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Temporal Projections for Strategic Planning in Human Resources

Projeções Temporais para Planejamento Estratégico em Recursos Humanos

Proyecciones Temporales para la Planificación Estratégica en Recursos Humanos

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Abstract
Objective: The objective of this study is to explore the use of time series projection models in predicting absenteeism within Human Resources (HR). It aims to compare different models to improve organizational action planning and decision-making.
Methodology/Procedural Methods: This research employs a quantitative approach, using time series models such as ARIMA, Holt-Winters, and SARIMA. These models are applied to predict absenteeism in HR, demonstrating the strengths and limitations of each in the context of organizational planning.
Originality/Relevance: This study addresses the gap in the theoretical application of time series projections within the HR field, specifically focusing on absenteeism prediction. It contributes to academic relevance by providing insights into the practical utility of time series models for HR decision-making, an area that has not been extensively explored.
Main Results: The results indicate that time series projection is a powerful tool for improving HR decision-making, offering valuable insights into absenteeism trends and organizational productivity. The comparison of ARIMA, Holt-Winters, and SARIMA models highlights their respective advantages and limitations.
Theoretical/Methodological Contributions: This study provides significant contributions by comparing various time series models in the context of absenteeism prediction. It offers a clear understanding of which model performs best in specific HR scenarios and provides metrics for evaluating success.
Social/Managerial Contributions: The findings have direct implications for HR managers, providing them with actionable tools to predict absenteeism and plan more effectively, thereby improving organizational productivity and mitigating potential challenges.

Keywords: Time series, absenteeism, ARIMA, Holt-Winters, SARIMA, HR planning

Resumo

Objetivo: O objetivo deste estudo é explorar o uso de modelos de projeção de séries temporais na previsão de absenteísmo em Recursos Humanos (RH). Ele visa comparar diferentes modelos para melhorar o planejamento de ações organizacionais e a tomada de decisões.
Metodologia/Métodos Procedimentais: Esta pesquisa emprega uma abordagem quantitativa, usando modelos de séries temporais como ARIMA, Holt-Winters e SARIMA. Esses modelos são aplicados para prever o absenteísmo em RH, demonstrando os pontos fortes e as limitações de cada um no contexto do planejamento organizacional.
Originalidade/Relevância: Este estudo aborda a lacuna na aplicação teórica de projeções de séries temporais no campo de RH, focando especificamente na previsão de absenteísmo. Ele contribui para a relevância acadêmica ao fornecer insights sobre a utilidade prática dos modelos de séries temporais para a tomada de decisões de RH, uma área que não foi

amplamente explorada.
Principais resultados: Os resultados indicam que a projeção de séries temporais é uma ferramenta poderosa para melhorar a tomada de decisões de RH, oferecendo insights valiosos sobre tendências de absenteísmo e produtividade organizacional. A comparação dos modelos ARIMA, Holt-Winters e SARIMA destaca suas respectivas vantagens e limitações.
Contribuições teóricas/metodológicas: Este estudo fornece contribuições significativas ao comparar vários modelos de séries temporais no contexto da previsão de absenteísmo. Ele oferece uma compreensão clara de qual modelo tem melhor desempenho em cenários específicos de RH e fornece métricas para avaliar o sucesso.
Contribuições sociais/gerenciais: As descobertas têm implicações diretas para os gerentes de RH, fornecendo a eles ferramentas acionáveis para prever o absenteísmo e planejar de forma mais eficaz, melhorando assim a produtividade organizacional e mitigando potenciais desafios.

Palavras-chaves: Séries temporais, absenteísmo, ARIMA, Holt-Winters, SARIMA, planejamento de RH

Resumen
Objetivo: El objetivo de este estudio es explorar el uso de modelos de proyección de series temporales para predecir el ausentismo laboral en Recursos Humanos (RR. HH.). Se busca comparar diferentes modelos para mejorar la planificación de acciones y la toma de decisiones organizacionales.
Metodología/Métodos de procedimiento: Esta investigación emplea un enfoque cuantitativo, utilizando modelos de series temporales como ARIMA, Holt-Winters y SARIMA. Estos modelos se aplican para predecir el ausentismo laboral en RR. HH., demostrando las fortalezas y limitaciones de cada uno en el contexto de la planificación organizacional.
Originalidad/Relevancia: Este estudio aborda la brecha en la aplicación teórica de las proyecciones de series temporales en el campo de los RR. HH., centrándose específicamente en la predicción del ausentismo laboral. Contribuye a la relevancia académica al proporcionar información sobre la utilidad práctica de los modelos de series temporales para la toma de decisiones en RR. HH., un área poco explorada.
Resultados principales: Los resultados indican que la proyección de series temporales es una herramienta poderosa para mejorar la toma de decisiones de RR. HH., ofreciendo información valiosa sobre las tendencias de ausentismo y la productividad organizacional. La comparación de los modelos ARIMA, Holt-Winters y SARIMA destaca sus respectivas ventajas y limitaciones.
Contribuciones teóricas/metodológicas: Este estudio aporta contribuciones significativas al comparar varios modelos de series temporales en el contexto de la predicción del ausentismo. Ofrece una comprensión clara de qué modelo funciona mejor en escenarios específicos de RR. HH. y proporciona métricas para evaluar su éxito.
Contribuciones sociales/gerenciales: Los hallazgos tienen implicaciones directas para los gerentes de RR. HH., proporcionándoles herramientas prácticas para predecir el ausentismo

y planificar de forma más eficaz, mejorando así la productividad organizacional y mitigando posibles desafíos.

Palabras clave: Series temporales, ausentismo, ARIMA, Holt-Winters, SARIMA, planificación de RR. HH.

1. Introduction

Strategic planning in human resources depends on the ability to predict future trends and behaviors. This study proposes the use of time series models to support this process. In strategic terms, Apex-Brasil has two objectives, valid for the period 2024 to 2027, which involve the direct participation of the Human Resources Management: To be a digital agency, with transversal, scalable business models, which deliver the best experience and value to customers and employees; and to develop an organizational culture of transversality, synergy and results.

These objectives corroborate the need for People Analytics actions, given the need for accurate diagnoses that support the actions of the organizational unit. The automation of in- ternal people management processes is a priority, for this purpose, it relies on the Personnel Administration Solution: Enterprise Resource Planning (ERP) System "Corpore RM" from the company TOTVS – People Management Module. Furthermore, there is a need to integrate the solution with other employees and personnel management data, requiring a more detailed analysis, as well as the integration of models that allow a single view of employees from different perspectives.

The study is motivated by the aim of contributing to the maintenance of human resources policies, regulations and processes updated and referenced in the best market practices, aimed at the Agency's Strategic Planning, with its own staff prepared, adequate, well-paid and with development prospects appropriate to the skills needed to meet the

Agency's challenges in its institutional mission.

When applying Time Series Projection models, the following algorithms will be used: Single Exponential Smoothing (SES), Holt-Winters, Error, Trend, Seasonality (ETS), Autore- gressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA). It is a challenge to analyze and extract data from the various existing human resources systems to under- stand each context and the diversity of existing attributes.

The general objective of this work is to propose and analyze the potential of time series projection models in predicting strategic indicators in Human Resources. The construction and selection of models that are more appropriate for predicting historical series for Apex-Brasil, based on primary data from several existing human resources management processes of absenteeism.

To achieve this, it will be necessary to achieve the following specific objectives:

- Analyze the context of human resources processes and extract, transform and load absenteeism data for the research.
- perform the systemic selection of variables that best correlate with human resources processes, to support the research and models.
- build, measure and evaluate prediction models.
- evaluate the results obtained together with the teams working at Apex-Brasil's Human Resources Management.

The success criteria is considered to be the evaluation of the proposed models and their comparison applied to Apex-Brasil data, stipulating the best model(s) applied, serving as a reference for the implementation of the indicated models in the Agency's computing environments, contributing to the decision-making process and analysis of Human Resources Policy to Absenteeism.

2. Theoretical Framework

2.1 People Analytics

People Analytics is an emerging discipline within data science that focuses on applying advanced analytical techniques to understand, manage, and improve the workforce. This approach involves analyzing large volumes of data about employees and candidates to

provideinsights that can guide strategic and operational decisions in organizations. The critical success factors for modeling in People Analytics will be explored, in addition to the best forecasting techniques.

The main aspects of the area indicate that for the application of People Analytics techniques to be effective, the following themes must be observed (Peeters et al., 2020): i) deliverables; ii) stakeholder management; iii) enablers; and iv) governance. All these areas of knowledge must be combined in the interest of seeking reference, best market practices, and predictive analysis (Rasmussen et al., 2024).

Given the competitive nature of information, which deals with strategic issues for organizations, academic publications are limited (Marler & Boudreau, 2017). In articles that relate to various sources, the generic nature of the information and the lack of exploration of employee databases and discussion of data science models are clear.

The range of topics and delivery possibilities are varied and complex. Given the social context of the area of study, the academic approach is still focused on generic aspects and re- quires greater depth and technical application (Tursunbayeva et al., 2018), therefore, grouping, prediction models will be proposed, analyzed and discussed to advance the research.

Among the most common objectives (Cho et al., 2023) are workforce planning, human resource development, improving the assertiveness of the recruitment and selection process, and improving employee performance, as shown in the following table:

	Analysis Objective	Types of Data Used	Resulting Insights
Workforce Planning	▪ Identify skill gaps ▪ Verify whether the right people are placed in the right position ▪ Retain top performers	▪ Labor market data ▪ Work portal documents ▪ Individual profile data (employment information, personal detail, educational background, work history, performance reviews) ▪ Employee behavior and collaboration data collected by sensors	▪ Essential skills for performance ▪ Long-term workforce supply and demand plan
HR Development	▪ Identify training needs ▪ Check the effectiveness of current training programs	▪ Training content ▪ Individual training history ▪ Performance appraisal data	▪ Automated and individualized training recommendation ▪ Correlation between training and performance
Recruitment and Selection	▪ Recruit talented applicants in efficient and timely manner ▪ Nudge desired manager behaviors ▪ Expanding the candidate pool	▪ CV data ▪ Social media data ▪ AI-assisted interview data ▪ Job market data ▪ Past candidates' recruitment information ▪ E-mail records	▪ Person-job fit of the applicant ▪ Performance prediction ▪ Hiring process improvement ▪ Desired manager competencies and traits
Performance Improvement	▪ Analyze HR factors influencing organizational outcomes ▪ Detect employee sentiment related to performance	▪ Administrative data ▪ Turnover data ▪ Employee surveys ▪ Performance appraisal data ▪ Financial statistics ▪ Pop-up questions data ▪ External/internal social media data ▪ Anonymous bulletin board	▪ Performance-inducing HR factors ▪ Negative elements affecting employee satisfaction

Figure 1: Analytics Application Models

Among the main deliverables of the discipline (Peeters et al., 2020) is organizational re- search, monitoring the various aspects of the employee and a culture based on results and evidence. Organizational research is an opportunity to use algorithms for better understanding and the possibility of a more balanced decision-making process (data-driven decision-making process) (Polzer, 2022), minimizing decision bias and greater statistical rigor.

