MODELLING THE IMPACT OF PREVENTIVE MAINTENANCE OVER THE LIFETIME OF EQUIPMENTS

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ABSTRACT

The presented approach aims to define and develop a probabilistic model to measure the effectiveness of preventive maintenance actions on equipment and thus, optimize maintenance plans. To do so, it is necessary to deal with heterogeneous data, such as experience feedback and experts. The Bayesian approach provides a theoretical framework to treat these data. A numerical study applied to electric power transformers is presented to validate the proposed approach. It results an evaluation of preventive maintenance effects and an actualized maintenance schedule.

INTRODUCTION

It is well known that asset management is an important sector in the various activities of generation, transmission and distribution of energy. It is important, to ensure proper management of assets, to have strict control on the various stakes involved in asset management. For instance, one can quote: economic stakes, security, dependability… etc. Our study focuses on the operational safety of power transformers. These systems represent significant entities in the power grid and can impact significantly on the previous stakes in case of failure. In this context and to ensure better management of assets, we aim to adapt the periods of preventive maintenance (PM) for power transformer's components.

In literature, there are several models and approaches dealing with the optimization of maintenance periods. Each method differs according to the criterion of optimization proposed or simply in the approach to reach that point. In [1] the authors propose, in order to minimize the costs involved by maintenance, determine a common interval for inspections and PM. In [2] the author proposes an approach based on costs induced by maintenance actions and the gain in production quality. The author concludes that the application of PM with defined periodicity is no longer justified when the ratio of these two parameters exceeds a certain threshold. Other approaches are based on the effect of maintenance on devices' aging to optimize the maintenance periods. Several models have been proposed for this purpose and have been summarized in [3]. These models are based on the principle of reduction of the age, where we assume that maintained equipment will see its age rejuvenated after maintenance. Some authors like in [4, 5] use these models to study strategies for replacement and maintenance under constraints of obsolescent equipment or to simulate degradation [6].

This document is presented as follows. In the next section, we present the problem that we address and the approaches and assumptions we use. We also give the definition of different notations used in this study. The next section is devoted to the presentation of the mathematical model and calculation methods. In the last section, we take a practical case for applying the theory and present examples of maintenance periods reviewed.

OBJECTIVES OF THE STUDY

The aim of our works is to determine a better definition of PM periods, or at least ensure that current maintenance is still relevant. To redefine PM periods, we choose to base on the risk of failure admitted by the Decision Maker (DM). To achieve this, we define a mathematical model based on lifetime function of maintained equipments, and we deduce the behaviour of unmaintained equipment. In some ways, the approach aims at determining the effect of PM actions on the life of an equipment and then remove them to keep only the behaviour of an unmaintained equipment (its intrinsic lifetime). Then, starting from the characteristics of unmaintained equipments, we vary the maintenance periods to analyze the evolution of risk of failures. The difficulty in this approach is to get to define the behaviour of unmaintained equipments. Indeed, available information concern operated equipments, so they are already maintained preventively. Note that, information arises from the Experience feedback (EXF) of the maintained equipments. In order to vary the sources of information, we propose to combine EXF data and experts opinion about equipment behaviour (Bayesian approach provides a theoretical framework to make this calculation).

NOTATIONS AND DEFINITIONS

Let be a device, subject to breakdowns due to wear or aging. We assume that a failure occurs unexpectedly, so we model this by a random variable (*rv*) T representing the instant of first failure and t any instant. We note:

$f(t)$	the lifetime density function.
$F(t)$	failure time distribution associated to $f(t)$.
N_t	the number of PM up to time t.
A_i	the virtual age of the material i^{th} PM.
t_i	time of i^{th} PM.
V_t	the virtual age at time t ($V_t = t - t_{N_t} + A_{N_t}$)

X_i	time elapsed between the $(i-1)^{th}$ maintenance and the i^{th} maintenance : $X_i = t_i - t_{i-1}$.
B_i	gain in life associated to the i^{th} PM.
α_j	the risk of failure associated to maintenance j.

Lifetime density function (Weibull density function)

We consider the Weibull distribution with two parameters as the lifetime density function ($t_0 = 0$):

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

such that β, η represent respectively, the shape parameter and scale parameter of f. On the other hand, the cumulative function $F(t)$, takes the form:

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}}$$

Virtual age model

This model, proposed by Kijima [7], describes the age of an operating equipment that undergoes successive maintenances. The assumption in this model is that, each PM prolongs component's life (or equivalently, delays the onset of failure), so that, the age of maintained equipment (called it's virtual age) is rejuvenated at time t: $V_t \leq t$.

