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Articles scientists

Diseño de Metodología de análisis de Mantenimiento a Equipo Industrial a través del uso de Filtro de Kalman y Redes Bayesianas Dinámicas

Design of Industrial Equipment Maintenance Analysis Methodology through the use of Kalman Filter and Dynamic Bayesian Networks

Projeto de uma Metodologia de Análise de Manutenção de Equipamentos Industriais através da utilização de Filtro de Kalman e Redes Bayesianas Dinâmicas

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Resumen

Debido al alto nivel de competencia industrial, las compañías buscan hacer cada vez más eficientes sus operaciones mediante la reducción de costos, sin afectar la calidad de sus productos. Una de las formas más comúnmente utilizadas para lograr este objetivo es optimizar el funcionamiento de los equipos productivos, por lo que en este trabajo de investigación se desarrolló una metodología para realizar el análisis de fallas, con el objetivo de identificar su causa raíz y mejorar el desempeño del equipo y maquinaria. La metodología emplea una red bayesiana dinámica para el análisis. Esta herramienta proporciona información sobre la probabilidad de ocurrencia de las fallas, lo que resulta sumamente útil, ya que permite establecer prioridades en las acciones correctivas para eliminarlas o reducir su incidencia, además, para los equipos que requieren monitoreo continuo, se emplea el filtro de Kalman y el filtro de Kalman extendido cuando corresponda, su propósito es eliminar el ruido en el proceso de adquisición de datos para obtener información confiable para el análisis, además, permite estimar con precisión el estado de ciertas variables en lugares donde es difícil o imposible colocar dispositivos de medición directa. La implementación de esta metodología permite una mejora sustancial en el proceso de análisis de fallas y, en consecuencia, hace más efectivas las acciones correctivas para su eliminación.

Palabras Clave: Redes bayesianas, red bayesiana dinámica, análisis de mantenimiento, Filtro de Kalman.

Abstract

Due to the high level of industrial competition companies strive to enhance their operational efficiency by reducing costs without affecting the quality of their products. One of the most common approaches to achieving this goal is optimizing the operation of production equipment. Therefore, this research develops a methodology for failure analysis aimed at identifying root causes and improving equipment and machinery performance. The methodology employs dynamic Bayesian network for failure analysis. This tool provides valuable information about the probability of failure occurrence, allowing the prioritization of corrective actions to eliminate failures and reduce their incidence. Additionally, for equipment requiring continuous monitoring, the Kalman filter and, when applicable, the extended Kalman filter are employed., Its purpose is to eliminate noise in the data acquisition process, ensuring reliable information for analysis. Moreover, it enables the accurate estimation of certain variables in locations where direct measurement is challenging or unfeasible. Implementing this methodology leads to substantial improvements in the failure analysis process, making corrective actions more effective in eliminating failures.

Keywords: Bayesian Networks, Dynamic Bayesian Networks, maintenance analysis, Kalman filter.

Resumo

Devido ao alto nível de competição industrial, as empresas buscam tornar suas operações cada vez mais eficientes, reduzindo custos, sem afetar a qualidade de seus produtos. Uma das formas mais utilizadas para atingir esse objetivo é otimizar a operação dos equipamentos de produção, por isso neste trabalho de pesquisa foi desenvolvida uma metodologia para realizar análises de falhas, com o objetivo de identificar sua causa raiz e melhorar o desempenho dos equipamentos e máquinas. A metodologia emprega uma rede bayesiana dinâmica para análise. Esta ferramenta fornece informações sobre a probabilidade de ocorrência de falhas, o que é extremamente útil, pois permite estabelecer prioridades nas ações corretivas para eliminá-las ou reduzir sua incidência. Além disso, para equipamentos que exigem monitoramento contínuo, o filtro de Kalman e o filtro de Kalman estendido são utilizados quando apropriado. Sua finalidade é eliminar ruídos no processo de aquisição de dados para obter informações confiáveis para análise. Além disso, permite estimar com precisão o estado de certas variáveis em locais onde é difícil ou impossível colocar dispositivos de medição direta. A implementação desta metodologia permite uma melhoria substancial no processo de análise de falhas e, consequentemente, torna mais eficazes as ações corretivas para a sua eliminação.

Palavras-chave: Redes bayesianas, rede bayesiana dinâmica, análise de manutenção, filtro de Kalman.

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Introduction

The performance of the industrial maintenance department has always been a challenge for production plant managers, since keeping the equipment in a functional state is key to achieving the objectives of the manufacturing department. This situation has driven the development of various strategies to improve the performance indicators of the department in charge of maintaining industrial equipment in optimal conditions and offering better service.

Different maintenance systems have been implemented to maintain the reliability and efficiency of industrial equipment. Some of the most commonly used techniques are preventive, proactive and predictive maintenance, the latter making use of machine learning techniques, which have emerged as a promising approach to address this challenge (Mourtzis, Siatras, & Angelopoulos, 2020).

