A Modelling Framework to Assess Maintenance Policy Performance in Electrical Production Plants

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Abstract:

A framework to qualitatively assess the performance of maintenance policies in electrical production plants is presented. A Monte Carlo simulation scheme is combined with fuzzy logic for modelling the component degradation. The novelty of the work consists in the modelling of the influence of the actual living conditions on the degradation of the specific component under analysis; this is done by using linguistic fuzzy rules which formalize the expert knowledge on the degradation process. An example of application regarding a water-feeding turbo pump is presented to illustrate the potential of the proposed approach.

1. Introduction

Since the opening of the electricity market, utilities have been forced to be more competitive by reacting promptly and reliably to the demand/offer dynamics. This entails efficient component maintenance policies, including ordinary maintenance, unexpected maintenance and restoration, which have a large impact on the plant performance and production costs. The establishment of a maintenance policy requires that various options be considered, of the type of maintenance plan (corrective, preventive, opportunistic, etc.), the type and timing of the maintenance tasks (overhaul, monitoring, scheduled replacement, etc.), the maintenance echelon (repair on site or in workshop), etc. The decisions on the maintenance policy must be taken considering various and typically conflicting criteria, e.g., availability, safety and costs. Given the dimension and complexity of the problem, maintenance policy decision making must be supported by system modelling and optimization.

In spite of the many efforts in this direction, it seems fair to say that in many practical maintenance decision making cases the situation is not so brilliant: maintenance policies are in many instances still based on the maintenance schedules recommended by the vendor, which are usually conservative or are only based on qualitative information driven by experience and engineering rationale (Zio, 2009); on the other hand, for their practical use maintenance optimization models should avoid excessive details and strive for a balance with the data available for the estimation of their parameters (van Rijn, 2007).

A common approach for defining maintenance policy is based on the use of stochastic models of the degradation, failure and repair processes; (Valdez-Flores & Feldman, 1989), (Singpurwalla, 1995), (van Noortwijk, 2009) provide detailed surveys on the stochastic models that have been successfully used for maintenance modelling in different domains (e.g., hydraulic structures, dikes (van Noortwijk, 2009), pipelines (Hong, 1999), cutting tools (Jeang, 1999), etc.). These models can be grouped into two main categories:

- Stochastic models describing the behaviour of the degradation process affecting a given component. It is assumed that failure occurs either when a critical parameter reaches a fixed or random threshold or when a traumatic event occurs (e.g., a random shock). Some examples of models of stochastic degradation processes belonging to this category can be found in (Barata, Guedes Soares, Marseguerra, & Zio, 2002), (Zille, Bérenguer, Grall, Despujols, & Lonchampt, 2007), (Saassouh, Dieulle, & Grall, 2007), (Deloux, Castanier, & Bérenguer, 2009).

- Stochastic models describing the evolution of the values of the components failure rates. In particular, stochastic processes like the doubly stochastic Poisson processes, shot noise, etc. (Singpurwalla, 1995) and (Cox, 1980), can be used for modelling directly the evolution of the failure rate of a component due to the influence of the dynamic environment. However, the failure rate of a component is an unobservable entity; thus, it is conceptually more direct to consider stochastic processes of covariates (which are observable and, often, measurable variables) for modelling the impact of the living conditions in which a component works on its failure behaviour. In this case, an hazard rate stochastic process is induced via stochastic processes of covariates (Singpurwalla, 1995).

An alternative and pragmatic approach, proposed in (MIL-HDBK-217F, 1995) suggests to multiply the base value of the component failure rate by empirical factors to account for the specific living conditions (e.g., environment, working cycles, etc.). Despite its pragmatism, the approach is not directly applicable in support to maintenance decision making, which would require also the knowledge (even qualitative) of the component degradation level in order to model the effects of the maintenance actions.

To address this problem, (Zille, Bérenguer, Grall, Despujols, & Lonchampt, 2007) have proposed a framework for modelling the degradation of a component as a discrete stochastic process using parametric probability density functions (pdfs) to characterize the transition times among the degradation states and accounting for the influence of the component actual living conditions by modulating the pdfs parameters. This approach can effectively model the process of component degradation allowing the assessment of a maintenance policy, but relies on a large number of statistical parameters which may be difficult to estimate in real applications due to lack of experimental data.

Indeed, in practice expert judgement is often the main source of information on the degradation behaviour of components. To effectively deal with such type of information, a fuzzy approach to the estimation of the component degradation state is proposed in this work. Linguistic fuzzy rules elicited from experts are used to describe the influence of the living conditions on the component degradation process. From the knowledge of the degradation state of the component, its failure and repair rates are then determined and used within a Monte Carlo simulation scheme for computing system availability and costs.

The present paper is structured as follows: in Section 2 the simulation framework is presented; Section 3 describes the proposed degradation model; in Section 4 a case study is presented and the results are commented. Finally, come conclusions are proposed in the last Section.

2. Assessment of Maintenance Policy Performance

The assessment of the performance of a maintenance policy is usually based on the computation of the system availability and costs. When dealing with complicated systems, the use of Monte Carlo simulation is preferable, in order to avoid the introduction of excessively simplifying hypotheses in the representation of the system behaviour (Marseguerra & Zio, 2002).

In the proposed approach, the rates characterizing the failure processes are not fixed a priori, but depend on the component degradation state, which evolves during the stochastic life of the system. To follow the time-dependence of the failure rates, which emerges from the degradation process, the time domain is discretized by dividing the mission time into bins of fixed duration Dt; at the beginning of each time bin, all the Monte Carlo simulation model parameters are updated and kept constant through the bin.

A key issue in this computational framework is the estimation of the Monte Carlo parameters (i.e., failure rates and repair rates) which depend on the degradation state of the components.

