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Assessment of the optimal preventive maintenance period using stochastic hybrid modelling

D'Urso D. [a], Sinatra A. [a], Compagno L. [a], Chiacchio F. [a]*

[a]*University of Catania, Department of Electrical Electronic and Computer Engineering*

Abstract

Also the maintenance world is heading towards the era of artificial intelligence applied to the evaluation of the residual life of devices and predictive maintenance. On the other hand, when the operating conditions can change significantly and randomly, influencing the performance of the system subject to aging phenomena, then the use of a stochastic hybrid approach for the reliability modeling of the system can lead to a closer representation of the reality. This latter approach is applied to the evaluation of the costs associated with the preventive maintenance of the bearings of a centrifugal pump used in petroleum processes. The evaluation is obtained by means of the Monte Carlo simulation methodology.

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Keywords: Stochastic Hybrid Automation; Monte Carlo Simulation; Preventive Maintenance; Bearings

1. Introduction

The mechanical design of a system requires to consider several aspects for ensuring its quality, like the (i) static, dynamic and thermal stresses; (ii) the order in which stresses follow each other over time, as in the case of material fatigue which generally does not adhere to the principle of superimposition of effects; (iii) the random features of the resistance of materials. Although the knowledge of the above-mentioned phenomena is consolidated also from the physical and mathematical (model-based) viewpoint, it can be noticed that the same awareness is not used for reliability, maintenance and prognostic purposes. This limits the capability to improve the evaluation of the operating

* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000 .
E-mail address: author@institute.xxx

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status and the remaining useful life of a device that, according to the most recent research lines [1], is more and more often inferred using some kind of artificial intelligence, based on the analysis of operating data (i.e., data driven).

As known, when it comes to the industrial field, maintenance refers to a general practice that combines at various levels many types of actions, such as organizational, management, technical and executive. In turns, the aim of maintenance is to:

- increase the performance of the productive equipment by minimizing the occurrence of failure, reduce the times of restoration and adjusting the optimal setting of the systems,
- reduce the operational costs (OPEX) of the activities, and
- guarantee the safety of the employees, of the environment and of the systems.

From the execution viewpoint, it is possible to distinguish between reactive or preventive maintenance [2]. The former consists of a set of rules and actions to perform only and after a failure of a system; whereas the latter consists of preventing the breakdown of a system by means of activities that must be carried out before a failure.

Preventive maintenance gives the chance for the research to investigate several deeper goals than the reactive one, like finding the optimal maintenance time that minimizes the system unavailability or identify the working condition deviations that should trigger a maintenance activity (condition-based maintenance). To this end, novel applications known as predictive maintenance have started to become very popular in literature because – with the aid of artificial intelligence and machine learning – they promise to be more effective than preventive model-based methodologies, or to integrate them. Unfortunately, the aid of artificial intelligence or machine learning methods come less when data are scarce, which is the case of consumables and cheap components used in numerous equipment of an industrial plant. In fact, industrial plants are made up of a considerable number of components which, despite are relevant for the continuity of the operations, due to their multiplicity and cheapness are not equipped with a set of transducers that allow a continuous control; consequently, the recording of data useful for the development of an artificial intelligence which improves maintenance and operations management appears unlikely. For example, let's consider the bearing component: its widespread diffusion is well-known and its relevance for the production availability of any industrial process is undoubted. On the other hand, it must be highlighted that maintenance of these components is often performed only when a failure has already happened or just during a periodic the inspection of a system. Nevertheless, as said, the physical principles that allow the design of such components are well-known and could help researchers to improve the knowledge of their operating status and remaining useful life, increasing the effectiveness of the diagnosis and related maintenance operations.

This paper focuses on the maintenance of the bearing and, in particular, it presents the application of a centrifugal pump as case study. Using the cutting-edge mathematical knowledge [3, 4] that allow to model the failure rate of such components with respect to the working and operational conditions, authors try to find out the remaining useful life of a device when operating, environmental and performance conditions change continuously. In order to demonstrate the impact of the workload, typical of an industrial process, a Monte Carlo simulation that implements different operational scenarios is proposed, showing how to assess the optimal period for a preventive maintenance.

