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# Prognostic methods for proton exchange membrane fuel cell under automotive load cycling: a review

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**Abstract:** This study presents a review of prognostic methods applied to automotive proton exchange membrane fuel cell (PEMFC). PEMFC durability is strongly affected when it is subjected to automotive load cycling (ALC). ALC is normally composed of four operation modes such as start-up, idle, transient high-current demand and shutdown. All of these operation modes drastically change the internal variables of the system like temperature, pressure, relative humidity etc. causing degradation of the fuel cell components in a short time. Prognostic methods could be a possible solution to tackle the PEMFC's low durability issue because they allow predicting the remaining useful life of the system in order to apply preventive maintenance plans. Therefore, the objective of this study is to review the prognostic techniques applied to PEMFC under ALC. In the first part of this study, a summary of PEMFC degradation mechanisms caused by ALC is realised based on literature review. In the second part, the prognostic methods review for automotive PEMFCs is carried out and a general synthesis and future challenges are given in the third part of the study.

## 1 Introduction

The low-temperature operation, high energy density (high autonomy), low-noise level generated and zero CO<sub>2</sub> emissions to the atmosphere are some of the positive features of proton exchange membrane fuel cell (PEMFC). All of these characteristics have motivated engineers to use PEMFC in different applications such as transport [1], stationary [2] or electronic portable devices [3]. Transport application is interesting because it could improve the quality of air and the comfort of citizens by reducing the noise level produced by the conventional gasoline/diesel transport. However, PEMFC stack presents generally two drawbacks which block the industrial development of this technology: a short lifetime under automotive load cycling (ALC) and the high cost of manufacturing of its components.

The US Department of Energy (ODE) [4] defines the objectives in terms of energy cost and a lifetime of automotive PEMFC so that it can be competitive against conventional transport. The target cost should be around \$30 kW and the lifetime target should be: 5000 h for vehicles and 20,000 h for buses.

The PEMFC lifetime strongly depends on the material of the components [electrodes, membrane, gas diffusion layer (GDL) and bipolar plates], the gas contaminants and the working conditions imposed by the used load profile. An automotive load profile normally leads to serious difficulties for the thermal, gasses and the water management system of PEMFC [5]. These difficulties can induce to reversible degradations such as flooding or drying membrane condition [6, 7] and irreversible degradations such as membrane rupture, platinum dissolution, carbon corrosion, GDL deformation, etc. [8–10]. All of these reversible and irreversible degradations accelerate the normal deterioration of the system [11].

Four principal modes are normally identified in a regular ALC: the start-up/shutdown, idle, high current demand and load variation in a short time [12]. These modes directly influence on the operation conditions and thus on the PEMFC durability if there is not an adequate thermal, gas and water management. However, start-up/shutdown and fast load variation cycles seem to be the two modes which could affect in greater proportion the fuel cell (FC) lifetime [13]. One study realised under laboratory conditions confirms that start-up/shutdown and fast load variation cycles

contribute to 44 and 28% to the PEMFC degradation, respectively [14]. This can be due to the fact that PEMFC presents a low power dynamic and thus it cannot accept high-power demand in a short period of time [15].

Prognostic and health management (PHM) strategy presents a potential solution to extend automotive PEMFC durability. This strategy is principally based on three activities: data collection, analysis and decision-making. Data collection concerns the system characterisation and data processing. Analysis realises two important tasks: the diagnostic and prognostic. Diagnostic determines the actual state of health (SoH) of the system and the failures are classified. Prognostic predicts the future evolution and declare the remaining useful life (RUL) of the system. For the third activity, all of the information is evaluated in order to make decisions regarding the planning of preventive maintenance actions [16]. Based on this, PHM strategy decreases the costly reparation working and teaches how to better operate the system in order to avoid the expected faults.

