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Diagnostics and Prognostics for the Wind-Hydrogen Plant

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Abstract: The HAEOLUS project aims to integrate a fully functioning 2.5 MW electrolyser in a 45 MW wind farm. The wind farm remoteness and Norway's cold winters will represent very extreme conditions for Haeolus' demonstration, that consequently will be completely remotely controlled and monitored. In this scenario a primary target will be the development of suited strategies for remote system operations and anticipative maintenance. System monitoring and fault detection will be the object of the diagnostic algorithm, while risk analysis and failure prediction for predictive maintenance will be the object of the prognostic and health management (PHM) approach.

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Table of Contents

1 Introduction

HAEOLUS project aims to integrate a fully functioning 2.5 MW electrolyser in a 45 MW wind farm. The wind farm remoteness and Norway's cold winters will represent very extreme conditions for HAEOLUS' demonstration, which consequently will be completely remotely controlled and monitored. In this scenario, a primary target will be the development of suited strategies for remote system operations and anticipative maintenance. As a consequence, critical system operations and components behaviours are analysed to select the best performance indicators for current state monitoring and durability prediction. Performance indicators are defined as available measurable variables or a combination thereof able to characterize system operations under normal, faulty and failure modes. System monitoring and fault detection will be the object of the diagnostic algorithm, while the risk analysis and the failure prediction for predictive maintenance will be the object of the prognostic and health management (PHM) approach. The details of the proposed methodologies will be explained, such as their interactions with the control strategies in remote applications.

The HAEOLUS concept is mainly based on both *power-to-gas* and *gas-to-power* strategies, as shown in figure 1. The Raggovidda wind farm is able to produce 45 MW of electrical power, currently injected into the electrical grid. The power-to-gas approach is introduced to produce and store hydrogen, for example when the energy produced by the wind farm is higher than the grid demand. For this purpose, a proton exchange membrane electrolyser (PEMEL) of 2.5 MW is integrated to the actual plant. The gas-to-power approach is dedicated to transform the stored hydrogen in electricity, for example when the energy produced by the wind farm is not sufficient to fulfil the grid demand. For this purpose, a proton exchange membrane fuel cell (PEMFC) of 100 kW is integrated to the actual plant. Moreover, the produced hydrogen can be directly sold to external consumers. It is worth noting that the power rate of the fuel cell is small, in comparison with the wind farm and the electrolyser, because it only intends to re-electrify the produced H_2 while the local H_2 market is developed.

A control monitoring system is then developed to manage the different strategies. The best grid equilibrium between the produced energy and the demand is obtained with the control system aimed to optimize the different energy flows. The optimal solution is obtained considering the actual states-of-health and the related costs for the energy production of the different devices. It is worth noting that, due to the wind farm remoteness and the extreme climatic conditions, a remote control is required. In this framework, both system diagnosis and prognostic strategies are required to prevent critical faulty conditions and analyse the system's ageing. In case of emerging faulty conditions, fault detection and isolation is performed by the diagnostic algorithm, that will send alarms to the control system to change the operation mode for system recovery or stop the system (if necessary) for safety reasons. The prognostics algorithm is mainly used to predict the system ageing in order to schedule the preventive maintenance. Moreover, the costs variations introduced by the system ageing both in energy and gas production are evaluated. Advanced diagnostics and prognostics algorithms are then scheduled in both power-to-gas and gas-to-power configurations, respectively for the electrolyser and the fuel cell systems monitoring. The approach for algorithms development and strategies selection are reported in the following; however, because H_2 re-electrification is not the main purpose of the project (re-electrification is scheduled during the local H_2 market development), more interest is given to the description of the electrolyser in the following, although the same techniques will be extended to the fuel cell.

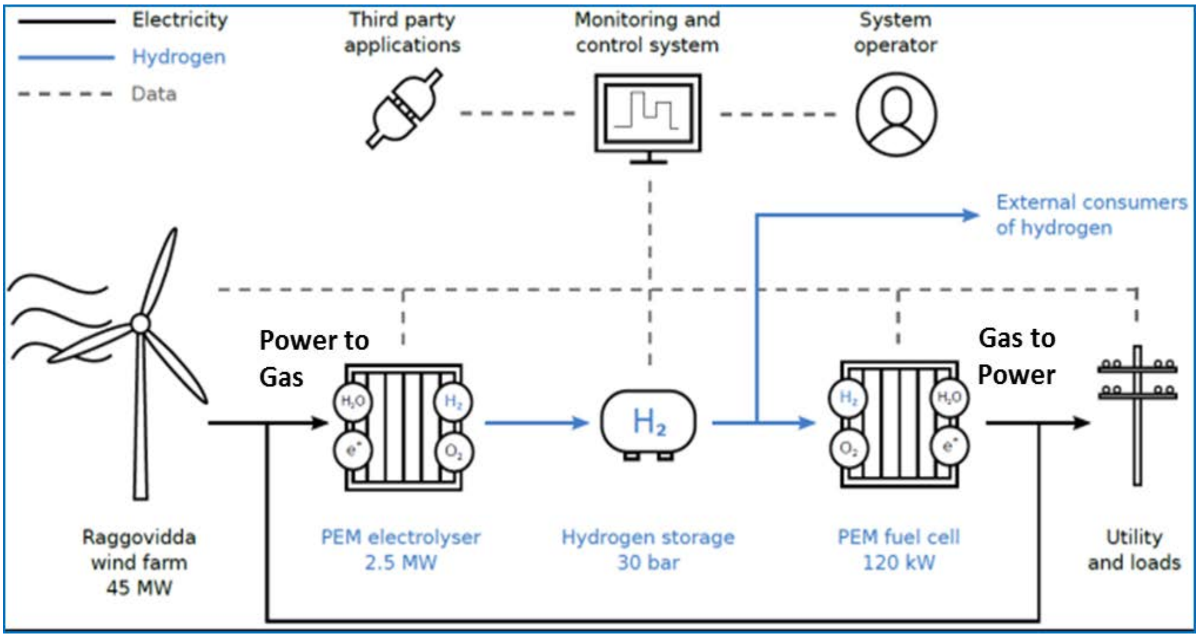

Figure 1: The HAEOLUS concept [1].