The paper is structured as follows: in section 2 the state of the art of dynamic reliability applied to maintenance is discussed; in section 3 the methodology and the use case is presented. Section 4 shows the result of the simulation model achieved and section 5 completes the paper with a final discussion and the research perspective.

2. State of the art

The dependability behavior of a complex system requires the accuracy of methodologies able to consider the dynamic change of the operational working conditions in which the system operates. Such methodologies, falling under the umbrella of the Dynamic Probabilistic Risk Assessment (DPRA), need to model the effects of the process variables like temperature, pressure, vibration, in the failure model of the system increasing the accuracy of the stochastic dependability analysis. This explains why DPRA is nowadays one of the most required activities of critical applications, like nuclear industry [5], and has started to be used also in other industrial fields [6].

The effectiveness of a DPRA model depends on the accuracy and on the detail level used to describe the physical and stochastic behaviour of a system process; due the complexity of the matter, several approaches are proposed, from an ad-hoc modeling to general-purpose methods with the aid of software tools. Generally, model-based techniques are characterized by well-defined hypotheses that identify a limited contour of operating conditions of a system [3], whereas data-driven methods need to rely on statistical inference to enrich the sampling set [7, 8] since they suffer of a lack of data from the field. Both these types of models can be solved analytically or via simulation and – as shown in literature – numerous are the contributions that present innovative ensemble modeling with Bayesian network simulation approaches coupling discrete-event and time-driven simulation [9, 10] based on Stochastic Hybrid Automaton [11].

In DPRA, the failure rate of a system component is one of the most critical parameters of a model. As it can be understood, it can vary with a change of the operational and environmental conditions, and literature present a variegate stream of works that address this topic [12-14]. In a previous paper [3] of the same authors, the study of this parameter has been discussed for the bearings of an electrical engine to assess the reliability of the system. Analysing the contribution of the thermal aging it was demonstrated that the operational and ambient temperatures can significantly affect the workload stress of the components and – in turn – the remaining useful life of the system. In general, the dynamic change of workload, typical of the production schedule of an industrial process, creates the need for an ad-hoc maintenance strategy that can differ from industry to industry as different components in an asset can have different maintenance policies [15]. This means that the Operation and Maintenance function of an industry (O&M) should be able to tune such activities according to their specific productive features. In [16] it was formulated an integrated decisions of maintenance and production using a Markov Decision Process but, as discussed in [15] it is crucial to set a maintenance program able to coordinate the maintenance policies of all components, to minimize costs associated with maintenance and downtime. In [17] a decision support aid for deciding the maintenance strategy by monitoring any change in the machine tool manufacturing accuracy is proposed. In [18] authors try to determine the best time for performing a preventive maintenance of the system, finding also the number of spare parts and facilities in single-item replacement so that the average cost per unit time is minimized, whereas [19] develops an optimal condition-based maintenance (CBM) strategy for a single-unit system during two-stage failure characterized by two different deterioration pace of the item to demonstrate that this causes different scenarios for the optimal CBM strategy.

This paper focuses on the analysis of a single-unit system which, in authors' opinion, is worth of further investigation as far as it concerns the interdependencies among the dynamic continuous changes of the operative working conditions and its inner properties like aging and failure rate. During its lifecycle, these latter can affect the system reliability and availability generating, in turn, the need to improve its maintenance strategy.

3. Methodology

In order to show the application of a stochastic-hybrid reliability model, a case of study is now presented. The process diagram which depicts the main steps of the proposed strategy is described in [22]. As explained in [10], such a modeling requires the coupling of a stochastic and of a deterministic model which describe the behavior of a mechanical system. The mathematical relationships of these two models are presented and linked with each other. Thus, it is demonstrated that the variation of the operating conditions requires a deep Monte Carlo simulating process to overcome the difficulty of solving the hybrid stochastic model, whose complexity increases when the optimal maintenance plan is searched. In the following, as regard to the operating conditions, only the variation of the temperature T is taken into account.

3.1. The Case Study: the bearings calculation.

Figure 1 shows the longitudinal section of a process centrifugal pump for oil & gas application. Bearings B life has to be evaluated in order to define a preventive maintenance plan. Bearings, technical features and operating conditions are reported in table 1.

