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An application for structural reliability based on probabilistic condition

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Abstract: The study of structural reliability has taken on great importance as numerical tools, whether in the probabilistic or deterministic field, become more assertive. However, the use in a complementary and interactive way has not been observed. In this context, the present work seeks to propose a virtual numerical simulation that uses information from the two aforementioned areas aiming at the evaluation of the probabilistic condition of an asset, extrapolating the grounded concept of Condition-based maintenance (CBM), incorporating as an extension of the concept the knowledge from probabilistic studies. Therefore, there will be Probabilistic Condition-based maintenance (PCBM). Using the concepts of structural reliability and its methods for evaluating the structural integrity of a mechanical system in operation subjected to dynamic forces, the probability of component failure will be determined, as well as its safety index and its evolution over time. of time. For this, a software with graphical user interface (GUI) is developed, in MATLAB, to ease the use by the designer. In this, the user can also perform comparative analyzes between different simulation loops as well as choose which types of statistical models to implement. The validation of the software is based on experimental results where the correlations between the probabilistic and deterministic models are carried out, thus verifying the possibility of using this methodology as a support in the decision-making process regarding the most appropriate moment of maintenance intervention for a certain level of security.

Keywords: structural reliability, fatigue, structural health monitoring, maintenance

INTRODUCTION

The global financial crisis installed in the past years has caused profound changes in society and, consequently, also in the industrial environment. The requirement for cost reduction and optimization, associated with a need to increase productivity, is a keynote in all operations spread across the globe. If in the past an asset could be discarded at a certain point in its useful life for the acquisition of a new one without a careful judgment, today, due to limited financial resources, it is no longer possible (Oh & Kim, 2022; Wang et al., 2021). In this scenario, structural reliability emerges with very useful tools for engineering.

Structural reliability is a relatively new topic and has been evolving rapidly in recent years. The first mathematical formulation of structural safety problems can be attributed to (Mayer, 1926), followed by the works of (Streletskii, 1947) and (Wierzbicki, 1936). The last two authors identified that the strength and load parameters are random variables, therefore, for each structure, there is an associated failure probability. However, these concepts were only developed two decades after, but the formulations and functions involved were difficult to solve for the technical resources of the time.

In the above scenario, practical applications of reliability analysis were only possible with the pioneering works of Cornell and Lind in the late 60s and early 70s. In the following years, several works were developed by several researchers regarding structural reliability applied in the design phase as well as in the evaluation of existing structures, in addition to the development of methods for optimizing these analyzes. According to the development of the area, some studies use structural reliability as a tool to support the decision-making process (Gomes, 2013).

A few maintenance engineering management techniques and actions are used to minimize failures and their consequences. Among these techniques, those that use the concept of condition-based maintenance (CBM) seek to answer these questions regarding the predictability of a failure. In a way, this technique is successful in many situations, but there is still room for the real probability of failure of this asset under certain operating conditions and deterioration and its evolution over time.

Therefore, initiatives for the evaluation of existing structures through the concepts of structural reliability are observed in several works (Nunes et al., 2017). These concepts are used to support the decision process regarding inspections and maintenance policies. However, an objective and systematic approach to the use of parameters generated by structural reliability analysis for application in daily operations, through maintenance engineering, still requires further development.

In this way, the present work seeks to contribute to the decision process, regarding possible interventions in an asset or structure, through software that applies a methodology for evaluating the level of safety and probability of failure through structural reliability. The concept of this methodology, which from now on will be called probabilistic condition-based maintenance (PCBM), is an expansion of the existing concept of CBM, where the safety index itself and/or the probability of failure become the monitoring variable.

In addition to what was previously exposed, the motivation for carrying out the present work is given by the possibility that from the monitoring of the evolution of the safety parameters and probability of failure over time, the ideal moment of intervention can be established, as well as changes in operational aspects so that the asset returns to an acceptable level of security. Although this paper presents the theoretical concepts necessary for the development of what is proposed here, more details regarding PCBM can be found in (Teixeira & Landre Jr, 2016).

