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Assessment of the Performance of a Fully Electric Vehicle Subsystem in Presence of a Prognostic and Health Monitoring System

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To achieve the aims of reducing energy consumption and CO2 emissions, Fully Electric Vehicle (FEV) needs to reach significant market shares. However, the advent of FEVs in mass production presents new challenges to automotive manufacturers due to the immaturity of the new building blocks, which can reduce FEV's safety and reliability. In this context, research activity is currently devoted to the development of prognostics and health management systems (PHMSs) which aim at providing information on the failsafe state of the FEV subsystem and at the prediction of its Remaining Useful Life (RUL). The objective of the present paper is to develop a method to assess the reliability and availability of a FEV subsystem which is monitored by a prognostics and health management system. The method proposed for the assessment is based on Monte Carlo Simulation.

1. Introduction

The reduction of greenhouse emissions are one of the most important goals of the environmental protection policy. European commission sets limits in order to achieve a reduction of CO2 emission by 20% since 1990 until 2020 (European Commission, 2012). Despite this objective, since the 85% of world energy production is based on fossil fuels and the consumption of this type of fuels is expected to increase as population grows, greenhouse emissions are difficult to reduce. In this context, Fully Electric Vehicles (FEV) introduce a way to reduce fossil fuel consumption by substituting Internal Combustion Engine with electrical powertrain and batteries (Sedano et al., 2013). However, since the immaturity of these technologies introduces problems in terms of the FEV reliability, availability and safety, research activity is currently devoted to the development and test of Prognostic Health Monitoring System for the FEVs most critical subsystems (Sedano et al., 2013). Among these research activities, the European Project “Electrical powertrain Health Monitoring for Increased Safety of FEVs” (HEMIS) is developing a prognostic system to monitor the condition of the FEV powertrain and, thus, increasing the vehicle safety and reducing the maintenance cost. The PHMS will receive signals from the FEVs components and sends information to the driver about the occurrence of failures and the remaining useful life of its components (Baraldi et al., 2012; Benkedjouh et al., 2013; Vichare and Pecht, 2006).
In this context, the objective of the present paper is to develop a method for the assessment of the performance of the FEV subsystems in presence of a PHMS. In practice, we want to answer to the question: “Which benefits in terms of reliability and availability of the FEV subsystems do we expect by using PHMSs?” The answer to this question requires the development of a model for the computation of the availability and reliability of the subsystems which takes into account the operation of the PHMS. In this work, the problem has been addressed by resorting to Monte Carlo simulation (Zio, 2013).
The paper is organized as follows: Section 2 states the problem; Section 3 illustrates the method used for the reliability and availability assessment. Section 4 discuss the case study and the obtained results; finally, in Section 5 some conclusions and remarks are drawn.

2. Problem Statement

We consider a generic subsystem of a FEV, and we assume that it can 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. Once Failure A occurs, it instantaneously causes the failure of the system and its unavailability. We assume that the failure time associated to failure A is exponentially distributed, with failure rate λ_A. Failure B (Figure 1), instead, consists in a gradual degradation of the system which is represented by a discrete process with a safe, degraded and failed state (Baraldi et al., 2013a).

The transition time from the safe to the degraded state is assumed to be exponentially distributed, with failure rate λ_{DEG}, whereas the transition time from the degraded to the failure B state is represented by a Weibull distribution with parameters λ_W and α_W: A Weibull distribution is used to take into account the fact that, once the system is degraded, the hazard rate characterizing failure mode B increases with time (Johnson et al., 1994).

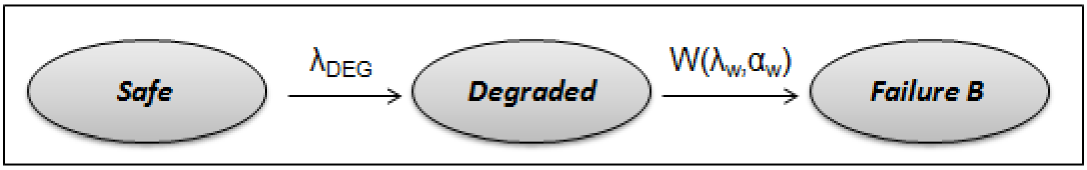

Figure 1: diagram representing failure mode B

Considering the presence of the two failure modes A and B, the system can be in the 5 states reported in Table 1, i.e. one safe state (State 0), one degradation state (State 2), and three failed states (States 1, 3, 4). Once the system is failed, it is unavailable and must be repaired. Repair times are represented by exponential distributions with different repair rates μ_A and μ_B for failures of type A and B, respectively. Figure 2 shows the diagram of the system states.