Models such as ARIMA and Holt-Winters are widely used for projections in areas such as economics and organizational management. In the context of human resources, these techniques help to anticipate demand and reduce risks. Below is presented more techniques object of comparison in this study.

2.1 Data Mining and Forecast and Time Series Models

Simple Exponential Smoothing (SES)

SES is a simple method that smooths historical data to make predictions. The smoothing formula is:

$$\hat{y}_{t+1} = \alpha y_t + (1 - \alpha)\hat{y}_t \quad (1)$$

where α is the smoothing coefficient (Gardner, 1985).

Relevance Analysis (Gardner, 1985 e Chatfield, 1978):

- Advantages: Simplicity; easy to implement; and requires little historical data.
- Disadvantages: Does not capture trends; does not capture seasonality; and limited effectiveness for complex time series.
- Recommended Uses: Time series without trend or seasonality; short-term sales forecast; and demand forecast for stable products.
- Assessment Criteria:

MAE: Average of absolute error values;
MSE: Mean squared errors.
RMSE: Square root of the mean of the squared errors.

Holt-Winters

The Holt-Winters model considers seasonality in addition to trends

$$\hat{y}_{t+m} = l_t + mb_t + s_{t+m-L}$$

$$l_t = \alpha \frac{y_t}{s_{t-L}} + (1 - \alpha)(l_{t-1} + b_{t-1})$$

$$b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1}$$

$$s_t = \gamma \frac{y_t}{l_t} + (1 - \gamma)s_{t-L}$$

where s_t is the seasonal component and L is the seasonal period (Winters, 1960).

Relevance Analysis (Winters, 1960; Gardner, 1985 e Hyndman & Athanasopoulos, 2021):

- Advantages: Captures trends and seasonality; suitable for seasonal time series; and flexi- ble to different seasonal patterns.

- Disadvantages: Increased complexity; requires adjustment of more parameters; and may be sensitive to outliers.
- Recommended Uses: Time series with strong seasonal patterns; seasonal sales forecast; and capacity planning.
- Assessment Criteria:

MAE: Average of absolute error values;

MSE: Mean squared errors; It is

RMSE: Square root of the mean of the squared errors.

Autoregressive Integrated Moving Average - ARIMA

ARIMA is a flexible model that combines autoregressive components, moving averages and integration:

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t \qquad (2)$$

where ϕ are the autoregressive coefficients, θ are the moving average coefficients and ε_t

is the error (Hyndman & Athanasopoulos, 2021).

Relevance Analysis (Box et al., 2016; Hamilton, 1994 e Hyndman & Athanasopoulos, 2021):

- Advantages: Flexible modeling of temporal components; captures seasonal and trend patterns; and broad applicability in different domains.
- Disadvantages: Determination of parameters can be complex; requires stationary time series; and is sensitive to outliers.
- Recommended Uses: Time series with strong temporal dependence; sales forecast; and economic analysis.
- Assessment Criteria:

Mean Absolute Error (MAE): Average of absolute error values; Mean Squared Error (MSE): Mean squared errors; It is

Akaike Information Criterion (AIC): Penalizes models with many parameters.

SARIMA

SARIMA extends ARIMA to capture seasonality in data:

$$y_t = c + \phi(B)y_t + \theta(B)\varepsilon_t \quad (3)$$

where $\phi(B)$ and $\theta(B)$ are delay polynomials that include seasonal components (Hyndman & Athanasopoulos, 2021).

Relevance Analysis (Box et al., 2016; Hamilton, 1994 e Hyndman & Athanasopoulos, 2021):

- Advantages: Captures seasonality; extension of ARIMA to seasonal patterns; and suitable for complex seasonal time series.
- Disadvantages: Increased complexity; requires adjustment of many parameters; and sensitive to outliers.
- Recommended Uses: Time series with regular seasonal patterns; seasonal sales forecast; and analysis of meteorological data.
- Assessment Criteria:

MAE: Average of absolute error values;

MSE: Mean squared errors; It is

AIC: Penalizes models with many parameters.

Related Works

The use of time series to improve the forecasting performance of ideal models confirms that the time series modeling approach has the ability to predict employee turnover for the specific scenario observed in this work, as indicated by Zhu et al. 2017). Addition- ally, Bandeira (Bandeira et al., 2020) demonstrates that the combination of forecasting methods proves to be valuable, for a weighting scheme based on the performance of each model.

Margherita (2022) reviews the literature on applications (descriptive and di- agnostic/prescriptive) and value (employee value and organizational value). We also speculate on an "exponential" vision of HR analytics enabled by the affirmation of artificial intelligence and cognitive technologies, highlighting forecasting techniques as tools for predicting Human Resources themes.

In the field of application of forecasting techniques in the topic of people analytics, Xu et al., (2019) performed talent flow analysis in the field of human resource planning, brain drain monitoring, and future workforce forecasting with the approach of using multi-stage time series forecasting. The results also indicated that the proposed model can provide reasonable performance even if historical talent flow data is not completely available.

3. Methodology

The models applied include SES, Holt-Winters, ARIMA and SARIMA. Absenteeism data were collected and processed for seasonality, trend and residual analysis. In view of the general and specific objectives set, the Cross-Industry Standard Process for Data Mining Method (CRISP-DM) (Chapman & et al., 2000), this Model will be used as a reference, going through all the proposed phases, namely:

1. *Business Understanding - human resources processes at Apex-Brasil*, where the con- text of each process analyzed will be defined, the business and Human Resources (HR) guidelines will be understood, and the scope of the research to be studied will be defined.

2. *Pre-processing and exploratory analysis of data*, where the data will be extracted, transformed and loaded (ETL), with the following phases: Data identification and collec- tion; checking for cleanliness and integrity; seeking data convergence; and loading and consolidation of tables. After the tables have been consolidated, exploratory data analysis will be performed, validating the data to be processed, using techniques and algorithms in Language and using R Libraries to better understand the context, with the following phases: analysis of numerical and categorical variables; summarization, identification of erroneous, missing and outliers values; graphical visualization; identification of noise, if applicable.

3. *Modeling*, using descriptive or predictive machine learning techniques, where the aim is to analyze and determine the most relevant time series projection model(s); and demon- strate the visualization of the results.

4. *Discussions*, where, based on the results found, demonstrate the suitability of the mod- els used and proposed and discuss the best application for the business context and its consequences for the research objectives. and

5. *Evaluation and conclusions*, defining the model for implementation, operation and evo- lutionary and corrective maintenance of the selected and adjusted models, as well as the visualization of the results and the analysis references, refining the entire scope of work.

4. Presentation Discussion of Results

Business understanding - human resources processes at Apex-Brasil

The scope of this study was defined based on meetings held with the Human Resources (HR) and Information Technology (IT) teams at Apex-Brasil. It was agreed that data from employees who were active on 12/31/2023 would be used in the period between 01/2019 and 12/2023. In addition, to making a forecast of absenteeism and leaves for the years 2024 and 2025, so that the most appropriate technique can be verified for this purpose and future comparison with the results obtained.

Therefore, in the context of *People Analytics*, Apex-Brasil, based on this study, will now have the most appropriate data science techniques for its internal environment, supporting HR policies and action plans (Waters et al., 2018) and Edwards & Edwards, 2019).

Understanding, pre-processing and exploratory analysis of data

In this step, the data was extracted, transformed and loaded (ETL). After loading the data into RStudio, Exploratory Data Analysis (EDA) was performed, the preliminary results of which are presented below.

Data Extraction

Using the report model of the Totvs RM Integrated System - People Management, queries were performed in the database, with the extraction of the data sample, characterized in the previous section. Two files were generated, with the following configuratio

4.1 ***Dataset*** - Absenteeism information ("ATESTADOS-2019-2023"): with 18 attributes and 689 lines, containing information on absenteeism time series, with reasons and history from 2019 to 2023. After the transformation analysis, 3 attributes and 7,664 lines remained.

Data Transformation

In the data transformation phase, new columns were generated in the employee database to facilitate analysis, such as consolidated information, transformation and control of entry and exit from work as a factor.

Data Load

To load and parallelize the information processing, the **R** language was used, with the **Sparklyr** and **Dyplir** libraries (Alcoforado, 2021) in **RStudio**, enabling the use of the **Spark** system and the respective data processing. Both datasets were treated to deal with missing and/or missing data. After data transformation, the Extraction, Transformation and Load (ETL) process was completed, with the classification of the variables as numerical and categorical.

4.2 Modeling

In the forecasting experiment, the SES and Auto.ARIMA models are the most effective for the dataset used, with Auto.ARIMA slightly better given the lower RMSE, MAE and MAPE values. The Holt-Winters models (both additive and multiplicative) and Custom SARIMA have significantly larger errors and are therefore less recommended for this analysis.

Time series projection involves analyzing data from a temporal sequence to make future predictions. They help the organization to prepare for future challenges, with the possibility of anticipation and greater success in the business context. In HR practices, they serve to define seasonality and forecast people's budgets or behaviors such as Absenteeism, which has its ac- tivities projected on the timeline, both of which are of fundamental importance for corporate results and productivity.

Time Series Analysis

Considering the Graph in Figure [2], the analysis of the Absenteeism Minutes data reveals that there is no clear trend of increase or decrease over the analyzed period, indicating a certain stability with sporadic peaks. The values show a certain stability, with constant fluctuations over time, suggesting that absenteeism does not follow a linear pattern of growth or decline.

Several significant peaks are observed at different times, with a large peak in 2023 standing out, possibly linked to seasonal events, with factors that caused mass absences. The data pattern suggests the presence of seasonality, with repetitions in certain periods, which justifies a more detailed analysis to identify possible causes of these absences. In addition, the high variability in the data, with large monthly fluctuations, indicates that absences are not uniform over time and may be influenced by different external factors.