2 Approach for algorithms development

In order to develop advanced diagnostics and prognostics algorithms, the PEM electrolyser and the PEM fuel cell systems (including their ancillaries) are considered as the key elements for the monitoring of the power-to-gas and gas-to-power processes. Both devices are developed and provided by the project partner Hydrogenics.

The electrolyser, to be installed in Berlevåg and for which the characteristics are reported in Table 1, has 3 operations modes:

1. *Off:* the electrolyser is not generating H_2 and is depressurized. No energy consumption.
2. *Standby:* the electrolyser is not generating H_2 but is pressurized. Small energy consumption (a few kW).
3. *On:* the electrolyser is generating H_2. Energy consumption depends on the H_2 generation.

The study of the normal and abnormal operating conditions and the system monitoring are the object of the diagnosis approach. However, the electrolyser presents a gradual performance degradation due to the system components ageing. According to Hydrogenics, an efficiency degradation of 2 % at rated power and per 8000 h of operation is considered as reference ageing. Particularly, the life cycle is determined by two parameters: 40 000 working hours and 5000 on/off switching cycles. Working cycles variations in real applications can change the efficiency degradation ratio. The prognostics algorithm will evaluate the possible ageing variation and estimate the remaining useful life (RUL) of the system. In case of ageing acceleration, the maintenance plan will be adapted.

Table 1. 2.5MW Hydrogenic PEM electrolyser data.

2.5 MW PEM Electrolyser	
Parameter	**Value**
Nominal Power	2.5 MW
Minimum Power	0.3 MW
Maximum Power	3.25 MW
Efficiency degradation at rated power and considering 8000 h operations / year	2 %/year
Hydrogen delivery pressure	30 bar
Hydrogen production rate	45 kg/hour
Start-up time (cold start)	1200 seconds
Response time (warm start)	30 seconds
Shut down time	1 seconds
Ramp rate up/down	60 MW/min
Standby consumption	1 kW
Calendar life	20 Years
Cycle life	5000 on/off cycles
	40 000 operation hours

As for the electrolyser, the data of the PEM fuel cell (manufactured by Hydrogenics as part of the INGRID EU co-funded project: www.ingridproject.eu) are reported in Table 2. Both diagnosis and prognostics approaches will also be developed for the FC system on the basis of the ones for the electrolyser.

Table 2. 120 kW Hydrogenics PEM fuel cell data

120 kW PEM Fuel Cell	
Parameter	**Value**
Nominal Power	120 kW
Minimum Power	12 kW (10%)
Maximum Power	132 kW
Peak Efficiency	50 %
Hydrogen consumption rate	9 kg/hour
Response time (warm start)	300 seconds
Warms start time	<5 seconds
Ramp rate up/down	<3 seconds to full power

The operations of both the electrolyser and the fuel-cell systems are then tested to develop advanced diagnosis and prognostics algorithms. Based on Hydrogenics' systems data-bases, technical schemes and maintenance plans, information is collected both for normal, stressed, faulty and aged operating conditions. Figure 2 shows the approach adopted in the HAEOLUS project for prognostics and diagnostics algorithm development.

It is possible to separate the different activities in two major categories: the off-line and the on-board activities. The experimental data provided by Hydrogenics is used in off-line applications; a first part exploited in model tuning and algorithms development and a second part dedicated to the algorithms off-line validation. A first activity (the yellow case) related to the data analysis and model development is scheduled to study the performance variations related to system operations and ageing variations. The simulation results are used to increase knowledge on system response to abnormal operating conditions and to complete the reference database for algorithm development.

Subsequently, the activity related to the algorithm development (the light blue case) is started. It is worth noting that, if a model-based approach is adopted off-line for data analysis and the simulation of system operations, in case of diagnostics and prognostics algorithms development a data-driven approach is selected. This choice is consistent with the on-board final application. In fact, the data-driven approaches appear as an optimal solution for on-board implementation (the green case); more details will be given in sections 4 and 5. The on-board applications will take into account the reference maintenance plan and the on-board measurements. Starting from the measurements acquired during the actual operations, the monitoring and diagnosis algorithm will detect the current state-of-health and generate alarms in case of abnormal operations.

In parallel, the prognostics algorithm will evaluate system ageing to predict the system's lifetime. In case of ageing acceleration, the reference maintenance plan will be changed/adapted for predictive maintenance. Moreover, the system ageing evolution will be employed to evaluate the cost variations in energy conversion and gas production. The obtained results will be processed through a decision-making procedure and integrated into the control unit for an optimal system management and maintenance.

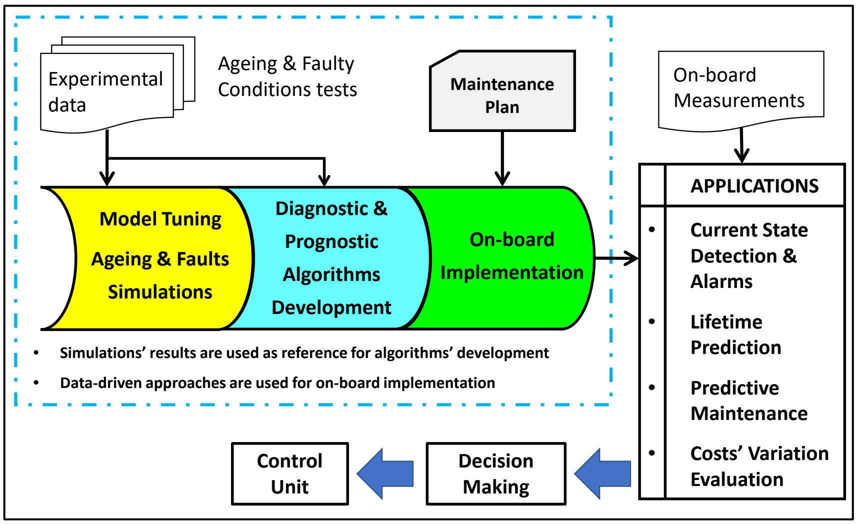

Figure 2: The approach for prognostic and diagnosis algorithms development [2].

3 Off-line modelling and data analysis

The preliminary activity of the system model development used to study the performance variations related to the system operations are presented in this section. Both the experimental data analysis and the model simulation results are used to increase the knowledge on the system response to the abnormal operating conditions and to complete the reference database for algorithm development, in particular for system ageing.

