New Approaches in Time Series Analysis: Health Data Application

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ABSTRACT: *It is important to analyze and interpret health data correctly. In particular, data analysis methods can make future predictions with statistical methods while also profiling the data. Estimation of the number of patients, especially in the field of health, is important for the hospital to provide quality health care to the patient and to ensure patient and health personnel satisfaction.*

In this study, a monthly data set between 2010 and 2021 was simulated over the number of patients admitted to the emergency department of a state hospital in İzmir between 2020-2021 and the number of patients was estimated by time series methods. The exponential smoothing method, which is frequently used in the literature, and the Ata methods, which is a new approach, were used for modeling. Performance comparisons were made according to the mean absolute percentage error (MAPE), mean absolute scaled error (MASE) and mean absolute error (MAE) criteria, and it was determined that Ata(1,0,1)(A,N,A) method, which is a new approach in the time series, gave better results at the end of the study.

KEYWORDS: *Ata Method, Exponential Smoothing, Health Data, Time Series*

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1. INTRODUCTION

Health services offered to patients in Turkey are provided by public and private units & hospitals. These health services offered include diagnosis, treatment, disease prevention and follow-up of patients (Kavuncubaşı & Yıldırım, 2015). Emergency services within hospital units are an important component of health systems with their ability to provide instant and basic care services to patients and are the departments with the highest patient density (Sarıyer, 2018). In recent years, the number of applications to emergency services has been increasing day by day. This leads to disruption of the services provided in the emergency department, changes in the satisfaction of healthcare workers and patients, operational decisions by hospital managers, financial difficulties for the hospital, difficulty or interruption of patient diagnosis, treatment and follow-up processes (Sarıyer et al., 2017). In this case, estimating the demand for emergency services with minimum errors will ensure that these service disruptions are at a minimum level. For the estimation of the demand data coming to the hospital, time series methods with the time variable are used in the literature.

A time series can be defined as a chain of measurements that occur sequentially and consist of a variable that follows each other in a non-random order. The frequency of data points can be in many ways, such as hourly, daily, weekly, monthly, quarterly, or yearly, depending on the variable to be estimated in the time series. By using statistical methods in time series data, a mathematical model of predicting future events is established in the presence of known events. When estimating in the time series, future events are predicted based on past trends, assuming that future trends will be similar to past trends (Karakaş, 2019).

Time series methods are applied to different data types in many fields. These forecasts made using time series include financial data (stock market index values, exchange rates, investment instruments, pricing…), energy data (electricity consumption), environmental data (weather, precipitation…), health data (number of patients, material demand, budget…), production data (sales, demand, storage…) and data from many other fields. The time series methods used in these areas also differ. In particular, the time series methods used are in the literature with trend estimation, moving averages, Holt Winter's exponential smoothing, ARIMA models and Ata method.

When establishing time series models, the systematic structure of the time series is taken into account. There are four components in this systematic structure: “trend”, “seasonality”, “cyclicality” and “irregular movements”. In addition, the concept of stationarity in time series analysis is defined as the time series properties (mean, variance, covariance, moment) do not change according to time or the series is free from periodic fluctuations. Since the stationarity in the time series is one of the important concepts to be able to apply statistical methods, it should be examined first (Duru, 2007).

Time series methods with time variables are used in the literature for estimating the number of patients in health data according to departments or certain periods, estimating medical supplies demand or budget estimation.

Irmak et al. (2012) used ARIMA, artificial neural networks (ANN) and exponential smoothing methods in their study in which they estimated hospital densities over a 96-month data set starting from January 2001. Forecasting estimates were made between January 2009 and September 2009. ARIMA (3,1,0), ANN (2 neurons, 1 hidden layer) and Holt's Winters additive method were found as best estimates. Among these three methods, Holt's Winters additive model is the best model (R^2=0.924, MAPE=6.11, MAE=2.29).

