A new modeling framework of component degradation

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ABSTRACT: Modeling the degradation process of a component is a fundamental issue for maintenance policy definition. In this work, a degradation model based on the concept of component 'effective age' is proposed. The effective age of a component is treated like a physical variable, indicative of its degradation state, and allows to describe the fact that age may evolve faster or slower than chronological time in adverse or favorable working conditions, respectively. Under this concept, the objective of degradation modeling becomes the identification of the relations between the environmental and operating conditions of the component and its effective age. In particular, the proposed degradation modeling paradigm is thought to be applied to the situation, very common in practice, in which the only available information to build the model is that elicited from experts. The proposed modeling framework is applied to a real case study of a medium voltage test network.

1 INTRODUCTION

The aim of the present work is to propose a methodology to build a model in support of maintenance decision-making for a generic electrical component, in the case in which the only available information comes from an expert. This information is subjective, qualitative and very often in implicit form; for example, experts usually resort to linguistic variables like "*high*", "*often*" and "*slow*" and provide qualitative statements like '*the environmental conditions are good*'. Thus, the information elicited from experts needs to be properly interpreted, represented and propagated through the model. To do this, the present work resorts to the theoretical framework of Fuzzy Logic (FL, Bojadziev & Bojadziev, 1996), due to its capability of dealing with imprecise variables and linguistic statements. In this respect, notice that if compared with Probability theory, the FL framework allows to treat uncertainty in a way more adherent to the expert's way of reasoning.

The reminder of the paper is organized as follows: Section 2 illustrates in details the modeling solutions adopted to address the degradation process. Section 3 describes the model of the impact of the maintenance actions on the evolution of the degradation mechanism. Section 4 is dedicated to the description of the method proposed to estimate the maintenance policy performance indicators. A case study dealing with the optimization of a Condition-Based Maintenance (CBM) policy of a medium-voltage circuit breaker is presented in Section 5. Results are given in Section 6 and conclusions are drawn in the last Section.

2 DEGRADATION MODEL

In all generality, the effectiveness and precision of degradation models increase when these are able to capture the specificity of the component, which derives from the particular environmental and operating conditions in which it works. In fact, in analogy to what happens with human beings, two similar components (i.e., of the same production lot) with the same calendar age will probably be in a different state if they have been operated differently, in different environmental conditions and/or under different stress levels. To model such situation, we resort to the concept of 'effective age' of a component to describe the fact that age may evolve faster or slower than chronological time in adverse or favorable working conditions, respectively (Martorell et al., 1999, Kijima, 1989, Vesely, 1987, Samanta et al., 1991). Then, the effective age can be taken as indicator of the degradation state of the component; in other words, it can be considered like a physical variable that is representative of the health state of the component (e.g., in the same way as the crack length may be used to indicate the degradation state of a mechanical component, Baraldi et al., 2011). Under this concept, the objective of degradation modeling becomes the identification of the relations between the environmental and operating conditions of the component and its 'effective age'.

The practical view undertaken in this work of building a degradation model based only on the expert's information compels to properly address two issues:

1. The degradation process needs to be modeled as a discrete-state process, in recognition of the fact that experts are more familiar with this way of thinking of the degradation mechanisms (Baraldi et al., 2011).
2. There is no stochastic model available to describe the degradation behavior in normal operating conditions.

These two features call for the development of a new degradation modeling paradigm; what we propose is discussed in the following.

Firstly, the concept of effective age (indicated by $w(t)$) is introduced as defined in the following Equation and sketched in Figure 1:

$$w(t) = \Psi(IF(t')) \cdot (t - t') + w(t') \qquad for\ t' \le t \le t'' \quad (1)$$

$$w(0) = 0$$

where $\Psi(IF_1(t'),...,IF_k(t'))$ is the 'age speed', which depends on the values of the Influencing Factors (IFs, i.e., conditioning aspects of the component life such as environment, quality, etc.) at *t=t'*; its value is 1 in nominal working conditions. The variable t' is the last time instant at which the occurrence of an event has changed the age speed of the component; finally, t'' is the next time instant at which the age speed will experience a further change (i.e., between t' and t'' no event occurs that changes the age speed).