STRUCTURAL RELIABILITY METHODS

According to (Melchers, 1999), the study of structural reliability is related to the calculation and prediction of the probability of violation of a limit state for an engineering structural system at any time during its life. In other words, it means that structural reliability has as its principle the determination of the probability of failure of a structure and, consequently, the characterization of its safety index. The determination of its failure probability and its safety index can be carried out both in the design phase and in its operational phase. Also, according to (Nowak & Collins, 2012), the concepts of structural reliability can be applied both in the design of new structures and in the evaluation of existing structures.

In the bibliography, there are several methods applied to structural reliability, among which are: First order second moment (FOSM), advanced first-order second moment (AFOSM), first-order reliability method (FORM), second-order reliability method (SORM), and Monte Carlo. The choice of which method to apply varies according to the statistical characteristics of the input data and, in this paper, the FORM method was applied due to the system used in the development of the PCBM reference model for the software developed in (Teixeira & Landre Jr, 2016). According to the last author, the criterion for defining the structural reliability method used was based on the characteristics of the probability distributions and their function types. However, more details on the other methods can be found in (Nowak & Collins, 2012).

First Order Reliability Method - FORM

The FORM and SORM analytical methods share the characteristic of making it possible to calculate the probability of failure and safety index through transformations of the random variables that define the problem studied, to reduce the need for greater computational resources due to the lack of numeric integration.

In the FORM method, random variable U, whose distributions are any and may or may not be dependent on each other, are transformed into statistically independent standard normal variables V. The fault function $G(U)$ is written as a function of the variables V as $g(V)$. After that, the fault surface $g(V) = 0.0$ is approximated by a linear (or hyperplane) surface at the point with the shortest distance to the origin, identified as V^* (it is the design point in the space of reduced variables). From this, the probability of failure can be simply calculated by Equation (1).

$$P_f = \Phi(-\beta) \tag{1}$$

Where β is the distance from the point V^* to the origin and is calculated by Equation (2).

$$\beta = |V^*| \tag{2}$$

Therefore, there is Equation (3):

$$V^* = -\alpha\beta \quad \rightarrow \quad g(V) = \beta - \sum_{i=1}^{n} \alpha_i v_i \tag{3}$$

Where α is the vector normal to the fault surface at the design point. Figure 1.a illustrates the procedure for calculating the probability of failure by the FORM method for the case of two random variables.

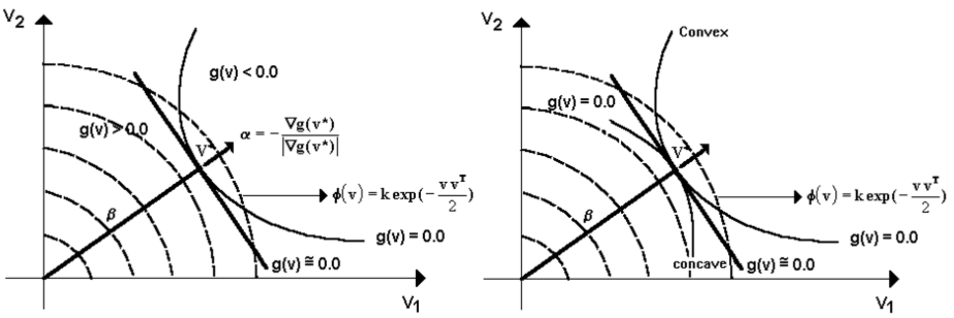

Figure 1 – Graphic representation of the FORM method (a) and approximation for concave and convex surfaces (b). (Sangrillo, 1994)

It should be noted that the FORM method is a method that calculates the probability of failure approximately and depending on the form of the function $g(V)$ in the space of reduced variables. As shown in Figure 1.b, this approximation can be pro-safety when $g(V)$ is convex around the design point or be unsafe otherwise. However, for practical cases of structures, the difference between the real value and the approximate value of the failure probability is irrelevant.

The main challenges in the FORM method are the search for the design point V^* and the transformation of the variables into standard normal variables. As will be seen below, the transformation of the variables can be done using equivalent normal distributions and the design point can be obtained by solving an optimization problem - or nonlinear programming.

