Failure rate modelling of an electric motor: Monte Carlo simulations based on Military Standard and SKF methods

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Abstract: The faults prognosis of industrial systems or components is the challenge that researchers are widely dealing with, usually armed with data-driven or model-based (or process-driven) algorithms. The data-driven models are agnostic to the physical processes. Based on sample data (known as training data) machine learning algorithms construct the relationships between input and output data using statistical (machine learning) techniques in order to make predictions. As a consequence they can be ineffective since the future may be not closely dependent on the past described by the training data. On the other hand, the process-driven models trust on well-established physical laws trying to know everything about the system behavior and sometimes too much for computing capabilities.

Model-based oriented modelers wrote this paper: the failure rate of electric engine is coded taking into account aging and relevant operational conditions (thermal aging) of bearings; more in particular the Military Standard and SKF techniques are compared; while the former predicts more conservative behaviors, the latter, taking into account lubrication conditions, enables to better capture the operative temperature contribution. The reliability model proposed can be considered as a primitive kind of intelligence of a new class of electric motors: cyber physical oriented.

Keywords: Stochastic hybrid automaton; thermal aging modelling.

1.Introduction

The stochastic modelling of classical reliability theory undoubtedly has several advantages; techniques such as Fault Tree Analysis (FTA) and Reliability Block Diagrams (RBDs) are simple to understand and apply; and their resolution is rapid and direct because they are characterized by a simple mathematical formalism. However, the hypotheses behind these techniques give rise to models that do not properly describe the real functioning of a system. In this regard, in recent years research in this area has focused on the study of the dynamic evolution of systems and on understanding how boundary conditions, as well as aging, can influence dynamics (not just two-stage) and the reliability of the system. The branch of reliability theory that deals with this topic has been named Dynamic Probabilistic Risk Assessment (DPRA) or Dynamic Reliability. Literature presents several researches (Babykina, G., Brinzei, N., Aubry, J.-F. and Deleuze, G., 2016; Yuehua, C., Liang, J., Bin, J. and Ningyun, L., 2019) that, focusing on specific problem of Dynamic Reliability, are able to propose an ad-hoc modelling for solving it. Analysing these works, it is possible to distinguish between pure analytical models, pure simulation and hybrid methodologies that combine the two previous approaches. In the end, the choice of one methodology depends on the complexity of the case study and on the level of detail and precision that the modeller wants to achieve. As it can be understood, these types of resolutions are not general enough and have a big main limitation: they can capture only dual state operations conditions (on/off) and failure rates without taking into account the operative environment in which the systems performs (operative temperature, pressure etc.). To tackle this important issue, in a recent paper, Chiacchio et al., 2016, conceived the Stochastic Hybrid Fault Tree Automaton (SHyFTA) a hybrid mathematical methodology that combines a deterministic model and a Dynamic Fault Tree (DFT) model of a system. The deterministic model must describe the physical process underlying the functioning of the system, while the DFT must model the stochastic behaviour that determines the evolution of system components status over time. These two models are related through the use of appropriate shared variables so that any change in the deterministic model triggers an immediate change on the stochastic model and vice-versa. Typically, a variation in the enabling conditions of the system, caused by a change in the deterministic model, affects the failure / repair behaviour managed in the stochastic model. On the contrary, a variation in the stochastic process can modify the physical behaviour of the system, and consequently its dynamics managed by the deterministic process, and thus influence the latter. The augmented modeling capability of the SHyFTA, Chiacchio et al. 2020, needs a tailored modeling of the deterministic scenario which is focused.

Therefore, the aim of this study is to develop a failure rate model dedicated to a very common class of components, such as the electric motor, in order to begin to collect a kind of model library; the electric motor behaviour is modelled starting from two different perspectives: the Military Standard - a milestone in the classical literature of the failure methods analysis – and the SKF method – a new and interesting approach to the problem we are looking at.