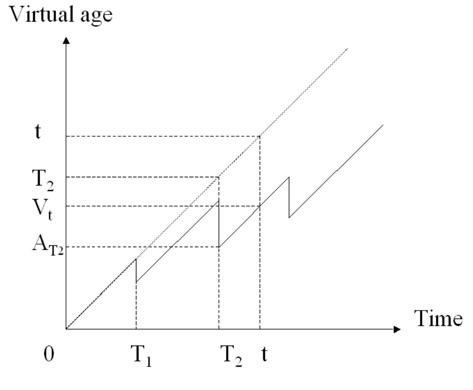


Figure 1: Virtual age of a maintained equipment

Bayesian approach

In this study, we question power transformer experts to have an evaluation of the parameters (respectively β and η) that represent respectively, the average ageing of the equipment and its average lifecycle in addition to uncertainties related to their responses.
This approach is used to provide another source of information and update data. Thus, in Figure 2, the updated (posterior) lifetime density curve is between the two curves issued from the EXF and experts.

Bayes' theorem
Let (Ω, A, P) a probabilistic space and let X be the *rv* associated to a random experiment. If X is continuous then we call Bayesian theorem the following relation:

$$f(\theta / x) = \frac{L(\theta / x) f(\theta)}{\int L(\theta / x) f(\theta) d\theta} ;$$

- x a realization of the experiment;
- θ the parameters that characterize the experiment;
- $L(\theta / x)$ likelihood function (issued from EXF);
- $f(\theta)$ prior density function (issued from the experts);
- $f(\theta / x)$ posterior density function.

HYPOTHESIS OF THE MODELE

- The PMs are supposed periodic.
- We only look at PMs occurring before first failure.
- The transformer is a system composed of five subunits: the tank, overvoltage detector, in charge tap changer, refrigeration circuit and electrical components.
- The analysis of preventive maintenance effects is done on each subunit independently of each other.
- The annual operating time of a material is of 8760 hours.

MODELLING

Modelling PM effects

To model the impact of PM actions on equipment, we use the reduction of age model. Assume that, after each PM, equipment is rejuvenated to some extent. To do so, we implement models of Arithmetic Reduction of Age (ARA) so that, the equipment is rejuvenated to a proportion of elapsed time up to the last observed maintenance (Kijima type 2 [7]):

$$A_k = (1-B_k)(A_{k-1} + X_k) \Rightarrow A_k = \sum_{i=1}^{k}\left(\prod_{j=i}^{k}(1-B_j)\right)X_i$$

To determine B_j values ($B_j \in [0,1]$), we ask experts to evaluate, directly on scale, the gain of life due to PM. Each gain is associated to a quantitative value of B_j:

Extent of gain	**Gain $B_j \in [0,1]$**
Weak	0,1
Mean	0,5
Strong	0,7

Table 1: Gain scale

Modelling experts opinion on the ageing and the average lifecycle

To model the average ageing of a component using experts (denoted β_p), we propose an ageing scale such that, each ageing intensity is associated to a value of β_p :

Ageing intensity	β_p
None	1
Weak	1,5
Mean	2
Strong	3

Table 2: Ageing scale

To estimate the scale parameter by experts: η_p, we question the experts about the average lifetime of subunits.

Modelling an unmaintained equipment

Experts inform us about maintenance actions effectiveness, that allows us at determining the posterior lifetime function of unmaintained equipments (by exploiting the different sources of information: Experts + EXF).

For the prior, we use the experts information on aging and average lifetime. Thus, we determine the parameters β_p, η_p that define the Weibull prior density function.

The likelihood is obtained from the data of unmaintained equipments (using ARA models). The parameters β, η of this distribution are obtained by likelihood maximisation. Likelihood is of the form:

$$L(\beta,\eta / t_1,\dots,t_n) = \prod_{i=1}^{k} \frac{\beta}{\eta}\left(\frac{t_i}{\eta}\right)^{\beta-1} e^{-\left(\frac{t_i}{\eta}\right)^{\beta}} \prod_{k+1}^{n} e^{-\left(\frac{t_s}{\eta}\right)^{\beta}}$$

Here, we consider k failures and $(n-k)$ censored data [8]. Using the Bayesian computation, we determine the posterior density function of unmaintained equipments. (its intrinsic lifetime function)

NEW PM PERIODS

We use in this part, the gain due to maintenance actions and the intrinsic behaviour of equipments, to provide, for each new period of PM, the effect they have on the probability of failure (risk of failure). This is done based on Kijima's model to determine the age that would have equipments undergoing the new period of PM.

Thus, for each new period j, we determine the associated risk of failure α_j through $F(t)$.

The results obtained after simulation of several periods are represented by a curve (see numerical results in the next section). The new periods are determined by changing the current period. For example, in our study we determine the new PM period by adding or subtracting one year (8760 h) for the current period.

NUMERICAL RESULTS

In this numerical application, we take as case of study the structure of the tank. We therefore follow the previous steps to determine the possible periods of PM, according to a risk of failure given by the DM. We assume that PMs performed on the tank are the visual control (VC) and the auditory control (AC). After interviewing experts, we get (referring to Table 2) the following gains in life:

Type of maintenance	Gain	Actual PM period
VC	0,1	17520 h
AC	0,1	17520 h

Experts' data

Interviewing experts on aging and average lifespan of a tank we get $\beta_p = 1$ and $\eta_p = 30$ years ($26{,}3 \times 10^4$ h).