There are several possibilities for transforming random U variables into statistically independent, standard normal variables. However, the methodology most used in structural reliability is based on the transformation of correlated normal variables into statistically independent normal variables. This transformation is known as the Nataf, Kiureghian, and Liu transformation. If U U contains only normal variables and these are correlated with each other in a set of standards, statically independent normal variables can be obtained by the following transformation described in Equation (4):

$$\boldsymbol{V} = \Gamma\sigma^{-1}(\boldsymbol{U} - \boldsymbol{m}) \tag{4}$$

Where m is the vector with the means of the variables U, $*$ is a diagonal matrix containing the standard deviations of the variables U. $\Gamma = \boldsymbol{L^{-1}}$, where L is the lower triangular matrix obtained from the Cholesky decomposition of the matrix of correlation coefficients of U, and is expressed by Equation (5).

$$\boldsymbol{L} = \begin{bmatrix} L_{11} & 0 & 0 & 0 \\ L_{12} & L_{22} & 0 & 0 \\ . & . & . & . \\ L_{1n} & L_{2n} & . & L_{nn} \end{bmatrix} \tag{5}$$

Where n is the number of random variables involved in the transformation and the terms L_{ij} are defined by Equation (6).

$$\begin{gathered} L_{11} = 1.0 \\ L_{i1} = \rho_{i1} \qquad \text{i=1, n} \\ L_{ik} = \frac{1}{L_{kk}}\left(\rho_{ik} - \sum_{j=1}^{k-1} L_{ij}\, L_{kj}\right) \quad 1<\text{k}<\text{I} \\ L_{ii} = \sqrt{1 - \sum_{j=1}^{i-1} L_{ij}^2} \qquad \text{i}>1 \end{gathered} \tag{6}$$

Where ρ_{ij} is the correlation coefficient between the variables U_i and U_j. As will be seen in the next item, to determine the design point it is necessary to define the Jacobian of the transformation (Equation 7).

$$\boldsymbol{J} = \frac{\partial \boldsymbol{V}}{\partial \boldsymbol{U}} \tag{7}$$

And from Equation (4), there is Equation (8):

$$\boldsymbol{J} = \Gamma\, \sigma^{-1} \tag{8}$$

In most cases, the variables are not normal and for these cases, then, an equivalent normal transformation can be used to operate with Equation (4). It should be noted that the transformation into equivalent normal does not consider cases where the variables are correlated. In the case of correlated variables, it is also possible to use the same transformation to obtain equivalent normal, provided that the correlation coefficients between the original variables are corrected for correlation coefficients between the equivalent normal.

Let U_i and U_j with any and dependent probability distributions, whose dependence is defined by the correlation coefficient ρ_{ij}. Then, the equivalent correlation coefficient between the two normal distributions equivalent to the variables U_i and U_j can be defined by Equation (9):

$$\rho_{ij}^{E} = F\rho_{ij} \tag{9}$$

Where F is a value that depends only on ρ_{ij} and the coefficients of variation of the variables U_i and U_j. This value does not depend on the point where the transformation is being performed. (der Kiureghian & Liu, 1986) developed analytic expressions for the F factor for a large number of probability distributions.

Once the equivalent normal for the variables U and their equivalent correlations are defined, Equation (4) can then be used to obtain statistically independent standard normal variables V. The Nataf transformation operates with the marginal distribution of random variables and with the correlation coefficient between the variables, that is, the joint probability density function $f_u(\boldsymbol{U})$ is not known. For this reason, it is said that such information, marginal distribution, and correlation coefficients, are incomplete probabilistic information. However, this is the case for most practical applications.

In the case where complete probabilistic information is known, i.e., $f_u(\boldsymbol{U})$ is known, the transformation of Rosenblatt Madsen is the most suitable for the transformation of variables V into U. This transformation is defined by Equation (10).

$$\begin{aligned} V_1 &= \Phi^{-1}\left(F_{U_1}(U_1)\right) \\ V_2 &= \Phi^{-1}\left(F_{U_2}(U_2/U_1)\right) \\ &\vdots \\ V_n &= \Phi^{-1}\left(F_{U_n}(U_n/U_1U_2\cdots U_n)\right) \end{aligned} \tag{10}$$

Where F_{U_i} is the cumulative probability function of the variable Ui conditioned to known values of the variables U1, U2, ..., Ui-1 and $\Phi^{-1}(.)$ is the inverse of the standard normal cumulative function.

