HEMIS

ELECTRICAL POWERTRAIN HEALTH MONITORING FOR INCREASED SAFETY OF FEVs

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Guidelines for the approach to integrate hybrid data in a prognosis system

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Document History

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0.2	12/06/2014	VTT	Revision of the document highlighting some misprints and some sentence difficult to read
1.0	16/06/2014	POLIMI	Final version of the document
1.1	30/09/2014	POLIMI	Answer to the review comment. The procedure for PHMS development has been modified in order to include the SWOT analysis for the selection of the physical characteristics (Section 2.5) and its application to the PMSM and the capacitor monitoring (Section 3.5). The choice of the PHM algorithms has been motivated and justified in Section 3.6
2.0	07/10/2014	CEIT	Second version delivered after minor changes

Executive Summary

The development of a Prognostic and Health Monitoring System (PHMS) for a new design technological system such as the powertrain of a Fully Electric Vehicle (FEV) is a complex task which requires the management of multiple and hybrid sources of information and knowledge, including, for example, expert judgment, analytical models of degradation mechanisms and experimental data. Taking advantages of the HEMIS project experience, this deliverable presents a novel systematic procedure for the development of a PHMS for a new design technological system and shows its application with respect to the FEV powertrain.

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1. Introduction

The immaturity of some building blocks of new design technological system equipment may affect their availability and reliability. In order to enhance the confidence of the final users with respect to the new technology, increase its safety and reduce the maintenance costs, an attractive option is the use of a prognostic and health management system. In this context, this work proposes a systematic procedure for the development of a PHMS for new design technological system.

Since we have to deal with an immature technology whose functional behavior is not completely known, the first step of the system analysis strategy is the identification of the most critical components and corresponding failure modes which can affect the equipment. This is performed by FMECA analysis [1], and the computation of the Risk Priority Number (RPN) [2]. Furthermore, the components characterized by the highest maintenance costs have to be identified.

Once the most critical components and their failure modes have been identified, it is necessary to investigate the degradation mechanisms which can cause the identified failure modes and/or which are causing high maintenance costs. This analysis provides a physical point of view on the degradation processes occurring in the system, augmenting the comprehension of the system possible behavior and directing the successive analysis on the identified critical components. Then, it is necessary to select the signals to be measured in order to monitor the health state of the component. This selection is driven by both physical and economic considerations, taking also into account whether it is physically possible to measure a specific signal, the precision and cost of the measurement and the algorithms available for the component monitoring. A SWOT analysis is performed for the final selection of the signal to be used.

At this stage, we can proceed with the development of the PHM algorithms. Depending on the characteristics of the degradation mechanisms (e.g., sudden or gradual), the objective can be the diagnosis or the prognosis of the failure. In the former case, the diagnostic system provides a detection of the onset of a component anomalous behavior and the identification of its causes and an assessment of the failure intensity, whereas a prognostic system aims at the prediction of the system Remaining Useful Life (RUL). The availability of degradation data and/or physical degradation models drives the choice of the monitoring algorithms which can be model-based, data-driven or hybrid.

Then, in order to verify the performance of the developed algorithms, we have defined a validation strategy based on three steps:

i) proof of concept, i.e. an internal validation based on literature and/or simulated data;

ii) verification, i.e., once the algorithm has been internally validated, it is tuned and verified using real experimental data;

iii) deployment, i.e. a field validation based on real data collected during operation of the component. Notice that this validation step can be performed only when the new design technological system is built.

Finally, once the PHMS has been developed and the algorithms verified, it is important to assess the benefits of its application to the overall safety and availability of the equipment [3].

The proposed procedure is illustrated with respect to the development of a PHMS for the powertrain of Fully Electric Vehicles (FEV) performed within the present project. An analysis of the safety of the FEV performed within the European Project HEMIS (Electrical Powertrain Health Monitoring for Increased Safety of FEVs) has shown that FEV, due to the immaturity of some building blocks, are characterized by a Minimum Endogenous Mortality (MEM) rate higher than the requirement for its commercialization, which is set equal to $2 \cdot 10^{-4}$ fatalities/person$\cdot$year. This has motivated the development of a PHMS for the most critical components of a FEV. In particular we show the procedure followed for the identification of the most critical degradation mechanisms and for the development of the PHMS for two of them, i.e., the Permanent Magnet Synchronous Motor (PMSM) demagnetization and the electrolytic capacitor degradation due to electrolyte vaporization.

The algorithm developed for the PMSM monitoring is based on the application of the Hilbert-Huang Transform (HHT) to the stator current and the degradation level assessment using a data-driven fuzzy similarity based approach [4]. The Hilbert Huang Transform has been used since it provides good performance when used for processing real noisy non-stationary data such as those that we expect to collect on a FEV.

With respect to the electrolytic capacitor, we have identified the Equivalent Series Resistance (ESR) as health indicator and we have developed a particle filtering model-based algorithm for the estimation of the degradation level and the prediction of the RUL of the capacitor under varying operative conditions [5]. The particle-filtering based method has been chosen in order to take into account possible imprecision of the physical model and the measurement noise.

2. Definition of a systematic procedure for PHMS development

The main objective of this Deliverable is the definition of a systematic strategy to be followed for the development of a PHMS for new design technological system for which the overall associated risk or the expected maintenance costs are considered to be not acceptable. Since we are dealing with a new technology characterized by the immaturity of the some building blocks and very poor information on their behaviour in real applications, we aim at developing a systematic procedure which is able to take advantages from all the available sources of information, such as expert judgement, physical degradation models and experimental data. The proposed strategy is based on the following eight steps:

1. Identification of the system failure modes by performing a Failure Mode, Effects and Criticality Analysis (FMECA)
2. Identification of the most critical failure modes by computing the Risk Priority Number (RPN)
3. Identification of the maintenance cost significant components
4. Identification of the most critical degradation mechanisms
5. Identification of the physical characteristics to be monitored by the PHMS
6. PHM algorithm development
7. Algorithm Validation through the following three phases
    a. Proof of Concept: an internal validation based on literature data or simulated data
    b. Verification: tuning of the algorithm based on experimental data
    c. Deployment: a field validation based on real data collected during operation of the component
8. Overall assessment of the PHMS benefits in terms of reliability and availability of the new design technological system

A brief description of the eight steps is provided in Table 1 whereas more details can be found in the following subsections 2.1-2.8.

Table 1. Brief description of the eight steps of the proposed procedure

Step	Objective	Method	Main Sources of information	Reference Deliverable
1	Identification of the system failure modes	FMECA	Expert Judgement (Risk Analyst, mechanical, chemical, process engineer)	2.1 3.1
2	Identification of the most critical failure modes	RPN computation	Expert Judgement (Risk Analyst, mechanical, chemical, process engineer) Component manufacturer data/experience	3.1
3	Identification of the maintenance cost significant component	Maintenance costs assessment	Expert Judgement (Risk Analyst, mechanical, chemical, process engineer) Data from vendors or maintainers of similar systems	3.1
4	Identification of the most critical degradation mechanisms	Literature review, Expert judgement, Physical investigation	Literature, Experience of manufacturers	4.1
5	Identification of the physical characteristics to be monitored by the PHMS.	Physic and economic assessment	Literature, Experience of manufacturers, Experts of sensors	4.1
6	PHM algorithm development	Depending on the available information	Physical model, Literature data	4.2
7	Algorithm Validation	Three steps procedure	Simulation data, Experimental data, Field data	4.2
8	Overall assessment of the PHMS benefits in terms of reliability and availability	Monte Carlo Simulation	Expert judgement, Literature data on failure and repair rates of the FEV components and of the PHMS	2.1 4.3

2.1 Step 1 - Identification of the system failure modes by performing a Failure Mode, Effects and Criticality Analysis (FMECA)

FMECA is an inductive analytical method which studies the effects of single component or function failures on the system [1][6][7]. The objective of FMECA is the identification of those failure modes of the components which could disable system operation or become initiators of accidents with significant external consequences. It is a useful approach for obtaining an exhaustive list of all potential initiating faults and information on their criticality. The FMECA analysis of a new design component is typically based on qualitative information based on expert knowledge. It is usually performed by teams formed by risk analysts and engineer experts of the technological system under investigation such as process, mechanical, electrical and electronic engineer.

2.2 Step 2 - Identification of the most critical failure modes by computing the Risk Priority Number (RPN)

Once an exhaustive list of all the potential failure modes is available, the second steps consists in the computation of the Risk Priority Numbers [2][6]. The objective is to identify those components which are most critical from the point of view of the risk. The RPN quantify the risk in terms of severity of the failure mode consequences (“Severity”), probability of occurrence (“Occurrence”) and probability of detecting the event (“Detection”). To this purpose, a qualitative scale measuring the three indicators “Severity”, “Occurrence” and “Detection” has to be introduced. Typically, the following linguistic labels and the associated numerical score for the “Severity” indicator are considered:

- ***1: Critical effect*** – Unavailability of the system to provide that function. Permanent damage to the system.
- ***2–3: Semi-critical effect*** – Permanent damage is sustained by a subsystem which affects the behaviour of the system, although the system is able to continue to function in a deteriorated state. The user is affected by the failure.
- ***4–5: Insignificant effect*** – The user does not sense the failure, or is hardly aware of it.

With respect to the “Occurrence” indicator, we consider:

- ***1: Very high***– Likely to occur frequently.
- ***2: High***– Likely to occur several times.
- ***3: Moderate***– Likely to occur at some time.
- ***4: Low***– Unlikely, but possible.
- ***5: Remote***– Improbable.

and with respect to the “Detection” indicator:

- ***1: Null*** – The failure will never be detected.
- ***2: Low*** – The failure will only be detected in certain circumstances.
- ***3–4: Medium*** – The failure could be detected, although there is not a specific detection system.
- ***5: Total*** – There is a specific detection system and the failure will be detected.

