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EVALUATION AND MONITORING OF KEY PERFORMANCE INDICATORS FOR MAINTENANCE BYSOFTWARE IN SUGAR-ENERGY INDUSTRY

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ABSTRACT: Maintenance Programming, Planning and Control (PPCM) methodology is a tool that contributes toincrease productivity in companies, while aims to adequately allocate resources when it comes to menage industrial maintenance. Planning to maximize result is an essential part of this tool and, for that, it disposes of elements such as Key Performance Indicators. In that case, extracting the correct data is fundamental. This paper aimed to build an interface, in Python language, able to display important maintenance KPI's from collected data for sugar-energy industry's harvesters, in order to determine reliability as the focus. It has also allowed the observation of their operational historic in order to analyze conditions and, thus, project a perspective of what to expect for the harvest to come. It's been noticed, then, that the time before failure consistently decreases along the asset's age and eventually the MTBF stabilizes around 20 hours. In MTTR, there's also a noticeably stability around 2 hours. For the Availability KPI, the organization presents great rate,not reaching under 90% all the period. And, due to the successful software as an interface, Reliability is also easy to analyze whenever necessary, determined from the other KPIs, composing an excellent tool for maintenance management.

KEYWORDS: Industrial Maintenance. KPI. Reliability. Python. PPCM.

INTRODUCTION

The strategic view on the management of industrial maintenance today is a determining resource. Today's market requires organizations to operate with intelligenceand methodism, and maintenance, in this context, becomes an essential element, since the global competitive scenario intensifies the need for maximum cost reduction and increased productivity in companies. According to Sousa (2020) and Ramos and Schrattner (2020), it is then convenient to highlight the role of Maintenance Programming, Planning and Control (PPCM), an applied methodology that consists of a set of activities aimed at the adequate allocation of resources for efficiency in maintenance, in a way that seeks, above all, the optimization of maintenance indicators. In short, good planning essentially seeks to maintain and improve the effectiveness and efficiencyof the service, and thus it is indeed a crucial and decisive issue (GRESSLER et al., 2020; FERREIRA et al., 2021; SANTOS, 2021).

According to NBR 5462 (1994), item 2.8.1, maintenance activity describes the set of measures taken in order to preserve or restore an item to a state in which it can perform its intended function. Thus, it makes sense to infer that well- planned and executed maintenance will result, mainly, in extending the useful life of equipment, reducing the breakdown of critical equipment, improving product quality, increasing equipment availability and other performance indicators (KARDEC; NASCIF, 2019; GRESSLER et al., 2020; SOUSA, 2020).

Therefore, it makes sense to state that one of the contributing elements to achieve the objectives is the establishment of measures that ensure the production capacity of an industrial plant as being as best and productive as possible and, for those, the equipment must have a low failure probability (SOUSA, 2020). Or, as mentioned by Gressler et al (2020), philosophies, such as Total Productive Maintenance (TPM) and Total Quality Control (TQC), and management support tools, such as Reliability Centered Maintenance (RCM), Failure Mode and Effect Analysis (FMEA), Reliability, Key Performance Indicators (KPI) and Software enable improvements that supports the necessary constant reach for World Class Maintenance. And so, the concept of key performance indicators, reliability and the use of maintenance management software should be introduced.

The maintenance indicators (or KPI) are defined as the set of information that seeks to measure and optimize processes, with the aim of increasing the efficiency and productivity of an organization. They propose models aimed at preventing and solving the most diverse problems that may occur within an organization. In this context, the monitoring of operating and maintenance parameters must be a priority to ensure a dynamic and controllable structure that allows readjustments to be carried out in its process and makes opportunities for action visible, which effectively means reducing repair rates (SANTOS, 2021; TAVARES, 2022).

