sustainability

Article

Leveraging Classical Statistical Methods for Sustainable Maintenance in Automotive Assembly Equipment

Juan Bucay-Valdiviezo [1], Pedro Escudero-Villa [2], Jenny Paredes-Fierro [2] and Manuel Ayala-Chauvin [1,*]

1 Centro de Investigaciones de Ciencias Humanas y de la Educación (CICHE), Universidad Tecnológica Indoamérica, Ambato 180103, Ecuador; jbucay@indoamerica.edu.ec
2 Facultad de Ingeniería, Universidad Nacional de Chimborazo, Riobamba 060108, Ecuador; pedro.escudero@unach.edu.ec (P.E.-V.); patricia.paredes@unach.edu.ec (J.P.-F.)
* Correspondence: mayala5@indoamerica.edu.ec

Abstract: Predictive maintenance management plays a crucial role in ensuring the reliable operation of equipment in industry. While continuous monitoring technology is available today, equipment without sensors limits continuous equipment state data recording. Predictive maintenance has been effectively carried out using artificial intelligence algorithms for datasets with sufficient data. However, replicating these results with limited data is challenging. This work proposes the use of time series models to implement predictive maintenance in the equipment of an automotive assembly company with few records available. For this purpose, three models are explored—Holt–Winters Exponential Smoothing (HWES), Autoregressive Integrated Moving Average (ARIMA), and Seasonal Autoregressive Integrated Moving Average (SARIMA)—to determine the most accurate forecasting of future equipment downtime and advocate the use of SAP PM for effective maintenance process management. The data were obtained from five equipment families from January 2020 to December 2022, representing 36 registers for each piece of equipment. After data fitting and forecasting, the results indicate that the SARIMA model best fits seasonal characteristics, and the forecasting offers valuable information to help in decision-making to avoid equipment downtime, despite having the highest error. The results were less favorable when handling datasets with random components, requiring model recalibration for short-term forecasting.

Keywords: predictive maintenance; SAP PM; Holt–Winters smoothing; ARIMA; SARIMA; condition monitoring

Citation: Bucay-Valdiviezo, J.; Escudero-Villa, P.; Paredes-Fierro, J.; Ayala-Chauvin, M. Leveraging Classical Statistical Methods for Sustainable Maintenance in Automotive Assembly Equipment. *Sustainability* **2023**, *15*, 15604. https://doi.org/10.3390/su152115604

Academic Editor: Guido Perboli

Received: 28 September 2023
Revised: 30 October 2023
Accepted: 31 October 2023
Published: 3 November 2023

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 toward 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 forecasting equipment failures. The methods include time series analysis, regression analysis, survival analysis, and 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 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 have 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 has been evaluated by comparing them with modern data-driven techniques [2,17,34], assessing the performance, advantages, and limitations of each approach in predictive maintenance contexts. The drawback to the effective use of modern techniques lies in the insufficiency of data, as a sufficient quantity of records is necessary for enabling learning in an intelligent system. Additionally, maintenance management plays a critical role in ensuring operational efficiency, minimizing downtime, and optimizing asset performance. To address 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, emerges as a tool that streamlines and enhances maintenance activities across various industries, with reported positive results [35,36].

Despite the development of new tools that help optimize maintenance management processes, as well as 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 are limited data available. This is particularly the case when applying these methods to new equipment, where historical data are not accessible even when a real-time monitoring system is implemented. To provide an alternative solution for such scenarios, this study proposes the utilization of classical statistical time series methods to forecast downtime in automotive assembly equipment. 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. The forecasted data serve as essential information for maintenance management using the SAP PM tool and its continuous database feeding capabilities. Additionally, we analyze the effectiveness of using the forecasted data to facilitate decision-making and prevent equipment downtime.

2. Materials and Methods

To implement predictive maintenance in a system managed by SAP PM, we followed a clearly defined workflow, as illustrated in Figure 1. The data from scheduled maintenance were 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 forecasted 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.

