Proton Exchange Membrane Fuel Cell System Prognostics and Decision-Making: Current Status and Perspectives

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Abstract

Proton exchange membrane fuel cell (PEMFC), as an attractive alternative power source, has seen its increasing deployment in both automotive and small stationary applications. To improve the durability of the PEMFC system, which is one of the primary challenges standing in the way of its successful market introduction, recent research has engaged in developing prognostics and health management methods. Although the prognostics methods have been extensively studied to improve the prediction accuracy, some critical issues have not been fully addressed. For example, few studies have looked into the prognostics methods by different criteria and under dynamic operation conditions, and none of them have investigated the data availability and quality for PEMFC prognostics. Due to the lack of more comprehensive and general prognostics methods as well as the limitations in data, studies in the post-prognostics decision-making phase have hardly ever been initiated. This paper tends to provide a full review of the existing prognostics research by analysing the prognostics scales, horizon, threshold, and the use of methods. The data used in the previous studies has also been investigated. Moreover, four principal directions of post-prognostics decision-making have been proposed and discussed. ~~This paper reviews the prognostics methods by analysing the prognostics scales, horizon, threshold and the use of methods for different operating conditions and reports the available experimental datasets used for PHM studies and their limitations. Then, we point out that the current research is devoted to investigating the fuel cell prognostics, but the post-prognostics decision-making phase has not been sufficiently studied due to the lack of datasets, inconclusive problematics and incomplete methodology. In this paper, four post-prognostics subjects are analysed and discussed, including~~

~~degradation tolerant control, multi-stack control, energy management, and maintenance scheduling.~~ According to the findings, research challenges and development perspectives in the aspects of data, prognostics and decision-making are proposed.

Keywords:
dataset, decision-making, health management, PEMFC, prognostics

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Nomenclature

Abbreviations

$ANFIS$ adaptive neuro fuzzy inference system

$DBN - ELM$ deep belief network extreme learning machine

DOE Department of Energy

$ECSA$ electrochemical surface area

EIS electrochemical impedance spectroscopy

EKF extended Kalman filter

EMS energy management strategy

EOL end of life

ESN echo state network

$GMDH$ group method of data handling

GRU gated recurrent unit

H_2 hydrogen

$HITP$ hardware-in-the-loop

IoT internet of things

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LPV linear parameter varying

$LSTM$ long short term memory

$LWPR$ locally weighted projection regression

$MAPE$ mean absolute percentage error

MEA membrane-electrode assembly

MPC model predictive control

$PEMFC$ proton exchange membrane fuel cell

PF particle filter

PHM prognostics and health management

R^2 R squared error

$RMSE$ root mean square error

RUL remaining useful life

SOH state of health

$SW-ELM$ summation wavelet extreme learning machine

UKF unscented Kalman filter

Physics symbols

D_{fc} fuel cell degradation

P_{actual} actual power

P_{rated} rated power

$P_{required}$ required power

t_λ time to start prognostics

t_f time of EOL

1. Introduction

Proton exchange membrane fuel cell (PEMFC) has seen its increasing deployment in both on-board and stationary applications, which is an attractive alternative to fossil fuel devices with high energy output and no pollutants. In today's fast energy transition period, minimizing fuel cell system costs is an important task for its successful market introduction. The approach towards this goal is threefold - components design, production, and operations, as shown in Figure 1. In addition to the efforts made in the design and assembly process, enhanced efficiency and durability can be expected through appropriate stack operation. ~~The Department of Energy (DOE)'s Fuel Cell Technologies Office has set the 2020 target of 5,000 hours' durability for on-road fuel cell electric vehicles, which corresponds to an expected driving distance of 150,000 miles within a particular range of speeds, while the ultimate goal is 8000 hours [1].~~ According to an evaluation project launched by the National Renewable Energy Laboratory, the durability of on-board fuel cells has increased 1.5 times since 2006 and the maximum operation time has reached 5,605 hours, however, only 22% of the tested fuel cell stacks have passed 2,000 hours of operation [1]. The Fuel Cells and Hydrogen 2 Joint Undertaking has set the durability targets for the light duty fuel cell vehicles in its Multi-Annual Work Plan 2014-2020 (MAWP 2020) that the lifetime of the fuel cell system should be further improved to reach 6000 hours before 2024 and 7000 hours before 2030 [2].

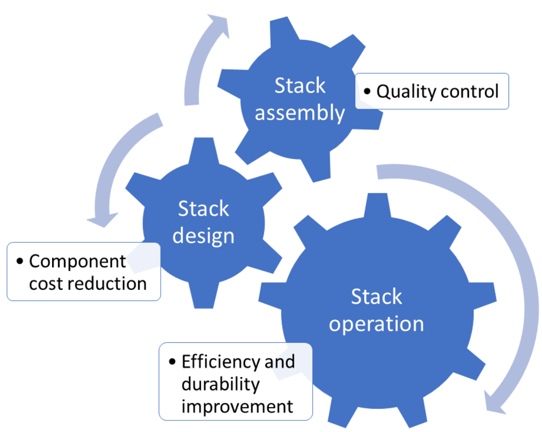


Figure 1: Techno-economic challenges of PEMFC commercialization

The durability issue of PEMFC systems has attracted increasing attention in recent years. Concerning the hydrogen-fuelled PEMFC itself, by its very nature, is prone to irreversible degradation phenomena during its storage and operation mode, leading to accelerated performance loss and shortened lifetime [3]. Neglecting the degradation could result in the misunderstanding of the components' available lifetime and the overconfidence of the system's health condition, which will cause serious consequences. The degradation modes and experimental techniques dedicated to studying the PEMFC stack durability in vehicular applications are reviewed in [4], which helps to understand the root causes of the fuel cell and conduct degradation mitigation control. Degradation-related parameters have been investigated in [5] on various fuel cell components and the reactant starvation, known as an important source of the stack degradation, has been analysed in [6] including its causes, consequences and mitigation measures. As the degradation remains as one of the weak points of PEMFC technology, efforts have been made to provide guidance to optimize the system control and management strategy and to prolong the stack lifetime. To meet this goal, monitoring the online health state for the fuel cell itself is of significant importance in assessing its health state and provide useful information. The necessity of developing internal state observers for fuel cell state estimation has been revealed in [7], in which the authors have argued that the observation of the internal state is important to the management of the gas, water and heat systems in fuel cell applications. Recently, prognostics and health management (PHM) exists and positions itself as an innovative discipline allowing to protect the integrity of the system, predict the downtime and avoid unanticipated operational failure. Jouin et al. [8] have reviewed the PHM activities in PEMFC applications. The PHM procedure contains a set of activities: data acquisition and processing, condition assessment, diagnostic, prognostics, decision support and human-machine interface. It allows us to evaluate the system's reliability in real operating conditions and improve the system's durability by predicting its approaching failures and making corresponding operations. They have also pointed out that prognostics, as an important process in PHM, has been actively investigated for PEMFC applications, while post-prognostics phases, i.e. decision-making, need more investigation efforts. Moreover, Lin et al. [9] have reviewed fuel cell prognostics methods from different scenarios such as health monitoring, fault diagnosis, prolonging life span, etc. and separates the applied methods into data-driven, model-based and filter-based methods. In order to select different prognostics methods, Sutharssan et al. [10] have reviewed different applications in fuel cell prognostics, e.g. degradation mechanisms, failure models, accelerated tests, etc. Moreover, Liu et al. [11] have reviewed the degradation indexes for PEMFCs that have been applied in different prognostics methods, in which the authors have pointed out that for the PEMFCs operating under dynamic conditions, traditional indexes can hardly be applied to predict degradation performance.

However, the existing review papers focus majorly on prognostics methods, which are investigated based on finished experimental degradation data, i.e. they use the historical data from the system to perform prognostics and validate the performance with these offline data. Although these methods contribute to predicting the remaining useful life (RUL), post-prognostics decisions are lacking. Developing an integrated PHM cycle to benefit not only from the results of the prognostics but also health management pathways is demanding [12]. A general framework of PHM has been proposed in [13], in which the health state of the stack corresponds to the modifications of the stack quality, maintenance schedules, operating conditions, as well as the monitoring phase. In this paper, both prognostics and decision-making phases are reviewed and analysed. The question on how to make use of the RUL information to prolong the fuel cell lifetime has been proposed towards the real objective of PHM. This paper reviews the existing fuel cell prognostics methods from the perspective of PHM by analysing the prognostics scales, horizon, threshold and the use of methods and their performance. It also reports the available PEMFC experimental datasets used for prognostics studies and their limitations, which are never been investigated in other relevant papers. We also point out that the post-prognostics decision-making phase has not been sufficiently studied due to the lack of datasets, inconclusive problematics and incomplete methodology. To this regard, four post-prognostics subjects have been analysed and discussed in this paper, including degradation tolerant control, multi-stack control, energy management and maintenance scheduling. Prognostics-enabled decision-making methodologies of these matters are described. According to the findings, remaining challenges and perspectives regarding data, prognostics methods and prospective post-prognostics decision-making actuations are proposed.