This paper is organized as follows: section 2 presents the state of the art of Dynamic Reliability. Section 3 introduces to the case study and section 4 to the methodology. In Section 5 the results of the Monte Carlo simulation are presented; and in section 6 conclusions and future works are discussed.

2.State of the art

Figure 1 shows a breakdown of the three main categories of the stochastic methods used in the dependability assessment. As shown, Fault Tree Analysis (FTA) is a common pattern of each category because it has been object of continuous modification over the last few years, improving its expressiveness and accuracy. The Static Fault Tree (SFT) formalism provides an easy way to model and understand the failure behaviour of a system using OR and AND Boolean gates. They can be solved with analytic algorithms able to provide an exact result. Nevertheless, the SFT assumptions do not allow to model complex systems characterized by temporal and dynamic dependencies, typical of real case studies.

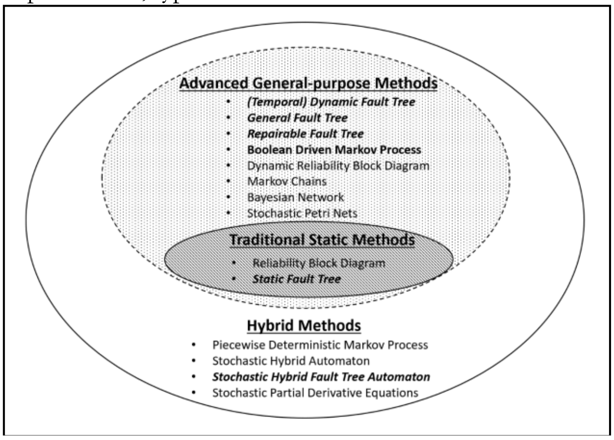

Figure 1: breakdown of the categories of stochastic modelling methods for the dependability assessment.

A state-of-the-art survey demonstrates that several modifications of the original FTA formalism have been attempted to overcome the limitations of the SFT. These techniques are grouped into the second category of models, here named as "Advanced & General-Purpose Methods". The main improvements over the "Traditional Static Methods" focus on the capability to model complex failure dependencies such as time-event sequences, multi-state degradation, and standby policies (Misra, K.B., 2008). However, various methodologies do not have the same properties, and the use of one or the other approach depends on the dependability problem under study. Among the various techniques, Dynamic Fault Tree (DFT) and Temporal Dynamic Fault Trees (TDFT) are the most known method which addresses temporal events through dynamic gates whereas Generalized Fault Trees (GFT) and Boolean Driven Markov Processes (Codetta-Raiteri, D., 2011; Bouissou, M., 2008) allow to model repair transitions. The resolution of the above-mentioned models is not as simple as SFT, and accordingly, the following three techniques are generally adopted: (i) algebraic methods (Merle, G., Roussel, J.-M. and Lesage, J.-J., 2011; Merle, G., Roussel, J.-M., Lesage, J.-J. and Bobbio, A., 2010), (ii) conversion into an equivalent model (Aslansefat, K. and Latif-Shabgahi, G.R., 2019), and (iii) simulation (Ruijters, E., Reijsbergen, D., de Boer, P.T. and Stoelinga, M., 2019).