The simplified schemes of the electrolyser (PEMEL) and of the fuel cell (PEMFC) systems adopted for model development are shown in Figures 3 and 4, respectively. The major hypotheses for both systems models are summed up in the following:

1. The control unit will force the balance of plant (BoP) operations to attain the target values for stack operations.
2. The stack is assumed as the system model core.
3. The stack operation set-up will change with ageing, as well as its consumption.
4. The BoP components operations and performance will change with the stack ageing.
5. The resulting variation of the BoP components operations depends both on the stack ageing and on the BoP components ageing.

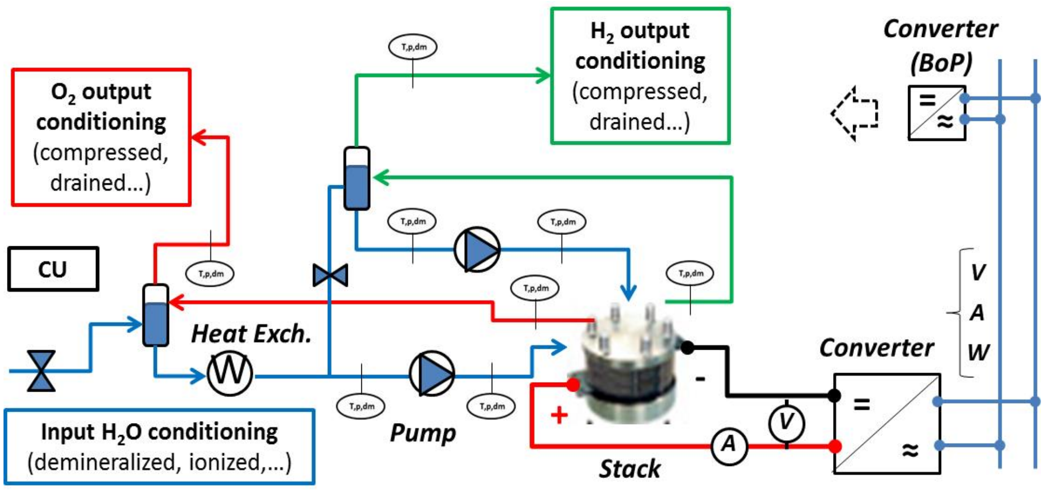

Figure 3: Simplified scheme for model development of the PEMEL system.

According to the previous hypotheses, the stacks sub-models are assumed as the model core, both for the PEMEL and for the PEMFC models. For this reason, physical models are developed for these components, while simplified sub-models (black box or grey-box models, depending on the available data) are introduced for the BoP components. According to the project purposes, the simplified BoP sub-models are more focused on the evaluation of the power consumption variations with ageing. Particularly for the electrolyser (referred in Figure 3), the water pumps for liquid circulation in the PEMEL stack are considered as well as the heat exchanger for the system warm-up and cooling. In analogy for the fuel cell (referred in Figure 4), the water pump and the heat exchanger of the cooling system and the air compressor are considered for the BoP energy consumptions evaluation, while the hydrogen re-circulation and purging are considered to evaluate the hydrogen consumption.

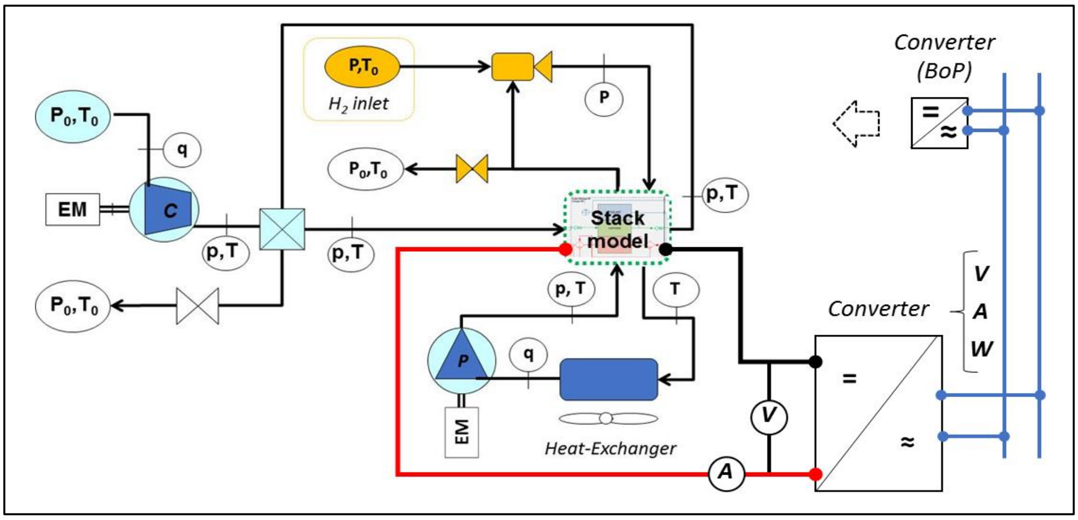

Figure 4: Simplified scheme for model development of the PEMFC system.

The stacks performance is expressed by the voltage and current density relationship of equations (1) and (2). The input variables are the operating current (*I*), the gas pressures (p_{H2} , p_{O2}) and the working temperature (*T*).

$$V = N_c * V_{cell} \qquad \text{(eq. 1)}$$

$$V_{cell}(I, p_{H_2}, p_{O_2}, T) = V_{OCV}(p_{H_2}, p_{O_2}, T) \pm V_{Act}(I, T) \pm V_{Ohm}(I, T) \pm V_{Diff}(I, p_{H_2}, p_{O_2}, T) \qquad \text{(eq. 2)}$$

where the open-circuit voltage (OCV) is calculated from the Nernst equations. Depending on the technology to study:

- In case of the PEMEL, V_{Act}, V_{Ohm} and V_{Diff} are the activation, ohmic and diffusion over-potentials; as a consequence, these terms are added to the OCV value.
- In case of the PEMFC, V_{Act}, V_{Ohm} and V_{Diff} are the activation, ohmic and diffusion losses; as a consequence, these terms are subtracted from the OCV value.