The paper is organized as follows: Section 2 introduces the problematics of prognostics, in which a rich study on prognostics scales, horizon, threshold and methods are reviewed, and the effects of datasets are analysed. Section 3 outlines the potential study areas of post-prognostics decision-making. Finally, Section 4 summarizes the challenges and perspectives before concluding.

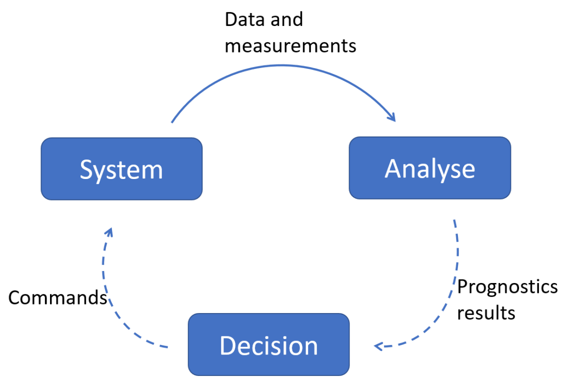


Figure 2: Prognostics in a closed loop

2. Problematics of PEMFC prognostics

The prognostics process can be summarized as a process of estimating a system's RUL and its uncertainties. The definition of RUL refers to the period between the current instant t_c and the instant where the failure threshold at t_f - end of life (EOL) is reached. The international organization for standardization (ISO) committee has defined prognostics as [14]:

> Standard ISO 13381 (2004). *The aim of prognostics is the "estimation of time to failure and risk for one or more existing and future failure modes".*

Prognostics appears to be a key process which makes the current industries think more about "predict to prevent" rather than "fail to fix". The principle of implementing prognostics is shown in Figure 3. The first part of prognostics process is to learn from the operating system and to extract the degradation feature from the available measurements. When the measurement is no longer available, the second part is to forecast the future information without available measurements. The prediction is made based on the training process and the expected result is the RUL and its uncertainty based on the definition of the EOL threshold.

This section reviews the existing PEMFC prognostics studies from different aspects: prognostics scales, prognostics horizon, design of the EOL threshold and prognostics methods. Moreover, the current situation and quality of the available datasets used for fuel cell prognostics purpose are analysed.

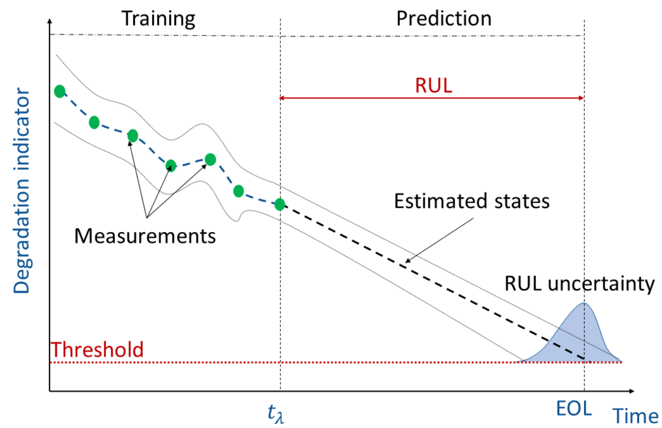


Figure 3: General principle of prognostics

2.1. Prognostics scales

2.1.1. Component level

A PEMFC stack is an assembly of several cells in series, while a single cell is composed of several components: electrodes, membrane, bipolar plates, gas diffusion layers and sealing gaskets, as shown in Figure 4. The performance degradation of the stack is due to the different level of degradation on these components [13]. Jahnke et al. [15] have reviewed the performance and degradation models on the component scale, while only the ones applied to prognostics studies are considered in this paper.

According to Jouin et al. [13], electrodes and membrane are identified as the most significant degrading components in the cell. The electrodes consist of the catalyst and the carbon supports, while the catalyst usually suffers from Pt dissolution, coarsening and coalescence process. Efforts have been conducted to model the internal degradation mechanisms regarding the electrodes. For example, Zhang et al. [16] have proposed an ageing modelling method for fuel cell catalyst, which is used for the health monitoring and prognostics of PEMFCs. In this work, the degradation rate of the electrochemical surface area (ECSA) has been estimated based on the operating conditions. Similarly, a mathematical model has been proposed in [17] to represent the ECSA reduction rate as well as the stack voltage decay, which allows proper estimation of RUL under different operating conditions. Other works have proposed to identify the evolution of the PEMFC degradation by monitoring the membrane thickness [18, 19]. A fused model has been

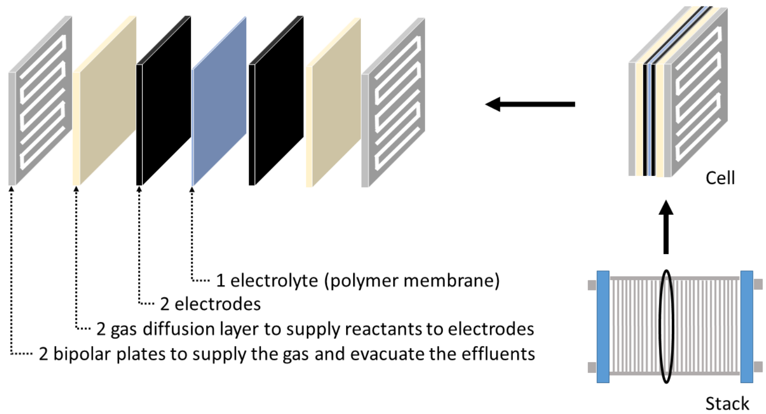


Figure 4: Structure of a single cell in a PEMFC stack

proposed in [20] to predict the degradation of the electrode and membrane based on a series of degradation indexes, i.e. the average radius of Pt particles, ECSA and membrane thickness.

The hydrophobicity loss of the gas diffusion layer has also been identified as a degradation index of the PEMFC in [21] through hydrophilic pore network modelling. However, it was based on rough approximations and the method has not been verified. Besides, the degradation of bipolar plates and sealing gaskets mainly leads to the increase of the contact resistance. Although one can estimate the change of the impedance of a PEMFC using electrochemical impedance spectroscopy (EIS), it is difficult to separate the contributors: the change of the impedance could result from interfacial charge-transfer resistance, membrane resistance, contact resistance, mass transport resistant, double-layer capacitance, and Faradaic pseudo-capacitance, etc. Therefore, few studies have used the performance loss of them individually as degradation indexes due to the difficulties in capturing their changes [13].

Nevertheless, the current prognostics works on the component level consider the ageing mechanisms of the PEMFC in a separated way, in which the coupled phenomena is not taken into account. Moreover, Jahnke et al. [15] have pointed out that the use of Butler-Volmer theory cannot be justified to describe the electron transfer reactions in nanomaterials with an evolving structure. Robin et al. have presented an indirect coupling approach in [22], in which the degradation rate is given by a look-up table. It helps to determine the degrading state of the fuel cell, however, when it comes to prognostics, predictions are hard to be made.

2.1.2. Stack level

Most prognostics works nowadays are conducted on the stack level [23]. This is due to the fact that no matter what is the cause of the fuel cell performance loss, it can be observed from its stack voltage decay, however, the voltage decay of each cell might not be the same, e.g., the edge cells degrade faster. Besides, as the purpose of prognostics is to predict the RUL, analysing the stack voltage degradation is sufficient to do so unless the specific measurement is required.

To date, most prognostics works on the stack level are developed for the PEMFCs operating under constant load. For example, Jouin et al. [24] have proposed a prognostics method by adapting the particle filtering process and the algorithm is validated by a long-term experimental dataset with constant load. A considerable number of works have been conducted using this dataset by developing different prognostics strategies [25, 26, 27]. Besides, Morando et al. have used a recurrent neural network to estimate the RULs by separating the voltage degradation signal into the approximation part and the detail part. The tested PEMFC stack is operated under a constant current profile of 0.6 A/cm^2 [28]. The development of the prognostics strategies applied to constant loads have enriched the choices of fuel cell prognostics methods, however, most of them are not applicable to the fuel cells operated dynamically, especially for those in automotive applications.

Prognostics strategies for the PEMFCs operating under dynamic loads have not been fully developed. This is due to the difficulties in catching the varying parameters in dynamic operating conditions and also due to the scarcity of the open-source datasets [29]. Under dynamic loads, the stack voltage is varying according to the load changing so that the challenge should be extracting its degradation trend. Li et al. [30] have developed a prognostics strategy for an ageing PEMFC stack operating in a hybrid system, in which a linear parameter varying model is deployed to reformulate the fuel cell voltage degradation. Using the same dataset, Yue et al. [31] have proposed to decompose the voltage signal through multiplicative decomposition. However, it requires the fuel cell to operate under a cyclic load profile. It is hard to apply these methods for on-board vehicle applications if the driving conditions remain unpredictable. Zhang et al. have proposed an empirical PEMFC life prediction model in [32] based on driving conditions. Zuo et al. [33] have proposed to predict the dynamic voltage by defining certain current levels, i.e. extract the voltage values under the same current and then perform prognostics. Moreover, Bressel et al. [34] have introduced a degradation coefficient to the state estimation model. This method supposes that the degradation can be tracked through a single linear state variable. The prognostics strategy is applied to a PEMFC system operated under a μ-CHP profile.

