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TEMA:

APROVECHANDO LOS MÉTODOS ESTADÍSTICOS CLÁSICOS PARA EL MANTENIMIENTO SOSTENIBLE EN EQUIPOS DE ENSAMBLAJE DE AUTOMÓVILES

Trabajo previo a la obtención del título de Máster en Diseño Industrial y de Procesos

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UNIVERSIDAD TECNOLÓGICA INDOÁMERICA

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RESUMEN EJECUTIVO

La gestión del mantenimiento predictivo desempeña un papel crucial para garantizar el funcionamiento fiable de los equipos en la industria. Si bien la tecnología de monitoreo continuo está disponible en la actualidad, los equipos sin sensores limitan el registro continuo de datos del estado del equipo. El mantenimiento predictivo se ha llevado a cabo de forma eficaz utilizando algoritmos de inteligencia artificial para conjuntos de datos con datos suficientes. Sin embargo, replicar estos resultados con datos limitados es un desafío. Este trabajo propone el uso de modelos de series de tiempo para implementar mantenimiento predictivo en los equipos de una empresa ensambladora de automóviles con pocos registros disponibles. Para este propósito, se exploran tres modelos: el suavizado exponencial de Holt-Winters (HWES), el promedio móvil integrado autorregresivo (ARIMA) y el promedio móvil integrado autorregresivo estacional (SARIMA), para determinar el pronóstico más preciso del tiempo de inactividad futuro de los equipos y recomendar el uso. de SAP PM para una gestión eficaz del proceso de mantenimiento. Los datos se obtuvieron de cinco familias de equipos desde enero de 2020 hasta diciembre de 2022, representando 36 registros para cada equipo. Después del ajuste de datos y la previsión, los resultados indican que el modelo SARIMA se adapta mejor a las características estacionales, y la previsión ofrece información valiosa para ayudar en la toma de decisiones para evitar el tiempo de inactividad de los equipos, a pesar de tener el mayor error. Los resultados fueron menos favorables cuando se manejaron conjuntos de datos con componentes aleatorios, lo que requirió la recalibración del modelo para realizar pronósticos a corto plazo.

DESCRIPTORES: Mantenimiento predictivo, SAP PM, Suavizado Holt-Winters, ARIMA, SARIMA, Monitoreo de condición.

UNIVERSIDAD TECNOLÓGICA INDOÁMERICA

POSGRADOS

Master´s Degree in Industrial and Process Design

AUTHOR: Ing. Bucay Valdiviezo Juan Carlos

TUTOR: Ing. Escudero Villa Pedro Fernando, PhD

ABSTRACT

LEVERAGING CLASSICAL STATISTICAL METHODS FOR SUSTAINABLE MAINTENANCE IN AUTOMOTIVE ASSEMBLY EQUIPMENT.

Predictive maintenance management plays a crucial role in ensuring the reliable operation of equipment in the industry. While continuous monitoring technology is currently available, sensorless equipment limits the continuous recording of equipment condition data. Predictive maintenance has been effectively performed using artificial intelligence algorithms for data sets with sufficient data. However, replicating these results with limited data is challenging. This paper proposes the use of time series models to implement predictive maintenance on the equipment of an automotive assembly company with few available records. For this purpose, three models are explored: Holt-Winters exponential smoothing (HWES), autoregressive integrated moving average (ARIMA), and Holt-Winters exponential smoothing (HWES). and seasonal autoregressive integrated moving average (SARIMA), to determine the most accurate forecast of future equipment downtime and recommend the use of SAP PM for effective management of the maintenance process. Data was obtained from five equipment families from January 2020 to December 2022, representing 36 records for each piece of equipment. After data adjustment and forecasting, the results indicate that the SARIMA model is better suited to seasonal characteristics, and the forecast provides valuable information to aid in decision-making to avoid equipment downtime, despite having the largest error. Results were less favorable when handling data sets with random components, which required recalibration of the model for short-term forecasting.

