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Desarrollo de una metodología para el cálculo de la confiabilidad en una de las áreas de proceso de la empresa ensambladora de vehículos denominada Ciauto Cía. Ltda.

Development of a methodology for calculating reliability in one of the process areas of the vehicle assembly company called Ciauto Cía. Ltd.

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Palabras claves: Sistema reparable, modelo NHPP, Crow Amsaa, Log-lineal, confiabilidad.

Resumen

El análisis de confiabilidad de los sistemas críticos en el sector industrial es una herramienta de gran utilidad para mejorar la toma de decisiones en el departamento de mantenimiento. Generalmente, los métodos de análisis de confiabilidad tradicionales asumen restauraciones de los equipos a su condición original, pero en la práctica esto no sucede, pues generalmente se realizan intervenciones para corregir únicamente la falla que se presenta en ese momento; por este motivo, la presente investigación tuvo como objetivo el desarrollo de una metodología para conocer la confiabilidad actual de activos reparables en donde se ejecutan reparaciones mínimas, y su predicción a 5 años, con el cálculo de la intensidad de fallas y el tiempo medio entre fallas. La muestra se seleccionó a partir de los registros del historial de falla desde enero de 2022 a mayo de 2024 de la planta de soldadura de una ensambladora de vehículos, se realizó un diagrama Jack Knife para priorizar al análisis de los sistemas que más paradas productivas por reparación hayan generado. Se realizó un test de tendencia para determinar el sesgo que tienen los datos históricos y así poder ajustarlos a procesos estocásticos no-homogéneos de Poisson, se utilizó el modelo Crow Amsaa y Log-lineal para seleccionar aquel que mejor se ajuste a los datos y sea capaz de generar pronósticos con el menor error posible. Del estudio realizado, se determinó que los sistemas que más paradas productivas han ocasionado son las soldadoras SP-43 y SP-16, y el JIG MB-10. Para el sistema SP-43, el modelo que generó el menor error para un pronóstico dentro de 5 años fue Crow Amsaa con una estimación de 48 fallas y una falla cada 233 horas de trabajo, mientras que para los sistemas SP-16 y JIG MB-10, el modelo log-lineal presentó el mejor ajuste, pronosticando 19 fallas, una falla cada 987 horas y 22 fallas, una cada 822 horas de operación respectivamente.

Keywords: Repairable system, NHPP model, Crow

Abstract

The reliability analysis of critical systems in the industrial sector is a very useful tool to improve decision making in the maintenance department. Generally, traditional reliability

Amsaa, Log-linear, reliability.

analysis methods assume restorations of the equipment to its original condition, but in practice this does not happen, since interventions are generally carried out to correct only the failure that occurs at that moment; For this reason, the objective of this research was to develop a methodology to know the current reliability of repairable assets where minimal repairs are carried out, and its prediction for 5 years, with the calculation of the intensity of failures and the average time between failures . The sample was selected from the failure history records from January 2022 to May 2024 of the welding plant of a vehicle assembler, a Jack Knife diagram was made to prioritize the analysis of the systems that cause the most productive stops per repair have generated. A trend test was carried out to determine the bias that the historical data have and thus be able to adjust them to non-homogeneous Poisson stochastic processes, the Crow Amsaa and Log-linear model was used to select the one that best fits the data and is capable of generating forecasts with the lowest possible error. From the study carried out, it was determined that the systems that have caused the most productive stops are the SP-43 and SP-16 welding machines, and the MB-10 JIG. For the SP-43 system, the model that generated the lowest error for a forecast within 5 years was Crow Amsaa with an estimate of 48 failures and one failure every 233 work hours, while for the SP-16 and JIG MB systems -10, the log-linear model presented the best fit, predicting 19 failures, one failure every 987 hours and 22 failures, one every 822 hours of operation respectively.

Introduction

Reliability assessment plays a key role in improving availability and productivity in the automotive assembly industry, through the implementation of planned maintenance in the right way.(Soltanali et al., 2020). The importance of developing a methodology to calculate reliability lies in that it serves to guarantee and improve the performance of the systems, allows to evaluate and predict the probability that it will function correctly during a given period of time, provides useful information for decision making in maintenance management and planning, and is useful when implementing effective strategies that will serve as support for future maintenance plans according to the current conditions of the equipment, optimizing the production process, increasing profitability and plant safety. For this reason, the present research not only studies the expected increase in failures in repairable systems with minimal repairs, but also seeks to highlight the importance of proposing more effective and proactive maintenance strategies to improve the future situation.

Reliability analysis is widely used in industrial applications.(Hu et al., 2021)This methodology allows to determine and understand the failure behavior and the possible estimation of a forecast of the number of failure events, which leads to identifying which are the equipment in which new failure events may occur, as well as their long-term operational behavior. The exact moment in which a piece of equipment will fail cannot be determined with certainty, however, the behavior of the failure history and the help of statistics can be used to estimate the probability of the event occurring.(Gasca et al., 2017)The validity of the results obtained depends on the precision and accuracy of the data, although on several occasions there is not enough failure data and confidence intervals for the reliability indices cannot be obtained.(Carlos R Batista-Rodriguez, 2017).

Reliability, availability and maintainability in the automotive industry are a crucial factor, as companies seek efficient production and operational continuity to meet market demands, reduce operating and maintenance costs, and increase the competitiveness of their organization.(Echeverr, 2018), adopting a culture of continuous improvement(Dias et al., 2019).

Systems are divided into non-repairable and repairable. Where, if a system is non-repairable it presents a single failure throughout its life.(Brown et al., 2023), while in a repairable system there are several failure modes. The most prominent models for the analysis of the reliability of repairable systems subject to minimal repairs are the non-homogeneous Poisson processes(Slimacek & Lindqvist, 2017)and for such systems, reliability calculation involves the analysis of operating times and failure rates in failure-repair cycles.

The interest in controlling reliability, maintainability and availability in different industries arises due to the need to guarantee efficient operations with the least downtime. Reliability is the probability that an element can perform its required function during a set time interval and under defined conditions; if there are no failures, the equipment is totally reliable; if the failure frequency is very low, the reliability of the equipment is still acceptable; but if the failure frequency is very high, the equipment is unreliable. This analysis is of vital importance when maintaining productivity is required. Maintainability plays a fundamental role as it allows for quick and effective repairs. Meanwhile, availability refers to the capacity of the equipment to be in operating conditions in a given

ISSN: 2602-8085
Vol. 8 No. 3, pp. 137 – 160, July – September 2024

time.

The focus of this research is the development of an efficient methodology that is capable of improving maintenance management and maximizing the reliability of its equipment, contributing to greater operational efficiency. In this study, two non-homogeneous Poisson models with different intensity functions were applied, the Crow Amsaa model and the log-linear model to estimate or predict the number of failures in a 5-year period, so that the company's maintenance area can make decisions based on the results obtained regarding the failure rate of the systems and the reduction of the mean time between failures; For the calculation, the failures of all the systems of the welding plant of a vehicle assembler will be analyzed according to the data obtained from January 2022 to May 2024.

