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Dynamic failure rate model of an electric motor comparing the Military Standard and Svenska Kullagerfabriken (SKF) methods

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Abstract

Electric motors are industrial systems' components widely diffused enabling all productive processes and safety equipment. They are affected by aging effect with a contribution based on the environmental condition on which they work. In order to design efficient maintenance plans, the behaviour of their main components, such as bearings and winding, has to be predicted. Therefore, a model-based methodology is applied aiming at codifying the failure rate of an electric engine, taking into account the thermal aging and relevant environment boundary conditions in which bearings and winding operate. The winding failure mode is coded by means of the Military standard technique while the bearings one is simulated comparing the Military Standard and the Svenska Kullagerfabriken (SKF) techniques. While the former predicts more conservative behaviours, the latter, taking into account lubrication conditions, dynamic loads and a better knowledge of materials quality, enables to capture the evolution of the operative conditions. The proposed reliability model can capture both the deterministic and stochastic behaviour of the electric motor: it belongs to the field of hybrid automaton application; the model is coded by means of the emerging software framework called SHYFTOO. The proposed model and the Monte Carlo simulation process that performs its evolution can support the development of a new class of electric motors: a cyber-physical oriented electric motor.

Keywords: Monte Carlo Simulation; Dynamic Reliability; Cyber Physical Systems; Thernal Aging; Stochastic Hybrid Automatons

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1. Introduction

Reliability engineering has been conceived to evaluate the capability of a system to complete the tasks for which it is designed. To this end, reliability engineering builds upon mathematical and stochastic theories that offer the main tools to compute the probability of failure of a system and analyze management and maintenance strategies to extend the life of a system. The main techniques of the classical theory, like Fault Tree Analysis (FTA) and Reliability Block Diagrams (RBDs), are characterized by a simple mathematical formalism and, in this way, their solution is fast and direct [31]. However, these models do not properly describe the real functioning of a system: they can capture only dual state operations conditions (on/off) assuming that the operative environment in which the system performs (operative temperature, pressure etc.) is fixed. Due to this limitation, in recent years, research has focused on understanding how the physical dynamics of the system, as well as the surrounding conditions, can also influence the stochastic process that governs the reliability of the system over time. The branch of reliability theory that evaluates these complex dependencies is called Dynamic Probabilistic Risk Assessment (DPRA) or Dynamic Reliability. In literature there are several papers [1, 2] that, starting from a specific problem of Dynamic Reliability, manage to develop a tailored model able to solve it. These works are very heterogeneous: among them, it is possible to find both purely analytical and purely simulation models, as well as hybrid modelling that recombine the two different approaches. The complexity of the case study and the level of detail and precision that the modeler wants to achieve determines what model technique has to be adopted in order to perform the system reliability study.

In a recent paper [3], a new formalism called Stochastic Hybrid Fault Tree Automaton (SHyFTA) has been conceived. This methodology is based on a hybrid mathematical formalism that combines a deterministic model and a stochastic model, represented by a Dynamic Fault Tree (DFT) model of a system. The deterministic model has the function of describing the physical process at the basis of the functioning of the system, while the DFT must model the evolution of system components status over time. The two models are related with appropriate shared variables so that they influence each other: every change in the deterministic model induces a change also in the stochastic one and vice-versa. Specifically, a variation in the boundary conditions of the system affects the failure/repair behaviour managed by the stochastic model. On the other hand, a variation of the stochastic process (e.g., the restoration or the failure of a component) can influence the physical behaviour of the system and, in loop, again the stochastic behaviour. For this reason, the SHyFTA model [4] needs an ad-hoc modeling of the deterministic and of the stochastic processes. This represents one of the highest barriers for the adoption of such methodology that requires a deep knowledge of the relationships that link working conditions, physical processes and modes of failure of the system components. More specifically, one of the most complex activities for a risk engineer is to model the failure rate of a component that, as it can be understood, is not static as in the hypothesis of random failures but it varies with respect to the modification of the working and surrounding conditions. As shown in [5-7], literature offers several contributions that address this type of problem demonstrating a vivid interest of researchers and risk practitioners.