This research work proposes a methodology for the analysis of equipment failures through the use of dynamic Bayesian networks, as a viable alternative for industry and companies. Its objective is to find the root cause of the problems and implement corrective actions, establishing priorities based on the probability of occurrence of failures, in order to improve the performance of the maintenance department and achieve the goal of managing in a more efficient way the expenses generated by maintenance and downtime in productive and non-productive equipment due to failures. The dynamic component of the Bayesian network is used to model complex relationships between various system parameters, allowing an accurate prediction of the equipment status and its failure patterns (Saeidi et al., 2019).

One of the advantages of the proposed methodology for failure analysis in maintenance is the improvement in obtaining data on equipment that requires monitoring of key parameters in real time. This is achieved by using the Kalman filter, which eliminates possible noise that could generate incorrect or inaccurate readings, thus obtaining reliable information for analysis. In this method, the Kalman filter is used to eliminate noise from the signals received from the parameters measured for monitoring the status of the selected equipment.

The use of the Kalman filter allows obtaining signals from the parameters used for monitoring without noise, which makes it possible to determine the status of the device with an acceptable level of reliability and to schedule corrective and preventive actions before failures occur in the monitored equipment or device.

The increasing availability of data obtained from monitoring the condition of critical equipment has opened new opportunities for the development of data-driven maintenance algorithms. A considerable number of industrial applications require the measurement of a large number of physical variables to obtain sufficient and quality information in the system to obtain the desired level of performance. However, some of these variables cannot be measured, either due to their cost or reliability problems. In this context, the Kalman filter plays a key role in many industrial applications (Auger, et al., 2013).

The need to have the necessary information for decision making is essential in the manufacturing industry, the collection of data for equipment monitoring through the use of different types of instruments that provide valuable information to determine the status of a piece of equipment, however, this information is not always accurate, due to different causes such as variation in the measuring instruments, distances between the sensor and the computer, temperature, etc., this causes the information collected by the measuring instruments to not be statistically reliable.

In other cases, the parameters of interest cannot always be measured directly, so it is necessary to estimate them from the available information, by using tools such as the Kalman filter which is used in many fields such as navigation, aerospace engineering, space engineering, physics, audio signals and control engineering (Ai, Ai, Gray, Salzburger, & Styles, 2023) , it is also useful for smoothing noisy signals, however, it is not always easy to estimate the exact state of a system due to several reasons, including the imperfection of the mathematical model, dynamic environments, error with inadequate distribution (Non-Gaussian), inadequate parameters and lack of linearity.

Table 1 shows some notations used in different published articles to refer to the most common concepts on Kalman filter topics, some of them cited in this research paper.

Table 1. Notations used in various studies.

Parameter	Notation			
State estimation in time k	$x_{e[k]}$			
Prediction in time k+1 (State estimated a priori)	$x_{p[k+1]}$	$x_{[k+1\|k]}$	$x^{-}_{[k+1]}$	$\hat{x}_{k+1}$
Estimated status a posteriori	$x_{e[k+1]}$	$x_{[k+1\|k+1]}$	$x^{+}_{[k+1]}$	
Estimating the error in the covariance matrix at time k	$P_{e[k]}$	P_t		
Predicting the covariance error matrix at time k+1	$P_{p[k+1]}$			
Measurement vector in time k	y_k	z_k		

Source: Own elaboration

Materials and methods

Industrial Maintenance

In the industry there are different techniques for equipment maintenance, the main objective of which is to keep the equipment in a functional state and to eliminate or reduce as much as possible unscheduled downtime due to equipment failures. Among the most widely used systems in the industry, due to their proven effectiveness, are the following:

Predictive maintenance, which is a technique based on the periodic monitoring and analysis of some equipment parameters during its operation that allows identifying failures in early stages (Altoé Mendes, Riva Tonini, Rodrigues Muniz, and Bravin Donadel, 2016).

Preventive maintenance, which is defined as the activity in which tasks are performed according to prescribed criteria or in predetermined time periods. To establish optimal maintenance periods, a detailed and comprehensive assessment is required. However, this assessment is generally not performed, and instead the manufacturer's recommendations are applied (Sánchez-Herguedas, Mena-Nieto, Crespo-Marquez, & Rodrigo-Muñoz, 2024).

Corrective maintenance, which involves restoring equipment functionality after a failure has occurred. This approach minimizes the cost of servicing the equipment, thereby extending the maintenance interval, but comes at the expense of an increased risk of equipment unavailability and increased repair time and cost, resulting from equipment downtime caused by unscheduled shutdowns. (Moleda , Małysiak-Mrozek , Ding , Sunderam , & Mrozek , 2023).

Bayesian Networks

In Bayesian networks (BN), directed acyclic graphs (DAGs) are used to describe conditional dependencies between random variables $X_{1,}X_2, \ldots\ldots X_n$. There is a one-to-one mapping between the n nodes of the DAG and the variables, and the directed edges between the nodes denote the dependency between the variables (Grzegorczyk, 2024).

