Revista Iberoamericana para la Investigación y el Desarrollo Educativo
ISSN 2007 - 7467

https://doi.org/10.23913/ride.v13i25.1361

Artículos científicos

Análisis de sobrevivencia de una herramienta mediante un modelo de redes bayesianas-CPH

Survival Analysis of a Tool Using a Bayesian Network Model-CPH

Análise de sobrevivência de uma ferramenta usando um modelo de rede CPH-Bayesiana

Jorge Adolfo Pinto Santos
Tecnológico Nacional de México, Instituto Tecnológico de Ciudad Juárez, México
jorge.ps@itcj.edu.mx
https://orcid.org/0000-0001-9614-2764

Manuel Arnoldo Rodríguez Medina
Tecnológico Nacional de México, Instituto Tecnológico de Ciudad Juárez, México
manuel.rm1@cdjuarez.tecnm.mx
https://orcid.org/0000-0002-8922-4718

Eduardo Rafael Poblano-Ojinaga
Tecnológico Nacional de México, Instituto Tecnológico de La Laguna, México
e_poblano@yahoo.com
https://orcid.org/0000-0003-3482-7252

Manuel Iván Rodríguez Borbón
New Mexico State University, U.S.A.
ivanrodr@nmsu.edu
https://orcid.org/0000-0001-8405-4599

Perla Ivette Gómez Zepeda
Tecnológico Nacional de México, Instituto Tecnológico de Ciudad Juárez, México
perla.gz@cdjuarez.tecnm.mx
https://orcid.org/0000-0002-1767-5982

Resumen

Uno de los grandes problemas de la industria es el mantenimiento, y específicamente el cambio de las herramientas típicas de desgaste. Actualmente, las empresas manejan el mantenimiento productivo total, que centra a los técnicos de mantenimiento principalmente en el mantenimiento correctivo y en menor grado, en el mantenimiento preventivo. Sin embargo, muy pocas empresas hacen análisis de manera formal del mantenimiento predictivo. El establecer una metodología para el mantenimiento predictivo requiere analizar los diferentes modelos de degradación de la herramienta mediante la relación de esta con la función de distribución de probabilidad que desarrolla. Este documento contempla el análisis de un electrodo para soldadura de contacto (ultrasónica) a través del comportamiento de su degradación, gracias a lo cual es posible obtener la función de densidad de probabilidad que se ajusta mejor al comportamiento del desgaste de la herramienta. Además, se determinan los factores que influyen en el no cumplimiento en la resistencia a la tensión de las piezas soldadas. Se utiliza el modelo de riesgo proporcional de Cox y las técnicas del diseño de experimentos, lo que se considera como la base para implementar el programa de mantenimiento predictivo.

Palabras clave: análisis de degradación, análisis de supervivencia, mantenimiento predictivo, modelo de riesgo proporcional de Cox, red bayesiana.

Abstract

One of the major problems in the industry is maintenance, and specifically the replacement of typical wear tools. Currently, companies manage total productive maintenance, which focuses maintenance technicians mainly on corrective maintenance and, to a lesser degree, on preventive maintenance. However, very few companies formally analyze predictive maintenance. Establishing a methodology for predictive maintenance requires analyzing the different degradation models of the tool by relating it to the probability distribution function it develops. This paper contemplates the analysis of an electrode for contact (ultrasonic) welding through the behavior of its degradation, thanks to which it is possible to obtain the probability density function that best fits the behavior of tool wear. In addition, the factors influencing non-compliance in the tensile strength of welded parts are determined. The Cox proportional hazard model and design of experiments techniques are used, which is considered as the basis for implementing the predictive maintenance program.

Keywords: degradation analysis, survival analysis, predictive maintenance, Cox proportional hazard model, Bayesian network.

Resumo

Um dos maiores problemas na indústria é a manutenção, e especificamente a substituição de ferramentas de desgaste típicas. Actualmente, as empresas lidam com a manutenção produtiva total, que concentra os técnicos de manutenção principalmente na manutenção correctiva e, em menor medida, na manutenção preventiva. No entanto, muito poucas empresas analisam formalmente a manutenção preditiva. O estabelecimento de uma metodologia de manutenção preditiva requer a análise dos diferentes modelos de degradação da ferramenta, relacionando-a com a função de distribuição de probabilidade que desenvolve. Este artigo considera a análise de um eléctrodo de soldadura por contacto (ultra-sons) através do seu comportamento de degradação, graças ao qual é possível obter a função de densidade de probabilidade que melhor se adapta ao comportamento de desgaste da ferramenta. Além disso, são determinados os factores que influenciam o incumprimento na resistência à tracção das peças soldadas. O modelo de risco proporcional Cox e a concepção de técnicas experimentais são utilizados, o que é considerado como a base para a implementação do programa de manutenção preditiva.