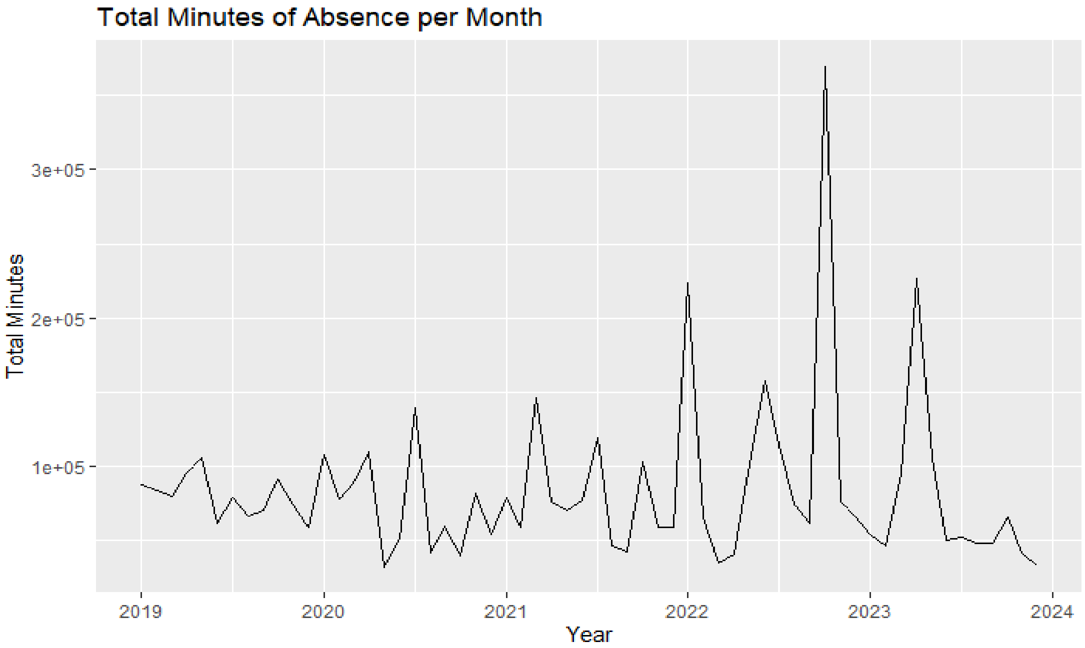

Figure 2: Total Minutes of Absence per Month

Seasonality Chart Analysis

The seasonality graph, as shown in Figure [3], shows the total minutes of absence per month, comparing different years from 2019 to 2023. This type of graph is useful for identifying seasonal patterns that repeat themselves over the years.

The analysis of absence data reveals the presence of seasonal patterns, with a clear increase in absences in certain months of the year, especially in October, which showed a significant peak in 2023. In addition, the months of April, May and October show considerable variations from one year to the next, which suggests possible seasonal influences or specific events that occur in these periods. Regarding annual variations, it is observed that the magnitude of absences varies substantially over the years. For example, the year 2023 stands out with a very high peak in October, while other years show smaller peaks that are more distributed throughout the year. Years like 2020 and 2022 appear to have less variability in total minutes absent throughout the year compared to 2023.

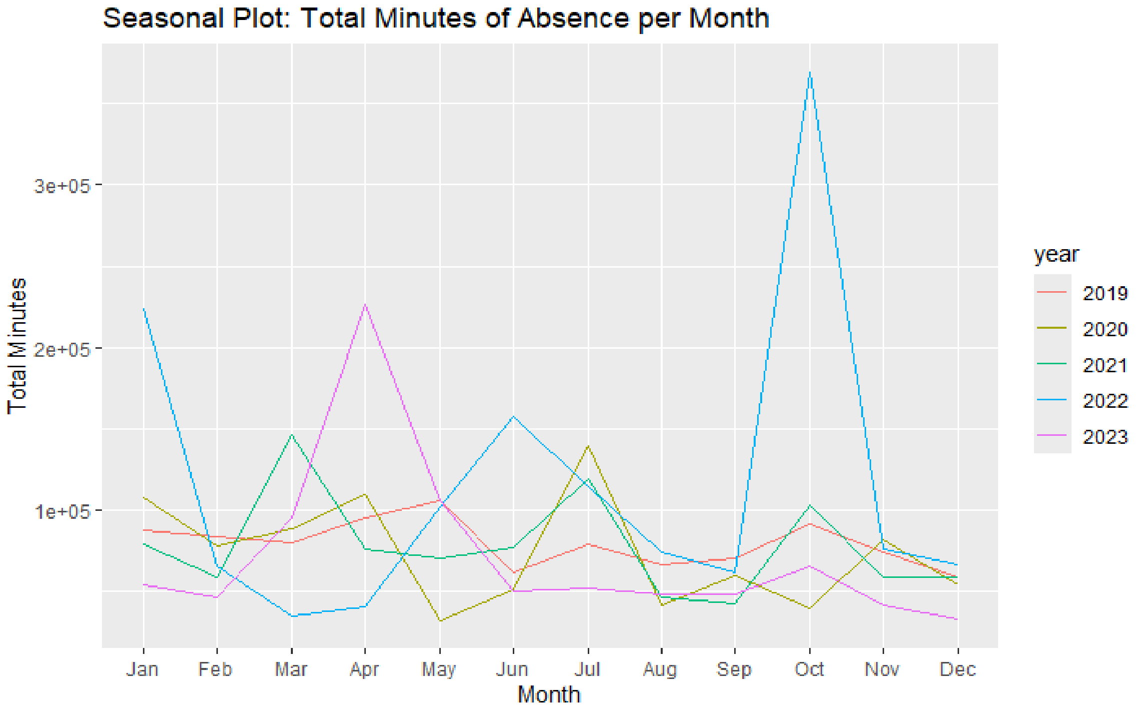

Figure 3: Seasonal Plot: Total Minutes of Absence per Month

Furthermore, some months, such as February and March, tend to have fewer minutes of absence in most years, although there is some variation in specific years. When interpreting the results, the extreme peak in October 2023 stands out, as seen above, which may indicate an atypical event, such as organizational changes that led to a massive increase in absences. The presence of peaks in specific months suggests the influence of seasonal factors, which may include vacation periods, seasonal illnesses, or other recurring events. Comparing different years reveals that, despite there being a seasonal trend, the intensity of absences varies considerably from year to year, indicating that, in addition to seasonality, there are other contextual factors that influence these data.

Lag Chart Analysis

The lag plot in Figure [4] demonstrates the relationship between time series at different lags and how the total minutes of absence vary over time. This type of plot is useful for identifying autocorrelations and repeating patterns over time. The relationship between the value of the time series and its lags, ranging from 1 to 16 periods, with the colors indicating the different months to represent seasonality throughout the year.

The smaller lags, such as Lag 1 and Lag 2, show a closer and more consistent relationship with the value of the time series. This suggests that the recent values of the series are strongly correlated with the subsequent periods. However, as the lag increases, the correlation between the past and current values appears to decrease, indicating that the dependence on the more distant past values is less.

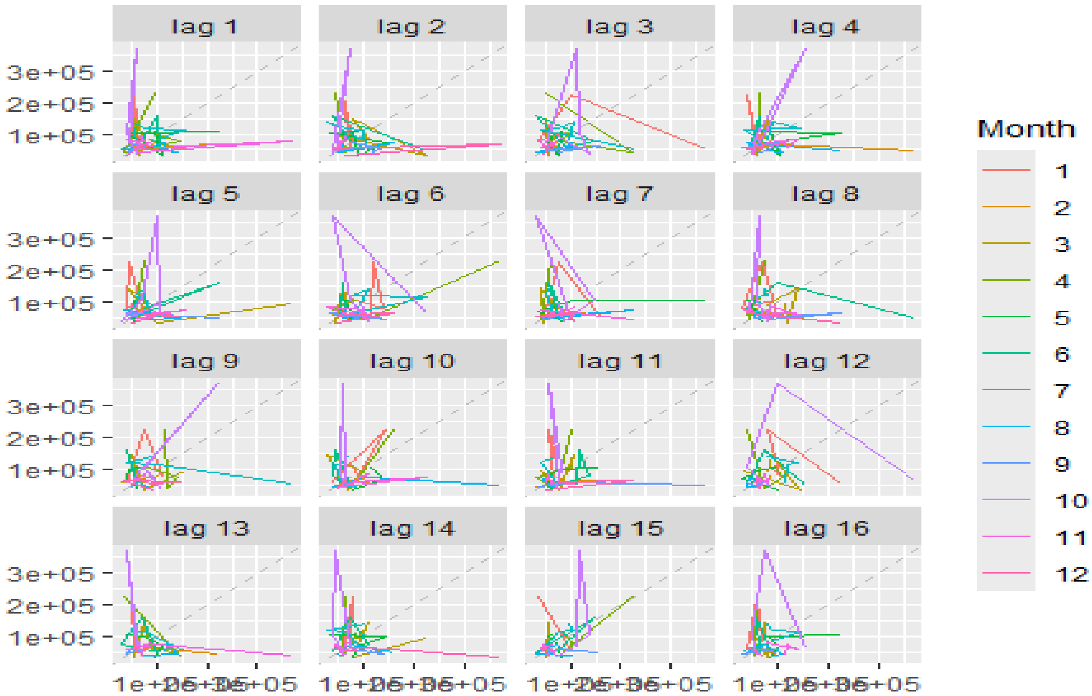

Figure 4: Lag Analysis

Furthermore, the presence of monthly seasonality is visible in the colors that represent different months. In some lags, there is a clear separation of the colors, suggesting that certain months have a more evident influence on subsequent values. Some months show higher patterns, while others show lower patterns, which may be a reflection of seasonal factors or recurring events specific to each period of the year.

As the lag increases towards the medium term (5-8), the dispersion of the points also increases, indicating that the correlation begins to decrease. This behavior is expected, since events that occurred further apart in time tend to have less direct influence on each other, weakening the correlation with increasing lag.

In long-term lags (9-16), the dispersion of the points continues to increase, and the correlation patterns become less clear. This suggests that absence values at very distant periods in time show little or no direct correlation, indicating that the influence of an absence value is temporary and decreases over time.

The presence of repetitive patterns in certain months over the lags may indicate the existence of seasonality in the time series. For example, if absence in a given month tends to repeat itself after 12 months (lag 12), this reinforces the hypothesis of an annual seasonal component, which manifests itself at regular intervals over time.