In practice, data are rarely available in the form suitable for the Rosenblatt transformation and therefore the Nataf transformation is the most used. Even for cases where the joint probability distribution of the variables is known, the Nataf model can be used. One of the fundamental steps for calculating the probability of failure by the FORM method is to find the point $\boldsymbol{V}^*$ on the fault surface closest to the origin. This can be formulated as a P1 optimization problem with a constraint such as that described in Equation (11).

$$\begin{aligned} &P1 : \ min\,i\,mize \quad |\boldsymbol{V}| \\ &in\,function\,of \quad g(\boldsymbol{V}) = 0 \end{aligned} \tag{11}$$

There are several optimization algorithms to solve this problem, but one of the most used algorithms is commonly identified as HLRF and is summarized by the following recursive expression in Equation (12).

$$\boldsymbol{V}^{K+1} = \frac{1}{|\nabla g(\boldsymbol{V}^K)|^2}\left[\nabla g(\boldsymbol{V}^K)^T\boldsymbol{V}^K - g(\boldsymbol{V}^K)\right]\nabla g(\boldsymbol{V}^K) \tag{12}$$

Where $\nabla g(\boldsymbol{V}^K)$ is the gradient of the fault function in the reduced space and $g(\boldsymbol{V}^K)$ is the value of the fault function, both evaluated at the point $\boldsymbol{V}^K$. To use the HL-RF method, the following relations are extremely useful (Equation 13):

$$\begin{aligned} g(\boldsymbol{V}) &= G(\boldsymbol{U}) \\ \boldsymbol{V} &= \Gamma\sigma^{-1}(\boldsymbol{U} - \boldsymbol{m}) \\ \nabla g(\boldsymbol{V}) &= (\mathbf{J}^{-1})^T\ \nabla G(\mathbf{U}) \end{aligned} \tag{13}$$

Where $\nabla G(\boldsymbol{U})$ is the gradient of the original space failure function evaluated at point U.

MECHANICAL MAINTENANCE TECHNIQUES

In general, the maintenance function can be defined as a set of technical and managerial actions taken throughout the life of the asset to maintain or restore its required function (Shin & Jun, 2015), several techniques have been developed, since around the second half of the last century, to improve maintenance assertiveness. According to (Moubray, 2000), this evolution can be divided into three generations: The first, based on repair after damage; the second, with scheduled reviews and the beginning of the use of computers, and the third, where the availability of more developed computers allows versatility in the study and prediction of failures.

According to NBR 5462/1994, there are three types of maintenance: Corrective, systematic, and predictive; the latter being also called condition-based maintenance. However, there are divergences regarding this in the literature. For (Viana, 2002), the types and maintenance can be classified as corrective, preventive, and predictive. For the author, this occurs because the types of maintenance are nothing more than ways of directing interventions in production instruments. With this, the technique diverges and is adapted according to the needs of the company that uses it.

CBM and PCBM

Condition-based maintenance, or predictive maintenance, is nothing more than what its name suggests, that is, preventive maintenance on an asset based on the operational condition that this asset is in. An important characteristic of this type of maintenance is the monitoring of the equipment through measurements carried out when it is in full operation, which allows for greater availability since it will only undergo intervention when it is close to a failure limit previously established by the team. maintenance.

Predictive maintenance stands out for its feature of anticipating the diagnosis of possible asset failures. It is performed close to the failure or at the most appropriate time, considering other operational requirements (BRANCO, 2006). These are activities based on the results of periodic quantitative inspections, which are performed by measuring parameters to monitor degradation and detect signs of failure. It is usually known as predictive maintenance and will be more efficient when there are measurable parameters with their threshold values (XENOS, 2004).

Predictive maintenance can also be defined as the activity of monitoring certain parameters of the equipment that indicate its performance, systematically, to identify the exact moment of intervention of the equipment. (Moubray, 2000) illustrates the concept of condition-based maintenance or predictive maintenance through the P-F curve illustrated in Figure q. In this illustration, point P indicates the time when a defect was found in an asset that is in evolution. Point F is the potential failure of this asset, arising from the evolution of the defect found in P. Predictive maintenance must be responsible for monitoring this evolution to determine the best time to act before the failure occurs unexpectedly.