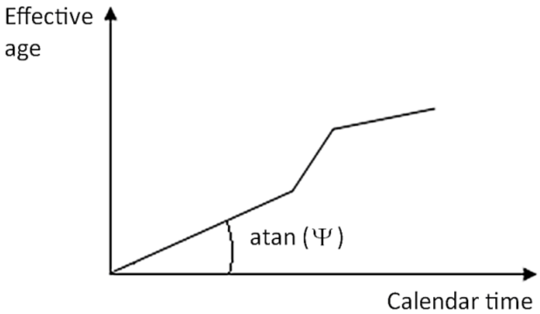

Figure 1: Example of time evolution of the effective age depending on the component working conditions through the age speed Ψ.

Once the effective age has been defined, the possible degradation states of the system need to be identified. To this aim, $n-1$ thresholds, $w_1,...,w_{n-1}$, are set on the effective age, which define the n degradation states *D=1, 2,..., n* (Figure 2). In this way, a relation between the effective age of the component and its discrete degradation states is established.

The next step is to model the dependence of the age speed Ψ on the component working conditions; these latter are characterized by means of a set of *K* IFs identified by the expert which define the function $\Psi(IF_1,...,IF_K)$. In this regard, direct elicitation from the expert of the value of the age speed is not feasible, since this concept tends to remain intangible. Rather, what one can do is to ask the expert to assess, for a given combination of the IFs, the length of the time interval that the component takes to change its degradation state, and connect the age speed to this value. For example, if the expert knows that in certain conditions (characterized by a particular set of values $\{IF_1^*,...,IF_K^*\}$ of the IFs) the transition time between degradation states *D*=2 and *D*=3 is $t_{2\to3}^*$, then the corresponding age speed Ψ^* can be defined as:

$$\Psi* = \frac{w_2 - w_1}{t_{2\to3}^*} \qquad (2)$$

where w_1 and w_2 are the thresholds on the effective age which separate *D=1* from *D=2* and *D=2* from *D=3*, respectively (Figure 2). However, since the information provided from the expert is expected to be of the form *"If* the environment is *Mild*, *then* the transition time is *Small"*, a fuzzy approach (Bojadziev & Bojadziev, 1996) is applied to deal with this type of qualitative information.

In practice, the Universe of Discourse (UoD, i.e., the set containing all the possible values) of each IF is firstly partitioned in a suitable number of fuzzy sets, e.g., "Good", "Medium" and "Heavy".

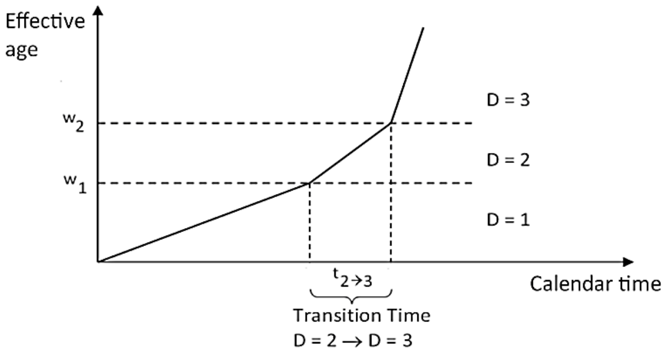

Figure 2: Depending on the IFs, the expert specifies the age speed by giving the transition time between one degradation state and the following one.

The same is done for the transition time, which may be reasonably partitioned in "Small", "Medium" and "High", according to the expert's view. Then, a set of fuzzy rules are elicited from the expert to relate each combination of the IFs to the transition time. For the sake of clarity, we recall that fuzzy rules are made up of two parts: antecedent or premise and consequence or conclusion; for example, the antecedents of the rule *"If* IF_1 is Good *and .... and* IF_K is Heavy *then* the transition time is *Small"* are '*If* IF_1 is Good',…, *If* IF_K is Heavy', whereas the consequent is 'the transition time is *Small'*. A degree of truth is associated to each of the antecedents of every rule, which describes to what extent the values of the variables describing the current situation under analysis match the expert view (e.g., the degree of truth that the current value of IF_1 belongs to the set Good, from the expert's point of view). Then, a degree of truth is assigned to each rule, inferred on the basis of the degrees of truth of its constituents. Finally, all the rules are logically aggregated to provide a fuzzy set that describes the implication on transition time; this set is finally defuzzified (Bojadziev & Bojadziev, 1996) into a crisp value of the transition time, which is provided in input to Eq. (2) to find the age speed.