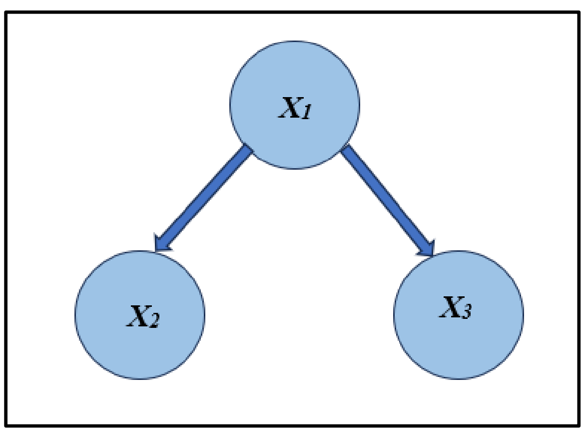
The joint probability distribution over all the variables in the network can be determined by calculating the product of all the prior and conditional probability distributions and its mathematical representation is shown in equation (1).

$$\Pr(X) = \Pr(X_1 X_2, \ldots, X_n) = \prod_{i=1}^{n} \Pr(X_i | P_a(X_i)) \quad (1)$$

The structure of a Bayesian network and its numerical probabilities can be obtained from experts or by learning from data. (Kraisangka and Druzdzel, 2018).

Figure 1 shows a diagram of a simple Bayesian network, where a circle or ellipse represents the nodes of the graph, the variables identified as are shown inside the circle, $X_{1,}X_2, X_{3\,,}$ and the arrows, also called arcs of the graph, indicate the causal relationships between these random variables. For example, in this diagram, the variables X_2 and X_3 have a causal dependence on the variable X_1 .

Figure 1. Basic configuration of a Bayesian network.



Source: Own elaboration

Bayes' Theorem

Bayes' theorem can be represented in a mathematical formula that relates the unconditional and conditional probabilities of events A and B, where B is an event with prior information and A is a conditional event, and A is a conditional event, further assuming $P(B) \neq 0$, so that the probability of A occurring given B, can be determined by equation (2) (Conrady and Joufee, 2015).

$$P(A|B) = P(A) * \frac{P(B|A)}{P(B)} \quad (2)$$

where:

$P(A)$It is the marginal probability (also called unconditional probability) that event A occurs;

$P(A|B)$ represents the conditional probability of event A occurring once event B has occurred.

$P(B)$indicates the marginal probability of occurrence of event B and

$\frac{P(B|A)}{P(B)}$ represents the likelihood ratio, also known as the Bayes factor.

Dynamic Bayesian Networks

Bayesian networks cannot accurately represent the dynamic relationship between process parameters, however, a dynamic Bayesian network can be created to incorporate the influence of the time dimension within the Bayesian network (Mao, et al., 2023). Dynamic Bayesian networks are an extension of Bayesian networks that model domains from a temporal perspective; in essence, they are time-extended Bayesian networks (Saada, Kouppas, Li, & Meng, 2022). Its biggest advantage is that it can easily work with uncertain or missing data and its prediction results are reliable and reasonable (Wei, Yu, & Li, 2023). Time steps reflect the change in the state/probabilities of the parameters in the model. Dynamic Bayesian networks describe discrete time series consisting of observations of variables over multiple instants of time called time steps or time intervals, the time between two consecutive intervals is assumed to be always the same. According to Leão et al (2021), a dynamic Bayesian network is a pair (B_0 , $B_{\rightarrow}$) where:

B_0 is an a priori Bayesian network, which defines the joint probability distribution on the variable in $t = 0$ (it is assumed that the first time interval in a dynamic Bayesian network is $t = 0$ and the last is $t = T$), that is $B_0 = P(X|0|)$.

$B_{\rightarrow}$It is the game of all transition networks$B_{\rightarrow}[0{:}T]$ $con\ t \epsilon \{1 \dots \dots T\}$