The aim of this paper is to propose a failure rate modeling focused on a very common class of components, such as the asynchronous motor. The electric motor behaviour is modelled starting from two different perspectives: the Military Standard [8] – reference point in the classical literature of the failure methods analysis – and the Svenska Kullagerfabriken (SKF) [9] method – a new and interesting approach to evaluate the basic rating life of rolling bearings. SKF is a Swedish bearing and seal manufacturing company founded in Gothenburg, Sweden, in 1907. SKF is the world's largest bearing manufacturer and employs 44,000 people in 108 manufacturing units. It has the largest industrial distributor network in the industry, with 17,000 distributor locations encompassing 130 countries [30].

This work enhances the analysis conducted in a previous paper [10] about failure rate modelling of an electric motor focusing not only on bearings but also on windings. Whereas in [10] the preliminary results have been achieved by mean of an Excel Spreadsheet, in this paper the simulation model is developed inside the framework of SHyFTOO [24], refining the integration step of the simulation process. This allowed to improve the simulation results because it was possible to consider with more accuracy the ambient temperature which varies continuously with the daily hours.

This paper is organized as follows: Section 2 presents a survey on Dynamic Reliability and dynamic failure rate models. Section 3 explains the case study and Section 4 the methodology. In Section 5 the results of the Monte Carlo simulation are shown; and in Section 6 conclusions and future works are discussed.

2. State of the art

Dynamic Reliability is and umbrella term used to encompass general methodologies and ad-hoc modelling for analyzing the dependability behaviour of a complex system [11]. The main difference with the traditional methods of the reliability engineering is that Dynamic Reliability wants to dig for the combined actions into a system of the physical dynamics and stochastic effects of a process. Among the former, pressure, temperature, vibration, forces or displacements can arise because of anormal working conditions and contribute tremendously to the failure of a system whereas, among the latter, it is possible to list random failure, degradation, shocks or aging. Thus, the objective of Dynamic Reliability is a more realistic model able to describe with more effectiveness the complexity of a dynamic process. For this reason, Dynamic Reliability has started to become one of the most important tools for critical industrial applications, like nuclear industry [12-14]. Nowadays, it is adopted also to increase the accuracy of the dependability analyses in other industrial fields [15-17].

One of the most critical elements for the success of a Dynamic Reliability analysis is the capability to implement a model able to describe with the adequate accuracy the interrelationships between physical and stochastic processes and, due the complexity of the matter, the approaches for the modeling of a Dynamic Reliability problem are variegate.

In model-based approaches the tendence of researchers is to identify a contour of conditions under which analyzing a process [18] before proposing a more general model; whereas data-driven methods, suffering of a lack of data field, use to rely on statistical inference methods to enrich the sampling set used to perform the dependability analysis [19, 20].

As shown in literature, the resolution of a Dynamic Reliability problem is often achieved adopting mathematical models and simulation. For instance, in [21] the software tool RADYBAN (Reliability Analysis with DYnamic BAyesian Networks) is used in combination with a dynamic Bayesian network to approach to dynamic reliability evaluation whereas, in [22], authors propose a framework based on recursive Bayesian method and Monte Carlo simulation to estimate the degradation state of a system composed of dependent degradation components whose conditions are monitored and to dynamically assess the system risk and RUL. Recently, a general framework for the Dynamic Reliability modelling coupling discrete-event and time-driven simulation has been illustrated [4] with the aid of a simulation software [23, 24] based on Stochastic Hybrid Automaton [1-3]. This stream of literature demonstrates the maturity of Dynamic Reliability engineering as for it concerns the modelling tools.

One of the most complex activities for the implementation of an effective Dynamic Reliability analysis is the capability to model the dynamic parameters that participate to the process description of the system failure. For instance, in a real process, the failure rate of a component is not static (as in the hypothesis of random failures) but varies with respect to the modification of the working and environmental conditions [25]. Literature present several types of methods for estimating the failure rate changing with respect to the type of application. In [26] a condition-based prognostic algorithm is adopted to study the failure rate update of a Steam Generator Tube; Malcom et al., [27], use the attractive radii models to determine the lightning incidence on wind turbines and estimate the percentage annual failure rate of wind turbine electrical components. In [28] a failure rate model using empirical physics of failure equations with associated uncertainties and sensitivity analysis is adopted for a tidal turbine pitch system, whereas in [29] a simulation model for the failure rate of a vibrating vehicle is presented. In [10], the analysis of the dynamic failure rate of the bearings of the electrical engine has been carried out modelling the contribution of the thermal aging. It is shown that the boundary conditions and the ambient and the operative temperature affect significantly the remaining useful life of the component.

