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Medicine demand forecasting: An assessment of a private hospital in Pernambuco

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Abstract

The efficient management of materials in the healthcare sector is crucial to avoid interruptions in the treatment of hospitalized patients, especially when demand is unpredictable and based on criteria of criticality, urgency and clinical status. In complex hospital environments with high-cost materials, demand forecasting becomes essential. This study aimed to compare demand forecast models for medicines used in the urgency and emergency sector of a private hospital in the Agreste Pernambucano. The methodology involves the selection of items and data collection using the company's information system. The ABC analysis identified 27 highly relevant drugs, and different models were tested, including experience-based parameters and hyperparameter optimization. The forecasts covered the period from January to November 2023. The results indicated the Holt-Winters Additive model as most suitable for 21 medications, Holt-Winters Multiplicative for 3, and ARIMA for the others, standing out for its precision. This study strengthens decision-making in the management of medication stocks, improving demand management and ensuring continuous treatments for patients.

Keywords

Demand forecasting, time-series analysis, medicines, inventory management.

1. Introduction

Healthcare organizations, specifically hospitals, perform an essential role which can directly affect the population's life expectancy (Enami, 2021). In this process, pharmaceutical assistance plays a crucial role, as a bottleneck found in the forecast of demands in this area, can lead to a tragedy, and can even cost a patient's life. It is a fact that hospital managers need to make resource allocation decisions every day, even in times of uncertainty, as ensuring service delivery is the core activity of these organizations. In general, it is possible to observe that the predictions of these demands are carried out without the support of a formal method, simply based on empiricism and the experience of managers (Enami, 2021).

In this context, Neto & Filho (1998) states that medicines have great impact on logistics management, given that they are items of high importance for the process of basic care for patients in a hospital unit. Given the high number of products with varied demand behavior patterns and inherent peculiar characteristics medicines, the need for differentiated control increases (Santos & Rodrigues, 2006). Therefore, time series models prove to be an excellent tool to predict demands and assist managers in their planning and control. According to Nielsen (2021) time series analysis leads us to understand statistical information from data points from a chronological order, given their temporal characteristic, in order to understand past events to predict future behaviors.

Furthermore, it is important to highlight the urgent nature of the care provided by a hospital unit, given that a failure or lack of medication may result in the loss of a patient's life. Therefore, when talking about medicines dispensed in the urgency and emergency sector of a hospital unit, use methods and techniques that enable the managing and forecasting demand in the most accurate way possible is necessary and essential. It should be noted that it is with this data that senior management is able to outline the better purchasing, acquisition, distribution strategies, etc.

Taking into account that an estimate of future demand is fundamental and essential in the daily lives of organizations, this work aims to test the different demand forecasting models applied specifically to 27 different medicines that were selected based on the ABC curve, dispensed exclusively in the urgency and emergency of a private hospital unit, located in the interior of Pernambuco. In addition to this introductory section, the article is organized as follows: section 2 presents a theoretical review of demand forecasting. Section 3 describes the proposed method, whose results are presented in section 4. Finally, section 5 closes the study with the conclusions and suggestions for future work.

2. Theoretical Reference

2.1. Demand Forecast

Demand forecasting is of fundamental importance in any organization, as it can provide information that supports the company's planning and control in its several departments (Ballou, 2006). With this thought, it is healthy to imagine that the Demand forecasting is essential for planning in all organizations. It should be noted that demand forecasting seeks to capture information from its processes about the forward value of an item or set of items (Moreira, 2008; Fang; Wang & Yan, 2020).

Demand forecasting methods can be grouped into qualitative and quantitative, or a combination of both. According to Kotler & Keller (2012), qualitative methods they are used in problems where there is no historical data available to make predictions. In these cases, qualitative methods include scenario analysis, opinions and judgments personnel, market research, etc. At the other end, quantitative methods are those in which historical data is processed to arrive at an optimal demand forecast method (Kotler & Keller, 2012). Selecting a demand forecast model is a primary task and must be based on specific and similar situations, as the result presented by the method allows organizations to direct their production, inventory and purchasing plans, seeking to minimize errors and meeting the demands (Cecatto & Belfiore, 2015).