Adequacy of medical equipment in emergency services is one of the planning issues that are very important for the effectiveness of the treatment. Yiğit (2016) conducted research on demand forecasting of medical supplies between 2011 and 2016. He used linear regression, Holt-Winters exponential smoothing and moving average methods in modeling serum set consumption obtained from Süleyman Demirel University Hospital. In the performance comparison of the models, Holt-Winters exponential smoothing method was found to be the best according to MAPE and MAD criteria.

Juang et al. (2017) used the ARIMA method to estimate the number of patients coming to the hospital monthly in their study conducted in Taiwan between 2009 and 2016.

Sarıyer (2018) used ARIMA and SARIMA methods from the time series method on the 90-day data set in his study for patient demand estimation in the data of a training hospital in İzmir between 2016 and 2017. According to MAPE performance criterion, ARIMA models with the lowest MAPE value were determined.

Karakaş (2019) found that there was no seasonality and trend in his patient demand study, which he carried out considering the number of patients who applied monthly to the pediatric intensive care unit of a hospital in Adana between 2015-2018. ARIMA, moving average and exponential smoothing methods were used to estimate the number of patients. To the lowest error values; moving average model with MAE (9.83), MAPE (7.14), MSE (78.09) was found to be the best model and quarterly forecasts were made on this model.

Esen&Kaya (2021), using the patients who came to the emergency department of a training hospital in Antalya between 2015-2019, estimated the number of patients to come by using the random forest model and the Holt-Winters model. They found that Holt-Winters model gave better results as a result of performance evaluation using MAPE, MAD, MSD criteria.

In the study conducted by Dedeoğlu&Çetin (2021), 104-week data was obtained from five different surgical departments of a private hospital and the importance of patient demand was emphasized. Holts Winters method, trend analysis, regression analysis, moving average and exponential smoothing methods were used. The collected data are divided according to 5 different surgical departments; The number of outpatients, the number of inpatients treated, and the number of surgeries were estimated. With regression analysis, the number of patients who needed outpatient treatment and surgery in two different surgical departments was estimated. In addition, with regression analysis, it was found that the number of days hospitalized and treated for all surgical departments affected the number of operations. In particular, it was determined according to MAD, MSE, MAPE criteria that the best model in outpatient demands was Holt's Winters method.

Yapar et al. (2018) examined the comparisons between the Ata method and the simple exponential smoothing method based on the simple versions of these two approaches. It was determined in the study that more sophisticated versions of Ata, which allow combinations and model selection, will inevitably perform much better. However, this method has not yet been used for patient demand.

The aim of this study is to estimate the number of patients coming to the emergency department on a monthly basis using the time series method, the exponential smoothing method (ETS), and the Ata method, which has entered the new literature, and their performances as mean absolute percent error (MAPE), mean absolute error (MAE) and mean absolute scaled error. (MASE) criteria. As a result of the study, it was envisaged that the proposed models could be used by hospital managers and in this way, the capacity and resource planning could be made in the most appropriate way by predicting the number of patients effectively in advance.

2. METHODOLOGY

Study Design and Group: The data used was produced for 10 years by simulation from the original data (2020-2021) obtained from the information system of one of the largest public hospitals operating in the city of İzmir, in the upper ranks of the B group, and the number of patients who came to the emergency room (N=963457). There are many variables in the original data. The data set was expanded by taking into account the correlation matrices, the means and standard deviations of the variables, and the start date of the new data was created monthly between January 2010 and December 2021.

Variables: There are two variables in the data set, the patient's admission date (date) and the "number of patients".

Statistical Analysis: The performance of monthly patient number estimations using exponential smoothing method (ETS) and Ata methods from time series methods was made with RStudio version 4.2.2 according to MAPE, MASE and MAE criteria.

Time Series Components and Stationarity Tests: Four main components are used to explain the models used in the time series. Trend component; indicates a long-term increase or decrease. It can be linear or curvilinear. The series does not exist around a fixed value. The series containing the trend component is in the group of non-stationary time series. In the seasonality component; there are constant movements that contain similar patterns at equal time intervals. It breaks the stationarity of the series. It is affected by factors such as weather conditions and consumer trends. The circularity component; they are large movements covering a period of more than one year. The difference from seasonality is that seasonality completes its development in a year at most. Cyclicity, on the other hand, completes its development in 20-30 years. It makes the series non-stationary. Finally, the irregular movements component; they are sudden and irregular jumps or collapses. It is usually caused by external causes. It occurs with effects such as earthquakes, rare accidents, natural disasters, wars, economic crises.