The interpretation of these results points to a strong autocorrelation at short lags, which suggests that absence values are significantly influenced by values from the immediately preceding months. This may be caused by continuous factors, such as the progression of an epidemic or internal organizational policies. Furthermore, the decrease in correlation with increasing lag is a common feature in many time series and indicates that events more distant in time have a decreasing influence on each other. Finally, the repetitive patterns observed at lags multiples of 12 reinforce the hypothesis of seasonality, suggesting an annual repetition of these absence events.

Autocorrelation Chart Analysis (ACF)

The Autocorrelation Plot (ACF), shown in Figure [6], is a statistical tool used to measure the correlation between values of a time series at different lags. It helps to identify the presence of seasonal patterns and the temporal dependence structure in the data.

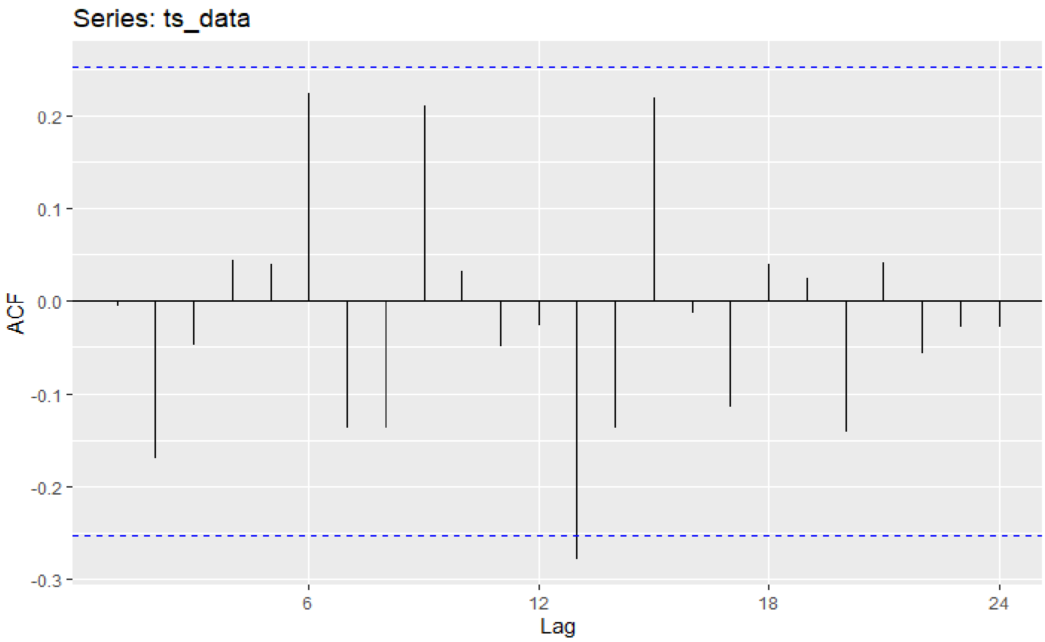

Figure 5: ACF Analysis

There are significant peaks of autocorrelation at lags 1, 2, 12 and 16; The positive auto- correlation at lags 1 and 2 indicates that there is a dependence between values close in time, that is, the absence values of one month are influenced by the values of the immediately preceding months; The significant peak at lag 12 suggests the presence of an annual seasonality, meaning that the absence patterns tend to repeat annually; and Another significant peak at lag 16 may indicate some influence of a different cycle or specific periodic events.

Negative autocorrelations exist at some lags (such as 6, 13 and 18) indicating that there is a reversal in the trend of the data at these points. This can be interpreted as periods of recovery or compensation after high absence events. Many lags do not show significant autocorrelation, suggesting that, outside of the identified lags, there is no strong temporal dependence in the data.

The presence of peaks at short lags (1 and 2) indicates that absence values are highly dependent on values from the preceding months. The significant peak at lag 12 confirms the annual seasonality observed previously, indicating that events occurring each year have a significant impact on absences. Negative correlations at specific lags suggest that, after periods of high absence, there is a tendency for subsequent values to recover or normalize.

Combined Analysis of Time Series Chart, ACF and PACF

The graphs in Figure [6], include the time series of Absenteeism Minutes per month, composed of the autocorrelation plot (ACF) and the partial autocorrelation plot (PACF). These graphs together are extremely useful for understanding the temporal structure of the data and for selecting appropriate models for forecasting.

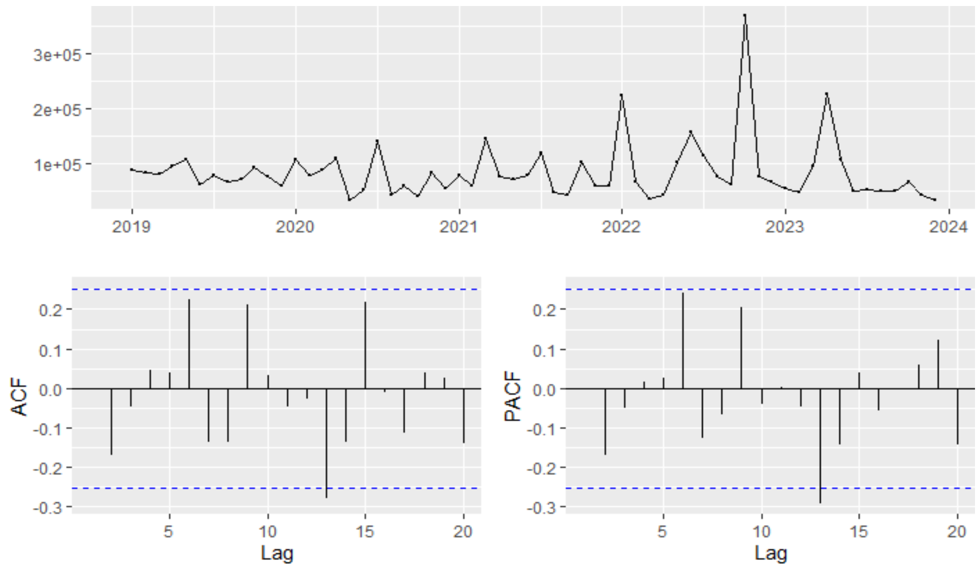

Figure 6: ACF and PACF Analysis

The Partial Autocorrelation Plot (PACF) shows spikes at short lags (1, 2) that confirm the short-term dependence observed in the ACF; Lag 12 in the PACF is also significant, reinforcing the presence of annual seasonality. The partial correlation decreases rapidly after the first few lags, indicating that most of the temporal dependence is captured by the first few lags.

The short-term dependence, indicated by the presence of spikes at short lags in both the ACF and the PACF, suggests that values close in time are strongly correlated. This can be modeled using low-order autoregressive (AR) terms. The significant spikes at lag 12 in both the ACF and the PACF confirm the annual seasonality, which can be modeled with seasonal terms. The negative autocorrelations at certain lags indicate the presence of recovery cycles after spikes, which can be important when fitting forecast models.

Additive Time Series Decomposition Analysis

The additive decomposition of a time series, in Figure [7] separates the data into three main components: trend, seasonality, and residuals. Each component provides distinct insights about the behavior of the data over time.

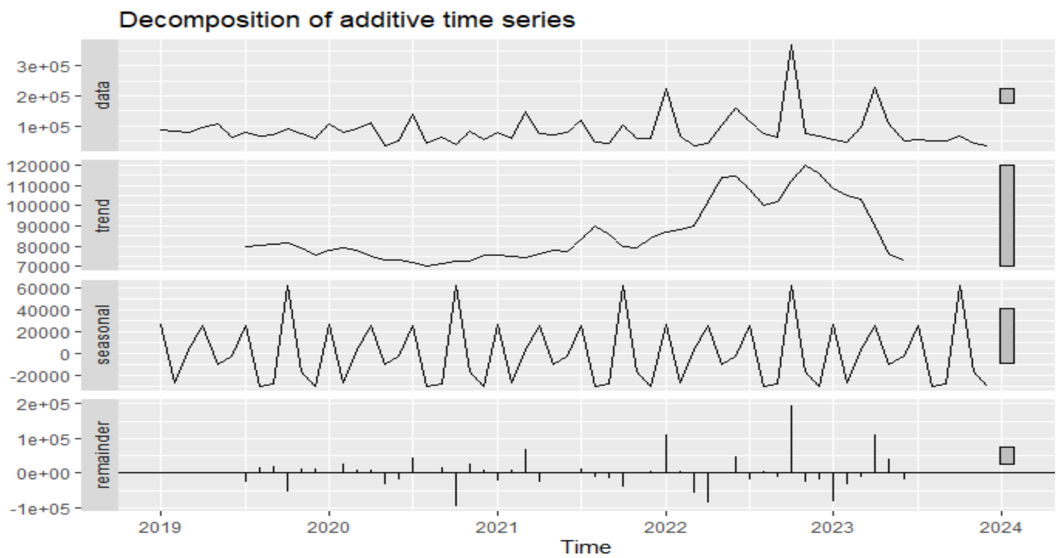

Figure 7: Decomposition of additive time series

Analyzing the decomposition components, we have that represents the time series of total absence minutes per month. It shows the underlying trend over time and a gradual increase in the trend is observed until mid-2022, followed by a decrease until 2024. It represents seasonal patterns that repeat annually, where seasonality is clear, with recurring peaks at specific periods each year, confirming the presence of a strong seasonal component. It contains fluctuations that are not explained by trend or seasonality. The residuals show some significant variations, especially in 2023, suggesting the presence of atypical events.