The last generation in the history of industrial maintenance is intensely influenced by a greater valuation for reliability, availability and maintainability, indicators where failures serve as the basis for building a system that minimizes the possibility of their repetition. According to Kardec and Nascif (2019), preventive maintenance becomes a priority onlyif not for production and unplanned corrective maintenance brings harm to maintenance indicators and the company. It is easy to visualize the indispensability of constant recurrence to the resources and measurements that make its control possible and accessible.

As Santos (2021) points out, an organization "needs to carry out several projects with a view to improving maintenance and investing resources to improve quality"; it is in this scenario that it is worth highlighting the contribution of data intelligence and computer science.

It makes sense to say that the automation of tasks is an inevitable trend that results from the advancement of information technology. It is a system made up of mechanical or electronic devices, components of an organization, intended for theoperation and control of production processes which does not require direct human intervention. It infers, inevitably, by nature, in a generation of volume of information that needs to be worked on, polished and discussed to rase relevant information, requiring a large amount of work to clean up the variables and make them palatable to the understanding of the general public (RAMOS; SCHRATTNER, 2020; NETO, 2021). It is thus valid to emphasize the importance of searching for resources, elements and methodologies that cooperate with the treatment and conversion of information into its logical and understandable form from a managerial point of view. At this point, data science has the necessary validation resources in a practical and fast way, capable of dealing with a large volume of data and accurately while highlighting the points of interest (FERREIRA et al, 2021).

In fact, in an increasingly complex, integrated and automated industry, the use ofsoftware for maintenance is a tool that optimizes resources and their use, validates Gressler et al. (2021), not only does it mean taking advantage of available technology, but today it essentially reflects a management posture in the face of the new market. This can be corroborated by the following statement by Ramos and Schrattner (2020): "one of the crucial points for the RCM is information, with theuse of good maintenance management software the collection of information tends to be more effective and allows its subsequent management".

With that focus, the present case study seeks to evaluate the maintenance indicators directly related to reliability: availability, Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), and availability, through the use of a library developed completely in software, for situational analysis applied to the internal record database of the maintenance history of the factory in the sugar and alcohol industrial segment Diana Bioenergia® take from the period of 5 years (2018, 2019, 2020, 2021 and 2022) specifically for the sugarcane Harvester, currently one of the main and most fundamental, in terms of availability, assets owned by the organization. The research is part of one of the stages of the ConfIA Project, designed to apply Machine Learning to predict the reliability of the same asset; even so, the isolated library will remain working faster and more accurately for continuous identification of critical points, highlighting good performance and acting as an auxiliary metric in decision-making when it comes to Maintenance Programming, Planning and Control.

KEY PERFORMANCE INDICATORS

As stated, the research aims the analysis of both the general situation of the indicators necessary for the reliability analysis, that is, availability, MTBF, MTTR, as well as reliability key indicator itself.

The mean time between failures is the ratio between the total time of hours the equipment worked by the number of corrective maintenance interventions in a given observed period (Equation 1). If MT is the variable that represents the time spent under repair (mean time), it is clear why it should be subtracted from the time theoretically defined as an operable asset. In addition, Corrêa (2021) suggests the application of the correction factor +1 in the denominator of the equation that more accurately readjuststhe MTBF indicator for short periods.

$$MTBF = \frac{(\sum Operational\ Time_{period} - \sum Time\ Spent\ for\ Repair_{period})}{Quantity\ of\ Repairing\ Services\ Executed + 1} \tag{1}$$

The mean time to repair, MTTR, is an indicator that analyzes the total maintenance time after a failure occurs (Equation 2). The calculation considers all the time dedicated to maintenance, since the problem was concepted, diagnosed and repaired to the final tests for the equipment to become operational again.

$$MTTR = \frac{\sum Time\ Spent\ for\ Repair_{period}}{Quantity\ of\ Repairing\ Services\ Executed} \tag{2}$$

Availability is another important conditional. It is the key performance indicator whose measurability indicates the proportion in which an item is available in relation to the total time (SOUSA, 2020; TAVARES, 2021). According to NBR 5462, it is the ability of an item to be able to perform a certain function, assuming that the necessary external resources are in hand to make this possible, at a given moment or during a given time interval. This can be represented mathematically according to Equation (3).