KEYWORDS: Predictive maintenance, SAP PM, Holt-Winters, ARIMA, SARIMA, Condition monitorin sustainability

MDPI

Article

Leveraging Classical Statistical Methods for a Sustainable Maintenance in Automotive Assembly Equipment

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Abstract: Predictive maintenance management plays a pivotal role in ensuring the reliability and efficient operation of automotive assembly equipment. Traditionally, managerial tools and sensing technology have been employed in the industry to enhance the maintenance process. However, despite improvements in equipment availability, the unpredictable downtime remains a significant challenge for maintenance managers. In this study, we propose an alternative approach to address this challenge and improve equipment availability in automotive assembly plants. We propose the utilization of classical statistical models to forecast future equipment downtime and advocate the use of SAP PM for effective maintenance process management. To achieve our objective, this research underscores the importance of collecting reliable maintenance historical data for each piece of equipment. We explore three time series models, Holt-Winters Exponential Smoothing (HWES), Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving Average (SARIMA), to identify the most accurate forecasting approach. The study yields alternative options for selecting the optimal time series model based on the specific behavior of the data. The SARIMA model best fits the data due to its stationary behavior, and this model shows effective results for time series with limited data, allowing us to anticipate random downtime in equipment.

Keywords: Predictive maintenance; SAP PM; Holt Winters smoothing; ARIMA; SARIMA; Condition monitoring.

Juan Bucay-Valdiviezo [1], Pedro Escudero-Villa [2], Jenny Paredes-Fierro [2,3], and Ignacio Ayala-Chauvin [1,*]**Citation:** To be added by editorial staff during production.

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1. Introduction

In recent years, predictive maintenance has emerged as a groundbreaking approach that has revolutionized how industries manage their assets and equipment. Traditional maintenance strategies, often characterized by fixed schedules or reactive responses, have proven to be costly, inefficient, and sometimes even detrimental to operations. The concept of predictive maintenance, on the other hand, harnesses the power of advanced technologies, data-driven insights, condition monitoring, and real-time monitoring to usher in a new era of efficiency, reliability, and sustainability [1–5]. Predictive maintenance leverages cutting-edge techniques, such as machine learning, data analytics, statistical models, and sensor technologies, to forecast when equipment failure or degradation is likely to occur [2,6,7]. By analyzing historical data, identifying patterns, and detecting anomalies, the tools can proactively address issues before they escalate into costly downtime, unexpected breakdowns, or safety hazards. This proactive approach not only extends the lifespan of equipment but also optimizes operational continuity and enhances overall productivity [8]. The significance of predictive maintenance extends across a multitude of sectors, ranging from manufacturing and energy production to transportation and healthcare [9–11]. As organizations seek ways to minimize operational disruptions, reduce maintenance costs, and maximize the value of their assets, the adoption of predictive maintenance strategies has become a pivotal step towards achieving these goals [12].

Common statistical methods used in predictive maintenance encompass a range of techniques designed to analyze historical data for detecting anomalies and forecast equipment failures. The methods include the time series analysis, regression analysis, survival analysis, Bayesian methods, among others [13,14]. The time series analysis forms a fundamental aspect of predictive maintenance using classical statistical methods. In this context, many works have been explored various time series models, including autoregressive integrated moving average (ARIMA) [15–17], exponential smoothing (ES) [18,19], and stationary autoregressive integrated moving average (SARIMA) [20,21]. These models capture patterns and trends within historical data, enabling accurate forecasting of future equipment failures, and have been applied in different industry environments. Statistical process control (SPC) techniques have been employed to monitor equipment performance and identify anomalies that could lead to potential failures using physical or software aided charts and statistical control methods to detect deviations from normal operation, facilitating timely maintenance interventions [22,23]. Weibull analysis, survival analysis, and other reliability models have been used to assess equipment degradation over time and forecast impending failures [24–27]. Studies have investigated the modeling of failure data to uncover underlying failure mechanisms and patterns [28]. Parametric and non-parametric methods have been applied to analyze failure data distributions and identify factors influencing failure rates. Predictive maintenance involving classical statistical methods often addresses uncertainties associated with forecasting.