The increasing trend until mid-2022 may indicate factors that increased absences during this period, such as changes in organizational policies or external events. The subsequent decrease in the trend may reflect the implementation of new absence management policies or a recovery after a significant event. The strong seasonal component confirms that there are patterns that repeat annually, as we saw in the ACF and PACF graphs. These patterns may be attributed to recurring seasonal events such as holidays, seasonal epidemics, or other periodic factors. Residuals capture variations not explained by trend or seasonality, including exceptional events. Significant fluctuations in 2023 may indicate atypical events that resulted in increases in absence not predicted by trend or seasonalit

A*plicative Time Series Decomposition Analysis*

Multiplicative decomposition of a time series divides the data into three main components: trend, seasonality, and residuals. Unlike additive decomposition, multiplicative decom- position is used when the seasonal variation increases or decreases proportionally to the level of the series. Figure [8], demonstrates the result of the model:

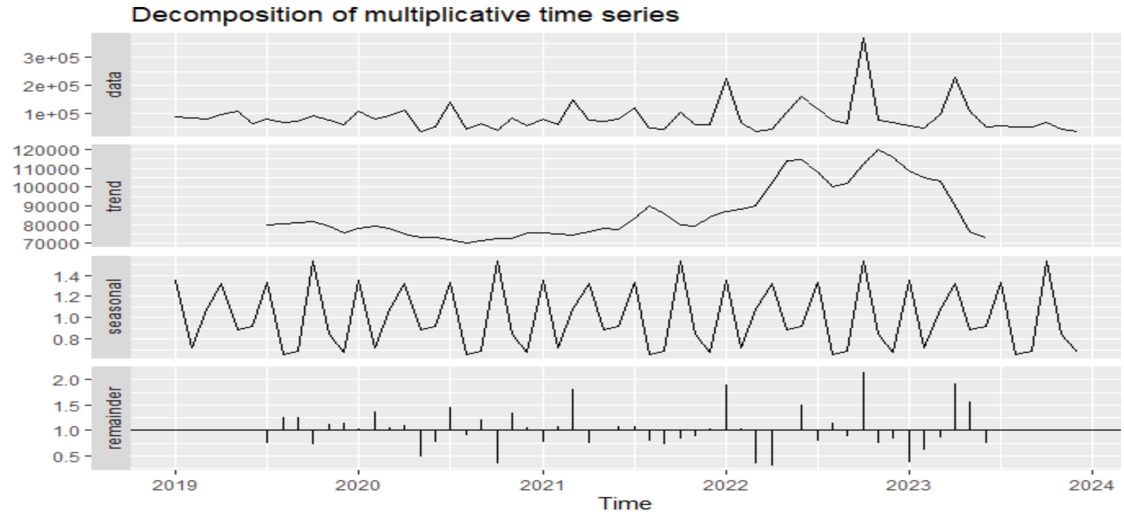

Figure 8: Decomposition of Multiplicative time series

In the time series decomposition, each component plays a specific role in the interpretation of the monthly absence data. The original series represents Total Absentee Minutes per month, providing the overall view of the data over time. The underlying trend shows a gradual increase until mid-2022, followed by a decrease that extends through 2024, similar to the behavior observed in an additive decomposition. This trend component helps to understand the general direction of absences over the period.

The seasonal component highlights patterns that repeat annually and are expressed as multiplicative factors. The seasonality is clear and consistent, with peaks at specific times each year, suggesting the influence of regular events that affect absences in certain months. The remainder, or “waste,” component contains fluctuations that are not explained by the trend or seasonality, expressed as proportions. This residual component shows some significant variations, especially in 2023, indicating the presence of atypical events that caused changes in absences.

The multiplicative seasonal component reveals that seasonal variation is proportional to the series level, i.e., seasonal peaks and valleys become more pronounced during periods of greater absence. This strong seasonal component confirms the presence of annual patterns that influence absences, evidencing recurring seasonal factors. Finally, the residuals capture variations that are not explained by the trend or seasonality, including exceptional events. Again, the significant fluctuations observed in 2023 suggest the occurrence of atypical events that resulted in increases in absences not predicted by the trend or seasonality, indicating that these events may have directly impacted absence behavior.

Analysis of Prediction Charts and Residuals of the SES Model

The graph in Figure [9] below shows the forecast of Absentee Minutes using the Simple Exponential Smoothing (SES) model. It demonstrates the comparison between the forecast and the actual data. The black line represents the actual data on total absence minutes, while the light blue line indicates the values fitted by the SES model. Additionally, the blue shaded area around the forecast line represents the confidence interval of the forecasts, providing an estimate of the uncertainty around the predicted values

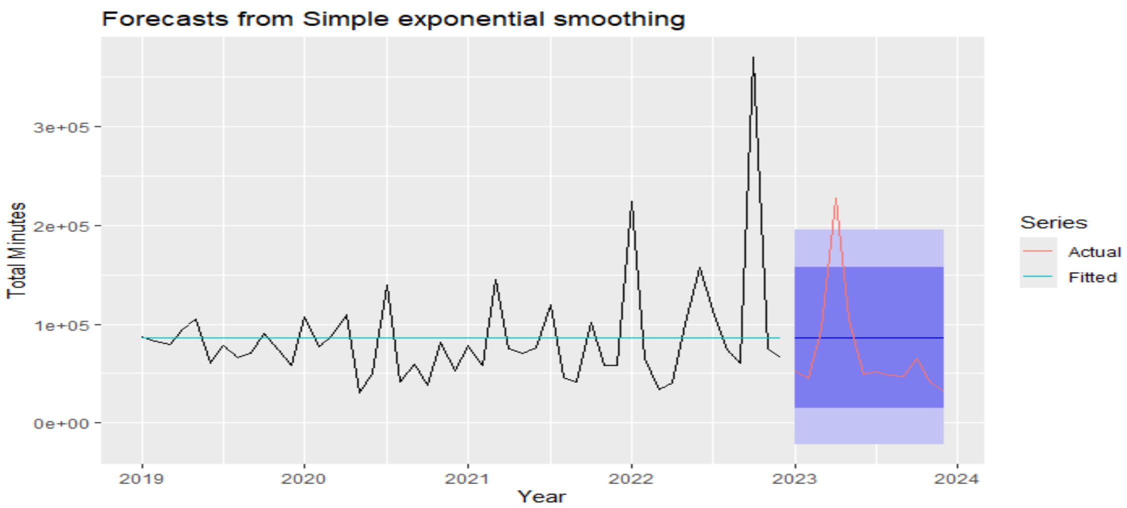

Figure 9: Forecast SES

In terms of performance, the SES model fits historical data well, but the forecast appears to significantly underestimate absence peaks, especially the large peak recorded in 2023. The forecast remains at a relatively constant level, without capturing the variability observed in

historical data. This suggests that the model may not be ideal for series with high variability or sporadic peaks, such as those observed in the absence data.

When analyzing the SES residuals graph, as shown in Figure [**??**], we can see that over time it reveals some limitations in its ability to capture absence peaks. In the upper graph, we can see the residuals, which are the differences between the actual values and the values adjusted by the model. There are large variations in these residuals, especially in peak periods, which indicates that the model is not effective in capturing these extreme events. Residual Chart (SES Residuals):

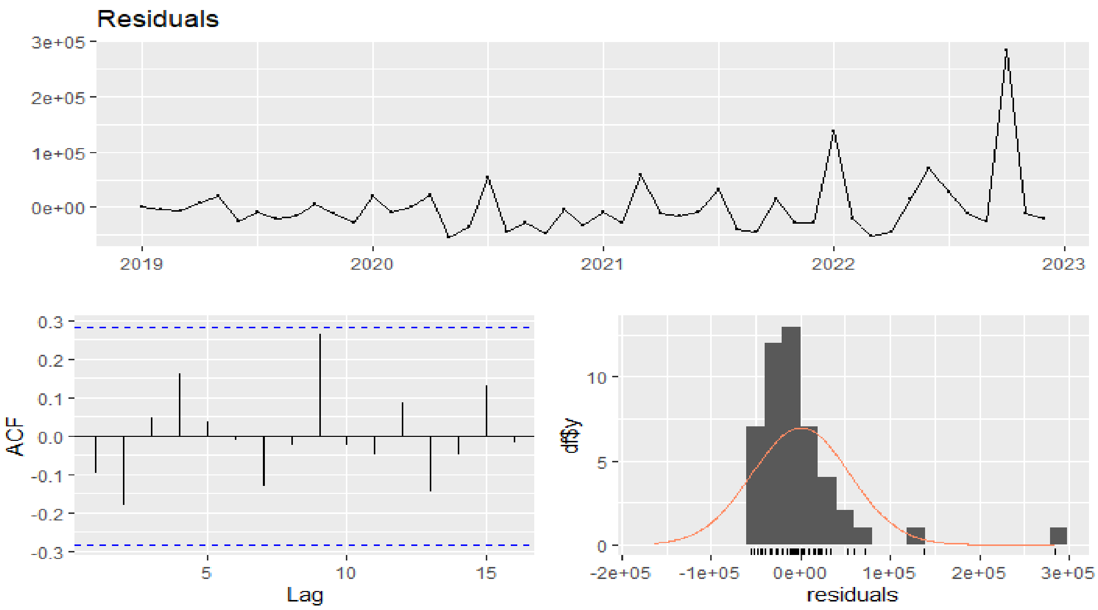

Figure 10: SES Residuals

The residual autocorrelation (ACF) plot shows the correlation between the residuals at different lags and presents significant peaks at some of them. This suggests that the residuals are not purely random and that the SES model does not capture certain underlying patterns in the data. Finally, the residual histogram reveals the distribution of the residuals, which is skewed and has a long tail on the right. This indicates the presence of large positive residual values, suggesting that the model often underestimates the true values, especially at some specific points. These findings reinforce the need for adjustments to the model or na alternative model to better capture the variability of the absence data. Interpretation of the results reveals some limitations of the SES model in capturing the dynamics of the absence data. First, the model underestimates the absence peaks, failing to adequately represent the periods of high absence. This is evidenced by the large positive residuals and the constant forecast, which does notreflect the true variations in the data. Furthermore, the presence of significant autocorrelation in the residuals indicates that the model does not capture all temporal patterns, suggesting the need for a more complex model that takes into account temporal dependence and seasonality. The analysis of the distribution of residuals shows an asymmetry, indicating that there are large discrepancies between the actual values and the adjusted values at some points, possibly due to the presence of atypical events or regime changes that the SES model does not capture.

In conclusion, the SES model proves to be insufficient to capture the complexity and variability of absence data. The use of more advanced models that incorporate seasonality and trend, together with a more detailed analysis of atypical events, can significantly improve the accuracy of forecasts and contribute to more effective management of absences.

Analysis of Prediction Plots and Residuals of the Holt-Winters Model - Additive

The graph below, in Figure [11], shows the forecast of Absenteeism Minutes from the additive Holt-Winters model. Analyzing the forecast versus actual data with the Holt-Winters model reveals an attempt to capture the dynamics of the absence data by breaking it down into different components. The black line represents the actual data on total absence minutes, while the colored lines highlight the different components of the model. The level component is represented by the magenta line, the seasonal component by the green line, the trend component by the cyan line, and the model-fitted values by the blue line. The blue shaded area around the forecasts indicates the confidence interval, providing a margin of uncertainty around the predicted values.