The current prognostics methods on the PEMFC stack level mostly evaluate the overall performance loss, while lacking the insights of the intrinsic degradation analysis. As the time-varying online operating conditions can deviate the fuel cell degradation phenomena, developing degradation identification and prognostics strategies that can be adapted to random external conditions is required.

2.2. Prognostics horizon

The prognostics horizon is used to evaluate whether a prognostics algorithm is good to leave enough duration for the future corresponding operation based on the prognostics results. As shown in Figure 5, the prognostics performed at time instant t_λ is said to well represent the current health state only if the RUL estimation is in the acceptable error zone. As the shortening of the prognostics horizon, the acceptable error zone is shrinking and the acceptable error margin differs according to applications. Moreover, it has been defined as 16% of the original value for early prediction and 8% for late prediction for a horizon of 300 hours [35]. It is important to ensure the accuracy of the RUL prediction in the case of a greater prognostics horizon in order to schedule the maintenance and the corrective actions to an earlier extend and to achieve more effective cost minimization and risk mitigation.

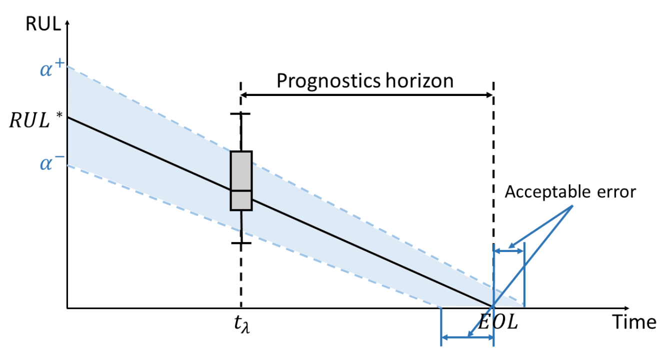


Figure 5: Demonstration of prognostics horizon

Zhou et al. [36] have proposed an improved grey prediction model by adding a Fourier function to the error correction term of the grey model to consider the varying prognostics horizon, therefore, to improve the prediction accuracy even if only limited measurements are available. Xie et al. [37] have found that recurrent neural networks are efficient tools when conducting short-term fuel cell degradation prediction and have used a fused method to improve the short-term prediction accuracy. Long short-term memory framework can benefit from the short memory of the prediction steps to update the network so that to make reliable long-term predictions. Several PEMFC prognostics works are conducted based on this method [38, 39, 40].

In the framework of PHM, making decisions and performing maintenance activities strongly depends on the prognostics horizon because different actions regarding control and management should be deployed for the system failing in different time horizons [41]. Few studies have investigated the relationship between the fuel cell prognostics performance and the prognostics horizon, which have put backwards the development of decision-making methods in PEMFC systems.

2.3. EOL threshold

One of the metrics to quantify the prognostics results is the RUL, while the RUL is calculated according to the definition of EOL threshold [35]. The EOL threshold is usually set as a certain percentage of the original value from the fuel cell's health state. The commonly used EOL threshold of the PEMFC system is defined by the United States Department of Energy, which is losing a percentage of 10% of its nominal power. This criterion is given only considering the power loss but not the operational utility of the system. It is used to calculate the RUL of the stack in many research works [42, 43]. For the dataset described in [24], 96% of the initial stack voltage is selected as the EOL considering the length of the dataset in many works [44, 45]. A state-of-health (SOH) estimation method proposed in [46] has used a degradation path γ to indicate SOH, in which a value of 0.15 is deduced from the EIS measurements. The prognostics method proposed in [47] have used 34% of the degrading state variable as the EOL threshold. Using a different dataset, the state estimation method proposed in [48] have used 50% degradation of the state variable as the EOL threshold for the RUL calculation to have a life of about 1550 hours. The uncertainty of EOL threshold can impact the prognostics performance. Studies in [26] have set the EOL thresholds at 10% and 15% of the initial stack voltage, respectively and the prognostics strategies showed different performance on the two different EOL thresholds, while the quantity of the learning data affects the prediction accuracy. In [49], the authors have proposed to calculate the RUL of the stack based on the reference value of the requested power and keep tracking the maximum available power of the fuel cell to perform degradation tolerant control.

The definition of EOL threshold affects directly the prognostics results, however, it is difficult to determine as it is an unknown value with prospective nature, and it may change due to the variation of operating conditions. If the power profile is known, e.g., implementing a specific mission, the EOL threshold can be easily determined.

2.4. Prognostics methods

Prognostics methods are categorized into three types: 1) data-driven methods; 2) model-based methods; and 3) hybrid methods [10]. It is also true with respect to the RUL prediction. Previous research has reviewed numerous degradation identification and estimation methods but not all of them can be applied to predict the RUL due to the parameter complexity and measurability [11]. This section does not aim to execute an exhaustive survey for all the methods but focus on those dedicated to performing prognostics and predicting the RUL.

2.4.1. Data-driven method

Data-driven methods are applied to perform prognostics when sufficient data is available to learn the system behaviour using a "black-box" model. Using data-driven methods, the black-box models are created directly from the data, and they are able to project the future states or match similar patterns in the historical datasets. No precise physical model is required. Different from model-based methods, data-driven methods can reflect the inherent relationships by learning the historical and monitoring data and then predict the future trend. Thus, this approach gradually becomes the main methodology for fuel cell prognostics due to the easy-to-use and flexible modelling properties [50].

In the state-of-the-art, traditional neural networks [45, 51], echo-state networks (ESNs) [28, 30, 31], long short term memory networks (LSTMs) [38, 40] and adaptive neuro fuzzy inference system (ANFIS) [25] and other methods have been adapted to predict fuel cell's RULs. Efforts have been made to improve the prediction performance of data-driven prognostics methods and reduce the requirements of the degradation data. For example, two recurrent neural networks have been developed in [33] including LSTM and the one with the gated recurrent unit, which show good prognostics performance with root-mean-square-error (RMSE) values under 0.02 for the PEMFC stack operating under dynamic profile. A constraint-based summation wavelet-extreme learning machine has been proposed in [26], in which the authors point out that constraints are necessary for any connectionist methods to in case of limited measurements.

The accuracy of the data-driven prognostics methods depends on the confidence level of the training data as the behaviour models (black-box models) are established only based on historical measurements [10, 52]. The future states are propagated only due to the models and the measurements since there is no physical meaning. The predicted results of data-driven methods are usually deterministic values so that the confidence level cannot be examined in most cases. Therefore, in prognostics applications, challenges are confronted in obtaining enough data to ensure the prediction accuracy. Besides, over-fitting issues of the algorithm, as well as the adaptability of changing operating conditions should be addressed. Another challenge is to configure the connectionist network, such as the number of connecting points and layers, dropout rate and other model parameters. Most of the research has defined the configuration according to the human expertise and engineering experience [37]. Some researchers have used searching algorithms to select good parameters for the data-driven models, however, it is time-consumption and requires huge computation [39]. Remarkable research works using data-driven prognostics methods are summarized in Table 1, which concludes the method, the load profile, the prognostics scale, the achieved prediction accuracy and the pros and cons.

2.4.2. Model-based method

Model-based prognostics method is to develop mathematical equations that include many physical parameters to predict the physics governing failures. Many researchers have used precise electrochemical models to predict the power sources' health states [61]. An accurate physical model can facilitate the RUL prediction because it can reproduce the behaviour of the system and therefore, to calculate the estimated output without any calculation burden [62]. Once an appropriate model is found for certain conditions, the prediction results are reliable to the users.

A physical model that used for the prognostics purpose must contain time-dependent parameters. For example, a PEMFC model has been proposed in [62] that can be inserted in the prognostics process. It consists of a static part and a dynamic part. The static part models the activation loss at the electrodes, which can be identified by fitting the polarization curves. The dynamic model is developed according to the changing impedance of an equivalent circuit model, in which the parameters are tuned by fitting the EIS spectrum. Similarly, Pan et al. [44] have used an analytical equivalent circuit model to assess the fuel cell health, in which the parameters are tuned