3 MAINTENANCE MODEL

A number of maintenance models in which the maintenance actions impact on the effective age have been proposed in the literature (e.g., Martorell et al., 1999, Wang, 2002, Pham & Wang, 1996, Doyent & Gaudoin, 2004, Kumar & Klfesjö, 1994). However, these models do not fulfill the requisite of relying only on the knowledge of the expert, who usually does not think in terms of age reduction to judge the efficiency of a repair. To this aim, a set $\{O_1, O_2, \ldots, O_n\}$ containing all the possible outcomes of a repair action is introduced; each member of this set represents the degradation state in which the component is left after the maintenance action. Namely, O_0 refers to the As Bad As Old (ABAO) maintenance actions, whereas the generic outcome O_i describes the event "after the repair, the degradation state of the component is left to the beginning of $D=i$". The expert is asked to assess the likelihood that the maintenance action will actually bring the component in $D=i$, for $i=1, 2, \ldots, n$. In the spirit of this work, the likelihood of a future event is partitioned in 4 fuzzy sets, namely "Very low", "Low", "High" and "Very High", as shown in Figure 3.

For example, let us consider the particular situation in which only three degradation states are defined (i.e., $D=1, 2, 3$), and the CBM policy foresees that the component overtakes repair actions if it is found in degradation state $D=2$ at inspection; no maintenance action is performed in $D=1$, whereas the component is replaced if found in $D=3$. Then, the possible outcomes of a repair action are:

- O_0: the degradation is left unchanged (ABAO)
- O_1: the degradation is lowered to the beginning of $D=1$ (As Good As New, AGAN)
- O_2: the degradation is lowered to the beginning of $D=2$
- O_3: the degradation is increased to the beginning of $D=3$ (bad maintenance)

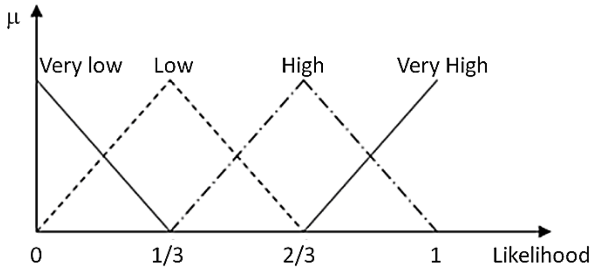

Figure 3: Fuzzification of the likelihood of the events O_i.

For the sake of simplicity, let us assume that the expert believes that only the outcomes O_0 and O_2 are possible. In this case, denoting by L_0 and L_2 the likelihood that the outcome of a repair will be O_0 and O_2, respectively, the expert's assessment may be expressed by the following sentences:

- L_0 is Low
- L_2 is High

On the other side, several factors may influence the likelihood of the outcome of a repair, such as the number of repairs already done, the starting degradation state, the skill of the operator, etc. In the present illustrative example, only the number of repairs overtaken in the past is considered. In particular, two fuzzy sets "Low" and "High" for the linguistic variable "number of repairs already done" are defined (Figure 4).

In this case, denoting by N the number of repairs performed on the component, the expert's assessments may be expressed by the following rules:

1) *If* N is Low *then* L_2 is High.
2) *If* N is Low *then* L_0 is Low.
3) *If* N is High *then* L_2 is Low.
4) *If* N is High *then* L_0 is High.

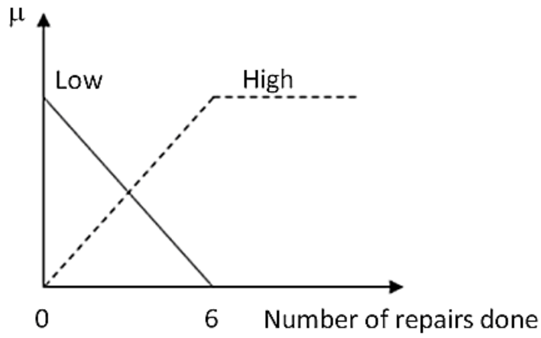

Figure 4: Fuzzification of the number of repairs already done.

These rules can be implemented for any specific value of N; then, rules 1) and 3) are aggregated to give L_2, and rules 2) and 4) to give L_0. Two crisp values are finally obtained from the defuzzification of L_2 and L_0, which are then normalized to represent the probabilities associated to the two possible results of the maintenance action.

4 INTEGRATION OF THE FUZZY MODEL AND MONTE CARLO SIMULATION

One relevant issue in the quantification of the model proposed is the integration of the FL model, which provides the failure rate associated to the degradation state, and the Monte Carlo (MC) module, which simulates the stochastic failure behavior of the component and the changes in the IFs caused by random external events. The output provided by the simulation module is the estimation of the component mean unavailability over the mission time, which is taken in this work to measure the performance of the maintenance policy to be assessed.