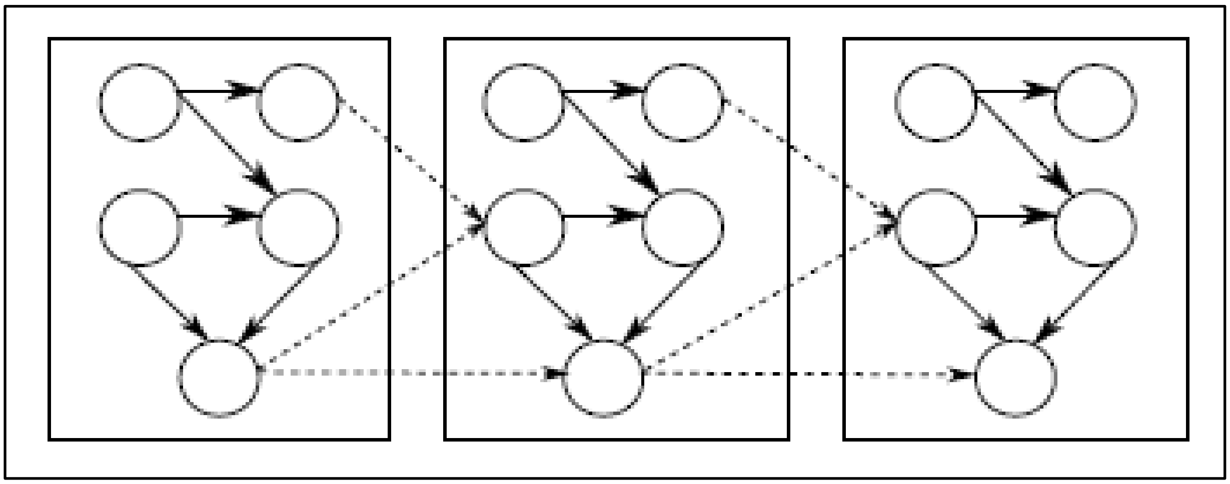
The distribution over the variables in the time interval t is defined as:

$(B_0\ , B_{\rightarrow}) = P(X[t]|X[0{:}t-1]$ (Leão, Madeira, Gromicho, de Carvalho, and Carvalho, 2021).

Dynamic Bayesian networks are not limited to a single time series, they support both temporal and non-temporal nodes in the same model with temporal nodes being the initial conditions in time. $t = 0$. Dynamic Bayesian networks are probabilistic graphical models that describe uncertainty in diverse situations (Khan, Khan, & Veitch, 2020).

Figure 2 shows a general form of representation of a dynamic Bayesian network, in which time series are modeled with windows represented at a time instant T, in which a Bayesian network is generated that at each time instant receives information from time instant T-1 in addition to the observable variables. The dotted lines represent the flow of information between the time windows (Reguero Alvarez, 2011).

Figure 2. Structure of a dynamic Bayesian network.



Source: (Reguero Alvarez, 2011)

Kalman filter

Kalman filter is a recursive algorithm that uses a set of mathematical equations and data inputs to estimate the factors such as position, velocity, and true values of measurements of an object when the measurement values have some level of uncertainty. Using this filter allows to determine the internal state of a dynamic linear system by processing a set of discrete measurements of a system in a reliable manner. Both the measurements and the system are subject to random disturbances, also called noise, and this technique removes interferences in the signals and provides accurate data. Kalman R. E. (1960) published a paper describing a recursive solution for discrete linear data filtering problems and addresses the estimation of the state of a discrete-time controlled process, governed by the stochastic equation (3).

$$x_{k+1} = A_k x_k + B u_k + w_k \tag{3}$$

The measurement vector at time k is defined by equation (4).

$$z_k = H_k x_k + v_k \tag{4}$$

Where the random variables $w_k$represent the process noise and $v_k$the measurement noise, which are assumed to be independent of each other, with a normal distribution with zero mean. In addition, $A_k$is the state transition matrix which maps the effect of each state parameter of the system at time *k* to the state of the system at time *k+1* (e.g. temperature and pressure at time *k* affect the pressure at time *k+1*). H_k is the transformation matrix that maps the parameters of the state vector to the measurement domain (Welch and Bishop, 1997) .

In the case of continuous time, discrete measurements and non-linear systems the state vector $\dot{x}(t)$can be represented by equation (5) and the measurement available at an instant t_k $(z(t_k)$ by equation (6).

$$\dot{x}(t) = f\big(x(t), u(t)\big) + w(t) \tag{5}$$

$$z(t_k) = g\big(x(t_k), u(t_k)\big) + v(t_k) \tag{6}$$

where $u(t)$represents the system input, the system noise is represented by $w(t)$ while $v(t_k)$ the measurement noise, which are considered as Gaussian processes with covariance matrices Q for the system noise and R for the measurement noise (González-Cagigal, Rosendo-Macías, and Gómez-Expósito, 2019).

Kalman filter can be used for joint estimation of state and parameters in which both the state variables and parameters in the model are simultaneously estimated (Huang, Li, & Yan, 2010). In this research work, Kalman filter is used to perform an analysis of the data provided from a three-phase generator to know its state.

Other typical uses of the Kalman filter include, in addition to smoothing noisy data, providing estimates of parameters of interest. Common applications include global positioning system receivers, phase-locked loops in radio equipment, smoothing the output of laptop (Faragher, 2012) trackpads , and many more applications. For a dynamic system, the estimation of its internal states is important because in real-time applications the number of sensors that can be implemented is limited, and some sensors are too expensive to implement and not all physical components can always be measured (Shabbouei Hagh, Mohammadi, Mikkola, and Handroos, 2023).