$$Availability = \frac{MTBF_{accumulated}}{MTBF_{accumulated} + MTTR_{accumulated}} * 100\% \tag{3}$$

Sousa (2020) states that "an item is considered reliable only if it performs the required function for a predetermined percentage of time by the manufacturing company or by the one that uses the item". Reliability is the ability of an item to perform satisfactorily its function, under pre-arranged conditions, in a time interval (useful life) (NBR 5462, 1994). An item, according to the same Norma Brasileira (NBR, or *Brazilian norm*, in literal translation), would be defined as any part, component, device, subsystem, functional unit, equipment or system that can be considered individually. Kardec and Nascif (2019) define that, as it is a probability, the reliability should vary from 0 to 1, or from 0% to 100%.

$$R(t) = e^{-\lambda t} \qquad (4)$$

In this case, it's defined a new lambda variable, λ, called Failure Rate, describedas the inverse of MTBF, in the form of:

$$Failure\ Rete = \lambda = \frac{1}{MTBF} \qquad (5)$$

Since, according to the equations presented, reliability depends so essentially on other indicators, modeling the times until failure in any quantitative method of reliability and availability is a key element. Thus, analysis mechanisms are used to help achieving the best interpretation of the indicator. The support of a modelingsoftware is often used and allows the generation of curves that adjust these times; the most used being Exponential, Gamma, Lognormal and the Weibull curve (GOMES and ANDRADE, 2020). The Weibull curve, thus, comes to allow visualization of a failureor repairing time distribution for reliability data. By assuming the failure rate, λ, as a constant, the equation by the Weibull analysis method can be assumed by equation.

SOFTWARE

In fact, a system to meet any demands must not only be efficient but also be as less complex and simplified as possible. “In industry 4.0, machines, parts, systems and human beings will be highly connected and highly integrated” (GRESSLER et al., 2020), which is why knowing how to deal with the new format and the new trend in industry is fundamental. The increasingly complex reality requires increasingly comprehensive computerized systems and the choice to use software becomes strategic, as this type of approach solves a variety of problems and needs, providing the desired information at all times, both from a technical point of view as managerial.

Thus, the so-called integrated development environment (IDE), is the place that, with features and facilitating tools, allows the development of software; some of those: an editor for source code (language) and a compiler to read it. The concept of library for computing, in this case, means a file with a collection of subprograms used in the development ofa software, with the aim of facilitating programming. The libraries contain auxiliary codes and data, which organize the predefined code to be used in the desired applications (TAVARES, 2022).

The language chosen here was Python, said to be one of the programming languages with the best applicability projection when compared to other languages (BRITO, ANDRADE E DELAMARO, 2022), due to its great purpose, dynamism, orientation and usability in a vast application field. This is due to the versatility and variety of resources that come together to make it as a more simplistic and universal dynamic language to learn, while having a range of specific andfacilitated libraries and frameworks; besides being buildable for free.

Therefore, it is intuitive to assume possibly that the use of the Python languageis also capable of determining alone, when served by a conniving database, the calculation and tendency of industrial indicators as a use in managerial decision makingin PPCM, is extremely valid and logical.

SUGAR AND ALCOHOL INDUSTRIAL SEGMENT

In the period after the Second World War, the state of São Paulo became the main producing region in the country when it comes to sugar and alcohol, accounting for 59% of national production in 2017. And so it continues, with a similar projection in the future (this can be seen in Table 1 when evaluating the evolution of significance between the most impactful states in the field). Therefore, although originating from the history of Brazilian agriculture and its origins, considering that the sugar-energy sector still represents one of the most important production chains in Brazilian agribusiness, it is, fundamentally, an industry segment subject to constant research and improvement.