In order to improve the FEV performances we consider the introduction of a PHMS which is able to detect the degradation of the FEV subsystem, i.e. its transition from State 0 to State 2, but it is not able to identify failures of type A. If a degraded condition is detected, the maintenance starts instantaneously.

Table 1: List of the system states of the considered system without in absence of a PHMS

State	Failure Mode A	Failure Mode B	System State
0	No	No	Safe
1	Yes	No	Failed
2	No	Degraded	Safe
3	No	Yes	Failed
4	Yes	Degraded	Failed

The duration of the repair action is represented by an exponential distribution with repair rate μ_{DEG} and we assume that the component is restored into an as good as new condition (State 0) after the maintenance. We consider the possibility that the PHMS has a failure which causes its unavailability and, thus, causes the impossibility of detecting the degradation of the system. The failure time is represented by an exponential distribution with failure rate λ_{PHMS}. The failure of the PHMS is not repaired except that in case of repair after a failure of type B. Furthermore, if the PHMS is available and the system is degraded, the time necessary for the detection is represented by an exponential distribution with parameters λ_{Det}. Table 2 reports all the possible combinations of the component failure and degradation states and the associated states of the system. Figure 3 shows all the possible transitions between the states. The objective of this work is the computation of the system availability and reliability.

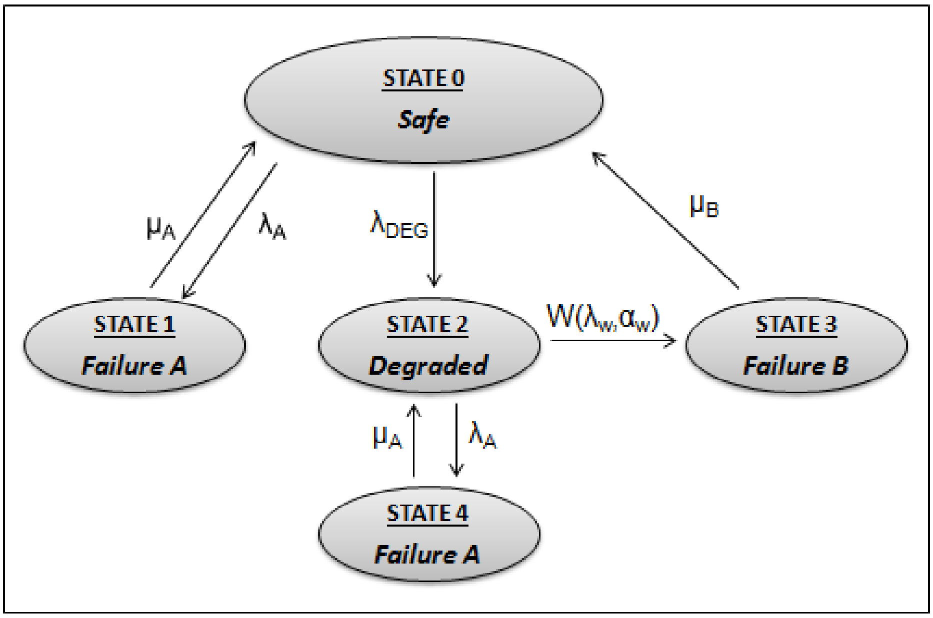

Figure 2: Diagram of the system states and transitions in absence of a PHMS

Table 2: 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

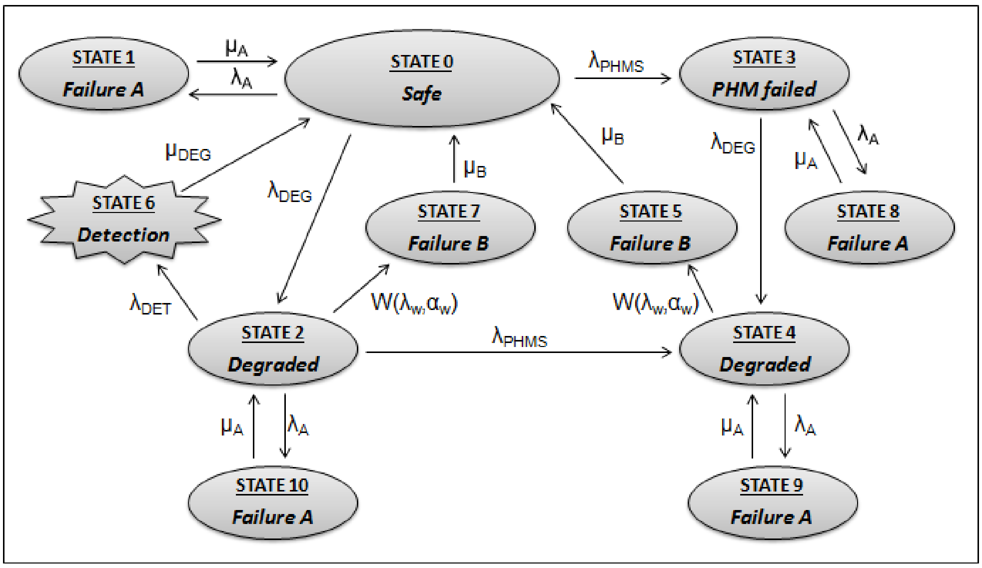

Figure 3: diagram of the system states and transitions in presence of a PHMS

3. Methods

Given the complexity of the system in terms of number of states and type of transitions, we resort to Monte Carlo simulation to compute the overall system availability and reliability (Zio et al., 2006; Baraldi et al., 2013b). In particular, we have employed a direct Monte Carlo method. For any trial of the Monte Carlo simulation, the system history starts from state 0 and all transition times are sampled from the corresponding probability distributions and arranged in ascending order. The first transition of the system corresponds to that with associated the minimum transition time. The same procedure is repeated for any transition until the mission time is reached. Each Monte Carlo trial is associated to two counters: a reliability and an availability counter. In each reliability counter we have a Boolean indicator which indicates if the system has never failed before the mission time. In each unavailability counters we accumulate the time in which the component has been unavailable, i.e. in a "failed" state.