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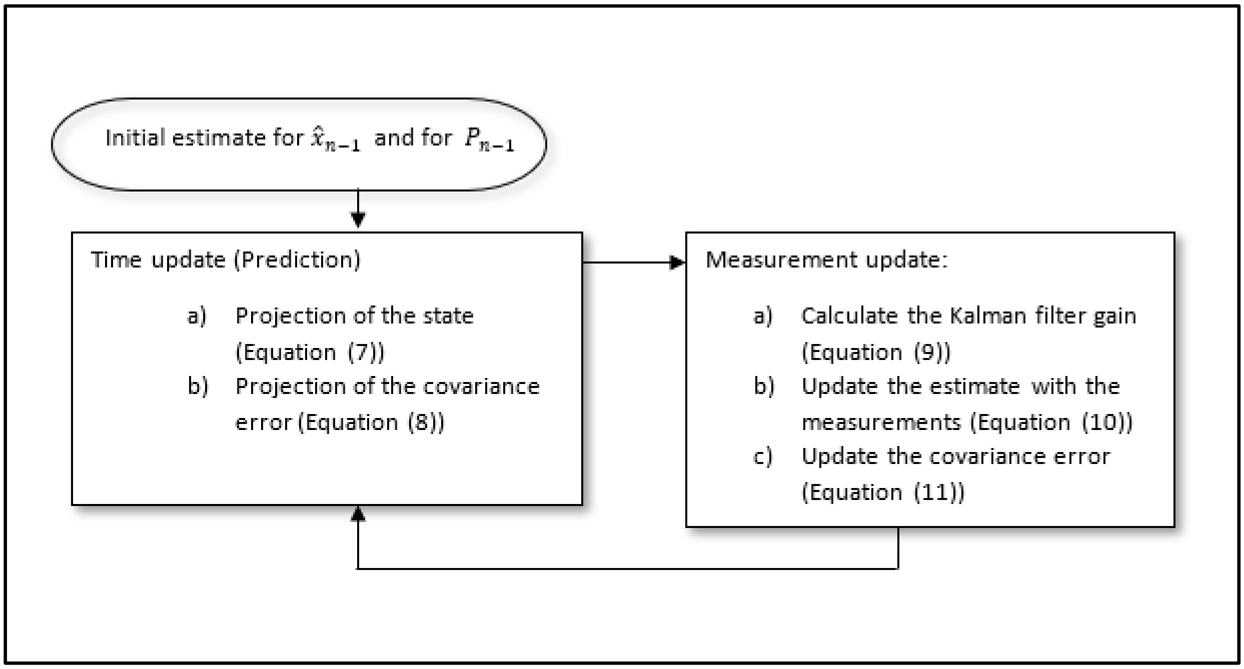
There are two processes involved in the Kalman filter algorithm, one is prediction and the other is correction, as shown in Figure 3, equations (7) and (8) are used for time update calculation and equations (9), (10) and (11) for the correction stage.

Figure 3. Kalman filter algorithm



Source: Prepared by the authors based on information from (Babu and Parthasarathy, 2022)

Because Kalman filters are recursive in nature, the process is repeated at each time step, resulting in a new estimate and an updated covariance with the predicted state at subsequent iterations (Babu and Parthasarathy, 2022).

Thus, the Kalman filter algorithm is described in two steps: prediction and correction: In the prediction stage, equation (7) generates an a priori estimate, while in equation (8) the covariance of the error associated with the a priori estimate is obtained.

$$\hat{x}_n = A\hat{x}_{n-1} + Bu_n \quad (7)$$

$$P_n = AP_{n-1}A^T + Q \quad (8)$$

In the correction stage, equation (9) helps us to obtain the Kalman filter gain, equation (10) helps us to obtain the a posteriori estimate with the new measurements, while equation (11) calculates the covariance of the error associated with the a posteriori estimate.

$$K_n = P_{n,n-1}H^T(HP_{n,n-1}H^T + R_n)^{-1} \quad (9)$$

$$\hat{x}_n = A\hat{x}_{n,n-1} + K_n(Z_n - H\hat{x}_n) \quad (10)$$

$$P_{(n|n)} = (I - K_kH_k)P_{k|k-1} \quad (11)$$

where *K* represents the Kalman gain, $P_{n|n}$ the uncertainty estimates for the current state, H the observation matrix, R_n the uncertainty matrix in the measurements, and Z_n the state vector of the measurements (Babu & Parthasarathy, 2022).

Covariance matrices provide information about the quality of the estimates, however, if the state or noise covariance matrices are not estimated correctly, the covariance matrix in the error estimate has no meaning.

Masnadi-Shirazi et al. (2019) provide a tutorial and a step-by-step mathematical procedure for the derivation of the Kalman filter equations. These authors consider the target state vector $x_k \in \mathbb{R}^n$, with k as a time index and the discrete-time stochastic model is represented by equation (12).

$$x_k = \phi_{k-1}(x_{k-1}, u_{k-1}) \quad (12)$$

Where ϕ_{k-1} is a known, possibly non-linear, function of the state x_{k-1} and u_{k-1} is the noise which accounts for poorly posed models or errors in the established objectives. It should also be considered that the process measurements are $z_k \in \mathbb{R}^m$, which are related by equation (13).

$$z_k = h_k(x_k, w_k) \quad (13)$$

h_k is a known function, possibly non-linear and w_k is the measurement noise, which is assumed to be white noise, as is u_{k-1}, both with known probability distribution functions and independent of each other.