3. Case Study

The case study on which this paper focuses is the squirrel cage asynchronous motor (so called because the shape of its rotor refers to that of a squirrel cage). This component is a critical component because is as widespread in many industrial processes as cheap. Currently, it does not have many transducers enabling to forecast the remaining useful life of the component. Nevertheless, the adoption of a dynamic reliability model, like the one thereby proposed, coded onboard in a cheap hardware, can benefit of the information acquired by non-intrusive sensors, like IOT, able to measure the physical properties required by the model, such as vibration, temperature, efficiency or even (acoustic) pressure. This can represent an alternative approach to data-driven prognostic that require the support of complex network of intelligent systems for analyzing the big data acquired by the component sensors.

As Figure 1 shows, a squirrel cage induction motor consists of the following parts: motor shaft, rotor and stator.

The latter are composed of windings (both three-phase and with the same pole pitch), fans and bearings. The air gap (i.e. the distance between rotor and stator) of the asynchronous motors is necessary to allow the free rotation of the rotor and it acts as a dielectric. Its thickness is constant, and it is a few tenths of a millimeters or at least as small, as allowed by mechanical tolerances.

The principle of operation of the motor is simple: an alternating current is passed through the stator windings; this produces a rotating magnetic field. Stator magnetic field induces a current in the rotor winding, which produces its own magnetic field. The interaction of the magnetic fields produced by the stator and rotor windings generates a torque on the squirrel-cage rotor.

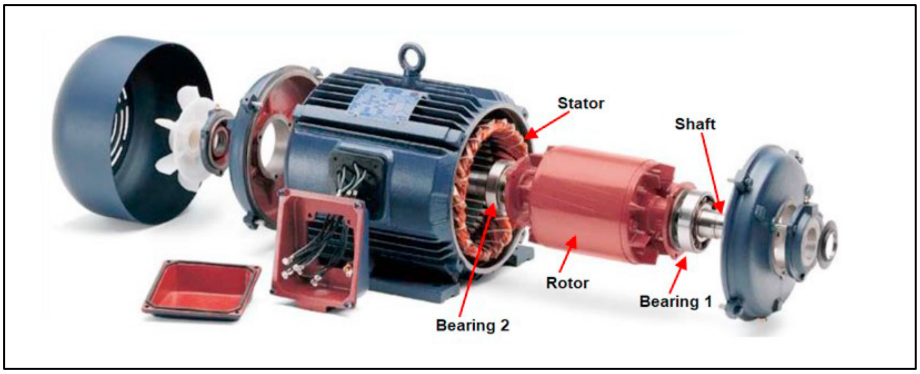

Figure 1: exploded view of an asynchronous motor.

There is a strong correlation between the operating temperature and the life of the insulation; in particular, each increase in the operating temperature of 10 ℃ leads to a halving of the life of insulation. The effect of thermal aging is to make the insulation vulnerable to other stresses that cause stress. A solution to increase the thermal duration of the insulation consists in reducing the operating temperature or using materials with a higher insulation class.

Bearings in an electrical motor are needed for several reasons: to support and locate the rotor, to keep the air gap small and consistent and to transfer the loads from the shaft to the motor. Bearings are also affected by thermal aging. This effect can be taken into account by means of the Military Standard and SKF methodologies as reported in the next sections.

4. Methodology

4.1. The Military Standard

The Military Standard MIL-HDBK-217 [8] is a manual written more than 50 years ago in the United States and that for the first time has defined a standardized methodology for measuring reliability.

As regards to an electric motor, it proposes a model for an average failure rate which can be considered constant and equals to:

$$\lambda_P = \left[\frac{\lambda_1}{A\alpha_B} + \frac{\lambda_2}{B\alpha_W}\right] \tag{1}$$

where:

- α_B is the Weibull Characteristic Life for Motor Bearings,

$$\alpha_B = \left[10^{\left(2{,}534 - \frac{2357}{T_A + 273}\right)} + \frac{1}{10^{\left(20 - \frac{4500}{T_A + 273}\right)} + 300} \right]^{-1} \tag{2}$$

- α_W is the Weibull Characteristic Life for Motor Windings, and

$$\alpha_W = 10^{\left(\frac{2357}{T_A + 273} - 1{,}83\right)} \tag{3}$$

- T_A is the Ambient Temperature (°C).