Table 1: Summary of PEMFC data-driven prognostics studies

	Publication	Year	Method	Load profile	Prognostics scale	Prediction accuracy	Pros and Cons
Data-driven method	Silva et al. [25]	2014	ANFIS	Constant load	Stack level	$R^2 > 0.95$	**Pros:** model-free without complex physical parameters; easy to implement; high generality. **Cons:** need a great amount of data to ensure the accuracy; need human expertise to configure the algorithms; the prediction results are deterministic; sometimes encounter over-fitting issues; time and computation consuming.
	Javed et al. [26]	2015	SW-ELM	Constant load	Stack level	$R^2 = 0.91$ for one stack and $R^2 = 0.91$ for the other stack	
	Yin et al. [53]	2016	LWPR	Constant load	Stack level	Not applied	
	Morando et al. [28]	2017	ESN	Constant load	Stack level	$MAPE = 0.97\%$	
	Liu et al. [47]	2017	GMDH network	Constant load	Stack level	$RMSE = 0.09$ for one stack and $RMSE = 0.06$ for the other stack	
	Zhu et al. [54]	2018	Gaussian process	Constant load	Stack level	Within $\pm 10\%$ error zone of the actual RUL	
	Zhou et al. [45]	2018	Neural network	Constant load	Stack level	RUL estimation error $<$ 30%	
	Ma et al. [38]	2018	LSTM	Constant load	Stack level	$RMSE = 0.0040$ and $MAPE = 0.0013$	
	Mezzi et al. [55]	2018	ESN	Constant load	Stack level	Average RUL error = 30 hours	
	Li et al. [30]	2018	ESN	Automotive dynamic cycle	Stack level	Within the confidence interval of 95%	
	Chen et al. [51]	2019	Neural network	Constant/dynamic load	Stack level	$MAPE < 1.04\%$	
	Hua et al. [56]	2020	ESN	Constant load	Stack level	$RMSE = 0.0110$	
	Vichard et al. [42]	2020	ESN	Automotive dynamic cycle	Stack level	Normalized $RMSE$ = 0.098	
	Yue et al. [31]	2020	ESN	Automotive dynamic cycle	Stack level	Average $RMSE = 0.07$	
	Wang et al. [40]	2020	Stacked LSTM	Constant load	Stack level	Normalized weighted-sum error = 0.9633	
	Pan et al. [57]	2020	Stacked LSTM	Constant load	Stack level	$RMSE < 0.01$	
	Meraghni et al. [58]	2020	Stacked LSTM	Constant load	Stack level	Relative accuracy > 0.9	
	Xie et al. [37]	2020	PF-LSTM	Constant load	Stack level	$R^2 > 0.91$	
	Xie et al. [59]	2020	DBN-ELM	Constant load	Stack level	$R^2 > 0.91$	
	Chen et al. [60]	2020	Wavelet neural network	Dynamic load	Stack level	$MAPE = 5.18\%$	
	Ma et al. [39]	2020	Stacked LSTM	Constant load	Stack level	Relative accuracy = 0.95	
	Zuo et al. [33]	2021	LSTM and GRU	Automotive dynamic cycle	Stack level	$RMSE < 0.0040$	

based on EIS measurements by linear regression. A similar approach has been found in [63]. Besides, EIS measurements are also applied to fuel cell component degradation analysis because different operating conditions and degradation degrees will lead to the derivation of the arc shapes, as shown in Figure 7. By extracting features from the EIS measurements, predictions could be performed [64]. For example, an identification method to find the low-frequency resistance, i.e. the rightmost intersection with the real axis of the EIS arcs, has been proposed in [65], which can estimate the fuel cell degradation with only small disruptions. Pivac et al. [66] have used the same parameter on the EIS arcs as the indicator of stack degradation and built an equivalent circuit model to represent the degradation of the catalyst layer.

However, PEMFC systems are dynamic, time-varying and nonlinear electrochemical systems, and the internal reactions and failure modes are very complicated, which change under different operating conditions. Therefore, it is not easy (even impossible) to find precise physical models or mathematical models to describe detailed fuel cell degradation mechanisms and failure modes. Even if the physical model is available, it is hard to represent it in the analytic form and the model built for one application cannot be transferred to another application. Moreover, although efforts have been made to find accurate and dynamic degradation models, the difficulties in measurements have limited the development of model-based prognostics methods. For example, a degradation model has been proposed in [67] to simulate the pinhole formation process on the membrane during the chemical degradation. The required measurement is conducted on the microscale. Other degradation modelling works may even be performed on the nanoscale [68]. It is technically and economically infeasible to install micro-sensors (nano-sensors) on the stack in order to catch its degradation without specific needs. These models are not favourable for industrial employment. Typical model-based PEMFC prognostics methods are summarized in Table 2.

2.4.3. Hybrid method

Rather than finding the exact relationship using multiple physical parameters, research has been conducted to use hybrid methods to perform prognostics on the PEMFC. The hybrid methods combine the two previous types of prognostics methods, which develop models to describe the degradation process mathematically, while the model parameters changing over time are estimated by learning algorithms. This kind of method avoids the complicated process to study the internal degradation mechanisms regarding different fuel cell components and uses a substitute way to construct

Table 2: Summary of model-based PEMFC prognostics studies

	Publication	Year	Method	Load profile	Prognostics scale	Prediction accuracy	Pros and Cons
Model-based method	Zhang et al. [16]	2014	Pt catalyst degradation model	Constant load	Component level	Within the confidence interval of 95%	**Pros:** good accuracy once the model is adapted to a certain system; less training data; less computation burden. **Cons:** nearly impossible to find precise degradation model due to complex parameters to be defined; models developed for one system can hardly be transferred to another system with different operating conditions; some measurements needed in the model are not economically or technically feasible.
	Lechartier et al. [62]	2015	Semi-mechanism degradation model	Constant load	Stack level	$RMSE = 0.5103$	
	Polverino et al. [17]	2016	ECSA degradation model	Constant load	Component level	Not applied	
	Kim et al. [63]	2016	EIS feature extraction	Constant load	Stack level	Average weighted-sum error =5.32e-6	
	Hu et al. [43]	2018	Semi-mechanism degradation model	Automotive dynamic cycle	Stack level	Predicted voltage deviation of 1%	
	Pivac et al. [66]	2018	EIS feature extraction	Accelerated stress test	Component level	Not applied	
	Pei et al. [69]	2019	Empirical model	Constant load	Stack level	Not applied	
	Pan et al. [44]	2020	EIS feature extraction	Constant load	Stack level	Average weighted-sum error =3.9409e-6 for one stack and =8.2021e-6 for the other stack	
	Halvorsen et al. [65]	2020	EIS feature extraction	Accelerated stress test	Component level	Not applied	
	Ao et al. [70]	2020	ECSA degradation model	Automotive dynamic cycle	Component/stack level	Relative error = 8.18%	
	Ou et al. [71]	2021	Semi-empirical model with recovery identification	Automotive dynamic cycle	Stack level	Within the confidence interval of 95%	

behaviour models. Yuan et al. [7] have reviewed the model-based observers that are used for fuel cell prognostics. To this end, the PEMFC is represented by an equivalent circuit model and the prognostics is executed by solving state space models through filtering algorithms: extend Kalman filter (EKF) [48], unscented Kalman filter (UKF) [51, 72], particle filter (PF) [73, 23, 46, 74], etc. The prognostics is implemented by propagating the current estimated health state and its uncertainty to the future. The learning process could be model-based, data-driven or a combination of both, because both physical models and data can be integrated into the state vector model [75].

Hybrid prognostics methods are favourable for the good prediction performance and as they need only a few parameters to build the models, the modelling process is simplified compared to model-based methods. Owing to the learning process, the hybrid methods also share the advantage of good generality from data-driven methods. Besides, the uncertainties are easy to be represented when applying filtering-based hybrid prognostics methods so that the prediction results tend to be more reliable by defining the confidence level. Efforts have been made to improve the filtering-based hybrid prognostics methods, for example, in [76], instead of using the uniform distribution for the parameter initialization of the PF, the initialization procedure has been improved by the historical EOL data, which considers more parameter uncertainties.

Hybrid methods are widely used in fuel cell prognostics and are of high flexibility in applications, however, the implementation cost may get heavier. Although building physical models is not a primary condition for hybrid methods, it still needs the expertise knowledge on the system degradation. If the degradation process is complex, it will add to the calculation burden of the training procedure. Therefore, it is very important to find a compromise between the model complexity and the training expense when applying hybrid prognostics methods. Table 3 summarized the representative works using hybrid prognostics for PEMFC applications.

2.5. Long-term experimental datasets

As discussed above, prognostics methods are developed to adapt the characteristics of the datasets, in other words, the datasets can affect the performance of prognostics methods. Currently, only a few available long-term experimental datasets dedicated to the PEMFC prognostics research are available. This section has reviewed these datasets and has pointed out the limitations by analysing the data quality.

Table 3: Summary of hybrid PEMFC prognostics studies

	Publication	Year	Method	Load profile	Prognostics scale	Prediction accuracy	Pros and Cons
Hybrid method	Zhang et al. [72]	2012	UKF	Constant load	Stack level	Within the confidence interval of 95%	**Pros:** high accuracy; use more applicable model (grey model) with fewer physical parameters; good generality. **Cons:** need both knowledge on the degradation mechanism and training data; highly dependent to the initial settings of model parameters.
	Jouin et al. [23]	2014	PF	Constant load	Stack level	Relative accuracy > 0.9	
	Kimotho et al. [73]	2015	PF	Constant load	Stack level	IEEE 2014 PHM Challenge score of 0.77	
	Jouin et al. [24]	2015	PF	Constant load	Stack level	$MAPE = 0.33\% - 5.06\%$	
	Jouin et al. [77]	2015	PF	Combined heat and power profile	Stack level	$R^2 = 0.8$	
	Ibrahim et al. [78]	2016	Wavelet transform	Constant load	Stack level	Relative RUL error $<$ 2.81%	
	Bressel et al. [48]	2016	EKF	Constant load	Stack level	Within $\pm 10\%$ error zone of the actual RUL	
	Jha et al. [74]	2016	PF	Constant load	Stack level	Relative accuracy $= 0.96$	
	Liu et al. [29]	2017	UKF	Constant load	Stack level	Within $\pm 10\%$ error zone of the actual RUL	
	Mao et al. [79]	2017	PF	Constant load	Stack level	Prediction error of 2.71e-4 for constant load and 0.04 for dynamic load	
	Yang et al. [80]	2017	PF	Constant load	Stack level	$RMSE < 0.01$	
	Zhou et al. [81]	2017	NARNN model	Constant load	Stack level	$RMSE = 0.069$	
	Cheng et al. [27]	2018	PF	Constant load	Stack level	Length of confidence interval < 20 hours	
	Chen et al. [82]	2019	UKF	Automotive dynamic cycle	Stack level	Average relative error $=$ 2.03%	
	Zhang et al. [46]	2019	PF	Constant load	Stack level		

2.5.1. Current situation

A survey on the available datasets used for performing prognostics is conducted. It is summarized in Figure 6. Most of the datasets are under privacy policy and not available but for project members, which has limited the production of research works.