Assuming now that ϕ_k and h_k are linear functions and assuming that the noise and initial state distributions are Gaussian, one can write the following linear/Gaussian model consisting of the following three parts:

1. - A difference vector defined by equation (14).

$$x_{k+1} = \Phi_k x_k + u_k \quad k = 0,1,2,3 \ldots. \quad (14)$$

Which defines how the random vector $x_k$changes over time.

2.- An initial random vector x_0 with an initial estimate $\hat{x}_0$ with a value in the initial covariance P_0.

3.- Process measurements calculated from equation (15).

$$z_k = H_k x_k + w_k \quad k = 0,1,2 \ldots \quad (15)$$

A key limitation for many applications of the Kalman filter is the assumption of linear models for the system and the measurement, as well as Gaussian distributions for the system state, process, and measurement noise. This has motivated the development of a number of extensions for nonlinear systems. Several variations of the Kalman filter have been developed to improve its performance. The extended Kalman filter (EKF) and the unscented Kalman filter are widely used for nonlinear systems, which are approximated to linear systems by linearization techniques (Aghamolki, Miao, Fan, Jiang, & Manjure, 2015). However, since the extended Kalman filter uses linearization to convert a nonlinear system into a partially linear one, its performance may be affected in highly nonlinear systems (Kim, Petrunin, & Shin, 2022).

Extended Kalman Filter

For non-linear processes a commonly used technique is the extended Kalman filter, which linearizes a non-linear function f at a time k-1 and predicts the image at a time k, the estimation is done in two steps: the time update equations, and the measurement update equations. The time update equations (16) and (17) are:

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_{k)} \quad (16)$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F^T + Q_k \quad (17)$$

Where $Q_k$is a positive definite matrix representing the process noise covariance and $F_k$by equation (18).

$$F_k = \frac{\partial f}{\partial x}\left(\hat{x}_{k-1|k-1}, u_k\right) \quad (18)$$

The measurement update equations are used to correct the estimated states and the predicted error covariance in the time update equations by comparing the estimated states with the measurements represented by equations (19), (20) and (21).

$$K_k = P_{k|k-1} H_K^T (H_k P_k H_K^T + R_k)^{-1} \quad (19)$$

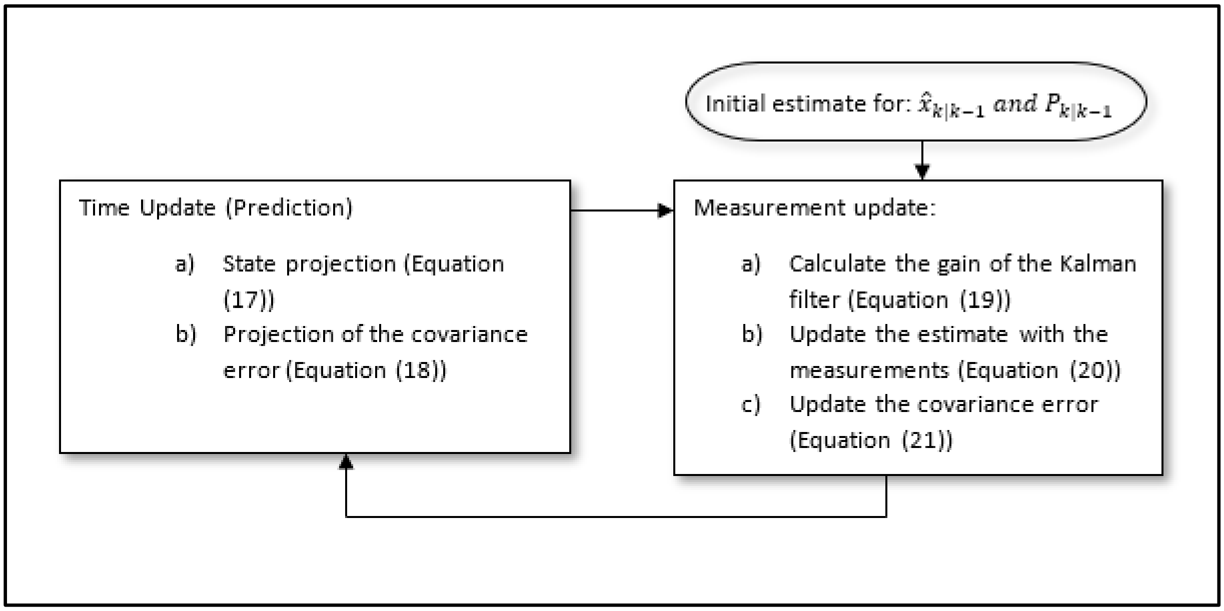
$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(y_k - H_k \hat{x}_{k|k-1} \quad (20)$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \quad (21)$$

where R_k is a positive definite matrix representing the noise covariance of the measurements and H_k is the Jacobian of $h(x_k)$. (Gaouti, Colin, Thiam, & Mazellier, 2021).