The “Monitoramento da Cobertura de Uso do Solo” (monitoring of land coverage and use) in Brazil, carried out by Instituto Brasileiro de Geografia e Estatística (IBGE, or *Brazilian Institute of Geography and Statistics*, by literal translation) between 2000 and 2016, shows an increase in the Brazilian agricultural area (IBGE, 2019). Carvalho (2020) states, about this case, that the cultivation of sugarcane comprises “the third largest production in area and currently occupies around nine million hectares, 16 concentrated mainly in the state of São Paulo”. It is also interesting to point out from studies by Carvalho (2020), which review sustainability in cultivated areas, that the use of technology provides the design of environmentally less aggressive projects, as they allow the formulation of alternatives with less impact. Which can be done by technologies, such as automatized and digital-integrated ones.

“In all Brazilian mills, the technology for producing ethanol and sugar is very similar from the point of view of processes, but there are variations in the types and qualities of equipment, operational controls and, mainly, at management levels. In addition, currently, there is good integration between the agricultural and industrial areas of the plants, which allows optimizing the entire production chain in units with good management” (CARVALHO, 2020).

As highlighted by Feltre and Perosa (2020) and Carvalho (2020), the growing adherence to technologies such as mechanized harvesting and production is a reality in the sugar and alcohol sector, whose philosophy is directly responsible for its continued importance within the national agribusiness scenario.

Table 1. Temporal comparison of sugarcane cultivated area between states (%).

State	1990	2015
São Paulo	41,9%	56,4%
Goiás	2,5%	9,6%
Minas Gerais	7,0%	9,2%
Mato Grosso do Sul	1,6%	6,3%
Paraná	3,7%	5,9%
Alagoas	13,0%	2,8%
Mato Grosso	1,5%	2,7%
Pernambuco	11,0%	2,1%
Other States	17,9%	5,0%

Source: Feltre e Perosa (2020) (adapted).

The company is a power plant in the sugar-energy sector at the town of Avanhandava, SP's countryside. As part of the São Paulo mesoregion of Araçatuba, Diana® occupies one of the most influential regions for sugarcane cultivation, as shown in Table 2. Between 2000 and 2015, according to Feltre and Perosa (2020), the area cultivated in the region of Araçatuba increased by 217%, whereas between 1990 and 1999 it had reached almost 67%. In addition to being well located, the organization must make use of any methodology that takes full advantage of the production system and variety of assets it has. The company works with advanced technologies, specially within the harvest extracting, while making use of completely mechanized Harvesters, the asset aimed by this research.

Table 2. Temporal comparison of sugarcane cultivated area between mesoregions (%).).

Mesoregion	1990	2015
Ribeirão Preto (SP)	28,0%	24,5%
São José do Rio Preto (SP)	8,0%	18,3%
Bauru (SP)	16,0%	11,4%
Presidente Prudente (SP)	4,0%	9,9%
Araçatuba (SP)	5,0%	8,9%
Araraquara (SP)	8,0%	7,0%
Assis (SP)	8,0%	6,8%
Piracicaba (SP)	13,0%	5,5%
Campinas (SP)	8,0%	4,5%
Marília (SP)	1,0%	1,6%
Itapetininga (SP)	2,0%	1,2%
Macro Metropolitana Paulista (SP)	1,0%	0,4%
Vale do Paraíba Paulista (SP)	0%	0%
Litoral Sul Paulista (SP)	--	0%
Metropolitana de São Paulo (SP)	0%	0%

MATERIALS AND METHODES

When software is approached as a resource for PPCM, it is imperative that the imputation of data is carried out correctly in order to obtain the results as desirable (REMOS; SCHRATTNER, 2020). For that, a good planner is necessary, and a good planner needs precise parameters. In this sense, the first stage of the work dealt with the knowledge of the procedures when it comes to programming and maintenance control for

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the Harvesters, as well as the methodology adopted for recording the service orders, conducted by contact with employees and processes developed in the company through an internship. Table 3 summarizes information on the harvesters in the system.

Table 3. General information on the assets.