State of the art:

In the automotive industry, a topic of growing interest is the improvement of productivity, due to the need to guarantee efficiency and reduce maintenance costs, which is why methodologies have been adopted to optimize reliability, availability and maintainability.(Soltanali et al., 2019).

Operational reliability is the ability of a system to perform the required function, within a certain operational context, for a specific period of time.(Echeverr, 2018); in mathematical terms it corresponds to the inverse function of the probability of failure(Cruz et al., 2017), and allows for improved equipment availability, which leads to an increase in economic benefits for the organization.(Montalvo et al., 2022).

The research of Orrantia et al., addresses the development of a methodology to measure reliability in assembly lines. This methodology consists of five stages that include the identification of the study area, the collection of relevant information such as the start and end time of a stop, the reason and the problem that occurred; the application of the mathematical model where the calculated variables: delivery capacity, efficiency index, quality and availability, are analyzed through probabilistic distributions and the best fit distribution is selected, which has the smallest value of the Anderson-Darling statistic; the analysis of results, a stage in which the critical indexes that affect reliability are considered; and finally, the proposal for improvements.(Orrantia Daniel et al., 2022).

According to Zuo and Xiao, in the area of reliability, past research assumed that the system under analysis returned to its condition as when it was new, but these situations are not real in practice, because when the system is in operation, all components are affected by the effect of aging.(Zuo & Xiao, 2022).

For reliability analysis, non-repairable and repairable systems are identified, where minimal repairs can be carried out, i.e. maintenance activities to repair only the defective component, and perfect repairs, where the system operates as effectively as when it was new.(Wu et al., 2024).

Whereas, Mun and Kvam propose the use of non-homogeneous Poisson models (NHPP) for modeling monotonic failure data for minimal repairs in a repairable system, where the performance of this is restored to precisely the same condition as it was before failure, i.e., the one that can be recovered to its operational condition without necessarily replacing all the components of the system after repair. These models are widely used because they are mathematically manageable and flexible due to their ability to model a wide variety of real repair processes.(Mun et al., 2021). The NHPP model is characterized by its intensity function. The ROCOF or rate of occurrence of failures of the NHPP is equivalent to the risk function and the monotonic ways to calculate it are the log-linear model analyzed by Cox and Lewis and the power law model studied by Crow.(Krivtsov, 2007)

The proportional intensity models based on NHPP, are log-linear and Crow Amsaa which is an extension of the power law model, which are characterized by being able to model the behavior of a system in its useful life stage.(Bacha & Bellaouar, 2023).

In situations where it is required to obtain the most probable values of a distribution, the maximum likelihood method is used to estimate the parameters of the models using numerical methods such as Newton-Raphson. This approach allows to justify the selection of the model that best fits the data.(Chávez-Cadena et al., 2020),(Bacha & Bellaouar, 2023).

Regarding the analysis of the performance of NHPP models, research with similar objectives has used the mean square error MSE, mean absolute error MAE, mean absolute percentage error MAPE(Kim & Kim, 2016),(Chik et al., 2018),(Alsultan & Sulaiman, 2024)and the calculation of the correlation coefficient R2(NK Srivastava & Mondal, 2014)to determine the model that best fits the data.

These studies set a precedent for future research and highlight the importance of reliability calculation in the automotive industry to find optimal solutions, obtain maximum production and achieve business success.(Paez Advincula, 2022).

There are simulation methodologies that allow predicting and understanding the operational behavior of equipment, which makes it possible to estimate a forecast of failure events. Non-parametric estimators are sometimes used to calculate reliability, which are useful when there are censored data, small sample sizes, or unknown distributions.(Ramírez Montoya et al., 2022).

Materials and methods:

The development of this methodology consists of five stages, and prior to its development, the failure records of a vehicle assembly plant whose production areas are: welding, painting and assembly were obtained; after an analysis of the frequency of failures and repair times, the welding plant was selected as the most critical area. The information collected includes the repair times from January 2022 to May 2024 of all the plant systems whose operating time is 2880 hours per year and the systems that caused the most line stoppages were evaluated.

Stage 1 consisted of purging the welding plant's maintenance history database, where duplicate records, inconsistent information, irrelevant failure modes and recording errors were eliminated in order to ensure the usefulness of the data to be analyzed. This was a crucial step since the quantity and quality of information is of great importance to minimize errors. In this stage, a thorough review and correction of errors in the records was carried out manually, which were analyzed individually.

In stage 2, the study area was identified, where a Jack Knife diagram was made to prioritize the analysis of the plant's acute-critical systems, prioritizing those with the longest mean repair time (MTTR), which was calculated from the base of the failure history.

The information was organized at the system level as shown in Table 1, where the start and end date of each event, the failure mode, the time to repair (TTR) in hours were captured. In addition, the time to failure (TTF) was calculated which provides valuable information for making future forecasts in a given time interval.

In stage 3, a statistical study was conducted aimed at repairable equipment, because its operational state can be restored with a repair after the occurrence of a failure, it can present more than one failure mode during its useful life and the failure rate varies over time. A graphical and analytical analysis of the trend of the system data was performed in order to detect if the systems have a significant tendency of decreasing the time between failures and can be modeled with the Non-Homogeneous Poisson process, which is one of the stochastic processes used in reliability engineering for its ability to predict the number of events that occur randomly in a time t with a variable event rate.(Alghamdi & Qurashi, 2023).

Stage 4 consists of the application of the Crow Amsaa and Log-linear models to forecast the accumulated number of failures in an accumulated operating time, as well as the estimated MTBF for the next five years of system operation.

In the final stage, the accuracy of the models used was evaluated by calculating forecast errors, in order to choose the one that guarantees reliable predictions.

Nelson Aalen diagram:

Figure 1 graphically shows the trend in failure time data and reliability degradation over time for a repairable system that has had minimal interventions throughout its useful life.

Laplace trend test

The Laplace test is a monotonous test that allows verifying whether the data follows a stochastic process.(Alghamdi & Qurashi, 2023)and is widely used to identify trends in data sets, as it is considered the most appropriate test to infer whether the data set is of the NHPP type.(Hou et al., 2022).

The Laplace trend test when the system has been observed untilt_0It is represented by equation (1).

$$\boldsymbol{U} = \frac{\frac{\sum_{i=1}^{n} t_i}{n} - \frac{t_0}{2}}{t_0 . \sqrt{\frac{1}{12.n}}}, \qquad (1)$$

Where,$t_i$are the accumulated failure times, is the observation time of the failures and n is the number of events that occurred.t_0

In addition, it makes it easier to recognize the growth or decrease in reliability, the hypotheses to be tested are: If U = 0 the process is stationary, if U > 0 there is an increasing trend (sad system) and if U < 0 there is a decreasing trend (happy system).

Non-homogeneous Poisson model

Among the theories for modeling the reliability of repairable systems, there is the non-homogeneous Poisson process, which is robust and has the advantage of handling discrete data such as the number or rate of occurrence of failures, which is why they are applied to the analysis of failures and useful life of various engineering systems.(Hashimoto & Takizawa, 2021).