Although the category of "Advanced & General-Purpose Methods" is powerful, the main limitation of all these formalisms is that they are purely stochastic models. With these models, the boundary conditions must be fixed as input of the model, whereby the description of the stochastic events of the model gets limited to the usage of static probability density functions. Hybrid methods (Fan, M., Zeng, Z., Zio, E., Kang, R. and Chen, Y. A, 2017; Riley, D.D., Koutsoukos, X. and Riley, K., 2010; Yuehua, C., Liang, J., Bin, J. and Ningyun, L., 2019; Kabir, S., Aslansefat, K., Sorokos, I., Papadopoulos, Y. and Konur, S., 2020), falling under the umbrella of Dynamic Reliability, alleviate this issue, and, as shown in Figure 1, they embrace the scope covered by the other categories. Dynamic Reliability aims to relax the rigid hypotheses of traditional reliability enabling the possibility to model multi-state systems and consider changes of the nominal design condition of a system. As matter of fact, a component does not always operate around the nominal design operative conditions, resulting in deviations of performance and wearing-out. In order to simplify the modelling of such problems, recent studies have proposed methodologies based on the separation of concerns that allows the independent modelling of the deterministic and stochastic processes (Manno, et al., 2013). In this category of methods, the Stochastic Hybrid Fault Tree Automaton (SHyFTA) is the one that mostly resembles to the FTA (Chiacchio et al. 2016). As shown in figure 2, a SHyFTA model is comprised of two interdependent models: the deterministic and stochastic processes. In a SHyFTA model, the deterministic process can be modelled by any mathematical formulation (including simulation) capable of describing the dynamics of the physical process of the system.

The Stochastic Hybrid Automaton is not easy to use and solve because it models, without constraints, any type of dependency. For this reason it needs to be tailored on the particular case of study and the most appropriate resolution method is based on Monte Carlo simulation.

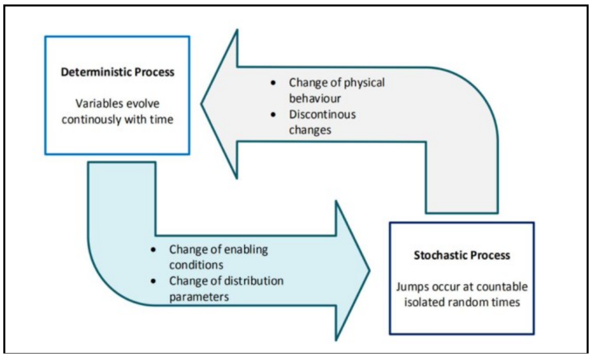

Figure 2: interaction between deterministic and stochastic processes characterizing a SHyFTA

3.The case of study

The case study focused on this paper refers to the squirrel cage asynchronous motor (so called because the shape of its rotor refers to that of a squirrel cage). This device is a key machine in all industrial fields, and it is a device that is not equipped with many transducers so that predictive maintenance is not permitted.

As figure 3 shows, the main components of an asynchronous motor are rotor, stator and motor shaft. Rotor and stator, in turn, are composed of windings, fans and bearings. The air gap of the asynchronous machines has a constant thickness and two three-phase windings with the same pole pitch are housed in the rotor and stator slots. The stator winding can be star-connected, or triangle-connected, while the rotor winding is short-circuited. When an alternating current is passed through the stator windings, a rotating magnetic field is produced. This 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 produces a torque on the squirrel-cage rotor.

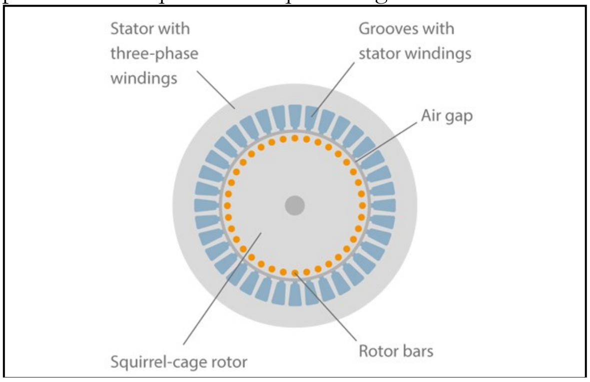

Figure 3: sectional view of an asynchronous motor

As regard to windings, (see figure 4) 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 °C 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. To increase the thermal duration of the insulation, it is possible to reduce the operating temperature or use materials with a higher insulation class.