Palavras-chave: análise da degradação, análise de sobrevivência, manutenção preditiva, modelo de risco proporcional Cox, rede Bayesiana.

Fecha Recepción: Abril 2022 **Fecha Aceptación:** Noviembre 2022

Introduction

Ciudad Juárez, Chihuahua, Mexico, is the city with the largest production of harnesses for the automotive sector in the world, which is why it is considered the world capital of harness making. The key manufacturing operations that are designed for the elaboration of a harness are: cable cutting, stripping, crimping, molding, welding, taping, among others. Welding operations are generally considered critical, with ultrasonic welding being the one that systematically produces the greatest number of problems within the process.

This project is carried out in one of the largest automotive harness plants in Ciudad Juárez, whose main clients are companies such as Ford, Chrysler, GM, Honda, Toyota, among others. The improvement in the tensile strength of welded parts is proposed as a general purpose, because this is the one that causes the highest costs of waste and rework in the process.

Within the welding process, the main problem that is identified is found in the change of the tool used, better known as Anvil, which must be removed for rectification before it begins to generate parts with low tensile strength and therefore both defective. This document describes a methodology and the bases to implement predictive maintenance in the ultrasonic welding operation.

In this paper, the use of probability and statistical techniques is considered, especially Bayesian networks, which currently have an important boom in research. For example, Straub and Der Kiureghian (2012) combine Bayesian networks and structural reliability methods to create a new computational framework, called Enhanced Bayesian Network (eBN), for reliability and risk analysis of engineering structures and infrastructures. On the other hand, Zhang, Qin, Jiang and Huang (2018) propose a probabilistic analysis model for a pipeline network based on Bayesian networks in order to carry out a sensitive analysis of accidents. While Kraisangka and Druzdzel (2018) provide a method to encode knowledge of existing Cox proportional hazards (CPH) models for Bayesian networks, and conclude that these networks interpreted from the CPH model can be more useful in practice than Kaplan-Meier estimation or Bayesian networks learned from the data. The results presented here support the above, since the application of Bayesian networks-CPH was successful in the welding process, generating savings in the amount of $270,000.

Materials and methods

The methodology described in this document first involves obtaining data from the welding process resulting from the pull test (destructive test) using a dynamometer, whose measurement system has been previously verified through a repeatability and reproducibility (R&R) analysis. The data were processed to obtain their probability density function: the Weibull distribution was the best fit.

The next step was to determine the significant factors in the tensile strength of the welded parts. For this, an experiment was designed considering the most important factors of the welding process, which are: energy, pressure and amplitude. It was an experiment with three factors at seven levels each (73), which was run and analyzed without considering interactions.

Subsequently, a Bayesian network was designed for the analysis that allowed to make better inferences and as a consequence significantly improve the welding process. The improvement that is considered most important was determining the tool change time (Anvil), thanks to which it was possible to anticipate failure, that is, parts with low pull resistance appeared. The main intention of the project was to determine the failure distribution of the tensile strength of the welded parts and relate this to the significant factors of the process, to later analyze and improve the process through established controls, and with this, finally, determine the welding electrode change time.

Theoretical framework

Kraisangka y Druzdzel (2018) and Allison (2010) mention that survival analysis is a set of statistical methods that help model relationships between a set of predictor variables and an output variable, in addition to helping to predict when an event will occur. Cai, Liu, Liu, Chang, and Jiang (2020) consider reliability to be the probability that an item will perform its required function under given operating conditions for a set time interval. It should also be noted that this can be evaluated using appropriate statistical inference techniques, such as fault trees, reliability block diagrams, Markov models, Monte Carlo method via Markov chains (MCMC), response surface methodology, first-order reliability methods, and Bayesian networks.

Bayesian networks

Bayesian networks are a graphical modeling tool that allows specifying the probability distributions of a set of interrelated variables that can represent a specific situation (Bermejo, 2019). A Bayesian network is a means of representation that aims to organize knowledge of a particular situation into a coherent "whole".

There are three main methods used for modeling situations using Bayesian networks. The first method is mostly subjective, as it reflects your own knowledge and that of others in the network. The second synthesizes the knowledge of another type of formal knowledge. These two methods mentioned above are known as knowledge representation (KR) approximation. The third method is based on learning the networks from data, such as human reliability data, software reliability, medical diagnoses, among others.