Then the prioritization of the failure modes is achieved by considering the “Risk Priority Numbers” (RPN) for each failure mode, defined by the simple product of the “Severity”, “Occurrence” and “Detection” scores:

$$RPN = Severity \times Occurrence \times Detection$$

Notice that the obtained RPN numbers characterize high risks with low RPN values. The critical failure modes to be taken into account in the remaining part of the analysis are those characterized by a RPN lower than a prefixed threshold usually taken equal to 35, although it depends from the specific technological system. In the case in which after the development of the PHMS, the obtained overall risk (assessed in the 8^{th} step of the procedure) is still not acceptable, an option is to develop a PHMS dedicated to the components characterized by failure modes with the lowest RPN above the threshold; then the threshold value can be increased and new failure modes have to be considered.

The computation of the RPN number is based on expert judgment and is usually performed by the same team which has developed the FMECA.

2.3 Step 3 - Identification of the maintenance cost significant component

After the RPN classification, it is necessary to identify the most critical components from the point of view of the maintenance costs; in particular, the components to be considered in this step are generally characterized by high failure rate, high repair costs, low maintainability and long lead time for spare parts [8]. This analysis, together with the RPN classification, allows us to properly select the most significant component to be considered avoiding a waste of time and money. In practice, the following steps of the analysis will be applied to the union of the component identified in steps 2 and 3.

2.4 Step 4 - Identification of the most critical degradation mechanisms.

Once the critical failure modes have been selected in the previous step, it is necessary to identify the corresponding responsible degradation mechanisms. This is a complex task which may require investigating the failure modes from a physical point of view. Information coming from experts of the degradation mechanisms and from the analysis of failures in similar components should be considered. If several degradation mechanisms can cause the same failure modes, the most likely to occur should be identified and the successive analysis will focus on them.

2.5 Step 5 - Identification of the physical characteristics to be monitored by the PHMS.

The objective of this step is to identify those physical characteristics which can provide useful information to the PHMS for monitoring the component degradation state and predicting its useful time. With the term physical characteristics we intend signals which can be measured thanks to sensors and which are somehow correlated with the component health state or which describe the component operation mode and the environment. Operation mode and environment are considered since it has been shown that they can have a strong impact on the component degradation [9]. This step is performed by firstly identifying a list of possible physical characteristics by considering the following sources of information:

- the indications contained in the column “detection method” of the FMECA analysis;
- information and knowledge on the degradation process such as the signals used in analytical and/or empirical models of the degradation process, expert judgments on factors that may influence the component degradation or that can be correlated with the component degradation state.

Once the candidate physical characteristics have been identified, the final selection of those to be effectively used to monitor the component degradation and to predict the component Remaining Useful Life (RUL) is driven by the following considerations:

- the possibility of detecting and diagnosing the components failures and predict its RUL using the proposed physical characteristics;
- an assessment of the feasibility and cost of performing the measurements, their accuracy and the complexity of the associated data processing.

Finally, with respect to the detection of the system degradation, we are looking for physical characteristics which have different behaviours in case of normal operation or in case of system degradation. The diagnosis of the failure mode requires that the measurements collected during degradation processes leading to different failure modes should be in different zones in the space of the physical characteristics.

With respect to the prognostic task, the following three properties of the physical characteristics are desirable [10]:

- **Monotonicity**: physical characteristics are wished to present an overall positive or negative trend in time, excluding possible self-healing situations.

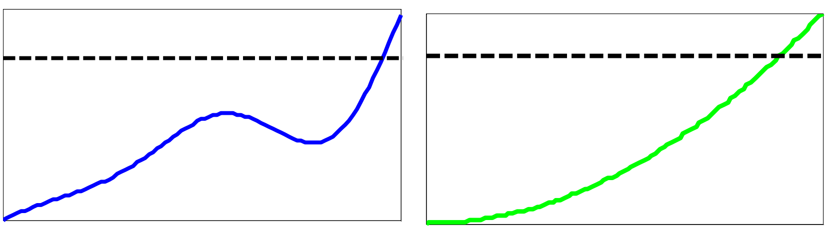

Figure 1: Example of non-monotonic signal (left) and monotonic signal (right)

• **Prognosability**: the distribution of the final value that a physical characteristic takes at failure is wished to be 'peaked', i.e. not too wide-spread.

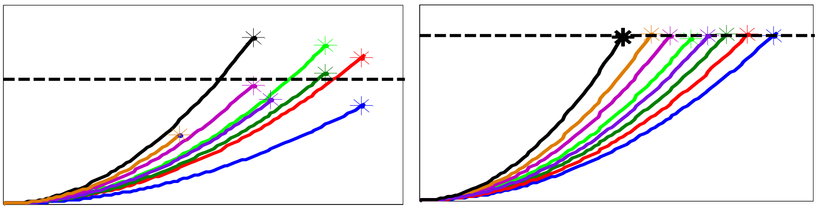

Figure 2: Example of a bad prognostic signal (left) and a good prognostic signal (right)

• **Trendability**: The entire histories of evolution of the physical characteristics towards failure are wished to have quite similar underlying shapes, describable with a common underlying functional form.

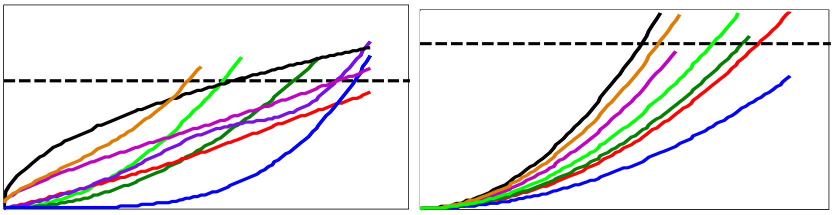

Figure 3: Example of a signal characterized by bad trendability (left) and a signal characterized by good trendability (right)

In order to systematically consider all the identified physical characteristics and, thus, to proper consider all the possible solutions, Strengths, Weaknesses, Opportunities and Threats (SWOT) analysis has been performed. A SWOT analysis is a general structured planning method used to analyze possible situations. In this case, focusing on the selection of the signals to be used for the component monitoring, the analysis is based on the assessment of:

- **Strengths**, i.e. characteristics of the signal that can give advantage for monitoring the component with respect to other signals.
- **Weaknesses**, i.e. characteristics of the selected signal that can cause problems with respect to the goals of the PHMS.
- **Opportunities**, i.e. characteristics of the selected signal that could be exploited to have an advantage.
- **Threats**, i.e. characteristics of the selected signal that are influenced by the environmental conditions and that could lead to troubles for the PHMS goals

In this context, the identification of SWOTs is important because they can provide a clearer overview of the global situation, thus informing about the possible issues that will be faced in the development of the PHMS, helping to plan the further steps in order to achieve the objective.

2.6 Step 6 - PHM algorithm development

The objective of this step is the practical implementation of the PHM algorithms. The nature of these algorithms strictly depends on the characteristics of the degradation mechanisms, which can be sudden or gradual. According to this, the information provided by the PHM algorithms is different: in the former case, diagnostic algorithms which detect the onset of the failure, identify its cause and assess its intensity are used; in the latter case, prognostic algorithms which predict the system Remaining Useful Life (RUL) are used. Furthermore, depending on the availability of physical degradation models or degradation data or both, the PHM algorithms can be model-based, data-driven or hybrid, respectively.

2.7 Step 7 - Algorithm Validation

Once the algorithms have been developed, we have defined a validation strategy based on the following three steps:

i) **Proof of concept**: an internal validation based on literature and/or simulated data;

ii) **Verification:** tuning and verification of the algorithm by using real experimental data;

iii) **Deployment:** field validation of the algorithm based on real data collected during operation of the component. This validation step can be performed only when the new design technological system is built.

The application of the proposed validation strategy is able to provide reliable information about the effective applicability of the developed algorithm to the real operation of the system and to quantify the performance of the algorithm.

2.8 Step 8 - Overall assessment of the PHMS benefits in terms of reliability and availability

Once the developed algorithms have been fully validated, it is important to assess the benefits provided by the PHMS in terms of reliability and availability. A possibility to achieve this goal is to resort to Monte Carlo simulation [11]. This overall assessment can also be useful in order to optimize the efforts needed for the effective construction of the PHMS: for example, if the PHMS rate of detection of a failure changes from 0.7 to 0.8, and the associated availability of the system changes consequently from 0.975 to 0.979, then the costs needed for the improvement of the PHMS detection rate are not justified by the correspondent improvement of the system availability.

In what follows the proposed procedure is shown with respect to the powertrain of a FEV, focusing in particular on two of the most critical components: the Permanent Magnet Synchronous Motor (PMSM) and the Electrolytic Capacitor.

3. Application of the method

3.1 FMECA

The application of the FMECA analysis to a new design system such as the FEV powertrain has required a clear definition of the system architecture (Figure 4). Then, a Preliminary Hazard Analysis (PHA) has been performed in order to identify the most critical functional hazards relating to the functionality of the FEV, such as acceleration and deceleration, vehicle handling and stopping distance.