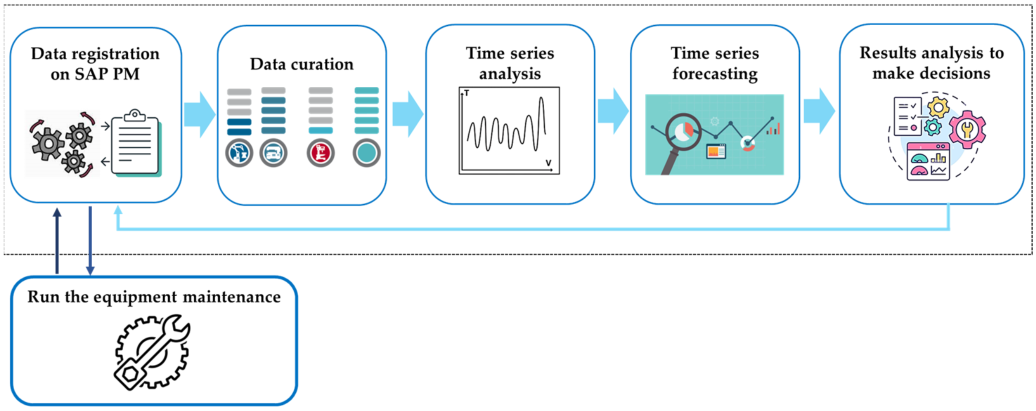

Figure 1. Flow chart for the implementation of predictive maintenance in a system managed by SAP PM, where the maintenance data are registered in the SAP environment as an initial dataset, then the data are grouped into five families, to analyze the time series. The series is forecasted, and the results are evaluated to make decisions, update the new data in SAP, and run the equipment maintenance.

2.1. Maintenance Data Registration

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

Table 1. Equipment downtime log for a 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 management tool allows for planning, executing, and controlling maintenance tasks and logistics performed in the production plant. It involves 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, and weight, among others. The maintenance routing sheets provide detailed maintenance tasks that need to be performed at regular intervals. We used three types of maintenance routing sheets: equipment routing sheets (IA01/IA02/IA03); technical location routing sheets (IA11/IA12/IA13), known as the "T" type; and maintenance instructions (IA05/IA06/IA07), known as the "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 8, representing the working hours, and then by 60 to convert them to minutes, defining the time series. However, there was an exception for machines that operated in groups. Some machines ran 24 h a day throughout the year (phosphate passivation equipment and e-coat), while others only worked for 8 h shifts, 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, e-coat, 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 operational availability indicator.

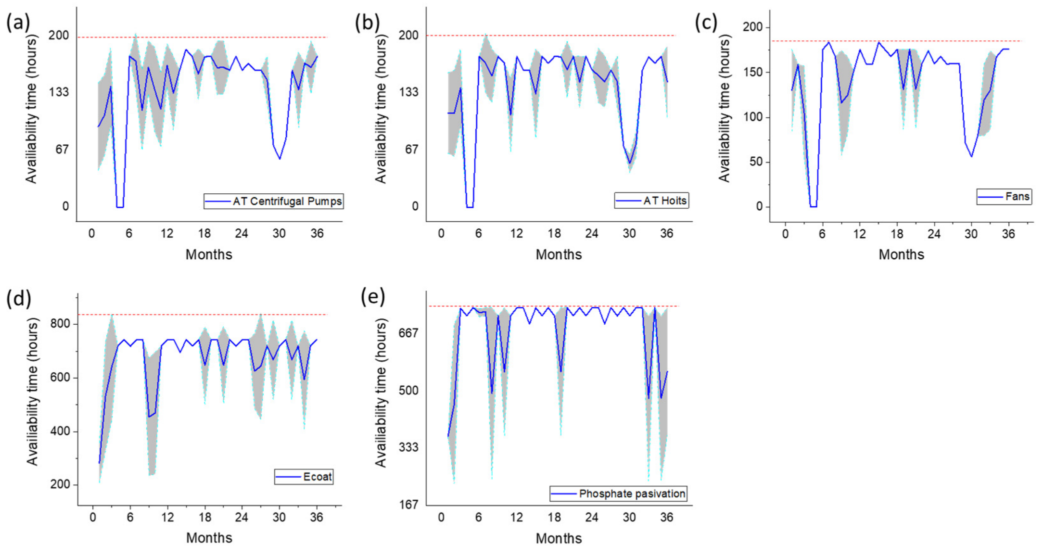

Figure 2. Maintenance historical time series obtained by the SAP PM register for each equipment family; the red line corresponds to the maximum operational availability time for (**a**) centrifugal pumps, (**b**) electromechanical hoists, (**c**) fans, (**d**) e-coat, and (**e**) phosphate passivation equipment.