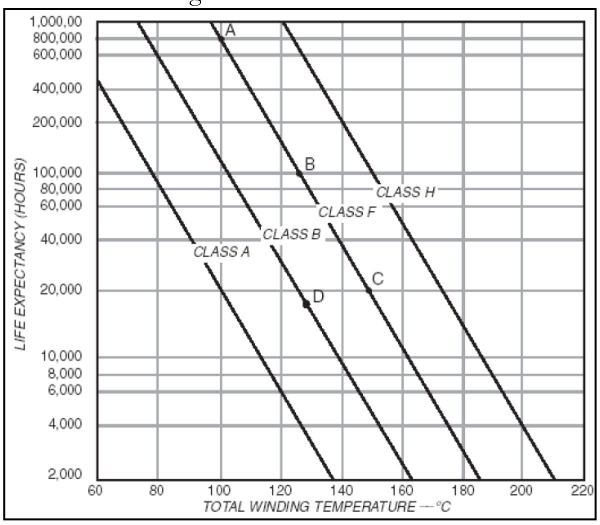

Figure 4: relationship between temperature and insulation life expectancy

The purpose of bearings in an electric motor is to support and locate the rotor to keep the air gap (i.e. the distance between rotor and stator) small and consistent and transfer the loads from the shaft to the motor. Bearings are also thermal aging affected which can be taken into account by means of the Military Standard and SKF methodologies as below reported.

4.Methodology

4.1 The military standard

Military Standard MIL-HDBK-217 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 for an electric motor, it modelled an average failure rate, which can be considered constant, equal to:

$$\lambda_P = \left[\frac{\lambda_1}{A\alpha_B} + \frac{\lambda_2}{B\alpha_W}\right]\ (1/h)$$

where:

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

is the Weibull Characteristic Life for Motor Bearings;

$$\alpha_W = 10^{\left[\frac{2357}{T_A+273}-1{,}83\right]}$$

is the Weibull Characteristic Life for Motor Windings;

T_A is the Ambient Temperature (°C).

As Table 1 shows, α_B and α_W values strongly depend on the operating temperature, which is therefore treated as a constant operating quantity over time.

The following tables (Table 2 and Table 3) show 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 LC that is the system design life cycle (in hours) or the motor preventive maintenance interval, if motors will be periodically replaced or refurbished.

Table 1: $\boldsymbol{\alpha_B}$ and $\boldsymbol{\alpha_W}$ values starting from the operating temperature

T_A (°C)	α_B (h)	α_W (h)	T_A (°C)	α_B (h)	α_W (h)
0	3.800	5.4E+06	70	22.000	1.1E+05
10	13.000	3.2E+06	80	14.000	7.0E+04
20	39.000	1.6 E+06	90	9.100	4.6E+04
30	78.000	8.9 E+05	100	6.100	3.1E+04
40	80.000	5.0 E+05	110	4.200	2.1E+04
50	55.000	2.9 E+05	120	2.900	1.5E+04
60	35.000	1.8 E+05	130	2.100	1.0E+04

4.1 SKF bearing life calculation

In 1977, the ISO introduced the formula for bearing life, which is as follows:

$$L_{na} = a_1 a_2 a_3 \left(\frac{C}{P}\right)^p$$

where:

L_{na} is the correct life in millions of revolutions (the index n represents the difference between the required reliability and that of 100%);

a_1 is the corrective factor of the duration relating to reliability;

a_2 is the corrective factor of the duration relating to the material;

a_3 is the corrective factor of the duration relating to the operating conditions;

C = size selection based on rating life;

P = basic dynamic load rating;

p = exponent of the life equation that depends on the type of bearings examined (= 3 for ball bearings).

Table 2: A and B 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

Table 3: λ_1 and λ_2 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

The coefficient relating to the material is considered approximate to 1, considering that the steel used by SKF 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 a_3 depends on the viscosity ratio κ. This parameter is defined as the ratio between the viscosity ν of the lubricant actually used and that 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 1 of the Appendix A 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 2 of the Appendix A.
Since factors a_2 and a_3 are interdependent, SKF (Swedish company leader in the supply of rolling bearings) 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

$$L_{na} = a_1 a_{23} L_{10}$$

Provided there is a normal degree of cleanliness, the values of a_{23} can be obtained from diagram in Figure 3 of the Appendix A as a function of the viscosity ratio.