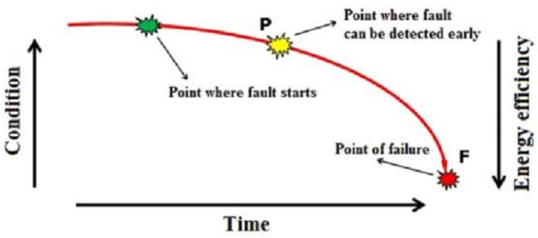

Figure 2 – PF curve. (Silva, 2021).

Reliability studies come from two specific lines: The first is deterministic, which is based on calculated or collected data, obtained from analytical and experimental studies; while the second follows the probabilistic approach, in which the results are treated statistically and, consequently, make it possible to infer future results. While CBM is a deterministic technique, PCBM is probabilistic. As performed in (Teixeira & Landre Jr, 2016), even though the PCBM removes the uncertainties of deterministic evaluations, both systems can be used in a complementary way.

After defining the FORM as a structural reliability method, the application of PCBM requires the probability distribution for the chosen random variables – in the present work, the limit of resistance to maximum and minimum stresses. For these variables, the statistical characteristics related to the mean, standard deviation, and coefficient of variation are calculated. On the other hand, still for the probability distribution, several methods can be used according to the fitting for the input data, among which the Weibull, Log-normal, Log-logistics, Normal, and Logistics functions stand out - as the source of these statistical functions. As a result, reliability indices (β) and probability of failure are obtained.

Therefore, PCBM uses experimental data or virtual simulations of mechanical systems subjected to dynamic efforts, thus generating the reliability and failure probability indices. Therefore, these two parameters are the variables to be monitored in the proposed model. In this concept, the software to be developed by the present work should also be able to receive data from both above-mentioned scenarios as input. With this, another derived functionality is the possibility of evaluating the correlation between a virtual model and a physical system.

APPLICATION FOR USING PCBM

The software developed in the present work for simulations involving the PCBM is presented in Figure 3, together with its main functionalities. For its development, MATLAB software was used.