At present, Bayesian networks have been used to represent models in different fields, mainly those that present a certain degree of uncertainty. That is: Bayesian networks are probabilistic Directed Acyclic Graph (DAG) models that can be used for uncertainty analysis. Cai et al. (2020), Khorshidi, Gunawan and Ibrahim (2016) and Darwiche (2009) propose the following definition of a Bayesian network:

A Bayesian network for variables Z is a pair (G, Θ) as:

- *G is a DAG over the variables Z, called the structure of the network.*
- Θ is a set of conditional probability tables (CPTs), one for each variable in Z, called the parameterization of the network.

Set $\Theta_{X|U}$ will be used to represent the CPTs for the variable X and its parents U, referring to the set XU as a family network. The parameters of the network, represented by $\theta_{X|U}$, will be the values assigned by CPT $\Theta_{X|U}$ to conditional probability Pr $(\theta_{X|U})$. The $\sum_X \theta_{X|U} = 1$ for any instantiation of parents U.

Cai et al. (2020) state that Bayesian networks use nodes to represent variables and arcs to represent significant direct dependencies between the joined nodes, as well as conditional probabilities to quantify the dependencies.

Let us consider n random variables $X_1, X_2, \dots, X_n$ and a DAG with n nodes, where the node $j(1 \leq j \leq n)$ is associated with the variable X_j, and the graph is the Bayesian network representing the variables involved by:

$$P(X_1, X_2, \dots, X_n) = \prod_{j=1}^{n} P\left(X_j \middle| pa(X_j)\right)$$

There, $pa(X_j)$ denotes the set of all variables X_j and an arc will connect node i to node j in the graph.

Now, be a Bayesian network with vertices $X = \{X_1, X_2, \dots, X_n\}$. Then you specify a unique joint probability distribution $P(X)$ given by all the CPTs specified in the same Bayesian network.

Using the chain rule and the assumptions of conditional independence, the joint probabilities of the variables can be computed $U = \{X_1, X_2, \dots, X_n\}$ through:

$$P(U) = \prod_{i=1}^{n} P\left(X_i \middle| Pa(X_i)\right)$$

That is, the products of the conditional probabilities of X_i y sus padres.

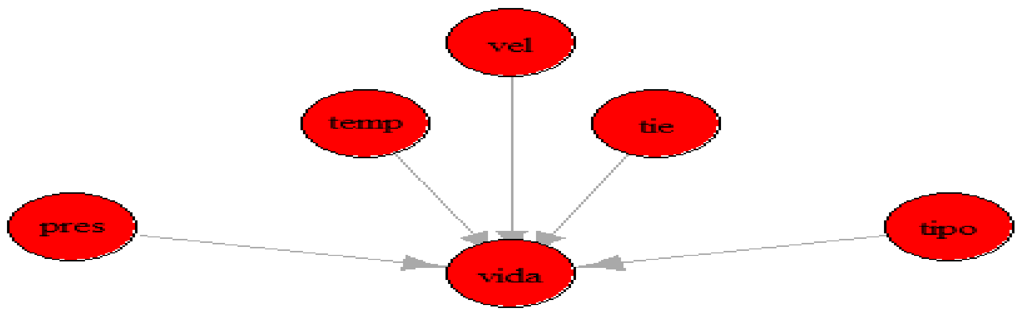
Next, a set of codes for the graphic construction of the Bayesian network is shown once the variables (nodes) and their relationships (arcs) have been determined. Figure 1 shows the result of the code according to the R package bnlearn (Scutari, 2010).

```
library (igraph, warn.conflicts = FALSE)
gr2 <- graph (c(1,6, 2,6, 3,6, 4,6, 5,6))
```

Revista Iberoamericana para la Investigación y el Desarrollo Educativo
ISSN 2007 - 7467

```
plot (gr2, vertex.label = c('pres', 'temp', 'vel', 'tie', 'tipo', 'vida'),
layout = matrix (c(-15,200, -5,650, 0,1000, 5,650, 15,200, 0,0), byrow = TRUE, ncol = 2),
 vertex .size = 30, vertex.color = 'red', vertex.label.cex = 1,
vertex.label.color = 'blue', vertex.frame.color = 'black', asp = 0.5, edge.arrow.size = 1)
```

Figure 1. Bayesian network example



Source: self made

Cox proportional hazard model

In accordance with Kraisangka y Druzdzel (2018), The CPH model is one of the most popular techniques in survival analysis. The CPH model can be compared to a multiple linear regression technique in which the relationship between risk and related explanatory variables is analyzed over a period of time. The survival analysis focuses mainly on modeling the occurrences of the time elapsed until the event occurs.

The survival probability of a device, after a certain time t, or the survival function is defined as:

$$S(t) = \Pr(T > t) \tag{1}$$

In this case, T is a variable that represents the moment in which an event of interest occurs. The baseline survival probability, represented by t_0, can be equal to one or some baseline survival probability, which will decrease to zero over time.

