Predictive maintenance and control tool for hydrogen-energy systems in an industrial framework

Gaultier Gibey[a*], Elodie Pahon[a], Noureddine Zerhouni[a], Daniel Hissel[a,b]
[a]Université Marie et Louis Pasteur, UTBM, SupMicroTech-ENSMM, CNRS, Institut FEMTO-ST, FCLAB, Belfort, France
[b]Institut Universitaire de France (IUF), France
E-Mail: {gaultier.gibey@univ-fcomte.fr, elodie.pahon@utbm.fr, noureddine.zerhouni@ens2m.fr, daniel.hissel@univ-fcomte.fr}

Acknowledgements

This work has been supported by the EIPHI Graduate School (contract ANR-17-EURE-0002) and the Region Bourgogne Franche-Comté.

Keywords

«Hydrogen», «Predictive Control prognosis», «Prognostics», «Reliability», «Fuel Cell system».

Abstract

In this paper, the structure and different axes for the realization of an efficient predictive tool have been defined, to improve durability, availability, reliability, performance, safety and operating costs of hydrogen-energy systems. The predictive tool based on predictive maintenance and predictive control is intended to be marketed economically.

Introduction

Hydrogen energy systems, i.e. Proton Exchange Membrane Hydrogen Fuel Cell (PEMFC) systems, Proton Exchange Membrane Water Electrolyser (PEMWE) systems or a hybridization of the two, are complex and multiphysical systems (electrical, electrochemical, thermal and fluidic) that require advanced maintenance and control resources to achieve durability, availability, reliability, performance, safety and operating costs competitive with conventional systems. In an industrial and commercial context, these maintenance and control systems will need to use measurements that are always available on a hydrogen-energy system. In addition, the algorithms used must be compatible with real time. To meet these requirements, a predictive tool appears to be a promising solution. The predictive tool comprises 2 components: predictive control and predictive maintenance of the Remaining Useful Life (RUL) of power components. Artificial intelligence approaches appear to be of great interest in achieving a high-performance predictive tool. Indeed, the use of physical models for hydrogen-energy systems, being complex and multiphysical, is not feasible given that not all the physical principles governing their operation are yet fully understood. In the literature, several predictive control and RUL prediction methods for hydrogen-energy systems have been developed using artificial intelligence.