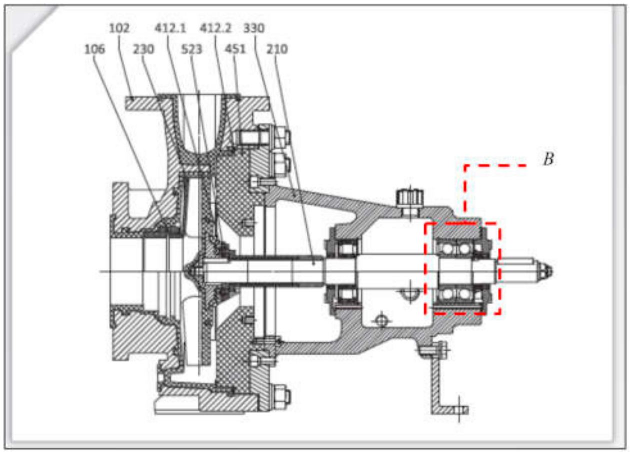

Fig. 1. Centrifugal pump longitudinal section; B: ball bearings, single raw with angular contact, pair arranged (back to back).

Table 1. Main parameter of the bearing dimensions

Variable	Symbol	Value	UoM
Internal diameter	d	60	mm
External diameter	D	130	mm
Calculation factor 1	e	1.14	-
Viscosity grade[1]	ISOVG	32	-
Basic dynamic load	C	104	kN
Calculation factor 2	c	1.62	
Static load	C_0	76.5	kN
Fatigue load limit	P_u	3.2	kN
Calculation factor 3	X	0.57	
Calculation factor 4	Y_0	0.93	

Table 2. Dynamic features and operating conditions (oil lubrification)

Variable	Symbol	Value	UoM
Angular Speed	n	3000	rpm
Average Operating Temperature	T	85	°C
Radial load	F_r	13.0	kN
Axial load	F_a	26.0	kN

According to Palmgreen and Miner [21] design process, the bearing life with a cumulated probability of 10% can be evaluated by means of the following formula:

$$L_{10h} = \frac{10^6}{60n}\left(\frac{C'}{P}\right)^p \qquad (1)$$

where:

- p depends on the shape of the bearing rolling bodies (p=3 for ball bearings);
- n is the angular speed;
- C' is the basic dynamic load of the pair arranged application (kN) which can be evaluated using the load capacity of each bearing, C (see table 1), with the following formula: $C' = c \cdot C = 168{,}5\ kN$;

- P is the effective load, which is the composition of the radial and the axial loads that stress the bearings. It depends on the proportion between the axial and the radial loads. In case of bearings arranged in pair, the following formula can be used to define the overall load:

$$P = \begin{cases} F_r + Y_1 F_a, \frac{F_a}{F_r} \leq e \\ XF_r + Y_2 F_a, \frac{F_a}{F_r} > e \end{cases} \quad (2)$$

Bearings show usually a time to failure distributed according to a Weibull probability density function, with shape factor β in the range [2..3] and expected time to failure, α:

$$F(t) = 1 - e^{-(\frac{t}{\alpha})^{\beta}} \quad (3)$$

The expected time to failure α can be evaluated considering the equation of the bearing life with a cumulated probability of 10% (eq. 1) and the inverse function of the Weibull time to failure cumulative density distribution, as follows:

$$[F(t) = 0.1]^{-1} = L_{10h} = \frac{10^6}{60^n}\left(\frac{C'}{\mathrm{P}}\right)^p \quad (4)$$

Imposing p = β, it is possible to write:

$$0.1 = 1 - e^{-(\frac{L_{10h}}{\alpha})^{\beta}} \quad (5)$$

therefore,

$$\alpha = \frac{10^6}{60^n}\left(\frac{C'}{\mathrm{P}}\right)^{\beta} \Big/ -\ln{(0.9)}^{\frac{1}{\beta}} \quad (6)$$

Experimental data provided by SKF [4] show that the expected time to failure, α, depends on the lubrication which in turns depends on the angular speed, the bearing dimensions (average diameter), the lubricant grade and the contamination of the air in which the system operates. The bearing expected life L_{10h} fits the variation of the above-mentioned variables by means of a corrective factor, named α_{SKF}. On the base of the SKF abacus (Figure 2), a fitting process has been performed, in order to find out the independent parameter which enables to link the continuous change of operating temperature, T, as reported below.