Therefore, many works explored techniques for quantifying uncertainty intervals, providing a range of possible outcomes, and aiding decision-making [29–31]. Most works present case studies and applications demonstrating the efficacy of predictive maintenance using classical statistical methods across industries such as manufacturing, energy, and transportation [32,33]. These studies offer insights into successful implementations and real-world outcomes. The effectiveness of statistical methods was evaluated comparing with modern data-driven techniques [2,17,34], assessing the performance, advantages, and limitations of each approach in predictive maintenance contexts. The drawback for the effective use of modern techniques is the absence of a sufficient quantity of data, as it is necessary to have enough records to enable learning in an intelligent system. I addition to this, the maintenance management plays a critical role in ensuring operational efficiency, minimizing downtime, and optimizing asset performance. To meet these challenges, organizations are increasingly turning to advanced solutions that integrate technology and management processes. Among these solutions, SAP Plant Maintenance (SAP PM), an integral part of the comprehensive SAP Enterprise Resource Planning (ERP) suite, stands out as a tool that streamlines and enhances maintenance activities across various industries, with good results reported [35,36].

Despite the development of new tools that help optimize maintenance management processes and the use of established and robust techniques, such as machine learning for predictive maintenance, there is a significant challenge in effectively executing these tools when there is limited data available. This is particularly the case when applying these methods to new equipment, where historical data is not accessible even when is implemented a real time monitoring system. With the aim of providing an alternative solution for such scenarios, this study proposes the utilization of classical statistical time series methods to forecast downtime in automotive assembly equipment. The forecasted data is intended to serve as crucial information for maintenance management through the utilization of the SAP PM tool and its capabilities for continuously database feeding. To achieve this objective, three time series models are evaluated across five different equipment families within the plant. Forecasts are made, and their effectiveness is validated through error calculations. Furthermore, the efficacy of utilizing the forecasted data for decision-making via the maintenance manager is analyzed.

2. Materials and Methods

To implement predictive maintenance in a system man-aged by SAP PM, we followed a clearly defined workflow, as illustrated in Figure 1. The data from scheduled maintenance was regularly registered and managed in a database. This information was collected and curated to form a time series, which was then utilized for analysis and the application of statistical models. Three distinct time series models were employed to determine the most accurate forecasts. These forecast-ed outcomes are vital for decision-making and are recorded in the management tool based on the forecasts. This information was then used to facilitate equipment maintenance procedures.

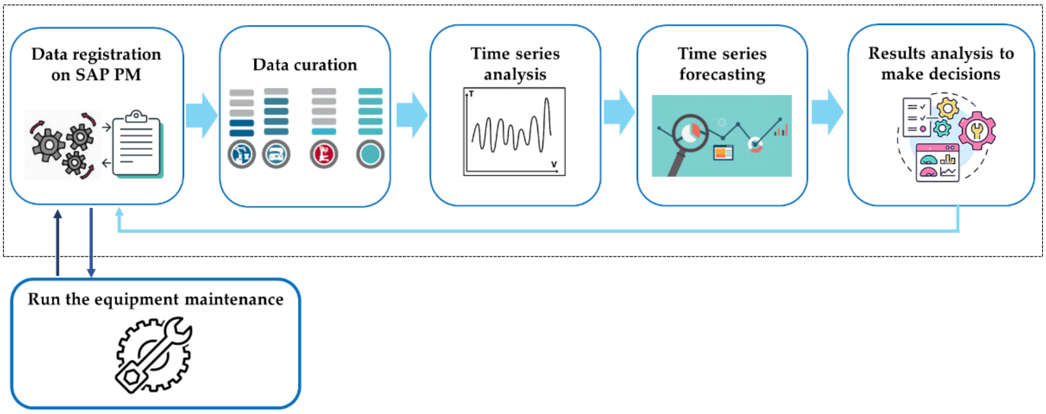

Figure 1. Flow chart for the implementation of predictive maintenance in a system managed by SAP PM.

2.1. *Maintenance data registration*

The data was registered using the SAP PM 7.0 tool, As shown in Table 1, the information includes the register of each equipment in an automotive production plant corresponding to the variables: operational time requirements, productive days, recorded failures by month, and the causes of those failures, which provide insights into machinery availability. The documented history of failures was defined by the production department.