In the case of predictive control, Dirkes et al. [1], have developed an integrated approach to prescriptively manage the lifetime and condition of PEMFCs. A PEMFC degradation model was used to estimate service life as a function of operating parameters. The parameters used were cathode inlet pressure, coolant inlet temperature, coolant temperature difference across the PEM, relative humidity at the cathode inlet and cathode stoichiometry. The authors report that this prescriptive approach has improved predictive maintenance, in particular by maximizing RUL using control parameter modification (predictive control). This approach considerably improves current maintenance of PEMFC systems, however, for industrial fuel cell systems, it is only rarely possible to obtain the relative humidity at the cathode inlet. It should also be noted that the condition of the PEMFC is assessed using the remaining film thickness by the open circuit voltage (OCV), and that the condition of the cathodic catalyst layer (CCL) is assessed using the electrochemical surface area (ECSA). These indicators cannot be used in industrial and commercial systems (real-time systems). In a later work from the same authors [2] the second part of the prescriptive PEMFC service life management method was presented. This hybrid approach to predict and improve the RUL of PEMFCs to meet sustainability requirements provided very good results. However, as in the first article, health indicators and the control parameter (relative humidity at the cathode inlet) are not always available on real-time systems. From now on, methods for predicting RUL using artificial intelligence for hydrogen-energy systems will be discussed. In Gibey et al. [3], a prescriptive maintenance tool for hydrogen-energy systems has been designed and defined according to 4 aspects, which are respectively, planning maintenance interventions only when strictly necessary (breakdown prediction and PEMFC stack voltage prediction for RUL estimation), predictive control, fault detection in different system components (objects, sensors and power components) and system architecture optimization. Several data-driven diagnostic and prognostic approaches to respectively estimate the state of a PEMFC and predict its RUL have been developed. Several data-driven diagnostic and prognostic approaches to respectively estimate the state of a PEMFC and predict its RUL have been developed, using always-available measurements to take into consideration the constraints of a real-time system. It should be pointed out that prior data science steps have been introduced to smooth and reduce the number of redundant data, thus improving computation time during training and inference. The authors report very good diagnostic and prognostic results for prescriptive maintenance of hydrogen-energy systems. These prescriptive maintenance approaches seem to be very interesting. In this paper, similar approaches will be developed for predictive maintenance and predictive control of hydrogen-energy systems. In another work by the same authors [4], a data-driven approach to predicting the RUL of a low-temperature PEMFC (LT-PEMFC) has been developed. The authors report that this approach makes it possible to optimize preventive maintenance using predictive maintenance, and to predict the state of health of the system. To this end, the authors compared an LSTM and an ESN, both of which achieved very good prediction results with fast computation times. It should be pointed out that this approach appears to be very interesting for RUL prediction, as it uses measurements that are always available on real-time systems (PEMFC stack voltage). In Yue et al. [5], a multi-stage Echo State Network (ESN) for predicting the degradation of a PEMFC operating under dynamic load and in real time has been developed. A genetic algorithm is used to optimize a sliding window in order to recursively reformulate the input sequence. A non-linear regression model was used to extract a degradation indicator from voltage segmentation. This approach, validated under dynamic load, achieved very good results in terms of computation time and prediction performance. In addition, this approach uses measurements that are always available on real-time systems, in this case the voltage and temperature of the PEMFC. In Chanal et al. [6], a Bidirectional Multi-Reservoir ESN (MR-BiESN), was developed to predict the voltage of a low-temperature PEMFC. The proposed architecture, using multiple reservoirs in parallel, has enabled to better capture the different dynamics present in a PEMFC system. This approach was also compared to a Bidirectional Long Short-Term Memory (BiLSTM), and it was shown that MR-BiESN has 1200 times fewer parameters to optimize. This approach achieved very good prediction results while using a measurement that is always available on a real-time system, in this case the PEMFC stack voltage. Wang et al. [7] proposed a prediction of the voltage degradation of a PEMFC, using a BiLSTM with an attention mechanism (BiLSTM-AT). The proposed approach also has a sliding window on the RUL to provide better prediction results. The authors tested this method on two PEMFC from the IEEE PHM 2014 Data Challenge. Compared to the LSTM based on the attention mechanism, the BiLSTM-AT is found to be more accurate in predicting the RUL of PEMFC. The addition of the attention mechanism seems to be an interesting way of improving prediction performance. Hua et al. [8] have proposed to improve the classical ESN for PEMFC RUL prediction. They developed MIMO-ESN, which are ESN with multiple inputs and outputs. The MIMO-ESN can have 1, 2 or 3 inputs, which correspond to the stack parameters (descriptors), such as the stack voltage, the charge current, the stack temperature, the inlet gas pressure. The authors have shown that the accuracy of the prediction has been greatly improved by using multiple inputs. Moreover, it is indicated that the ESN with 2 inputs (water inlet temperature and stack voltage) obtained the best prediction results. From a PrM point of view, the use of many parameters will induce a considerable number of sensors, which have a significant cost and require regular maintenance. Therefore, the MIMO-ESN must be used with sensors that are not constraining in terms of maintenance and cost. In Prakash et al. [9], a model-based approach to degradation detection and RUL prediction for

PEMWE has been developed. The model used is a Diagnostic Bond Graph (DBG), and the residual Analytical Redundancy Relations (ARRs) represent the residual evolution trend for RUL prediction. The residual signals corresponding to the fault indicators are evaluated by numerically evaluating the ARRs, which correspond to the various system sensors, namely cell current, anode and cathode pressures, stack temperature and mass flow from the stack to the oxygen/hydrogen separator. This residual-based approach has been shown to achieve good predictive accuracy. However, this method has not been tested on a real system, and has only been validated by simulation. Furthermore, the measurements used are always available on an industrial system, except for the mass flow rate, which can nevertheless be reconstructed using the fluid's volume flow rate and density. Liu et al. [10] In the first phase, a machine learning algorithm based on an evolutionary algorithm and an adaptive neuro-fuzzy system is used to predict the long-term degradation trend. In the second phase, the remaining lifetime is estimated from the degradation data obtained, using a semi-empirical PEMFC degradation model and an adaptive unscented Kalman filter. Finally, the proposed hybrid prognostic method is validated using experimental PEMFC aging data. Test results show that this method can accurately predict the long-term degradation trend and estimate the remaining lifetime of PEMFCs. The authors report improved prediction accuracy and faster convergence than other ensemble model-based methods. The method proposed is interesting in that it provides good prediction results for both the short and long term.