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

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

The mean time between failures (MTF) was given by

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

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

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

and the operational availability time is given by

$$\text{D} = \frac{\text{Availiability time}}{\text{Required time}} \tag{4}$$

In this case, the most relevant data were for 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.

2.3. Time Series Models

Three time series models were used to forecast equipment downtime. Holt–Winters Exponential Smoothing (HWES) has been used for short-term forecasting time series in economics and practical applications [18,37]; Autoregressive Integrated Moving Average (ARIMA) is traditionally used to forecast time series with stationary behavior in different applications from supply chains, economics, and basic sciences [15,38,39]; and Seasonal Autoregressive Integrated Moving Average (SARIMA) has shown effective results when working with time series exhibiting seasonal behavior [40,41]. The three models were applied to the five equipment families shown in Figure 2.

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

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

Here, $F_{(i+k)}$ is the forecast at step $i + k$, $(L_i + k * B_i)$ corresponds to the 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 sequence of calculation is shown in Figure 3a.

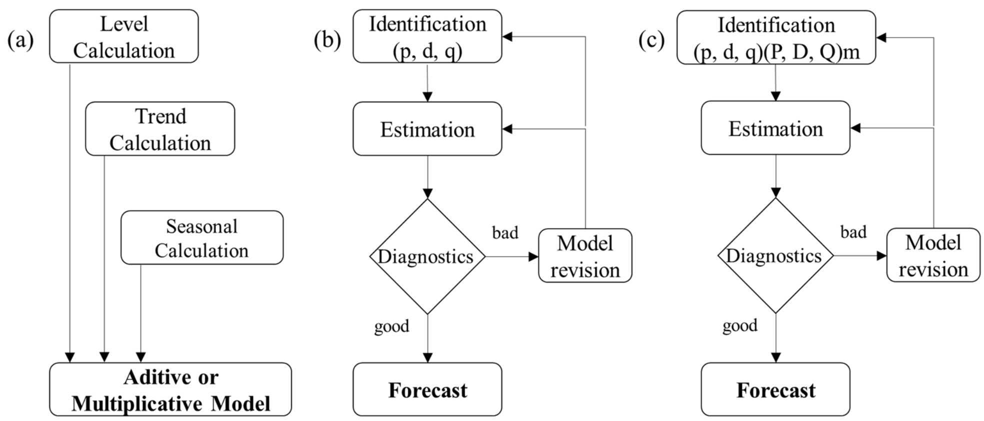

Figure 3. Algorithm schematic for (**a**) HWES, where the calculation result allows us to identify whether the model is additive or multiplicative; (**b**) ARIMA, which fits the model through parameters (p, d, q); and (**c**) SARIMA, which adds the seasonal component (P, D, Q)m to ARIMA parameters (p, d, q).

The classical statistical method ARIMA allows us to forecast time series via the use of basic statistics to identify patterns and model components, providing estimations through least squares and maximum likelihood methods. It uses graphs of the 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

$$Y_t = f(Y_t - k,\ e_t - k) + e_t \text{ and } k > 0. \tag{6}$$

where $Y_t - k$ is the accurate forecasting, and $e_t - k$ is the residual errors. A diagnostic validation allows us to decide whether to revise the model or proceed to forecasting, as shown in Figure 3b.

The SARIMA model is similar to ARIMA; the main difference lies in including an additional set of autoregressive and moving average components, incorporating seasonality to non-seasonal components, represented by the last two terms in the following equation:

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

These last two terms correspond to the parameter (P, D, Q)m added in the identification process in Figure 3c. The three models were constructed using RStudio Version 2023.06.1+524.

For the selection of ARIMA and SARIMA models, the Akaike information criterion (AIC) was used to evaluate how well the models fit the data. The AIC values allowed for the selection of (p, d, q) parameters for each equipment family, and the selected models were used to fit and forecast.

3. Results

We evaluated the operational availability time for the equipment families in the plant in three phases. First, we assessed it via 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 programmed 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 by 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

To enhance 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.

The AIC parameters obtained before the selection of models are shown in Table 2. The parameters (p, d, q) are shown in Figure 4 for ARIMA and SARIMA. For SARIMA, the seasonal parameter (P, D, Q)m was added, which was the same for the five equipment families.