Table 1. Equipment downtime log for the specific area in the plant (painting area).

Demag input keystroke 1000 kg						
Area	**Equipment**	**Specialty**	**Date**	**Time (min)**	**Shift**	**Failure**
Elpo	keystroke	Electromechanical transportation	19/1/2023	**65.00**	**First**	Down relay damage
Elpo	keystroke	Electromechanical transportation	25/2/2023	**36.00**	**First**	Damaged chain, broken link

The manager tool allows to plan, execute, and control maintenance tasks and logistics performed in the production plant. It involved gathering information ranging from macro-level technical locations to micro-level frequencies and maintenance tasks. The maintenance transactions are executed using codes that are directed to different management areas, according to the database, registers of equipment characteristics, catalogs, workstations, technical locations, equipment, material lists, routing sheets, and maintenance plans.

For our case study, we followed a sequential flowchart with steps to reach maintenance plans based on the previously obtained forecasting times. Each step involved gathering preliminary information and ensuring its constant updating. The equipment list was coded using transaction IR01 to obtain the data. For this point, we referred to the inventories obtained from the company, which provided technical specifications such as serial numbers, power ratings, amperages, manufacturing years, weight, among others. The maintenance routing sheets provide detailed maintenance tasks that need to be performed at regular intervals. We use three types of maintenance routing sheets: equipment routing sheet (IA01/IA02/IA03), technical location routing sheet (IA11/IA12/IA13) known as "T" type, and maintenance instruction (IA05/IA06/IA07) known as "A" type.

2.2. Data curation and times series

Based on the task designations created in the routing sheets, the execution frequencies were updated. In this case, a weekly maintenance schedule was used as the baseline, and the frequencies were followed over time. For our study, we filtered the machinery data from the last three years of operations, considering only the working days, which averaged 22 days per month. The required time was calculated by multiplying the number of working days by 60 to convert them to minutes and then by 8, representing the working hours, defining the time series. However, there was an exception for machines that operated in groups. Some machines ran 24 hours a day throughout the year (Phosphate passivation equipment and ECOAT), while others only worked for an 8-hour shift, which was an important factor in determining the required time. The plant equipment was classified by type, obtaining 5 groups or families to facilitate the analysis (Centrifugal pumps, Hoists, Fans, Ecoat, and Phosphate passivation equipment), as shown in Figure 2. Each group shared similar characteristics and maintenance plans. To obtain the failure data, we calculated the available times, mean time between failures, mean repair times, and the operational availability indicator.

For the available time was used the relation between the required time and failure time,

$$\mathrm{AT} = \frac{\text{Required time}}{\text{Failure time}} \tag{1}$$

The mean time between failures (MTF) given by,

$$\mathrm{MTF} = \frac{\text{Total time avaiable} - \text{Inactive time}}{\text{Number of breakdowns}} \tag{2}$$

The average repair time relates the total maintenance time and the number of breakdowns,

$$\mathrm{TMPR} = \frac{\text{Total maintenace time}}{\text{Number of breakdowns}} \tag{3}$$

and the operational availability time given by,

$$D = \frac{\text{Availiability time}}{\text{Required time}} \quad (4)$$

In this case, the most relevant data was the average operational availability time. This allowed us to create graphs that indicated the behavior of the machinery over time and to conduct a statistical analysis of trend lines.