Crow-Amsaa Model: The Crow AMSAA model, also known as power law process (PLP) is used and studied for reliability growth analysis.(P.W. Srivastava & Jain, 2011)

Using maximum likelihood estimation, the parameters$\hat{\beta}$and , can be calculated with the equations$\hat{\lambda}$(2) and (3)

$$\hat{\beta} = \frac{n}{\sum_{i=1}^{n} \ln\left(\frac{t_n}{t_i}\right)}, \qquad (2)$$

ISSN: 2602-8085
Vol. 8 No. 3, pp. 137 – 160, July – September 2024

$$\hat{\lambda} = \frac{n}{t_n^{\hat{\beta}}}, \qquad (3)$$

Where, is the accumulated time interval for each failure, is the accumulated time until the last failure and n is the total failure record.$t_i t_n$

The hypotheses to be tested are:

If reliability deteriorates$\beta > 1$

If reliability growth$\beta < 1$

If failure rate is constant.$\beta = 1$

The increase or decrease in reliability can be quantified by observing aspects such as MTBF or failure rate over time.(P.W. Srivastava & Jain, 2011).

The fault intensity function is given by equation (4).$\lambda(t)$

$$\lambda(t) = \beta\lambda t^{\beta-1}; t \geq 0;\ \lambda, \beta > 0 \quad (4)$$

Where,$\beta$is the shape parameter, which represents the trend of the failure rate over time and is the scale parameter, which shows the intensity of failures in the system.λ

While the calculation of the mean time between failures (MTBF), is defined by equation (5)

$$MTBF(t) = \frac{1}{\lambda(t)}, \qquad (5)$$

Log-Linear Model

The log-linear model is able to describe processes with a monotonous trend during the operating time.

The instantaneous failure rate is given by equation (6).

$$\lambda(t) = e^{\alpha_0 + \alpha_1 t}, \qquad (6)$$

Ciencia Digital
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Vol. 8 No. 3, pp. 137 – 160, July – September 2024
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Where,$\alpha_0$is the scale parameter, is the growth parameter that determines the improvement or deterioration of the system over time and t is the operating timeα_1(Hashimoto & Takizawa, 2021).

The parameters$\alpha_1$and are given by equations (7) and (8).$\hat{\alpha}_0$

$$\sum_{i=1}^{n} t_i + \frac{n}{\alpha_1} = \frac{nt_n}{1 - e^{-\alpha_1 t_n}}, \qquad (7)$$

$$\hat{\alpha}_0 = \ln\left(\frac{n\hat{\alpha}_1}{e^{\alpha_1 t_n} - 1}\right), \qquad (8)$$

The calculation of the expected number of failures is defined by equation (9).

$$E\big(N(t_2) - N(t_1)\big) = \frac{e^{\alpha_0}}{\alpha_1}\left(e^{\alpha_1 t_2} - e^{\alpha_1 t_1}\right), \qquad (9)$$

Instead, the expected number of failures during the lifetime is obtained with equation (10)

$$n(t) = \frac{e^{\alpha_0}}{\alpha_1}\left(e^{\alpha_1 t}\right), \qquad (10)$$

MTBF is calculated using equation (11).

$$MTBF\ (t_1, t_2) = \frac{\alpha_1(t_2 - t_1)}{e^{\alpha_0}\left(e^{\alpha_1 t_2} - e^{\alpha_1 t_1}\right)}, \qquad (11)$$

Measuring model error

There are criteria for selecting the model that best fits the data. The most significant criterion is the criterion of determination and quality of fit criteria such as bias, mean square error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). In addition, the coefficient of determination R2 was measured.(Alghamdi & Qurashi, 2023)Below are the expressions to measure each error.

Coefficient of determination

The R value is able to measure the successful fit of the model, from the variance of the data evaluated(Kim & Kim, 2016).

$$\boldsymbol{R^2} = 1 - \frac{\sum_{t=1}^{n}(m_t - \widehat{m}_t)^2}{\sum_{t=1}^{n}(m_t - \overline{m})^2}, \qquad (12)$$

Where, are the observed values of the dependent variable, are the predictions of the model and is the mean of the observed values.$m_t \widehat{m}_t \overline{m}$

The model with the highest and closest to 1 is considered the most efficient model.R^2(Kim & Kim, 2016).

Mean Square Error (MSE)

$$\boldsymbol{MSE} = \frac{\sum_{t=1}^{n} |m(t) - \widehat{m}(t)|^2}{n - k}, \qquad (13)$$

Where, is the total number of observed data, are the observed values, are the values predicted by the model for each observation and k is the number of parameters estimated in the model.$nm_t\widehat{m}_t$

Mean absolute error (MAE)

$$\boldsymbol{MAE} = \frac{1}{n}\sum_{t=1}^{n} |m(t) - \widehat{m}(t)|, \qquad (14)$$

Where, is the total number of observed data, are the observed values, are the values predicted by the model.$nm_t\widehat{m}_t$

Mean absolute percentage error (MAPE)

To compare the models and determine which is the best, the mean absolute percentage error (MAPE) is also used, according to the following formula:

$$\boldsymbol{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \frac{|m(t) - \widehat{m}(t)|}{m(t)}, \qquad (15)$$

Where m(t) represents the actual value, yn the estimated value and the number of observations$\widehat{m}(t)$(Alsultan & Sulaiman, 2024).

In the final stage, the predictive capacity of each model was evaluated and the one showing the lowest possible error rate was selected.

Results and discussion:

In the present study, predictive models were analyzed to analyse repairable systems in a welding plant of a vehicle assembly plant, with the aim of evaluating reliability by predicting the cumulative number of failures and the mean time between failures (MTBF).

In this section, the results obtained after completing the five stages of the research are presented.

Figure 1 shows a logarithmic scatter graph, called a Jack Knife diagram, used as a

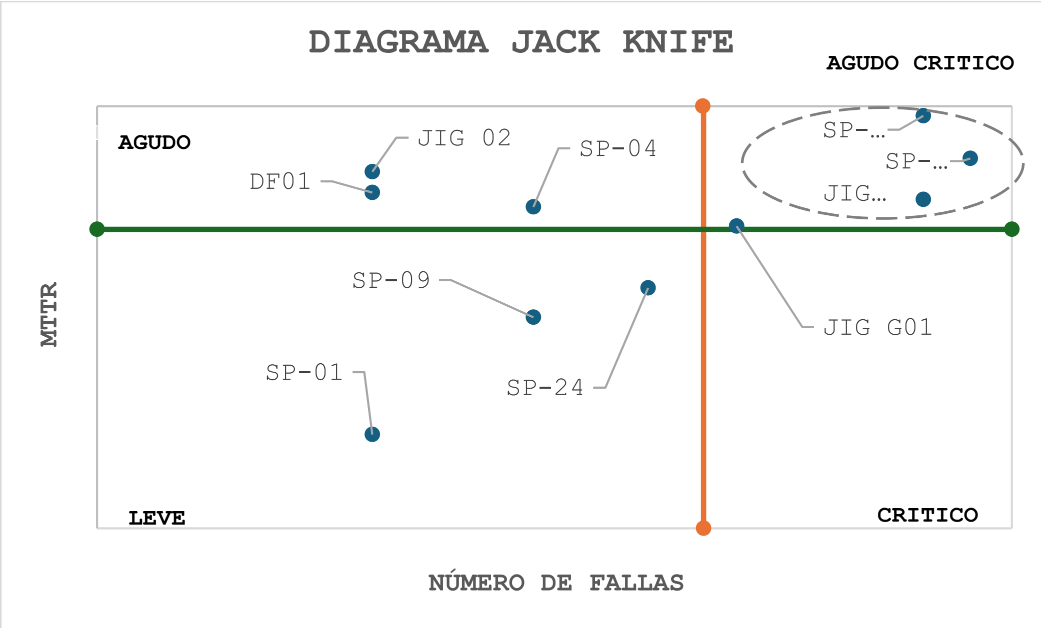
ISSN: 2602-8085
Vol. 8 No. 3, pp. 137 – 160, July – September 2024