Nowadays, prognostic is considered as a key activity of the PHM strategy because it can provide the RUL of the system, therefore, some prevention actions and energy management strategies can be applied. This could improve the performance, extend the lifetime and reduce the repairing works of FCs. Three approaches are identified to forecast the automotive PEMFC RUL: data-driven, model-based and hybrid approaches. The data-driven approach uses intelligent computation methods such as neural network [17], machine learning (ML) [18], neuro-fuzzy inference system [19] or relevance vector machine (RVM) [20], to train a behavioural model based on degradation data. Model-based uses less degradation data but it requires deep knowledge about the degradation mechanisms of the system in order to develop a physical model. Moreover, the physical model parameters should be identified. Hybrid method combines the physical model with intelligent computation methods.

Considering the low durability and the high interest of PEMFC for transport applications, a publication that makes a review of prognostic methods applied to FC vehicle load cycles is lacking. Therefore, this paper puts in evidence the actual state of the art of prognostic applied only to automotive PEMFC. This works reviews each technique concerning: the achieved prediction horizon (PH),

the used health indicator and the accuracy of the performed prognostic. To achieve this aim, the paper is organised as follows: Section 2 presents the main degrading factors of the PEMFC structure caused by driving cycles. Section 3 presents the concepts of prognostic, SoH and RUL then the works on prognostic methods under ALC are reviewed. Section 4 presents a general synthesis of the review and the future challenges. Section 5 presents the conclusions.

## 2 PEMFC degradation in automotive applications

PEMFC can reach a lifetime of 30.000 h when it is subjected to constant power profiles. However, this energy source drastically accelerates its degradation process under vehicle and humidification and thermal load cycling, in this case, the PEMFC lifetime is reduced to <5.000 h [4]. A classical ALC is characterised by start-up/shutdown cycling, idle cycling, high-power demand cycling and fast load changing cycling as is presented in Fig. 1. The humidification and thermal cycling represent the temperature and relative humidity (RH) variations during operation influenced by the used profile load. Both the load and the thermal-RH cycling impact directly the PEMFC structure (membrane, electrodes, GDL and bipolar plates) contributing to materials deterioration and thus the system ageing.

### 2.1 Variable load cycling

Start-up and shutdown repetitions can lead to a high differential potential, which provokes carbon corrosion [22]. This irreversible degradation occurs in the presence of a  $H_2 - O_2$  atmosphere at the anode due to stop modes for a long time which cause the reactant crossover phenomenon. This phenomenon consists of the cross of oxygen gases through the membrane from cathode to anode. When hydrogen is introduced into the anode side due to the start-up mode, the hydrogen cannot occupy all the active area because of the presence of oxygen. At that time, a high potential [close to the open-circuit voltage (OCV) value] occurs in the cathode side which leads to a carbon (C) corrosion [10, 12, 23]. A similar phenomenon occurs during the shutdown if the anode is filled with oxygen.

Idle cycling can also affect the PEMFC durability, especially if the FC vehicle has to stop for a long time in this case, the PEMFC is only providing the auxiliaries power demand. This power

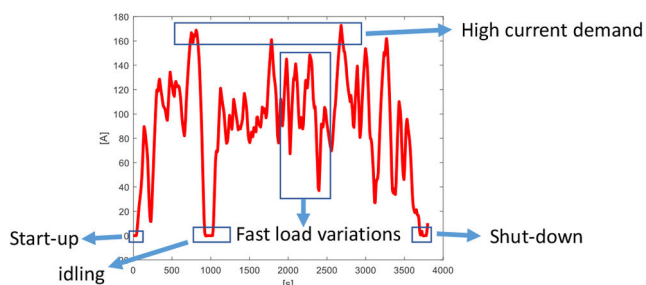


Fig. 1 Classic ALC [21]

Table 1 Synthesis of the ALC effects on the PEMFC structure

Cycle	Operation condition	Degradation type	PEMFC component	Ref.
start-up/shutdown	high potential, OCV	carbon corrosion, Pt dissolution	Pt/C electrodes	[22, 31] [12, 32] [10]
idle	OCV, high potential	Pt particles dissolution Pt particles deposition over the membrane	Pt/C electrodes and membrane	[9, 33] [34]
fast load variations	high current, high temperature	carbon support corrosion, active surface loss GDL structure deformation	Pt/C electrodes, GDL	[25, 32] [35]
high current demand	high current and high temperature	pinholes creation in the membrane Pt particle sintering	Pt/C electrodes and membrane	[5, 36]
thermal	high temperature and low RH low temperature and high RH	protonic conductivity loss, membrane fracture GDL pores blocked, active surface loss electrodes corrosion	membrane GDL, Pt/C electrodes, membrane	[9, 37] [29, 38]