Furthermore, it should be mentioned that demand forecasting involves a process, in which according to Lustosa, Mesquita & Oliveira (2008), the first step is the identification of the object that if you want to forecast, along with the items that will make up the forecast. The next step, as recommended by Lustosa, Mesquita & Oliveira (2008), is the choice of approach, be it quantitative, qualitative or both. Finally, it is necessary to select the forecasting method that will be used in the problem (Lustosa; Mesquita & Oliveira, 2008).

The literature encompasses several different models that were used to describe the behavior of a particular series. These models were constructed from several factors, such as: behavior of the phenomenon, nature, object of analysis, etc. Demand forecasting models is an area that has attracted attention in recent decades, for example of the works of (Albrecht *et al*., 2019; Makridakis, Hyndman & Petropoulos, 2020; Parmezan, Souza & Batista, 2019; Haq *et* al., 2021; Zhu, Jaarsveld & Dekker, 2020). In the midst of this scenario, an important quantitative methodology for forecasting of demand are the time series, which will be discussed below.

2.2. Time Series

Karlin (2014) defines time series as the single realization of a stochastic and godic process, that is, when just the realization of a single process is enough to characterize it. We can also understand time series as "a set of ordered observations in time and that present serial dependence, that is, dependence between instants of time" (Enami, 2021).

Time series still have some characteristics, such as seasonality, cycle and trend (Corrar & Theophilo, 2008; Fernandes & Filho, 2010). It is possible that some variations may exist and that these will not fit into any of the characteristics described previously, therefore, it can be considered a randomness or irregularity, normally caused by the environment. Therefore, when choosing a model of time series, the behavior of the problem data must be taken into account (Assumpção & Rosa, 2022). Then, the prediction technique is designed from the behavior and monitoring of your generated forecasts, as well as through confirmation of validity and accuracy with historical data (Fernandes & Filho, 2010).

As mentioned, there are several models for forecasting demands and for this, it is necessary to carry out statistical analyzes of the data, in order to identify the most peculiar characteristics of the problem data. Next, some models will be discussed demand forecasting available in the literature.

2.3. Demand Forecasting Models

Forecasting demand levels is a primary and extremely important activity for all organizations, given that it provides basic input information for planning and control of all areas of the company. To do this, use a formal method to predict the demand appears to be an essential and highly important alternative.

The Simple Moving Average (MMS) is a common model and widely used in organizations in general, mainly due to its simplicity and because it requires little historical data (Corrar & Theophilo, 2008). It is noteworthy that the MMS is suitable for short-term forecasting problems, in which the trend and seasonality can be ignored or simply ignored.

The Weighted Moving Average (MMP) is also a simple demand forecast model, with greater flexibility than the MMS, which requires the attribution of different weights to the values of the time series (Corrar & Theophilo, 2008). The weights are distributed exponentially, with more recent values receiving greater weights and more recent weights old ones with lower weights. From the exponential smoothing of the MMP it is possible generate forecasts for future periods, as long as the effect of the trend is small or non-existent. As can be seen, even though it is simple and flexible, MMP has limitations for identify more complex patterns in a time series.

It is also possible that the series of the problem in question has volatility and to deal with Therefore, Simple Exponential Smoothing (SES) techniques are an excellent alternative (Morettin & Toloi, 2018). SES techniques admit that these extreme values of the series temporal values are random and, therefore, they use methods to smooth these values in order to identify patterns.

On the other hand, the Holt-Winters model incorporates seasonality and trend into its calculations and is considered an extension of the Holt model, which captures seasonal fluctuations that happen regularly over a given period of time. This method involves applying of three equations to estimate the level, trend and seasonality of a time series. This one model is widely used in various fields, such as sales forecasting, energy demand, climate forecast, etc (Hyndman & Athanasopoulos, 2018). This technique is one of the more powerful for modeling time series with seasonality.

The Autoregressive Integrated Moving Average (ARIMA) model consists of a time series forecasting that combines autoregressive linear regression (AR) with moving average (MA) and differencing, to make the time series stationary. Areas such as finance, economics, engineering and social sciences use this method very rigorously to predict time series (Box & Jenkins, 1970). The Seasonal Autoregressive Integrated model Moving Average (SARIMA) is an extension of the ARIMA model, which considers seasonality of series allows the forecasting of seasonal time series. Brockwell & Davis (2016) discuss that the SARIMA model takes into account seasonal differences and seasonal AR components and MA.