The activation phenomena of the electrochemical reaction are influenced by physical and chemical parameters, such as temperature, catalyst and active reaction site properties; the Butler-Volmer equation is typically used to model their effects [3]. The ohmic losses are obtained combining membrane, electrodes, bipolar plate and contacts resistances. Diffusion phenomena are due to the mass transport limitation in porous electrodes, and diffusion equations are often used to model their effects [3]. It is worth noting that, depending on the operating mode (electrolyser or fuel cell), the electrochemical reactions are inversed, and model equations will then be different for PEMEL and PEMFC. For more details on the activation, ohmic and diffusion physical equations, the reader can refer to the literature ([3] and [4,5] for the PEMEL and for the PEMFC, respectively).

Stack ageing is also analysed and integrated into the model equations. A parameter variation analysis shows that, for the PEMFC, all performance losses (activation, ohmic and diffusion) increase with ageing, while for the PEMEL diffusion over-potential variations can be neglected with respect to the activation and ohmic over-potentials variations [3]. The results of the stack model identification and ageing simulation are reported in Figures 5 and 7 for the PEMEL and the PEMFC, respectively. The hypothesis of linear ageing is assumed in accordance with Hydrogenics' specifications and test results. The simulated aged profile refers to the condition of 10% of the performance losses at nominal operating conditions. A good matching between the PEMEL stack measurements and model simulation results at the beginning of life can be observed in Figure 5.

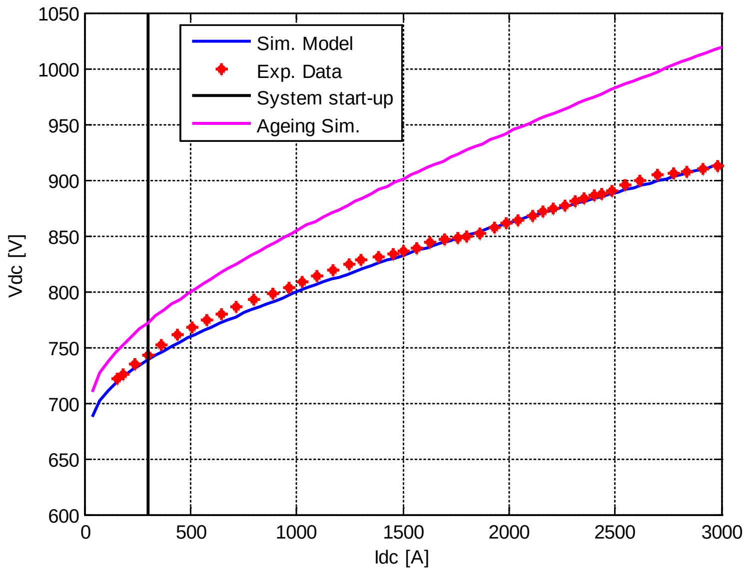

Figure 5: Results of simulation of the PEMEL stack model.

The consumption variation with ageing of the PEMEL system is also simulated and reported in Figure 6. Full dots represent the stack experimental data, while the circles are the system measurements. Full lines represent the simulated beginning of life conditions, while the dashed lines refer to the simulation of 40 000 h of operating conditions (10% of performance losses).

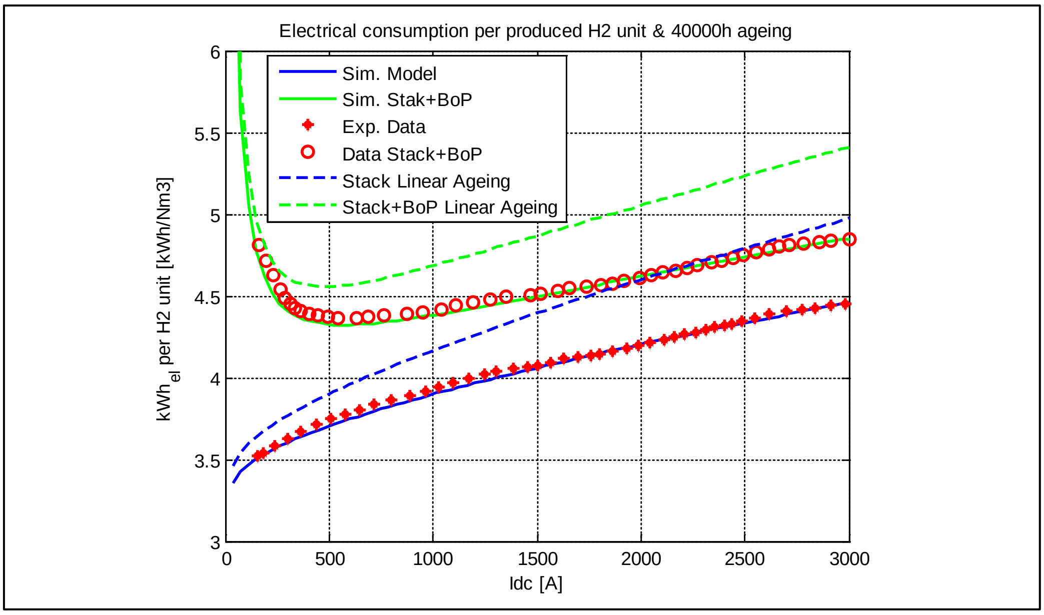

Figure 6: Results of simulation of the PEMEL system consumption variation with ageing.

Figure 7 shows the PEMFC stack performance at the beginning of life and at 10% performance loss. A good match between PEMEL stack measurements and model simulation at beginning of life is observed.

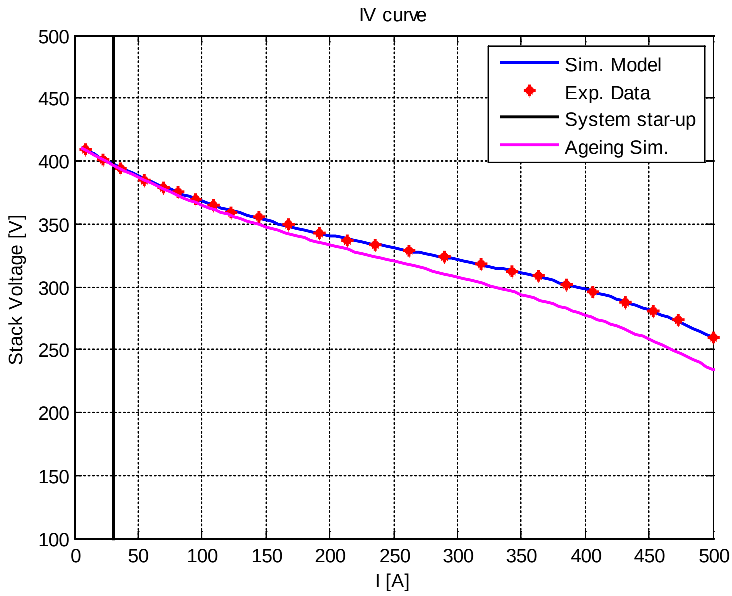

Figure 7: Results of simulation of the PEMFC stack model.