demand is generally low and thus all the cells of the stack experiment a high voltage (0.9–0.95 V) close to the OCV condition. OCV condition impacts directly over the electrodes causing dissolution of platinum (Pt) particles and carbon support corrosion. Moreover, these Pt particles are deposited over the polymer membrane forming a Pt band [9]. Therefore, the effective electrochemical surface area (ECSA) and the membrane protonic conductivity are reduced. These irreversible degradations can rapidly cause a high drop of the PEMFC performance.

PEMFC can suffer from gas starvation due to its limited power dynamic [24]. The gas starvation phenomenon occurs in the presence of fast load changing cycles and when the system presents poor  $H_2/O_2$  supply management [25]. This phenomenon causes carbon support corrosion of the catalytic layer and the reduction of the effective ECSA area. Then, these degradations lead to electrochemical reaction losses.

High current demand tends to cause local hot spots over the membrane by the temperature rise. In this way, hot spots can provoke pinholes in the membrane and Pt particle sintering affecting the effective ECSA area of electrodes. High potential cycling under low RH of the reactant gases causes corrosion of the Pt/C electrodes and GDL degradation [5].

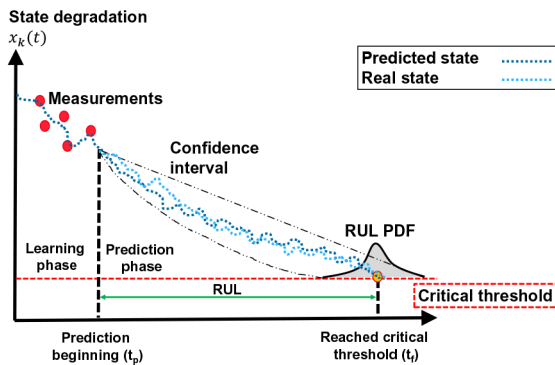
### 2.2 Humidification and thermal cycling

Humidification and thermal cycling in an automotive PEMFC are generally caused by the variable load cycling. Water and thermal management subsystems are necessary to buffer the temperature and hydration state against variable loads. In one hand, if there is poor thermal management, i.e. a high operation temperature, more than 80°C, the system will present serious issues regarding the performance and component deterioration. In terms of performance, the PEMFC reduces its power dynamic response and increases the start-up time [26]. In terms of component deterioration, the high temperature can cause membrane thinning and promote the Pt particle growth [27, 28]. In the other hand, if there is inadequate water management, the PEMFC will also face difficulties regarding components degradation and performance losses caused by flooding and drying conditions.

Flooding condition, which is caused by a bad purge management strategy, can block the GDL pores. When GDL pores are blocked the reactant gas from the bipolar plates cannot reach the catalytic layer and the apparent active surface can decrease inducing a loss of performance. Moreover, the water excess accelerates the corrosion of electrodes, the GDL and the membrane [29]. Membrane drying is caused, primarily, by insufficient humidification, water evaporation and the electro-osmosis effect [30]. This drying condition can affect the normal process inside the PEMFC stack such as reduction of protonic conductivity through the membrane. Moreover, experimental results show that a dehydrated membrane is more sensitive to hole creation, which can facilitate the membrane fracture [9]. A synthesis of the main ALC effects on the PEMFC components is summarised in Table 1.