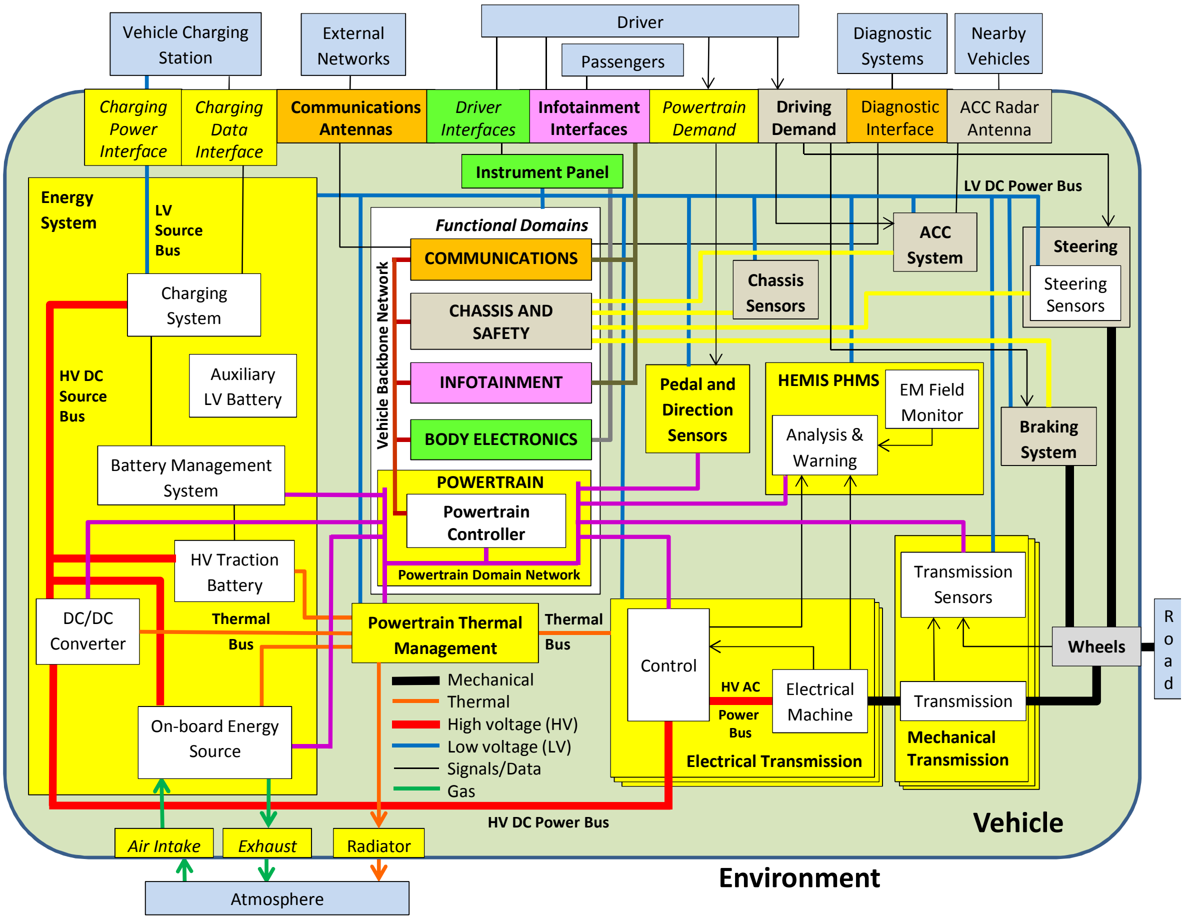

Figure 4: HEMIS generic electric vehicle architecture - Functional view

Based on the results of the PHA, the potential functional failure mechanisms of a generic electrical powertrain have been analysed using fault tree analysis [7]. In particular, the functional failures identified by the PHA have been used as top events of fault trees which allow unfolding backward their causes down to their FEV component basic failures. Then, for each identified component failures a Failure Mode, Effects and Criticality Analyses (FMECA) has been developed [1][6].

The FMECA is applied at a functional level, considering a variety of functional failure modes caused by modifications of the provided functions such as:

- Undemanded
- Excessive
- Insufficient
- Lack
- Loss
- Degraded
- Intermittent
- Erratic
- Oscillatory
- Reversed
- Late
- Early

Notice that not all the modifications can be considered for all the functions, but one has to consider those modifications appropriate to the nature of the specific function. The analysis has allowed identifying 180 failure modes in the powertrain of the FEV.

Table 2 shows the results of the FMECA for the functions carried out by 2 components of the FEV: the Permanent Magnet Synchronous Motor (PMSM) and the electrolytic capacitor.

Table 2. Results of FMECA

Subsystem and Functions	Failure Mode	Causes	Subsystem Effect	System Effect	Hazard at vehicle level	Recommended Actions
Rotor Magnetic Field Source (PM)						
Create Rotor magnetic field in drive mode	No rotor magnetic field	Permanent magnet loss magnetization, Rotor shaft failure	No rotation	Seized rotor	Vehicle will not move	Implement PHMS
Create Rotor magnetic field in drive mode	Loss of rotor magnetic field	Rotor core delaminating, Rotor shaft failure	Loss of rotation	Loss of rotor rotation	Vehicle will stop suddenly	Implement PHMS
Create Rotor magnetic field in drive mode	Insufficient rotor magnetic field	Decrease in magnetization in Permanent magnets due to increased ambient temperature; Misalignment of rotor components	Insufficient rotation	Insufficient rotation	Vehicle may have unreliable drive	Implement PHMS
DC Bus Link Capacitor						
Stabilize HV DC Power Bus	Increased ripple	Thermal stress, self-heating	LowDC voltage	Poor efficiency. Batteries may get damaged	Insufficient vehicle acceleration / instability	PHMS measures capacitor variables

3.2 Risk Priority Number (RPN) computation

According to Section 2.2, the next step of the analysis requires the computation of the RPN for the 180 failure modes identified by the FMECA. The RPN value can be used to prioritize the failure modes associated with high risk and thus requiring corrective actions. Table 3 shows the failure modes listed in Table 2 with the addition of new columns reporting the quantitative evaluation of “Severity”, “Occurrence”, “Detection” and the obtained RPN. Notice that the numbering scheme described above associates higher risks with lower RPN values.

Three critical components for the motor (PMSM, stator windings, shaft bearings) and two critical component for the control (capacitor and inverter) have been selected since they are characterized by RPN values lower than 35 [6]. In the following part of the Deliverable, the description of the PHMS algorithm development will be presented considering only the PMSM and the capacitor.

Table 3. Results of FMECA and their associated RPN

Subsystem and Functions	Failure Mode	Causes	Subsystem Effect	System Effect	Hazard at vehicle level	S	O	D	RPN	Recommended Actions
DC Bus Link Capacitor										
Stabilize HV DC Power Bus	Increased ripple	Thermal stress, self-heating	LowDC voltage	Poor efficiency. Batteries may get damaged	Insufficient vehicle acceleration / instability	3	1	3	9	PHMS measures capacitor variables
Rotor Magnetic Field Source (PM)										
Create Rotor magnetic field in drive mode	No rotor magnetic field	Permanent magnet loss magnetization, Rotor shaft failure	No rotation	Seized rotor	Vehicle will not move	1	1	1	1	Implement Traction Machine condition monitoring
Create Rotor magnetic field in drive mode	Loss of rotor magnetic field	Rotor core delaminating, Rotor shaft failure	Loss of rotation	Loss of rotor rotation	Vehicle will stop suddenly	1	1	1	1	Implement Traction Machine condition monitoring
Create Rotor magnetic field in drive mode	Insufficient rotor magnetic field	Decrease in magnetization in Permanent magnets due to increased ambient temperature; Misalignment of rotor components	Insufficient rotation	Insufficient rotation	Vehicle may have unreliable drive	2	1	1	2	Implement Traction Machine condition monitoring

3.3 Identification of the maintenance cost significant component

This step of the analysis requires identifying those components of the FEV for which high maintenance costs are expected. Within the HEMIS project, this has been performed with the help of FEV manufacturers. In this case, they have agreed that the list of the critical failure modes identified in Step 2 includes the components which are expected to have associated the highest maintenance costs.

3.4 Degradation mechanisms identification

This step of the analysis is dedicated to the identification of the degradation mechanisms responsible for the critical failure modes identified in the previous steps. Section 3.4.1 will illustrate those for the PMSM, Section 3.4.2 those for the capacitor.

3.4.1 PMSM

The main failure mode which affects the PMSM field source is the loss of magnetic flux. This failure mode is particularly critical from the point of view of its consequences on the entire motor system: it can cause poor starting performance, excessive vibrations, and higher thermal stresses which can lead to a further deterioration of the rotor and to secondary failures of the stator [12]. According to Table 2, it is possible to notice that all the three failure modes identified for the PMSM are caused by the same degradation mechanism, i.e. the permanent magnet demagnetization. The necessity of supplying high torque density using a permanent magnet requires the use of rare earth minerals, such as Neodymium-Iron-Boron (NIB). Given the difficulties to handle these types of alloys with metallurgical techniques, they are often ground to powder and then pressed. This process produces magnets which are hard and brittle, and, thus, may easily break if they suffer any shock. Furthermore, if permanent magnets experience high temperature they may suffer of irreversible demagnetization. Another cause of loss of magnetic flux in PMSM is the rotor pole displacement. Given the different causes of this degradation mechanism and the fact that the loss of magnetic flux is often an abrupt process, the objective of a PHMS is the detection of the degradation and the assessment of the degradation level, whereas the prediction of the Remaining Useful Life (RUL) seems not possible.

3.4.2 Capacitor

According to [5][13][14], the main failure mode of the electrolytic capacitor is the electrolyte vaporization, which is due to chemical reactions occurring inside the component and driven by the component temperature. The component degradation is due to a combined effect of electrical, thermal, mechanical, and environmental stresses and is accelerated if the component experiences high temperatures during the operation. It has to be specified that this degradation mechanism is gradual and does not lead to an abrupt failure of the component, but rather to a gradual loss of functionality. This allows developing an algorithm for the assessment of the degradation level and the prediction of the component Remaining Useful Life (RUL).

3.5 Identification and assessment of the physical characteristics to be monitored

In Section 3.4 we have identified the degradation mechanisms involved in the most critical failure modes affecting the PMSM and the capacitor. In this Section we aim at identifying the most significant physical characteristics which contain information correlated to the component degradation state and, thus, should be considered in order to monitor the health state of the components. The selection of these physical characteristics is driven by:

- an analysis of the information content of the physical characteristics with respect to the description of the degradation process. In practice, we have to consider whether the selected physical characteristics allow to detect, diagnosis and prognosis the degradation mechanisms.
- an assessment of the physical and the economic feasibility of measuring the selected physical characteristics, which depend on the effective possibility of positioning the sensor and the sensor cost, respectively.

Section 3.5.1 will be dedicated to the identification of the physical characteristics to be used to monitor the PMSM, Section 3.4.2 those for the capacitor.

3.5.1 PMSM

With respect to the Permanent Magnet Synchronous Motor, according to the literature works [15][16][17][18][19], the following physical characteristics are recognized to be related with the loss of magnetic field :

- Magnet temperature
- Back-Electromotive Force
- Magnetic flux
- Vibration
- Stator currents
- Stator voltages
- Speed
- Torque

In order to deeply investigate the identified physical characteristics identified for the health monitoring of the PMSM, a SWOT analysis has been performed (Table 4).