2.4. Forecast errors

Demand forecast errors are composed of the relationship between the forecast value and the actual level of estimated demand. It is possible that the values discovered for the future will not be fully mirrored by past data and therefore the demand forecast may contain errors at some level (Ballou, 2006). Such errors can assume positive or negative values and there is also the possibility of them canceling each other out, bringing their sum to zero.

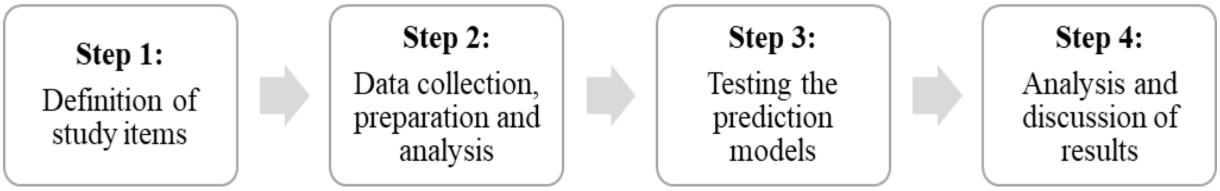
In order to avoid these problems, several ways of calculating the sum of these errors have been developed and can be selected to compare the performance of different demand forecast models. The most common criteria are:

- Mean Square Erro (MSE);
- Rout Mean Square Erro (RMSE);
- Mean Absolute Deviation (MAD);
- Mean Absolute Percentual Erro (MAPE).

3. Methodology

This work was developed at the Pharmaceutical Supply Center (CAF) of a private hospital in the city of Caruaru, Pernambuco. Unimed Caruaru Hospital (HUC) has more than 417 cooperating doctors divided into 45 specialties and more than 80 thousand customers. Its area of activity covers more than 50 cities in Pernambuco. The HUC CAF is responsible for ensuring the supply, distribution, access, control, traceability and rational use of medicines and materials, including medicines dispensed to the urgency and emergency sector for use by patients receiving care at the hospital. It is worth noting that the CAF operates 24 hours a day, dividing work shifts into two 12-hour shifts, with 36 hours off, better known as a 12x36 shift. The research method of the work consists of four stages as shown in Figure 1.

Figure 1: Study method steps



Source: Prepared by the authors (2023)

In stage 1, the demand for more accurate predictions related to the most commonly used medications in the hospital's emergency department was identified. This is due to the fact that this sector acts as the main entrance for patients and also records the greater volume of medication administration on a daily basis. Furthermore, when there is a advance knowledge about the quantity that will be consumed, greater power can be obtained negotiating with suppliers and consequently making more assertive purchases and exact time.

In stage 2, data was collected through the company's information system, obtaining the monthly consumption report by product from January 2019 to December 2022, thus, analyzing this mass of data for the subsequent creation of the historical series in which the models were based. The output records of 620 different products were used, where 27 were chosen after classification and analysis of the ABC curve. At this stage, graphs of the real demands of the product under study, in order to detect seasonality, level, trend and cycle components. Statistical tests were also carried out in order to validate some hypotheses of the demands obtained.

Stage 3 included the application of demand forecasting methods of Simple Moving Average (MMS), Weighted Moving Average (MMP), Simple Exponential Smoothing (SES), Holt-Winters Additive and Multiplicative, ARIMA and SARIMA. The models were applied twice, using the parameters for the models in two ways, the first way random and the second using the Grid Search technique, with MMS being discarded the second time, because the only parameter used was the 3-day time window to start forecasting. At in a random manner, all parameters were defined based on the researchers' previous experience with demand forecast models. In the second, Grid Search was used, which is a hyperparameter optimization technique capable of testing all possible combinations in order of finding the best combination that maximizes the chosen evaluation metric. The choices of the parameters took into account the lowest information criterion Akaike Information Criterion (AIC) and Rout Mean Square Error (RMSE) found during search and optimization. The models were developed and integrated in Python, using Visual Studio Code.

Finally, in step 4, the applied models were analyzed in order to identify the model that predicts with greater accuracy, where the Mean Absolute Percentage was selected at the time Error (MAPE), given its advantages of independence of scales and interpretation.

4. Results

From the analysis of medication dispensing data, it is evident that the time series show multiple fluctuations over time. To assess the stationarity of the data and allow the use of appropriate models, a statistical test, the ADF test, was performed using a significance level of 0.05. The results found for the product demands can be seen in Table 1.