The solution proposed in (Baraldi et al., 2011) to embed the fuzzy module in the MC scheme is adopted in this work. Briefly, a large number of trials or histories (i.e., random walks of the system from one configuration to another) are simulated and the portion of mission time in which the system is in a down state is collected in every trial; finally, these values are averaged to provide an estimation of the desired quantity, i.e., the average unavailability over the mission time.

5 CASE STUDY

The objective of the present case study is to optimize the maintenance of a Medium-Voltage Circuit-Breaker (MVCB), which protects a short circuit network for testing various devices such as breakers, isolators, disconnector switches, etc. (Figure 5). The breaker is placed just after the generator, and its main function is to interrupt the short circuit current when required.

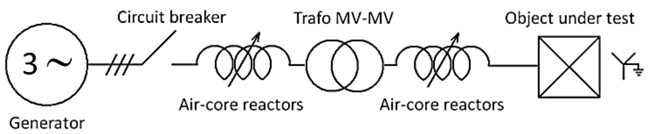

Figure 5: Overview of the Medium Voltage test network.

Every time the MVCB interrupts the current, an electric arc takes place between its contacts, which consequently, wear off. If the degradation state is Very Bad, then the breaker loses its interrupting capability; in this case, the arc is not readily extinguished and serious damages can occur before other emergency systems clear the fault. A CBM policy is performed to prevent the wear from reaching a critical value. This is based on periodic visual inspections, in which the breaker is disassembled and the degradation state of the contacts controlled. In particular, three alternative scenarios are possible upon inspection:

- Contacts are as good as new: no action is taken and the breaker is put back together.
- Contacts are worn but the interrupting capability is still good: in this case, manual polishing is performed to smooth the surface of the contacts and decrease their electrical resistance.
- Contacts are heavily worn: the interrupting capability is at risk and they must be replaced with new ones.

Since maintenance actions, as well as failures, have a cost, the best Inspection Interval (II) is a non trivial issue which can be effectively addressed by means of a MC simulation over a long time span, e.g., 15 years.

The results of the process to elicit from the expert the information to build the model are summarized in the following.

5.1 *Degradation states*

The contact resistance is a good indicator of the contacts degradation. This quantity has never been measured, but it is possible to conceive a practical procedure to get this information at every inspection. Three degradation states can be defined:

- *D=1*: contacts are as good as new.
- *D=2*: contact resistance is affected by arc wear, and maintenance (contact polishing) can effectively reduce it.
- *D=3*: contacts must be replaced.

A failure event may also occur in every degradation state. It is assumed that the failure times are exponentially distributed, with failure rates that depend on the degradation states.

5.2 *Influencing factors*

The only variable that characterizes the environment is the interrupted current in each test: the higher the interrupted current, the heavier the wear by arc erosion. Most of the current settings range from 10 to 50 kA, so we introduce three fuzzy sets for the environment, namely “Low”, “Medium” and “High”. For the sake of simplicity, triangular membership functions are considered (Bojadziev & Bojadziev, 1996)0 (Figure 6).

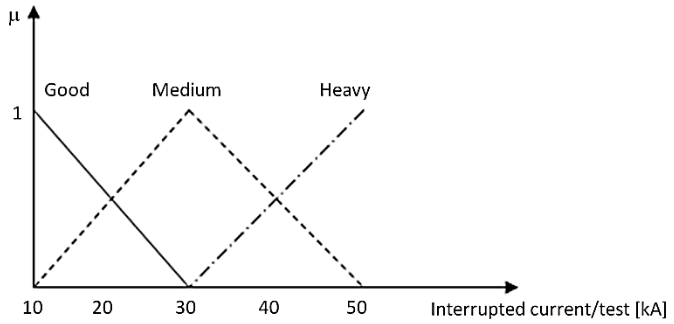

Figure 6: Fuzzy set definition for the environment, according to the interrupted current.

5.3 *Effect of the influencing factors on the effective age*

When the contacts are new, or as good as new (*D=1*), an initial arc wear takes place. This process is rapid (two or three months) and fairly independent on the interrupting conditions. On the other hand, when the contacts are in degradation state *D=2* the value of the interrupted current heavily influences the transition time toward state *D=3*, in which the contacts ability to interrupt the current is compromised. Table 1 summarizes the expert assessments, which lies on the fuzzification of the transition time shown in Figure 7.

Table 1: Expert's estimation of the transition time.