In all generality, let us consider a system made up of C components. The i-th component is affected by M_i degradation processes, which may be influenced by the failure/degradation behaviour of the other $C-1$ components of the system. The generic j-th degradation process impacts on a number N_j^i of failure modes whose stochastic occurrence in time is described by N_j^i different failure rates $\lambda_{j,k}^i$, $k = 1,2,\ldots,N_j^i$.

A macro-state of availability ξ_i is assigned to the generic i-th component; it can take two mutually exclusive values:

- ‘ON’ which indicates that the component is working.
- ‘OFF’ which indicates that the component is not working.

Assuming independence between the degradation mechanisms, the value of the failure rate of the generic i-th component, whose macro-state is ‘ON’, is:

$$\lambda_i = \sum_{j=1}^{M_i} \sum_{k=1}^{N_j^i} \lambda_{j,k}^i$$

The case of dependence between the degradation mechanisms is not addressed in this work; however, it seems important to remark that unjustifiably ignoring dependence may result in an underestimation of the system reliability (Wang & Coit, 2004).

The macro-state ‘OFF’ has a number of possible sub-states that specify the condition of the component while not working (e.g., under corrective maintenance, under preventive maintenance, waiting for the availability of the repair team, etc.). A repair state μ_i is associated to the generic component i, whose macro-state is 'OFF'; the value is assumed to be dependent directly on the type of the maintenance action, the influencing factors (IFs) of the actual living conditions and the degradation state of the component.

3. Estimation of the Parameters of the Monte Carlo Simulation Model

This section is dedicated to the description of the approach for the estimation of the values of the parameters needed in the Monte Carlo simulation modelling framework (i.e., failure and repair rates) taking into account the influencing factors of the actual living conditions.

3.1 Degradation and Failure Processes

The macro-state 'ON' of the component i can be further specified by a vector

$$\boldsymbol{D}^i = (D_1^i, D_2^i, \ldots, D_{M_i}^i)$$

whose elements are the states of the M_i degradation processes affecting the component. The generic degradation mechanism, D_j^i, can take a set of S_j^i discrete values, i.e., the degradation process is modelled as a discrete-state process. Such assumption reflects the operator direct experience on the degradation process, which is described in terms of states identified by symptoms and corresponding to maintenance actions. In this respect, it has been assumed that two degradation states are distinct if they differ at least for one of the following characteristics:

- Symptoms: two degradation states are distinct if they have different symptoms or different symptom intensities.
- Maintenance decision after a control: two degradation states are distinct if the operator, after a control in which the degradation mechanism is checked, takes different maintenance decisions (no action, partial repair, substitution, etc.).
- Failure rates: two degradation states are distinct if the expert associates different failure rates to them.

To each degradation state of each degradation mechanism, D_j^i, the vector $\boldsymbol{\lambda}_j^i = (\lambda_{j,1}^i, \lambda_{j,2}^i, \ldots, \lambda_{j,N_j^i}^i)$ of the failure rates related to the N_j^i failure modes influenced by the j-th degradation process is univocally associated.

The modelling framework proposed appears quite flexible and detailed in the representation of the component degradation and failure behaviour. As such, it offers a general modelling power, which however must be carefully tailored in light of the data and information available for estimating the model parameters. Thus, it is expected that its use in practice be made in a form which is balanced (i.e., more or less detailed) with the robustness of the parameters estimation allowed by the particular case considered.

3.2 Fuzzy Parameter Estimation (FPE) model

The FPE model has the goal of estimating the values of the parameters needed by the Monte Carlo simulation model (i.e., failure and repair rates), taking into account the influencing factors of the actual living conditions. The FPE model interacts with the Monte Carlo simulation model whenever an estimation of the parameters is needed (i.e., at the begin of each time bin, when a failure occurs, when a maintenance action is performed).

The degradation process is modelled as a discrete-state process and a failure rate is associated to each degradation state; the problem is then that of linking the living conditions experienced by the component to its degradation state. Unfortunately, the relationships between the IFs and the degradation states are not completely known. To handle the associated uncertainties, in this work a fuzzy logic approach is proposed, in which the link between the IFs and the degradation states is described by means of Fuzzy Rule Bases (FRBs).

Failure Rate Estimation

The first aim of the FPE model is to estimate the degradation state of the components taking into account the living conditions in which they work. In this respect, three issues have to be addressed: the identification of the IFs, their model description and the evaluation of their effects on each degradation mechanism. Three modules are proposed to tackle these issues:

- Central Module (CM);
- Backward Module (BM);
- Forward Module (FM).

Central Module
The Central Module is intended to identify the IFs that actually influence the considered degradation mechanism; both expert opinion and physical models from literature can constitute the knowledge base to support this phase. To aid this task, five general Influencing Factors (IFs) are introduced, divided into two groups. The first group includes the re-configurable IFs:

- IF_1: Environment. It includes the environmental variables (temperature, humidity, vibration, etc.) which are expected to influence the degradation and failure behaviour of the component. It is considered re-configurable because some interventions can be done in order to modify its value; for example, the external temperature or humidity can be controlled, if possible, by setting up heating or air conditioning systems, the vibration level can be reduced by performing maintenance actions to eliminate the cause of vibration, etc.
- IF_2: Operational Mode. The set of variables which influence the stress conditions of the component (e.g. duty cycle, frequency of stops/re-starts, etc.); they can be changed during the life time of the component, depending on the demands and opportunities of operation.
- IF_3: Maintenance Policy. It contains all the variables related to the maintenance characteristics (corrective, preventive, opportunistic, frequency of inspection, etc.). Changes from periodic to condition-based maintenance or changes of the periods between two successive inspections may be economically profitable in different phases of the component life, so that the maintenance policy is often dynamically re-calibrated during the components mission time.

The second group contains the fixed, not re-configurable IFs:

- IF_4: Age.

– IF_5: Quality (e.g., of design, materials, manufacturing, etc.).