The hazard function is given by:

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{PR(t \le T < t + \Delta t \setminus T \ge t)}{\Delta \mathrm{t}} \tag{2}$$

T is a time variable that represents the risk of an event occurring at time t. Risk is measured in a small time interval Δt. A $\lambda(t)$ It is called the risk function or rate and is defined as the rate of events at time t conditioned on reliability up to or after time t (Rodríguez,

Rodríguez, Rodríguez, Alvarado and Sha 2017). Likewise, the hazard rate indicates the number of events per time interval (Cox, 1972).

The relationship between the hazard rate and the survival function is described below:

$$\lambda(t) = -\frac{d}{dt}\log S(t) \tag{3}$$

Or:

$$S(t) = e^{\int_0^t \lambda(u)du} \tag{4}$$

Equation 4 shows that the survival function can be calculated from the hazard function. The cumulative failure function and the survival function are complementary functions. Therefore:

$$F(t) = 1 - S(t) = 1 - e^{\int_0^t \lambda(u)du} \tag{5}$$

In survival analysis, the hazard function can be represented by any probability distribution, or it can be modeled by regression techniques. The CPH model provides an assessment of survival based on risk factors that are associated with the events indicated in the model. A simple CPH model consists of time-independent risk factors. The hazard function in a CPH model is expressed as:

$$\lambda(t) = \lambda_0(t)e^{\beta\prime X} \tag{6}$$

The risk model is mainly composed of two parts: the base risk function $\lambda_0(t)$ and the parameter effects set $\beta' \cdot X = \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$.

The baseline risk function determines threats at a fundamental level from the explanatory variables, for example, when risk factors are absent.

The hazard function denotes that the risk for individual i at time t is the product of two factors (Allison, 2010):

a) A function $\lambda_0(t)$ which is not specified, except that it cannot be negative.

b) A linear function of a set of k fixed covariates, which is then exponentiated.

The function $\lambda_0(t)$ can be thought of as the hazard function for an individual whose covariates all have values of zero.

Taking the logarithm of both sides, we can rewrite the model as:

$$\log \lambda(t) = \log \lambda_0(t) + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

If $\log \lambda_0(t) = \alpha(t)$, then you get:

$$\log \lambda(t) = \alpha(t) + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{7}$$

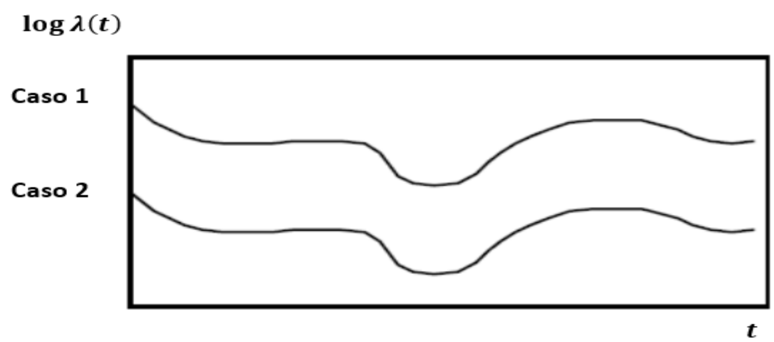
Now, if we take the risk ratio for two individuals i and j in equation 6, we get:

$$\gamma = \frac{\lambda_i(t)}{\lambda_j(t)} = \frac{\lambda_0(t)\exp(\beta_{in}{}' \cdot X_{in})}{\lambda_0(t)\exp(\beta_{jn}{}' \cdot X_{jn})} = \frac{e^{\beta'_{in} \cdot X_{in}}}{e^{\beta'_{jn} \cdot X_{jn}}}$$

$$\gamma = e^{\beta_1(x_{i1}-x_{j1})+\cdots+\beta_n(x_{in}-x_{jn})} \tag{8}$$

With this, the proportion of risks constant in time is obtained; This equation is called the proportional hazards model. This model has the characteristic that, when plotting the logarithm for each of the individuals, said risk functions must be strictly parallel (figure 2).

Figure 2. Parallel Functions of Log Risk of the Proportional Hazards Model



Source: Allison (2010)

Partial likelihood function

In the Cox regression model the parameters $\beta = (\beta_1 \cdots \beta_p)$ they are estimated by maximizing the logarithm of the so-called partial likelihood function. The maximization of said function $\hat{\beta} = (\hat{\beta}_1 \cdots \hat{\beta}_p)$ It is carried out using numerical methods and in this way the estimate is obtained.