Table 1: ADF test results

Product	P-value	Product	P-value	Product	P-value	Product	P-value
P1	0.008123	P8	7.22E-02	P15	0.126600	P22	0.002087
P2	0.011948	P9	0.110156	P16	0.000994	P23	0.017362
P3	0.065359	P10	0.301375	P17	0.002079	P24	0.016038
P4	0.471020	P11	0.070204	P18	0.747887	P25	0.115028
P5	0.000151	P12	0.401483	P19	0.075419	P26	0.128720
P6	0.000217	P13	0.220401	P20	0.003492	P27	0.002235
P7	0.009039	P14	0.937049	P21	0.355271	-	-

The values obtained indicated that the demands for products P3, P4, P9, P10, P11, P12, P13, P14, P15, P18, P19, P21, P25 and P26 do not accept the null hypothesis, that is, they are considered non-stationary. On the other hand, the demands of the other products reject the null hypothesis, indicating that they are stationary

Table 2: ADF test results – 1 differentiation

Product	P-value	Product	P-value	Product	P-value
P3	4.35E-03	P12	0.000001	P19	0.004617
P4	0.223437	P13	4.49E-04	P21	0.002047615
P9	7.15E-05	P14	5.55E-02	P25	4.77151E-16
P10	0.000028	P15	7.25E-03	P26	1.46374E-06
P11	0.009186	P18	0.086731	-	-

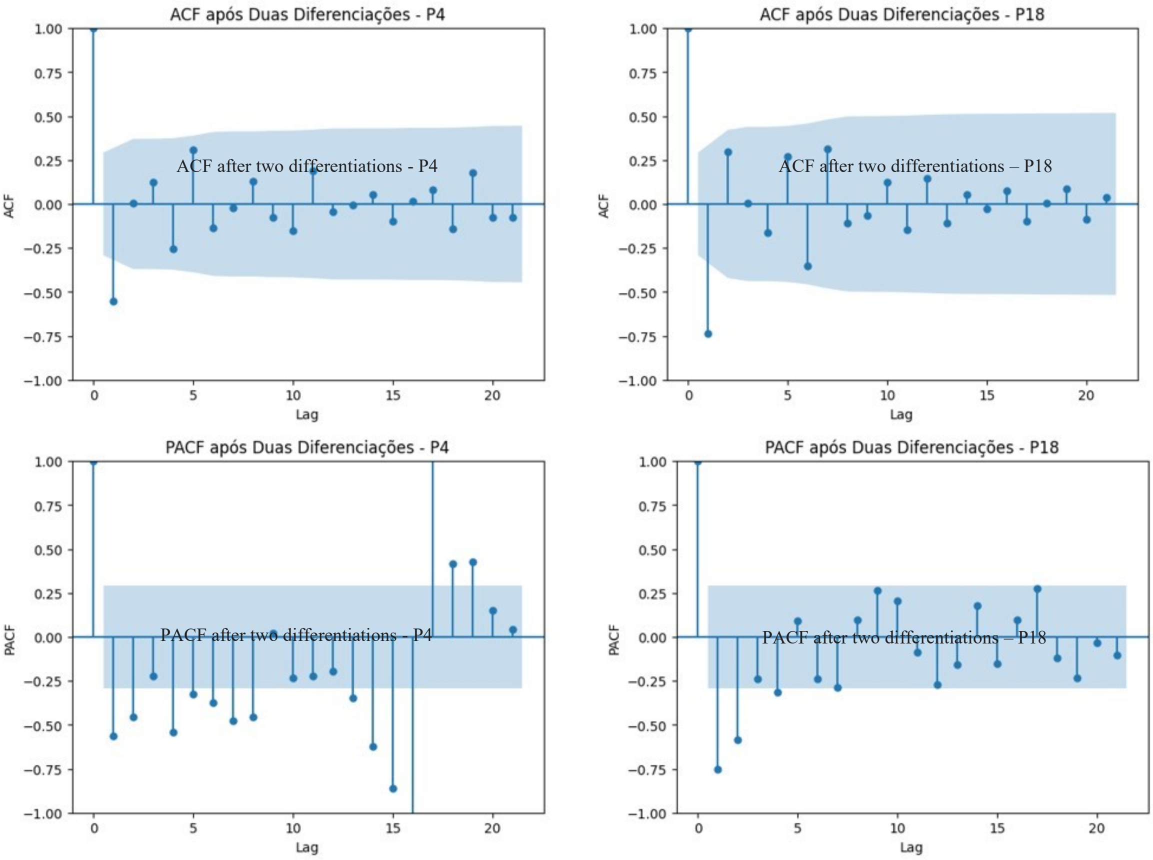
To confer stationary properties to the previously non-stationary demand data, a transformation procedure was performed, which included the application of differentiation methods and Box-Cox transformation. Subsequently, a new assessment The stationarity of the transformed data was carried out using the ADF test. The results arising from this stage, subsequent to the application of the first differentiation operation, are shown in Table 2. The analysis demonstrates that only the series corresponding to products P4 and P18 have not yet demonstrated stationary properties, therefore implying the need to apply an additional differentiation operation. After application of this second differentiation operation, it was observed that stationarity was obtained in the seriesreferring to the two aforementioned products, as illustrated in Table 3.