Table 2. AIC values for the selection of ARIMA and SARIMA models.

Model	Centrifugal Pumps	Electromechanical Hoists	Fans	E-Coat	Phosphate Passivation Equipment
ARIMA	504.39	456.31	450.95	492.93	457.15
SARIMA	261.42	241.57	234.33	245.19	222.28

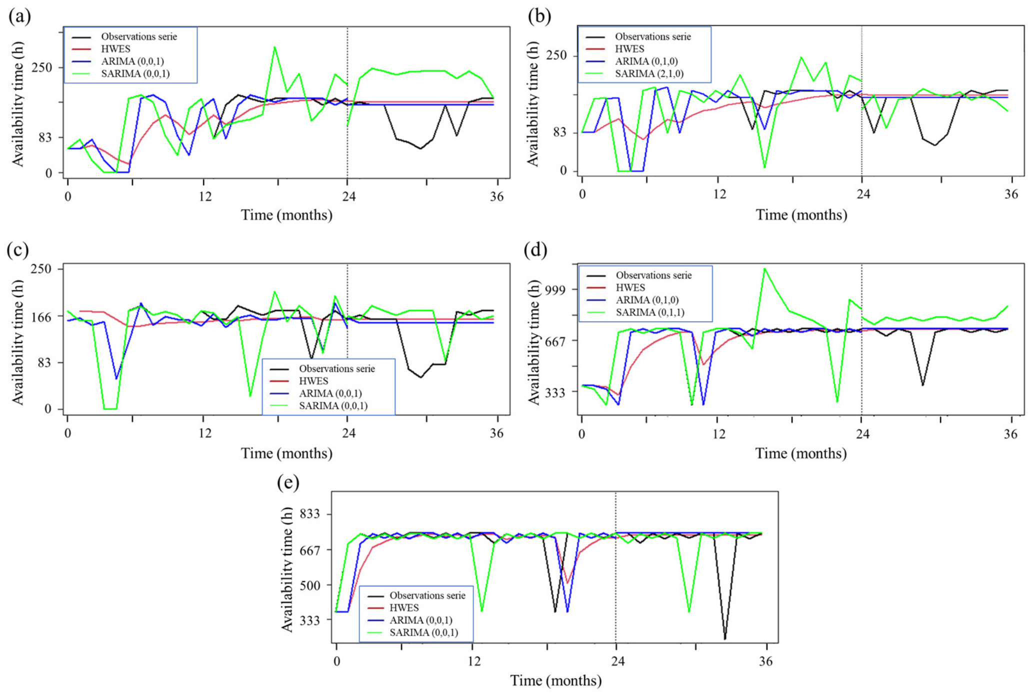

Figure 4. Forecasting for the available time of an individual element of the equipment families (**a**) centrifugal pump, (**b**) hoists, (**c**) fans, (**d**) e-coat, and (**e**) phosphate passivation equipment. The parameters (p, d, q) were selected according to data fitting performance in ARIMA, and for SARIMA, the parameters (0, 1, 0) were added for the five families.

The forecasting results depicted in Figure 4 were evaluated as follows. 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 by 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, the seasonality was broken by 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 values forecasted by 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) maintained a linear trend, while SARIMA (2, 1, 0) reacted to these changes by following the seasonality of the last six 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 family, HWES and ARIMA (0, 0, 1) forecasted the trend of the next four observations, whereas SARIMA (0, 0, 1) forecasted 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 similar behavior in the case of the e-coat 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 forecasted the first month in line with the observations and then maintained a linear trend, approximating the values for odd months. HWES, on the other hand, provided forecasted values that closely match the observations for odd months. In both cases, the forecasted values would be useful for taking action as long as the observations maintain a seasonal behavior because these models did not forecast the trend change observed at the 31st observation. SARIMA (0, 0, 1), in this scenario, forecasted inversely for the first four observations and anticipated 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.

The Root-Mean-Square Percentage Error (RMSPE) was obtained for the three models as shown in Table 3. For centrifugal pumps, HWES yielded minimal errors due to the flatness of the forecasting data. Therefore, its deviation from the original data is minimal, but this does not imply that its forecasting is the best when compared with ARIMA and SARIMA. A similar case occurred for the e-coat family; in this case, the first four forecasted values would serve as a guide for decision-making. For electromechanical hoists, SARIMA presented a minimal error, and the forecasting data provide valuable information for the first three values, which approximate the observation trend. For fans and phosphate passivation equipment, ARIMA had lower errors. In both cases, the forecasting data also exhibited a flat response, minimizing the deviation from the original data, but the forecasting results do not offer valuable information. SARIMA, despite having the highest error in this family, still offers value by guiding decision-making to prevent downtimes.