Following this literature review of the various methods for prognosticating the RUL of PEMFCs, a comparison between a BiESN and a BiLSTM on the same dataset will be proposed in this paper. The paper is constructed as follows. First, the predictive tool for hydrogen-energy systems will be defined and explained, then its two components will be examined, starting with predictive maintenance and ending with predictive control.

Predictive tool for hydrogen-energy systems

In this sub-section, the various aspects of developing a high-performance predictive tool for hydrogen-energy systems will be discussed. The idea is to improve hydrogen-energy systems in terms of performance, durability, reliability, availability, safety, and operating costs by predicting stack voltage in order to estimate the RUL and maximizing it by modifying control variables, thus greatly reducing costly breakdowns and carrying out maintenance work only when strictly necessary or at strategic times such as during machine shutdowns or periods of reduced activity. The predictive tool comprises 2 components, which can be seen in figure (1), and which are respectively:

- Predictive maintenance: This involves predicting the stack voltage (PEMFC or PEMWE) in order to estimate the remaining service life (RUL) of power components.
- Predictive control: This component uses stack voltage prediction to estimate the RUL. In this case, the idea is to obtain the highest possible RUL for the system, while ensuring the necessary power output. To achieve this, the RUL will be used as an objective function, i.e. it will be estimated regularly, and if it is found to be falling, then a modification of the control variables will be made to maximize it. It should be noted that a threshold will be set to take account of natural aging and prediction errors.

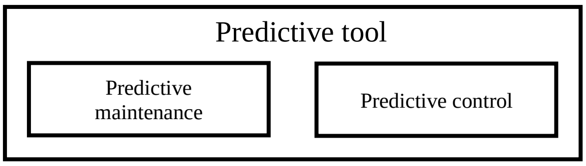

Fig. 1: Architecture of the predictive tool for hydrogen-energy systems.

Predictive maintenance of hydrogen-energy systems

In this sub-section, predictive maintenance of hydrogen-energy systems, which looks very interesting and promising, will be discussed. The idea is to predict the stack voltage in order to estimate the RUL of power components for maintenance interventions.

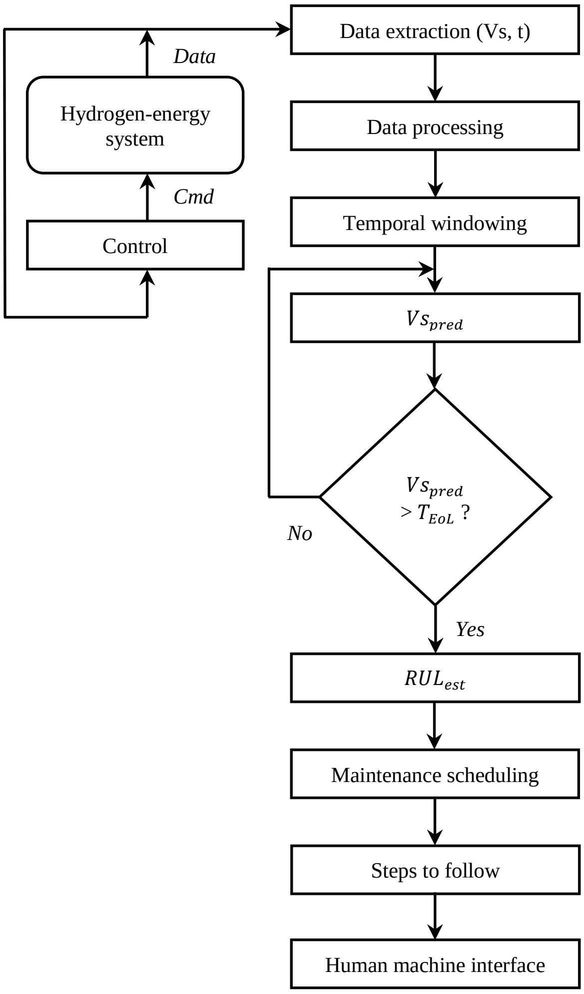

Fig. 2: Stack voltage prediction to estimate RUL for predictive maintenance of hydrogen-energy, inspired by [3].