**Table 2** Review summary

Method	Approach/technique	Health indicator	Citations
model-based	BFA	voltage (internal resistance, limit current)	Bressel <i>et al.</i> [39]
	EMBOC	voltage (empirical parameters)	Chen <i>et al.</i> [40], Zhang <i>et al.</i> [41]
		voltage	Pei <i>et al.</i> [42, 43], Chen <i>et al.</i> [21]
	CDM	membrane conductivity	Lu <i>et al.</i> [44], Hu <i>et al.</i> [45], Zhang <i>et al.</i> [5]
data-based	wavelet-extreme learning machine	ECSA degradation	Mayur <i>et al.</i> [46], Han <i>et al.</i> [47]
	recurrent neural network	power	Mayur <i>et al.</i> [48]
	echo state network	voltage	Javed <i>et al.</i> [49]
	grey neural network + window moving method	voltage	Ma <i>et al.</i> [50]
hybrid	LPV model + echo state network	voltage	Vichard <i>et al.</i> [51]
	ML + genetic algorithm	voltage	Chen <i>et al.</i> [52]
		voltage	Li <i>et al.</i> [53, 54]
		voltage	Chen <i>et al.</i> [55]

**Fig. 2** Prognostic process**Fig. 3** Methodology of BFA

### 3 Prognostic methods under ALC

This section first introduces the prognostic, the SoH and the RUL definition. Second, the prognostic methods are reviewed and are classified into three categories: model-based, data-based and hybrids as is well summarised in Table 2.

#### 3.1 Introduction to prognostic

Before reviewing the work on prognostic methods under ALC, the concept of prognostic is introduced in this subsection. Moreover, the two principal steps to do prognostic are presented afterwards.

**3.1.1 Definition:** The concept of prognostic is based on the strategy ‘predict to prevent’ instead of ‘fail to fix’ used by diagnostic. This basic idea of prognostic allows to design preventive maintenance schemes in order to improve the safety, reliability, performance and reduce the repair cost of the system. That is why the prognostic activity has recently gained much of interest for academy and industry.

In the literature, there are several definitions of prognostic [56], but some authors are not too clear and to confuse the concept of prognostic with diagnostic [57, 58]. In order to normalise the concept of prognostic, this paper considers the proposed definition which is given by the International Organization for Standardization: prognostic is an estimation of time to failure and risk for one or more existing and future failures modes [59]. Accordingly, prognostic is a process whose main objective is to estimate the RUL before a failure occurs based on the actual SoH of the system.

**3.1.2 Prognostic process:** Regardless of the approach used (data-driven, model based or hybrid approach), the prognostic process is divided into two phases: the learning phase and the prediction

phase. During the learning phase, a degradation model is trained using parameter measurements of interest from sensors. The degradation model is adjusted to the real system in order to estimate the current SoH of the system. The SoH of the system is linked to a selected health indicator, this index can be directly related to the component deterioration such as a degradation mechanism, e.g. the electrode degradation or indirectly related to the studied fault such as the voltage. The training phase finalise when no more historical data are available which corresponds to the time of prediction beginning ( $t_p$ ). Once the degradation model is trained, this is used to estimate the system evolution until the chosen failure criterion ( $t_f$ ) is reached, this period of time is also known in the literature as the PH. The RUL can be obtained by the difference between  $t_f$  and  $t_p$ . The entire process is presented in Fig. 2.

#### 3.2 Model-based method

Model-based prognostics can be classified into three categories: Bayesian filter approach (BFA), empirical models based on the operation conditions and component degradation models based on the physical knowledge of the system [60].

**3.2.1 Bayesian filter approach:** Bayesian filtering approaches such as particle filter (PF) or Kalman filters (KFs) are widely used in literature to predict the PEMFC RUL [61–63]. However, PF presents some disadvantages in the degradation prediction of PEMFC under ALC. PF has the particularity of being able to handle non-linear models with non-Gaussian noise but it is computationally costly. To overcome this issue, KFs such as the extended KF (EKF) and the unscented KF (UKF) are more used for automotive PEMFC.

A methodology used by Celaya *et al.* [64] for electrolytic capacitor prognosis is adapted for PEMFC lifespan prediction. The principal steps of this methodology are presented in Fig. 3. The first step consists of collecting data from the real PEMFC to adapt a degradation model and to validate the results of the proposed method. The second step is related to selecting the ageing parameters to be estimated. The third step is dedicated to building the deterioration model based on the selected ageing parameters. The two latter steps, the SoH and the RUL estimation are normally carried out by using the EKF or UKF algorithm combined with the degradation model.