Table 1 and Table 2 show the characteristic values for A, B, λ_1 and λ_2. As it is possible to see, these values depend on the type of device considered and on the parameter of the system design life cycle (in hours), known as LC, or the motor preventive maintenance interval, if motors will be periodically replaced or refurbished.

Table 1. A and B Determination in Military Standard Model.

Motor type	A	B
Electrical (general)	1.9	1.1
Sensor	0.48	0.29
Servo	2.4	1.7
Stepper	11	5.4

Table 2: λ_1 and λ_2 Determination in Military Standard Model

LC/α_B or LC/α_W	λ_1 or λ_2
0-0.10	0.13
0.11-0.20	0.15
0.21-0.30	0.23
0.31-0.40	0.31
0.41-0.50	0.41
051-0.60	0.51
0.61-0.70	0.61
0.71-0.80	0.68
0.81-0.90	0.76
>1	1

As shown in Table 3, α_B and α_W values depend strongly on the operating temperature. In the Military Standard, this latter can be treated as constant parameters over time. Clearly, the longer is the mission time, the less is the model able to catch the variation of the operating temperature, resulting in a coarse model. When the standard deviation of the operative temperature is not negligible, compared to the mean value, the model can fail to a large extent.

Table 3: α_B and α_W values starting from the operating temperature.

T_A (°C)	α_B (h)	α_W (h)
0	3,800	5.4E+06
10	13,000	3.2E+06
20	39,000	1.6 E+06
30	78,000	8.9 E+05
40	80,000	5.0 E+05
50	55,000	2.9 E+05
60	35,000	1.8 E+05
70	22,000	1.1E+05
80	14,000	7.0E+04
90	9,100	4.6E+04
100	6,100	3.1E+04
110	4,200	2.1E+04
120	2,900	1.5E+04
130	2,100	1.0E+04

4.2. SKF Bearing Life Calculation

In 1977, the ISO introduced the formula to evaluate the adjusted bearing fatigue in millions of revolutions, L_{na} (where the index n represents the expected unreliability at the mission time, e.g.: L_{10} means 10% of unreliability). In particular:

$$L_{na} = \alpha_1 \alpha_2 \alpha_3 \left(\frac{C}{P}\right)^p \quad (4)$$

where:

- α_1 is the corrective factor of the selected reliability level,
- α_2 is the corrective factor of the material,
- α_3 is the corrective factor of the operating conditions,
- C is the Dynamic Load Coefficient,
- P is the Equivalent Dynamic Load and
- p depends on the type of rolling elements (= 3 for ball rolling elements).

The coefficient relating to the material is approximated to 1, considering that the steel used by SKF [9] has better durability characteristics than those on which the ISO formulas are based. The factor relating to operating conditions is essentially linked to the lubrication of the bearing, provided that the operating temperatures are not excessively high. In the cleaning conditions prevailing in an adequately protected application, the factor α_3 depends on the viscosity ratio κ. This parameter is defined as the ratio between the viscosity ν of the lubricant used and the parameter ν_1, necessary for adequate lubrication (both are kinematic viscosities referred to the operating temperature). Viscosity ν_1 can be determined from the diagram in Figure 2 as long as mineral oil is used. When the operating temperature is known from experience or can otherwise be determined, the viscosity corresponding to the reference temperature of 40 °C established by an international standard can be obtained from diagram in Figure 3.

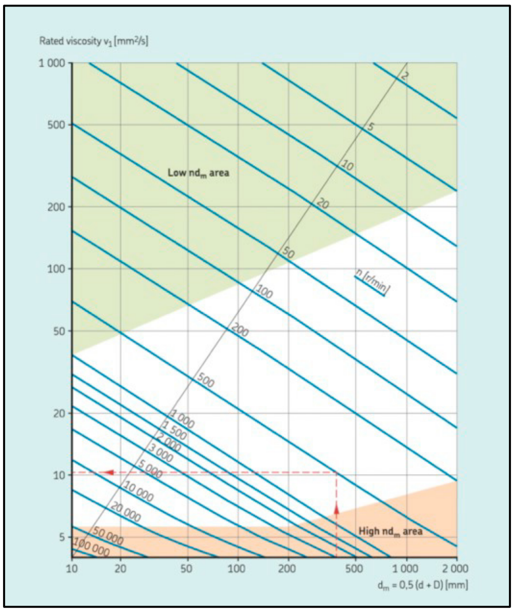

Figure 2: estimation of the rated viscosity ν_1[9].