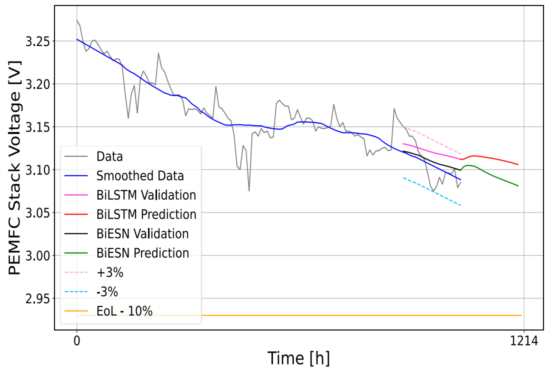

Fig. 3: BiESN and BiLSTM results for PEMFC system stack voltage prediction.

Artificial intelligence (AI) algorithms are a good way of achieving this, as they enable high predictive accuracy with fast computation times for training and inference. The fast computation time during training means that the algorithm can be re-trained online when the trend changes, while the fast computation time during inference means that the algorithm can be re-calculated to ensure the quality of the prediction.

Nevertheless, prior data science steps have been carried out to filter, smooth and reduce the number of redundant data to improve computation time. Figure (2) shows the various stages in the process of predicting the stack voltage in order to estimate the RUL of power components (PEMFC or PEMWE), with the aim of planning and carrying out maintenance work only when strictly necessary, thus improving on conventional preventive maintenance, which follows a fixed schedule that generates high maintenance costs. The various steps involved in predictive maintenance of hydrogen-energy systems are as follows:

- The data needed to estimate the RUL will be extracted, i.e. stack voltage and time.
- The data will also be used for predictive maintenance. To achieve this, the data will be processed to reduce the number of redundant data to improve computation time, eliminate peaks at 0V corresponding to system shutdowns or passage through the OCV using a logic filter, and finally smooth the data to eliminate noise using the Savitzky-Golay filter.
- A regular sliding window will be used to inject a sequence into a prediction algorithm, typically a Bidirectional Echo State Network (BiESN), whose size will be adjusted according to the size of the sequence used in this algorithm.
- The stack voltage is then predicted over time using the prediction algorithm.
- This prediction is then compared with the end-of-life threshold, noted “T_EoL” in figure (2). If the predicted voltage is greater than the EoL threshold, then no RUL will be estimated. On the other hand, if the predicted

voltage is below the EoL threshold, then a RUL will be estimated. It should be noted that RUL prediction must be carried out at least 100 hours in advance, to enable operators to carry out the maintenance required to restore the system before it can no longer perform its mission.

- In the case of a RUL estimated at least 100 hours in advance, the maintenance schedule and the various actions to be implemented to repair the system will be transmitted to a Human Machine Interface (HMI) to inform the maintenance operators of the steps to be taken.
- Predictive maintenance of hydrogen energy systems makes it possible to estimate the RUL of power components, so that maintenance work can be scheduled and carried out only when strictly necessary, thereby improving reliability, availability, performance, durability, safety and operating costs. To this end, the use of data-driven predictive algorithms appears to be one of the most promising solutions for complex and multi-physics hydrogen-energy systems. In this paper, a data-driven method has been developed by comparing two well-known prediction algorithms, in this case BiESN and BiLSTM. The dataset used comes from the IEEE PHM Data Challenge, in which a 500W low-temperature PEMFC operating at 70A current with +-5% current ripples was run for 1055h. Only the stack voltage over time was used to estimate the RUL in order to suit the constraints of a real-time system, i.e. the use of always-available data on this type of system as well as fast computation time for the algorithms during prediction. The setting parameters of these algorithms are shown in Table (1) and their results in figure (3).

Table 1: BiESN and BiLSTM settings

	BiESN	BiLSTM
Data splitting	Training (80%)	Training (80%) Validation (20%)
Setting parameters	Epochs: 1000 Batch size: 320 Patience: 300 Activation function: Relu Number of neurons: 100	
Prediction performance evaluation metric	Satisfied horizon (SH)	
Computation time	Training (20s) Prediction	Training (32s) Prediction (0.6s)

The result of the BiESN and BiLSTM predictions are very satisfactory, respecting the satisfied horizon evaluation metric, which corresponds to an error of +-3% between the actual validation data and the validation data estimated by the algorithm, in addition, the computation time is less than 1s (0.58s and 0.6s respectively), enabling predictions to be re-run very regularly. It's also worth noting that training times are very fast (20s and 32s respectively), enabling algorithms to be re-trained online. Furthermore, the voltage of the PEMFC stack was predicted 164 hours in advance in order to plan maintenance interventions before the system can no longer fulfil its mission. On this dataset, no RUL has been estimated as the PEMFC stack voltage has not crossed the end-of-life threshold noted "EoL -10%" on figure (3).