Backward Module

The Backward Module relates the selected IFs with measurable variables which describe the living conditions, by means of fuzzy logic-based models. The motivation for adopting a fuzzy logic modelling framework is due to the fact that most of the IFs are expected to be more easily represented and assessed by the experts using linguistic statements rather than numeric variables; for example, "the environment is favourable" or "the maintenance is efficient" are clear expert statements of qualitative nature, whereas it could be difficult to establish a numerical scale representing the environment or the maintenance.

The construction of the fuzzy logic model for the assessment of the generic i-th IF, IF_i, is based on the following steps:

- Define the linguistic terms qualitatively representing the levels of the IF_i (e.g., Environment = IF_1 ≡ (Soft, Medium, Heavy)).
- Set the range of variability (Universe of Discourse, UoD in fuzzy arithmetic terminology) of the IF_i and partition it into the fuzzy sets representative of the defined linguistic terms, with their ambiguity.
- Identify the measurable physical variables that define the IF_i (e.g., IF_1; measurable variables: 'Temperature', 'Humidity', 'Width of the temperature range in a day', 'Wind', etc.).
- Define the linguistic terms qualitatively representing the values that each measurable variable can take (e.g., Temperature ≡ (Low, Medium, High)).
- Partition the physical measurement ranges of the input physical variables into fuzzy sets representative of the linguistic terms (e.g., Temperature ≡ Low; support of the fuzzy set: $[-5, 20]\ °C$).
- Define the set of fuzzy inference rules (Fuzzy Rule Base, FRB), which relate the linguistic terms (fuzzy sets) of the input physical variables to those of the output level of the IF_i (e.g., if 'Temperature' is 'High' and 'Humidity' is 'High' then 'Environment' is 'Heavy') and then the fuzzy inference engine to be used. In this work, a Mamdani-like fuzzy system has been employed (Babuska, 1998).

Once the model has been developed, it can be used for the assessment of the IF_i level. Notice that the output of the model is a fuzzy value which accounts for the ambiguity inherent in the assessment.

Forward Module

The Forward Module establishes the functional relationship between the level of the IFs and the failure rates, taking into account the influence of the living conditions on the degradation process. The objective of the FM is to provide a description, in terms of fuzzy rules, of how the IFs impact on the evolution of the degradation process. In particular, given the relationship between the degradation states and the failure rates, the FM is put into practice by assessing the vector of the degradation state, $\boldsymbol{D}_i$, for those components whose macro-state is 'ON'. This assessment is performed by fuzzy logic models (one for each degradation mechanism of each component) built on FRBs which link the IFs to the vectors $\boldsymbol{D}_i$ (Baraldi, Zio, Compare, Rossetti & Despujol 2009).

Once the generic j-th degradation mechanism of the i-th component has been estimated, the vector $\boldsymbol{\lambda}_j^i$ of the failure rates towards the component failure modes is univocally associated. The numerical values of such failure rates can be obtained either from historical data or from expert opinion.

Obviously, there is no universal method for defining the FRB which models the relations of interest: the knowledge of the physical problem (e.g., literature models, expert judgement and historical data) needs to be formalized for expressing the role played by the various elements affecting the dynamics of the degradation process.

Repair Rate Estimation

The repair rates, μ_i, of the components under maintenance, i.e. for which $\xi_i =$ 'OFF', generally depend on their living conditions and on the type of the maintenance action. The estimation of the repair rates is based on:

- The current time instant, t, provided by the system clock time.
- The vectors $\boldsymbol{D}_i$, $i = 1,2,\ldots,C$, of the components degradation states. The maintenance actions, in practice, may depend on the values of these vectors, e.g. a repair action is foreseen if the state achieved by the j-th degradation mechanism, D_j^i, is greater than a threshold d_j^i. The repair rates also depend on the values of the vectors $\boldsymbol{D}_i$, e.g., the Mean Time To Repair (MTTR) of the degradation process j may be different from that of the degradation process k.

The knowledge base of this module is the maintenance manager, which univocally associates a maintenance action to a certain component state (i.e., defines the maintenance policy). In the particular case when the maintenance actions have a fixed duration, the MC module is provided directly with the value of duration of such actions.

4. Case Study

4.1 Introduction

In order to illustrate the application of the proposed methodology, an example concerning a Water-Feeding Turbo Pump (WFTP) of a steam generator of a nuclear power plant has been considered. A team of experts has identified the degradation processes affecting the components of the WFTP and the associated IFs and symptoms. A risk-importance analysis has been carried out to identify the components and their degradation processes, whose detailed modelling would improve the accuracy in the representation of the system failure behaviour. Following the obtained results, the case study for the present work has been focused on the contact fatigue degradation mechanism of the seals of the WFTP. No consideration has been given to other components and their degradation processes, although some may lead to an acceleration of the degradation process under consideration.

The degradation of the seals of the WFTP due to contact fatigue is caused by the development of cracks that affect the ability of the seals to avoid leaks. The creation and propagation of these cracks is a complex physical phenomenon, which has been modelled in a number of different ways (Marquis & Solin, 1999), (Shigley, Mischke, & Brown, 2004). According to these models, the degradation is mainly influenced by the loads applied on the component, its constitutive materials and production process and some geometrical factors characterizing the crack such as its size, notch radius, position with respect to the direction of the loads, etc.

The model presented in this work is based on the assumption that the length of the most critical crack of the component defines its degradation level. Moreover, it is assumed that the length of the crack can only increase in time and preventive maintenance on the component has the effect of decreasing the speed of propagation of the crack (e.g., reducing the fatigue strength by increasing the notch radius of the most critical crack (Marquis & Solin, 1999)), but cannot reduce its length. In the modelling, the following three degradation states are considered:

1. 'Good': the component is as new or almost new; no maintenance actions are foreseen if the component is in this state; the failure rate is $\lambda = 10^{-5}\ h^{-1}$.
2. 'Medium': the seals of the WFTP in this state need some actions aimed at decreasing the crack growth rapidity; the failure rate in this state is $\lambda = 5 \cdot 10^{-4}\ h^{-1}$.
3. 'Bad': if the component is in this degradation state it is convenient to replace it; the failure rate in this state is $\lambda = 10^{-3}\ h^{-1}$.