Table 4. SWOT analysis of the physical characteristics identified for monitoring the performance of the PMSM.

MAGNET TEMPERATURE	**Strength** It is easy and cheap to be measured; directly related to the degradation of the motor and to the load conditions	**Weakness** It is highly influenced by environmental changes and operation cycles.
	Opportunity; Direct indicator of possible hot spots in the motor causing fast degradation of the component. *Possible algorithms for PMSM monitoring based on these physical characteristics:* a threshold approach that in case of excessive high temperature gives an alarm in order to avoid fast degradation of the component	**Threat** In order to detect the presence of hot spots several sensors are needed, thus increasing the monitoring costs. If used alone, it does not allow the anticipation of the presence of a hot spot, but it just detects the hot spot. Thus, it is not usable for early prediction of the failure
STATOR CURRENTS	**Strength** Several motor and control system failures, such as the loss of magnetic field have influence on the stator current signal	**Weakness** Heavily influenced by several degradation mechanisms of different components. In the case in which several degradation mechanisms are occurring at the same time, it is difficult to identify them
	Opportunity It is a signal already measured in FEV powertrains. Thus, its use by the PHMS would not cause an increase of the overall costs. *Possible algorithms for PMSM monitoring based on this physical characteristics*: data-driven algorithms which compare the acquired current signal with baseline signals corresponding to component with different levels of degradation	**Threat** The selection of the measurement device is a critical point; depending on the selected sensor, the accuracy and the frequency range will be different
SPEED	**Strength** Motor speed describes the motor operational conditions and can have a strong influence on several physical characteristics that are useful for PMSM monitoring	**Weakness** The cost of the measurement device is high; speed is not directly related to the load conditions of the motor which remarkably influence the behavior of other physical characteristics.
	Opportunity It allows to identify specific FEV operational conditions in which the behavior of other physical characteristics can be compared for PMSM monitoring. *Possible algorithms for PMSM monitoring based on these physical characteristics*: It cannot be employed alone, but it can provide useful information on the motor operational conditions. It can be applied in combination with other signals in data-drive approaches for the component monitoring.	**Threat** Since motor speed has a large range of variations, a long data collection campaign is necessary for its use in data-driven approaches.
Vibration	**Strength** Physical characteristic which is highly influenced by different motor component faults, such as those involving bearings, shaft and PMSM	**Weakness** High prize of the sensor. If different component failures are occurring at the same time, it is difficult to identify them by using this signal.
	Opportunity Since the physical characteristic behavior is related to long term failures in rotary machine; it could be useful for prognosis. *Possible algorithms for PMSM monitoring based on this physical characteristics*: data-driven algorithm for the assessment of the component health state and for the RUL prediction. Necessity of pretreatment of the raw measurement with frequency and time-frequency transforms	**Threat** Affected by the vibration of the overall car; physical dynamics of sprung masses must be understood to obtain information related to the component degradation

Stator Voltages	**Strength** Physical characteristic which is highly influenced by different motor component faults	**Weakness** Only the voltage of the DC bus line is already measured in FEVs. Thus, in order to measure Stator Voltage, also the voltage of AC phases has to be measured. This requires the use of another sensor.
	Opportunity Highly related to the current: the combined monitoring of both stator current and voltages allows to reveal a great number of failures. *Algorithm approach*: see that proposed for stator current	**Threat** The information that could be obtained will vary depending on the frequency range and the accuracy of the selected sensor
Magnetic Flux	**Strength** Direct indicator of the demagnetization of the permanent magnet	**Weakness** Very noisy measurements; each flowing current in the FEV generates a magnetic field which may hide the motor demagnetization
	Opportunity It is related to several degradation mechanisms of the powertrain; it could be used for monitoring different components. *Algorithm approach*: possibility of data-driven algorithm for the assessment of the component health state or threshold approach for avoiding excessive component degradation	**Threat** Necessary to resort to different sensors in order to monitor magnetic fluxes generated from switching currents at different frequencies
Torque	**Strength** Physical characteristic associated to the angular speed and to the current flowing through the motor; it is directly related to the load conditions and allows knowing if the mechanical answer of the motor is correct or not	**Weakness** The cost of the measurement device is very high; the benefits provided by its monitoring are lower than the costs required
	Opportunity It could be very useful in order to identify the FEV load conditions. This would allow comparing physical characteristic measurement in similar conditions. *Algorithm approach*: possibility of model-based algorithm for the assessment of the component health state	**Threat** Necessary to identify a monitoring strategy based on the use of other variables in order to identify the load

The final selection of the physical characteristics to be used is driven by the necessity of reducing their number, using physical characteristics easy and cheap to be measured with the necessary accuracy and that, at the same time, contain the information necessary for the PHMS. This selection process has involved experts of sensors and the developers of the PHMS algorithms. With respect to the loss of magnetic field, considering the SWOT analysis, we have selected the following two physical characteristics:

- **Stator Current**: this is a source of high quality information regarding the motor degradation. In particular, according to [17][18][19], information on the health state of the magnetic source can be provided by the current spectrum. Notice that the measurement of this feature can be performed during motor operation under load, without requiring the interruption of the motor operation. According to [4] the Hilbert-Huang Transforms of the stator currents can be used to detect motor demagnetization and to assess its demagnetization level. It has been shown that it allows detecting not only failures appearance but also failure precursors. Furthermore, this signal is already measured in most motor drives as a control feature, and thus its use by the PHMS is not causing an extra cost.

- **Motor Temperature**: Temperature measurement provides information about the proper function of the magnets. Magnets demagnetization can be induced by thermal processes. Thus, temperature is an important parameter to monitor, although is highly influenced by operational and environmental conditions.

Table 5 reports an analysis of the measurements devices which can be used to measure the stator current and the motor temperature.

Table 5. Assessment of the physical characteristics selected for monitoring the performance of the PMSM.

Parameters	Measurement device	Intrusive to electrical machine	On/off line	Measurement frequency	Cost	Aprox. Sensor prize	Accuracy	Feasibility
Current	Hall effect sensor (LEM)	No	On	Continous	medium	20 € - 150 €	<+-1 % error of IPN when measuring it at 25ºC. Linearity is maintained until 1.5 times Ipn, with thermal drift as low as 0.3mV/K. Low noise	Already used in commercial applications for control purposes, should be installed.
Temperature	Thermocouple	Yes	On	Continous	medium	60€	Exceeds special limit error and EN 60584-2: Tolerance Class1	Temperature increase is the most common response of failures. Thus their installation in different part of the machine is highly recommended. However, access to the machine is required
	Infra-red Camera	No	On	Periodically	high	5000 €	2% error at 25°C nominal	Very expensive equipment. Expert data analysis system required, therefore not recommended for on-line measurement

3.5.2 Capacitor

According to the literature works [5][13][14], capacitor monitoring can be based on the following physical characteristics:

- Equivalent Series Resistance (ESR)
- Capacity
- Capacitor Surface Temperature

In order to deeply investigate the identified physical characteristics, a SWOT analysis has been performed (Table 6).

Table 6. SWOT analysis of the physical characteristics identified for monitoring the performance of the electrolytic capacitor

EQUIVALENT SERIES RESISTANCE (ESR)	**Strength** Direct indication of the component degradation	**Weakness** Physical characteristic influenced by the temperature at which the measurement is performed
	Opportunity A physical degradation model which describes ESR evolution with time is available. Thus, ESR is suitable for predicting the capacitor failure time. <u>*Possible algorithms for capacitor monitoring based on these physical characteristics*</u>: the availability of a model of the degradation process allows to develop a model-based prognostic approach. In order to properly treat the ESR measurement error and the model inaccuracy a Bayesian filtering technique should be employed	**Threat** 1) ESR cannot be measured during vehicle operation; 2) It is necessary to develop a measurement circuit which inject high frequency current on the capacitor at FEV start up
CAPACITOR SURFACE TEMPERATURE	**Strength** It can be easily measured. The sensor is cheap. The temperature has a remarkable influence on the degradation process	**Weakness** It would be necessary to know the temperature inside the capacitor, but since this is too expensive and difficult to do, we consider the temperature on the surface
	Opportunity It influences the ESR and Capacity measurement. Thus, it is necessary for the assessment of the capacitor degradation state and the prediction of the degradation evolution. <u>*Possible algorithms for capacitor monitoring based on this physical characteristics*</u>: - possibility of a threshold approach for the detection of excessive temperatures which will cause fast component degradation. - Temperature is also necessary in model-based approaches being one of the signals considered in the physical model	**Threat** In order to perform the assessment of the capacitor degradation and the prediction of its failure time, it is necessary to store the measured temperature values.
Capacity	**Strength** Direct indication of the component degradation	**Weakness** Measurement influenced by the measurement frequency and temperature. The analytic degradation model for the capacity evolution with time is reported to be less accurate than that of the ESR
	Opportunity it is easier to be measured than the ESR; possibility of develop an analytic degradation model which describes the capacity evolution with time. <u>*Possible algorithms for capacitor monitoring based on this physical characteristics*</u>: model-based algorithm for the RUL prediction based on a Bayesian filtering technique	**Threat** The analysis of the obtained measurement in order to identify the pre charge slope can require high computation resources

Considering the results of the SWOT analysis, we have decided to use for the development of the PHMS the two following physical characteristics:

- **Equivalent Series Resistance (ESR)**: the vaporization of the electrolyte entails an increase of the ESR value. This determines an increase of the temperature due to the Joule effect leading to a further and faster vaporization of the electrolyte which further increase the ESR value. The main drawback of the ESR measurement is that it implies the injection of high frequency current in the DC link. Thus, the integration of this physical characteristics in the PHMS is intrusive and it can be measured only off line, mainly at the starting sequence of the vehicle, by designing a dedicated sensor.
- **Capacitor Surface Temperature (T)**: since the rate of the chemical reactions of the capacitor electrolyte is highly influenced by the temperature inside the capacitor, modelling the capacitor degradation requires the availability of information on the temperature. Given the difficulty of measuring the temperature inside the capacitor, its value is usually estimated from the capacitor surface temperature, which is more easily observable.