prioritization method which allows identifying the systems that have caused the most line stoppages in the welding plant, that is, those that have most affected the company's productivity according to records from 2022 to 2024.

The systems were classified into different categories: acute-critical, critical, acute, and mild. The result of this prioritization method determined that systems SP-01, SP-09, and SP-24 are part of a mild zone; DF01, JIG 02, and SP-04 are considered acute; JIG G01 is located in the critical zone; while systems SP-43, SP-16, and JIG MB-10 require greater attention from the maintenance department, as they are considered acute-critical because they cause more interruptions and occur more frequently than the other systems in the plant.

Figure 1

Jack Knife Diagram - Prioritization Method



Once the acute-critical systems were identified, the data was analyzed and the times until failure were calculated.

Table 1

SP-43 welder repair times

SP-43 WELDING MACHINE					
No.	**START DATE**	**END DATE**	**FAILURE MODE**	**TTR**	**TTF**
1	04/01/2022 11:48	04/01/2022 12:02	Electrical fault of gun	0.23	
2	08/03/2022 11:46	08/03/2022 12:52	SP43B rocker cable broken	1.10	5064.83
3	10/27/2022 8:35 AM	10/27/2022 8:55 AM	Misaligned gun tips	0.33	2036.05

Ciencia Digital
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Vol. 8 No. 3, pp. 137 – 160, July – September 2024
www.cienciadigital.org

4	09/12/2022 14:55	09/12/2022 16:47	Electrical fault of gun	1.87	1039.87
5	10/04/2023 8:22	10/04/2023 9:30	Electrical fault of gun	1.13	2920.72
6	12/05/2023 9:45	12/05/2023 10:00	Broken rocker cable	0.25	768.50
7	06/22/2023 12:00	06/22/2023 1:30 PM	Broken welding spiral	1.50	987.50
8	04/08/2023 12:35	04/08/2023 12:45	Broken secondary cable	0.17	1031.25
9	07/09/2023 7:55	07/09/2023 8:07	Broken primary cable	0.20	811.37

Table 2

SP-16 Welder Repair Times

SP-16 WELDING MACHINE					
No.	**START DATE**	**END DATE**	**FAILURE MODE**	**TTR**	**TTF**
1	10/31/2022 11:45	10/31/2022 12:20 PM	Electrical fault of gun	0.58	
2	01/17/2023 12:57 PM	01/17/2023 1:11 PM	Electrical fault of gun	0.23	1872.85
3	03/27/2023 9:20 AM	03/27/2023 10:00	Broken rocker cable	0.67	1652.82
4	08/09/2023 8:27	08/09/2023 8:40	Electrical fault of gun	0.22	3238.66
5	05/09/2023 10:15	05/09/2023 12:15	Electrical fault of gun	2.00	651.58
6	10/13/2023 8:45 AM	10/13/2023 9:00 AM	Broken secondary cable	0.25	908.75
7	01/15/2024 9:55	01/15/2024 1:15 PM	Electrical fault of gun	3.33	2260.25
8	05/29/2024 11:05	05/29/2024 11:25	Broken rocker cable	0.33	3238.17

Table 3

Repair times for MB-10 clamping equipment

MB-10 CLAMPING EQUIPMENT					
No.	**START DATE**	**END DATE**	**FAILURE MODE**	**TTR**	**TTF**
1	01/18/2022 7:50 AM	01/18/2022 8:30 AM	Broken pin	0.67	
2	02/28/2022 10:35	02/28/2022 10:45	Broken pin	3.22	989.30
3	03/28/2022 8:43 AM	03/28/2022 8:50 AM	Broken pin	0.12	667.03
4	07/22/2022 11:25	07/22/2022 11:45	Broken piston kit	0.33	2786.92
5	07/25/2022 14:16	07/25/2022 14:30	Deregulated dual signal sensor	0.23	74.75
6	10/17/2022 7:45 AM	10/17/2022 7:52 AM	Broken pin	0.12	2009,37
7	01/25/2023 9:00	01/25/2023 9:15	Broken control hose	0.25	2401.38
8	03/14/2023 10:15	03/14/2023 10:47	Deregulated inductive sensor	0.53	1153.53

Figure 2 presents the survival analysis called Nelson-Aalen diagram, used as a graphical method for visualizing the accumulation of times until failure in a time interval. An increasing trend is observed, so it is assumed that the failure rate increases with time and that these are unstable systems.

Ciencia Digital
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Vol. 8 No. 3, pp. 137 – 160, July – September 2024
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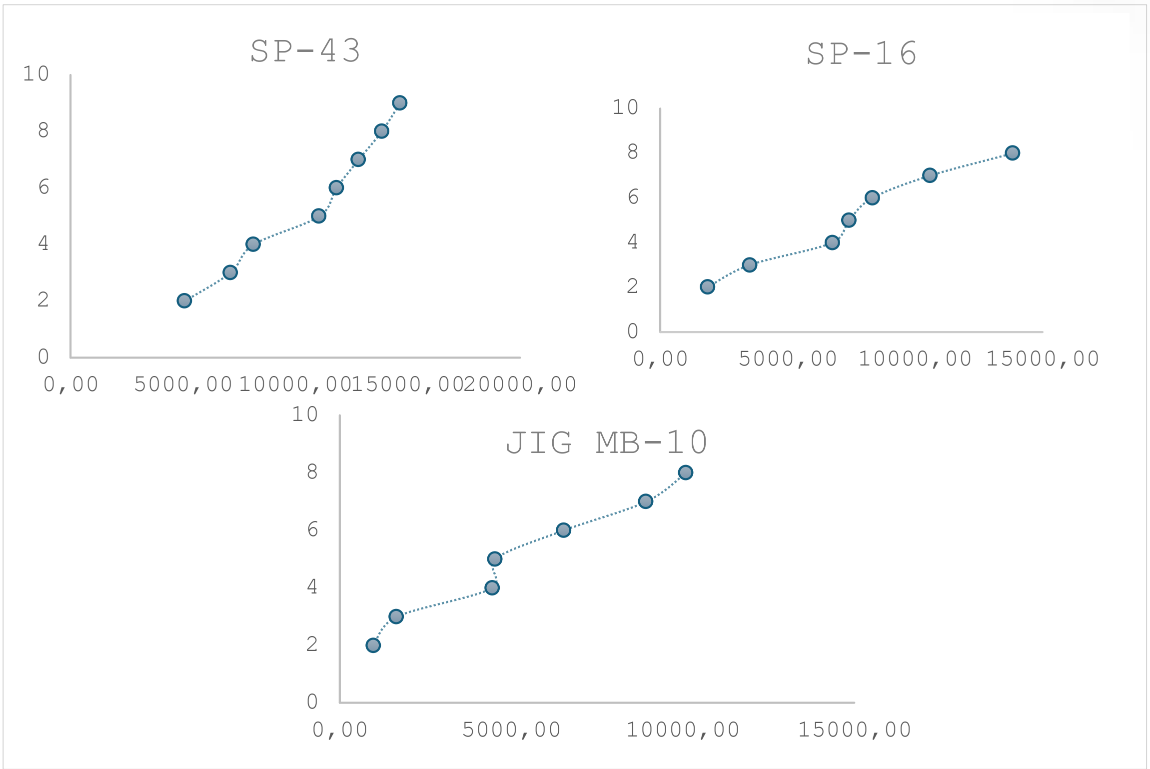
Figure 2