Figure 4 shows the operation diagram of the extended Kalman filter with the time and measurement update equations.

Figure 4. Operation diagram of the extended Kalman filter.



Source: Own elaboration based on information from (Gaouti, Colin, Thiam, and Mazellier, 2021)

Results

Industrial Equipment Maintenance Analysis Method through the use of Kalman Filter and Dynamic Bayesian Networks

As a result of the analysis carried out, a methodology for failure analysis was developed that can be applied to any industrial equipment included in a maintenance program, with the aim of keeping it in optimal operating conditions. This methodology incorporates the technique of dynamic Bayesian networks, which allows the evaluation of the temporal relationship between the equipment parameters and the management of conditional probabilities of failure, which facilitates the prioritization of corrective actions. For equipment that requires real-time monitoring, the Kalman filter is used to increase the reliability of the data obtained.

Figure 5 shows the flow to follow to perform the analysis of Industrial Equipment Maintenance through the use of Kalman filters and Dynamic Bayesian Networks. The first step consists of selecting the equipment to be analyzed, whose variables influence each other over time and can be evaluated through dynamic Bayesian networks (DBN). This system is useful for evaluating the effect of various factors in complex systems, such as those whose performance depends on multiple interdependent variables.

Step 2 involves the selection of variables to be analyzed. These variables are selected based on their impact on the functionality of the equipment and their suitability for analysis using Dynamic Bayesian Networks. Specific variables are not explicitly listed as they would vary depending on the equipment being analyzed, i.e. the variables to be analyzed are those relevant to the operation of the chosen equipment and its failure modes, and which can be effectively monitored and incorporated into the DBN model. It is important to select variables that influence each other over time, as this dynamic relationship is paramount to analysis using Dynamic Bayesian Networks.

In step 3 of the process, it is determined whether continuous monitoring of any variable of interest is necessary for the correct operation of the selected equipment. If this need is confirmed, the system is classified as linear or non-linear in order to determine which type of Kalman filter is most suitable.

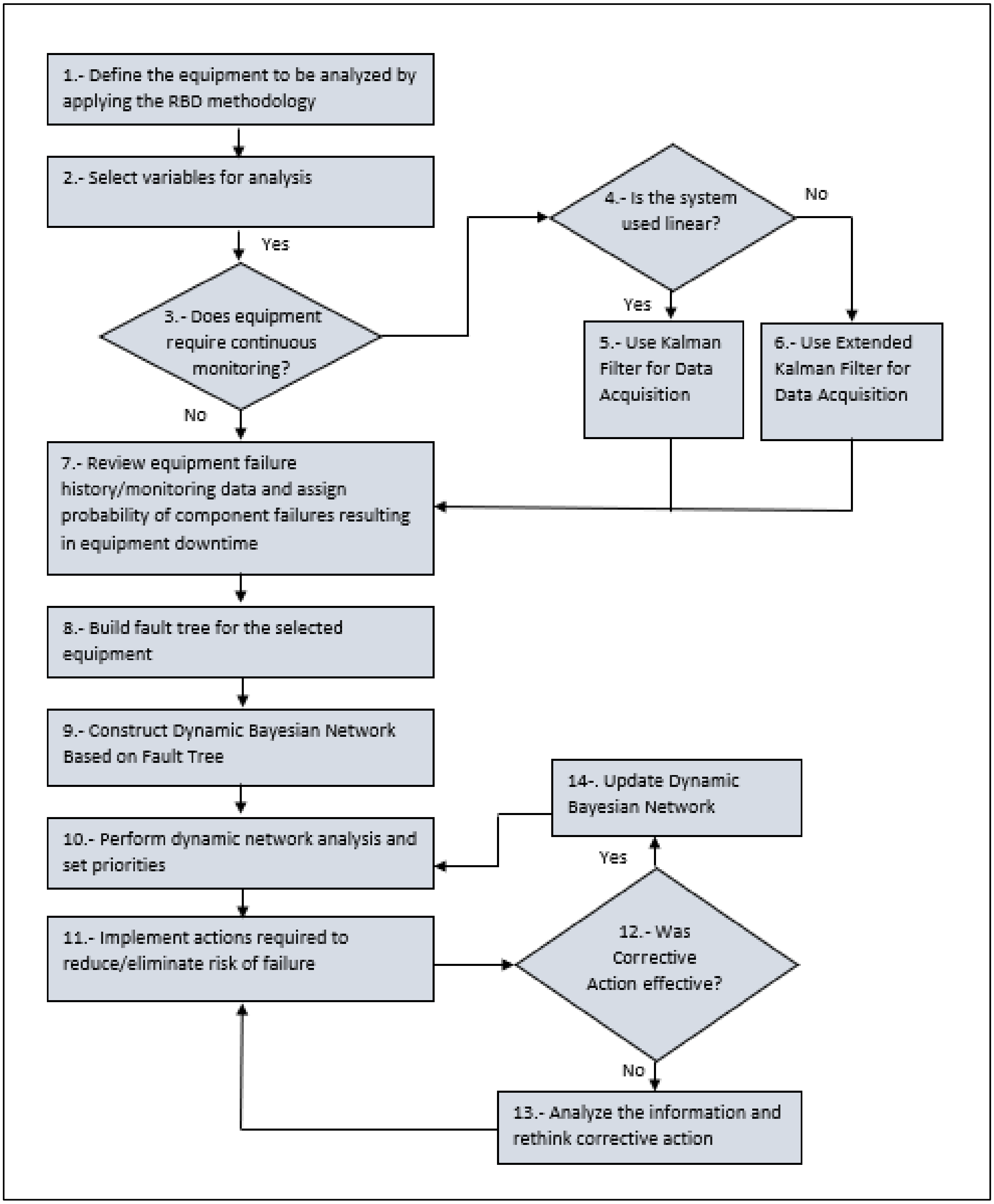
- If the system is linear, the standard Kalman filter is used for data acquisition as it provides accurate and reliable estimates (step 5).
- If the system is non-linear, the extended Kalman filter is used, an adapted version of the standard filter that allows a better estimation of the variables (step 6).