Table 3: ADF test results – 2 differentiations

Product	P-value	Product	P-value
P4	1.11E-06	P18	1.65E-03

Figure 2 confirmed that the data were stationary, which was corroborated by the ACF and PACF charts corresponding to the products. With stationary data, it was possible continue with the application of forecasting models.

Figure 2: ACF and PACF of P4 and P18



After stationarizing all data series, all data series were applied.the proposed models. These models were implemented with parameters selected from in a random manner, with the purpose of obtaining initial results and subsequent evaluation of their values. After obtaining these preliminary results, we proceeded to identify the most effective models for each product, as detailed in Table 4.

Table 4: Best models and associated errors

Product	Model	MAPE	Product	Model	MAPE	Product	Model	MAPE
P1	Winter-Add	18.78	P10	Winter-Add	10.19	P19	Winter-Mul	24.91
P2	Winter-Mul	14.20	P11	Winter-Add	16.46	P20	Winter-Add	17.56
P3	ARIMA	20.28	P12	Winter-Mul	16.33	P21	Winter-Mul	14.96
P4	Winter-Add	14.74	P13	Winter-Add	24.64	P22	Winter-Add	15.97
P5	Winter-Add	16.21	P14	Winter-Add	23.63	P23	Winter-Mul	22.81
P6	Winter-Add	12.47	P15	Winter-Add	24.03	P24	Winter-Mul	18.71
P7	Winter-Add	36.58	P16	Winter-Add	16.64	P25	Winter-Add	9.31
P8	Winter-Add	13.24	P17	Winter-Add	19.52	P26	Winter-Add	14.80
P9	Winter-Mul	16.83	P18	Winter-Add	13.71	P27	Winter-Add	19.89

In addition to selecting the optimized models, the percentage discrepancies between the generated forecasts and the observed demands for the respective period were also assessed. The specific values of the constant parameters used in each selected model were set to [0.3, 0.1, 0.1], representing, respectively, the parameters associated with the level, trend and seasonality. As far as the ARIMA model is concerned, the coefficients [1, 1, 1] were used for the values of parameters p, d and q.

Subsequently, the Grid Search technique was used, which consists of carrying out a search systematically and exhaustively in a pre-defined search space to find the best hyperparameters of the models. This technique consists of carrying out a systematic search for a grid of previously defined parameter values for each model. To implement the methodology, a continuous interval was adopted in the domain of values between 0 and 1. The discretization of this interval was carried out in increments of 0.01, 0.05 and 0.1 for the different models, namely, Weighted Moving Average (MMP), Smoothing Simple Exponential (SES), Holt and Holt-Winters. In the case of ARIMA and SARIMA models, the exploration of the parameter space covered only the components p, d and q, with the pertinent values derived from the sets [5, 2, 5] and [10, 2, 5].

The temporal results acquired during the exploration of each model were organized in a tabular format, as presented in Table 5. This meticulous search aimed at identification of optimized parameters can be conceptualized as a component of significant importance in the context of obtaining predictions characterized by high accuracy and efficiency. Consequently, this approach strengthens the foundations underlying the decisions assertive decision-making.

Table 5: Model Search Time by Interval

Interval	MMP	SES	Holt	Holt-Winters	ARIMA	SARIMA
(0, 1, 0.01)	9m7s	12,8s	15,50s	343m23s	4m9s	236m53s
(0, 1, 0.05)	32s	5s	1m20s	101m14s	2m42s	157m26s
(0, 1, 0.1)	13s	3s	16s	9m1s	59s	70m

After determining the optimal forecast parameters for each interval defined with in relation to each product, a subsequent step involved carrying out additional projectionsdemand, with the aim of capturing the results arising from the implementation of theseidentified parameters. Subsequently, a thorough analysis was conducted to evaluate the outstanding results obtained, accompanied by a meticulous evaluation of the confidence intervals associated with the models adopted. The models that demonstrated the most promising models, categorized as the best models, are summarized in Table 6.