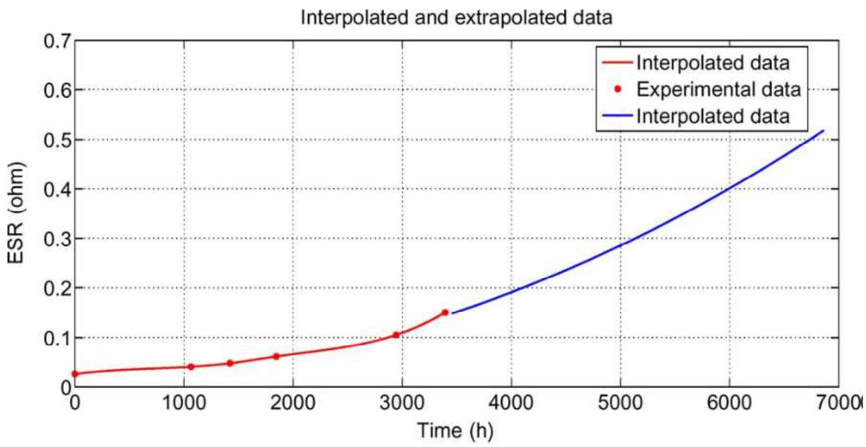

Figure 5: ESR characteristic time evolution (taken from [5]).

Figure 5 shows the time evolution of the ESR obtained during experimental laboratory test [5]. As expected, ESR is characterized by a monotonic behaviour with time, and thus it is characterized by the properties of monotonocity, prognosability and trendability described in Section 2.5 and can be used as degradation indicator.

Table 7 reports an analysis of the measurements devices which can be used to measure the ESR and the capacitor surface temperature.

Table 7. Assessment of the physical characteristics selected for monitoring the performance of the Capacitor

Parameters	Measurement device	Intrusive	On/off line	Measurement frequency	Cost	Aprox. Sensor prize	Accuracy	Feasibility
Resistance	ESR meter	Yes	On	At start	medium	30,00 €	Related to temperature drift of components of the PCB. Further tests are required.	A PCB manufacturing is required for the measurement of this characteristic. It is very intrusive for the inverter and the DC Bus. However, it profoundly demonstrated in the literature that it is related to the capacitor degradation, therefore it is highly recommended its implementation
Temperature	Thermocouple	Yes	On	Continous	medium	60,00 €	Exceeds special limits error and EN 60584-2: Tolerance Class 1	The temperature rise in normal operation conditions is related to the degradation of the capacitor, thus, it is very recommended.

3.6 PHM Algorithm development

In the following Subsections, the approach followed to develop the monitoring algorithms for the PMSM (Subsection 3.6.1) and the capacitor (Subsection 3.6.2) is discussed.

The choice of the PHM methods is firstly driven by the necessity of taking into account the information available to characterize the degradation process. In the case of the PMSM, since no physics-based model of the degradation process is available, we resort to a data-driven approach where the relationship between the measured signals and the component degradation is learnt from simulated examples. Furthermore, the choice of the data-driven approach should also consider that: i) the input of the PHMS will be very noisy data measured by sensors installed on the car, ii) the environmental and operational conditions faced by the FEV during operation are expected to be non-stationary. Considering i) and ii) we have decided to pre-treat the data using Hilbert Huang Transforms which is apt for noisy and non-stationary signals.

On the other side, in the case of the capacitor degradation, a physics-based model of the degradation process is available, and, thus, it will be used for the prognosis of the component RUL. In order to take into account the uncertainty in the ESR and Temperature measurement process and possible inaccuracy of the model, we have decided to adopt a Bayesian filtering approach. Since a classical Kalman Filter approach cannot be applied being the noise terms in the degradation and measurement equations non additive, a particle filtering approach has been adopted.

3.6.1 Methodology – PMSM

The proposed approach to monitor the PMSM using the information contained in the stator current is based on two steps:

i) the extraction of the Hilbert spectra of the stator current;
ii) the comparison of the obtained spectra with respect to spectra characterizing different levels of PMSM degradation.

This two steps procedure has been developed given the difficulties of a direct use of the highly oscillating raw current signal and the consequent necessity of pretreat the signal in order to identify the relevant information. Appendixes A.1 and A.2 illustrate the procedure followed for the computation of the Hilbert spectra, which is based on the application of the Empirical Mode Decomposition for the extraction of the Intrinsic Mode Functions (IMFs) and the application of the Hilbert transform to each IMF in order to identify the Hilbert Spectra.

The developed method for the assessment of the demagnetization level relies on the comparison of the Hilbert spectra of the PMSM of the monitored motor with that of reference spectra characterizing different levels of PMSM degradation. The properly developed technique is based on the use of a similarity algorithm and requires the availability of the spectra characterizing motors with different levels of degradation. Thus, an empirical, data-driven approach has been followed given the absence of physical models describing the loss of magnetic field degradation mechanism and its effect on the stator current. A second monitoring system of the PMSM is also developed by considering the motor temperature. In particular, if the motor temperature exceeds a properly defined threshold, the driver is informed of the risk of magnet demagnetization. The choice of the Temperature threshold is performed by considering physical knowledge on the temperature at which the demagnetization process may start and a safety margin.

3.6.2 Methodology – Capacitor

According to Section 3.4, the physical characteristics to be considered for the development of the monitoring of the electrolytic capacitor are the Equivalent Series Resistance (ESR) and the surface temperature of the capacitor. Since a model describing the ESR evolution due to capacitor degradation is available, a model-based prognostic algorithm has been used for the prediction of the capacitor remaining useful life. In particular, in order to take into account the uncertainty of the degradation and measurement processes, a sequential Bayesian approach called Particle Filtering (PF) has been used. Appendix B.1 discusses the model describing the capacitor degradation, whereas Appendix B.2 illustrates the developed PF approach. Notice that the development of the prognostic algorithm has required the definition of a degradation index, called ESR_{norm}, independent from the capacitor operational conditions and based on parameters estimated by performing laboratory tests.

3.7 Algorithm Validation

According to Section 2.7, the proposed validation strategy for the PHM algorithms is divided in the following three steps:

i) **Proof of concept**: internal validation based on literature and/or simulated data;
ii) **Verification:** tuning and verification of the algorithm by using real experimental data;
iii) **Deployment:** field validation of the algorithm based on real data collected during operation of the FEV.

Section 3.7.1 is dedicated to the PMSM, whereas Section 3.7.2 to the capacitor. Each Section will firstly illustrate the proof of concept of the algorithms and then the experimental set up which has been established in order to perform the verification of the algorithm with experimental data. Notice that the field validation in the deployment phase based on real data collected during FEV operation requires the availability of a real FEV.

3.7.1 PMSM

Proof of concept

In order to perform the proof of concept of the developed algorithm, we have simulated the behavior of PMSM in healthy conditions and with different levels of demagnetization.

The simulation has been performed in MathWork's Simulink environment with Simscape and SimPowerSystems. The model of the 3 phase PMSM was modified so that it was possible to change its flux linkage in order to represent the demagnetization of the motor. The motor is driven by the PWM inverter which was added to the system. Inputs to the model are torque and speed demand, whereas the considered output is only the phase of the stator current.

The obtained dataset consists of ten simulated stator current transients (phase α) of a PMSM: one transient represents the normal operating condition, i.e. the permanent magnet is not degraded, while the other nine represent the behaviour of the stator current under different levels of demagnetization. In these simulations the motor speed was increased linearly from 0 rpm to 1800 rpm over 4.5 seconds starting from 0.5s, in order to represent typical operating conditions of an automotive drive, which are continuously varying. In order to represent the degradation of the permanent magnet, the simulations were performed with different values of the flux linkage, a motor parameter which represents the demagnetization level of the permanent magnet. The nine transients representing different levels of demagnetization are characterized by values of the flux linkage comprised in the range between the 10% and the 90% of the nominal value, and in particular they are characterized by steps of the 10%: the lower the flux linkage, the larger the degradation level. In order to develop and test a monitoring algorithm, we have selected four transients to be used as the training dataset to which refer the spectra comparison. The selected four training transients are characterized by 20%, 50%, 80% and 100% of the nominal flux linkage value; the remaining six transients, characterized by 10%, 30%, 40%, 60%, 70% and 90% of the nominal flux linkage value will be used as test transients.

For each training transient signal we have computed the EMD obtaining i=5 IMFs. Figure 6 shows the Hilbert spectrum of the four considered transients, which are characterized by an increasing value of flux linkage, i.e. decreasing degradation level. The 3D space of the Hilbert spectrum is represented on a 2D figure, using a color scale in order to represent the amplitude of the obtained IMFs. Notice that the color scale is the same for all the subfigures of Figure 6.