In a time series, the concept of stationarity, which is that the features do not change with time or that the series is free from periodic fluctuations, is the first case to be examined when analyzing. The situations that break the stationarity are when the series contains one or more of its components. This situation can be avoided by making a difference or log transformation. "Augmented Dickey-Fuller", "KPSS Test for Trend Stationarity" and "Phillips-Perron Unit Root Test" are used to test the stationarity statistically. In order for the time series to be stationary, Augmented and Phillips-Perron used H_0 should be rejected, in KPSS Test H_0 should be accepted.

Time Series Models: First of all, a structural model is defined to better understand and interpret the data. At this stage, the time series elements are determined, the time graph is drawn, and the correlation of the variable with itself over time is obtained with the help of the correlogram. Then, models are established with different methods. While graphs of time series components are obtained by decomposition, the model is established and predictions are made with methods such as Trend Analysis, Smoothing (Simple Exponential Smoothing, Holt's Linear Trend method), Box Jenkins (ARIMA) and Ata. Finally, the prediction performances of the obtained models are compared. Time series can also be classified according to whether they are univariate or multivariate. The "trend method" comes first among the univariate methods.

The basic assumption in the smoothing methods used in time series is that the structure observed in the past will continue in the future. Deviations from this structure are tried to be eliminated by correcting the margins of error with some coefficients and including them in the model (Benli, 2015). The ETS method, which is expressed as exponential smoothing, means “Error-Trend-Seasonality”. While this method was first described by Pegels (1969), Hyndman et al. developed by a taxonomy (Hyndman et al., 2008). In the model created by this method, the time series is divided into these 3 components, and if the change of each over time changes exponentially (multiplicative, M), if it changes linearly (additive, A) model is selected and the estimation is made accordingly. Therefore, the contents of error, trend and seasonality are given according to a certain taxonomy. Error: “M” or “A”, Trend: “none, Null (N)”, “A”, “Additional damped, (Ad)”, “M”, “multiplicative damped, (Md)”, Seasonality: “none, N”, “M”, “A”. The components in the ETS taxonomy have clear interpretations (Yılmaz&Vupa Çilengiroğlu, 2022). Smoothing methods can be grouped under two headings (simple exponential smoothing and Holt Winters method). With the additive error, the trend and seasonality-free model is formed as ETS(A,N,N), which is actually a simple exponential smoothing. When the error is multiplicative, the ETS(M,N,N) model is formed and this is a simple exponential smoothing. Holt's linear method is equivalent to ETS(A,A,N) when there is no seasonality but the error is additive, and ETS(M,A,N) when it is multiplicative.

Simple Exponential Smoothing Method: In the simple exponential smoothing method, exponentially decreasing weights are given for the newest and oldest observations. Thus, by giving more weight to new observations, the data is made more suitable for modeling (Bağcı, 2020). In order to apply this method, first of all, the weights of the observations are created by determining the smoothing parameter ranging from zero to one and an α coefficient. With this α coefficient, it is determined how fast the weight decreases for previous observations (Benli, 2014). Moreover α coefficient also ensures that different observation values contribute to the model with different weights (Üreten, 2005). This method is often used to make short-term forecasts. In addition, this method aims to eliminate the changes caused by random factors. With this method, instead of taking a simple arithmetic average, a kind of weighted average is taken by giving appropriate weights to the final actual and estimated values. (Sahin&Kocadağ, 2020).
Since the smoothing in the time series is expressed as the weighted average of the observed values at points close to that point in time, the trend at a particular point in time is considered as the sum of the trend and random error.

$$F_{t+1} = \alpha Y_t + (1 - \alpha) F_t \quad (1)$$

F_{t+1}: Forecast value in the next period, α: Smoothing parameter, Y_t: The realized value in the period, F_t: Forecast value in the period

Accurate determination of alpha value is important for forecast performance. As the alpha grows, there is a faster response to the latest changes in the time series, while the smoothing rate will decrease (Esen&Kaya, 2021).