The reduction of PEMFC system power due to stack ageing is shown in Figure 8. Measurements (red points) refer to system net power (the power absorbed by BoP ancillaries is deducted from the power generated by the stack). The full line represents power simulation at beginning of life, while the dashed line refers to simulation of 40 000 h of operating conditions (10% of performance loss).

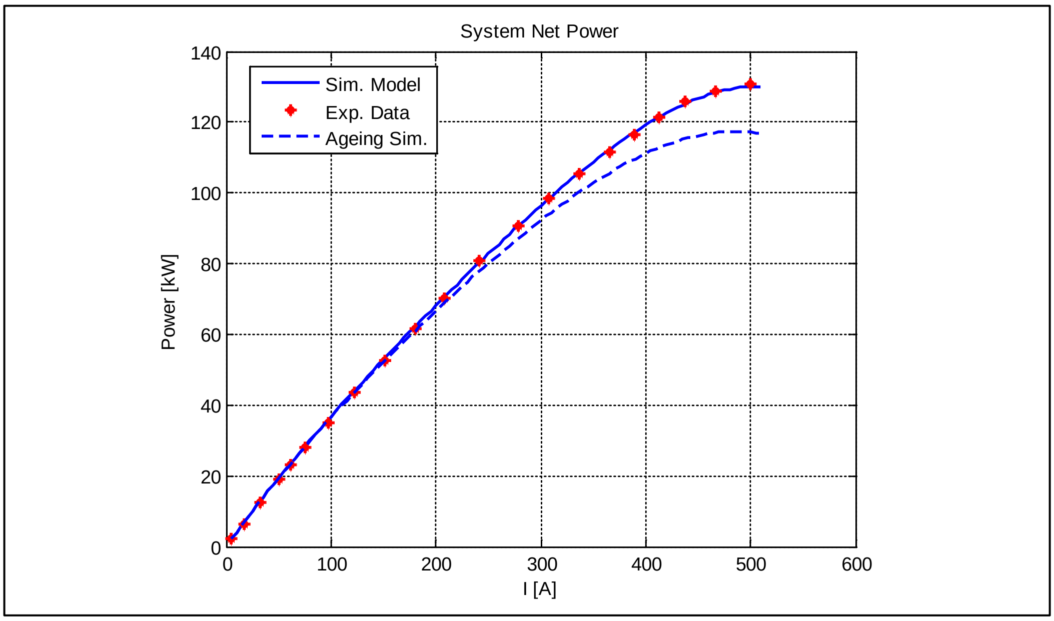

Figure 8: Results of simulation of the PEMFC system power reduction with ageing.

In the next sections, both the diagnosis and prognostics approaches are introduced. Results of linear ageing simulations of both the PEMEL and the PEMFC systems are assumed as reference trends in the prognostics algorithm development, while data treatment will be more exploited in diagnosis approaches.

4 Diagnosis approach

4.1 Introduction

The occurrence of abnormal operating conditions in electrochemical devices, such as the PEMEL and the PEMFC systems, can introduce system faults and degradation mechanisms. A suitable diagnostic tool aims at identifying system faults in real time. For this purpose, fault detection is based on on-board comparison between actual measured data and expected ones evaluated in normal and abnormal system operation [6]. The model-based approach performs the diagnosis by evaluating the residuals between measured data and model outputs. Subsequently, an inference analysis is done to detect the possible abnormal behaviour and isolate the fault origins [7]. Model-based methodologies usually depend on parameter estimation, parity-state equations or state-observers approaches.

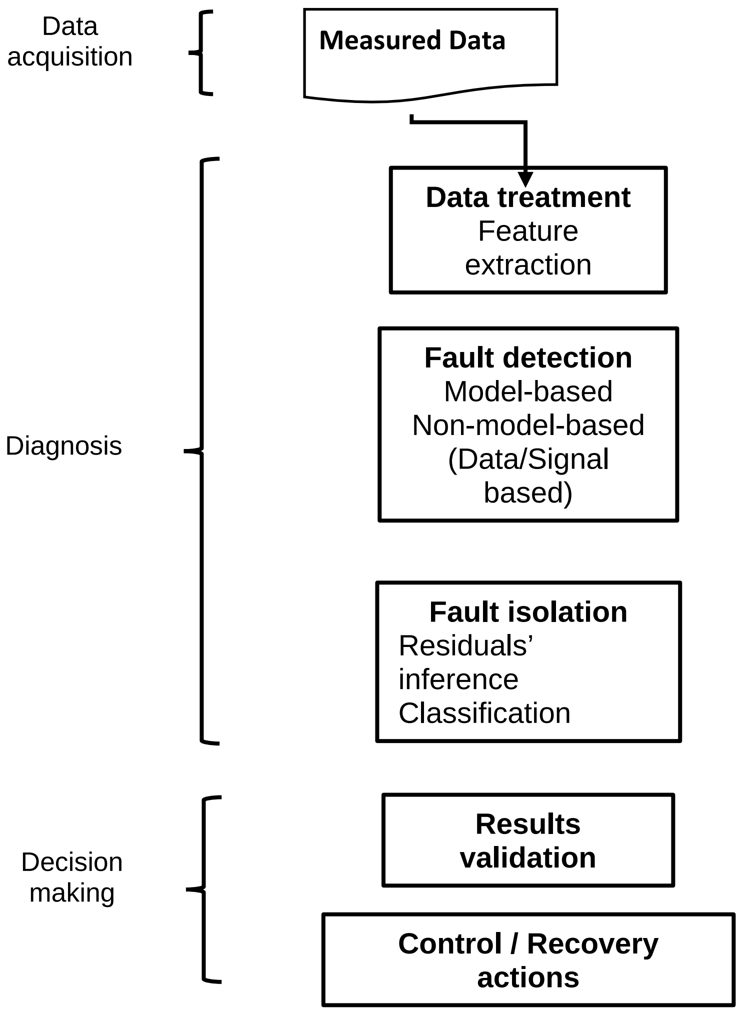

Figure 9: Scheme of diagnosis algorithm development, adapted from [6].

