parameters include components lifetime, Weibull reliability parameters (Beta and Eta) for RUL prediction, maintenance cost data, and percentages of resulting improvements for each component. We acknowledge that these estimations are based on expert judgment and assumptions, which will be further refined with empirical data as the development of the digital twin progresses. Specifically, parameters such as β and η will be derived from real-time monitoring data collected for each component of the fuel cell within the digital twin.

Table 1. Predictive maintenance model parameters.

Component	**Weibull Parameters**		**Maintenance Cost and Resulting Improvement**			
	Eta (η)	Beta (β)	Repair (£)	% Improvement	Replacement (£)	% Improvement
PEM	10,000 hrs	0.8	200	40	1,000	100
GDS	8,000 hrs	1.2	150		800	
CS	12,000 hrs	1.0	250		1,200	
EC	7,000 hrs	0.9	100		600	
HC	15,000 hrs	1.1	300		1,400	

The following assumptions have been considered in model development:

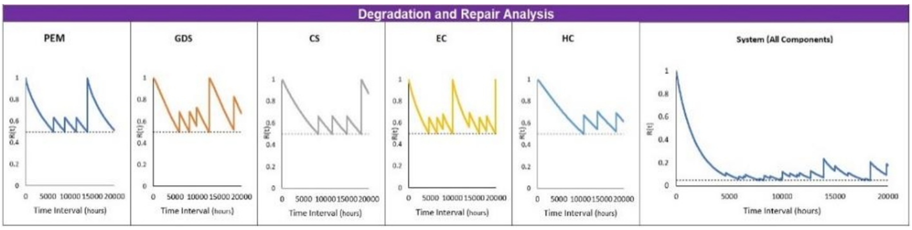
- PEM and EC components are prone to early life failures, hence assigned $\beta<1$.
- CS component experiences a constant failure rate, hence assigned $\beta=1$.
- GDS and HC components are prone to failures due to aging, hence assigned $\beta>1$.
- The expected lifetime of each component is used as an estimate for the η parameter.
- Two types of maintenance strategies are considered: Repair or Replacement.

The predictive maintenance model has been designed to minimise user input while delivering essential outputs necessary for informed and proactive decision-making regarding fuel cell maintenance. The required user inputs and resulting outputs are outlined below:

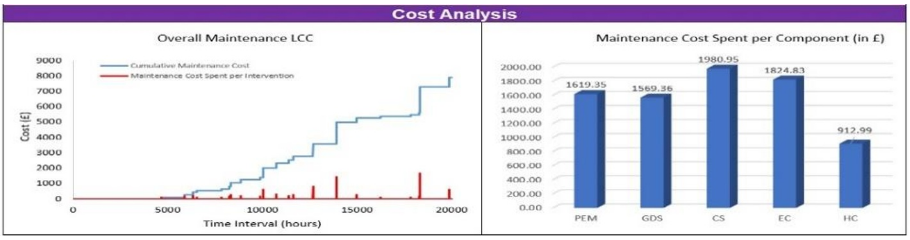
- *User Inputs:*
  - Desired period of analysis
  - Current age of components
- *User Outputs:*
  - Degradation curves
  - Maintenance cost analysis
  - Maintenance schedule

1.4.2 Implementation and Results

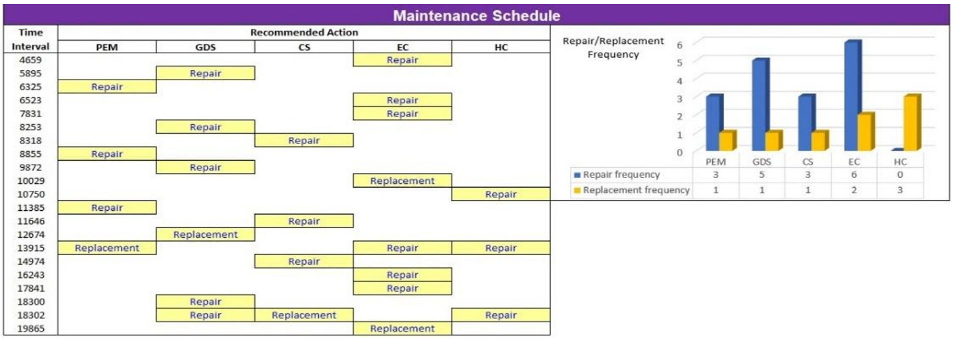
To implement the proposed predictive maintenance model, a tool based on VBA programming language has been developed. It utilises estimated data for each component (Table 1) and employs algorithms to simulate degradation, repair, and maintenance processes over the fuel cell system's lifetime. Considering 20,000 hours as a desired period of analysis with brand-new fuel cell components, Figure 5 shows screenshots of the main results obtained. Screen (a) presents degradation curves for components and the whole system throughout the analysis period. These curves show the RUL and illustrate the effects of different repair and replacement strategies on component condition. Screen (b) provides detailed analysis and insights into the maintenance cost of the fuel cell. It shows cumulative costs, costs per intervention, and cost breakdown per component. And screen (c) presents a predictive maintenance schedule for each component based on RUL and cost analysis. Additionally, it shows statistics on repair and replacement implemented for each component.



(a) RUL and degradation process analysis



(b) Maintenance cost analysis



Time Interval	Recommended Action: PEM	GDS	CS	EC	HC
4659				Repair	
5895		Repair			
6325	Repair				
6523				Repair	
7831				Repair	
8253		Repair			
8318			Repair		
8855	Repair				
9872		Repair			
10029				Replacement	
10750					Repair
11385	Repair				
11646			Repair		
12674		Replacement			
13915	Replacement			Repair	Repair
14974			Repair		
16243				Repair	
17841				Repair	
18300		Repair			
18302		Repair	Replacement		Repair
19865				Replacement	

(c) Maintenance schedule and statistics

Fig. 5. Screenshots of the predictive maintenance model results.

Conclusion

The integration of digital twin in managing fuel cell of electric vehicles offers potential benefits in terms of operational reliability and sustainability. By continuously monitoring critical parameters and predicting the RUL of fuel cell components, digital twins facilitate proactive maintenance planning. The predictive maintenance model developed in this study employs advanced algorithms to optimise maintenance schedules based on real-time data and cost analysis. The initial implementation, despite relying on simulated data, demonstrates the model's potential to enhance fuel cell system performance by minimising downtime and extending component lifetime.

As digital twin model continues to evolve, the accuracy and reliability of predictive maintenance models will improve with the integration of empirical data. This will further enhance the ability of digital twins to support informed decision-making and resource allocation, promoting more sustainable and efficient urban transportation systems. Future research should focus on refining the model with real-world data and exploring the broader implications of digital twin model in various sectors of urban infrastructure. Ultimately, the application of digital twins in fuel cell of electric vehicles highlights their potential in fostering smarter and more resilient cities.

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