Nelson-Aalen diagram



To verify the hypothesis that the failure data satisfy the characteristics of a NHPP, and to verify whether it is suitable, a statistical test called the Laplace test was performed using equation (1), with a significance level of 0.10.

Table 4

Trend test

SYSTEM	STATISTICIAN U
SP-43	2.16
SP-16	0.37
JIG MB-10	0.24

All the values obtained are U>0, so the hypothesis of the existence of an increasing trend is accepted and it is assumed that it is a sad system.

The parameters of the studied models were estimated with the equations obtained with the maximum likelihood method, equation (2) and (3) for the Crow Amsaa model and (7) and (8) for the parameters of the log-linear model. For this last model, the Newton-Raphson numerical method was used with the help of the scipy library in Python.

Ciencia Digital
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www.cienciadigital.org

Table 5

Estimation of model parameters

MODEL	PARAMETERS	SP-43	SP-16	JIG MB-10
Crow Amsaa	β	2,611	1,278	1,110
	λ	1.05 x 10-10	3.05 x 10-5	2.51 x 10-4
Log-linear	α_0	-9,373	-7,842	-7,435
	α_1	0.0002056	3.54 x 10-5	3.13 x 10-5

Once the parameters of the models were calculated, they were used to estimate or forecast the number of failures expected in an operating period t for repairable systems, in which the minimum repair required to put the equipment into operation again is carried out. The number of failures predicted for the next 5 years with the two models studied is shown in Table 3.

Table 6

Estimated number of failures in 5 years

Cumulative operating time (h)	Expected number of failures					
	SP-43		SP-16		JIG MB-10	
	Crow Amsaa Model	Log-linear model	Crow Amsaa Model	Log-linear model	Crow Amsaa Model	Log-linear model
17545,56	13	8	9	9	9	9
20425,56	19	13	11	11	12	12
23305,56	27	23	13	13	14	15
26185,56	36	41	15	16	16	18
29065,56	48	74	17	19	19	22

Figures 3, 4 and 5 correspond to the graphs of the accumulated number of failures in a cumulative operating time of the SP-43, SP-16 and JIG MB-10 systems respectively. The first points comprise the known accumulated failures taken from the maintenance history database, while the following ones are part of a forecast zone and are random values created from the previously collected information. For these graphs, the forecasts of the Crow Amsaa model are presented on the left side (a) and the log-linear model on the right side (b).

ISSN: 2602-8085
Vol. 8 No. 3, pp. 137 – 160, July – September 2024
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Figure 3

Number of projected failures (SP-43)

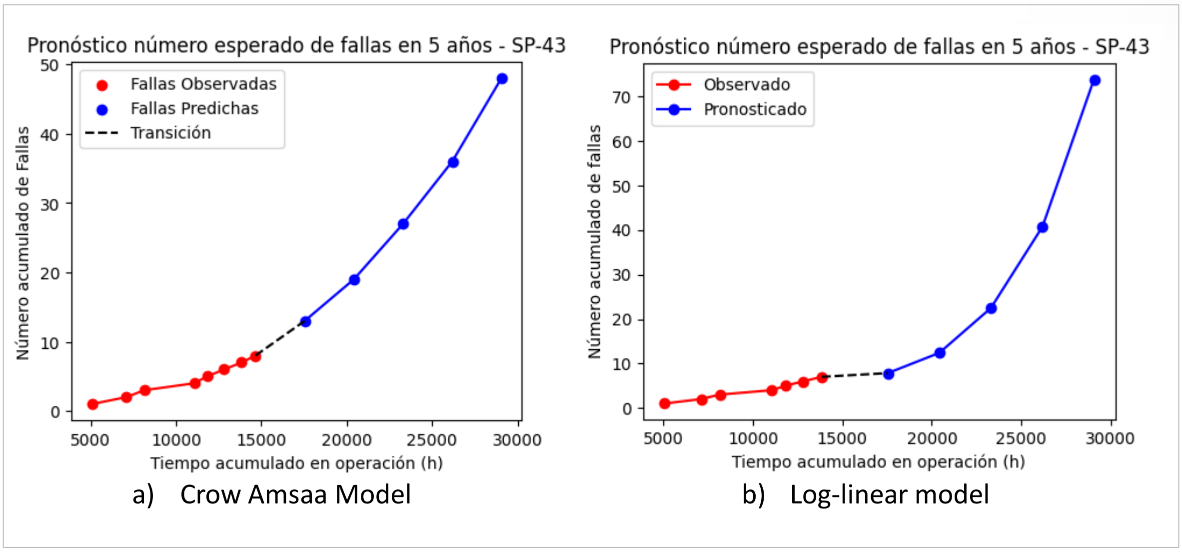
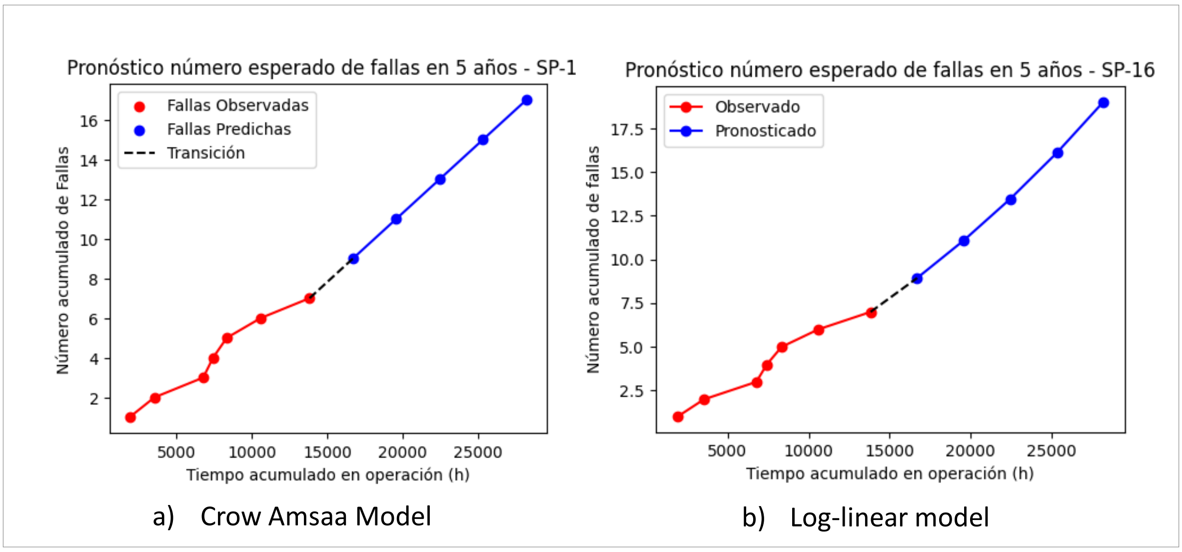