Notice that the superscripts and subscripts of the failure rate, $\lambda_{j,k}^{i}$, previously introduced have been omitted since only one component with one degradation mechanism and one failure mode is considered.

In this case study, the following maintenance actions are assumed to be performed on the component:

- Control: periodic overhaul check of the component. It is assumed that the degradation state is easily visible and to be detected it does not need a laboratory test or disassembling of the component. This action is considered to be of negligible duration. Furthermore, this is the only scheduled action.
- Preventive maintenance: maintenance action conditioned by the result of a control. The preventive maintenance action is dependent on the result of a control action. If the component is found to be in state 'Good', no action is performed. If the degradation state is 'Medium', the component undergoes a repairing action aiming at slowing down the degradation process: this action has a duration of $2\ h$. Finally, if the component is in state 'Bad', it is replaced: this action takes $20\ h$ of time.
- Corrective maintenance: maintenance action following a failure of the component. The corrective action is assumed to be the replacement of the component. Due to the fact that this event is unscheduled, this action brings an additional duration of $10\ h$, with respect to the replacement after a control, leading to a total duration of $30\ h$. In particular, the additional time may be caused by the supplementary time needed for performing the procedure of replacement after failure or to the time elapsed between the occurrence of the failure and the start of the replacement actions.

Since in this case study all the considered actions have deterministic duration, it is not necessary to estimate the repair rates.

The values of the parameters characterizing the system are reported in

Table 1

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~~Table 1~~. These have been set with arbitrary engineering rationale.

Parameter	Value
Mission time	$10^5 h$
Control Period	$7000\ h$
Duration of a repair action	$2\ h$
Duration of a replacement action	$20\ h$
Additional time related to a failure	$10\ h$
Cost of a control action	$5\ \$$
Cost of a repair action	$10\ \$$
Cost of a replacement action	$1000\ \$$
Additional cost related to a failure	$1000\ \$$

Table 1. Values of the parameters characterizing the system.

The final objective of this case study is the identification of the optimal control period (i.e., the time interval which leads to the best performance in terms of availability and costs).

4.2 Fuzzy Parameter Estimation

Failure Rate Estimation

In this Section, the three modules described in Section 3.2.1 are put to work for estimating the failure rates in the considered case study.

Central Module
The definition of the model of the degradation process requires the identification of the IFs influencing the degradation state evolution of the component. In the present case study, this has been done by resorting to a FMECA analysis performed by safety analysts. The identified IFs are the following:

- IF_1: Environment. It is assumed that the influence of the environment on the considered degradation mechanism is mainly caused by the vibrations in the location at which the component works. In particular, the measurable variables on which the IF_1 depends are the mean values of the frequency and of the amplitude of the vibration fundamental wave in the time elapsed since the component has started to work. The Universe of Discourse (UoD) of this IF, arbitrarily scaled on $[0,1]$, is partitioned into three Fuzzy Sets: 'Soft', 'Medium' and 'Heavy'.
- IF_3: Maintenance. The component is periodically inspected by operators to control its degradation level. The maintenance policy, a priori established, requires that no maintenance action is performed if the degradation state is found 'Good' at control whereas a corrective maintenance action is performed if the component is found in state 'Medium' and a replacement action is carried out when the component is in degradation state 'Bad'. A variation of the period between two successive controls causes a modification of the degradation process; in particular, the more frequent are the controls the less is the time in which the degradation advances without any action for reducing its speed. To describe this IF, the three Fuzzy Sets 'Frequent', 'Medium' and 'Rare' are identified by the expert on the UoD $[0, 2 \cdot 10^4]\ h$ of the control period variable.
- IF_4: Age. This IF measures the time since the component has been working. The UoD of this IF is the interval $[0, T_{Miss}]$, with mission time $T_{Miss} = 10^5\ h$; on this interval, three Fuzzy Sets 'Young', 'Medium' and 'Old' are defined by the expert

by means of triangular membership functions. In general, the older the component the higher its degradation level.

The membership functions defining the fuzzy sets of the IFs are defined by experts on the basis of their knowledge and engineering sense of practice (Figure 1~~Figure 1~~).

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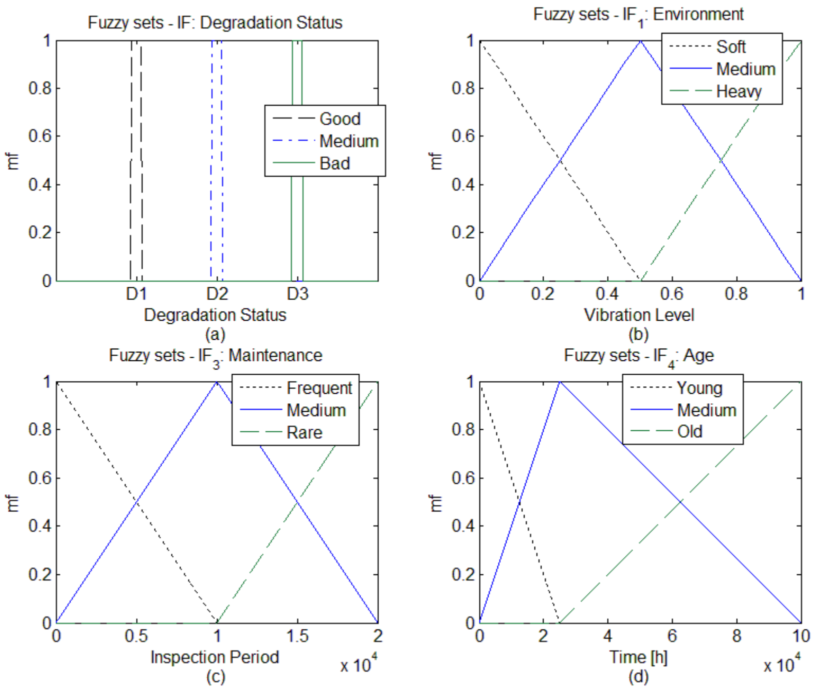

Figure 1. Fuzzy sets partitioning the degradation state (a), the IF 'Environment' (b), the IF 'Maintenance' (c) and the IF 'Age' (d).