Let's define and fix the angular speed n, the lubricant grade of viscosity ISOVG, the overall load P, the air contamination quality η_c and the fatigue load limit P_u: *n = 3000 rpm; ISOVG = 32;* P_u *= 3.2 kN; P = 11.52 kN*; η_c *= 0.1* (typical air contamination quality which correspond to application without any protection gaskets, see SKF handbook [4]).

The nominal viscosity, ν_1, and the viscosity ν can be evaluated by means of the experimental abacus of Figure 2.

In particular, the nominal viscosity $\nu_1 = 7.5 mm^2/s$ that can be inferred by the intersection of the lines of viscosity (blue segments) using the information of the angular speed (3000 rpm) and the parameter $d_m = 0.5(d+D)$ of Table 1.

The viscosity ν(T), as variable of the operating temperature, is arranged by means of a sixth order equation fitting process:

$$\upsilon(T) = a_6T^6 + a_5T^5 + a_4T^4 + a_3T^3 + a_2T^2 + a_1T^1 + a_0 \quad (7)$$

where, a_0 = 300.83, a_1 = -19.22991, $a_2 = 5.961616\cdot10^{-1}$, $a_3 = -1.04102\cdot10^{-2}$, $a_4 = 1.034209\cdot10^{-4}$, $a_5 = -5.44187\cdot10^{-7}$, $a_6 = 1.176035\cdot10^{-9}$. Moreover,

$$k(T) = \frac{\nu(T)}{\nu_1} \quad (8)$$

and

$$\alpha_{SKF} = \phi[\eta_c \frac{P_u}{P}, k(T)] \quad (9)$$

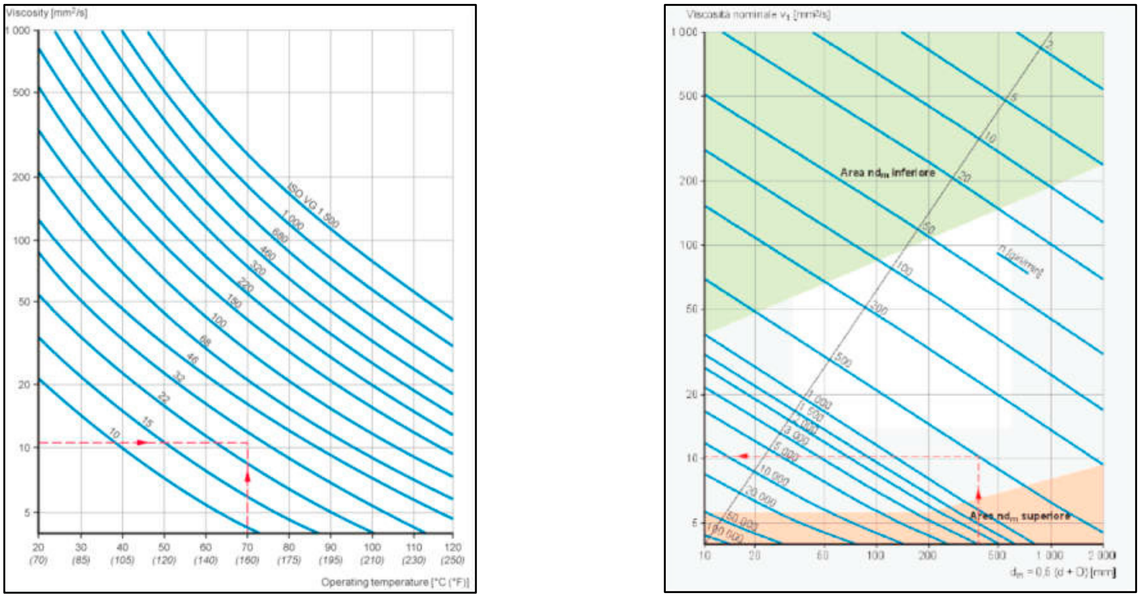

Fig. 2. Abacus of the viscosity and of the nominal viscosity (curtesy of SKF).