Figure 4

Number of projected failures (SP-16)



ISSN: 2602-8085
Vol. 8 No. 3, pp. 137 – 160, July – September 2024
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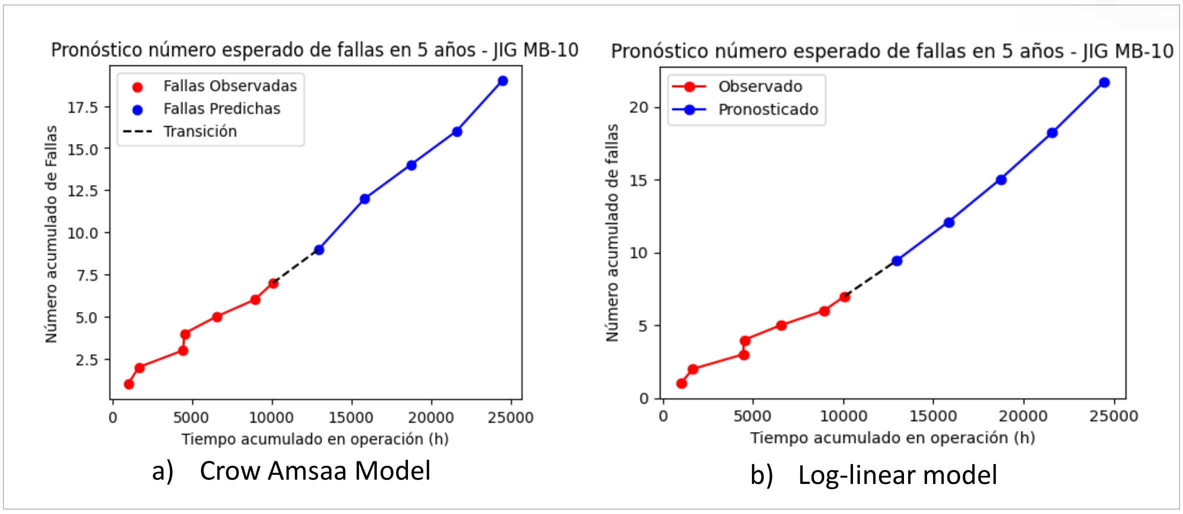
Figure 5

Number of projected failures (JIG MB-10)



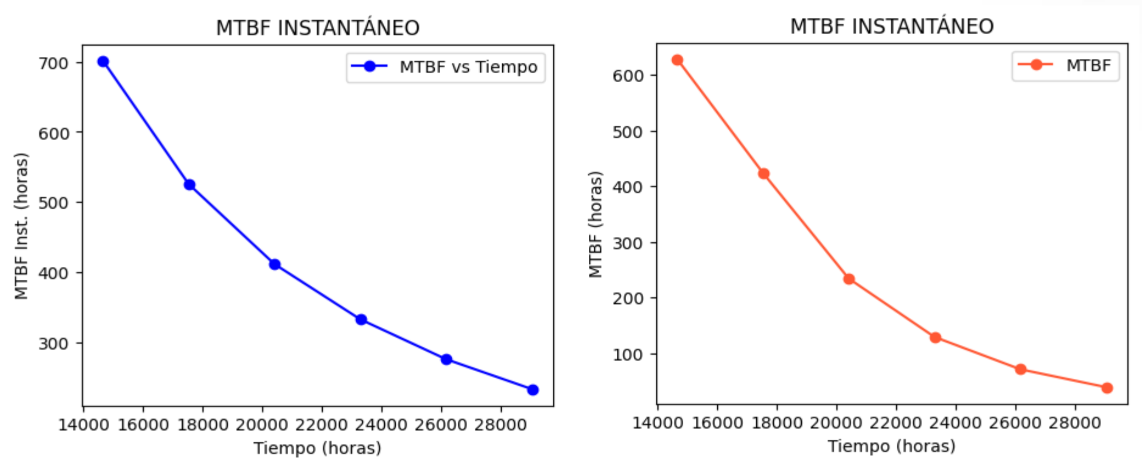
For SP-43, the Crow Amsaa model predicted 13 failures in the first year from last observation, 19, 27, 36 and 48 for year two, three, four and five respectively, while the log-linear model predicted 8, 12, 22, 40 and 73 failures. For SP-16, the Crow Amsaa model estimated 9, 11, 13, 15 and 17 failures for the next 5 years of operation; while the log-linear model estimated 8, 11, 13, 16 and 19 failures. For JIG MB-10, the Crow Amsaa model projected 9, 12, 14, 16 and 19 failures for the next 5 years; on the other hand, the log-linear model projected 9, 12, 15, 18 and 21 failures.

This predicted increase reflects the degradation of the systems analyzed as a whole due to the fact that only minimal repairs are made, which can accumulate over time and generate failures more frequently.

For the reliability analysis, the mean time between failures (MTBF) was calculated, in order to know the interval in hours that can pass for a failure to occur. Knowing this time is significant because it is an indicator of the expected performance of the equipment.(de Abreu et al., 2018).