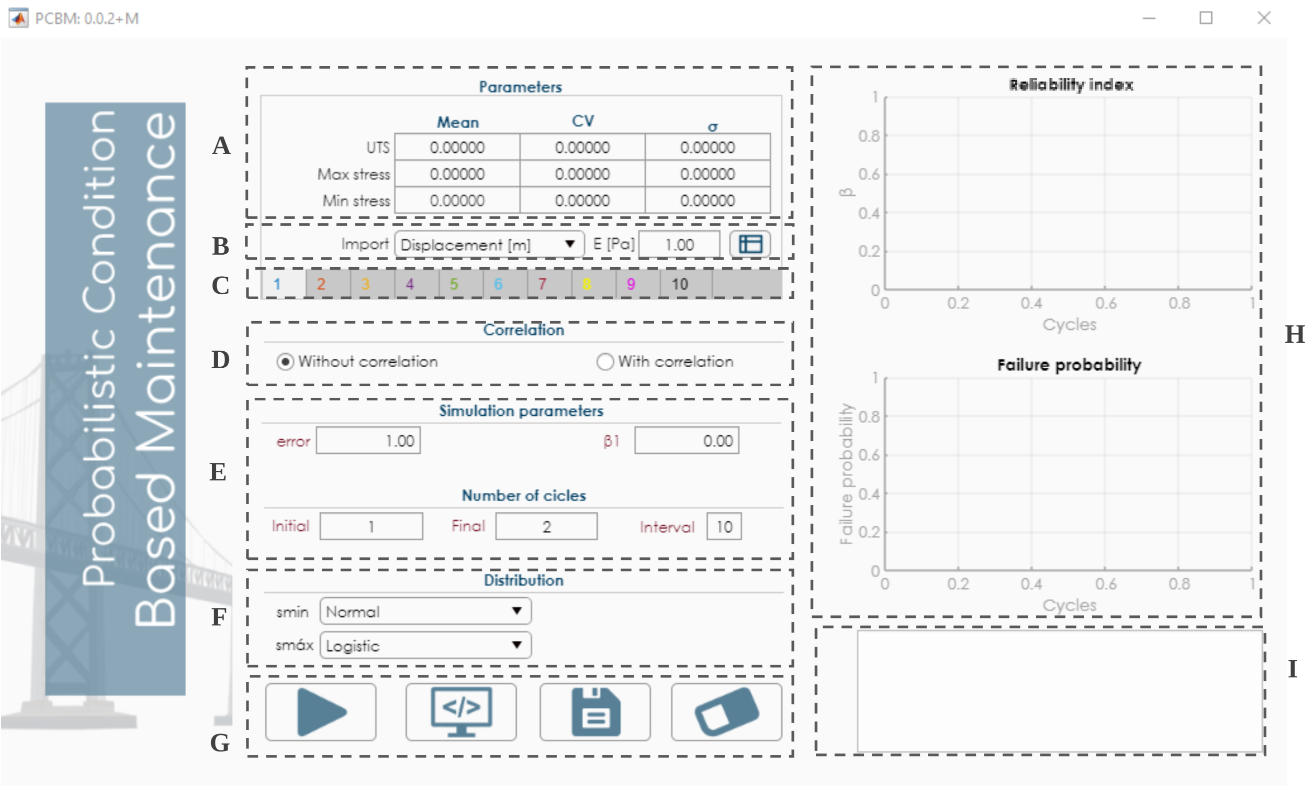

Figure 3 – PCBM software

The fields indicated in the figure above are described below:

A: In this region, the mean, variation coefficient (CV), and standard deviation (SIGMA) values of the maximum and minimum stresses are inserted, in addition to the ultimate tensile strength (UTS). The data can be entered manually, if previously calculated, or the user can import a spreadsheet with the data curve in time. The software automatically calculates these statistical parameters;

B: As previously mentioned in this text, the software must be able to work with both experimental data and data from virtual simulations, as in the case of finite element analysis (FEA), for example. As in this case, the data usually comes in the form of tension, instead of the displacement data coming from strain gauges in the analysis with physical systems, the user can define Young's modulus of the material to perform the conversion of values, according to Hook's Law, if you select the strain gauge option;

C: Up to 10 analyzes can be performed simultaneously, allowing comparison between different cases;

D: According to the FORM method, the user can choose whether or not to correlate the data;

E: Definition of simulation parameters, i.e., admissible error (after all, an iteration method is used during the simulation) and simulation step;

F: Choose which type of distribution the software should use. Available functions: Weibull, log-normal, log-logistics, normal, extreme, and logistics;

G: Respectively, buttons to run the analysis, observe the simulation log, save the simulation results/log and delete all imputed data;

H: Graphs of the results obtained;

I: Simulation log and table presentation of the results.

Before the data are input into the model, however, the software needs to pre-process the data. In this pre-processing, an algorithm was developed responsible for finding the peaks and valleys of the input signal, which are relative, respectively, to the maximum and minimum tensions. Even before this point and especially for data obtained via strain gauge, the software applies a moving-average filter, a common method used for smoothing noisy data, in the imputed data aiming to remove the noise coming from the collection. As shown in Figure 4. such pre-processing is displayed for user evaluation whenever the user chooses to import the tension (or displacement) curve from a spreadsheet. In addition, the first collection points are also disregarded.

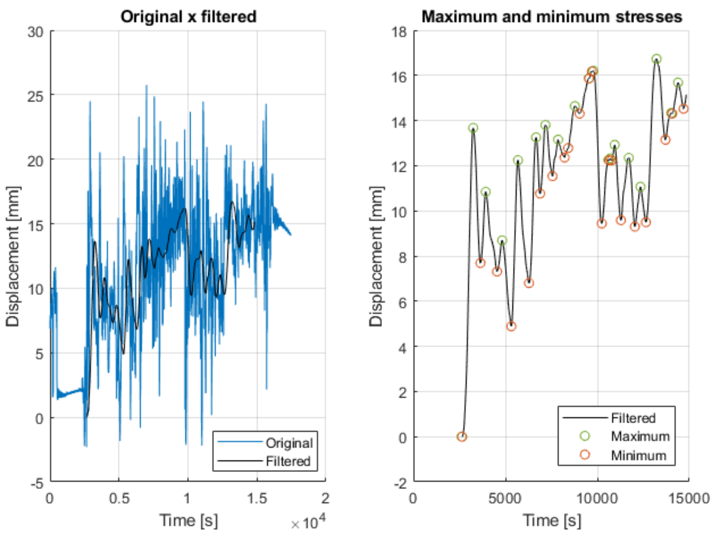

Figure 4 – Filtered and original signal.