5.Monte Carlo simulations
Two simulation models (coupling the deterministic and stochastic system behavior) have been coded in the MS Excel® environment, both according to the Monte Carlo simulation method: the first one is based on the model proposed by the SKF method, while the second one on the Military Standard experimental data set. Only bearings dynamics was simulated.
As regards the simulation based on the SKF model, a single row deep groove ball bearing (d=30 mm and D=42 mm) has been considered. The boundary conditions of the simulation are: the operating temperature with values equal to the time series of the average monthly temperatures in the last year; the dynamics loads, C=4.490 N, P=450 N; the angular velocity, n=1.000 rpm; the simulation model was coded according to the discrete time driven method with a time step Δt=730 h (one month).
Figure 5 shows trends of reliability which are evaluated, over a 3 years horizon, with or without taking in to account the thermal aging behaviour (TH-A or -A), following the method by which SKF and the Military Standard Handbook consider the operative temperature (TA) contribution; when thermal aging is not considered, the operative temperature is the fixed value TA=20 °C.

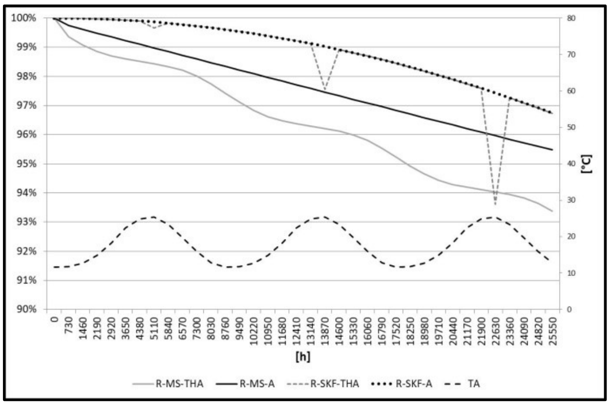

Figure 5: reliability trends according SKF and Military standard methods with or without thermal aging

Figure 6 shows the trends of the failure rate, h(t), over a 3 years period; it is possible to see a good degree of coherence between the curves of the two reliabilities here too.

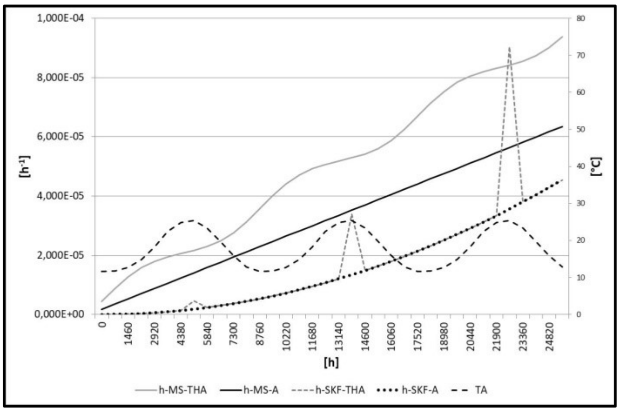

Figure 6: failure rate trends according SKF and Military standard methods with or without thermal aging

As regards the simulation based on the Military Standard model, formulas and tables mentioned in section 3.1 has been used and the same operative time series of the SKF simulation has used for the operating temperature.
Looking at fig. 5 and 6 is clearly seen that the variability of operating temperature, TA, greatly affects the reliability

values over time; reliability trends evaluated by means of SKF methods are more optimistic than the Military standard ones; this is consistent with the fact that the Military Standard model is based on a fitting process of experimental results which regards a large amount of equipment with different levels of quality and, therefore, represents an average behaviour, while SKF procedure is based on a deeper knowledge about materials and bearings application.
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.