Forecast Chart (Holt-Winters Forecast Additive):

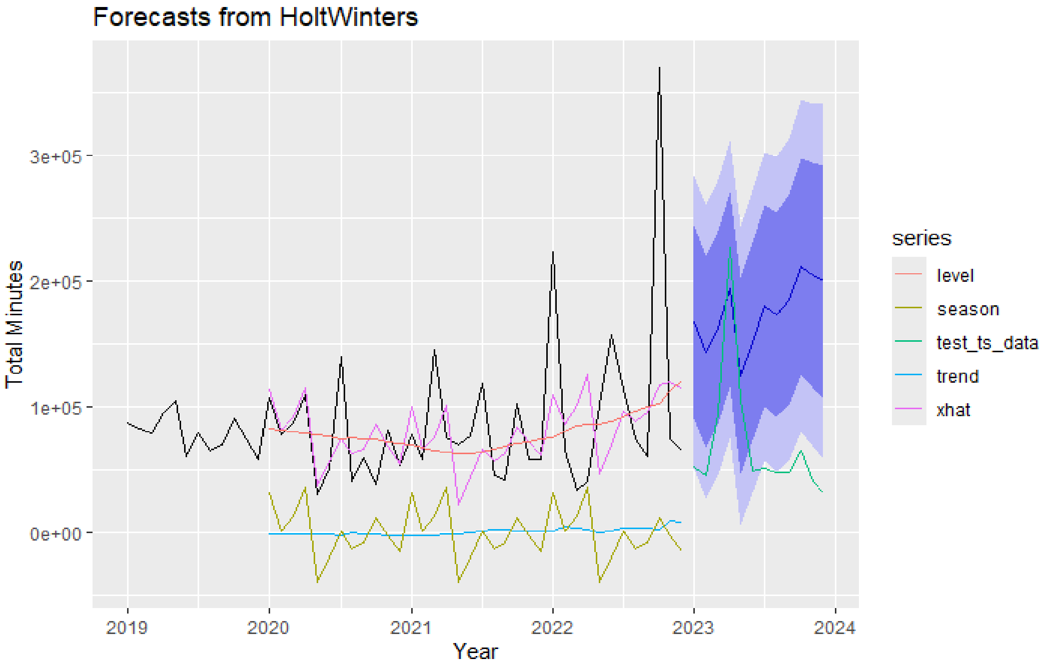

Figure 11: Forecast Holt-Winters - Additive

Regarding the model's performance, Holt-Winters seeks to capture both seasonality and trend in absence data. The resulting forecast shows greater variability and attempts to reflect some of the peaks observed in the actual data, although there is still a considerable underestimation of the highest peaks. This performance suggests that, despite the model's effort to follow the behavior of historical data, it still has limitations in fully capturing the amplitude of high absence events.

When analyzing the Residuals plot, as shown in Figure [12], over time, some limitations in fully capturing absence peaks are evident. The top plot shows the residuals, which are the differences between the actual values and the values fitted by the model, and reveals large variations in peak periods, which suggests that the model is unable to adequately represent these extreme events. The residual autocorrelation (ACF) plot shows the correlation of the residuals at different lags and shows significant peaks at some lags. This indicates that the residuals are not purely random, which points to patterns not captured by the Additive Holt-Winters model.

Residuals Chart (Holt-Winters Additive Residuals):

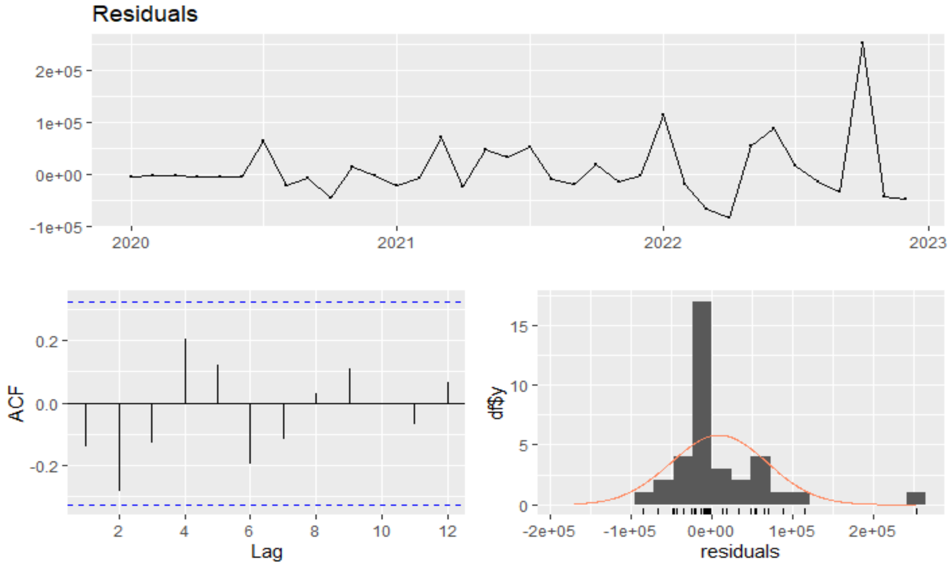

Figure 12: Holt-Winters - Additive Residuals

The distribution of residuals, represented in the histogram, reveals an asymmetry with a long tail on the right, indicating the presence of large positive residual values. This long tail suggests that the model often underestimates the true values at certain points, especially in high absence events. Taken together, these results highlight the need for adjustments to the model or consideration of alternatives that can better capture the variability and peaks in absence data.

The interpretation of the results of the Holt-Winters Additive model indicates that, although it seeks to capture seasonality and trends in absence data, it still has difficulty predicting the largest absence peaks. The analysis of the residuals reveals significant autocorrelation, suggesting that the model does not capture all the temporal patterns present in the data, which points to the need for a more sophisticated model that can account for temporal dependence and atypical events. In addition, the distribution of residuals presents an asymmetry, indicating large discrepancies between the true and adjusted values at some specific points in time. This asymmetry suggests the presence of atypical events or regime shifts that the Holt-Winters Additive model cannot capture.

In conclusion, although the Holt-Winters Additive model represents an improvement over the SES model, especially in capturing seasonality and trend, it still has limitations in predicting absence peaks. The use of more advanced models and an in-depth analysis of atypical events can contribute to improving the accuracy of forecasts and support absence management within the organization.

Analysis of Prediction Plots and Residuals of the Multiplicative Holt-Winters Model

The graph shows the projection of the multiplicative Holt-Winters model for Absenteeism at Apex-Brasil, as shown in Figure [13]. The analysis of forecast versus actual data using the Multiplicative Holt-Winters model provides a detailed view of the components of the model in relation to the absence data. The black line in the graph represents the actual data on total minutes of absence. The different components of the model are represented by colored lines: the level is indicated by the magenta line, the seasonality by the green line, and the trend by the cyan line. The values adjusted by the model, called "xhat," are represented by the blue line, while the blue shaded area around the forecast illustrates the confidence interval, providing a margin of uncertainty around the predicted values.

Forecast Chart (Holt-Winters Forecast Multiplicative):

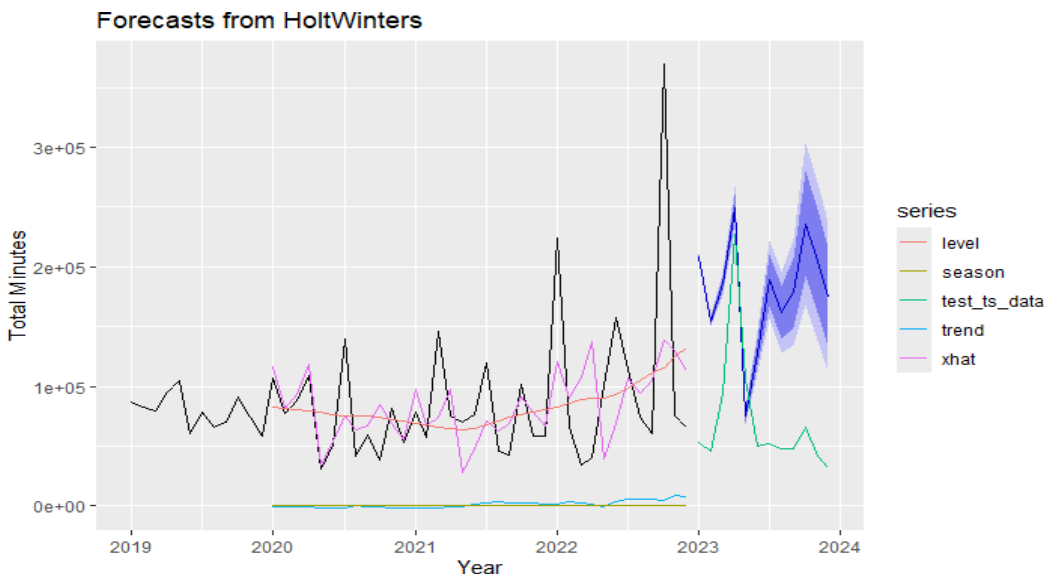

Figure 13*:* Forecast Holt-Winters - Multiplicative

In terms of performance, the Holt-Winters Multiplicative model seeks to capture both seasonality and trends in the data, providing a forecast with greater variability that attempts to reflect some of the peaks observed in the real data. However, there is still a significant underestimation of the highest peaks, indicating that, although the model captures part of the data behavior, it still has limitations when predicting the most intense periods of absence.

Considering the analysis of the model's residuals, we have Figure [14], where the analysis of the residuals of the Holt-Winters Multiplicative model over time highlights some limitations in fully capturing the absence peaks.