Finally, the software also has a sequence of informative windows to help the user during the simulation. If any value does not reach a numerical solution, for example, the user is informed and indicates the point in the simulation where such failure occurred.

SIMULATIONS

To validate the results of the software, some situations are proposed. In the first one, three different data inputs were considered to verify the influence of tension variation on the system lifetime. According to the data and results are shown in Figure 5, the first data entry considered the maximum and minimum tensions as 18 MPa and 5 MPa. For the second data input (orange curve), all data were kept constant except for the minimum tension, which was changed to 6 MPa, as well as for the third data input (yellow curve), where the minimum tension was changed to 7 MPa this time.

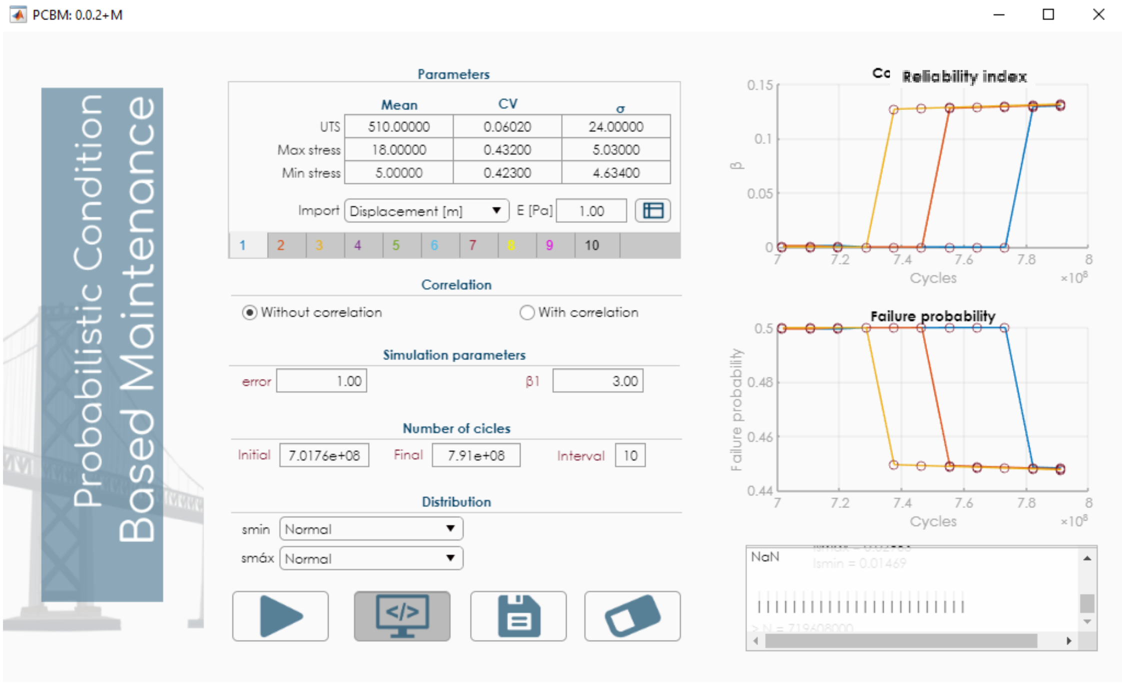

Figure 5 – Results of the first simulation. After execution, reliability index and failure probability charts are plotted. Likewise, the results are also presented just below the plots.

The results found to corroborate that the decrease between cycles of maximum and minimum tension values helps to extend the life of the mechanical system in terms of being possible to have more cycles with less probability of failure.

As previously discussed, the colors of the curves in the last figure reflect the colors of each of the 10 data entry tabs. For example, a green curve would refer to data entry 5. It should also be noted that if the user wishes to adjust the input parameters according to their analysis of the obtained response, all input parameters can be changed and a new simulation can be performed, allowing great flexibility and ease in the test flow. In this scenario, a new simulation is performed from the previously found data.