Table 3. RMSPE values for each equipment family and the models selected for forecasting.

Model	Centrifugal Pumps	Electromechanical Hoists	Fans	E-Coat	Phosphate Passivation Equipment
HWES	0.022991	1.449357	0.764357	0.285784	0.792640
ARIMA	0.058976	1.346239	0.711666	0.292658	0.744512
SARIMA	0.037975	1.282700	0.825702	0.351869	1.257262

3.3. Predictive Maintenance with SAP PM

Following the results illustrated in Figure 4, the forecasted values were recorded in the management tool, and the first four test maintenance cycles were executed for each equipment family. Before 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 the 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%. This resulted in a 15% cost savings for the first four maintenance cycles.

For the centrifugal pumps and the e-coat 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 Collection

Most of the data were collected via measures in situ following 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 the incompleteness of records or records lacking essential details, which, in turn, increases the risk of equipment failures. The historical data depicted in Figure 2 correspond 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. Methodology and Model Selection

The three models we used allowed us to fit and forecast the dataset for the equipment availability time. The computer resources required for these calculations were minimal, and the coding represents minimal complexity. The critical factor in selecting the best model for ARIMA and SARIMA is the Akaike Information Criterion, which evaluates how well the model fits the data. These values guided the selection of (p, d, q) parameters for each equipment family.

The HWES model was chosen due to the acceptable results it showed, particularly in forecasting seasonal time series effectively. However, the accuracy decreased when the dataset exhibited random behavior within a seasonal time series. As shown in Figure 4, the equipment under normal working conditions generated seasonal time series data, but for the first 16 observations, the presence of random behavior reduced the forecasting accuracy, resulting in only planar forecasting values. To achieve the best forecasts, the recommendation would be to use it only for seasonal time series data. However, the aim of utilizing this model is to obtain valid forecasting information that includes the entire dataset, even when it involves random behavior embedded in otherwise uniform seasonal time series. Similar results were achieved with ARIMA. In this case, this model was employed to forecast random time series with a certain level of accuracy [38]. For the maintenance dataset with random records, the forecasting information displayed a planar response following the model (0, 0, 1) and even for (0, 1, 0), which best suited a random walk. SARIMA was chosen to introduce the seasonal component and enhance the ARIMA results. With both components, the forecasting using SARIMA provided information to consider in decision-making.

4.3. Forecasting and Decision-Making

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, these random data contribute valuable insights to the database, as they mirror real-life situations and account for unforeseeable events during regular equipment operation. To address this complexity, an 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 seasonal behavior, where the statistical models exhibited their best fit to the data. Consequently, forecasting within this seasonal 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 presented 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, historical data were 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 savings of 15% regarding the operational availability time. However, for the family of centrifugal pumps and e-coat, 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.

Classifying equipment into families and employing time series models to forecast equipment downtimes are proposed as alternative methods for managing maintenance costs and enhancing equipment availability, eliminating the necessity for adopting sensor monitoring systems or transitioning to sensor-embedded equipment. Integrating sensors would yield the required data for the effective implementation of neural networks or AI algorithms. Despite the relative newness of the equipment used in this study, the absence of a sensing system has driven the concept of predictive maintenance toward sustainability. This approach also offers the potential to extend the equipment's lifespan while preserving optimal performance.

Author Contributions: Conceptualization, J.B.-V. and P.E.-V.; methodology, J.B.-V., P.E.-V. and M.A.-C.; software, J.B.-V. and J.P.-F.; validation, P.E.-V., J.P.-F. and M.A.-C.; formal analysis, J.P.-F. and P.E.-V.; investigation, J.B.-V., P.E.-V. and J.P.-F.; resources, J.B.-V. and M.A.-C.; data curation, J.B.-V. and J.P.-F.; writing—original draft preparation, J.B.-V. and P.E.-V.; writing—review and editing, P.E.-V., J.P.-F. and M.A.-C.; visualization, P.E.-V. and J.P.-F.; supervision, P.E.-V. and M.A.-C.; project administration, M.A.-C.; funding acquisition, M.A.-C. All authors have read and agreed to the published version of the manuscript.