On the contrary, in non-model-based approaches, fault information is obtained through heuristic knowledge (data-based) or signal processing (signal-based) or a combination thereof [8]. In this case, fault detection and isolation (FDI) is performed through fault classification procedures [8]. Therefore, depending on the considered approach, fault isolation is obtained by applying classification or residual/inference methods [6-8], as summarized in Figure 9.

4.2 Strategy selection

The model-based approach requires a deep knowledge of the physical and chemical phenomena occurring in the system under study. Models are classified on the basis of their knowledge content as: white-box (theoretical analytical models), grey-box (hybrid models) and black-box (such as artificial intelligence and statistical models). White-box models, based on physical equations, are frequently used to model electrochemical, thermal and fluid-dynamic phenomena. While this type of models has high genericity and accuracy, they involve several parameters that are often difficult to estimate [7]. Moreover, they are very time-consuming to solve differential equations. For these reasons, white-box models are mainly used in off-line applications, while for on-line diagnostics, black-box and grey-box models are typically preferred. Black-box models, based on data-driven approaches, do not require solving physical equations resulting in faster computational time. Nevertheless, their accuracy is strictly related to the training dataset, which usually requires long and onerous test campaigns. A trade-off can be achieved with grey-box models, that combine both physical knowledge and empirical formula. Conversely, non-model-based approaches can offer good accuracy with short computational time. Also, if suitable datasets (in analogy with black-box models) are required for their algorithm development, a lot of interest is currently focused on these approaches due to their adaptive capability [8,9]. The non-model-based family is composed of data-based and signal-based approaches. The first class, also named data-driven, is usually based on clustering techniques. They mainly involve artificial intelligence (AI) methods, such as artificial neural networks (ANN), fuzzy logic (FL) and adaptive neuro-fuzzy inference systems (ANFIS). Moreover, statistical approaches based on probability theory, such as principle component analysis (PCA) and Fisher discriminant analysis (FDA), are also used to ensure a suitable solution to deal with uncertainty in decision-making procedures [8]. On the contrary, the second class (signal-based) focuses on signal processing approaches, such as fast Fourier transform (FFT) for stationary signal analysis and wavelet transforms (WT) for non-stationary conditions [8].

In the framework of the HAEOLUS project, a non-model-based approach is considered for the diagnosis algorithm development. This choice is mainly due to the model's complexity for both the gas-to-power and power-to-gas systems (PEM stacks and ancillaries). The development of a suitable diagnostics tool for on-board applications requires a series of compromises between algorithm accuracy and costs (in terms of time and energy consumption). Cadet et al. [6] proposed a series of guidelines to choose, design and validate the diagnostic algorithms based on standard criteria. Algorithm performance is evaluated by comparing a series of validation indices extrapolated through a confusion (or contingency) matrix. Authors defined the precision for fault as the ratio between the correct detection to all diagnosed faults. In analogy, the recall for fault was defined as the ratio of the diagnosed faults to all of the actually occurring faults. The accuracy was evaluated as the percentage of the correct assignments including not only the correctly diagnosed ones, but also the correctly not occurring and not diagnosed samples.

Furthermore, authors also considered the cost criteria, including equipment costs, consumed energy and computation time. Li et al. [9] presented a comparative study of the different non-model-based approaches for PEMFC diagnosis based on Cadet et al. [6] indicators. It concluded that FDA combined with space vector machines (SVM) resulted in the most suitable solution for data-driven (statistical-based) on-board diagnosis. Particularly, in [10] authors combined FDA and spherical-shaped multiple-class support vector machine (SSM-SVM) approaches to extract features from single cell voltages of a PEMFC stack of 40 cells. The proposed algorithm allowed feature classification depending on both known health states and potential new failure mode occurrences, resulting in completely adaptive solution to new operating conditions. The incremental learning procedure of the diagnostics algorithm is pictured in Figure 10.

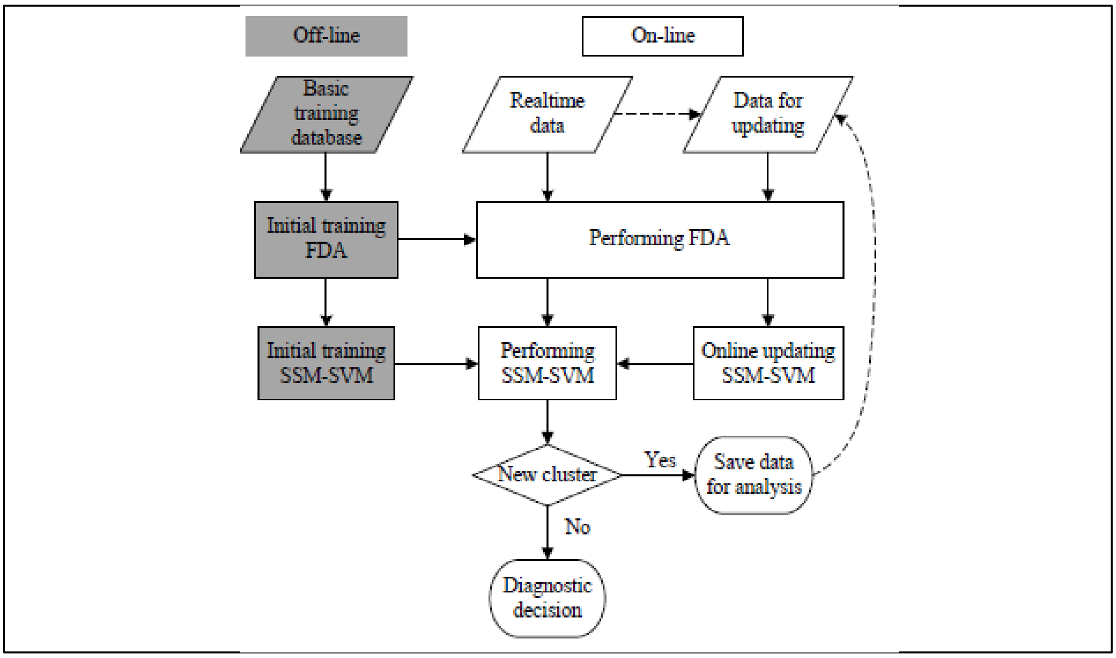

Figure 10: Data-driven diagnostic algorithm proposed by [10].