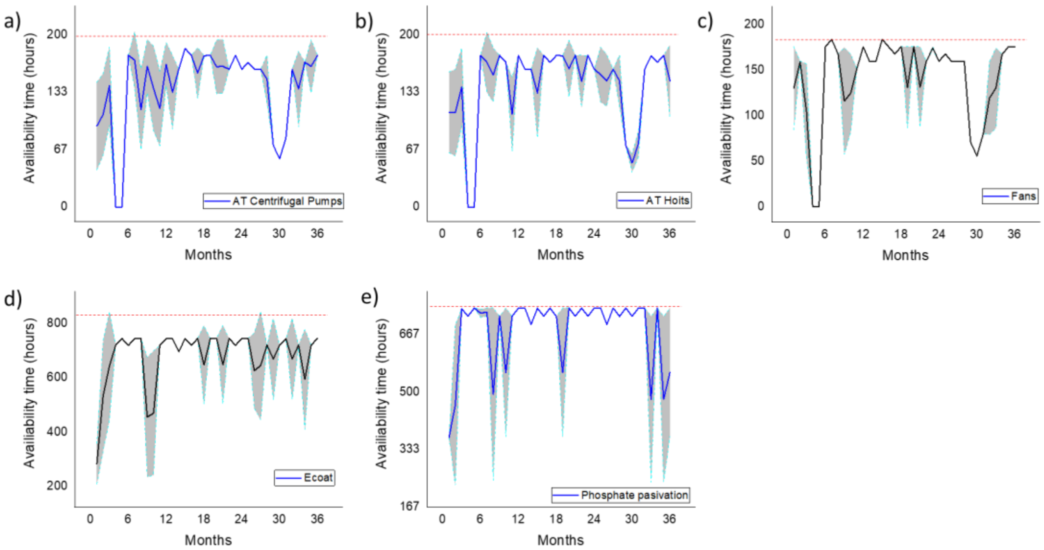

Figure 2. Maintenance historical time series obtained by SAP PM register for each equipment family, the red line corresponds to the maximum operational availability time for, a) Centrifugal pumps, b) Electromechanical hoits, c) Fans, d) Ecoat, e) Phosphate passivation equipment.

2.3. Time series models

Three time series models were used to forecast equipment downtime, namely Holt-Winters Exponential Smoothing (HWES) [18,37], Autoregressive Integrated Moving Average (ARIMA) [15,38,39], and Seasonal Autoregressive Integrated Moving Average (SARIMA) [40,41]. The results were compared to evaluate the forecasting accuracy of each method through error calculations.

HWES allows forecasting based on past observations, considering three components of time series, level, trend, and seasonality.

$$F_{(i+k)} = (L_i + k * B_i)(S_{(i+k-m)}) \quad (5)$$

Where, $F_{(i+k)}$ is the forecast at step $i+k$, $(L_i + k * B_i)$, correspond to estimated level at step $i+k$, and $S_{(i+k-m)}$ is the estimated seasonal variation of period length m, at the same step $i+k$.

The classical statistical method ARIMA allows to forecast time series by the use of basic statistics to identify patterns and model components, providing estimations through least squares and maximum likelihood methods. It uses graphs of Autocorrelation Function (ACF), and Partial Autocorrelation Function (PACF) of residuals to verify the validity of the model. The general equation of ARIMA is given by,

$$Y_t = f(Y_t - k,\, e_t - k) + e_t \; and \; k > 0. \quad (6)$$

Where $Y_t - k$ is the accurate forecasting, and $e_t - k$ the residual errors.

And SARIMA is similar to ARIMA, the main difference lies in including of additional set of autoregressive and moving average components, incorporating seasonality to non-seasonal components; the two last terms in the follow equation,

$$Y_t = c + \sum_{n=1}^{p} \alpha_n y_{t-n} + \sum_{n=1}^{q} \theta_n \epsilon_{t-n} + \sum_{n=1}^{P} \emptyset_n y_{t-sn} + \sum_{n=1}^{Q} \eta_n \epsilon_{t-sn} + \epsilon_t. \quad (7)$$

The application of these models was calculated using RStudio Version 2023.06.1+524.

3. Results

We evaluated the operational availability time for the equipment families in the plant in three phases. First, we assessed it with a periodic maintenance mechanism. Then, we evaluated it using the SAP PM tool. Finally, we used the forecasting data to assess the feasibility of managing predictive maintenance for the equipment families in the plant.