Backward Module

The tailoring of the BM to the considered case study consists in identifying the physical variables on which the IF$_1$ depends (the IF$_3$ and the IF$_4$ are already directly described by the variables control period and time, respectively). The vibration level, whose range of variability has been arbitrarily set to $[0, 1]$, adequately characterizes the defined IF$_1$ and its value is computed starting from the values of two physical variables measured by means of sensors (e.g., strain gauges): amplitude and frequency of the vibration fundamental wave. In particular, the mean values of these variables in the time elapsed since the system has started to work are given in input to the BM, which links them to the IF$_1$ by means of a FRB.

Figure 2~~Figure 2~~ shows the fuzzy sets, defined by means of triangular membership functions, partitioning the variables in input to the BM:

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1. 'Low', 'Medium' and 'High' are the fuzzy sets defined on the UoD $[0, 5]\ mm$ describing the mean value of the amplitude of the fundamental wave;

2. ‘Low’, ‘Medium’ and ‘High’ are the fuzzy sets defined on the UoD $[0, 200]\ Hz$ describing the mean value of the frequency of the fundamental wave.

Table 2 ~~Table 2~~ shows the rules that model the influence of the mean values of the Amplitude and the Frequency on the IF_1. For example, the bottom-right element of Table 1 represents the rule: *if* Amplitude *is* Low *and* Frequency *is* Low *then* IF_1 *is* Soft.

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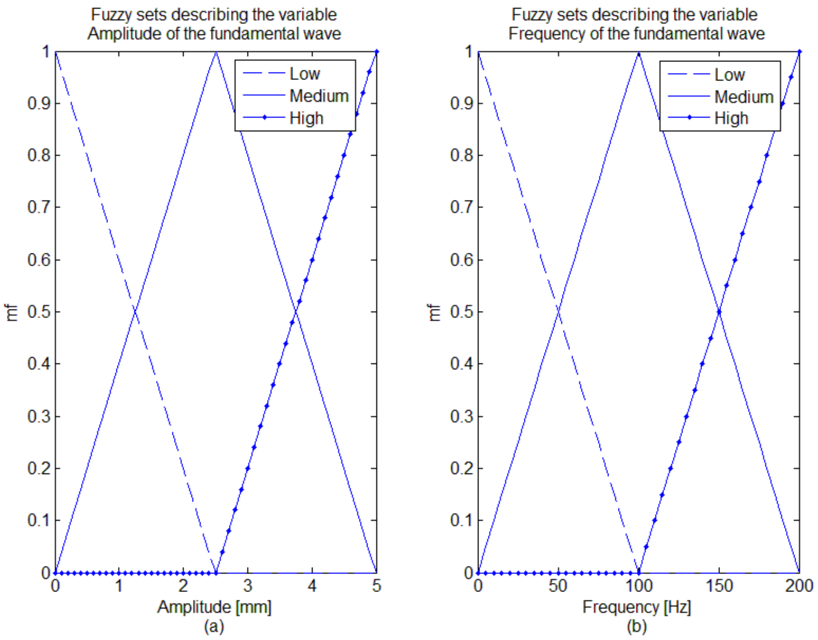

Figure 2. Fuzzy sets of the variables in input to the Backward Module.

		Mean frequency of the fundamental wave		
		High	*Medium*	*Low*
Mean amplitude of the fundamental wave	*High*	Heavy	Heavy	Medium
	Medium	Medium	Medium	Soft
	Low	Medium	Soft	Soft

Table 2. Fuzzy rules defining the relationship between the inputs and the outputs of the BM tailored to the IF1.

Generally speaking, the vibration in the location in which the system of interest works is caused by other components either because they are degrading (e.g., the increase of the eccentricity of the centre of gravity in rotating machines) or because they have been designed in such a way that a periodic load is applied on the other coupled components (e.g., alternating machines discharging loads on the same basement of the system of interest). Since, in general, the behaviour of both the components producing the vibration and the other components of the overall system (which modify the vibration wave) is stochastic, the vibration profile suffered by the components is also stochastic.

For simplicity, but without loss of generality, in the present case study, an arbitrarily chosen vibration profile is assumed in input to the BM, in terms of the mean amplitude and the mean frequency of the fundamental wave (Figure 3~~Figure 3~~).