Holt Winters Method: The Holt Winters method is used when the time series contains both trend and seasonality. This method produces forecasts with level, trend and seasonal parameters in each period of the time series (Gelper et al., 2010). The basic principle of this method is to define the initial value and weight of the parameters. The parameters α (level), β (trend), and δ (seasonal) are always updated in the time period (t), and the value of these weights ranges from 0 to 1. It changes until the initial values of all components are taken as 0.2 and then reduced to the minimum error level with an appropriate algorithm (Esen&Kaya, 2021). The Holt Winters method can be used in two different ways as “additive” or "multiplicative" depending on the seasonal component in the series. If seasonal changes remain constant throughout the series, "Holt Winters Additive exponential smoothing", if seasonal changes change proportionally with series level, "Holt Winters multiplicative exponential smoothing" method can be preferred (Akkan&Çalısır, 2022). The general formulas of the Holt Winters method are defined as follows (Elmunim et al., 2015).

Level: $L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1})$ (2)

Slope: $L_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$ (3)

Seasonality: $L_t = \delta(Y_t - L_t) + (1-\delta)S_{t-s}$ (4)

Adapted: $F_t = L_{t-1} + b_{t-1} + S_{t-s}$ (5)

Prediction: $F_{t+m} = L_t + b_t m + S_{t-s+m}$ (6)

Here the actual data (Y), level (L), trend (b), season (S). The forecast for the next period is given as (F). In addition, α, β and δ are level, trend and seasonal improvement coefficients. m indicates the predicted period, while s indicates the season amount (monthly number of days, annual number of months, etc.).

Ata Method: In the exponential smoothing method used in the literature, the amount of data points that can contribute to the estimation is not taken into account while weighting the historical data. However, it seems that the Ata method gives less weight to the distant past than exponential smoothing, and tends to give more weight to other recent observations. While all exponential smoothing models require initialization and initial values affect the quality of the predictions, especially for small n and α values, the Ata method does not require initialization and since parameter values are limited to integers, optimization of other parameters becomes simpler and faster (Yapar et al., 2019).

When obtaining a smoothing value at a given point in time in the Ata method, the smoothing parameters are changed considering how many observations can contribute by considering weights between observations. Therefore, the smoothing parameter of this method is a function of t, unlike exponential smoothing, in which observations are weighted only on their distance from the smoothing value, regardless of where the smoothing value is located on the timeline. The suggested form (additive or multiplicative) for Ata method is the Ata (p, q, ϕ) model (Çapar et al., 2022). The additive dumped form (p, q, ϕ) for Ata method can be calculated as follows.

$$S_t = \{\frac{p}{t} * X_t + \frac{t-p}{t} * (S_{t-1} + \phi * T_{t-1}), \quad t > p\ X_t, \quad t \le p \tag{7}$$

$$\hat{X}_t(h) = S_t + T_t\,(\phi + \phi^2 + \ldots + \phi^h) * T_t \tag{8}$$

It is expressed as the additive trended form (p, q, ϕ=1) for Ata without the damped effect in the trend component. The simple exponential smoothing model Brown (1959) is equal to the trend-free simple form (p, q=0, ϕ=1) for Ata. Holt's additive trend model (Holt, 1957) is equal to simple (p, q) for Ata.

In the display of Ata (p, q, ϕ) form (130, 110, 0.52), it is stated that the weight of the first 130 data is given as 0, then the weighting is made, the first 110 data are not taken into account in the trend, and the dumped value is 0.52.

Accuracy and Relevance in Time Series: Measuring the suitability and accuracy of the estimation in time series is also an important criterion. Error measurement can be made using mean absolute percentage error (MAPE), mean absolute error (MAE), and mean absolute scale error (MASE). MAPE is the percentage value of forecast errors. The MAE is the average sum of the difference between the actual and predicted values. The MASE is the ratio of the forecast error to the mean forecast error.