3.1. Maintenance with SAP

Before implementing SAP PM in the plant, we conducted an evaluation of equipment availability over the last twelve months. We found that with traditional pro-grammed maintenance, the lowest operational availability time was 78.84%, and the average was 94.47%. When using the management tool, the lowest value was 91.76%, and the average was 97.03%. This implies that by using the tool, equipment operational availability improved by 12.92% for the lowest register and 5.27% on average. The costs for corrective maintenance were similar for both methods, but the costs associated with the overall maintenance process (including preventive and corrective maintenance) reduced proportionally with increased availability time.

3.2. Forecasting of failures

With the aim of enhancing equipment availability through the implementation of the maintenance management tool, three time series models were applied to the data recorded over 36 months. We conducted the fitting for 24 observations and forecasted the next 12 values. To assess the performance of each model, we compared the forecasting errors for each equipment family, as illustrated in Figure 2.

For centrifugal pumps, we employed HWES, which exhibited a fitting pattern following the exponential trend of observations. ARIMA (0,0,1) was utilized, and its fitting was based on the average of the time series, with a one-observation displacement into the future until the 24th observation. In contrast, SARIMA (0,0,1) fit the observations completely until the 12th observation when the time series' seasonality changed. The time series exhibited a change at the 27th observation, and the forecasting of HWES and ARIMA could not react to this change due to being out of seasonality. SARIMA, on the other hand, showed a slight change starting at the 24th observation, following the seasonality of the last 6 observations. None of the three models provided valid forecasting from a statistical standpoint.

Regarding equipment availability, they broke the seasonality for unplanned corrective maintenance. For periodic maintenance, the ARIMA and SARIMA models significantly improved forecasting, but they did not react to random changes with the (0,0,1) model in both cases. The forecasted values with ARIMA and HWES allowed us to plan for maintenance within a three-month window in the future. Recalculating after monthly maintenance would provide useful information for planning the next three months of maintenance.

In the case of electromechanical hoists, where the first three-month window exhibits a change in seasonality, HWES and ARIMA (0,1,0) maintain a linear trend, while SARIMA (2,1,0) reacts to these changes by following the seasonality of the last 6 results. For this equipment family, the forecasts would be most beneficial for taking actions within the next three values, especially considering that SARIMA replicated the observations with a one-observation delay. These results would provide the opportunity to schedule maintenance a month later.

For the fan's family, HWES and ARIMA (0,0,1) forecast the trend of the next four observations, whereas SARIMA (0,0,1) forecasts only one observation before changing the trend. The forecasted changes at observations 28 and 31 would allow for taking action before a decrease in availability time. However, it would be necessary to recalculate the forecasts for a three-month window after each maintenance.

We observed a similar behavior in the case of the Ecoat family, where SARIMA (0,1,1) provided the best fit for the 24 observations and forecasted inversely within the initial three-month window. HWES and ARIMA (0,1,0) presented a linear trend for the next twelve months, and these results would be useful for planning actions one month in advance. In the case of SARIMA, the inverse of the first three forecasted values would be considered to act proactively before a decrease in equipment availability occurs in the 24th month.

For the phosphate passivation equipment family, HWES and ARIMA (0,0,1) fit the trend of observations with a one-month delay. ARIMA forecasts the first month in line with the observations and then maintains a linear trend, approximating the values for odd months. HWES, on the other hand, provides forecasted values that closely match the observations for odd months. In both cases, the forecasted values would be useful for taking actions as long as the observations maintain a seasonal behavior because these models do not forecast the trend change observed at the 31st observation. SARIMA (0,0,1), in this scenario, forecasts inversely for the first four observations and anticipates the change in seasonality three months in advance. In this case, SARIMA offers valuable information for taking proactive measures, making it possible to anticipate the change and minimize the impact on operational availability time.