EXF and rejuvenation due to PM

Our sample consists of 150 observed tanks. During the observation, 7 tanks generate an outage. The failures occur at respective dates: 21520 h, 17520 h, 43800 h, 8760 h, 52560 h, 17520 h, 56,560 h. The observation period (censorship) is 70080 h.

Applying the reduction of age according to the gains generated by VC and AC, we obtain the new respective dates of failure: 19768 h, 15768 h, 38719 h, 8760 h, 42731 h, 15768 h, 46731 h. The censorship is of 54226 h. Using likelihood maximisation, these data give us: $\beta = 1{,}26$ and $\eta = 15{,}3 \times 10^4$.

Posterior lifetime density function of unmaintained equipment

Bayes' theorem allows us to deduce the posterior parameters of the Weibull distribution: $\beta_0 = 1{,}04$ and $\eta_0 = 22{,}4 \times 10^4$. Then, we can represent the posterior lifetime function of an unmaintained tank (yellow curve in Figure 2).

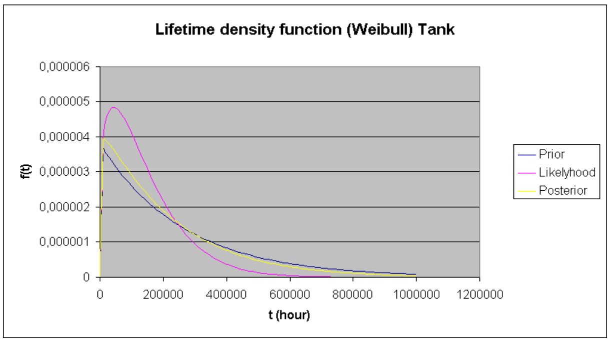
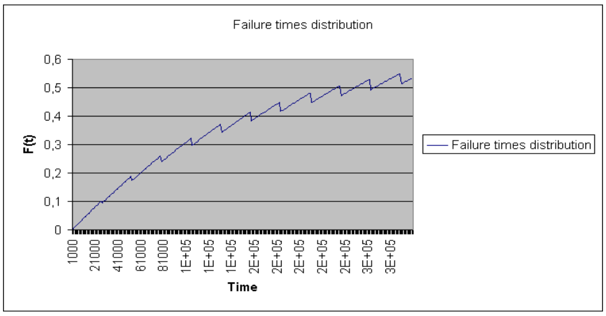


Figure 2: Lifetime function of unmaintained tank

PM period choice

The behaviour of an unmaintained tank being determined, it is possible to apply "fictitious" maintenance periods and determine for each one, the probability of failure given at time $t = MTTF_0$. $MTTF_0$ represents the mean time to first failure of an unmaintained equipment. Note that, when T follows a Weibull distribution, $MTTF \approx \eta$. Thus, for an unmaintained tank, we have: $MTTF_0 = \eta_0 = 22{,}4 \times 10^4$.

For VC and AC cases, we know that they are carried out every 2 years (17520 h). We vary the maintenance periods, taking for each PM (VC and AC) the following periods: 8760 h, 17520 h, 26280 h and 35040 h. For each period, we associate the probability of failure at time $t = MTTF_0$. For example, a PM period of 3 years for the CV, gives the following distribution of failure times:



at $t = MTTF_0 = 22{,}4 \times 10^4$, we have: $\alpha_{VC} = F(MTTF_0) = 0{,}47$. Thus, for each PM:

PM periods (VC or AC)		Risk of failure α_i at time $MTTF_0\,(i \in \{VC, AC\})$
Year	Hour	
1	8760	0,28
2	17520	0,42
3	26280	0,47
4	35040	0,51

Table 3: Risk of failure associated to VC or AC

Figure 3 summarizes the changing in risk of failure according to PM periods of Table 3:

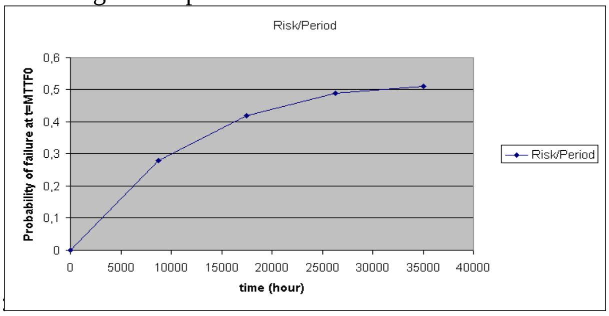


Figure 3: Risk of failure depending on PM periods

Figure 3 is valid for both types of maintenance (VC or AC) since they have the same frequencies and especially the same gain in life. Relying on this curve, the DM can determine (by linear interpolation for example), the proper period of maintenance based on the risk of failure he considers acceptable.

CONCLUSION

In this study, we were able to determine the behaviour of unmaintained equipment by removing the effects of PM actions over its lifetime: providing its intrinsic lifetime function. Starting from this, we apply several maintenance periods to vary the related risk of failure and thus determine the most appropriate PM period for the DM.
In this study, we relied on two sources of information: EXF and experts, in order to diversify sources of data. The opinion of experts allowed us to evaluate directly the gain in lifespan induced by PM.

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