Such profile "lived" by the component influences its degradation behaviour; the intensity of such influence is assessed by means of the dedicated fuzzy logic model built. Figure 4~~Figure 4~~ shows the activation profile in time of the fuzzy sets Low, Medium and High, representative of the vibration conditions in terms of mean amplitude (top Figure) and frequency (bottom Figure) of the fundamental wave. The combination of these activations by the FRB of Table 2 ~~Table 2~~ within a Mamdani inference system results in the time profile of the degrees of activation of the Soft, Medium and Heavy levels of IF_1 reported in Figure 5~~Figure 5~~. The Medium level is the most activated for large part of the mission time; Soft and Heavy levels are less activated, and in a similar way. In the first part of the mission time, the rule '*if* Amplitude *is* High *and* Frequency *is* Low *then* Environment *is* Medium' has the largest activation degree whereas the rules '*if* Amplitude *is* High *and* Frequency *is* Medium *then* Environment *is* Heavy' and '*if* Amplitude *is* Medium *and* Frequency *is* Low *then* Environment *is* Soft' are those with largest activation degrees among those with 'Heavy' and 'Soft' consequents, respectively. With the vibration profile of Figure 3~~Figure 3~~, the two latter rules increase their activation degrees up to the central part of the mission time as the activation degree of the first rule becomes smaller; this leads to the three levels having almost the same degree of activation of about 0.5 at $t = 5.5 \cdot 10^4\ h$: at this time, there is complete uncertainty on the influence of the IF_1 on the degradation level of the component; then, in the central part of the mission time, the activation degree of the set 'Medium' starts again to increase because the activation degree of the rule '*if* Amplitude *is* Medium *and* Frequency *is* Medium *then* Environment *is* Medium' becomes larger whereas the degrees of activation of the rules with consequents 'Heavy' and 'Low' begin to decrease.

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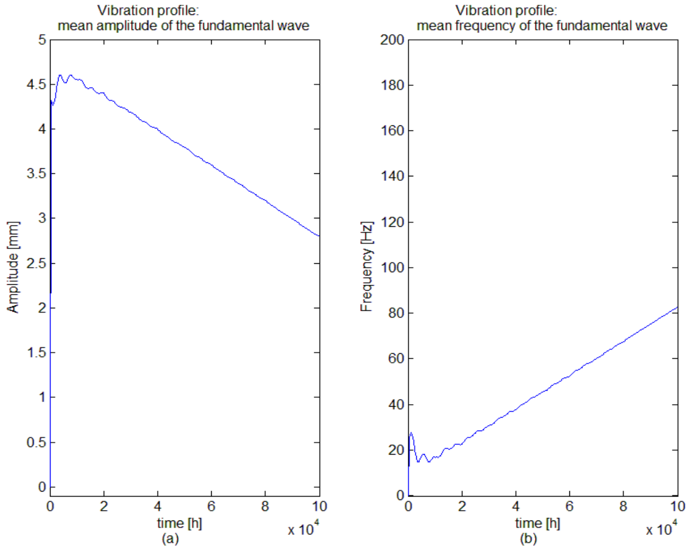

Figure 3. Vibration profile applied to the component, in terms of mean amplitude (to the left) and mean frequency (to the right).

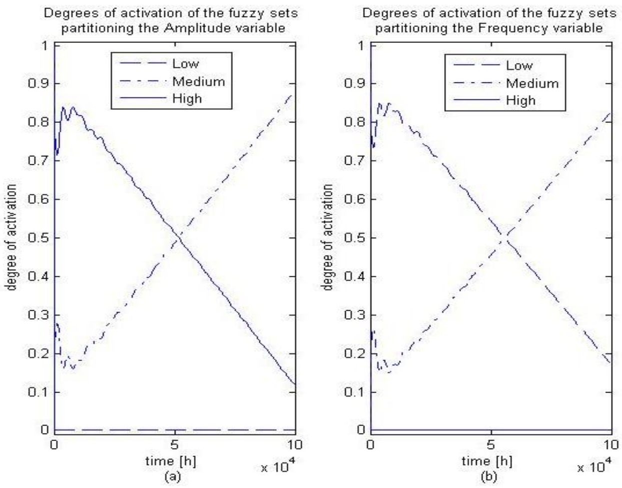

Figure 4. Degrees of activation of the fuzzy sets partitioning the variables in input to the Backward Module for the given vibration profile.

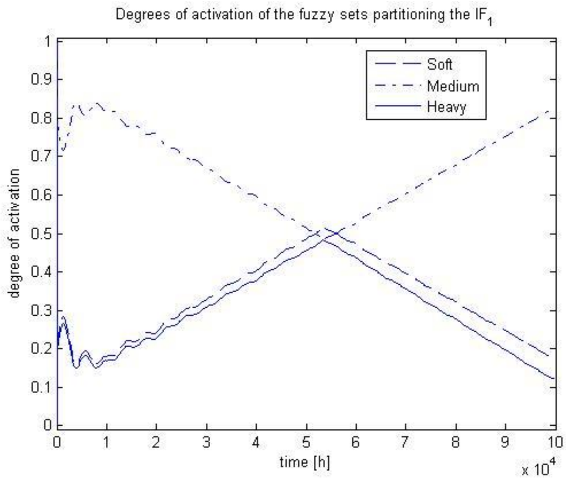

Figure 5. Degrees of activation of the fuzzy sets partitioning the IF1, for the given vibration profile.

Forward Module

The objective of the Forward Module is to provide a description, in terms of fuzzy rules, of how the IFs impact on the evolution of the degradation process. In other words, a FRB is built which links the identified IFs with the component degradation state and thus its failure rate.

In the considered case study, the Forward Module consists in identifying the failure rate of the seals of the WFTP. More precisely, a fuzzy model has been built based on rules as, for example: '*if* Environment *is* Soft *and* Maintenance *is* Frequent *and* Age *is* Young *and* Previous Degradation State *is* Good *then* Degradation State *is* Good'. As before, the rules defining the FRB are obtained from expert knowledge. The antecedent 'Previous Degradation State' has been introduced in order to ensure that the degradation state does not decrease as the age of the component increases.

The output fuzzy set 'Degradation State' is eventually defuzzyfied to limit the propagation of the uncertainty. Defuzzyfication is done by simply selecting the degradation state with the highest degree of activation.

Figure 6~~Figure 6~~ shows the application of the proposed model on the component which lives in the environment previously introduced and inspected every $7000\ h$, with no failures during the mission time.