Figure 6

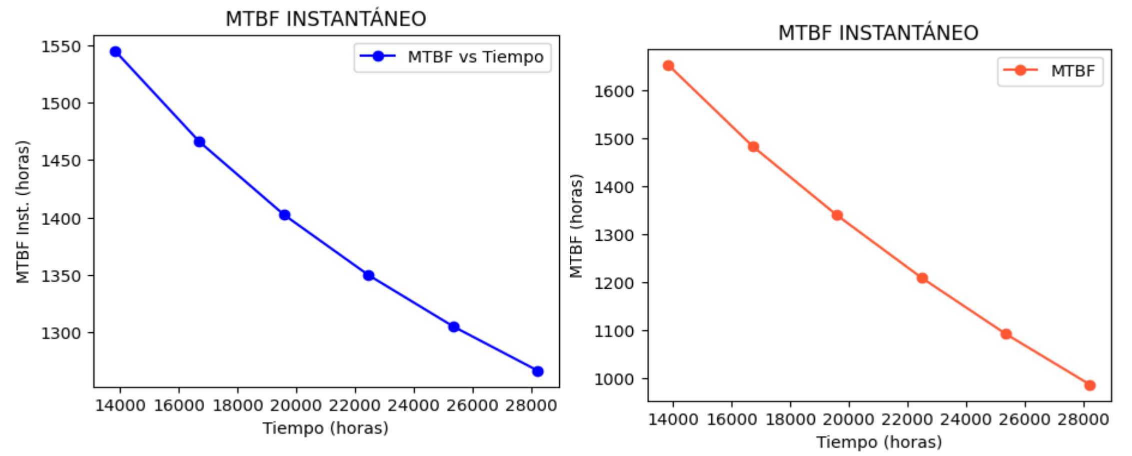
Projected mean time between failures for the next 5 years



a) Crow Amsaa Model b) Log-linear model

Figure 7

Projected mean time between failures for the next 5 years



a) Crow Amsaa Model b) Log-linear model

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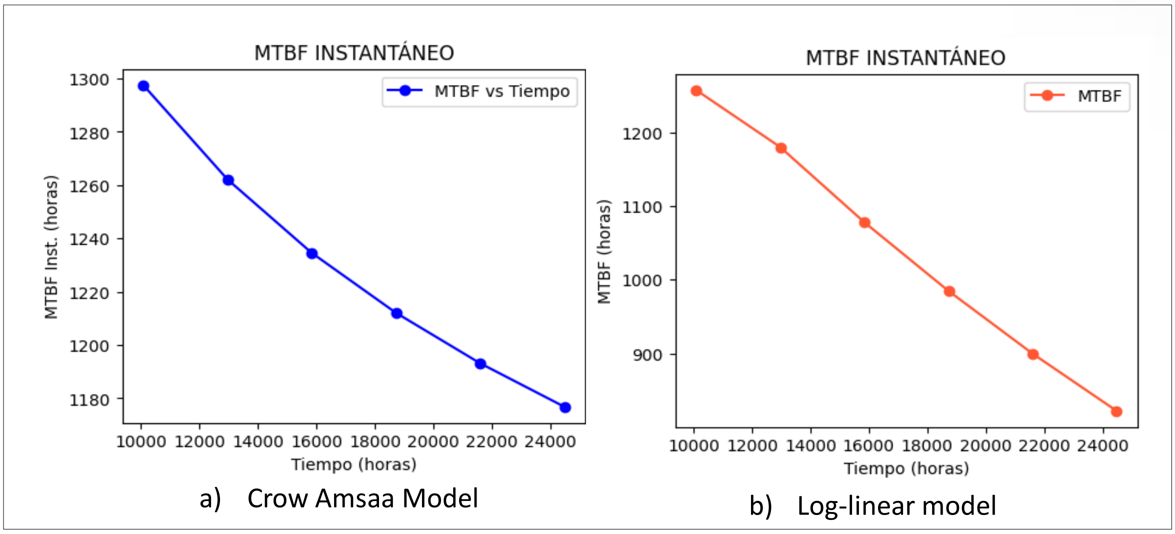
Figure 8

Projected mean time between failures for the next 5 years



Figures 6, 7 and 8 show the MTBF graphs as a function of time for the SP-43, SP-16 and JIG MB-10 systems respectively, the Crow Amsaa model (right) and the log-linear model (left). These graphs show a significant reduction in the time between failures, so effective maintenance strategies must be proposed to optimize operation over time.

The quality of the calculated estimates must be validated and incur the least possible error. The error measurement was performed to quantify the difference between the predicted values and the actual values.

The performance of the implemented NHPP models was evaluated through the measurement of coefficient of determination R2, mean square error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) to ensure the accuracy of the model proposed in the study. The results are shown in Table 7.

Table 7

Measuring model errors

	SP-43		SP-16		JIG MB-10	
	MODEL		MODEL		MODEL	
CRITERIA	**Crow-AMSAA**	**Log-Linear**	**Crow-AMSAA**	**Log-Linear**	**Crow-AMSAA**	**Log-Linear**
R^2	0.931	0.080	0.843	0.895	0.889	0.918
MSE	0.359	4,827	0.628	0.304	0.445	0.238
MAE	0.455	1,099	0.661	0.479	0.519	0.458
MAPE	19.11 %	24.24 %	22.26 %	16.22 %	21.35 %	19.79 %

The value of the error obtained was taken as the main criterion for selecting the best model; the Crow-Amsaa model presented all the errors evaluated with the lowest value. In addition, a value of the coefficient of determination R2 equal to 0.932 was determined, meaning that 93.2% of the variability in the dependent variable is explained by the predictive model, so it is assumed that this is a model whose estimates adequately fit the observed data of the SP-43 system.

In the case of the SP-16 and JIG MB-10 systems, the best-fitting model was log-linear according to the observation of the errors and the R2 coefficient of 0.895 and 0.918 respectively.

Conclusions

- In this study, two fundamental models for the reliability assessment of repairable systems have been explored: Crow-AMSAA and the Log-linear model, which offer powerful tools to analyze and predict the failure rate, and the mean time between failures (MTBF), essential parameters for effective asset management and maintenance planning.
- The comparative evaluation carried out has demonstrated the capacity of both models to effectively predict the number of failures and estimate the MTBF. The accuracy of these predictions was determined using standard metrics such as the Mean Square Error (MSE), the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE), providing a quantitative measure that allows observing the best fit of the model in relation to the observed data, in order to select and apply it correctly. According to the error measurement, it was determined that for the SP-43 system, the Crow Amsaa model has a greater forecasting capacity, while for the SP-16 and JIG MB10 systems the log-linear model presents a better fit; these models can be used to monitor and improve reliability, and optimize plant maintenance management.
- According to the analysis, it is observed that the repair rate of the systems increases over time, and there is a decrease in the mean time between failures (MTBF) intervals, which indicates a deterioration in the reliability of these, so it is necessary to propose maintenance strategies that allow increasing the mean time between failures, reducing production stops, and having a continuous evaluation of failures for the planning, programming and execution of maintenance tasks.

Conflict of interest

The authors declare that there is no conflict of interest in relation to the submitted article.