Due to the assumption made, $h_c \frac{P_u}{P}$ is a fixed parameter, the equation (2) can be fitted by means of the following linear system:

$$\alpha_{SKF} = \begin{cases} 0.546\, k(T) + \ 0.031, k(T) \leq 1 \\ 0.200\, k(T) + \ 0.400, k(T) > 1 \end{cases} \tag{10}$$

Once the corrective factor α_{SKF} can be evaluated as a continuous function of the operating temperature T, the failure rate of the bearing B can be computed as follows:

$$\alpha(T) = \frac{\alpha_{SKF} \frac{10^6}{60n} \left(\frac{C'}{P}\right)^{\beta}}{-\ln{(0.9)}^{\frac{1}{\beta}}} \tag{11}$$

$$h(t) = \frac{\beta}{\alpha(T)} \left(\frac{t}{\alpha(T)}\right)^{\beta-1} \tag{12}$$

Equation (3) enables to capture how the stochastic behavior of the system changes according to the operating temperature T, revealing a different performance. Figure 3 shows five different stochastic behavior of the bearings as a result of the contribution of the corrective factor $\boldsymbol{\alpha_{SKF}}$ which change depending on the operating temperature T. In order to capture the continuous changing behavior of the physical system, equation (3) can be also numerically discretized, integrating the differential function with a time step Δt as:

$$\Delta h = \frac{\beta}{\alpha(T_{i+1})} \left(\frac{i+1}{\alpha(T_{i+1})}\right)^{\beta-1} - \frac{\beta}{\alpha(T_i)} \left(\frac{i}{\alpha(T_i)}\right)^{\beta-1} \tag{13}$$

3.2. Preventive maintenance strategy

Preventive maintenance interventions aim at control the deterioration in reliability and to ensure that the actual failure rate is at or above the desired level. Preventive maintenance also includes inspections and regular maintenance activities, such as lubrication, cleaning of lines, and changing of filters, planned in order to avoid unforeseen failure of equipment and help to assure that equipment is operating in a satisfactory way [20]. By adopting the preventive maintenance strategy, the corrective interventions due to failures are limited but cannot be fully avoided.

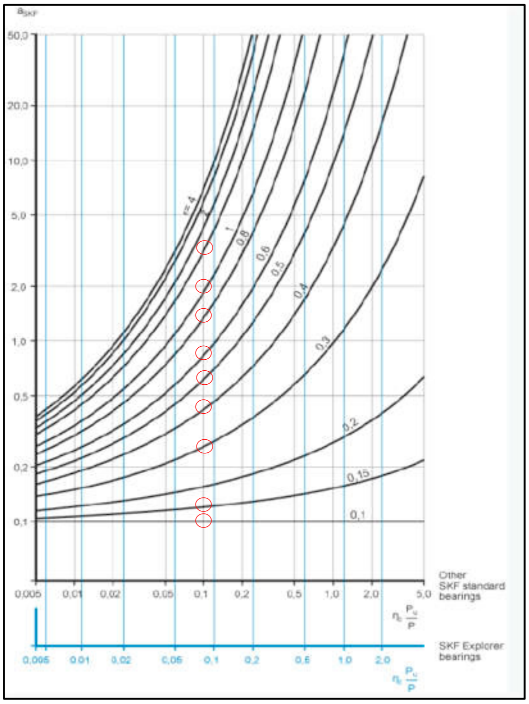

Fig. 3. Corrective factor α_{SKF} of bearings life (curtesy of SKF)

The constant date preventive maintenance plans the maintenance intervention after a fixed time since the last preventive one. The preventive interventions are triggered after a fixed time *Tp* since the last corrective or preventive maintenance intervention. Hereinafter, we assume to maintain the case study according to the constant interval preventive maintenance model.

A constant and optimal interval *Tpo* of preventive maintenance can be evaluated balancing preventive and corrective action costs under the following assumptions:

- the mean time to repair (*MTTR*) is very short compared with the mean time to failure (*MTTF*) and therefore can be neglected;
- the average preventive maintenance time of the entity is very short compared with the mean time to failure *(MTTF)* and therefore can be neglected;
- the equipment can be considered "as good as new" after the intervention of corrective/preventive maintenance;
- the cost of preventive maintenance must be less than the cost of corrective maintenance, because otherwise a preventive action would be useless;
- once restored/replaced, the entity always follows the same law of reliability *R(t)*;

the state of the system is always known.