In the second simulation presented here, the parameters of the three data sets used previously were kept constant. Now, however, the chosen distribution functions have been changed along with the simulation interval to obtain more accurate curves. With this, the results obtained are presented in Figure 6.

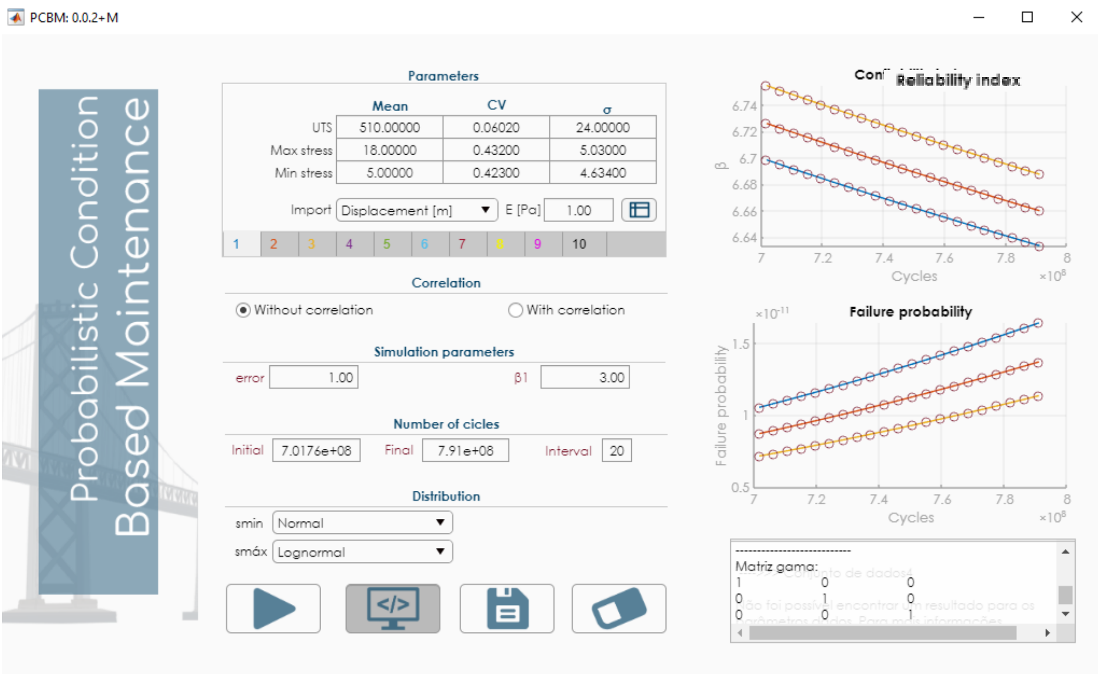

Figure 6 – Second simulation. The parameters of the first simulation were maintained, except for the distribution type. With this, it is noted the importance of the correct definition of the chosen distribution according to the imputed data.

CONCLUSIONS

Reliability studies come from two specific lines: A deterministic one, which is based on calculated and collected data; and probabilistic, in which statistical data makes it possible to infer future results. In the present work, a probabilistic method, the probabilistic condition-based maintenance, was used for the development of software that aims to assist in the mechanical maintenance routines of equipment and structures subjected to dynamic efforts. To this end, reliability indices and failure probability were generated, which were the variables to be monitored in the proposed model.

Starting from a PCBM model validated in (Teixeira & Landre Jr, 2016), the application developed in this paper achieved the proposed objectives since it was able to:

- Develop a graphical user interface for simple and dynamic use by the user;

- Allow the input of data from virtual simulation or physical experiments through extensometry, via electronic spreadsheet, and application of a filter and identification of maximum and minimum tensions for these data;

- Definition of parameters for the implementation of the FORM method of structural reliability;

- Definition of parameters for simulation such as number of cycles, the interval of cycles, and distribution functions;

- Presentation of data in chart format and simulation log, in addition to the possibility of exporting this data

Therefore, the software presented here presents itself as an interesting alternative for studies in the area due to its high application potential. As future steps to continue this research, is also suggested the implementation of other structural reliability methods, i.e., FOSM, AFOSM, and SORM.

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