MAPE: $\frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \widehat{Y_t}|}{Y_t} * 100$ (9)

MAE: $\frac{\sum_{i-1}^{n}|Y_t - \widehat{Y_t}|}{n}$ (10)

MASE: $\frac{1}{n}\sum_{t=1}^{n}|q(t)|$ (11)

The MAPE value, which is frequently used in the literature; If it is below 10%, the model is very well established, and the 10% and 20% range is classified as good (Dedeoğlu&Çetin, 2021).

3. FINDINGS

Descriptive statistics (mean ± standard deviation) of the monthly number of patients admitted to the emergency department between January 2010 and December 2021 were obtained (6691±1849). According to these statistics, the maximum number of monthly patients coming to the hospital was found in December (11554 in 2021), and the minimum number was in January (4017 in 2010).

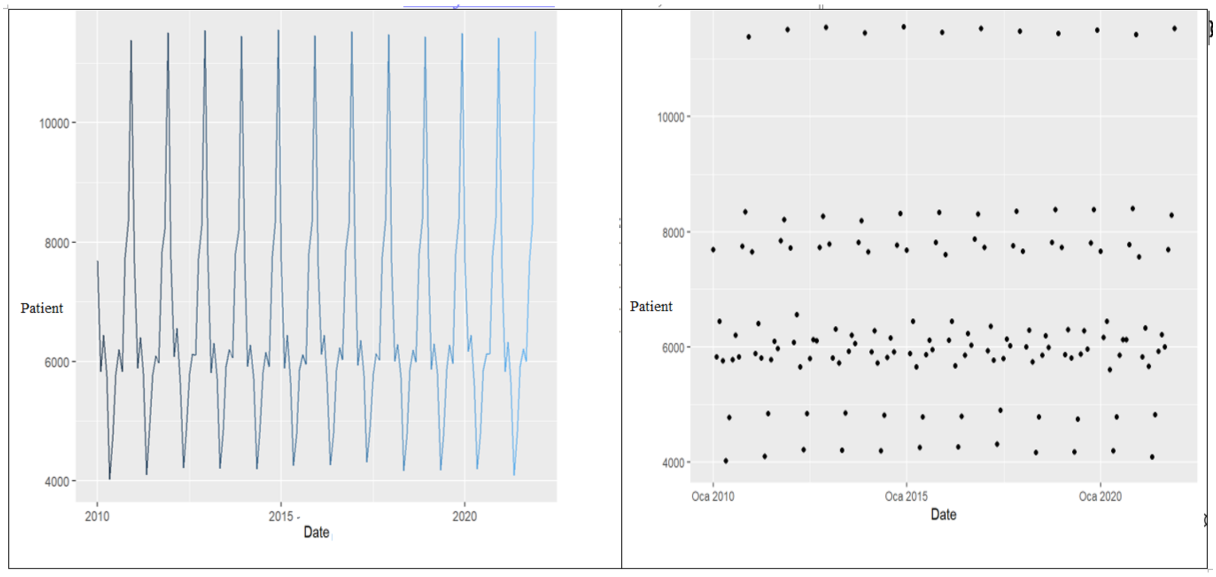

Figure 1. *Line and scatter plots of the number of patients between 2010-2021*

Time series features such as seasonality, trend and cyclicality can be determined with line and scatter graphs. The reason for this is the seasonality in the number of patients, as there is a continuous cycle with the following years in the line graph. In the scatterplot, it was determined that the number of patients who applied monthly was around 6000 people. Likewise, the presence of a pattern in this graph shows seasonality (Figure 1).

Seasonality can be determined by displaying the number of patients by month. In the data set, it was determined that the month with the least applications was May and the highest number of applications was in December, while an increase was observed from May to August, there was a continuous increase from September to December due to the seasonal effect (Figure 2).