Bressel *et al.* [39] presented the first work on PEMFC RUL estimation using BFA under an automotive data set of 175 h obtained in the laboratory. The authors propose an empirical degradation model based on the EKF algorithm to estimate the SoH and the RUL of an eight-cells PEMFC stack of CEA Liten. The PEMFC is subjected to a driving cycle aiming at simulating the power demand of an electric vehicle. The degradation models are linear and describe the evolution of the internal resistance and the limit current. However, both health indicators are lumped in one empirical parameter to be estimated. The algorithm is able to estimate the RUL after 40 h of operation by following a linear degradation pattern. Moreover, this algorithm only takes 22 s to

predict the RUL and presents a PH of 30 h. However, at the time between 80 and 100 h the prognostic results are under estimated. This is due to the fact that the proposed method uses linear models which are not in function of the operation conditions and only considers two ageing parameters. Moreover, the prognostic results are compared against ageing data which are obtained under laboratory conditions.

Zhang *et al.* [41] propose to use two different physical models, one is employed for describing the FC voltage by the supplied current and the second one is fed by periodic measurements from physical characterisations in order to acquire reliable information about the SoH evolution of the system. The selected SoH indicator in this work concerns the voltage. The prognostic procedure is accomplished using PF, then the prediction results from each filter are aggregated to obtain an ensemble of estimations. Prognostic results show that the fusion methodology presents better performance than using the models separately during a PH of 900 h, i.e. from 100 to 1000 h. However, during the time from 500 to 700 h the RUL prediction goes out of the accuracy bounds. Moreover, the authors use simulated deterioration data to validate the proposed method because of the lack of available real data.

Chen *et al.* [40] present a degradation model based on the UKF algorithm considering a real load profile. This load profile corresponds to collected data from an FC electric vehicle called MobyPost which completes the normal postal delivery mission in the actual road. The authors select three empirical voltage degradation models: a linear, a logarithmic and an exponential [65, 66]. Empirical parameters related to the voltage degradation are considered as SoH indexes. The logarithmic model presents the best performance to estimate the PEMFC SoH and it is chosen by the authors to predict the PEMFC degradation. The model is trained during 40 h and it covers a prognostic horizon of 10 h. However, the algorithm cannot describe the dynamic degradation of voltage and its trend is not well predicted.

**3.2.2 Empirical model based on the operation conditions (EMBOC):** Several authors accomplish the PEMFC lifetime prediction using EMBOCs as presented in Fig. 4. The operation conditions correspond to vehicle typical operation conditions, e.g. start-up and shutdown conditions, idle condition, high-power condition and fast load changing conditions. The proposed method presents the advantage of updating its degradation model considering the measured voltage changes during the vehicle operating conditions.

Pei *et al.* [42] propose a linear degradation model whose parameters are performance deterioration rates caused by load change cycling, start-stop cycling, idle condition and high-power load condition. These parameters are obtained using laboratory measurements. Then, the proposed model is validated against real data measured from an FC bus. The authors use the cell voltage as a health indicator. Although the proposed method can estimate the RUL of the FC in different operation modes, the method cannot describe the PEMFC degradation evolution in time and presents a high cost, i.e. there is a need of spending many hours in laboratory to identify the model parameters, 80 h for the start–stop test, 50 h for the idle test, 80 h for the load-changing test and 5 h and 30 min for the high-power load test.

Chen *et al.* [21] consider a similar method applied by Pei *et al.* [42] to estimate the PEMFC lifespan. Therefore, the voltage is considered as FC degradation index as well. The authors use the linear ageing model, which depends on the start–stop condition, the high-power condition, the load-changing condition and the idle condition. The model parameters are measured in laboratory considering the same PEMFC stack used by a real FC bus. The model can predict the FC degradation evolution after 200 h in real operation conditions and present a PH of 500 h. However, the predicted RUL shows a linear degradation trend and thus the dynamic degradation of the FC voltage is not well estimated.