After the Monte Carlo simulation of the system histories, reliability and availability have been estimate:

- The sum of the reliability counters is divided by the number of histories in order to give an estimation of the reliability of the system over the mission time.
- The sum of the unavailability counters is divided by the mission time and by the number of histories in order to give an estimation of the average unavailability of the system over the mission time.

Notice that this procedure corresponds to performing an ensemble average of the realizations of the stochastic process which represents the system life (Zio, 2013).

4. Case Study

Table 3 reports the parameters of the stochastic distributions used in the case study for the representation of the uncertainty in the transition times. Notice that the values are only indicatives and do not correspond to any real system.

The direct Monte Carlo method has been applied performing 10^6 simulations. Table 4 reports the obtained results, i.e. the system availability and reliability with the associate estimate uncertainty for a mission time of 2000 hours. Notice that, given the high number of performed simulation, the uncertainty of the estimations is very low. The use of the PHMS allows to obtain a significant gain with respect to the case without PHMS: the system reliability increases of about 10%. With respect to the system mean availability, it can be observed that it reaches high values also in the case without PHMS. This is due to the fact that in case of failure, the system is quickly repaired (fast mean repair times).

Table 3: Parameters of the probability distributions describing the different transition times

Transition time	Distribution	Parameters
Type A failure	Exponential	$\lambda_A = 1.2 \cdot 10^{-4}\ h^{-1}$
Type B failure	Weibull	$\lambda_w = 14$; $\alpha_w = 2.3$
PHMS failure	Exponential	$\lambda_{PHMS} = 2.5 \cdot 10^{-6}\ h^{-1}$
Degradation	Exponential	$\lambda_{deg} = 9.4 \cdot 10^{-5}\ h^{-1}$
PHMS detection	Exponential	$\lambda_{Det} = 0.2258\ h^{-1}$
Repair after failure A	Exponential	$\mu_A = 0.0833\ h^{-1}$
Repair after failure B	Exponential	$\mu_B = 0.00833\ h^{-1}$
Repair after the detection of the PHMS	Exponential	$\mu_{DEG} = 0.0417\ h^{-1}$