This function considers only the failure time probabilities, and not the censored data time probabilities.

$$L_{t_{(i)}}(\beta_1 \cdots \beta_p) = \frac{exp\left(\sum_{j=1}^{p} \beta_j X_{(i)j}\right)}{\sum_{l \in R(t_{(i)}} exp\left(\sum_{j=1}^{p} \beta_j X_{(l)j}\right)} \tag{9}$$

This is assuming that we have k times of death and that there are no ties. Therefore, they have $n-k$ censored times. The ordered death times are denoted by $t_{(1)}, \cdots, t_{(k)}$, y $R(t_{(i)})$ the set of subjects at risk over time $t_{(i)}$ for $i = 1, \cdots, k$. It is called $L_{t_{(i)}}(\beta_1 \cdots \beta_p) = L_i$ to the portions of the total likelihood due to the contribution of the different times of death $t_{(i)}$.

Results

The project was developed in a harness manufacturing plant in Ciudad Juárez, where a battery harness was specifically selected, which presented detachment problems when performing the pull test carried out at the end of the ultrasonic welding process. Table 1 shows the results of the pull test carried out during a set period of time. On analyzing the data, the behavior (pdf) was found to be in accordance with a Weibull distribution (see Figure 3).

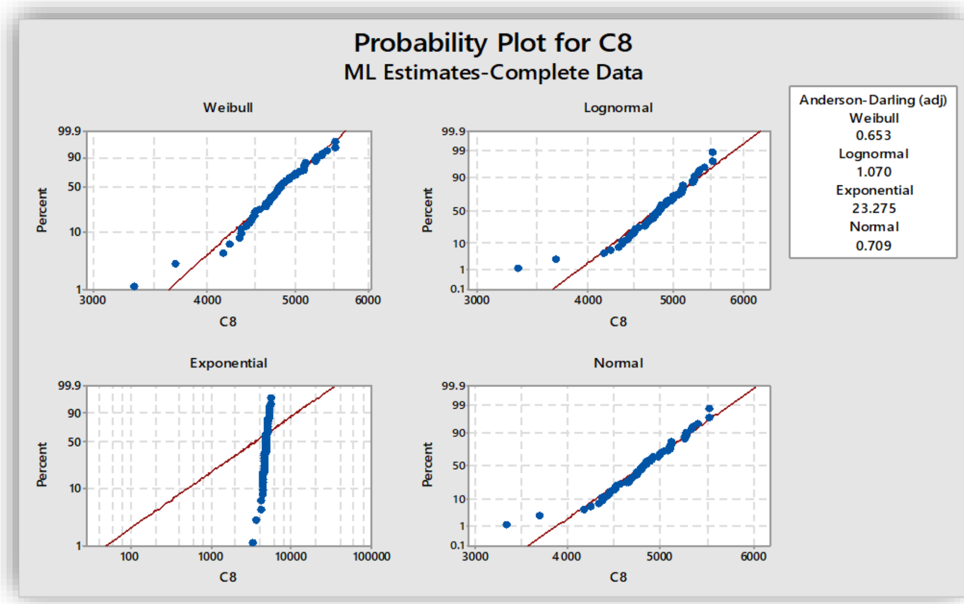
Construction of the CPH model

Table 1. Tensile strength data at current working conditions

5095.78	4560.86	4441.27	4741.64	5111.89	4512.83
5254.37	4821.02	3336.39	5261.59	4796.66	4696.92
4794.13	4985.84	4842.66	5523.42	4526.90	5347.55
5116.25	5001.84	4667.58	4359.99	5073.24	5276.86
4741.62	4680.51	5404.55	4847.42	4359.61	3686.19
4460.56	4824.47	5277.39	4508.32	4417.93	5334.00
5095.43	5094.03	4643.70	5113.57	4993.39	4963.89
4755.26	4910.01	4644.68	4493.22	4704.40	4847.95
4877.71	4236.22	5523.66	4776.01	4921.23	4337.76
5047.88	4173.46	4640.07	4905.87	4748.45	4768.42

Source: self made

Figure 3. Determination of the behavior of the data to establish the baseline showing that the data follow a Weibull distribution



Source: self made

Design of experiments

To check the significance of the factors, an experiment was designed with three factors at seven levels each (73). All 343 design combinations were run. The levels were taken from tests carried out and from the logbook of the technicians, whose experience indicated that parts that met the minimum specification could be welded. The factors and their levels are shown in Table 2.

Table 2. Factors and levels of design of experiments

Factor	Niveles	Valores						
Presión	7	2.65	2.67	2.70	2.73	2.76	2.79	2.81
Amplitud	7	0.58	0.64	0.71	0.77	0.84	0.90	0.97
Energía	7	154	786	1419	2051	2684	3317	3950

Source: self made

In the analysis of the results, all possible interactions of two and three factors were eliminated. The results are shown in table 3 with the analysis of variances.