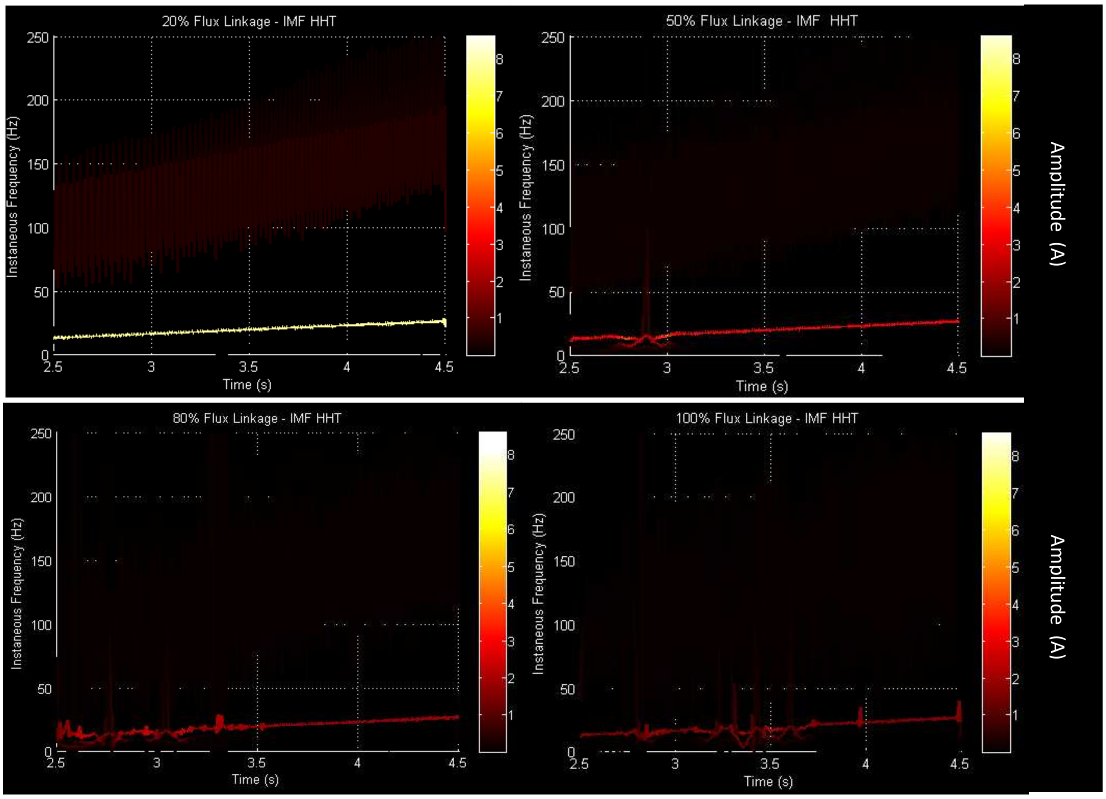

Figure 6: Hilbert Spectrum for 20%, 50%, 80%, 100% Flux Linkage

In order to highlight the most energetic IMFs, i.e. the IMFs characterized by the largest amplitude, we have decided to assign the black color to amplitude values close to zero and to use a black background with the intent of hiding the low energy IMFs. The effects of this choice are clearly noticeable: in the upper-left subfigure of Figure 6, the instantaneous frequency of the first IMF is a large band whose average increases from 100 Hz to 150 Hz, and is characterized by a dark red color, which represents a low amplitude. In the other three subfigures of Figure 6, the functional behaviors of the instantaneous frequencies of the first IMFs are almost the same, but it is not possible to notice them because they are characterized by a very dark color which makes them indistinguishable from the black background color. It is possible to notice the presence of these IMF frequencies only because they cover the white grid of the figure: this means that the energy levels of these IMFs are very low. However, the main difference highlighted by Figure 6 is the amplitude of the instantaneous frequencies of the second IMFs, which are all represented by a line continuously increasing from 15 Hz to 28 Hz. Although their functional behaviors are almost the same, they are characterized by different constant amplitude values, increasing from the 1.5 A of the nominal condition (dark red, bottom-right), to the 7.8 A of the most degraded condition (yellow, upper-left). Thus, using the Hilbert spectrum of the second IMFs it is possible to clearly distinguish between healthy and degraded conditions of the permanent magnet of the PMSM; furthermore, based on amplitude of these spectra it is also possible to distinguish and classify the different degradation levels. From a physical point of view, these results can be considered as expected: in fact, if the permanent magnet of a PMSM is demagnetized (i.e. the internal magnetic field is lower than in the nominal case), a larger stator current will be needed in order to produce the same acceleration.

The developed methodology enabled us to visually distinguish between different levels of demagnetization of the permanent magnet by observing and comparing the obtained pictures of the IMF HHTs (Figures 6).

The diagnosis of the level of degradation is usually performed by observing the representations of the HHT [4][25]; unfortunately this procedure is not automatic and, thus, is not suitable for its direct implementation on the PHMS for the FEV which has to aware the driver about the health state conditions of the component. For this reason, it has been necessary to develop an automatic classifier based on the brightness difference between the HHT representations, whose main purpose is to automatically identify which is the most similar HHT spectra with respect to the one obtained for the input signal.

The application of the methodology to the training data enabled us to train our algorithm, fixing a set of references to which address the comparison of the spectra in the successive applications to the test data. The training dataset contains the transients characterized by 20%, 50%, 80% and 100% of the nominal flux linkage: for each signal the IMF HHTs has been computed (Figure 6), leading to the creation of their correspondent brightness matrix.

Then, we have considered as test transients the remaining six stator current signals, which are characterized by 10%, 30%, 40%, 60%, 70% and 90% of the nominal flux linkage.

The methodology has been applied to each one of the six test transient signals, leading to obtain the correspondent HHT representation. Finally, we have created the brightness matrix characteristic of each test transient and computed its similarity value with respect to those obtained from the tra

Table 8: Degradation level assigned to the test data

Flux Linkage	Assigned Class
90%	**80%**
70%	**80%**
60%	**80%**
40%	**50%**
30%	**50%**
10%	**20%**

Table 8 reports the degradation class to which the test transients have been assigned. It is possible to observe that the obtained classification is satisfactory, leading to the correct assignment of each transient to its closer class of degradation. However, it has to be pointed out that the method is generally non-conservative; in fact, except for the transient characterized by the 90% of nominal flux linkage, which has been assigned to “80% flux linkage” degradation class, each transient is assigned to the closer low degraded class. Finally, in Figure 7 the comparison between the normalized similarity values to the degradation class of each test transient is reported: it is possible to notice the evolution of the similarity values associated to the test data starting from the lowest degraded transient, i.e. characterized by the 90% of the nominal flux linkage, to the largest degraded transient, i.e. characterized by the 10% of the nominal flux linkage; in each of the considered case the largest similarity value corresponds to the closest degradation class, as expected.

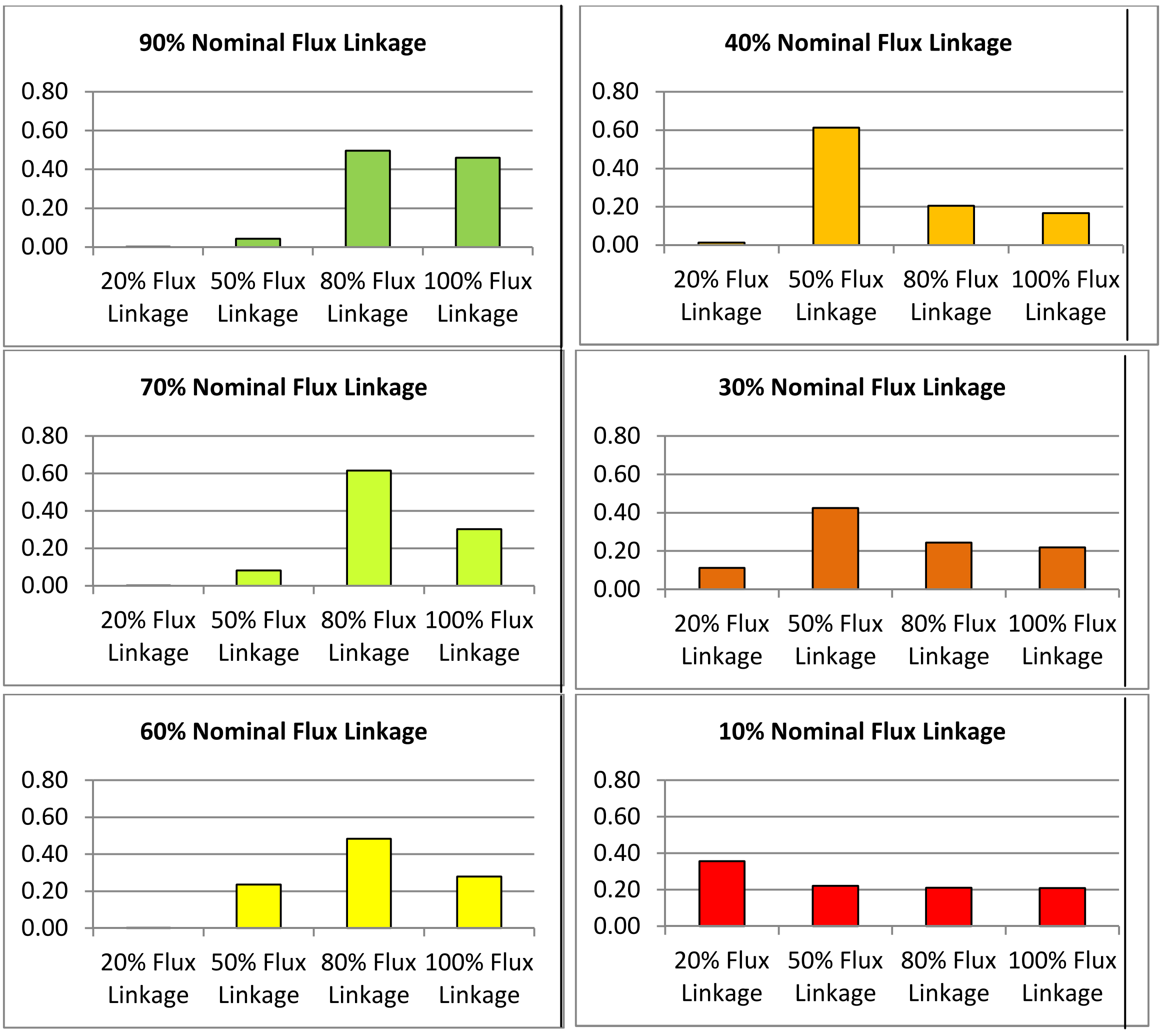

Figure 7: Similarity of the test transient with respect to the reference training transients characterized by the 20%, 50%, 80% and 100% of the nominal flux linkage.

Design of the experiment for the algorithm validation

The aim of model tuning is to increase algorithm robustness against different operating and environment conditions and to set the model parameters. To this purpose, within the HEMIS project we have decided to test real PMSM motors characterized by different levels of demagnetization and to measure the motor temperature and the stator current signals. The experiments will be performed on a test bench which allow considering different FEV operational conditions.

3.7.2 Capacitor

Proof of Concept

In this Section, the application of the prognostic algorithm to the prediction of the RUL of a degrading FEV capacitor is discussed. In the proof of concept phase, the developed method has been applied to a numerically simulated capacitor life.