Table 4: Obtained system reliability and availability

Results	With PHMS	Without PHMS
Reliability	$0.7605 \pm 1.35 \cdot 10^{-3}$	$0.6523 \pm 1.51 \cdot 10^{-3}$
Availability	$0.9948 \pm 5.23 \cdot 10^{-5}$	$0.9883 \pm 1.07 \cdot 10^{-4}$

Finally, it is interesting to investigate the influence of the PHMS performance on the system availability and reliability. To this purpose, we have performed several Monte Carlo simulation of the system behavior considering different values of the detection rate λ_{det}. Figures 4 and 5 show the dependence of the system availability and reliability from λ_{det}. Notice that, as expected, the system reliability and availability tend to increase if the performance of the PHMS increases (λ_{det} increases).

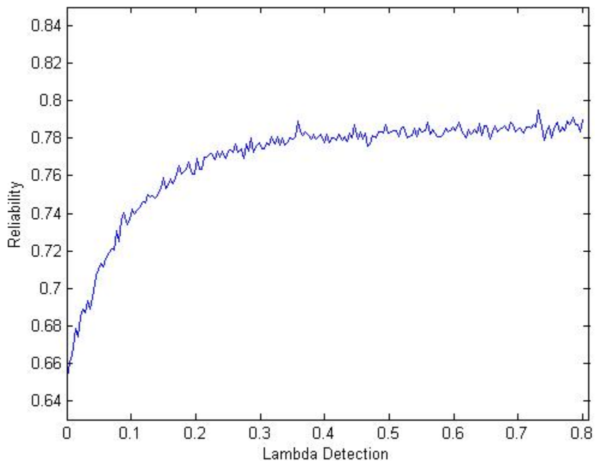

Figure 4: Sensitivity Analysis on Reliability

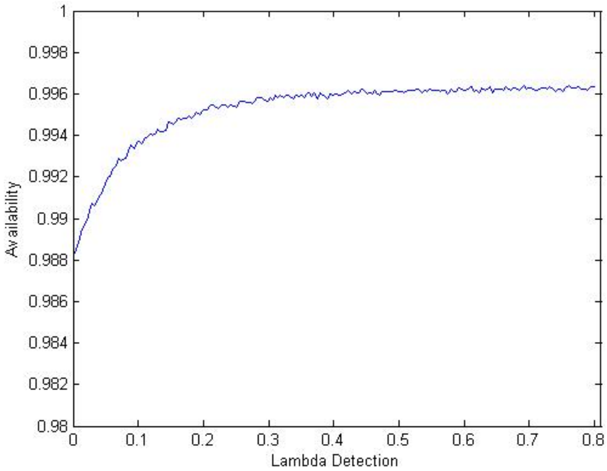

Figure 5: Sensitivity Analysis on Availability

Furthermore, due to the presence of failure A, which is not detected by the PHMS, system availability and reliability do not reach the value of 1, even if the PHMS is assumed to instantaneously detect the degradation.

Finally, it is interesting to observe that it seems not useful to increase the detection rate beyond 0.4 h^{-1} (i.e. to have a mean time to detection lower than 2.5 h) since this will not have any remarkable effect on the system reliability and availability.

5. Conclusion

In this work we have developed a method based on a direct Monte Carlo simulations for the assessment of the availability and reliability of a system which is monitored by a PHMS. The results obtained in the case study have shown that the use of a PHMS allow to remarkably increase the system reliability and slightly increase the system availability. Furthermore, it has also been shown that the performance of the PHMS, i.e. the time necessary to identify the system degradation, influences the system reliability and availability. As expected, reducing the mean time to detect the degradation has the effect of increasing the system performance, but it is not useful to reduce the mean detection time below a given value, since reliability and availability tend to reach an asymptotic value such that further reduction will not have effect on the overall system performance. In this work we have considered a condition based approach: the PHMS identifies the degradation of the system and this information is used to decide when to maintain the system. Future work will be developed to address the case in which the PHMS provides also an estimate of the system RUL ,which is then used, within a predictive maintenance approach, to properly plan the repair time.

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