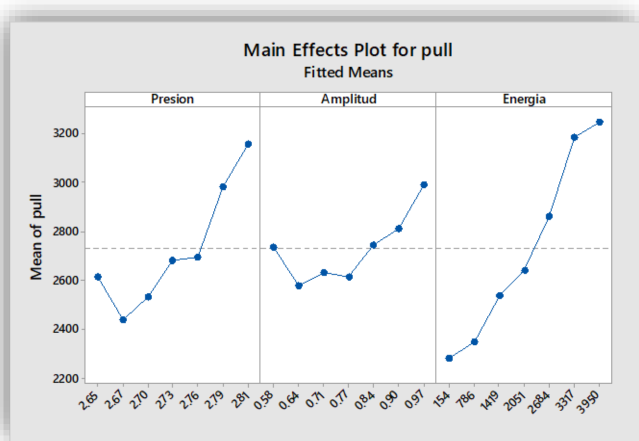
Table 3. analysis of variances

Source	DF	Adj SS	Adj MS	*F*-Value	*P*-Value
Model	18	68 236 028	3 790 890	24.69	0
Linear	18	68 236 028	3 790 890	24.69	0
Presión	6	18 871 084	3 145 181	20.48	0
Amplitud	6	5 977 604	996 267	6.49	0
Energía	6	43 387 340	7 231 223	47.09	0
Error	324	49 753 867	153 561		
Total	342	117 989 895			
Model Summary					
S	R-sq	R-sq(adj)	R-sq(pred)		
391.869	57.83 %	55.49 %	52.74 %		
Regression Equation					
pull = -8519 + 3702 Presión + 747 Amplitud + 0.2766 Energía					

Source: self made

As observed in the table, the three factors, pressure, amplitude and energy, were significant (p-value < 0.05). Figure 4 shows the factorial graphs where it can be seen that the recommended levels were: pressure = 0.81, amplitude = 0.97 and energy = 3950.

Figure 4. Plot of main effects: pressure, amplitude and energy

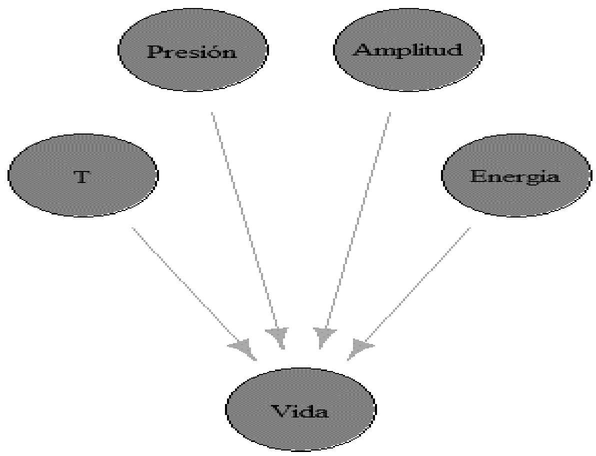


Source: self made

The following shows the R code for the construction of the Bayesian network of the significant factors and the resulting Bayesian network (figure 5).

```
library(igraph, warn.conflicts = FALSE)
gr1 <- graph(c(1,5, 2,5, 3,5, 4,5))
plot(gr1, vertex.label = c('T', 'Presión', 'Amplitud', 'Energía', 'Vida'), layout = matrix(c(-40,650, -20,1000, 20,1000, 40,650, 0,0), byrow = TRUE, ncol = 2), vertex.size = 70, vertex.color = 'blue', vertex.label.cex = 1, vertex.label.color = 'black', vertex.frame.color = 'black', asp = 1.5, edge.arrow.size = 0.75)
```

Figure 5. Construction of the Bayesian network with the significant factors



Source: self made

Table 4 shows the highest values of risk rate of energy, pressure and amplitude, as well as the levels of each of them. Likewise, the high survival values are shown in each of the levels of the different factors. A result of great importance, which was the main motivation for carrying out the aforementioned activities.

Table 4. Risk factors and their levels: hazard rates, hazard ratios, and survival

Factor de riesgo	Nivel 1	Nivel 2	Nivel 3	Nivel 4	Nivel 5	Nivel 6	Nivel 7
Energía	154	786	1419	2051	2684	3817	3950
Tasa de riesgo λ	*0.0143*	0.016	0.00229	0.0103	0.00563	0.0025	0.00241
Razón de riesgo γ	347	400	56	251	137	61	58
Supervivencia (S)	0.0306	0.018	*0.5699*	0.080	0.2524	0.542	0.5544
Presión	2.65	2.67	2.70	2.73	2.76	2.79	2.81
Tasa de riesgo λ	0.0045	*0.1015*	0.0075	0.00293	0.00219	0.001129	0.00908
Razón de riego γ	112	247	182	71	53	28	22
Supervivencia (S)	0.3228	0.0835	0.1509	0.4879	0.1590	0.7583	*0.8001*
Amplitud	0.53	0.64	0.71	0.77	0.84	0.90	0.97
Tasa de riesgo λ	0.00238	0.00608	*0.00745*	0.0069	0.0019	0.003313	0.00254
Razón de riesgo γ	58	148	182	168	46	49	62
Supervivencia (S)	0.558	0.2253	0.1609	0.1838	*0.6280*	0.6220	0.3360