Residuals Chart (Holt-Winters Multiplicative Residuals)

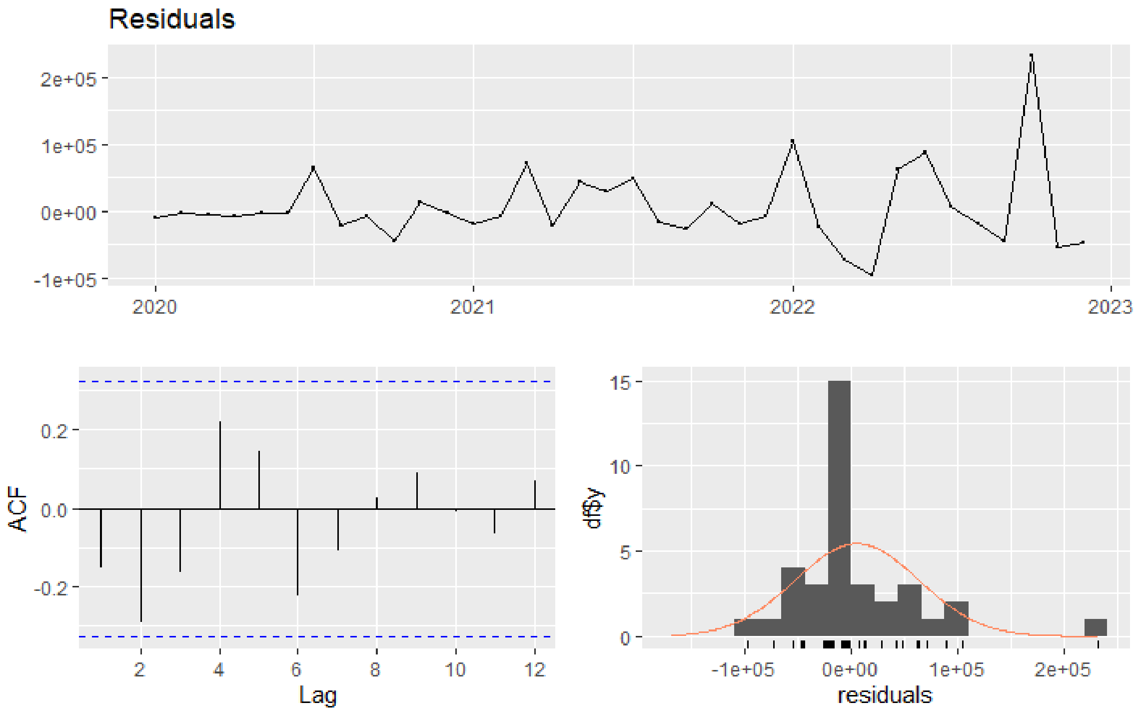

Figure 14: Holt-Winters - Multiplicative Residuals

The upper graph, which shows the residuals over time, shows large variations in peak periods, indicating that the model is unable to adequately represent these extreme absence events. The residual autocorrelation (ACF) plot reveals the correlation of the residuals at different lags and shows significant peaks at some lags, suggesting that the residuals are not completely random and that certain temporal patterns remain uncaptured by the model.

In addition, the histogram of residuals displays an asymmetric distribution, with a long tail on the right, signaling the presence of high positive residual values. This pattern indicates that the model tends to underestimate the true values at some points, especially during high absence events. These results suggest that, although the Multiplicative Holt-Winters Model captures some of the structure of the data, it still has difficulty adequately predicting peaks and extreme variations.

The interpretation of the results of the Multiplicative Holt-Winters Model points to some limitations in its ability to capture the full complexity of absence data. Although the model strives to capture seasonality and trend, it still struggles to represent the largest absence peaks. The presence of significant autocorrelation in the residuals suggests that the model is not capturing all temporal patterns, indicating the need for a more sophisticated model capable of dealing with temporal dependence and atypical events. In addition, the asymmetry in the distribution of residuals, evidenced by large discrepancies between the real and the fitted values at some points, suggests the occurrence of atypical events or regime changes that the Holt-Winters Multiplicative model cannot capture. These factors reveal the importance of exploring more advanced alternatives to improve forecast accuracy.

Comparison with the Holt-Winters Additive and Multiplicative Models, both models attempt to capture seasonality and trend in the data. However, the multiplicative model may be more appropriate when the seasonal variation is proportional to the level of the series. In overall performance, both models have limitations in capturing absence spikes, but the multiplicative model can provide a better understanding of proportional seasonality.

The Holt-Winters Multiplicative model provides a detailed understanding of proportional seasonality and trend in absence data. However, like the additive model, it has limitations in predicting absence spikes. Using more advanced models and detailed investigation of outliers can help improve forecast accuracy and absence management in the organization.

Analysis of ARIMA Model Prediction and Residual Graphs

The graph in Figure [15] shows the forecasts of Absenteeism Minutes from the Auto- ARIMA (0,0,0) model with a non-zero mean. The analysis of the forecast versus the actual data using the Auto-ARIMA (0,0,0) model with a non-zero mean reveals an attempt to fit the historical absence data. In the graph, the black line represents the actual data of the total absence minutes, while the red line shows the values adjusted by the Auto-ARIMA model.

Forecast Chart (Auto-ARIMA Forecast):

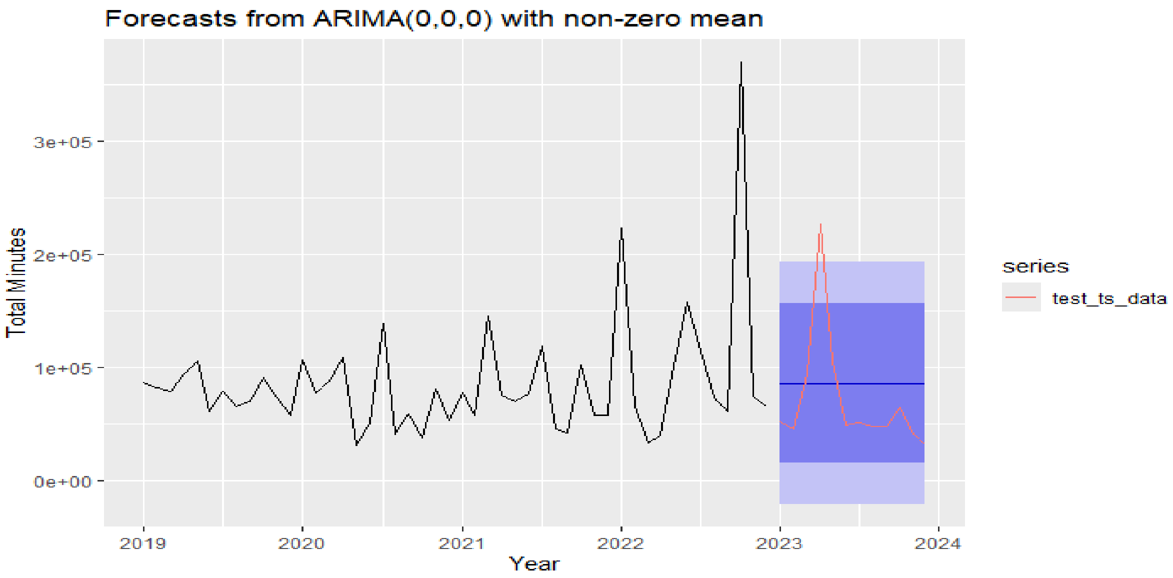

Figure 15: Forecast Auto-Arima

The blue shaded area around the forecast indicates the confidence interval, providing an estimate of uncertainty for the predicted values. In terms of performance, although the Auto- ARIMA (0,0,0) model is able to roughly align with historical data, it significantly underestimates the absence peaks, especially the large peak observed in 2023. The forecast remains at a relatively constant level, unable to capture the variability present in the actual data, which suggests that this model is not ideal for series with high variability peaks.

The analysis of the ARIMA model residuals, as shown in Figure [16] over time, reveals limitations in adequately capturing the absence peaks. The top graph shows the residuals, de- fined as the differences between the actual values and the fitted values, with large variations especially in peak periods, indicating that the model does not represent these extreme events well.

Residuals Chart (ARIMA Residuals):

The residual autocorrelation (ACF) plot shows the correlation of the residuals at different lags and presents significant peaks at some of them, suggesting that the residuals are not purely random and that there are temporal patterns that the ARIMA model cannot capture. In addition, the histogram of the residuals reveals an asymmetric distribution, with a long tail on the right, which indicates the presence of large positive residual values. This pattern suggests that the model tends to underestimate the real values at certain points, reinforcing the need for a more robust model to adequately capture the variability in the absence data.

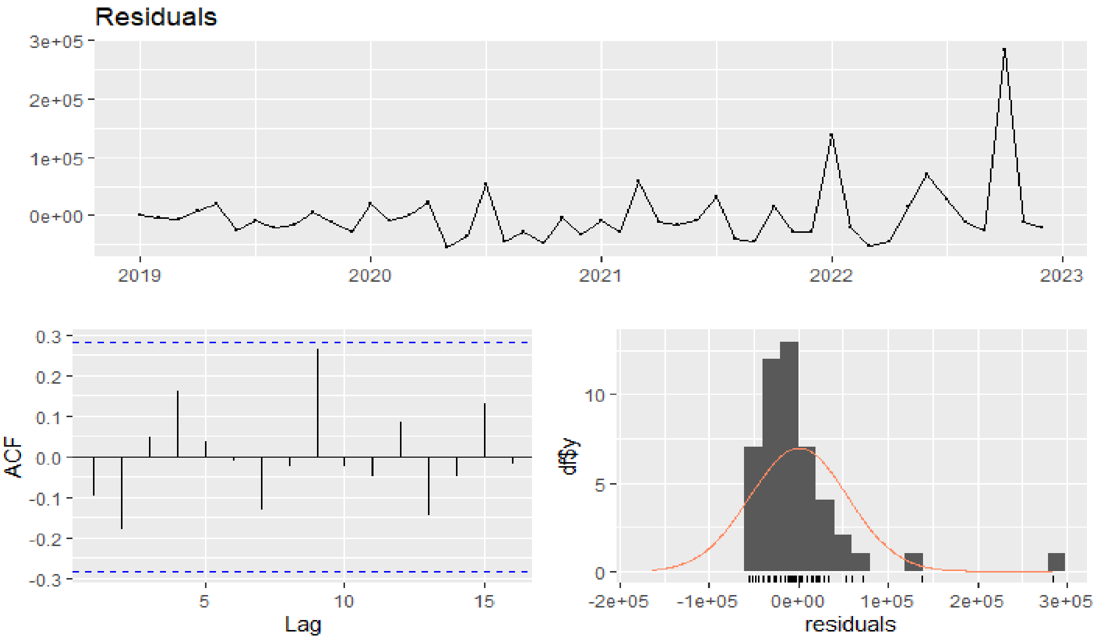

Figure 16: Auto-Arima Residuals

The interpretation of the results of the ARIMA (0,0,0) Model reveals significant limitations in capturing the absence peaks, with a marked underestimation of the real values in periods of high absence. This behavior is evidenced by the large positive residuals and by the forecast that remains constant, without reflecting the variability of the data. The presence of autocorrelation in the residuals indicates that the model does not capture all the temporal patterns, suggesting the need for a more complex model that takes into account temporal dependence and seasonality. Furthermore, the asymmetry in the distribution of residuals, marked by discrepancies between the actual and adjusted values at certain points in time, suggests the occurrence of atypical events or regime changes that the ARIMA model cannot capture.