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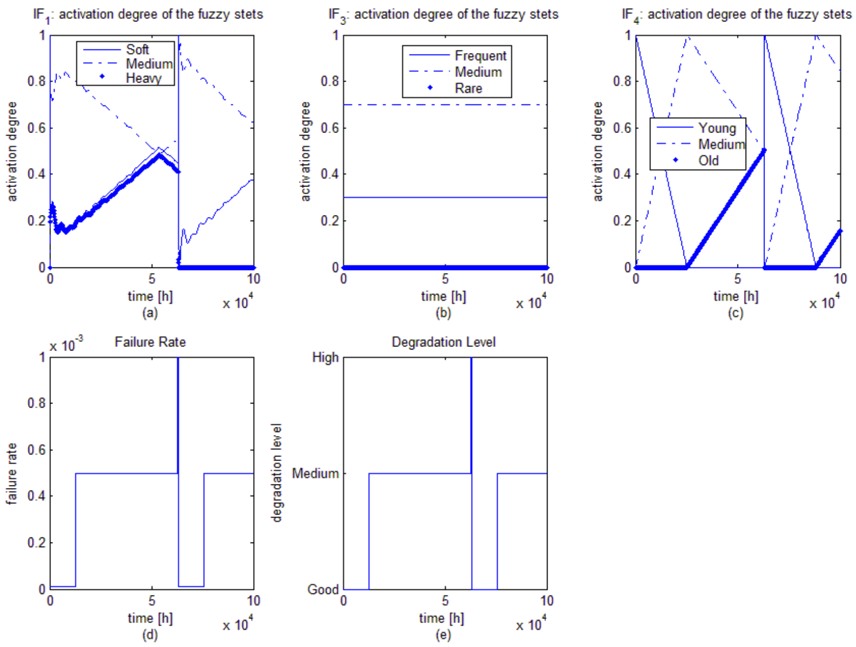

Figure 6. Activation degree of the IFs fuzzy sets and of the degradation state, failure rate value and defuzzyfied degradation state considering a control period of 7000 h when no failure occurs.

The evolution of IF_1 (Figure 6~~Figure 6~~(a)) and IF_4 (Figure 6~~Figure 6~~(c)) is straightforward until the time instant $t = 6.3 \cdot 10^4 h$, when the component is found to be in the degradation state "Bad" and it is replaced by a new one, whose age is zero and with no accumulated vibration. From that time on, the IF_1 is computed taking into account the vibration suffered by the newly installed component and the IF_4 evolves naturally as its age. The IF_3 (Figure 6~~Figure 6~~(b)) is constant, regardless the replacement of the component, since the maintenance policy is the same throughout the mission time.

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Figure 6~~Figure 6~~(e) shows the defuzzyfied degradation state of the component, which directly determines the failure rate value (Figure 6~~Figure 6~~(d)).

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4.3 Maintenance policy assessment

In the present Section, the results of the Monte Carlo unavailability estimation of the component presented in Section 4.1 are reported and discussed. The computational model has been developed in Fortran. Table 3~~Table 3~~ shows the values of the parameters used in the case study:

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Parameter	Value
Dt	$100\ h$
Number of MC trials	10000
CPU time (Intel Pentium, 1.6 GHz)	$56\ sec$

Table 3. Monte Carlo parameters.

The instantaneous unavailability of the component with the related 68.3% confidence interval (i.e., plus and minus one standard deviation) is shown in Figure 7~~Figure 7~~.

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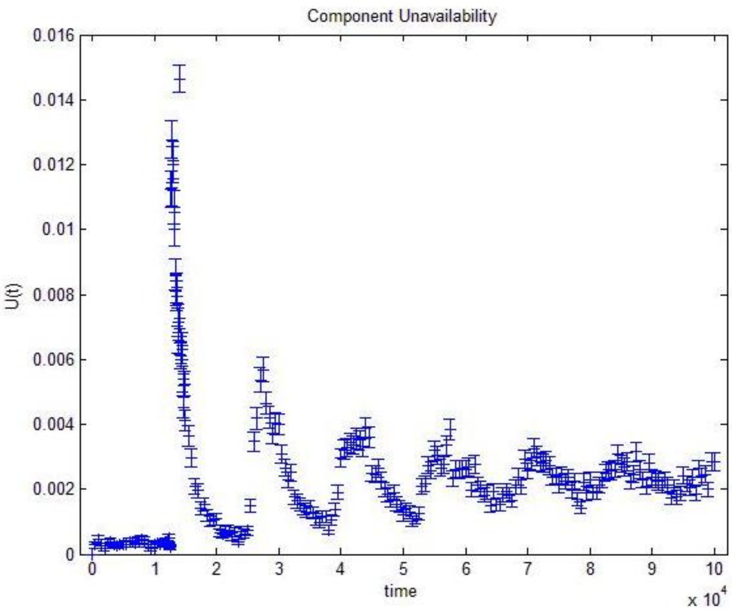

Figure 7. Instantaneous component unavailability and its standard deviation.

Two large peaks appear in the first part of the component mission time. The first, at $t = 1.26 \cdot 10^4\ h$, corresponds to the time instant in which the degradation process has a transition from degradation state 1 to 2, with the failure rate of the component worsening from $10^{-5}\ h^{-1}$ to $5 \cdot 10^{-5}\ h^{-1}$. After $t = 1.26 \cdot 10^4\ h$ two different conflicting trends are observed:

- an increase in the unavailability due to the contribution of those simulated components which have had a failure before $t = 1.26 \cdot 10^4\ h$ and thus reach the degradation state 2 with a delay;
- a decrease of the unavailability due to the reduced failure rate $(10^{-5}\ h^{-1})$ of those simulated components that have undertaken corrective maintenance.

The second effect is prevalent and thus the unavailability decreases. The second peak occurs at $t = 1.40 \cdot 10^4\ h$, when the first control occurs after the component has entered in degradation state 2 and thus all the simulated components that did not have a failure before are now unavailable, due to the downtime associated to the preventive maintenance action.