3.3. Preventive maintenance strategy

The expected cost of maintenance per unit of time can be evaluated by means of the following formula:

$$CMU(Tp) = \frac{Cp\ R(Tp) + Cc\ [1 - R(Tp)]}{Tcycle} \quad (14)$$

$$Tcycle = R\,(Tp)\;Tp + \int_0^{Tp} t\,f(t)dt \qquad (15)$$

$$f(t) = \frac{\beta}{\alpha}\cdot\left(\frac{t}{\alpha}\right)^{\beta-1}\cdot e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \qquad (16)$$

$$R(t) = e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \qquad (17)$$

where Cp and Cc are respectively the cost of preventive and corrective intervention; Cp = R(Tp) is the probability that the interval Tp is reached without the occurrence of any fault and therefore represents the probability of carrying out preventive maintenance; f(t) is the Weibull probability density function of the equipment time to failure.

Equations 14 and 15 can be numerically integrated and displayed over the Tp domain enabling to calculate the optimal interval Tpo=8.400 h (see Figure 4) where β, α(T) are indicated in Table 1. It is assumed a constant operative temperature T=85 °C and, corrective and preventive unitary costs are respectively $C_c=2.4\cdot10^6$ €/event and $C_p=2.4\cdot10^5$ €/event.

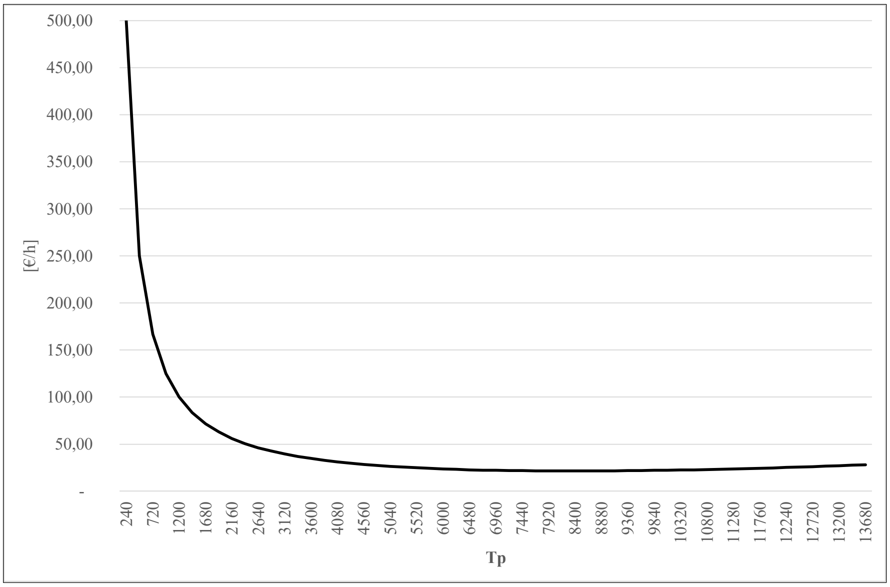

Fig.4 Cost of preventive maintenance per unit of time CMU(Tp).

3.4. The spreadsheet model

The system's model was coded by means of MS Excel® spreadsheet; the model belongs to time driven resolution approaches, with an elementary time step Δt=240 h. As regard to the model structure, three sub-modules were coded in order to: (i) capture the failure rate dependency on the operative temperature and cumulative age; (ii) perform the Monte Carlo simulation engine; it was coded comparing the reliability to reach the end of each time step, as a function of cumulative age and local operative temperature, with a random number taken from the range]0..1[; trace the time series of preventive and corrective maintenance intervention and calculate the item availability and the maintenance cost per unit of time.

Two different scenarios, respectively named *SA* and *SB*, have been simulated by means of the Monte Carlo methodology, performing a 200 steps random walk. The scenario SA models the behavior of the bearings system and outcomes of applying a preventive maintenance at constant age strategy while the operative temperature *T* is fixed

($T(t)=T_0=85$ °C) over the whole maintenance horizon; on the contrary, the scenario SB mimics the system's behavior and maintenance strategy outcomes while the operative temperature T varies according to the following equation:

$$T(t) = T_0 + \Delta T \, sen(\omega t) \qquad (18)$$

where: $T_0= 85$ °C is the average value of operation temperature; $\Delta T=20$ °C is the amplitude of the temperature variation; $\omega= 2\pi/R$ is the pulsation of the temperature variation as a function of the period $R=8760$ h.