Table 6: Best models with best parameters and associated errors by product

Product	Model	MAPE	Increment	Best_Param	Product	Model	MAPE	Increment	Best_Param
P1	Winter-Add	18.78	0.05	(0.96, 0.96, 0.96)	P15	Winter-Add	24.03	0.05	(0.96, 0.96, 0.96)
P2	Winter-Add	14.20	0.05	(0.96, 0.96, 0.96)	P16	Winter-Add	16.64	0.05	(0.96, 0.96, 0.96)
P3	ARIMA	20.28	0.01	(3, 0, 4)	P17	ARIMA	19.52	0.01	(4, 0, 4)
P4	Winter-Add	14.74	0.05	(0.96, 0.96, 0.96)	P18	Winter-Add	13.71	0.05	(0.01, 0.01, 0.01)
P5	ARIMA	16.21	0.05	(2, 0, 1)	P19	Winter-Add	24.91	0.05	(0.96, 0.96, 0.96)
P6	Winter-Add	12.47	0.1	(0.91, 0.91, 0.91)	P20	Winter-Add	17.56	Normal	(0.3, 0.1, 0.1)
P7	Winter-Add	36.58	Normal	(0.3, 0.1, 0.1)	P21	Winter-Add	14.96	0.05	(0.96, 0.96, 0.96)
P8	Winter-Add	13.24	Normal	(0.3, 0.1, 0.1)	P22	Winter-Add	15.97	Normal	(0.3, 0.1, 0.1)
P9	Winter-Mul	16.83	0.1	(0.91, 0.01, 0.01)	P23	Winter-Mul	22.81	0.05	(0.66, 0.01, 0.01)
P10	Winter-Add	10.19	0.05	(0.96, 0.96, 0.96)	P24	Winter-Add	18.71	0.1	(0.66, 0.01, 0.01)
P11	Winter-Add	16.46	0.05	(0.96, 0.96, 0.96)	P25	Winter-Add	9.31	Normal	(0.3, 0.1, 0.1)
P12	Winter-Mul	16.33	0.05	(0.96, 0.96, 0.96)	P26	Winter-Add	14.80	Normal	(0.3, 0.1, 0.1)
P13	Winter-Add	24.64	0.05	(0.96, 0.96, 0.96)	P27	Winter-Add	19.89	0.1	(0.31, 0.01, 0.01)
P14	Winter-Add	23.63	0.05	(0.96, 0.96, 0.96)	-	-	-	-	-

Through the evaluation of the optimal models derived from the application of the search method in grid (Grid Search) and models based on random parameter selection, was conducted an analysis aimed at identifying possible improvements in the accuracy metrics of these models. This assessment allowed the determination of the most appropriate models for each item under investigation, taking into account the results obtained in a new prediction phase. A Precision analysis revealed notable reductions in error values associated with the products listed in Table 8, in addition to investigating whether the models maintained their integrity or suffered some form of adjustment. On the other hand, Table 7 lists the scenarios in which the models do not were subject to any modification.

Table 7: Products without model change

Product	Previous model	Actual model	Reduction	Model comparison
P7	Winter-Add	Winter-Add	0.00%	Remains
P8	Winter-Add	Winter-Add	0.00%	Remains
P20	Winter-Add	Winter-Add	0.00%	Remains
P22	Winter-Add	Winter-Add	0.00%	Remains
P25	Winter-Add	Winter-Add	0.00%	Remains
P26	Winter-Add	Winter-Add	0.00%	Remains

With regard to the models used for each product, it is noteworthy that the Holt-Winters Additive has been successful in providing the most accurate estimates for forecasting of 21 different medicines. This success can be attributed to the characteristics of the products in exhibit seasonality of constant magnitude, which does not vary according to oscillations of the time series. This translates into the fact that the amplitude of seasonal variations remains invariable over time.

An additional aspect of notable interest lies in the observation that, among the group made up of the 21 medications listed previously, of the total, 12 items demonstrated values equal to your parameters. In this scenario, it can be assertively inferred that the search exploration approach of the Grid Search method gave considerable emphasis to the most important data recent, since the parameter values are close to 1.