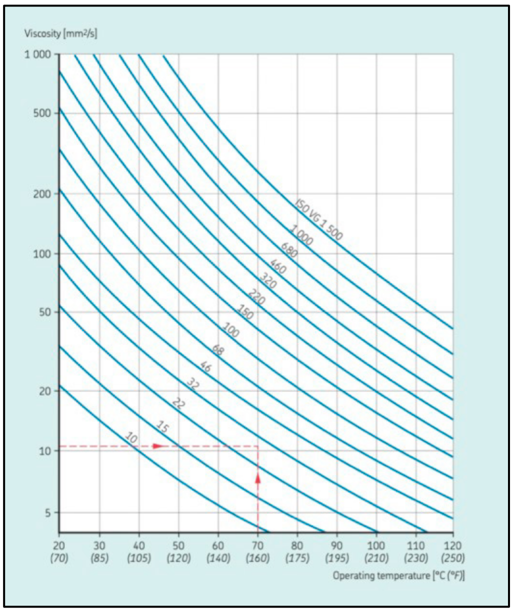

Figure 3: viscosity – temperature diagram [9].

Since factors a_2 and a_3 are interdependent, SKF has decided to replace them in the formula of the correct duration with a combined factor a_{23} for the material and lubrication, and therefore this formula becomes:

$$L_{na} = \alpha_1 \alpha_{23} L_{10} \quad (5)$$

Provided there is a normal degree of cleanliness, the values of a_{23} can be obtained from the diagram of Figure 4 as a function of the viscosity ratio.

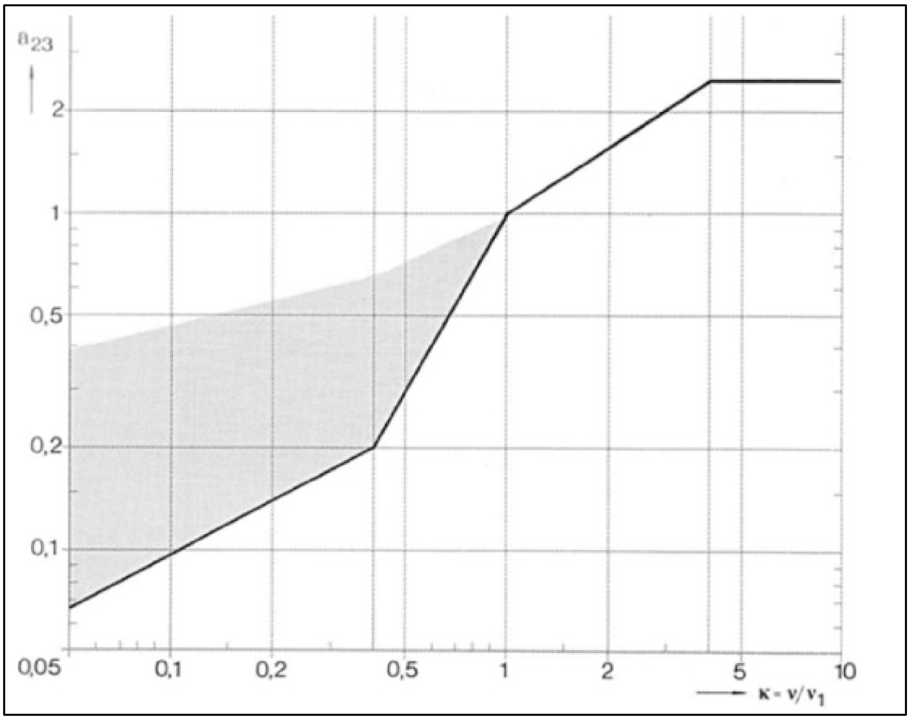

Figure 4: viscosity ratio, a_{23}, diagram [9].