Funding: The research was supported by Universidad Tecnológica Indoamérica grant (UTI-CICHE—No. 295.244.2022), entitled "Big data análisis y su impacto en la sociedad, educación e industria".

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Moens, P.; Vanden Hautte, S.; De Paepe, D.; Steenwinckel, B.; Verstichel, S.; Vandekerckhove, S.; Ongenae, F.; Van Hoecke, S. Event-Driven Dashboarding and Feedback for Improved Event Detection in Predictive Maintenance Applications. *Appl. Sci.* **2021**, *11*, 10371. [CrossRef]
2. Achouch, M.; Dimitrova, M.; Ziane, K.; Sattarpanah Karganroudi, S.; Dhouib, R.; Ibrahim, H.; Adda, M. On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. *Appl. Sci.* **2022**, *12*, 8081. [CrossRef]
3. Pimenov, D.Y.; Bustillo, A.; Wojciechowski, S.; Sharma, V.S.; Gupta, M.K.; Kuntoğlu, M. Artificial Intelligence Systems for Tool Condition Monitoring in Machining: Analysis and Critical Review. *J. Intell. Manuf.* **2023**, *34*, 2079–2121. [CrossRef]
4. Zhao, J.; Gao, C.; Tang, T. A Review of Sustainable Maintenance Strategies for Single Component and Multicomponent Equipment. *Sustainability* **2022**, *14*, 2992. [CrossRef]
5. Jasiulewicz-Kaczmarek, M.; Legutko, S.; Kluk, P. Maintenance 4.0 Technologies—New Opportunities for Sustainability Driven Maintenance. *Manag. Prod. Eng. Rev.* **2020**, *11*, 2. [CrossRef]
6. Murugiah, P.; Muthuramalingam, A.; Anandamurugan, S. A Design of Predictive Manufacturing System in IoT-Assisted Industry 4.0 Using Heuristic-Derived Deep Learning. *Int. J. Commun. Syst.* **2023**, *36*, e5432. [CrossRef]
7. Carvalho, T.P.; Soares, F.A.A.M.N.; Vita, R.; Francisco, R.d.P.; Basto, J.P.; Alcalá, S.G.S. A Systematic Literature Review of Machine Learning Methods Applied to Predictive Maintenance. *Comput. Ind. Eng.* **2019**, *137*, 106024. [CrossRef]
8. Möhring, M.; Schmidt, R.; Keller, B.; Sandkuhl, K.; Zimmermann, A. Predictive Maintenance Information Systems: The Underlying Conditions and Technological Aspects. *Int. J. Enterp. Inf. Syst.* **2020**, *16*, 22–37. [CrossRef]
9. Çoban, S.; Gökalp, M.O.; Gökalp, E.; Eren, P.E.; Koçyiğit, A. Predictive Maintenance in Healthcare Services with Big Data Technologies. In Proceedings of the 2018 IEEE 11th Conference on Service-Oriented Computing and Applications (SOCA), Paris, France, 20–22 November 2018; pp. 93–98.