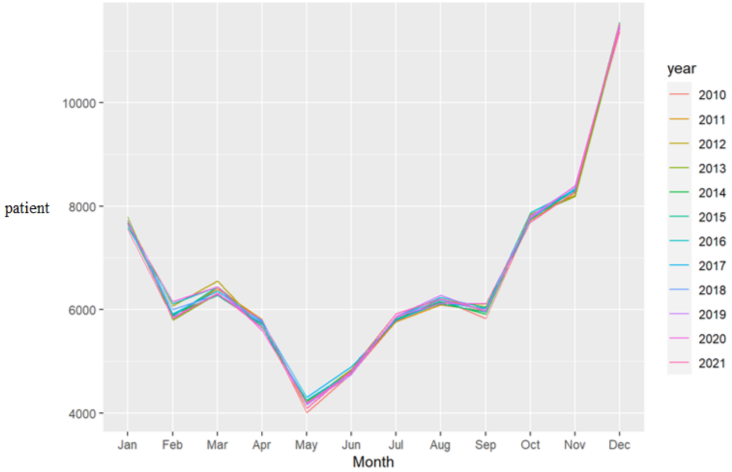

Figure 2. *Distribution of monthly incoming patients by months between 2010-2021*

By separating the time series into its main components, observed, trend, seasonality and cycle graphs of the observed raw data were obtained. With the trend graph, it is seen that there is no long-term increase or decrease in the data set, in other words, there is no trend. It was found that there is seasonality directly in the seasonality graph, and that it has a random component in the randomness graph, since there is no apparent irregular and sudden observation (Figure 3).

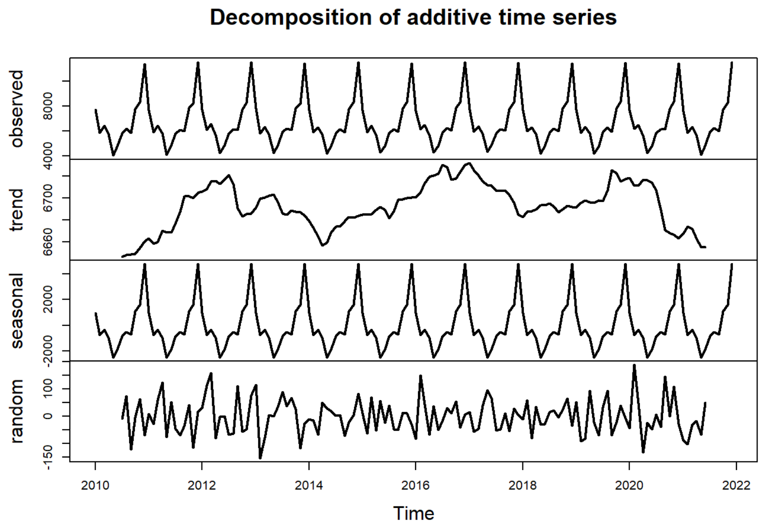

Figure 3. *Graphs of observation, trend, seasonality and randomness components of time series*

Stationarity tests (Augmented Dickey-Fuller, KPSS, Phillips-Perron Unit Root) were used to determine whether the seasonal effect really lost the stationarity. At the same time, the concept of stationarity required for establishing a time series model is the expectation that variance and mean should be constant over time. H_1 hypotheses of these tests are different for Augmented Dickey-Fuller (series is stationary), KPSS (level or trend is not stationary), and Phillips-Perron Unit Root tests (series has no unit root, is stationary). The p values of these tests for the data set were found to be 0.01, 0.10 and 0.01, respectively, and it was concluded that the series was stationary. After the series was determined to be stationary, time series models were used.

For the exponential smoothing method chosen for modeling, first of all, the data set was divided into two as 80% training and 20% test data, and the training data and model were left to learn. According to the result of the ETS model, the ETS (A,N,A) model was obtained as the best model in estimating the number of patients. In this model, it was found that the error component was additive (additive, A), the trend component was absent (null, N) and the seasonality component was additive (additive, A), and this model was used to estimate the number of patients for future years.