Zhang *et al.* [5] also present a lifetime prediction based on a linear empirical model. The empirical degradation model is in function of the load profile characteristics and based on a steady state electrochemical model. To run the model, the authors select data from the literature of voltage degradation rates at different

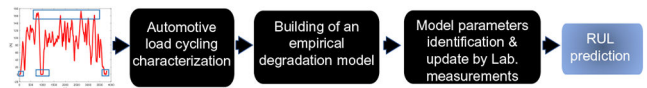


Fig. 4 Methodology using an EMBOC

load profiles to be used as the reference. The proposed method is only able to estimate an approximated value of the voltage degradation rate but it cannot describe the system ageing evolution. Moreover, the proposed method involves data from other types of PEMFC, which are made of other materials and components. Therefore, the prediction results are only approximations.

Lu *et al.* [44] propose a semi-empirical voltage deterioration model for a 5 kW PEMFC stack under a bus driving cycle. The degradation model considers a linear degradation rate of the internal resistance and the leakage current density parameters with the operation time. This model can describe the stack voltage degradation for 824 h but its prediction shows a linear trend. Moreover, the ageing tests used to validate the model results are performed under laboratory conditions.

Hu *et al.* [45] present a voltage degradation model to predict the lifetime of a PEMFC adapted on a hybrid bus. This model is composed of three parts: a linear, a logarithmic and an exponential part. Moreover, a degradation rate parameter is included into the model to take into account the effect of start-up/shutdown and the high-current demand cycles on the system deterioration. The model is validated during 200 h and the results show that it can closely reproduce the voltage evolution of the FC. However, 14-days of data are needed for the training phase and the models are too simplistic.

Pei *et al.* [43] propose a new estimation method based on their precedent work [42]. This prediction method consists of two non-linear formulas: the first one considers the hydrogen crossover variation and the second one is based on the system time response under automotive conditions. The authors validate the second formula using experimental data of two buses in different scenarios and considering the average cell voltage as SoH indicator. Results show that the method can correctly predict the tendency of the cell voltage deterioration with a horizon of 3000 h for both scenarios, but, its dynamic degradation is not well estimated.

**3.2.3 Component degradation model (CDM):** This method uses knowledge about the system and its mechanisms of degradation (the membrane degradation or the catalytic layer degradation) through the use of physics models. Moreover, the CDM method can provide prognosis results for long-term under realistic loads such as automotive applications.

Mayur *et al.* [46] present a PEMFC ageing prediction using a two-dimensional (2D) multi-physic cell model, which is applied to the New European Driving Cycle (NEDC). The model describes membrane degradation in terms of protonic conductivity decreasing. The authors assume a conductivity degradation that is linearly dependent on the local O<sub>2</sub> partial pressure in the cathode catalyst layer. This assumption is based on the known membrane degradation mechanism which is started by the O<sub>2</sub> crossover phenomenon from cathode to anode side [9], which depends linearly on the oxygen partial pressure. To predict the PEMFC RUL, the authors analyse the cell degradation state by simulating the FC providing the NEDC power demand. The simulations are finished until the PEMFC degrading fails to power the NEDC cycle. The prediction results show that the proposed approach can estimate the PEMFC ageing for >5.000 h. However, the model describes a quasi-linear membrane degradation due to the model assumption of being in the function of the partial pressure. Moreover, this model requires at least 30 h to simulate the membrane degradation under only one NEDC cycle.

Mayur *et al.* [48] used the same model as presented before [46] and use a time upscaling methodology to reduce the time of simulation for a faster PEMFC lifespan prediction. The authors use the 2D multi-physic model to predict the PEMFC lifetime under two driving cycles: the World harmonised light vehicles test cycle (WLTC) and the NEDC cycle. The multi-physic model can describe the ECSA degradation over the lifetime of the FC. The