Source: self made

Discussion

The assembly industry in Mexico, mainly the automotive industry, has become one of the main sources of foreign currency in Mexico. That the products of the maquiladora industry work correctly ensures, in the first place, the permanence of the industry in the country. The best way to achieve this is through the use of statistical tools considered within reliability engineering, such as reliability analysis, maintainability engineering and degradation analysis. According to Marjanović, Kvaščev, Tadić and Đurović (2011), system reliability is one of the main problems in today's industry, so the development of advanced system maintenance techniques is a relevant task. One of the aspects that are evaluated within maintenance is the wear of the elements that make up a mechanism, which implies not only detecting parts that cause equipment stoppage, but also analyzing the behavior of their degradation.

Degradation analysis consists of continuously verifying the specific function of the operation to determine the change in behavior, and relating the change to the tools that show wear, which allows determining the need for a change or rectification. . Degradation analysis could lead to obtaining a degradation function, and determining necessary parameters for maintenance programming, such as the average time to repair and the ideal times for tool changes, basic principles of predictive maintenance, anticipating the failure. There are other methods in the literature such as condition-based maintenance that contributes to reducing unexpected failures with minimal costs, as mentioned by Chen, Ye, Xiang and Zhang (2015), and that uses degradation information, however, the methods The results found in this research were relevant in its application and in the calculated benefits.

The project described in this document yielded a saving of 270,000 dollars, which it is considered can be extended to an annual saving, only in that operation, that is, in that production line, one of the seven similar lines that exist in the plant. , in which the analysis began following this methodology.

It is important to clarify that the success of the project was basically due to the support of management, in this case the continuous improvement manager, without whom it would not have been achieved. This is mentioned because the lack of support for its implementation, which implies machine time, human resources, the necessary materials and access to the facilities, are one of the main impediments that this type of project has.

Conclusion

The results obtained by introducing more complex concepts for process improvement, such as the CPH model, degradation analysis, Bayesian inference, and Bayesian network analysis, basically manage to reduce uncertainty in established inferences. Also, the introduction of a programmable software allows a good analysis of results, this from the reliable point of view, precisely due to the programming and the use of simulations through the MCMC method when Bayesian networks are used.

Projects of this type in the industry generally yield excellent results, but the most recurring problem for the implementation of methodologies that require machine time, materials and human resources is the support of the administration, because they see it as economic losses and not , through an effective application, as a way to generate significant savings over time. This is why it is always necessary to carry out a cost-benefit analysis to assess the economic-financial feasibility of this type of project.

Future lines of research

The area of quality control, reliability engineering and currently Bayesian inference have generated a wide range of future projects for the improvement of products and processes. The area of reliability and maintainability offer great opportunities for the development of projects. Specifically, the OEE = Availability x Performance x Quality is one of the most important indicators in manufacturing plants, and it is possible to improve it using the aforementioned concepts and applying the statistical tools that they entail.

A thank you to the National Council of Science and Technology for the support provided through national scholarships in doctoral and postdoctoral studies.

- Jorge A. Pinto Santos recipient of national scholarships for postgraduate studies (2017)
- Eduardo R. Poblano Ojinaga beneficiary of a postdoctoral fellowship in Mexico (2022)

References

Allison, P. D. (2010). *Survival Analysis Using SAS: A Practical Guide* (2nd ed.). Cary, United States: SAS Institute.

Bermejo, Q. G. 2019. *Aplicación de redes bayesianas en el análisis de supervivencia*. (Tesis de maestría). Centro de Investigación en Matemáticas, Guanajuato. Recuperado de http://cimat.repositorioinstitucional.mx/jspui/handle/1008/1055.

Cai, B., Liu, Y., Liu, Z., Chang, Y. and Jiang, L. (2020). Application of Bayesian Networks in Reliability Evaluation. In *Bayesian Networks for Reliability Engineering* (pp. 1-25). Singapore: Springer. Retrieved from https://doi.org/10.1007/978-981-13-6516-4_1.

Chen, N., Ye, Z. S., Xiang, Y. and Zhang, L. (2015). Condition-based maintenance using the inverse Gaussian degradation model. *European Journal of Operational Research, 243*(1), 190-199. Retrieved from https://doi.org/10.1016/j.ejor.2014.11.029.