Equipment Code	Equipment Description	Started	Stoped
A14	Colh Cana CASE A8800 48	2014	2021
B14	Colh Cana CASE A8800 49	2014	Operating
C14	Colh Cana CASE A8800 51	2014	Operating
D14	Colh Cana CASE A8800 53	2014	Operating
E14	Colh Cana CASE A8800 54	2014	Operating
F14	Colh Cana CASE A8800 52	2014	2021
A20	Colh Cana CASE A8810 61	2020	Operating
B20	Colh Cana CASE A8810 62	2020	Operating
A21	Colh Cana CASE A8810 65	2021	Operating
A11	Colh Cana J DEERE 3520 33	2011	2020
A13	Colh Cana J DEERE 3520 45	2013	2020
B11	Colh Cana J DEERE 3520 34	2011	2020
A18	Colh Cana CASE A8810 58	2018	Operating
B18	Colh Cana CASE A8810 59	2018	Operating
A19	Colh Cana J DEERE CH570 60	2019	Operating
B21	Colh Cana CASE A8810 64	2021	Operating
C20	Colh Cana CASE A8810 63	2020	Operating

It should be noted that the last two digits of the equipment code indicate the yearit was obtained; for example, the tagged Harvester “A14” was purchased by the company in 2014.

The first step deals with data pre-treatment, as usual by programming science, in order to adapt data as its most convenient form to serve the desired purpose. For this research, in order to evaluate key performance indicators concerning reliability, the restriction of the total data in the service orders specifically for the desired period and in the category of

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corrective maintenance is conducted. Since the main objective was to evaluate reliability, it is necessary to restrict the analysis to repairs that directly interfere with availability and occurred during the period of use, in this case, during the harvest periods conducted by the company, which can be seen in Table 4 (*as it was a goodharvesting year, there was an extra period within 2020). This meant a reduction from almost 52000 data down to 19500. The new spreadsheet generated, in .xlsx format, was used as the basis for the accumulated calculation of the MTTR.

Table 4. Harvesting periods conducted by the company between theyears of 2018 and 2021.

Year	Beginning	Ending
2018	01/04/2018	15/12/2018
2019	28/04/2019	08/11/2019
2020	01/04/2020	03/12/2020
2021	01/04/2021	13/11/2021
2022	01/04/2021	17/11/2022
Extra*	16/03/2020	31/03/2020

Finally, the code referred to the creation of the ConfIA Library could be programmed in Python. The complete program may be divided into a two-faced process: pre-treatment (Init function) and calculation (Relatório function). Firstly, Init function has the goal of fixing punctual problems (such as imparities when each Harvester began to work on each harvesting year or dates' format correction). As input, the Init function receives the original spreadsheet data considered through the *url* corresponding to its location in the system, a spreadsheet referring to the "linear" maintenance data, a spreadsheet referring to the dates of the asset's operational period, aspreadsheet referring to the harvesting period, and an alarm – valid for automatically segregating values above the imposed limit in order to locate probable errors in repair times (it is assumed that there is a value above which there is inadequacy in classifying the SO as corrective). "Linear" maintenance is the company's method of preserving the asset's integrity by performing preventive maintenance for a few days in the middle of the harvest period. Therefore, it is a time that can be eliminated from the total considered as available time for operation, especially influential in the calculation of the MTBF.

Once filtered, at last, Relatório function was planned as a system that calculated allthe indicators of interest, as well as the generation of a graphical interface where it would be possible to control and visually monitor changes over time, from the input variables: Equipment Code, and Beginning Date and Final Date – limits between which the calculation is generated. The calculable indicators are, therefore, the MTTR, MTBF, Failure Rate, Availability and the Reliability curve performed by the Weibull analysis. In addition, derived from the entered inputs, the function returns for knowledge purposes: the theoretical time of availability of the Harvester in the period involved in the calculation, as well as the repair times suffered, the number of repairs, and the S.O's recorded in the meantime.