According with the works of Li et al. [9,10] and depending on the available data, in HAEOLUS project, different features extraction/classification methods will be evaluated for algorithm development. Particularly, artificial intelligence (ANN, FL and ANFIS) and statistics-based (FDA and KFDA) techniques are under evaluation for features extraction, while SVM techniques will be considered for classification procedures. Currently, the project activity related to the off-line data analysis is started with the first PEMEL system data delivery. Algorithm development for on-board implementation is starting and waiting for the training dataset fulfilment.

5 Prognostic algorithm development and on-board applications

5.1 Introduction

Prognostics is an advanced strategy for system maintenance and reliability improvement. Its definition given by the International Organization for Standardization [11] is “the estimation of time to failure and risk for one or more existing and future failure modes”, where the word “failure” defines the component's inability to fulfil its function. Therefore, if the beginning of life (BoL) is usually adopted to indicate at time t=0, the end of life (EoL) is defined as the time t^C when the failure (critical condition) occurs. The capability to predict and anticipate the system failure is the main priority of prognostics. For this purpose, a measurable variable (or physical property) sensible to the system's ageing is usually identified as a performance factor and monitored during system operation [12]. Expert knowledge and ageing tests are usually considered to select the performance factor. In case of electrochemical devices such as PEMEL and PEMFC, the stack voltage is the most commonly used variable [13], while limitations of the real application on both voltage and power outputs are usually considered to define the EoL. In this framework, V^N defines the performance nominal value at the BoL, while V^C is the critical performance value at the EoL. The state of the performance factor will decrease with the system ageing from V^N to V^C [13]. In case of a complex system, with multi-failure modes, several performance factors must be identified. To compare the state of the different failure modes, a unitless damage function $D(t)$ is introduced [12]:

$$D(t) = \frac{V^N - V(t)}{V^N - V^C} \qquad \text{(eq. 3)}$$

This results in: $D(0) = 0$ and $D(t^C) = 1$.

Therefore, t^C is also defined as the system lifetime (for the considered failure mode). Therefore, the remaining useful life (RUL) is given by:

$$RUL = t^C - t^* \qquad \text{(eq. 4)}$$

where t^* is the corresponding time of the current state-of-health D(t*) [13]. It is worth noting that, in prognostics and health management approaches (PHM), the time variable is expressed in hours. In fact, this kind of study is not focused on system transitory conditions or sudden faults detections, but it is mainly aimed to predict and anticipate faults occurrence over long periods.

The current system state-of-health (SoH) is directly measured on board, via performance factor monitoring. These measurements are used to define the real system gradual degradation. However, to predict the future behaviour of the system, advanced prognostic techniques are introduced [14]. Several approaches, mainly model-based and data-driven, can be found in the literature [4,14-19]. In model-based approaches [4,14,15], system performance degradations are predicted by the model. The advantage of this approach is that the damage evolution for each system sub-component can be simulated and predicted and includes the components ageing interactions. However, complex model degradations are frequent. Moreover, if a degradation mode that was not considered during the model development occurs during the real operations, the results of the prediction will be affected. Therefore, in case of on-board applications, additional measurements are required to verify the model results consistence with the current state-of-health. In case of expected ageing deviation, an update of the ageing functions is performed [13]. Therefore this kind of solutions requires a hybridization with data-driven techniques [14,15].

On the contrary, in data-driven approaches, system performance degradation is directly evaluated based on measured data. The trend of performance degradation is then extrapolated through filters [16,17] and statistical or artificial intelligence methods [18,19]. The data-driven approach requires a first data set for algorithm learning. After that, the procedure is automatically updated with on-board measurements. Therefore, this kind of approach has the advantage of being adaptive using real measurements [18,19], and the predicted degradation trend changes also in case of ageing acceleration due to unexpected operating conditions.

Once the performance degradation trend is predicted, the system RUL is calculated based on eq. (4). If a sensible variation is stated between the reference trend of the system performance degradation and the new predicted trend, an alarm is sent, and the maintenance plan is adapted.

5.2 Strategy selection and algorithm development

In this work, the reference trend based on manufacturer specifications (linear ageing) is derived from the physical model (off-line) simulation results proposed in section 3. A data-driven approach is considered for real ageing prediction. Due to their higher capability and flexibility in approximating input-output functions [19], artificial intelligence methods based an artificial neural network (ANN) will be considered for PHM on-board implementation. The real advantage is that ANN is continuously improved with actual measurements, ensuring the best fit with the real evolution of the performance degradations. Therefore, system damage is evaluated as proposed in eq. (3). Figure 11 shows an example of qualitative results of the PHM on-board implementation.

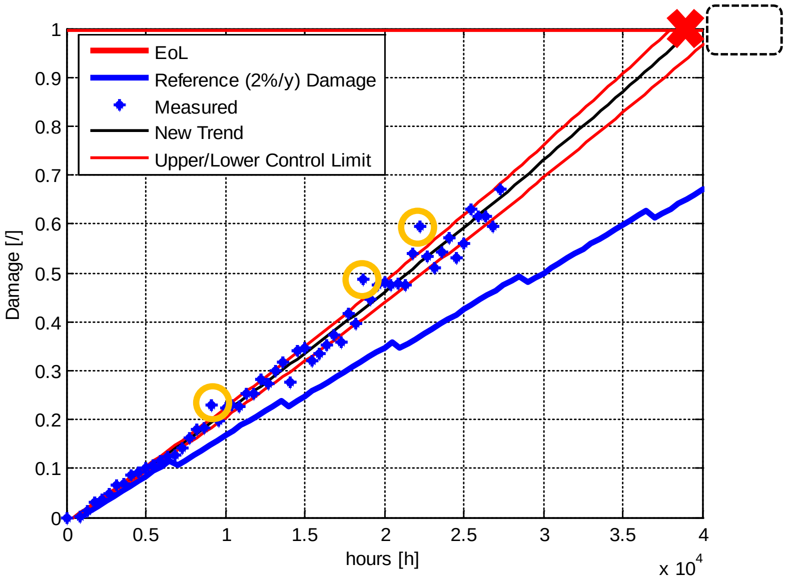

Figure 11: Qualitative representation of the on-board PHM procedure [2].