10. Ersöz, O.Ö.; İnal, A.F.; Aktepe, A.; Türker, A.K.; Ersöz, S. A Systematic Literature Review of the Predictive Maintenance from Transportation Systems Aspect. *Sustainability* **2022**, *14*, 14536. [CrossRef]
11. Cao, Q.; Samet, A.; Zanni-Merk, C.; de Bertrand de Beuvron, F.; Reich, C. Combining Chronicle Mining and Semantics for Predictive Maintenance in Manufacturing Processes. *Semant. Web* **2020**, *11*, 927–948. [CrossRef]
12. Hashe, V.T.; Mamatlepa, M.T. Application of Reliability Engineering in a Chemical Plant to Improve Productivity. In *Lecture Notes in Mechanical Engineering*; Springer: Berlin, Germany, 2020; pp. 547–557. [CrossRef]
13. Montero Jimenez, J.J.; Schwartz, S.; Vingerhoeds, R.; Grabot, B.; Salaün, M. Towards Multi-Model Approaches to Predictive Maintenance: A Systematic Literature Survey on Diagnostics and Prognostics. *J. Manuf. Syst.* **2020**, *56*, 539–557. [CrossRef]
14. Zhuang, L.; Xu, A.; Wang, X.-L. A Prognostic Driven Predictive Maintenance Framework Based on Bayesian Deep Learning. *Reliab. Eng. Syst. Saf.* **2023**, *234*, 109181. [CrossRef]
15. Fattah, J.; Ezzine, L.; Aman, Z.; El Moussami, H.; Lachhab, A. Forecasting of Demand Using ARIMA Model. *Int. J. Eng. Bus. Manag.* **2018**, *10*, 1847979018808673. [CrossRef]
16. Francis, F.; Mohan, M. ARIMA Model Based Real Time Trend Analysis for Predictive Maintenance. In Proceedings of the 2019 3rd International conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 12–14 June 2019; pp. 735–739.
17. Sobaszek, Ł.; Gola, A.; Kozłowski, E. Predictive Scheduling with Markov Chains and ARIMA Models. *Appl. Sci.* **2020**, *10*, 6121. [CrossRef]
18. Lima, S.; Gonçalves, A.M.; Costa, M. Time Series Forecasting Using Holt-Winters Exponential Smoothing: An Application to Economic Data. *AIP Conf. Proc.* **2019**, *2186*, 090003. [CrossRef]
19. Rodrigues, J.A.; Farinha, J.T.; Mendes, M.; Mateus, R.; Cardoso, A.M. Short and Long Forecast to Implement Predictive Maintenance in a Pulp Industry. *Eksploat. I Niezawodn.* **2022**, *24*, 33–41. [CrossRef]
20. Putchala, S.R.; Kotha, R.; Guda, V.; Ramadevi, Y. Transformer Data Analysis for Predictive Maintenance. In Proceedings of the Second International Conference on Advances in Computer Engineering and Communication Systems, Hyderabad, India, 3–14 August 2021; Reddy, A.B., Kiranmayee, B.V., Mukkamala, R.R., Srujan Raju, K., Eds.; Springer Nature: Singapore, 2022; pp. 217–230.
21. Rabbani, M.B.A.; Musarat, M.A.; Alaloul, W.S.; Rabbani, M.S.; Maqsoom, A.; Ayub, S.; Bukhari, H.; Altaf, M. A Comparison Between Seasonal Autoregressive Integrated Moving Average (SARIMA) and Exponential Smoothing (ES) Based on Time Series Model for Forecasting Road Accidents. *Arab. J. Sci. Eng.* **2021**, *46*, 11113–11138. [CrossRef]
22. Stefano, F. Maintenance Diagnosis Methodology Based on Metrological Characteristics, Statistical Process Control and FMEA Analysis. *Ir. Interdiscip. J. Sci. Res.* **2021**, *5*, 94–107.
23. Shivajee, V.; Singh, R.K.; Rastogi, S. Manufacturing Conversion Cost Reduction Using Quality Control Tools and Digitization of Real-Time Data. *J. Clean. Prod.* **2019**, *237*, 117678. [CrossRef]
24. Yang, Z.; Kanniainen, J.; Krogerus, T.; Emmert-Streib, F. Prognostic Modeling of Predictive Maintenance with Survival Analysis for Mobile Work Equipment. *Sci. Rep.* **2022**, *12*, 8529. [CrossRef]
25. Moat, G.; Coleman, S. Survival Analysis and Predictive Maintenance Models for Non-Sensored Assets in Facilities Management. In Proceedings of the 2021 IEEE International Conference on Big Data (Big Data), Orlando, FL, USA, 15–18 December 2021; pp. 4026–4034.
26. Bennis, A.; Mouysset, S.; Serrurier, M. Estimation of Conditional Mixture Weibull Distribution with Right Censored Data Using Neural Network for Time-to-Event Analysis. In Proceedings of the Advances in Knowledge Discovery and Data Mining, Singapore, 11–14 May 2020; Lauw, H.W., Wong, R.C.-W., Ntoulas, A., Lim, E.-P., Ng, S.-K., Pan, S.J., Eds.; Springer International Publishing: Cham, Switzerland, 2020; pp. 687–698.
27. Hu, J.; Chen, P. Predictive Maintenance of Systems Subject to Hard Failure Based on Proportional Hazards Model. *Reliab. Eng. Syst. Saf.* **2020**, *196*, 106707. [CrossRef]
28. Fuentes-Huerta, M.A.; González-González, D.S.; Cantú-Sifuentes, M.; Praga-Alejo, R.J. Fuzzy Reliability Centered Maintenance Considering Personnel Experience and Only Censored Data. *Comput. Ind. Eng.* **2021**, *158*, 107440. [CrossRef]
29. Duong, C.M.; Lim, T.-T. Use of Regression Models for Development of a Simple and Effective Biogas Decision-Support Tool. *Sci. Rep.* **2023**, *13*, 4933. [CrossRef] [PubMed]
30. Besiktepe, D.; Ozbek, M.E.; Atadero, R.A. Identification of the Criteria for Building Maintenance Decisions in Facility Management: First Step to Developing a Multi-Criteria Decision-Making Approach. *Buildings* **2020**, *10*, 166. [CrossRef]
31. Penadés-Plà, V.; García-Segura, T.; Martí, J.V.; Yepes, V. A Review of Multi-Criteria Decision-Making Methods Applied to the Sustainable Bridge Design. *Sustainability* **2016**, *8*, 1295. [CrossRef]
32. Nunes, P.; Santos, J.; Rocha, E. Challenges in Predictive Maintenance—A Review. *CIRP J. Manuf. Sci. Technol.* **2023**, *40*, 53–67. [CrossRef]
33. Tessoni, V.; Amoretti, M. Advanced Statistical and Machine Learning Methods for Multi-Step Multivariate Time Series Forecasting in Predictive Maintenance. *Procedia Comput. Sci.* **2022**, *200*, 748–757. [CrossRef]
34. Pandit, R.K.; Kolios, A.; Infield, D. Data-Driven Weather Forecasting Models Performance Comparison for Improving Offshore Wind Turbine Availability and Maintenance. *IET Renew. Power Gener.* **2020**, *14*, 2386–2394. [CrossRef]
35. Kumar, V.; Shankar, R.; Vrat, P. An Analysis of Industry 4.0 Implementation-Variables by Using SAP-LAP and e-IRP Approach. *Benchmarking* **2022**, *29*, 1606–1639. [CrossRef]