4. Findings

Both maintenance scenarios *SA* and *SB* have been simulated varying the preventive maintenance period in the range $Tp \in [960..28800]$ h. Process availability, *A* and *A(Tp)*, and cost of maintenance per unit of time, *CMU* and *CMU(Tp)*, have been defined to compare the simulated scenarios; where the dependency from the operative temperature T belongs to the scenario *SB*. Figure 5 shows the simulation process results and enables to discover that (i) until the preventive maintenance period is sufficiently short (*Tp~8400 h*), the specific maintenance cost and system's availability don't affect the maintenance scenarios; (ii) operative conditions of scenario *SB* imply to lower the preventive maintenance period (*Tp~6400 h*) to find an optimal equilibrium among maintenance costs; (iii) a longer preventive maintenance period application pushes to the corrective maintenance fields and results in higher specific costs; (iv) taking into account the stochastic hybrid behavior of the system enables a more rigorous availability evaluation.

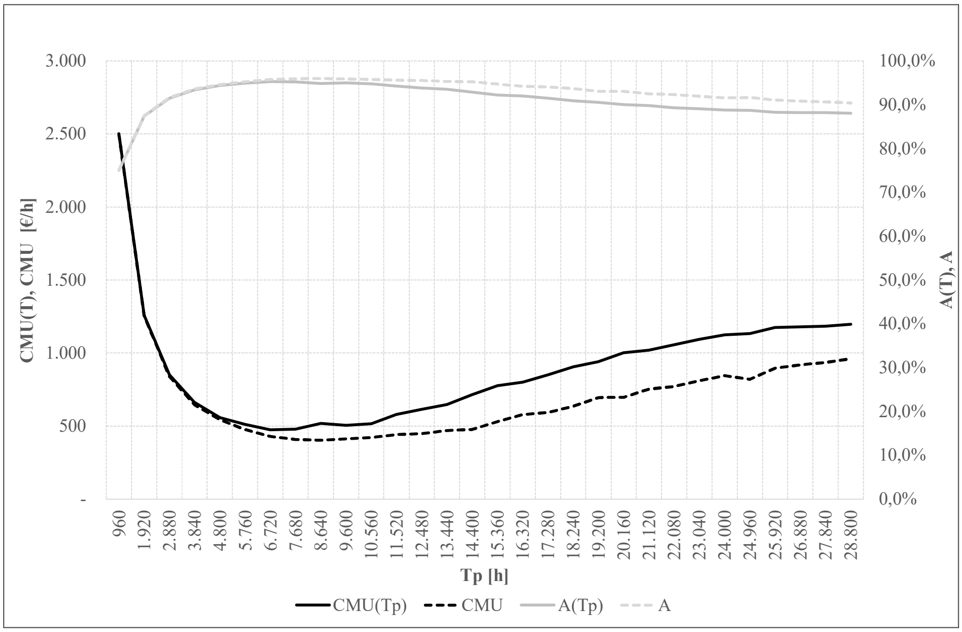

Fig. 5. Average cost per unit of time, CMU(Tp) - CMU, and availability, A(Tp) – A, as a function of *Tp* interval of preventive maintenance.

Conclusions

In this paper, a stochastic-hybrid reliability model for the assessment of the optimal period of preventive maintenance of a single-item bearing has been presented. The stochastic-hybrid model has been codified in order to describe the dynamic continuous changes of operating temperatures in which it operates, affecting the system aging. A Monte Carlo simulation has been implemented to simulate the system and analyse its availability. In this way it was possible to assess the optimal preventive maintenance period which minimises the cost of maintenance per unit of time. It was noticed that this modelling approach provides insights that are not captured by the static models, as the optimal preventive maintenance period is significantly lower than the one obtained with traditional static models.

In fact, an interesting management implication emerges: if the preventive maintenance period is short, the specific maintenance cost and system's availability don't affect the maintenance scenarios whereas the increasing of the preventive maintenance period results in higher specific costs.

It must be remarked that, in this paper, the algorithm did consider just the variation of the operational temperature. This can represent a limitation of our current research. Therefore, in the next future, it will be analysed the opportunity to integrate others operational parameters in the hybrid stochastic model and to use SHyFTOO [10], an advanced framework for the simulation of Stochastic Hybrid Automaton, that offers a more advanced and capable framework.

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