Bibliographic References

Alghamdi, S.M.A., & Qurashi, M.E. (2023). A comparison between the nonhomogeneous Poisson and α-series processes for estimating the machines' fault time of thermal electricity. International Journal of Advanced and Applied Sciences, 10(5), 12–19. https://doi.org/10.21833/ijaas.2023.05.002

Alsultan, FA, & Sulaiman, MS (2024). Bayesian Estimation of Power Law Function in Non-homogeneous Poisson Process Applied in Mosul Gas Power Plant - Iraq. Iraqi Journal of Science, 65(5), 2596–2604. https://doi.org/10.24996/ijs.2024.65.5.20

Bacha, S., & Bellaouar, A. (2023). Assessment of the Effectiveness of Maintenance Actions and the Influence of Covariates on the Reliability of Gas Turbines using the Extended Generalized Proportional Intensity Model. International Journal of Performability Engineering, 19(4), 283–290. https://doi.org/10.23940/ijpe.23.04.p7.283290

Brown, B., Liu, B., McIntyre, S., & Revie, M. (2023). Reliability evaluation of repairable systems considering component heterogeneity using frailty model. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 237(4), 654–670. https://doi.org/10.1177/1748006X221109341

Carlos R Batista-Rodríguez, RIU-S. (2017). Proposal of a bootstrapping methodology to calculate reliability indexes. Engineering and Competitiveness, 19(2), 102–108. https://www.redalyc.org/articulo.oa?id=291354828010

Chávez-Cadena, MI, Jiménez-Cargua, JW, & Cucuri-Pushug, MI (2020). Reliability, maintainability and availability (CMD) analysis of the formation water reinjection system. Koinonía Interdisciplinary Peer Review Journal, 5(9), 249. https://doi.org/10.35381/rkv5i9.647

Chik, L., Albrecht, D., & Kodikara, J. (2018). Modeling Failures in Water Mains Using the Minimum Monthly Antecedent Precipitation Index. Journal of Water Resources Planning and Management, 144(4), 1–6. https://doi.org/10.1061/(asce)wr.1943-5452.0000926

Cruz, P., Echaveguren, T., & González, P. (2017). Estimation of rollover potential of heavy vehicles using reliability principles. Construction Engineering Journal, 32(1), 5–14. https://doi.org/10.4067/s0718-50732017000100001

de Abreu, MNG, Esquerre, KPSOR, Massa, ARC d. G., & Pessoa, RWS (2018). Reliability analysis associated with maintenance of online analyzers. In Computer Aided Chemical Engineering (Vol. 44, Issue 2004). Elsevier Masson SAS. https://doi.org/10.1016/B978-0-444-64241-7.50220-2

Dias, P., Silva, FJG, Campilho, RDSG, Ferreira, LP, & Santos, T. (2019). Analysis and improvement of an assembly line in the automotive industry. Procedia

Manufacturing, 38(2019), 1444–1452. https://doi.org/10.1016/j.promfg.2020.01.143

Echeverr, A. (2018). Bibliographic analysis of operational reliability in complex technical systems. https://www.redalyc.org/journal/2251/225158799003/html/

Gasca, MC, Camargo, LL, & Medina, B. (2017). System for Evaluating the Reliability of Critical Equipment in the Industrial Sector. Technological Information, 28(4), 111–124. https://doi.org/10.4067/S0718-07642017000400014

Hashimoto, T., & Takizawa, S. (2021). Prediction of membrane failure in a water purification plant using nonhomogeneous poisson process models. Membranes, 11(11). https://doi.org/10.3390/membranes11110800

Hou, Y.F., Huang, CY, & Fang, CC (2022). Using the Methods of Statistical Data Analysis to Improve the Trustworthiness of Software Reliability Modeling. IEEE Access, 10, 25358–25375. https://doi.org/10.1109/ACCESS.2022.3154103

Hu, Z., Mansour, R., Olsson, M., & Du, X. (2021). Second-order reliability methods: a review and comparative study. Structural and Multidisciplinary Optimization, 64(6), 3233–3263. https://doi.org/10.1007/s00158-021-03013-y

Kim, K.S., & Kim, HC (2016). The performance analysis of the software reliability NHPP log-linear model depends on the viewpoint of the learning effects. Indian Journal of Science and Technology, 9(37). https://doi.org/10.17485/ijst/2016/v9i37/101785

Krivtsov, V. V. (2007). Practical extensions to NHPP application in repairable system reliability analysis. Reliability Engineering and System Safety, 92(5), 560–562. https://doi.org/10.1016/j.ress.2006.05.002

Montalvo, R.B., Villar, L., Armando, L., Concepción, D., Alfonso, A., Ángel, A., Soto, R., & Rodríguez, A. (2022). Modification of the 6 Sigma methodology for verification of the redesign of a rotary filter for a biological product. 30, 124–133. http://dx.doi.org/10.4067/S0718-33052022000100124

Mun, B.M., Kvam, P.H., & Bae, S.J. (2021). Mixed-Effects Nonhomogeneous Poisson Process Model for Multiple Repairable Systems. IEEE Access, 9, 71900–71908. https://doi.org/10.1109/ACCESS.2021.3077605

Orrantia Daniel, G., Sánchez Leal, J., De la Riva Rodríguez, J., Reyes Martínez, RM, & Herrera Ríos, EB (2022). Methodology for measuring reliability in assembly lines. RIDE Ibero-American Journal for Educational Research and Development, 12(24). https://doi.org/10.23913/ride.v12i24.1217

Paez Advincula, RR (2022). Importance of operational reliability engineering for business development. Industrial Data, 25(1), 137–156. https://doi.org/10.15381/idata.v25i1.21224

Ramírez Montoya, J., Ramos Ramírez, E., & Martínez Salazar, J.L. (2022). Estimation of the reliability function using Jackknife resampling and transformations. Ciencia e Ingeniería Neogranadina, 32(1), 71–82. https://doi.org/10.18359/rcin.5682

Slimacek, V., & Lindqvist, B.H. (2017). Nonhomogeneous Poisson process with nonparametric frailty and covariates. Reliability Engineering and System Safety, 167, 75–83. https://doi.org/10.1016/j.ress.2017.05.026

Soltanali, H., Garmabaki, A.H.S., Thaduri, A., Parida, A., Kumar, U., & Rohani, A. (2019). Sustainable production process: An application of reliability, availability, and maintainability methodologies in automotive manufacturing. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 233(4), 682–697. https://doi.org/10.1177/1748006X18818266

Soltanali, H., Rohani, A., Tabasizadeh, M., Abbaspour-Fard, M.H., & Parida, A. (2020). Operational reliability evaluation-based maintenance planning for automotive production line. Quality Technology & Quantitative Management, 17(2), 186–202. https://doi.org/10.1080/16843703.2019.1567664

Srivastava, N.K., & Mondal, S. (2014). Predictive maintenance using FMECA method and NHPP models. International Journal of Services and Operations Management, 19(3), 319–337. https://doi.org/10.1504/IJSOM.2014.065367

Srivastava, P.W., & Jain, N. (2011). Reliability prediction during development phase of a system. Quality Technology and Quantitative Management, 8(2), 111–124. https://doi.org/10.1080/16843703.2011.11673251

Wu, J., Dohi, T., & Okamura, H. (2024). A novel lifetime analysis of repairable systems via Daubechies wavelets. Annals of Operations Research, 1–4. https://doi.org/10.1007/s10479-024-06074-6

Zuo, K., & Xiao, M. (2022). A repairable multi-state system with a general α-series process and an order-replacement policy. Communications in Statistics - Theory and Methods, 51(20), 7021–7037. https://doi.org/10.1080/03610926.2020.1869991

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Vol. 8 No. 3, pp. 137 – 160, July – September 2024

Indexaciones