To compute the adjusted bearing life in hours, L_{10h} the following relation can be used:

$$L_{10h} = \frac{10^6 \cdot L_{10}}{60 \cdot n} \quad (6)$$

With the previous variable it is possible to compute the characteristic life of the bearing as follows:

$$a = L_{10h} \cdot \left(\ln\frac{1}{0.9}\right)^{-\frac{1}{p}} \quad (7)$$

and, finally, the dynamic instantaneous failure rate using the Weibull pdf:

$$h(t) = \frac{p \cdot (t)^{p-1}}{a^p} \quad (8)$$

We now define the mean time to failure and the reliability evaluated $R_{\Delta t}$ as regard to a mission time equals to the next discretization step. The former is the reciprocal of the instantaneous failure rate h(t) given that it can be considered as a constant in the infinitive time step, Δt, used to integrate the reliability (for short time step this is acceptable). The reliability $R_{\Delta t}$ represents the probability to survive from the time step i to the next time step i + Δt, assuming that the component has survived until i:

$$R_{\Delta t} = P(X < i + \Delta t \mid X > i) \quad (9)$$

This is an important information for the risk practitioners who decide whether or not replacing the component at any inspection.

5. Monte Carlo Simulation

Two simulation models (coupling the deterministic and stochastic system behaviour) have been coded with the SHyFTOO framework inside the Matlab environment. The first one is based on the failure rates model proposed by the SKF method [9], while the second one is coded using the Military Standard [8] formulation.

Table 4 presents the operative conditions and the main parameters of the simulation designed with the SHyFTOO, used to implement the simulation of the SKF model.

Table 4. Simulation parameter adopted for the SHyFTOO model.

Variable	Symbol	Value	Measure Unit
Type of rolling element	p	3	-
Dynamic Load Coefficient	C	4490	N
Equivalent Dynamic Load	P	[450, 900,.., 3600]	N
Angular velocity	N	3000	rpm

It is assumed that the electric motor operates for three years continuously (26280 h). The simulation model was coded according to a discrete time driven method using a time step Δt=1 h (one hour). Figure 5 shows the trends of the failure rate, *h(t)*, over three years, comparing the MLS and the SKF model without taking into account the ambient temperature. While the MLS is unsensitive to the Equivalent Dynamic Load (P), based on the interpolation of empirical data, the SKF can catch this variation which, in Figure 5, is plotted according to the range presented in Table 4, from 450 N to 3600N. The SHyFTA model computes failure rate values that can be higher or lower comparing to the average value of the MLS Standard, according to the actual boundary conditions.

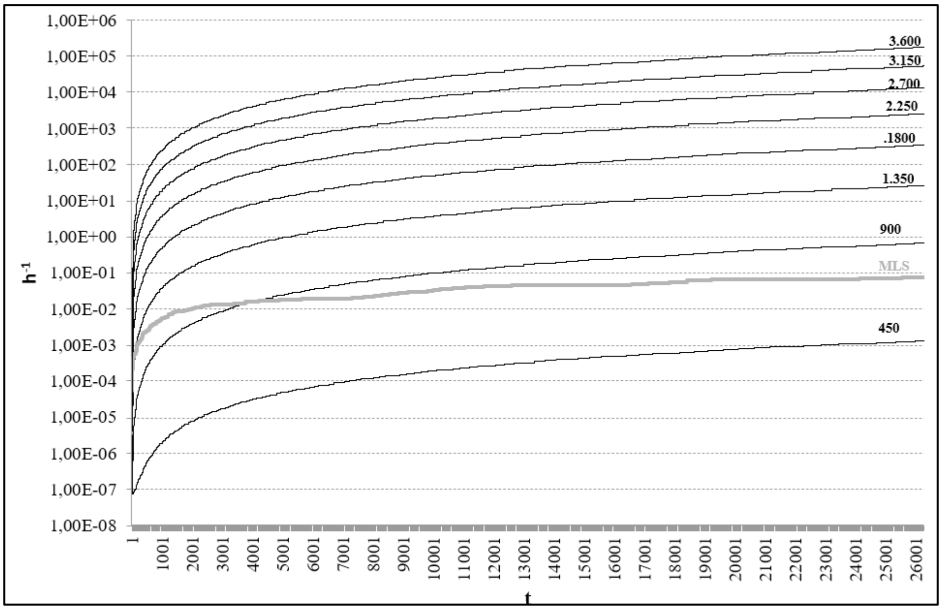

Figure 5: failure rate comparison between MLS and SKF for the electric motor with a fixed ambient temperature and varying the equivalent dynamic load.