Predictive control of hydrogen-energy systems

In this sub-section, predictive control of hydrogen-energy systems to maximize the RUL of power components (PEMFC and PEMWE) by modifying control variables will be discussed. In the context of hydrogen-energy systems, which are complex, multiphysical and non-linear, predictive control seems to hold great promise. Figure (4) shows a hydrogen energy system, which may be a PEMFC or PEMWE system.

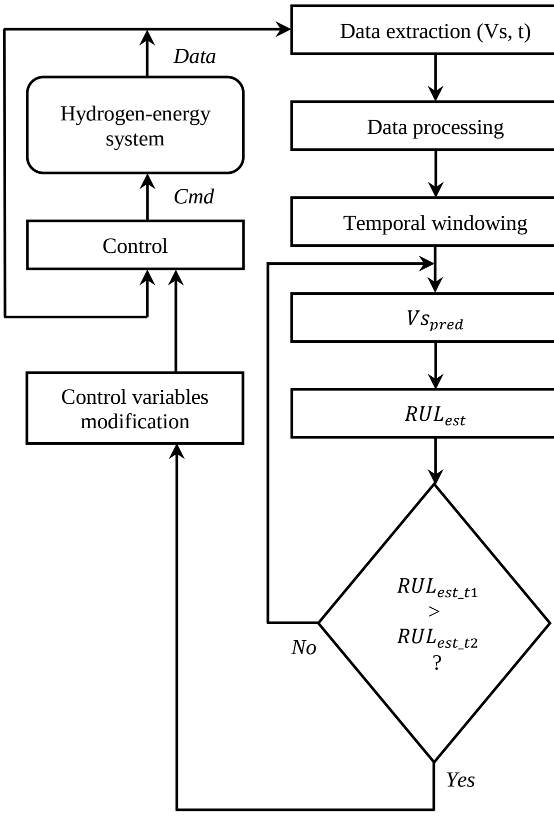

Fig. 4: Stack voltage prediction to estimate RUL for predictive control of hydrogen-energy systems, inspired by [3].

Data from the measurement sensors are transmitted to the control system to control the system. This data will also be used to estimate the RUL:

- The data needed to estimate the RUL will be extracted, i.e. stack voltage and time.
- The data will then be processed to reduce the number of redundant data to improve computation time, eliminate peaks at 0V corresponding to system shutdowns or passage through the VCO using a logic filter, and finally filter the data to eliminate noise using the Savitzky-Golay filter.
- A regular sliding window will be used to inject a sequence into a prediction algorithm, typically a BiESN, whose size will be adjusted according to the size of the sequence used in this algorithm.
- The stack voltage is then predicted over time using the prediction algorithm.
- This prediction of stack voltage is used to estimate the RUL. In predictive control, stack voltage must be predicted until the end-of-life threshold is reached, so that RUL can be estimated at any time.
- La RUL estimated at time t1, noted RUL_{est_t1} in figure (2), will be compared with that estimated at time t2, noted RUL_{est_t2} in figure (2). If the RUL estimated at time t1 is lower than that estimated at time t2, then no changes are made to the control variables.
- On the other hand, if the RUL estimated at time t1 is higher than that estimated at time t2, then the system has lost its service life. In this case, a prescription to modify the control variables will be transmitted in order to obtain the highest possible RUL while ensuring the necessary output power. It should also be noted that a threshold between the RUL estimated at time t1 and time t2 will be implemented, to represent performance losses due to natural aging and prediction errors.

Ultimately, predictive control makes it possible to maximize the RUL of power components in hydrogen-energy systems by modifying control variables, thereby increasing the lifetime, availability and efficiency of these systems.