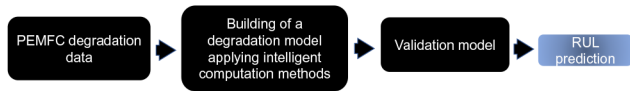


Fig. 5 Data-driven methodology

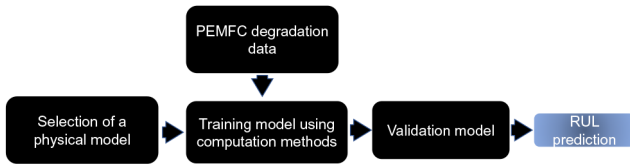


Fig. 6 Hybrid methodology

authors consider the end of life of the FC when the cell is not able to power the cycle demand anymore. The voltage prediction results show that when the PEMFC is subjected to the NEDC cycle the FC presents a faster degradation than considering the WLTC cycle. This is due to the fact that the NEDC cycle presents longer near-OCV operations. Moreover, the prediction results show that the proposed approach can capture the non-linearity of the cell degradation for >520 h. The limitation of this prediction method is the complexity of the proposed model and the fact that the prediction is performed for one single FC.

In [47], Han *et al.* presented a degradation model to predict the durability of a FC stack under three different driving cycles. This model considers the hydrogen/oxygen supply system and the PEMFC stack. The proposed method is more focused on estimating the degradation rate than on predicting the ageing evolution in time of the system.

### 3.3 Data-based method

Data-driven approach normally uses intelligent computation methods such as: neural network, ML, Neuro-fuzzy inference system or RVM, to build a degradation model and be able to estimate the ageing trend and the RUL of the PEMFC as is shown in Fig. 5.

Javed *et al.* [49] present the first prognostic application using a data-driven approach under a dynamic power profile. The authors develop an ensemble structure of summation wavelet-extreme learning machine models in order to do long-term SoH predictions of the stack. The application uses the power as the health indicator and the results show that the method presents a high precision, especially when it is initiated at 800 up to 1200 h, i.e. it achieves a PH of 400 h. However, when the proposed application uses less degradation data (600 h) for the training phase, the prognostic results do not have high precision as mentioned before.

Ma *et al.* [50, 67] proposed to use a long short-term memory recurrent neural network (LSTM-RNN) to estimate the ageing trend of three different types of PEMFC stacks. The LSTM-RNN is compared against a conventional neural network and an RVM. The results validate the superiority of LSTM-RNN technique against the other mentioned techniques. The proposed method can predict the tendency and the dynamic degradation of the FC during 4000 h, but, this method uses only the voltage as a health indicator of the system. Moreover, this work uses a cyclic current profile to simulate the operation modes of a real driving cycle.

Chen *et al.* [52] used a grey neural network and a moving window method to forecast the PEMFC deterioration. Moreover, the authors utilise the same degradation data presented in [40] to validate their proposal considering the voltage as a health indicator. The proposed method can predict the FC degradation during 50 h, however, the prediction results do not present a high accuracy when they are subjected to driving real conditions.

In [51], Vichard *et al.* utilised a degradation model based on echo state network (ESN) to predict the PEMFC stack RUL under start/stop cycles and variable temperature conditions. This proposed method is evaluated using a 5000 h durability test and the stack voltage is considered as the SoH index. The model is able to reproduce the variation and the tendency of the voltage during ca. 2.000 h, however, at least 60% (3.000 h) of data are required for the training phase.

Table 3 Comparison between the three presented prognostic methods

	Model based	Data based Hybrid	
physical knowledge	high	low	high
cell or stack prognostic	stack	stack	stack
max. PH under real conditions	3.000 h	4.000 h	350 h
can it capture the PEMFC non-linear degradation?	yes	yes	no

### 3.4 Hybrid method

Hybrid methods combine the two principal characteristics from model and data-based approach, i.e. they consider physical models and the intelligent computation techniques presented before. In general, this approach selects a physical model to describe the system degradation, then the model is trained by applying computation techniques and using ageing data. The trained model is used for validation and then for predicting the PEMFC RUL. All of these steps are summarised in Fig. 6.

Chen *et al.* [55] present a prediction method based on the wavelet analysis, ML and the genetic algorithm applied for the Mobypost (a 1 kW fuel-cell electric vehicle) under real operation conditions. The proposed method can describe the trend and the dynamic degradation of the stack voltage, but the method does not show high accuracy. In addition, the authors present only a prediction window of 10 h.