The simulation has firstly required to set possible temperature profiles which can be experienced by a FEV capacitor. According to the suggestions of motor experts, we have considered that the temperature variations experienced by the capacitor during its life are mainly caused by the variation of the environmental external temperature. Thus, the simulated temperature profiles are based on the following assumptions:

- the FEV is operating 4000 hours in a year (1000 hours each season);
- the seasonal mean temperatures experienced by the FEV capacitor depend from the season and are: T_{winter}=70°C, T_{spring}=85°C, T_{summer}=95°C, T_{autumn}=80 °C;
- in order to take into account temperature oscillations, the real temperature value experienced by the FEV is sampled from a Gaussian distribution with mean value equal to T_{winter}, T_{spring}, T_{summer}, T_{autumn} depending on the season, and standard deviation equal to 2°C for all cases.

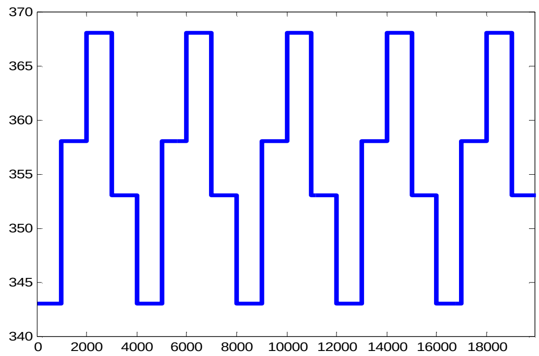

Figure 8. Average Temperature Profile

The simulation of the capacitor degradation has been performed considering the ALS30 Series electrolytic capacitor, whose nominal life at the nominal aging temperature of 85 °C is reported to be of 20000 hours. In practice, starting from the initial value ESR_{norm}=100%, by using the Eq. (B5) in Appendix B.2 and the simulated temperature profile we have numerically simulated the time evolution of the capacitor degradation (ESR_{norm}) until the failure time, i.e., the time at which the ESR of the capacitor reaches the double of its initial value. Figure 9 shows the simulated values of the considered 7 ESR measurements. The obtained simulated capacitor life will be referred to as the “true” capacitor life, considering the numerically simulated ESR measurements as the real available ESR measurements.

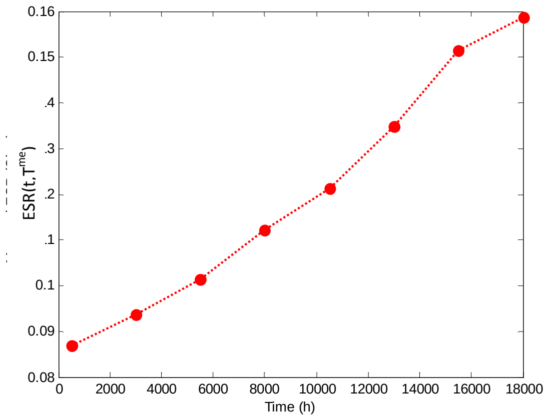

Figure 9. Numerical simulation of the measured ESR value ESR(t,T^{me})

The prognostic method described in Section 3.5.2 has then been applied to the simulated capacitor life. The prognostic method provides a satisfactory prediction of the RUL in the form of a probability density function.

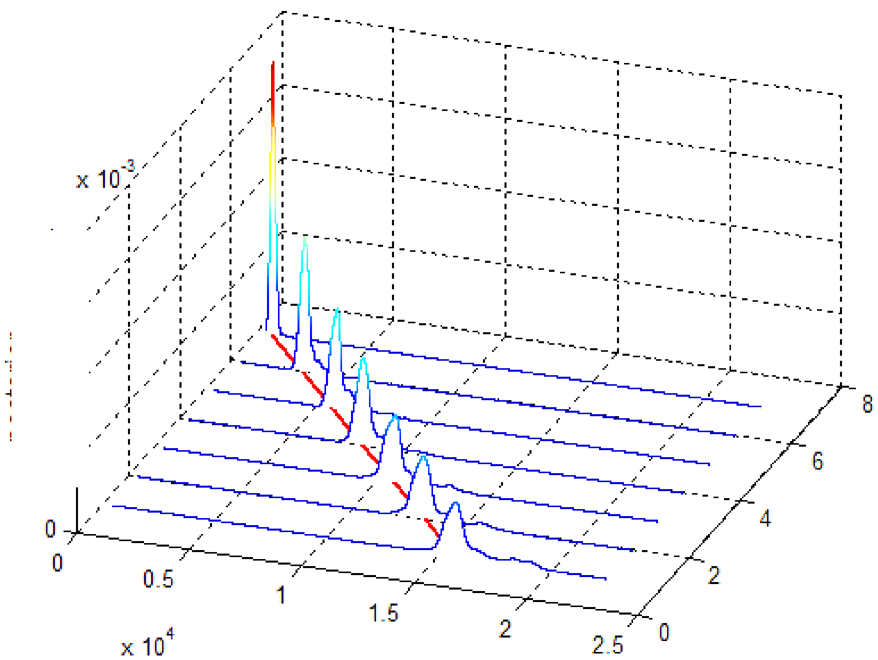

Figure 10. Evolution of the RUL prediction pdf according to the measurement number

In Figure 10, the real RUL of the component is represented by the solid line. Notice that the range of variability of the predicted RUL is clearly reducing from a large width at the first measurement (t=3000 h) to a narrow width at the last measurement (t=18000 h). This reduction of the RUL uncertainty is due to the acquired knowledge of the degradation provided by the ESR measurements, which allows updating the degradation probability distribution and leads to a more accurate assessment of the component degradation state.

Design of the experiment for the algorithm validation

Laboratory experiments are being performed at CEIT facilities within the European Project HEMIS in order to measure the ESR values during the life of degrading capacitors. The capacitor degradation is obtained by inserting the capacitor in an oven kept at a constant temperature of 145 °C, which is largely higher than the operative temperature (typically around 85°C); the oven temperature drives the chemical reactions responsible of the degradation of the capacitor, i.e. the electrolyte vaporization, thus causing an accelerated aging of the component [22]. The obtained data will be used to set the model parameters and to validate the algorithm.

3.8 Overall assessment of the benefits provided by the PHMS

In order to answer to the question: "Which benefits in terms of reliability and availability of the FEV powertrain do we expect by using the developed PHMS?", we need to define a method able to compute the availability and reliability of the FEV taking into account the operation of the PHMS. Some preliminary studies have been performed by considering a Monte Carlo simulation-based approach. In particular, we have considered a generic FEV component which may fail due to two different independent causes, namely failure modes A and B. Failure mode A leads to an abrupt failure, which cannot be predicted by observing physical signals related to the system operation and it instantaneously causes the failure of the system and its unavailability. Failure B, instead, consists in a gradual degradation of the system which is represented by a discrete process with a safe, degraded and failed state and the PHMS is assumed able to detect the degradation of the FEV subsystem. The overall system formed by the FEV component and the PHMS can be described by considering 11 states, each one characterized by different combination of failure mode A, failure mode B and PHMS failure (Table 9).

Table 9: List of the system states in presence of a PHMS

State	Failure Mode A	Failure Mode B	PHMS Failure	System State
0	No	No	No	Safe
1	Yes	No	No	Failed
2	No	Degraded	No	Safe
3	No	No	Yes	Safe
4	No	Degraded	Yes	Safe
5	No	Yes	Yes	Failed
6	No	Degraded	Detect	Safe
7	No	Yes	No	Failed
8	Yes	No	Yes	Failed
9	Yes	Degraded	Yes	Failed
10	Yes	No	No	Failed

Given the complexity of the system in terms of number of states and type of transitions, an interesting possibility which has been investigated in [11] was to resort to Monte Carlo simulation to compute the overall system availability and reliability.

4. Conclusion and further work

In this Deliverable we have proposed a general and systematic procedure for the development of a PHMS for a new design technological system. Two of the most critical degradation mechanisms which can occur in a FEV powertrain have been selected and the various steps for the algorithm development have been illustrated with respect to them. Future work will be devoted to the validation of the algorithm with experimental data and to the assessment of the safety level that can be achieved by adding the developed PHMS to the FEV.

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Appendix A

A.1 Empirical-Mode Decomposition (EMD)

An IMF is a function that satisfies two conditions: i) in the whole dataset, the number of extrema and the number of zero crossings must either be equal or differ at most by one; ii) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The EMD extracts the first IMF by the following sifting process [20]:

1) Find the upper envelope of $x(t)$ as the cubic spline interpolated of its local maxima, and the lower envelope, as the cubic spline interpolated of its local minima.
2) Compute the envelope mean $m(t)$ as the average of the upper and lower envelopes.
3) Compute $$h(t) = x(t) - m(t) \quad \text{(A1)}$$
4) If the sifting result $h(t)$ satisfies the criteria for an IMF, stop. Otherwise, treat $h(t)$ as the signal and iterate on $h(t)$ through steps 1–4.
5) The EMD extracts the next IMF by applying the aforementioned procedure to the residue

$$r_1(t) = x(t) - c_1(t) \quad \text{(A2)}$$

where $c_1(t)$ denotes the first IMF. This process is repeated until the last residue $r_n(t)$ has at most one local extreme. The first IMF component from the data contains the highest oscillation frequencies found in the original data x(t).

A.2 Hilbert-Huang Transform (HHT)

Once the IMFs have been obtained by means of the EMD method, the Hilbert transform is performed to each IMF component as follows:

$$H[c_i(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{c_i(\tau)}{t-\tau} d\tau \quad \text{(A3)}$$

which means that $c_i(t)$ and $H[c_i(t)]$ form a complex conjugate pair, so that an analytic signal z_i is defined as:

$$z_i(t) = a_i(t) e^{j\omega_i(t)} \quad \text{(A4)}$$

where $a_i(t)$ and $\omega_i(t)$ represent the instantaneous amplitude and frequency, respectively. To transform this temporal-space data to time–frequency space, the Hilbert transform is performed on each IMF component obtained by means of the EMD method as:

$$a_i(t) = \sqrt{c_i^2(t) + H^2[c_i(t)]} \quad \text{(A5)} \qquad \theta_i(t) = \arctan\left(\frac{H^2[c_i(t)]}{c_i(t)}\right) \quad \text{(A6)}$$

In this way, the instantaneous frequency $\omega_i(t)$ is given by:

$$\omega_i(t) = \frac{d\theta_i(t)}{dt} \quad \text{(A7)}$$

After performing the Hilbert transform on each IMF component, we can finally express the original data in the following form:

$$x(t) = \mathrm{Re} \sum_{i=1}^{n} a_i(t) \exp\left(j \int_{-\infty}^{t} \omega_i(t) dt \right) \qquad \text{(A8)}$$

where $Re\{\cdot\}$ denotes the real part of a complex quantity.