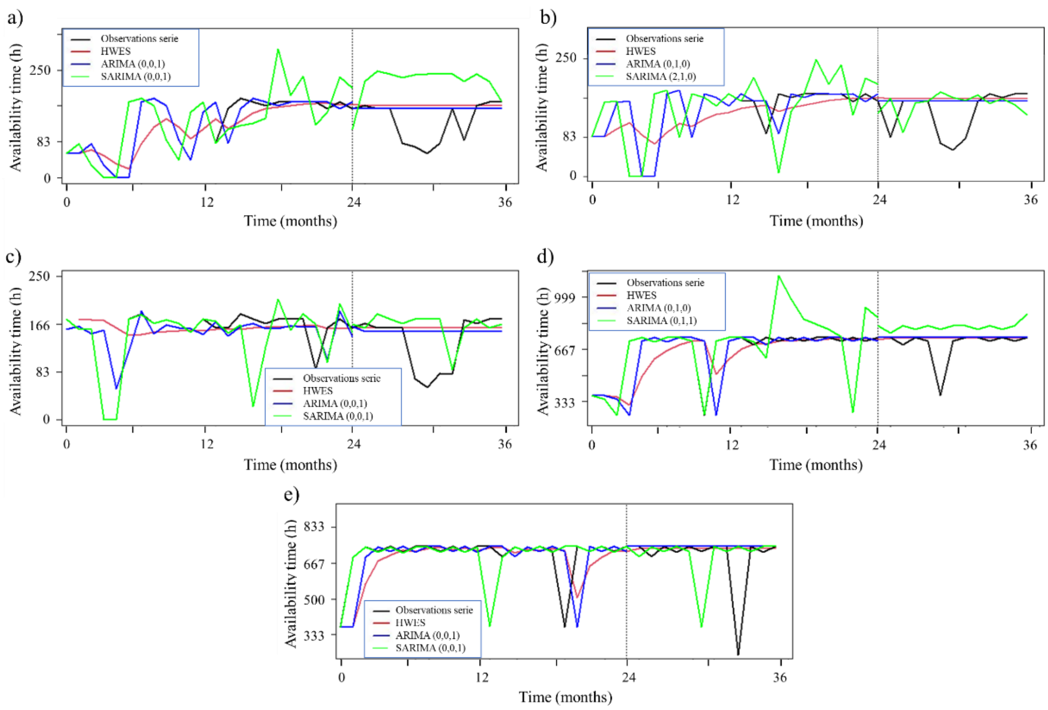

Figure 3. Forecasting for available time of an individual element of equipment family a) Centrifugal pump, b) Hoits, c) Fans, d) Ecoat, e) Phosphate passivation equipment.

3.3. Predictive maintenance with SAP PM

Following the results illustrated in Figure 3, the forecasted values were recorded in the management tool, and the first four test maintenance cycles were executed for each equipment family. Prior to the execution of predictive maintenance, it was necessary to evaluate the equipment's condition and act for the next intervention, whether it be preventive or corrective maintenance.

For the electromechanical hoists, fans, and phosphate passivation equipment, the forecasted values proved beneficial in preventing failures, thus improving operational availability time. However, this also increased the time allocated for analysis performed by the maintenance chief. The time dedicated to analysis and decision-making represented an additional 5% in maintenance costs, but the gained availability time through predictive maintenance exceeded 20%. These results resulted in a 15% cost savings for the first four maintenance cycles.

For the centrifugal pumps and the Ecoat family, there was only a slight improvement in uptime after the first maintenance, and it was necessary to evaluate the equipment to prevent future downtime. During these four months of testing, the models provided a good fit for seasonal preventive maintenance, but obtaining better forecasting would require more observations.

4. Discussion

4.1. Data colection

Most of the data was collected by measures in-situ following a planned maintenance, feeding the database of the management tool. The collection of data from maintenance workers represents a significant challenge due to the absence of crucial maintenance information details. Requesting feedback from workers typically involves additional time and increases the cost of maintenance. These situations have contributed to having incomplete records or records lacking essential details, which, in turn, increases the risk of equipment failures. The historical data depicted in **Figure 2**, corresponds to validated data, incorporating 20% of feedback provided to enhance the accuracy of the records.

The absence of sensors embedded in equipment significantly increases the uncertainty of the records, relying solely on feedback from workers. This, in turn, diminishes the effectiveness of forecasting accuracy, making it difficult to make informed decisions aimed at preventing equipment failures.