	Environment		
	Good	Medium	Heavy
Transition time $D=1 \rightarrow D=2$		Very small	
Transition time $D=2 \rightarrow D=3$	High	Medium	Small

5.4 *Maintenance*

An inspection of the contacts is scheduled at constant intervals. The maintenance actions depend on the degradation state in which the contacts are found at inspection:

- *D = 1*: No actions
- *D = 2*: Contacts polishing to reduce the contact resistance
- *D = 3*: Contacts replacement

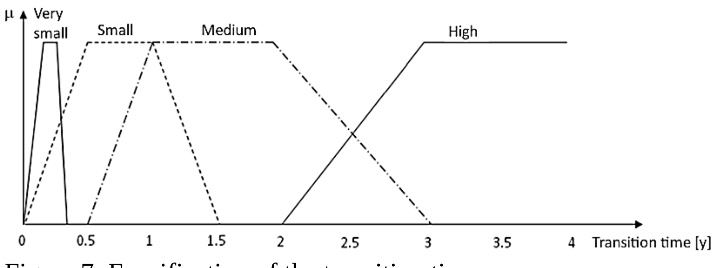

Figure 7: Fuzzification of the transition time.

The number of previous maintenances is considered as a factor that can influence the quality of a repair. The universe of discourse is partitioned by means of two fuzzy sets, "Low" and "High" respectively, as shown in Figure 4.

Table 2 summarizes the expert's assessment for what concerns the likelihood that a repair either will reduce the degradation state (L_2) or leave it as it currently is (L_0).

Table 2: Likelihood of the two possible outcomes of a repair, as a function of the number of repairs already done.

	Number of repairs already done	
	Low	High
L_0	Low	High
L_2	High	Low

5.5 *Parameter evaluation*

Table 3 summarizes the values of the parameters used in the simulation. The failure rates of the exponential distributed failure times in the three degradation states are λ_1 = 1.0e-6 h^{-1}, λ_2 = 2.1e-5 h^{-1} and λ_3 = 2.5e-2 h^{-1}, respectively.

Table 3: Summary of the simulation parameters.

Quantity	**Expert's assessment**
Inspection duration [h]	8
Maintenance duration [h]	8
Scheduled Replacement duration	16
Replacement duration after failure [h]	40

6 RESULTS

Figures 8 shows the results of the CBM model built according to the procedure described above. These results are provided by MC simulation of 5000 trials with the mission time of the component set to 15 working years. The computational time for each simulation is a mere few seconds on a regular desktop computer.

The average unavailability reaches a minimum in correspondence of II=3500 working hours. Further investigations show that this minimum corresponds to the situation in which an inspection takes place just before the component enters the third degradation state.

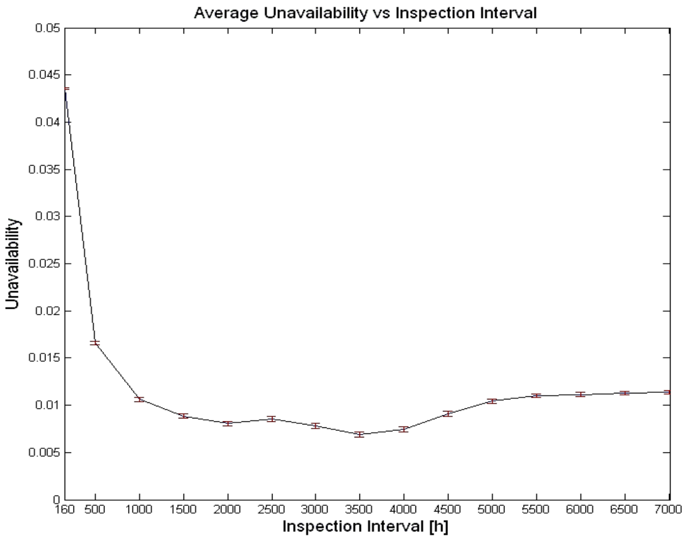

Figure 8: Average unavailability as a function of the II.

7 CONCLUSION

We have proposed a method to use the information elicited from an expert to build a maintenance model of a generic electrical component, which is then simulated in order to optimize the maintenance policy.

One key feature of the model lies in its capability of accounting for the actual working conditions in which the component operates. This capability comes from the fact that the aging process of the component is deduced step-by-step by means of interviews, in which the expert's experience on components working in different conditions with different aging behaviors is captured and made exploitable for modeling. In this setting, we have largely resorted to FL to represent and propagate the imprecision associated to the qualitative sentences of the expert.

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