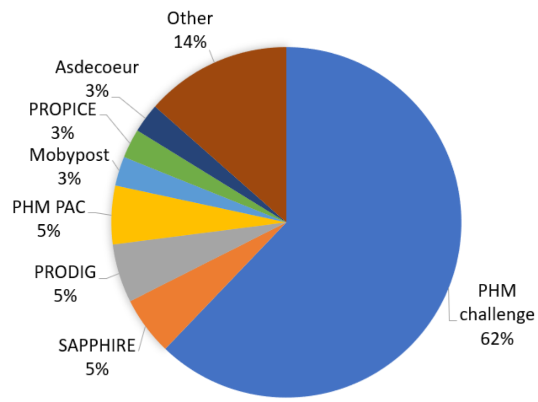
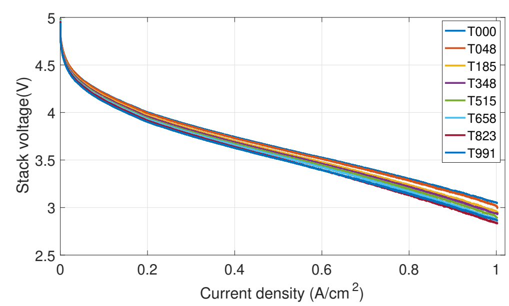
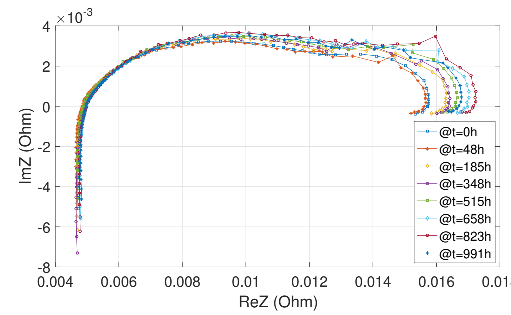


Figure 6: Statistics of datasets oriented for prognostics

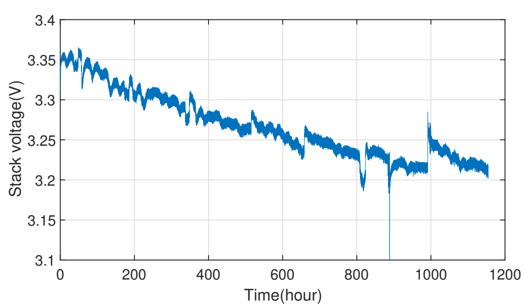
The mostly used PEMFC degradation dataset for prognostics is an open-source dataset that was released during the event of the IEEE PHM 2014 Data Challenge launched by the IEEE Reliability Society, FCLAB research federation, FEMTO-ST Institute, and the Laboratory of excellence ACTION [83]. It was collected from the ageing experiments carried out by the FCLAB Research Federation (FR CNRS 3539, France, http://eng.fclab.fr/) on its test facilities. The assembled fuel cell are 5-cell stacks. Each cell has an active area of 100 cm^2. Two long-term ageing experiments were launched with different operating conditions: constant and variable. The first stack was operated under its nominal current density (0.70 A/cm^2), while the second stack was tested with a ripple current (0.70 A/cm^2 with oscillations of 0.07 A/cm^2 at a frequency of 5 kHz). To identify the degradation, fuel cell characterizations were performed each week, i.e. every 160 hours approximately, i.e. at time $t = 0; 48; 185; 348; 515; 658; 823; 991h$, which includes polarization curves and EIS measurement. The polarization curves are measured under a current ramp from 0 A/cm^2 to 1 A/cm^2 of 1000 seconds. The air and H_2 flows are reduced until the current value reaches 20 A and are then kept constant. The EIS measurements are realized under different constant current: 0.70 A/cm^2, 0.45 A/cm^2, 0.20 A/cm^2. A period of 15 minutes is used to stabilize the stack. The results are showed in the Nyquist plots over a frequency range from 50 mHz to 10 kHz. Figure 7a and Figure 7b show examples of the characterization measurements, in which the shape changes of the polarization curves and the EIS arcs are caused by the stack degradation. By measuring the parameters from the measurements, models could be derived to study the stack ageing mechanism and conduct prognostics. To visualize directly the stack voltage degradation, historic voltage curves are plotted. Figure 7c shows the stack voltage drop signal over time in constant operating conditions, while Figure 7d shows the stack voltage drop signal in variable operating conditions with a ripple current.



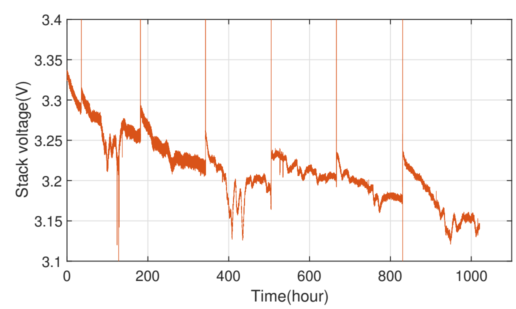
(a) Polarization curves of the 5-cell stack obtained overtime with current ramp from 0 A/cm^2 to 1 A/cm^2 of 1000s



(b) EIS plots of the 5-cell stack before polarization at 0.70 A/cm^2



(c) 5-cell stack voltage evolution under constant operating condition



(d) 5-cell stack voltage evolution under dynamic operating condition

Figure 7: Fuel cell characterizations and voltage evolution

Similar experiments have been conducted within the framework of the project PHM PAC [28] and the project PROPICE [48]. A micro combined heat and power (μ-CHP) dataset was reported in the framework of project SAPPHIRE [84], which come from a pilot project collaborated with the Electricity of France (EDF). The applied μ-CHP load profile simulates the behaviour of a stationary PEMFC application during a complete year. Relevant prognostics works are developed based on PF [77] and EKF [34], respectively. To demonstrate the on-board degrading performance of the fuel cell stack, two experiments are conducted in [30] and [42] in the framework of project PRODIG and project Asdecoeur, in which the stacks are deployed to dynamic load profiles and the prognostics strategies are developed based on data-driven methods. A similar dataset is released in [33] where a single PEMFC is conducted to the New European Driving Cycle (ECE R15) to test its durability. A 1000-hour data profile is produced. Ou et al. [71] have conducted stack durability tests for two PEMFCs with 15 cells and 30 cells, respectively, using a locomotive profile and generated 505-hour degradation data. Vichard et al. [85] have launched a long-term ageing experiment of an open-cathode PEMFC under an accelerated postal delivery driving cycle, which showed the considerable influence of the ambient temperature on the stack degradation. Moreover, there is another on-road fuel cell degradation dataset from the MobyPost project, where the fuel cell system acts as a range extender. It has operated 10 fuel cell hybrid electric vehicles for the real-world commercial postal delivery, which integrated lithium-ion batteries in the vehicle powertrain in order to deal with the transient power demand, and therefore, to avoid frequent startups and shutdowns of the fuel cell. This dataset has recorded the operating conditions including the load current and voltage, hydrogen pressure, temperature, relative humidity, state of charge of the battery and the hydrogen tank. A prognostics method based on neural networks has been developed using this data in [51]. Another similar dataset obtained from a fuel cell city bus in China is described in [43].

Other datasets conducted for fuel cell prognostics are obtained from accelerated stress tests, which are designed to target the electrocatalyst degradation. They are mostly used to estimate and predict the fuel cell degradation on the component level [65]. This kind of test is usually performed on a membrane-electrode assembly (MEA) in a single cell, which is operated under a potential cycling profile. The DoE's recommended cycling profile for electrocatalyst degradation is between 0.7V and 0.9V, while a degradation diagnostic study in [66] has accelerated the degradation process by cycling between 0.6V and 0.9V. Those tests focus on tracking the evolution of the MEA's internal parameters, which are conducted to develop degradation models but not to predict the RUL.

2.5.2. Quality of data

For the datasets as the one shown in Figure 7c, the degradation is not monotonous due to the monitoring characterizations. The most common characterization methods for PEMFCs in the laboratory are polarization curves and EIS measurement. When the operation is stopped for characterization, recoveries on the stack voltage could be observed, which indicate the reversible phenomena during the PEMFC ageing process. In practice, these reversible phenomena may be due to the changing operating conditions that affect the gas and water diffusion within the cells, i.e. starvation and flooding [13]. However, compared to the long-term irreversible performance decay of the fuel cell, these reversible phenomena can be recovered when the stack is brought back to its normal operation, i.e. quasi-static regime.