Figure 6 shows the same trends with the contribution of the ambient temperature. In this case, the Equivalent Dynamic Load has been fixed to 450N and the operating temperature of the simulation were taken by the historical time series of the hourly ambient temperature of the last three years of the city of Catania, Italy.

As regard to the thermal aging effect, taking into account the current lubrication conditions, the SKF procedure enables more detailed failure rates and reliability trends; this appears a fundamental antecedent in order to define a predictive and effective maintenance plan.

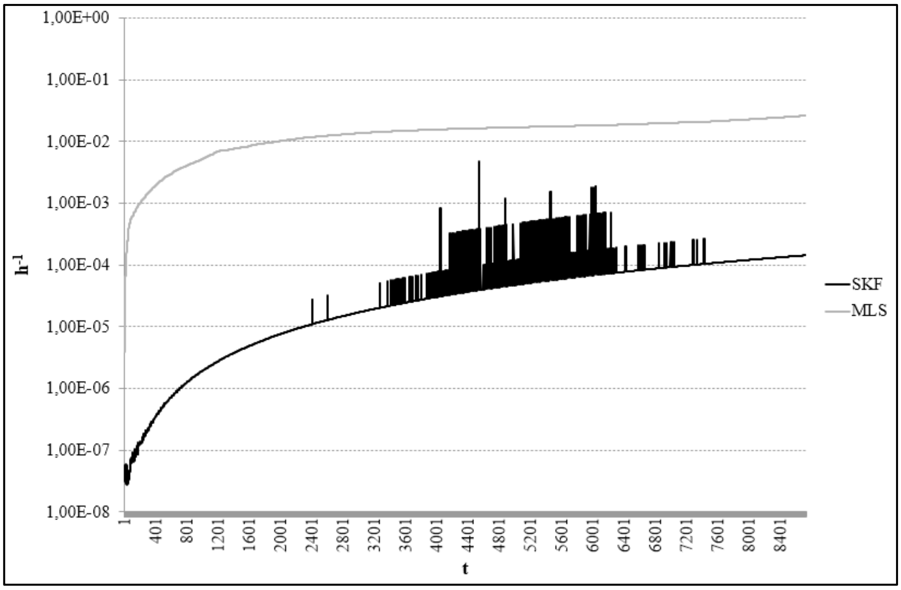

Figure 6: failure rate comparison between MLS and SKF for the electric motor with a fixed Equivalent Dynamic Load.

6. Conclusions

In this paper, the dynamic failure rate of an electric motor has been codified following the indications of the Military Standard and of the Svenska Kullagerfabriken (SKF). To this end, two simulation models have been implemented, extending the study presented in [10] and including the contribution of the windings.

Results show that both the two models are strongly dependent on the class of devices taken into account and on the working and environmental variables that characterize the process under investigation. It is possible to affirm above all that the Military Standard model is still a reference, but it can retrieve acceptable results only in the case in which the operating variables (such as temperature) are considered constant.

Since variable boundary conditions have been used in both simulations, SKF model has proven to be more suitable to capture unsteady state behaviours of the system. The SKF method applied to the reliability modelling of an electric motor can be considered for further evaluation by the use of dynamic reliability modelling like SHyFTA. To carry out these analyses, the SHyFTOO library has been used to code a Stochastic Hybrid Fault Tree Automaton model of the case study. Results are encouraging and suggest to adopt the SHyFTA formalism as hybrid modelling tool to expand the reliability analysis to other components of the electric motor including how the motor ignition affect the windings aging [32].

In this paper, the results of this study have been obtained by means of the simulation of these two different methodologies. Therefore, in future research, it is desirable the implementation of an experimental campaign which could further confirm the results of this preliminary analysis. In author's opinion, this study confirm that the design of a CPS-oriented electric motor able to support the SKF model equations described (where the reliability model discussed is fed by the cybernetic part electric motor) represents an opportunity and a research goal in this area.

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