6.Conclusions

Two simulations model have been carried out: results are strongly dependent to the class of devices taken into account, as well as their characteristic variables – as in the case with the bearing examined.
It is possible to affirm above all that the Military Standard model is still a reference, but 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 behaviors.
Without doubt, the SKF method applied to the reliability modelling of an electric motor can be considered the foundation of the new hybrid reliability modelling. It will be interesting to use SHyFTA as the main hybrid modelling tool and to expand the reliability analysis to the other components of the electric motor, especially the windings.
Results of the study, even though obtained by means of two different methodologies, are only simulated; this limitation is to be overcome comparing simulation findings whit a campaign of experimental data.
Finally, the design of a CPS-oriented electric motor (where the reliability model developed represents the cybernetic part of the designed system) represents an opportunity and a goal in research in this area.

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Appendix A.

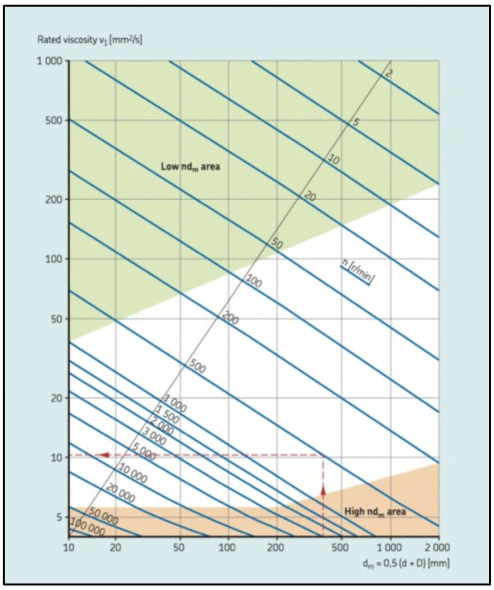

Figure A1: estimation of the rated viscosity $\boldsymbol{\nu_1}$

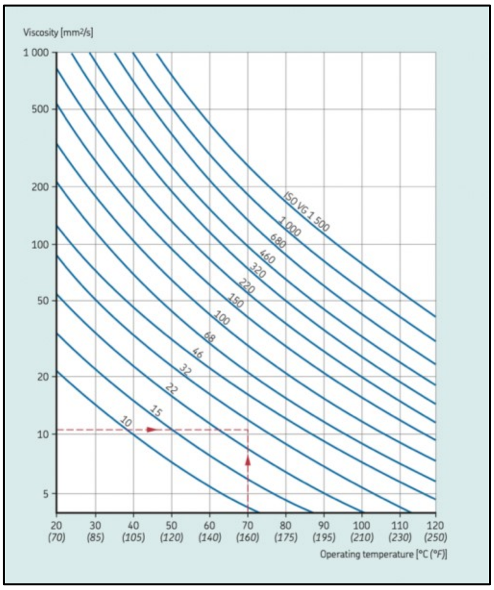

Figure A2: viscosity – temperature diagram

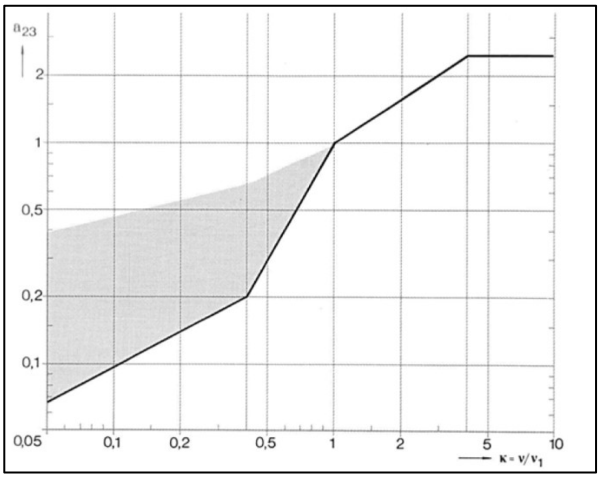

Figure A3: viscosity ratio - $\boldsymbol{a_{23}}$ diagram