The blue trend is the reference linear damage corresponding to the 2 % power losses per year, while the blue points represent damage values corresponding to the real measurements. ANN methods are used to identify the new trend of damage (black line). When the black damage line reaches the limit value of 1, the system's EoL is detected. A Control Chart (Shewhart chart) is then scheduled to monitor the system ageing and generate alarms during system operation, in case the measured damage is higher than the allowed upper control limit. The circled points in Figure 9 represent the control chart outliers (alarms conditions). It is worth noting that, as we predict the performance degradations trend, system consumption (efficiency) is also affected. Therefore, the predicted performance is used as a new input for the system model and the new consumption is evaluated. Particularly, in case of PEMEL, more electrical power will be required to produce 1 kg of hydrogen in case of ageing, compared to the BoL. On the contrary, in case of a PEMFC system, more hydrogen will be consumed to produce 1 kW of electrical power. The evaluation of consumption variations is then integrated into the decision making processes for cost optimization and system management. Subsequently, the new damage trend is compared with the reference one. If a sensible deviation is stated, the maintenance plan scheduled in case of linear ageing is changed as proposed in Figure 12. An additional advantage of the data-driven approaches, and in particular of ANN, is that, in case of damage recovery after maintenance, information is directly exploited by the algorithm to adapt to the predicted output.

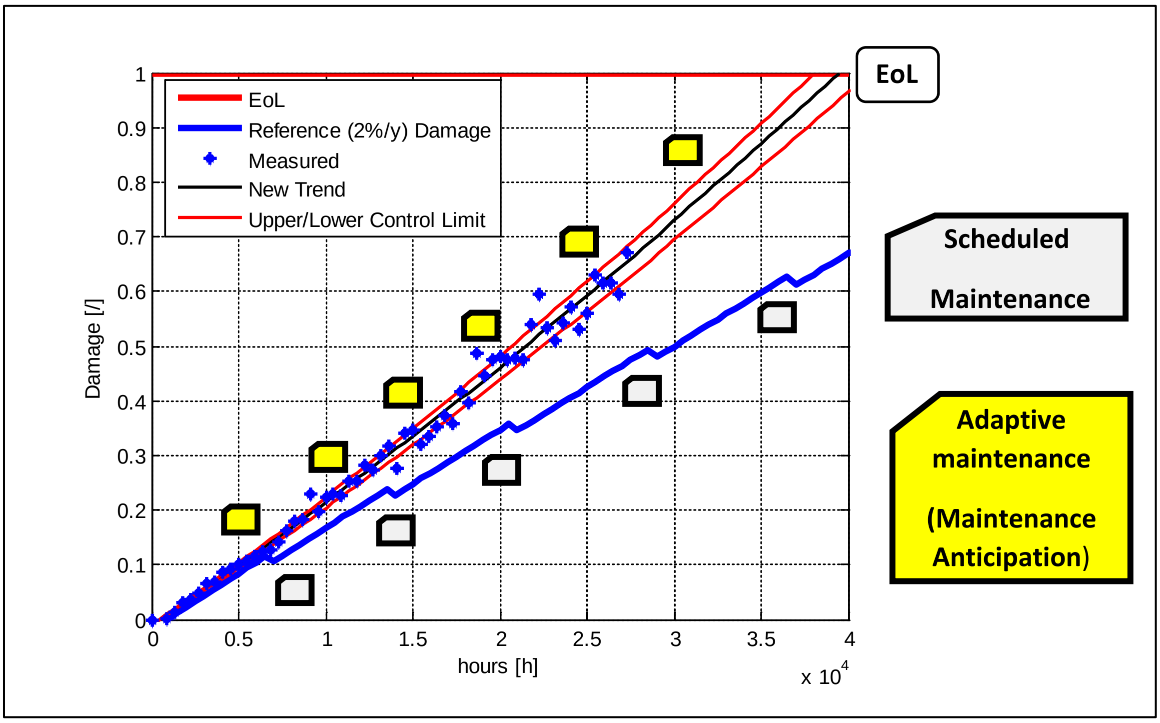

Figure 12: Maintenance variation/anticipation based on PHM results [2].

The proposed approach is adopted both for PEMEL and PEMFC systems. Currently the structure of the PHM algorithm is being created, as well as the model for the reference trend generation. The proposed approach is able to detect the current state of the system ageing and predict the RUL, generate alarms and suggest maintenance anticipation, and evaluate the operational costs variations with ageing. The on-board implementation activity is starting and will be considered closed with the ANN algorithm implementation and validation.

6 Conclusions and next steps

Abnormal operating conditions are usually causes of PEMEL and PEMFC stacks degradation affecting system performance. In this framework, the research activity mainly focuses on development of reliable tools for fault diagnosis and ageing prediction to increase system durability. This deliverable proposed the HAEOLUS project approach for on-board diagnosis and prognostics development for both the PEMEL and the PEMFC technologies. The available historical data were considered at first for system off-line modelling and understanding. A simplified model was developed for each technology to study the system ageing. Particularly, the reference ageing trends were simulated with respect to the manufacturer specifications. Reference trends were subsequently exploited in prognostics algorithm development.

Concerning the diagnosis algorithm, a data-driven approach was preferred due to its higher genericity and good accuracy. According with the literature, the structure of the diagnosis algorithm is under evaluation. Particularly, different feature extraction/classification methods will be evaluated for algorithm development. Artificial intelligence (ANN, FL and ANFIS) and statistics-based (FDA and KFDA) techniques appear as the best solutions for features extraction, while SVM techniques will be considered for the classification procedures. The on-board implementation of the diagnosis algorithm will start after the off-line data analysis and training dataset fulfilment. Concerning prognostics activities, the structure of the PHM algorithm is created as well as the model for the reference trend generation. The proposed approach will be able to detect the current state of the system ageing and predict the RUL. Alarms will be generated in case of ageing acceleration anticipating the scheduled maintenance. Finally, operational cost variations with system ageing will also be evaluated for system management optimization. An artificial intelligence approach is chosen for on-board applications, and, particularly, an ANN algorithm is under development. The on-board implementation activity is starting and will be considered closed with the ANN algorithm implementation and validation.

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