In summary, the ARIMA (0,0,0) model with a non-zero meaning provides an initial basis, but it is not sufficient to capture the complexity and variability of absence data. The use of more advanced models and an in-depth analysis of atypical events can contribute to improving the accuracy of forecasts and facilitating more effective management of absences in the organization.

Analysis of SARIMA Model Prediction and Residual Graphs

Below is the projection of Absenteeism Minutes from the SARIMA (1,0,2) (0,1,2) Model,

as shown in Figure [17]. The analysis of forecast versus actual data using the SARIMA (1,0,2) (0,1,2) model with drift shows an improved fit in capturing the seasonality and variability of absence data.

Forecast Chart (SARIMA Forecast):

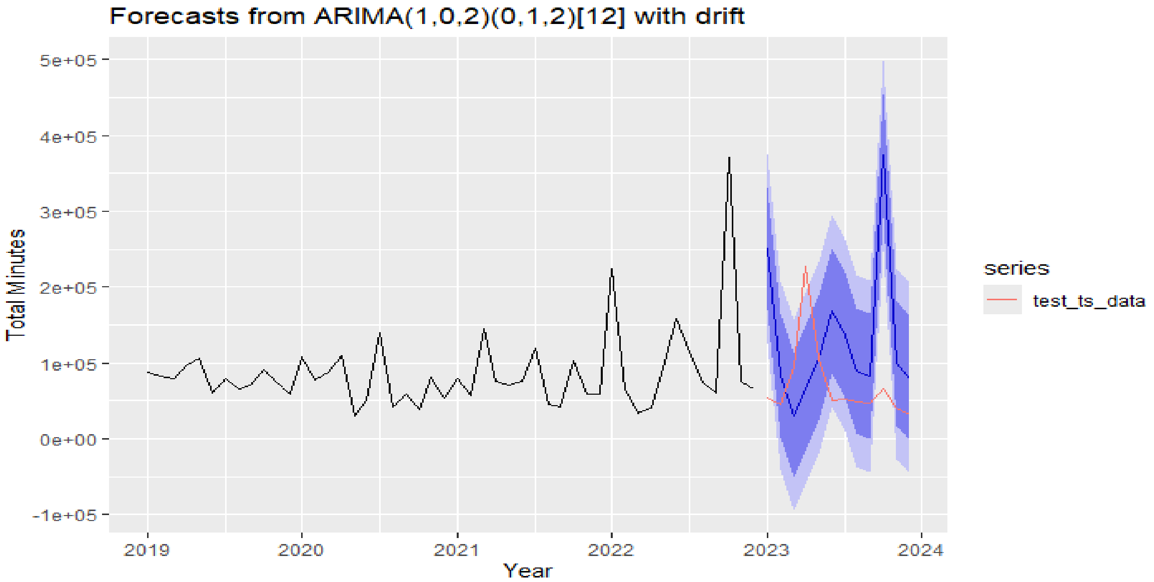

Figure 17: Forecast SARIMA

In the graph, the black line represents the actual data on total absence minutes, while the red line indicates the values fitted by the SARIMA Model. The blue shaded area around the forecast represents the confidence interval, providing a margin of uncertainty for the predicted values. In terms of performance, the SARIMA Model demonstrates a superior ability to reflect the seasonality and variability of the data compared to previous models. Although it still underestimates some absence peaks, it fits better to seasonal and historical patterns, providing a prediction that is more faithful to the behavior observed in the data.

The analysis of the residuals of the SARIMA Model, given Figure [**??**] and over time, shows improvements in the fit to the absence data. In the top graph, which presents the residuals over time, a reduction in extreme variations can be observed compared to previous models, indicating a more accurate fit to the historical data. The residual autocorrelation (ACF) plot reveals that most of the lags are within significant limits, suggesting that the residuals are closer to being random, although there are still some significant peaks.

Residuals Chart (SARIMA Residuals):

Regarding the distribution of residuals, the histogram shows a more symmetric distribution compared to previous models, despite a slight right tail, which indicates the presence of some high positive residual values. These results show that the SARIMA Model provides a better capture of the structure of the data, although there are still small discrepancies in periods of high absence.

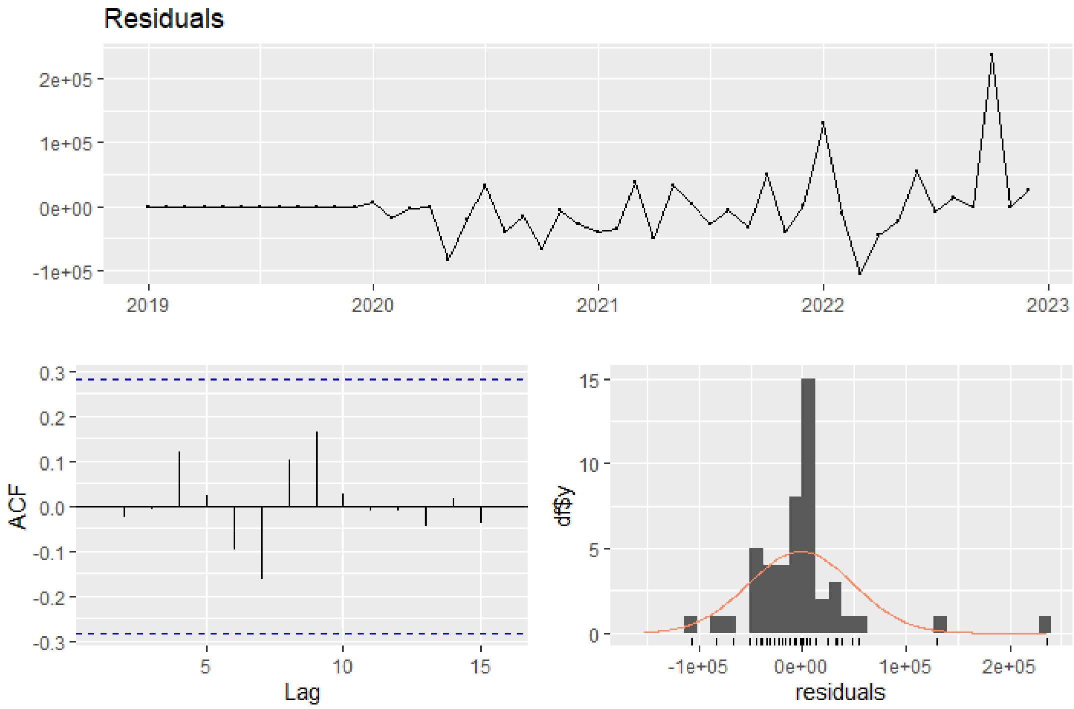

Figure 18: SARIMA Residuals

The interpretation of the results of the SARIMA Model highlights significant improvements in capturing the seasonality and variability of the absence data. The model fits more accurately the patterns observed in the historical data, reflecting an improved capture of seasonality. The analysis of the residuals shows a reduction in extreme variations, indicating that the SARIMA Model can better represent the underlying patterns of the data. In addition, the reduced presence of significant autocorrelation in the residuals suggests that the model captures more of the temporal patterns, although there may still be room for refinement.

The distribution of residuals is more symmetrical, which indicates an improved performance of the model, although the presence of some extreme residual values points to atypical events or possible regime shifts that have not yet been fully captured. In conclusion, the SARIMA model with bias offers a substantial improvement over previous models in capturing the seasonality and variability of absence data. However, to further improve forecast accuracy and absence management, additional adjustments and in-depth investigation of outlier events may be required

Forecast Model Comparison Table Analysis

Table [1], which compares the results of different forecasting models using three metrics: RMSE (root mean square error), MAE (mean absolute error), and MAPE (mean absolute percentage error).

The comparison of the forecasting models reveals that Simple Exponential Smoothing (SES) provides a good fit to the data, presenting low RMSE and MAE values, as well as a relatively low MAPE, which indicates modeling accuracy. The Holt-Winters Additive model, on the other hand, presents significantly higher errors than SES and Auto.ARIMA, suggesting that it has difficulty in adequately capturing the seasonality and trend of the data

Table 1
Comparison of Time Series Projection Models

Model	**RMSE**	**MAE**	**MAPE**
SES	53126.04	42531.73	0.71
Holt-Winters Addition	117785.67	108581.11	2.23
Holt-Winters Mult	121463.48	112116.55	2.25
Auto.ARIMA	53124.65	42529.18	0.71
Custom SARIMA	127503.54	96057.94	1.60

The Holt-Winters Multiplicative model shows even more errors, indicating that it is not suitable for this dataset. Auto.ARIMA, with almost identical performance to SES, stands out as one of the best options for forecasting, while the SARIMA model, although superior to the Holt-Winters models, still presents larger errors than SES and Auto.ARIMA, suggesting that it is not the best choice for this case.

It is recommended to consider additional adjustments or the integration of external factors to increase the accuracy of the models. Furthermore, an analysis of specific periods with high residuals can provide valuable insights to improve modeling and forecasting. Detailed analysis points to the superiority of the SES and Auto.ARIMA models, with Auto.ARIMA emerging as the best choice for absence forecasting in this dataset.

5. Discussion

The results show that time series projection can improve efficiency in human resources planning but requires continuous monitoring and periodic adjustments. In the forecasting experiment, the SES and Auto.ARIMA models are the most effective for the dataset used, although they have limitations, with Auto.ARIMA slightly better, given the lower values of RMSE, MAE and MAPE. The Holt-Winters (additive and multiplicative) and SARIMA models have significantly higher errors and are therefore less recommended for this analysis.

6. Conclusion

It is possible the prediction of employee absences, considering licenses and certificates, anticipating occupational health and safety actions to mitigate this impact. Model learning and experiment results demonstrated that clustering, classification and prediction models meet the challenge of implementing People Analytics in an organization. Using absenteeism data, it is possible to analyze and propose the segmentation of employees, their classification and the visualization of the projection over time. It is recommended to break down absence values by type to provide a more detailed view of employees.

To improve Forecasting Models, it is recommended to test other time series approaches, such as Prophet or models based on neural networks (LSTM), to improve forecast accuracy. In addition to performing a seasonal decomposition analysis to better understand the seasonal and trend components of absence data.

HR professionals should perform a sentiment analysis on employee feedback or comments to identify possible correlations with absence patterns and implement a continuous monitoring system to analyze absence data in real time, allowing for proactive adjustments and interventions.

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