Conclusion

In this article, the both aspects of a high-performance predictive tool have been defined and explained in order to improve durability, availability, reliability, performance, safety and operating costs of hydrogen-energy systems in an industrial framework. The first aspect is predictive maintenance, i.e. estimating the RUL in order to plan maintenance interventions when strictly necessary. The second component is predictive control of the system, which enables the control variables to be modified by comparing the RUL estimated at time t1 with the RUL estimated at time t2, while respecting the trade-off between performance and sustainability in order to deliver the required power while maximizing the RUL. Methods in the literature for data-driven RUL prognostics of PEMFCs and PEMWEs have been presented, with a view to finding the most interesting ones, taking into account the different constraints induced by a real-time system. In addition, two well-known prediction algorithms, BiESN and BiLSTM, were compared on an identical dataset, in order to estimate the RUL at least 100h in advance to anticipate and schedule maintenance interventions. It was shown that both algorithms achieved very good prediction results, using measurements always available on a real-time system (stack voltage and time). It should also be noted that preliminary filtering steps were implemented to greatly reduce the computation time, for training (20s and 32s respectively) to allow online re-training and for prediction (0.58s and 0.6s) to allow reiteration of the computation to ensure prediction quality. In future work, the prediction tool will be enhanced to consider faults detection and breakdowns prediction of system and subsystems. These various aspects will be carried out and validated experimentally for hydrogen-energy systems, i.e., for open-cathode and closed-cathode PEMFC systems, for wet-cathode and dry-cathode PEMWE systems, and for hybrid systems comprising at least one PEMFC and one PEMWE. In addition, this predictive tool is destined to be marketed to producers and integrators of hydrogen-energy systems for stationary and transport applications.

References

1. Dirkes, S.; Leidig, J.; Fisch, P.; Pischinger, S. Prescriptive Lifetime Management for PEM Fuel Cell Systems in Transportation Applications, Part I: State of the Art and Conceptual Design. *Energy Convers. Manag.* **2023**, *277*, 116598, doi:10.1016/j.enconman.2022.116598.
2. Dirkes, S.; Leidig, J.; Fisch, P.; Pischinger, S. Prescriptive Lifetime Management for PEM Fuel Cell Systems in Transportation Applications, Part II: On-Board Operando Feature Extraction, Condition Assessment and Lifetime Prediction. *Energy Convers. Manag.* **2023**, *283*, 116943, doi:10.1016/j.enconman.2023.116943.
3. Gibey, G.; Pahon, E.; Zerhouni, N.; Hissel, D. Diagnostic and Prognostic for Prescriptive Maintenance and Control of PEMFC Systems in an Industrial Framework. *J. Power Sources* **2024**, *613*, 234864, doi:10.1016/j.jpowsour.2024.234864.
4. Gibey, G.; Pahon, E.; Zerhouni, N.; Hissel, D. LT-PEMFC Remaining Useful Life Prediction for Predictive Maintenance. In Proceedings of the International Conference on Polymer Electrolyte Membrane Fuel Cells & Electrolysis. Materials, Systems & Applications; Lefkada, Greece, October 2023.
5. Yue, M.; Li, Z.; Roche, R.; Jemei, S.; Zerhouni, N. Degradation Identification and Prognostics of Proton Exchange Membrane Fuel Cell under Dynamic Load. *Control Eng. Pract.* **2022**, *118*, 104959, doi:10.1016/j.conengprac.2021.104959.
6. Chanal, D.; Steiner, N.Y.; Chamagne, D.; Pera, M.-C. Voltage Prognosis of PEMFC Estimated Using Multi-Reservoir Bidirectional Echo State Network. In Proceedings of the 2022 10th International Conference on Systems and Control (ICSC); November 2022; pp. 352–359.
7. Wang, F.-K.; Mamo, T.; Cheng, X.-B. Bi-Directional Long Short-Term Memory Recurrent Neural Network with Attention for Stack Voltage Degradation from Proton Exchange Membrane Fuel Cells. *J. Power Sources* **2020**, *461*, 228170, doi:10.1016/j.jpowsour.2020.228170.
8. Hua, Z.; Zheng, Z.; Péra, M.-C.; Gao, F. Remaining Useful Life Prediction of PEMFC Systems Based on the Multi-Input Echo State Network. *Appl. Energy* **2020**, *265*, 114791, doi:10.1016/j.apenergy.2020.114791.
9. Prakash, O.; Sood, S.; Boukerdja, M.; Ould-Bouamama, B.; Dieulot, J.-Y.; Gehin, A.-L.; Bressel, M. A Model-Based Prognosis Approach to Proton Exchange Membrane Water Electrolysis System. In Proceedings of the 2021 European Control Conference (ECC); June 2021; pp. 2133–2138.
10. Liu, H.; Chen, J.; Hissel, D.; Su, H. Remaining Useful Life Estimation for Proton Exchange Membrane Fuel Cells Using a Hybrid Method. *Appl. Energy* **2019**, *237*, 910–919, doi:10.1016/j.apenergy.2019.01.023.