36. Kohli, M. Using Machine Learning Algorithms on Data Residing in SAP ERP Application to Predict Equipment Failures. *Int. J. Eng. Technol. (UAE)* **2018**, *7*, 312–319. [CrossRef]
37. Chatfield, C.; Yar, M. Holt-Winters Forecasting: Some Practical Issues. *J. R. Stat. Soc. Ser. D Stat.* **1988**, *37*, 129–140. [CrossRef]
38. Escudero, P.; Alcocer, W.; Paredes, J. Recurrent Neural Networks and ARIMA Models for Euro/Dollar Exchange Rate Forecasting. *Appl. Sci.* **2021**, *11*, 5658. [CrossRef]
39. Du, Y. A Time Series Forecasting System Based on ARIMA for Industrial Big Data. In Proceedings of the International Conference on Computer, Artificial Intelligence, and Control Engineering (CAICE 2022), Xi'an, China, 25–27 February 2022; SPIE: Bellingham, WA, USA, 2022; Volume 12288, pp. 17–21.
40. Sirisha, U.M.; Belavagi, M.C.; Attigeri, G. Profit Prediction Using ARIMA, SARIMA and LSTM Models in Time Series Forecasting: A Comparison. *IEEE Access* **2022**, *10*, 124715–124727. [CrossRef]
41. Falatouri, T.; Darbanian, F.; Brandtner, P.; Udokwu, C. Predictive Analytics for Demand Forecasting—A Comparison of SARIMA and LSTM in Retail SCM. *Procedia Comput. Sci.* **2022**, *200*, 993–1003. [CrossRef]
42. Li, H.; Parikh, D.; He, Q.; Qian, B.; Li, Z.; Fang, D.; Hampapur, A. Improving Rail Network Velocity: A Machine Learning Approach to Predictive Maintenance. *Transp. Res. Part C Emerg. Technol.* **2014**, *45*, 17–26. [CrossRef]
43. Abidi, M.H.; Mohammed, M.K.; Alkhalefah, H. Predictive Maintenance Planning for Industry 4.0 Using Machine Learning for Sustainable Manufacturing. *Sustainability* **2022**, *14*, 3387. [CrossRef]