Efforts have been made to improve the prognostics performance with the existence of reversible degradation. Morando et al. [28] have proposed to divide the observed signal into static part and transient part and perform prognostics separately. To deal with the recoveries in the stack voltage, Kimotho et al. [73] have introduced a self-healing coefficient into the degradation model and used particle filtering to adapt the model with the observed data after each characterization. Jouin et al. [24] have proposed a combined degradation model including both irreversible and reversible degradation and used an ensemble of particle filters to estimate the model parameters and predict the RUL. Moreover, Zhang et al. [86] have used an equivalent circuit model to describe the polarization resistance and brought an idea of multi-level prognostics.

2.6. Partial synthesis

Recent years have seen rapid development in PEMFC prognostics in terms of prognostics methods and degradation modelling and estimation. More publications come out in recent five years, as shown in Figure 8. This survey is conducted by searching terms "PEM fuel cell" or "PEMFC", "prognostics" and/or "degradation prediction" in the title, abstract and keywords of all peer-reviewed articles in the major academic research databases.

Although more studies start to focus on solving PEMFC durability problems, some key issues have not been fully addressed. Based on the Table 1 - Table 3 and the previous analysis, the current prognostics works are mostly based on limited finished experimental datasets, operating conditions are rarely considered. Only a few works have developed prognostics methods for the PEMFCs operating under dynamic load. Although there is no preference in selecting the prognostics methods as each method has its pros and cons, we should consider the user requirement, data availability and degradation conditions. Besides, there is not a uniform performance evaluation criterion which is lacking for the moment and should be important in the prognostics-based decision-making process.

Prognostics and RUL are not the goals of PHM as how to use RUL to implement control and management and how to improve the PEMFC

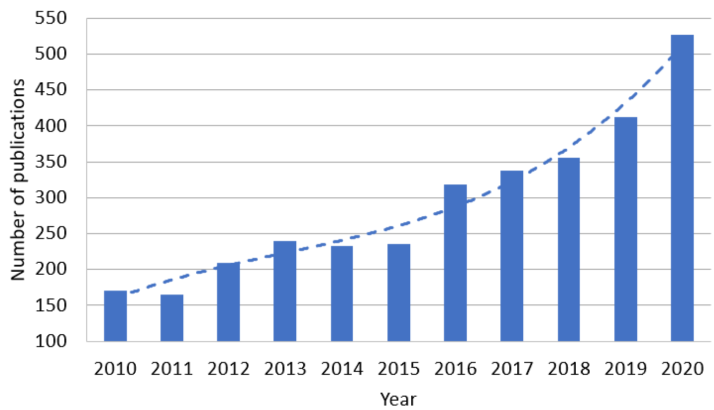


Figure 8: Yearly evolution of publications from 2010 to date containing terms "PEM fuel cell" or "PEMFC", "prognostics" and/or "degradation prediction". The search was made on the 20th February 2021.

durability are where the research orients. Post-prognostics and decision-making technologies are underdeveloped for the moment. They are discussed in the next section.

3. Post-prognostics: decision-making

As the ultimate objective of PHM is not to predict the RUL, but to take actions to prolong the lifetime of PEMFC systems. It exists in three levels: control, management and maintenance. In this section, four aspects of the post-prognostics decision-making phase are discussed. They are degradation tolerant control, multi-stack control, energy management and maintenance scheduling.

3.1. Degradation tolerant control

The majority of PEMFC control studies have focused on enabling power tracking capability on the system level, e.g., to control the oxygen flow rate in the cathode to protect it against reactant starvation. However, degradation tolerant control subject to address its durability issue is of scarcity. Deng et al. [87] have proposed a linear parameter varying (LPV) state space model which is oriented to design a fast linear controller for the PEMFC system. A model predictive control (MPC) strategy is proposed in [88] for the PEMFC system using a similar LPV model, on one hand, to track the power demand, and on the other hand, to ensure the maximum working efficiency and maximizing the stack durability. To enable MPC strategy on different scales, Jouin et al. [89] have proposed a combined prognostics method based on PF that can achieve accurate predictions on both short-term and long-term. Polverino et al. [90] have proposed a physical model-based control algorithm aiming at mitigating the stack degradation on ECSA. Similarly, a non-linear model predictive control strategy has been proposed in [91] to maximize the active catalytic surface area at the cathode catalyst layer and to avoid starvation at the catalyst sites. Moreover, Bressel et al. [49] have proposed a multi-physical LPV model for the PEMFC in the electrochemical macroscopic representation formalism. The degradation-related parameters are considered in the model to realize the ageing tolerant control. It allows regulating the required PEMFC power in presence of the performance decay. Cheng et al. have proposed in [92] that the degradation can be mitigated by managing the PEMFC air supply system. The control is realized based on the exhaust gas recirculation function included in the air supply system model, which can reduce the oxygen ration in the inlet air, and therefore, to mitigate the fuel cell output voltage degradation. Besides, the degradation tolerant control can also be conducted on a hybrid system. Kong et al. [93] have developed an interconnection and damping assignment-passivity based control strategy for a fuel cell/supercapacitor hybrid system, in which the degradation information is given by filtering state estimation. With the existence of fuel cell degradation, this method ensures the normal operation of the system, while avoiding overload.

Degradation tolerant control is very important to guarantee the integrity and the continuous operation of the fuel cell system without faults and shutdowns. The RUL information provided by prognostics algorithms should be combined with the control strategies as it should be taken into consideration not only the current degradation state but also the RUL corresponding to the system's EOL. Research on this issue still needs to be resolved and more efforts are needed.

3.2. Multi-stack control

The durability of a multi-stack fuel cell system depends not on the RUL of any single stack but the co-working mechanism of the stacks, which may contribute differently to the demanded power. Therefore, to maximize the lifetime of a fuel cell system composed of multiple stacks needs a control strategy to alter the operations between stacks. It could be regarded as an assignment optimization problem and optimization algorithms are deployed in the literature to find optimal solutions. Chretien et al. [94] have applied two convex optimization algorithms, i.e. the Mirror-prox for Saddle Points method and the Least Absolute Shrinkage and Selection Operator principle.

The optimization problem is solved by formulating a mathematical expression which minimizes the output power error and at the same time, adding the RUL of each stack as the constraint. A multi-stack control algorithm based on mixed-integer programming has been proposed in [95]. The control is realized owing to the successive optimal resolutions based on a fuel cell stack behaviour model considering the wear and tear process. Moreover, an optimal power allocation method considering the degree of PEMFC degradation in each stack has been proposed in [96], in which the degradation is considered by a virtual resistance model. The developed strategy can assure the normal operation of the multi-stack system even if one of the stacks fails.

To date, the multi-stack control strategies are developed for constant load demand case, while for variable load demand profile, the problem becomes complicated as not all the stacks should be used in low demand period. This needs the addition of a start-and-stop operation scheme. Besides, the well-developed prognostics strategies described in Section 2 have not been used for the multi-stack control. The existing methods are based on degradation models rather than online degradation prediction results.

3.3. Energy management

When using multiple power sources at the same time to supply a certain load, an energy management strategy (EMS) is developed to govern the energy distribution in the hybrid system. The performance of a hybrid system can be highly affected by the design of EMSs [64]. Based on non-exhausted bibliography research, for fuel cell hybrid systems, various EMSs have been developed to take power sources' degradation into consideration and therefore, to prolong the lifetime of the fuel cell or the overall system [97]. To be health-conscious, most researchers tend to develop degradation models for the PEMFCs to quantify performance degradation and to get the optimal solutions by designing rule-based and optimization-based EMSs [98]. The degradation models are integrated into the objective functions to minimize the overall cost or the hydrogen consumption. For example, fuel cell degradation origins such as low humidification and frequent and rapid voltage changes are considered in the EMS in [99] to mitigate the fuel cell degradation by setting key parameters. A robust fuzzy MPC method is proposed in [100] to coordinate the fuel cell degradation and energy storage system scheduling by formulating rule-based strategies. A deterministic dynamic programming strategy and a rule-based strategy have been developed in [101] to minimize the cost and at the same time, respect the operation limits to avoid degradation. A linear time-varying MPC strategy is proposed in [88] for the PEMFC system, which is, on one hand, to track the power demand, and on the other hand, to ensure the maximum working efficiency and maximizing the stack durability. Moreover, an equivalent consumption minimization strategy has been developed in [102], which considers the fuel cell degradation in the objective function.