Furthermore, it is essential to note that, as mentioned previously, the selection of parameters based on values close to 1 can considerably influence the reliability of predictions. This approach, which prioritizes the most recent data, can be especially appropriate in dynamic contexts, in which changes tend to occur frequently. However, it is worth highlighting the importance of a deeper analysis in order to assess the robustness and the generalization of these results in different scenarios. Furthermore, investigating the practical implications of this approach, both in terms of effectiveness and efficiency, constitutes a promising research topic for future investigation.

In contrast, medicines called P9, P12 and P23 demonstrated superior performance more accurate when submitted to the Multiplicative Holt-Winters model. This result suggests the possibility that the amplitude of seasonal variations in these products may be influenced by the level observed in the time series, that is, the magnitude of seasonal variations may increase or decrease in accordance with fluctuations in the level of the time series. In turn, drugs P3, P5 and P17 exhibited superior predictive performance when submitted to the ARIMA model. This result suggests the existence of an underlying pattern in sequential data, characterized by the presence of trend, seasonality and components of random variation.

Table 8: Products with improved accuracy

Product	Previous model	Actual model	Reduction	Model comparison
P1	Winter-Add	Winter-Add	3,69%	Remained
P2	Winter-Mul	Winter-Add	2,51%	Changed
P3	ARIMA	ARIMA	1,09%	Remained
P4	Winter-Add	Winter-Add	1,97%	Remained
P5	Winter-Add	ARIMA	0,62%	Remained
P6	Winter-Add	Winter-Add	0,74%	Remained
P9	Winter-Mul	Winter-Mul	0,50%	Remained
P10	Winter-Add	Winter-Add	1,68%	Remained
P11	Winter-Add	Winter-Add	4,36%	Remained
P12	Winter-Mul	Winter-Mul	307,00%	Remained
P13	Winter-Add	Winter-Add	4,24%	Remained
P14	Winter-Add	Winter-Add	4,00%	Remained
P15	Winter-Add	Winter-Add	4,00%	Remained
P16	Winter-Add	Winter-Add	3,90%	Remained
P17	Winter-Add	ARIMA	1,45%	Changed
P18	Winter-Add	Winter-Add	0,33%	Remained
P19	Winter-Mul	Winter-Add	5,17%	Changed
P21	Winter-Mul	Winter-Add	2,90%	Changed
P23	Winter-Mul	Winter-Mul	0,02%	Remained
P24	Winter-Mul	Winter-Add	0,26%	Changed
P27	Winter-Add	Winter-Add	0,18%	Remained

In Table 9 it is possible to observe the results of some of the drugs studied, as well as such as comparing their respective forecasts for the last four months, in addition to forecasts for the entire year 2023. In summary, the Holt-Winters Additive model was identified as the most suitable for 78% of medicines, presenting the best results in terms of accuracy. Those results provide valuable information for decision making regarding forecasting demand for the products investigated, allowing a more precise and efficient approach to inventory management and demand planning.

Table 9: Table of drug predictions

Data	P1	Winter-Add	P2	Winter-Add	P3	ARIMA	P4	Winter-Add	P5	ARIMA	P6	Winter-Add	P7	Winter-Add	P8	Winter-Add	P9	Winter-Mul
01/09/2022	2.472	2.276	2.014	1.936	2.079	2.147	1.567	1.604	799	748	627	657	685	558	526	518	504	552
01/10/2022	2.755	2.754	2.122	2.094	2.067	1.788	1.728	1.693	808	731	599	600	346	582	555	516	517	490
01/11/2022	3.098	3.055	2.245	2.114	1.990	1.490	2.012	1.970	905	739	595	569	198	338	479	824	510	535
01/12/2022	3.083	3.329	1.784	1.849	1.779	1.707	1.653	2.012	533	809	537	560	305	457	439	445	366	496
01/01/2023		2.619		2.097		2.095		1.034		536		522		652		430		331
01/02/2023		1.184		1.054		2.240		508		561		511		684		386		316
01/03/2023		2.250		1.715		1.951		566		600		507		463		421		366
01/04/2023		2.406		1.693		1.548		606		648		511		394		424		327
01/05/2023		2.533		1.821		1.505		469		698		521		415		448		351
01/06/2023		2.142		1.545		1.719		390		745		536		518		391		332
01/07/2023		1.210		1.017		1.739		161		787		553		408		382		319
01/08/2023		1.492		941		1.499		177		820		572		499		409		347
01/09/2023		1.661		1.114		1.359		132		844		589		531		420		349
01/10/2023		1.607		1.210		1.485		130		859		604		554		415		334
01/11/2023		1.734		1.334		1.622		127		865		616		315		568		345
01/12/2023		1.714		886		1.539		98		864		624		432		424		331