RESULTS AND DISCUSSION

From the calculations, thus, it is convenient to individualize the analysis of the main KPI's. The analysis was conducted by Excel. In order to serve as a consultation and validation basis, individual MTBF and MTTR charts per month for each machine were initially generated.

Once five years of data are available, it should be possible to understand some operational indicators in the meantime. Thus, it's reasonable to consider the analysis reduced to the machines more bought earlier than 2018, since they are harvesters without lack of data (complete life information). Therefore, the first years of operation available among these harvesters were grouped together, regardless of their year of purchase (e.g.: 2018 for A18 and 2020 for B20); same logic for the second, third, fourth and fifth years of operation. It should be noted that since the machines were obtained in different years, they have different operational lives and, therefore, make up different sample fields for analysis of operation per year of life – of course, a larger sample field, such as for the first year of operation will infer more precision of results in relation to a smaller one, such as in the fifth one.

Figures 1 and 2 represent the average result between each sample group in order to summarize the operational behavior displayed by the assets while they age.

When it comes to the MTTR – mean time to repair indicator, it's noticed it is constantly decaying, having suffered adrop of 27% over the first year, of 28% over the second, followed by 18%, 5% and 9%. This corroborates the assumption that at the beginning of the harvest, the time before failure should be longer, since the harvesters have just left other, much more complete and detailed maintenance, such as the off-season. In addition, up to the fourth year the drops are more significant while in the fourth and fifth years of operation, it becomes much more stable and without sudden drops.

Figure 2 indicates that MTTR has very regular and little changeable times, having increased over the third year of operation (6%, 37%, followed by 8%) and then decreased over the fifth year (7% and 3%, respectively). It is also curious how from the first to the third year there is an average increase of 0.5 hours, while in the fourth and fifth years there is muchgreater stability around 2 hours.

The big disparity from third to fourth year in both KPI's can be explained by the fact that the organization bought harvesters in 2021 and, this way, causing an optimization in all the KPI's in general. The different start time in the beginnings and endings derives from different operational time: coincidently every asset in their first year within the samples (machines bought earlier than 2018) started working on April and every asset in their second one, were done working by November.

From the average between the average data per year among the data in which the operating life of the equipment is completely described, weighted over the number of samples of each year, it is possible to obtain a new column of data that describes in general the average the behavior of the harvester in 5 years, projecting a basic idea of description of what its operational behavior will be approximately in the following year. Putting it in chronology, this would be in the 2023 harvest.

Figure 1. Mean time between failure per assets, per year of operation.

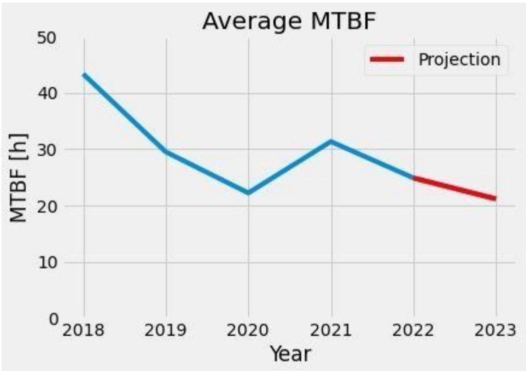
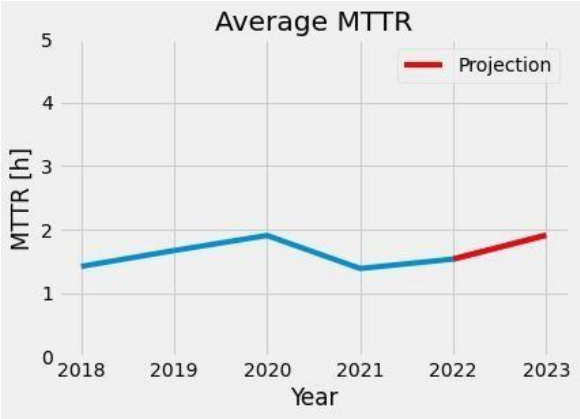
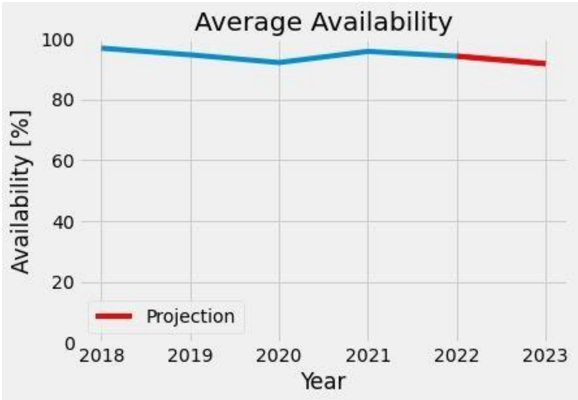