Cox, D. R. (1972). Regression Models and Life-Tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, *34*(2), 187-202.

Darwiche, A. (2009). *Modeling and Reasoning with Bayesian Networks*. Cambridge, United Kingdom: Cambridge University Press. Retrieved from https://doi.org/10.1017/cbo9780511811357.

Khorshidi, H. A., Gunawan, I. and Ibrahim, M. Y. (2016). Data-Driven System Reliability and Failure Behavior Modeling Using FMECA. *IEEE Transactions on Industrial*

Informatics, *12(3)*, 1253-1260. Retrieved from https://doi.org/10.1109/TII.2015.2431224.

Kraisangka, J. and Druzdzel, M. J. (2018). A Bayesian network interpretation of the Cox's proportional hazard model. *International Journal of Approximate Reasoning*, *103*, 195-211. Retrieved from https://doi.org/10.1016/j.ijar.2018.09.007.

Marjanović, A., Kvaščev, G., Tadić, P. and Đurović, Ž. (2011). Applications of predictive maintenance techniques in industrial systems. *Serbian Journal of Electrical Engineering*, *8*(3), 263-279. Retrieved from https://doi.org/10.1.1.1053.7344.

Rodríguez, M. I., Rodríguez, M. A., Rodríguez, L. A., Alvarado, A. and Sha, N. (2017). Reliability Estimation for Accelerated Life Tests Based on a Cox Proportional Hazard Model with Error Effect. *Quality and Reliability Engineering International*, *33(7)*, 1407-1416. Retrieved from https://doi.org/10.1002/qre.2113.

Scutari, M. (2010). Learning Bayesian Networks with the bnlearn R Package. *Journal of Statistical Software*, *35(3)*, 1-22. Retrieved from https://doi.org/10.18637/jss.v035.i03.

Straub, D. and Der Kiureghian, A. (2012). Bayesian Network Enhanced with Structural Reliability Methods: Application. *Journal of Engineering Mechanics*, *136*(10). Retrieved from https://doi.org/10.1061/(ASCE)EM.1943-7889.0000170.

Zhang, C., Qin, T., Jiang, B. and Huang, C. (2017). A comprehensive probabilistic analysis model of oil pipelines network based on Bayesian network. Paper presented at the 3rd International Conference on Advances in Energy Resources and Environment Engineering. Harbin, December 8-10, 2017.

Rol de Contribución	Autor(es)
Conceptualización	Jorge Adolfo Pinto Santos (principal), Manuel Arnoldo Rodríguez Medina (igual), Eduardo Rafael Poblano-Ojinaga (que apoya).
Metodología	Jorge Adolfo Pinto Santos (principal), Manuel Arnoldo Rodríguez Medina (igual), Salvador Noriega Morales (que apoya).
Software	Manuel Arnoldo Rodríguez Medina (principal), Manuel Iván Rodríguez Borbón (que apoya), Eduardo Rafael Poblano-Ojinaga (que apoya).
Validación	Jorge Adolfo Pinto Santos (principal), Manuel Arnoldo Rodríguez Medina (igual), Salvador Noriega Morales (que apoya).
Análisis formal	Jorge Adolfo Pinto Santos (principal), Rafael García Martínez (igual), Salvador Noriega Morales (que apoya).
Investigación	Jorge Adolfo Pinto Santos (principal), Manuel Arnoldo Rodríguez Medina (igual), Eduardo Rafael Poblano-Ojinaga (que apoya).
Recursos	Manuel Iván Rodríguez Borbón (principal), Jorge Adolfo Pinto Santos (que apoya).
Curación de datos	Jorge Adolfo Pinto Santos (principal), Manuel Arnoldo Rodríguez Medina (igual), Salvador Noriega Morales (que apoya).
Escritura - Preparación del borrador original	Manuel Arnoldo Rodríguez Medina (principal), Manuel Iván Rodríguez Borbón (que apoya).
Escritura - Revisión y edición	Salvador Noriega Morales (principal), Jorge Adolfo Pinto Santos (igual), Eduardo Rafael Poblano-Ojinaga (que apoya).
Visualización	Eduardo Rafael Poblano Ojinaga (principal), Manuel Arnoldo Rodríguez Medina (igual), Manuel Iván Rodríguez Borbón (que apoya).
Supervisión	Rafael García Martínez (principal), Salvador Noriega Morales (igual), Vianey Torres Argüelles (que apoya).

Administración de proyectos	Manuel Arnoldo Rodríguez Medina (principal), Eduardo Rafael Poblano-Ojinaga (que apoya).
Adquisición de fondos	Manuel Iván Rodríguez Borbón (principal), Jorge Adolfo Pinto Santos (que apoya).