4.2. Forecasting and decsition taking

One critical aspect when utilizing statistical models to forecast downtimes in equipment pertains to the equipment's lifespan, which becomes increasingly crucial as equipment approaches the end of its operational life. In the specific context of the equipment available within the area of study, a majority of it falls within the mid-point of its operational lifespan. Furthermore, routine maintenance activities result in stationary time series data in most cases. However, the initial twelve months of recorded data correspond to a period characterized by sporadic monitoring and maintenance due to the disruptions caused by the ongoing pandemic. Additionally, equipment availability experiences intermittent halts, including extended pauses for equipment preparation and unplanned stoppages due to equipment failures, as visually represented in **Figure 2**. The inclusion of random information in the recorded data has the effect of diminishing the effectiveness of forecasting accuracy when employing stationary-based models.

Nevertheless, this random data contributes valuable insights to the database, as it mirrors real-life situations and accounts for unforeseeable events during regular equipment operation. To address this complexity, the analysis of time series data was conducted over a 24-month period characterized by higher variability. Additionally, a second cluster was created for the last 12 months, characterized by stationary behavior, where the statistical models exhibited their best fit to the data. Consequently, forecasting within this stationary cluster yielded minimal error rates. This approach allowed for a more comprehensive understanding of equipment downtime forecasting, considering both variable and stable periods within the dataset.

The time series models employed for forecasting in this study were carefully chosen based on the observed data patterns, primarily because of the limited number of records available. In situations where datasets consist of a substantial number of observations, machine learning methods frequently emerge as the optimal choice for time series forecasting. These methods prove highly effective when working with datasets that encompass hundreds of records and often yield even better results when dealing with datasets containing thousands of records [7,42,43]. The advantage of employing machine learning techniques in such scenarios lies in their ability to capture complex patterns and relationships within the data. With a larger volume of records, these methods can learn more intricate and nuanced patterns, resulting in more accurate and reliable time series forecasts. However, in our specific case, the maintenance data were collected through periodic records, and the dataset consisted of fewer than 40 instances or incidents.

In industries where not all equipment benefits from continuous monitoring via sensors, yet the equipment remains within its operational lifespan, the implementation of time series models presents a valuable strategy for improving equipment uptime without the need to overhaul entire equipment fleets. This approach is not only effective but also economical, particularly when compared to the alternative of updating equipment families. By leveraging time series models, industries can accurately predict downtimes, optimizing equipment availability without incurring the significant costs associated with upgrading entire equipment inventories. This approach proves especially advantageous when dealing with datasets characterized by periodic records, as it allows for precise forecasting even in scenarios where registers are limited. Consequently, it stands as a practical and cost-effective solution for enhancing operational efficiency, especially when continuous sensor-based monitoring is not feasible.

5. Conclusions

In this work, we present an alternative approach to address the challenge of improving equipment availability in an automotive assembly plant. We used three time series models to forecast future equipment downtime, advocating the use of SAP PM for effective maintenance process management. For this proposal, the historical data was collected through direct measurements from equipment following scheduled maintenance in five equipment families. Subsequently, we analyzed the data to apply the time series models and identify which model best approximated the observations and offered better forecasting. The results of the forecasts were tested by assessing the feasibility of making maintenance decisions based on the equipment type.

The results showed that for three of the families (electromechanical hoist, fans, and phosphate passivation equipment), the models contributed to saving 15% of operational availability time. However, for the family of centrifugal pumps and Ecoat, the time saved was minimal because the forecasting values did not extend beyond a single event in the future, being restricted to the seasonal behavior of past events. When comparing these results with the times recorded using predictive maintenance planning, we observed a significant improvement in the management process and the application of the three models in this case study. The use of three models for each equipment dataset would be optimal, but it would necessitate an additional system to make decisions through continuous calculations and generate new forecasting results. The complexity increases when the implementation of forecasting models scales with the number of machines to be monitored.

The classification into equipment families and the use of time series model to forecast equipment downtimes is presented as an alternative option to control maintenance costs and improve equipment availability time, without the need to update with sensor monitoring systems or change to new sensor-embedded equipment. This option also provides the opportunity to maximize the lifespan of equipment with optimal performance.

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