Notice that in the considered case study it is extremely unlikely to achieve the degradation state 3: with a failure rate associated to the degradation state 2 equal to $5 \cdot 10^{-4}\ h^{-1}$ and a time interval of $4.98 \cdot 10^4\ h$ between the achievement of the degradation states 2 and 3, the probability of encountering a system in a degradation state 3 is smaller than $e^{-5 \cdot 10^{-4} \cdot 4.98 \cdot 10^4} = 1.39 \cdot 10^{-11}$. This is the reason of the non-appearance of a peak of unavailability at $t = 6.3 \cdot 10^4\ h$, at which the component would reach the degradation state 3 (Figure 6~~Figure 6~~).

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4.4 Maintenance Policy Optimization

The proposed framework has been used to optimize the maintenance policy described in Section 4; in particular, the optimization has been performed with respect to the Control Period.

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Figure 8
~~Figure 8~~ and Figure 9~~Figure 9~~ show the mean unavailability of the component and related 68.3% confidence interval and the maintenance costs for varying values of the Control Period.

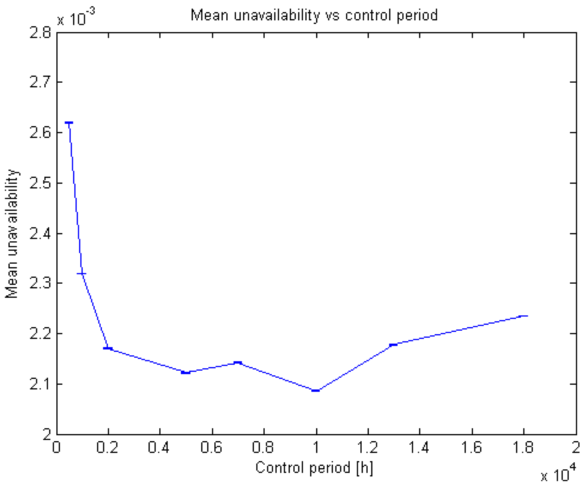

Figure 8. Estimated mean unavailability varying the Control Period, with related 68.3% confidence interval.

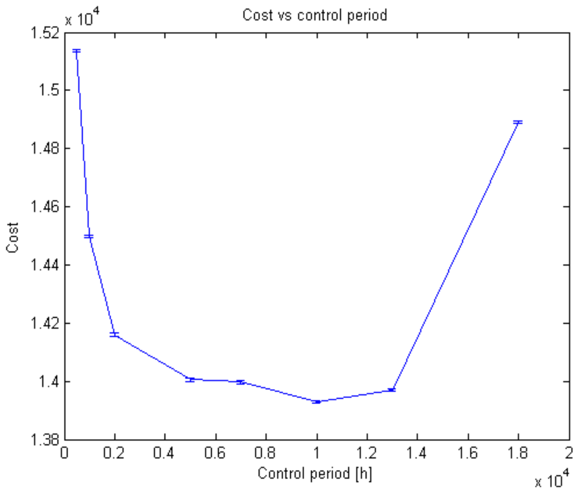

Figure 9. Estimated maintenance costs varying the Control Period, with related 68.3% confidence interval.

The mean unavailability shows an initially decreasing trend, with a first minimum in correspondence of a Control Period equal to $5000\,h$ and another, deeper one in correspondence of a Control Period of $10000\,h$, after which the trend starts increasing. The maintenance cost has a similar trend, but with only the minimum in correspondence of a Control Period of $10000\,h$.

One may then conclude that under the considered maintenance policy, the best Control Period is $10000\,h$, with respect to both availability and costs. On the other hand, the relative flatness of the minimum is such that there is a wide interval of Control Period values in which both the mean unavailability and the maintenance cost are small and with little variations, which gives a margin of operational flexibility for choosing the Control Period value also accounting for other criteria (e.g., opportunistic maintenance).

5. Conclusions

A novel modelling framework has been proposed for assessing the impact of the adopted maintenance policy and of the specific conditions in which a component works on the performance of the overall system of which the component is part.

Given the lack of experimental evidence on the influence of the living conditions of a component on its degradation, expert judgment is often used. This has suggested the use of a fuzzy approach for representing the expert knowledge in the degradation model. Then, Monte Carlo simulation is used to assess the goodness of the maintenance policy in terms of system availability.

To illustrate the approach, the modelling framework has been applied to the seals of the WFTP and their degradation due to contact fatigue. The proposed modelling approach has allowed the optimization of the control period, within the considered maintenance policy. The example has shown the potential of the approach but some issues remain open:

- ~~The~~ the validation on a multi-component system;
- ~~The~~ the definition of the maintenance policy is done only in terms of the control period and in terms of definition of the thresholds between the degradation levels. It does not account for the effectiveness of the maintenance tasks, the dependence of the effect of the maintenance action on some other factors (e.g., the number of maintenance interventions occurred in the past or the time since the last maintenance), the human errors that can happen when a maintenance action is performed, etc. Inclusion of these aspects could be needed when performing the comparison of different maintenance policies;
- ~~The~~ the operation of defuzzyfication performed on the output of the Forward Module, does not propagate the uncertainties affecting the degradation state reached by the component. This leads to MC simulations which sample from exponential distributions without considering the uncertainty of the parameters of those distributions~~.~~;
- ~~The~~ the Mamdani inference limits the activation degrees of the degradation states to values smaller than 1, i.e., it is not guaranteed that the maximum of the activation degree of the degradation state is equal to 1. This problem, which leads to a smaller confidence on the degradation state, may be overcome by considering more sophisticated inference systems.

As concluding remark, it seems important to stress one more time that the practical exploitation of the flexibility offered by the modelling framework proposed needs to be carefully managed with respect to the data available for the estimation of the many model parameters involved; this is fundamental in order to avoid over-parameterization of the model.

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