Li *et al.* [53] utilised an LPV model to describe the non-linear and time-varying properties of the PEMFC system. For the prognostic task, an ESN is implemented and the voltage is considered as a health indicator. The results are validated using experimental data from a 1500 h test. The prognostic method can estimate the degradation trend during ~700 h but it cannot track the dynamic ageing presented by the stack. In [54], the same authors propose to improve their prediction results, without modifying the LPV model and the SoH index, using an ensemble ESN instead of a conventional ESN. The method presents an acceptable (within the prediction boundaries defined by the authors) RUL prediction during the last 350 h of the experimental test. A comparative analysis of the precedent prognostic methods is presented in Table 3.

## 4 General synthesis and future challenges

This review shows the progress in the last years on the automotive PEMFC prognostic area. Three methods are found in literature to prognostic the PEMFC lifetime under ALC: model-based, data-driven and hybrid methods. It is important to note that the model-based method is commonly applied for transport applications because it requires less deterioration data than data-driven and hybrid approaches. All the proposed methods present promising results of RUL prediction, however, there are still too many challenges to overcome.

- The maximum predicted horizon is obtained by using the CDM method (>5.000 h), however, this prognostic is performed for one single FC. In terms of PEMFC stack and considering a non-linear degradation pattern (real deterioration data), the maximum PH achieved corresponds to 2.000 h, which is obtained by the ESN in [51].
- All the reported works based on Bayesian filtering (UKF and EKF) use empirical models. Moreover, these models are linear, logarithmic or exponential. The algorithm may lead to better prognostic results if a CDM is considered.
- Although the voltage is a parameter easily measurable and commonly used as is well shown in Table 3, the stack voltage is not enough to measure and distinguish the damages caused by all the different degradation mechanisms which occur in the PEMFC, e.g. the membrane degradation, the active layer degradation etc. A voltage drop is the result of multiple failures of the system. Therefore, the prognostic results could be

improved if the health indicator is directly related to the FC component degradation.

- Only a few of the mentioned works use field-based data to prognostic the automotive PEMFC lifetime. The other ones use ageing data measured in the laboratory. The degradation observed in realistic environmental conditions is different from those observed in the laboratory.
- As there is a lack of PEMFC ageing data under automobile load cycling, some authors validate their prognostic results assuming a linear degradation pattern. However, the decreasing tendency of the PEMFC voltage is not a monotonic function [39, 46].
- As it is mentioned in the previous section about the needed of historical system information for data-driven approach, some authors decide to use simulated data in order to implement and validate their methods.
- Data-driven and hybrid methods show a high performance in terms of precision during the RUL prediction process as it is presented in [50]. However, to do that, at least 60% of ageing data are needed to train the model and to obtain acceptable results.
- As is well known, hybrid methods benefit from the advantages from model-based and data-driven approaches, however, disadvantages are included too, i.e. degradation data under automotive conditions and good physical knowledge about the system are required, therefore, hybrid methods could be tough for PEMFC lifetime prediction under ALC.
- The PEMFC prediction using an EMBOCs is expensive, i.e. it is necessary to spend many hours in the laboratory to identify the model parameters. As well, CDM methods present the constraint for commercial systems RUL prognostic to obtain experimental data, e.g. ECSA or membrane degradation and will be able to directly validate its estimation results.
- More efforts need to be devoted to the work on the accelerated stress test (AST) for PEMFC under ALC in order to reduce the time and cost of the ageing test. Moreover, this may allow the academic community to perform more research on PEMFC RUL prognostic under vehicle load cycling. As well, data-driven and hybrid approaches, which require a large amount of data, may have more participation in this area.
- For newly designed or commercial automotive FCs where there is not too much available historical data to build a degradation model, required for data-driven approach, model-based methods seem to be the best solution to predict the RUL of recent systems as they do not need a large amount of data to perform prognostic.

## 5 Conclusion

This review presents the recent works on prognostic methods for automotive PEMFC. First, the main degrading factors of PEMFC caused by automobile load cycles are presented. Second, the prognostic definition is introduced and three prognosis methods are identified: model-based, data-driven and hybrid approach. Moreover, the current limitations about their proposed methodologies, the degradation models and the PHs are analysed. Last, the general synthesis and future challenges are provided.

## 6 References

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