Data	P10	Winter-Add	P11	Winter-Add	P12	Winter-Mul	P13	Winter-Add	P14	Winter-Add	P15	Winter-Add	P16	Winter-Add	P17	ARIMA	P18	Winter-Add
01/09/2022	474	433	257	237	486	430	173	174	372	366	75	73	249	240	130	168	188	195
01/10/2022	480	470	327	318	543	561	206	187	443	422	92	79	246	256	217	179	132	195
01/11/2022	538	505	303	292	512	552	152	159	546	529	84	88	202	207	112	144	193	189
01/12/2022	479	453	322	313	391	431	123	135	488	597	105	96	240	206	170	152	157	182
01/01/2023		443		348		345		173		417		153		264		146		218
01/02/2023		394		327		438		205		433		95		217		116		199
01/03/2023		391		320		420		239		447		115		329		140		199
01/04/2023		423		330		371		266		450		152		411		115		171
01/05/2023		448		325		360		292		442		109		367		113		200
01/06/2023		440		321		389		234		427		162		407		135		182
01/07/2023		407		325		392		158		411		101		344		108		196
01/08/2023		381		324		353		167		395		154		357		133		213
01/09/2023		381		322		328		201		382		151		434		141		210
01/10/2023		400		323		349		132		371		252		441		126		209
01/11/2023		414		323		368		156		362		186		431		164		203
01/12/2023		408		323		343		178		354		271		476		153		196

5. Conclusions

The objective of this study was to establish a comparison between different models demand forecast for medicines that are dispensed to the emergency service and emergency, within a private hospital located in the Agreste region of Pernambuco. After a systematic evaluation of the results obtained, and a subsequent selection of the most appropriate for each of the 27 medications in question, it was identified that the Holt Winters Additive model was the most suitable for 21 medications, the Holt-Winters Multiplicative model proved to be suitable for 3 medications, and the remaining three medications were better predicted by the ARIMA model. These selected models are intended to be used in the CAF and in the Pharmacies of the researched hospital itself, with the purpose of optimizing the procedures related to the acquisition, dispensing and storage of the medicines under analysis.

The results obtained indicated that the Holt-Winters Additive model demonstrated a greater accuracy in predictions for 78% of the medicines considered. These results were obtained through the application of the Grid Search method, which allowed the identification of the most effective parameters for each model. These parameters were then compared with predefined values, generated randomly. Note, however, that Even after this analysis, six medications showed superior performance when parameters were determined by the researchers, even if in a reduced proportion. Nevertheless, the institution chose to adopt the selected models, seeking to assess whether the discrepancies and accuracy of the forecasts were in line with the projections provided by the higher performance model.

It is important to highlight some limitations of this research, which restricted its attention to one specific sector within a single hospital. However, it is pertinent to emphasize the relevance of future research that can explore the generalization of the results obtained in this study to other hospital institutions in the same region. Furthermore, it would be beneficial to conduct a comprehensive assessment of models across all medicines to understand the behavior of their respective demands.

Future research could target alternative forecasting techniques and more robust models sophisticated, as well as incorporating additional variables of relevance in order to increase the forecast accuracy and optimize supply chain management. It is, moreover, plausible to examine the effectiveness and complexity involved in the search for hyperparameters, since certain values in the search space may present subtle or insignificant differences in relation to the pre-defined intervals. Furthermore, the feasibility of investigating the effectiveness and effort associated with the application of hyperparameter search techniques is considered, notably with regard to refers to the discrepancy observed in certain values in the search space, where variations in the intervals 0.01 and 0.05 they showed reduced or insignificant divergence. This implies also assess whether the time spent determining these parameters has an impact positive in the forecasting process. Furthermore, the possibility of optimizing and standardizing medication quotas or using dispensing systems in the unit is considered, in order to reduce the volume of stock and increase the accuracy of forecast estimates.

Conflict of Interest Declaration

The authors have no conflicts of interest to declare.

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