However, existing researches usually consider fuel cell degradation by setting constraints or using fitting degradation models in the strategies, which are less accurate and cannot assess the real degradation state of the system. The developed prognostics technologies such as those discussed in Section 3 are rarely applied to the energy management of HEV applications. To complete the PHM cycle for a hybrid fuel cell system, the decision-making process turns out to be a part of the EMS. As the degradation of the fuel cell leads to its reducing efficiency and therefore, high fuel consumption. Two control strategies have been proposed in [103]. The maximum power strategy requires larger fuel systems, while the fuel cell operated with maximum efficiency strategy consumes less hydrogen. However, the optimal point is shifted regarding a degraded fuel cell, i.e. the actual power provided by the fuel cell is lower than the required value based on the following equations:

$$P_{actual} = P_{required} \cdot (1 - D_{fc}) \tag{1}$$

$$D_{fc} = \frac{V_{actual}}{V_{rated}} \tag{2}$$

where D_{fc} is the degradation degree of the fuel cell. It can be represented as a ratio of the actual voltage to the rated voltage. Therefore, to obtain the corrected power value required in an energy management problem, the degradation degree of the fuel cell should be determined and the corrected value is written as:

$$P_{corrected} = \frac{P_{actual}}{1 - D_{fc}} \tag{3}$$

As the degradation degree can be predicted by prognostics, the remaining work should be developing a decision-making process that can make use of the prognostics information and generate appropriate commands on the system. Yue et al. [104] have proposed a health-conscious EMS by developing a prognostics-enabled decision-making process, which integrates the prognostics results into the design of the fuzzy logic controller. The results of prognostics are used to determine the degradation level of the power sources and the EMS is designed based on fuzzy logic control whose parameters are refined based on the degradation level using a decision fusion algorithm.

A MPC-based energy management strategy has been proposed in [105], in which the durability of the fuel cell has been considered by the output power slope of constraints.

3.4. Maintenance scheduling

In most industrial applications, to ensure the continuous and reliable operation of the system, the preventive maintenance is performed regularly, whether it is needed or not [106]. It is designed periodically based on the usage conditions of the equipment and the severity of the component degradation. However, to some extent, it causes over care which is a waste of time and money, especially when it needs to send technical personnel to remote operation area. Therefore, if the degradation status of the system can be predicted, maintenance can then be scheduled whenever it is needed, i.e. to be upgraded to the predictive maintenance, which is more dynamic. It automatically assesses the current health state of the system and predicts future failure. In this way, the maintenance interventions can be scheduled beforehand, and if the degradation can be regulated by the control module, the operation of the system can be improved, and the lifetime can be prolonged.

Predictive maintenance is attracting the favourable attention in the recent years in different applications, e.g. pump systems, aircraft and spacecraft, batteries, micro-electro-mechanical systems, etc., however, few predictive maintenance methods for PEMFC systems have been investigated yet [107, 108, 109]. Predictive maintenance methods proposed for other applications may inspire the development of predictive maintenance for PEMFC systems. For example, in the literature, Meng et al. [110] have reviewed the maintenance methods for lithium-ion batteries and have proposed that an optimal management/schedule strategy is necessary for reducing the downtime and minimizing operation cost for the battery system. Linear programming models have been used in [111] to include battery degradation process in the optimization and have achieved fewer battery replacements to reduce the maintenance cost. Moreover, Nguyen et al. [41] have proposed a new dynamic predictive maintenance framework based on an LSTM classifier. Based on the intelligent classification results, they have constructed an optimal decision model to determine whether to replace the engine and the time to order spare parts. A tree-based classification method has been proposed in [112] to implement predictive maintenance for the railway switches and the marginal benefit of usage has been proposed in [113] as the metric for the lithium-ion battery system operation and maximizing the total life-cycle benefit. Moreover, the Internet of Things (IoT) technique has been deployed in many industrial applications for the predictive maintenance owing to its smartness and advanced automatic process [58]. Those approaches have been applied to the industrial machinery monitoring, which are not necessarily applicable for PEMFC systems [114].

3.5. Partial synthesis

Even though research on PEMFC prognostics has seen significant progress, it is still not sufficient to be integrated into PHM as the post-prognostics decision-making phase has not been sufficiently investigated. Four aspects have been proposed in this section, i.e. degradation tolerant control, multi-stack control, energy management and maintenance scheduling, in which the degradation prediction of PEMFCs plays an important role. The first three aspects have seen recent advances in developing control and optimization strategies, however, prognostics should play a more important role in their further development. Predictive maintenance of PEMFC systems is actually undeveloped and requires more efforts in research. Methods like combinatorial optimization techniques, IoT, digital twin, case-based reasoning, knowledge-based modelling, etc., that have been applied to other applications could be migrated to the field of PHM on PEMFCs and inspire the development of predictive maintenance method for the fuel cell systems.

4. Challenges and perspectives

As stated above, the PHM process adopted in PEMFC applications is not completed due to its insufficient development in prognostics methods, as well as the decision-making methods. This is also due to the limitations in data, which influence the performance of prognostics methods, however, have not been fully studied yet. The remaining challenges and perspectives are revealed in this section.

4.1. Challenges and perspectives on data

4.1.1. Data volume and observability

To perform prognostics or implement post-prognostics decisions, sufficient data samples are necessary for the learning algorithms and modelling process, as well as in the validation stage. Data collected for this purpose is rarely found and the research is held behind by the limited data samples [115]. To overcome the insufficient data volume, methods have been investigated in an attempt to increase the data volume by duplicate or randomly generating data, i.e. grey forecasting, feature extraction, and virtual sample generation [106, 116]. Limited data also results in increasing uncertainty

[117]. Methods should be investigated to manage and reduce the uncertainty in the prognostics. On the other hand, the quality of data and the amount of information in the monitoring data may also influence the implementation of the prognostics. Different inspection policies considering the variation of degradation states must be investigated [118].

On the other hand, some developed prognostics models are based on specific physical parameters of the PEMFC system, while some of which are not easily accessed or measured without characteristic sensors, e.g., micro-sensors and nano-sensors. Although the technique of advanced sensors is on the way of developing, it increases the capital cost of the system and slows down the process of commercializing the application of PHM in engineering domains [110]. The possible measurements in a PEMFC system are summarized in Table 4, which are categorized according to their technical and economical feasibility. Developing reliable prognostics approaches with technically and economically observable data is one of the challenges faced by the researchers and the goal is to use a minimum number of actual sensors to monitor the degradation state change.

4.1.2. Data availability

Compared with other prognostics applications, such as batteries, power electronics, pump bearings, engine and turbine degradation, available datasets for PEMFC prognostics is very limited. This is due to the high requirements in the experimental capability of performing long-term fuel cell degradation tests and the high cost on the equipment. Moreover, few laboratories have published their experimental data for research, while most of them are private or not ready for publication. Open data service is very important to accelerate the development of PHM engineering on PEMFCs. In addition to *in-situ* experiments, pilot projects that can gather and distribute online operation data in the real world. They must be supported by the administration of the company and the government to simplify the data sharing procedure.

4.2. Challenges and perspectives on prognostics

4.2.1. Prognostics time scale

The degradation of PEMFCs, to its very nature, is a long-term phenomenon. In the light of the monitoring cost and the information level, the inspection intervals greater than one hour are usually considered in PEMFC prognostics [35]. However, the time scales of the related control, management, maintenance scheduling problems that are concerned in the post-prognostics decision-making phase may change. For example, the scheduled

Table 4: Feasibility of measurements in PEMFC systems

Feasibility	Measurements
Feasible	-System and stack voltage -Single-cell voltages -System and stack current -System and stack temperatures -Cooling water temperature -H_2 and air temperatures (inlet/ outlet) -H_2 and air pressures (inlet/ outlet) -Air compressor speed
Possible but not technically or economically feasible	-Stack impedance -Stack internal resistance -Stack internal temperatures
Technically or economically unfeasible	-Local current density -Membrane thickness -Active catalyst area -H_2 and air flows (inlet/ outlet) -Cooling circuit mass flow -H_2 and air hygrometry rate -Water content in PEM -Inlet gases composition -Outlet effluents composition

maintenance based on prognostics cannot be implemented immediately if the fuel cell system is under operation. The maintenance schedule should also be adapted to the order time. Oppositely, the control and management strategies acting directly on the fuel cell system can modify the control signal immediately or in a short period. An illustration of decision policies regarding spatial and time scales is shown in Figure 9.

To fulfil different post-prognostics decision-making missions, multi-dimensional and multi-scale models designed for PEMFC prognostics should be developed. Moreover, another problem in the validation stage of the post-prognostics decision-making process is how to continuously supervise the system and conduct immediate controls to avoid and to mitigate the degradation that appears as a long-term phenomenon. To solve this problem, multi-criteria optimization, operational research techniques, combinatorial optimization (heuristics and meta-heuristics), case-based reasoning and knowledge-based reasoning are the promising methods that are worth studying. Be-

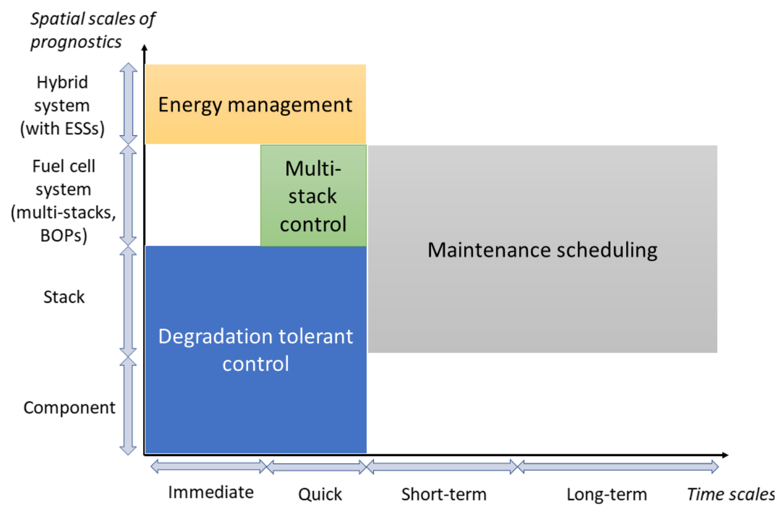


Figure 9: Spatial and time scales of post-prognostics decision-making process

sides, to implement control together with the scheduling and assignment problems is another underlying problem and should be considered to contribute to an integrated decision layer of PHM.