Figure 2. Mean time to repair per assets, per year of operation.



Then it will be possible to analyze the availability key performance indicator, given that it depends on the other parameters. Figure 3 describes the availability calculation for all Harvesters for the 5-year period (2018 to 2022). Based on the established parameters, the company currently has good availability, with a mean value of approximately 92%. Because the average availability is overall considerably high, by management decision, no harvesters will be bought next year, and that is why MTTR and MTBF seem to be lower for 2023's projection.

Figure 3. Availability (%) for all harvesters from 2018 to 2022 (%)



Finally, the reliability curves can be deduced from the Weibull analysis. In view of this, once the failure patternhas been assumed to be one of the random type, the failure rate, λ, becomes a constant and the assumed predisposition becomes as disposed by Equation (7). The ConfIA Module returns the calculated form of the Weibull Curve. To exemplify, this result can be visualized by Figure 4. By definition of the Weibull analysis for industrial maintenance, as per seen previously, this curve puts into perspective where

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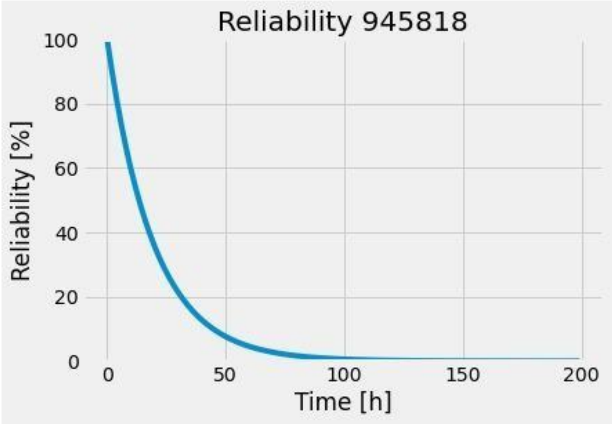
the organization is when it comes to availability and, therefore, makes it possible to plan more precisely how much time the equipment has operating before any failure possibly occurs, in order to avoid loosing time and resources both within the processes of its replacements as well as its repairing.

Figure 4. Availability (*100%) Weibull curves



CONCLUSION

Today's vision of industrial system allows opening for a variety of methodologies that makes it possible to deepen as well as amplify automatization of processes. Software science is one of the most effective ones, by reducing time, space and resources, and increasing efficiency and precision over all variables. That's why the use of programming languages and compilator programs are so encouraged, since it can basically be applied to any situation and adapt to every format necessary for detailed management. Python language being widely known for great performance and flexibility, aside from being of free use, is proven to be a useful tool and perfectly adequate to fit in this scenario.

ConfIA Library is a successful construction, based on specific company's parameters, that can precisely calculate all important key performance calculators to build a reliability curve and, thus, it may be used as a tool of reference for management's decision when it comes to the harvester's maintenance's planning, programming and control, plus operational methodologies, into the future.

The harvesters within the company premises are proven to have considerably high availability overall. However, it's useful to reinforce the importance of the methodic observation over each harvester in order to evaluate and compare so it's easier to find optimal points, and therefore replicate them, as well as replan the lowest ones.

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