Following this procedure, the amplitude and instantaneous frequency for every IMF at every time step are computed. This result can be projected on the time-frequency-energy space, with energy defined as the amplitude squared, enabling us to compare the Hilbert spectra of the simulated currents waveforms.

Appendix B

B.1 Capacitor Degradation Model

The degradation of the capacitor is mainly due to the chemical reactions occurring inside the component, which cause the vaporization of the contained electrolyte, leading to a loss of functionality. The physical processes occurring inside the component have been deeply investigated, and several degradation models can be found in literature [5][13][14][21][22]. Component degradation can be identified by monitoring the ESR: higher the degradation, higher the measured ESR value. According to [5], the ESR for a capacitor aging at constant temperature T^{ag} is given by:

$$\mathrm{ESR}(t, T^{ag}) = \mathrm{ESR}_0(T^{ag})e^{C(T^{ag})t} \quad \text{(B1)}$$

where $ESR_0(T^{ag})$ represents the initial ESR value of the capacitor at temperature T^{ag}, t the age of the capacitor and $C(T^{ag})$ a temperature-dependent coefficient which defines the degradation speed of the capacitor. In particular, the temperature coefficient $C(T^{ag})$ can be expressed as:

$$C(T^{ag}) = \frac{\ln 2}{\mathrm{Life}_{nom}(T_{nom})\exp\left[\frac{E_a}{k}\frac{(T_{nom}-T^{ag})}{T_{nom}\cdot T^{ag}}\right]} \quad \text{(B2)}$$

where $Life_{nom}$ represents the nominal life of the capacitor aged at the constant nominal temperature (T_{nom}), and the temperatures are expressed in Kelvin degrees. A detailed description of the semi-empirical procedure adopted for the definition of the macro-level physical model of Eqs. (B1) and (B2) can be found in [21].

It has to be emphasized that the measured ESR value depends on the measurement temperature: this means that if we measure the ESR value on the same degraded capacitor at a temperature T^{me} different from that at which the capacitor is degrading (T^{ag}), the measured value of ESR will be different. The relationship between the initial ESR for a new capacitor and the ESR measurements temperature T^{me} for a new capacitor is [5]:

$$\mathrm{ESR}(0, T^{me}) = \mathrm{ESR}_0(T^{me}) = \alpha + \beta e^{-T^{me}/\gamma} \quad \text{(B3)}$$

where α, β and γ are parameters characteristics of the capacitor.

B.2 A Particle Filtering (PF) Approach for RUL Estimation

Unfortunately, the relationship defining the influence of the measurement temperature T^{me} on the ESR for a degraded capacitor is unknown. Thus, since the FEV capacitor typically works at variable temperatures, the ESR cannot be directly used as degradation indicator for a capacitor experiencing different operational conditions such as those of FEV. For this reason, in order to define a degradation indicator which is independent from the temperature, we introduce a new degradation indicator defined by the ratio between the ESR measured at temperature T^{me} and its initial value at the same temperature T^{me}:

$$\mathrm{ESR}_{norm}(t) = \mathrm{ESR}(t, T^{me})/\mathrm{ESR}_0(T^{me}) \quad \text{(B4)}$$

where $ESR_0(T^{me})$ is computed by using Eq. (B3). Notice that, according to this new degradation indicator, if we consider a degraded capacitor and we measure its ESR value at different temperature, we obtain exactly the same ESR_{norm} value, which is independent from the temperature of the measurement and it expressed as a percentage. The failure threshold, i.e. a value of ESR_{norm} such that if it is exceeded the capacitor is considered failed, is set equal to ESR_{norm} = 200%. The rationale behind this choice is that the failure threshold for any capacitor is typically defined as the double of its initial ESR value [23]. The new degradation indicator allows overcoming the lack of knowledge on the relationship between the temperature and the measured ESR for a degraded capacitor. Thus, it is now possible to represent the degradation process as a first order Markov Process between time steps t_{k-1} and t_k; the new degradation equation is, then, defined as:

$$\mathrm{ESR_{norm}}(\mathrm{t_k}) = \mathrm{ESR_{norm}}(\mathrm{t_{k-1}})e^{C(T^{ag}_{k-1})} + \omega_{k-1} \qquad \text{(B5)}$$

where T^{ag}_{k-1} represents the aging temperature at time t_{k-1} and ω_{k-1} models the process noise.
Eq.(B5) represents the degradation state evolution and is independent from the measurement temperature T^{me}. There is only a dependence from the temperature T^{ag} experienced by the capacitor in the coefficient $C(T^{ag})$ defining the speed of degradation, which can be computed by using Eq.(B2). The equation linking the measured ESR and ESR_{norm} is:

$$\mathrm{ESR}(\mathrm{t_k}, \mathrm{T^{me}_k}) = \mathrm{ESR_{norm}}(\mathrm{t_k}) \cdot \left(\alpha + \beta e^{-\frac{T^{me}_k}{\gamma}}\right) + \eta_k \qquad \text{(B6)}$$

where T^{me}_k represents the measurement temperature at time t_k and η_k represents the measurement noise.
Figure B1 sketches the PF approach to prognostics based on the following three steps:

1. the estimation of the equipment degradation state at the present time based on a sequential Monte Carlo method; the state of the system is defined by the ESR_{norm} value. The PF approach requires the definition of a process equation, which in this case is given by Eq. (B5), and a measurement equation, which is given by Eq. (B6)
2. the prediction of the future evolution of the degradation state by Monte Carlo simulation
3. the computation of the equipment RUL.

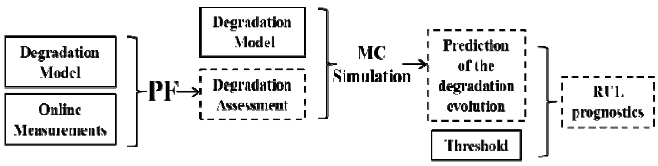

Figure B1. Sketch of the PF approach to fault prognostics

More details on the application of the PF approach to prognostics can be found in [24].
Notice that we resort to a PF instead that to a classic Kalman Filter framework because in Eq. (B5) we cannot express the noise as a Gaussian additive term. In practice, the Gaussian noise, to which the aging temperature T^{ag} is subject, affects the aging coefficient $C(T^{ag})$ (Eq. (B2)) and, then, Eq.(B5), thus becoming a non Gaussian additive term.

B.2.1 Parameter Estimation

According to the Particle Filtering model described in Section B.2 and used for the RUL prediction, we need to investigate the relationship between the initial ESR and the temperature for a new capacitor described by Eq. (B3). Since the parameters α, β and γ of Eq.(B3) are characteristic of the particular type of capacitor, we have performed experimental tests in order to identify the α, β and γ values for the considered capacitor. In particular, the experimental test procedure has been based on the following three steps:

- Setting of the desired temperature
- Once the stationary conditions are reached in the chamber, the temperature is maintained for 20 minutes in order to allow the internal layers of the capacitor to heat up.
- The ESR is measured at different frequencies, between 10 kHz and 1 MHz.

The procedure has been repeated at different temperatures in the range [12°C, 110°C], which is expected to be experienced by the FEV capacitor. The ESR measurements have been performed at steps of 15°C.

The obtained experimental laboratory results are shown in Figure B2, where the ESR measurements performed on a new capacitor at different temperatures and frequencies are reported.

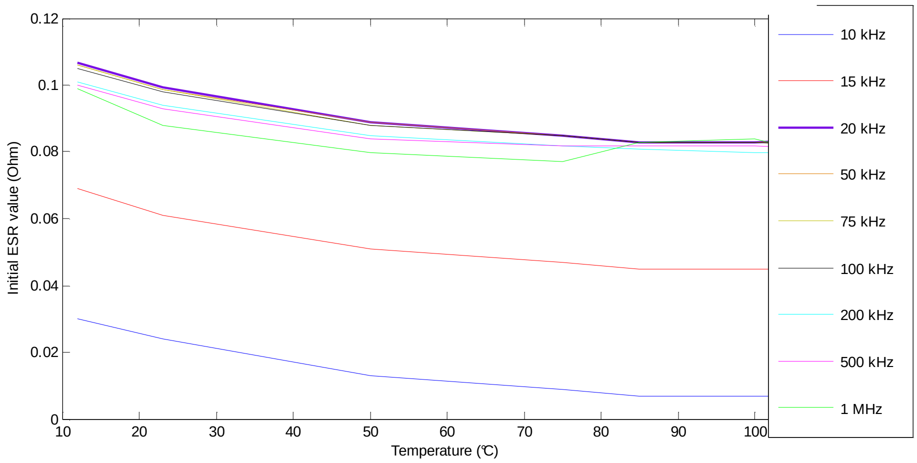

Figure B2. Experimental curve describing the variation of the initial ESR value ESR0(T^{me}), in Ohm, at different measurement frequencies

Notice that the ESR at a given temperature tends to increase when the frequency is increased from 10 kHz to 20 kHz, whereas further increasing of the frequency does not modify numerically the ESR measurements. Since the degradation index ESR_{norm} defined in Eq. (B4) is based on the ratio between the measured value of ESR and its initial value at the corresponding temperature, the most advantageous choice would be the measurement frequency with the highest associated absolute values of the ESR, which in this case corresponds to the 20 kHz curve. The rationale behind this consideration is that if we assume the same measurement noise, then its influence would be lower for the largest absolute values of the ESR.

Then, by resorting to an exponential regression method we have identified the following values for the experimental parameters α, β and γ:

α=0.0817 Ω β=0.037 Ω γ=30.682°C (B7)