4.2.2. Prognostics performance metrics

Another barrier holding behind the development of prognostics methods is the lack of uniform performance evaluation metrics. Current prognostics research tends to evaluate the prognostics results by comparing the real experimental data and calculating the accuracy and precision of the predictions. However, the performance of the prognostics methods regarding other properties of the results has rarely been investigated. Without specific performance evaluation metrics, it brings difficulties for the researchers to evaluate and distinguish one prognostics method from others and it is hard to define the progress on method improvement. To standardize prognostics performance metrics, three more aspects should be specified: the prognostics horizon, the confidence level to the results and the EOL threshold.

The prognostics horizon is very important to evaluate the prognostics performance as it is related to how much information is available from the beginning to the current state. Some studies have evaluated the prediction accuracy with respect to prognostics horizon, however, no clear relationship has been derived between them [23]. As the goal of PHM is to continuously monitor the health state of the system and conduct appropriate actions regarding the system's health state, it is important to develop reliable prognostics methods by taking the prognostics horizon into consideration.

Another scenario to evaluate the prognostics results is the confidence level. In some data-driven methods, deterministic values are used as the predicted RUL results, which are, to some extent, not reasonable. The prediction comes with uncertainty, therefore, it is necessary to evaluate the uncertainty when making predictions. The probability of the predicted RUL falling into the confidence interval is important to define the goodness of the prognostics results and to evaluate whether the prediction is early or late since late predictions may cause more serious problems than early predictions.

The last concern about performance evaluation is the EOL threshold. Decision-makers use the predicted RUL to make decisions that are integrated into the lifecycle of the systems, in which the RUL is determined by the definition of the system failure threshold. Current prognostics works have assigned static thresholds to represent the failure of the PEMFC stack, typically, a certain percentage of the initial voltage/power value. This value is usually reported to be determined based on the data length, i.e., prior knowledge of the dataset, which is unsupervised and contributes to the uncertainty of the predicted RUL [119]. But what if the prior knowledge does not exist? A possible solution could be to set the thresholds dynamically according to the operating conditions, the current degradation tendency parameters and the available maintenance choices [120]. As proposed in [121], integrating a classification method with online predictions is capable to adapt the threshold values considering the real-time operation state of the system. This kind of research can be migrated to the PEMFC applications, with which researchers can take measures to make the following post-prognostics decisions based on dynamic thresholds.

4.2.3. Method adaptability

Efforts have been made to improve the performance of prognostics with the existing prognostics methods, as discussed in Section 3. However, if the prognostics methods are to be used for the post-prognostics control strategies, several limitations of the methods appear. For example, internal stack parameters cannot be accessed experimentally, therefore, these parameters will be missing in the model-based approaches; while to be valid, data-driven approaches must be fed with a wide range of data, covering all the operation, degradation and ageing modes, which is very costly and sometimes not affordable for some applications. Besides, the prognostics methods proposed based on the characterization measurements are not applicable for real-time applications due to the inconvenience of disrupted operations. Therefore, to complete the PHM cycle of PEMFC applications, a probable way is to combine all approaches into a larger model, comprising a supervision level, where the processing consigns are sent to the appropriate model, and parameter exchange can flow in both directions depending on the limitation of each one.

4.3. Challenges and perspectives on post-prognostics decision-making

4.3.1. Uncertainty treatment

First and foremost, the insufficient development of post-prognostics decision-making phase is due to the difficulties in managing the uncertainties. In fact, the prognostics refers not only to the prediction of the RUL but also to its uncertainty. The uncertainties existing along with the prognostics procedure have a significant influence on the prognostics-based decision-making phase [122]. The entire process of PHM indicates that prognostics is a closed-loop procedure so that the uncertainties in each phase of this procedure are accumulated along with the operation. These uncertainties may contain uncertainty in the data, uncertainty in the prognostics algorithm and uncertainty in the post-prognostics decision-making process. An overview of sources of uncertainties is summarised in Table 5. Some of the uncertainties can be avoided, while others cannot. For example, uncertainty in the data can be eliminated to some extent as long as dedicated datasets can be used for the prognostics purpose with adequate measurements, sampling frequency, volume and normal operation. Uncertainties during the prognostics and decision-making process can hardly be avoided as they are due to the nature of the adopted methods. For these uncertainties, one should be able to quantify and manage them.

To deal with the uncertainty and to interpret it to facilitate the prognostics-based health management, efforts on its quantification and representation are required. When applying statistics technique to quantify the uncertainty, it is important to consider the variance of the predicted RUL [123]. Existing prognostics research using state-space models has considered the uncertainty of the variables when propagating them to the future, and is able to predict the future state uncertainty using probability distribution, however, the state-space models are supposed to be linear ones, which cannot represent the real-world nonlinear applications, e.g., fuel cell degradation, so that they bring uncertainty to the system by themselves. Monte Carlo sampling-based method should be one of the solutions to this problem by using infinite samples [117]. Future research needs to continue the study also on the applicability of the uncertainty management technique to PEMFC prognostics applications. Moreover, robust decision models for the decision-making process are required to deal with all the uncertainty generated in models, predictions, operating conditions, etc., described in Table 5.

Table 5: Sources of uncertainties in data, prognostics and decision-making process

Uncertainty in data	Uncertainty in prognostics	Uncertainty in decision-making
-Data observability	-Model uncertainties	-RUL uncertainties
-Sampling frequency	-Input uncertainties	-Control and management
-Data volume	-Measurement uncertainties	strategy uncertainties
-Test interruptions	-External uncertainties	-User uncertainties

4.3.2. Experimental validation

Present research on PEMFC prognostics is mostly based on finished experimental datasets and the performance is verified and validated by the pre-defined experimental results, i.e. precision, convergence, accuracy, etc. However, this is not the goal of PHM. The goal of PHM is to use the RUL predictions to perform continuous supervision and control actions on the system and therefore, to mitigate the degradation and enhance the durability. The validation of the post-prognostics decision-making phase in PHM is a quality assurance process [124], while it is lacking in most research due to the difficulties in executing such an experimental platform for thousands of hours and designing comparison experiments. Also, the high cost on the equipment and hydrogen has limited the implementation of such long-term experiments. Although some decision-related research has been conducted in the literature, none of them has been validated with online prognostics results. Moreover, appropriate protocols of testing the durability of PEMFCs should be designed [125]. The ageing process of the PEMFC differs from different operating conditions and the relationship between test protocols and the degradation performance should be studied.

For the present, hardware-in-the-loop (HITP) and power HITP may be the most favourable methods to validate the prognostics-based control strategies as it can simulate the complex real-time embedded systems by adding necessary mathematical representations. The prognostics and control algorithms can be implemented based on the value of the electrically emulated sensors in the system and changes in the control signals will act back on the system. It increases the flexibility of the test as it can test the system with different failure conditions, which is very important in the verification of prognostics algorithms. Besides, it can provide an efficient and safe environment for the researchers to test the controllers and increase the scope of the testing. The benefits are exceptional as the test is implemented with the closed-loop control.

5. Conclusion

As PEMFC systems are highly multiphysical and multiscale systems, the behaviour of the stack is hard to catch due to the high difficulty to access the internal parameters. Developing PHM methods is of prime importance for the successful system design, control, diagnostics and optimization. This paper has reviewed the PHM research developed for PEMFC systems in terms of the current status and perspectives of prognostics and decision-making methods. Current prognostics methods have seen their progressive development in recent years, however, there are certain problems that have not been clearly defined, e.g. prognostics horizon, failure threshold, evaluation metrics, etc., which have been discussed in this paper and is expected be standardized as the post-prognostic actuation is envisaged. The available experimental datasets used for PEMFC prognostics studies have been reported and the fact that most of the current prognostics studies were based on the same open-source dataset and the limitations of the dataset have barriered the development of the prognostics methods. Furthermore, methodologies of developing post-prognostics decision-making issues have been described.

According to the findings, remaining challenges and perspectives regarding data, prognostics methods and prospective post-prognostics decision-making actuations have been proposed. A prerequisite for further progress is to enhance the availability and the observability of the data used for the prognostics purpose. Then, the development of prognostics methods should rely on the improving performance metrics and adequate uncertainty treatment. Finally, importance should be paid to developing post-prognostics control and management strategies by solving the difficulties in incorporating the prognostics information and experimental validation.

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