Step 7 consists of reviewing the failure history of critical equipment that does not require continuous monitoring, as well as the results of continuous monitoring of variables, with the aim of identifying the failures that most affect the operation of the equipment.

- In step 8, a fault tree is created, which will serve as the basis for building the dynamic Bayesian network (step 9).
- As a result of this analysis, in step 10 priorities are established based on the probability of failure that could cause the equipment to stop.

Step 11 involves implementing actions on the equipment aimed at reducing the probability of occurrence of the analyzed failure. The effectiveness of the implemented corrective action is evaluated in step 12. If it is effective, the dynamic Bayesian network is updated in step 14 so that the information obtained can serve as a reference in subsequent analyses. If the implemented actions do not reduce the probability of failure, they must be reconsidered as many times as necessary until an effective solution is found (step 13).

Figure 5. Methodology for the analysis of industrial equipment maintenance using Kalman filters and dynamic Bayesian networks.



Source: Own elaboration

Discussion

The developed methodology is a useful tool to identify the root cause of problems, since, in addition to the use of dynamic Bayesian networks, it incorporates the Kalman filter, which allows analysis to be carried out and conclusions to be obtained based on reliable information, facilitating the implementation of effective corrective actions that directly address the problem and, thereby, improve the performance of production equipment and existing machinery in the industry subject to a maintenance program, which leads to an improvement in maintenance indicators, which directly impact the costs associated with equipment maintenance.

Although the calculations and procedures of the methodology, as well as the development of the dynamic Bayesian network, may seem extensive and complex, the use of computer programs speeds up the calculations and allows obtaining the results of the analysis and the probability tables in a relatively short time, as observed in the work of Ramos et al. (2024).

In addition, specialized personnel may modify certain maintenance programs to integrate the proposed methodology, allowing for rapid implementation of corrective actions and the assignment of priorities.

Among the most used programs for the analysis and construction of networks are R and BayesiaLab, used by Conrady and Jouffe (2015), because they have a sophisticated and user-friendly graphical interface.

Conclusions

The application of dynamic Bayesian networks is of great help to perform an in-depth analysis of the equipment's behavior and to visualize how the variables interact over time. This makes it possible to effectively find the causes that cause failures in the different equipment, which allows corrective actions to be taken that truly attack the root of the problems that cause failures in the equipment. In addition, this tool provides information on the probability of failures occurring, which allows corrective actions to be prioritized according to their impact and to reduce the incidence of failures, thus improving equipment performance. This approach directly impacts the main indicators of the maintenance department in the industrial field, such as the mean time between failures (MTBF) and the mean time to repair (MTTR).

This analysis method is applicable to any maintenance technique, as it allows effective data processing, which can be updated periodically to evaluate the interaction of variables at different time intervals.

The use of the Kalman filter in its different versions allows obtaining more reliable information, since, through appropriate software, it eliminates noise in the measurements that could generate incorrect readings and affect the quality of the analysis.

The application of this methodology improves maintenance indicators, making it a valuable tool for industrial maintenance departments seeking to optimize equipment performance and reduce costs.

Future Lines of Research

Given the importance of the maintenance department in industrial plants and the need to perform more efficient analyses to eliminate problems at the root, it is essential to integrate these techniques into the maintenance control software. Likewise, the proper selection of monitoring equipment is crucial to achieve continuous improvement objectives, which are essential in an increasingly competitive market.

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