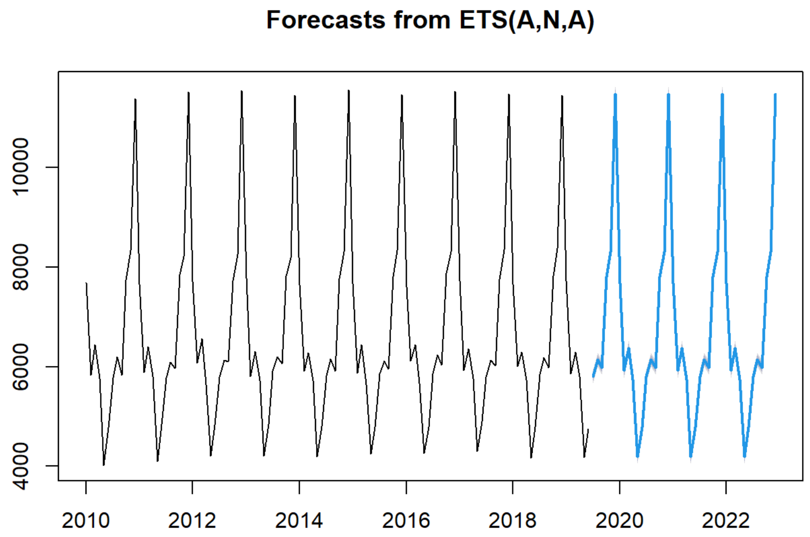

Figure 4. *ETS(A,N,A) forecast graph*

The alpha value of the established ETS model was 0.0002, the gamma value was 0.0001, the level value was 6687.63, the sigma value was 70.40 and the Akaike value was 1524.95.

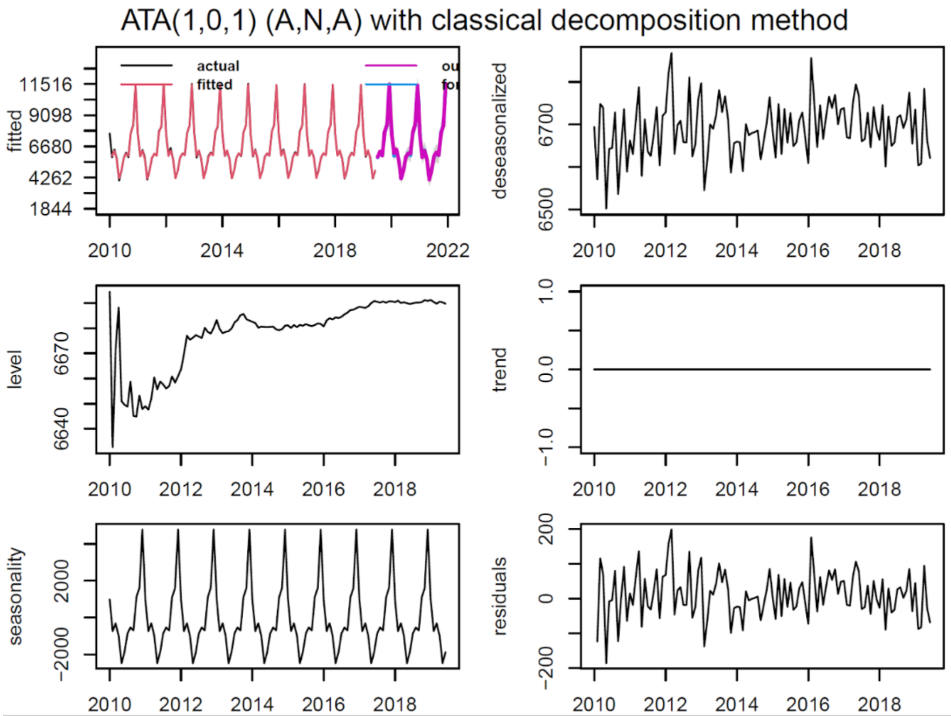

Figure 5.*ATA(1,0,1)(A,N,A) Decomposition Graph*

Future predictions were made in the "fitted" graph of the Ata model. The “Deseasonalized” chart shows the time-varying variation of the series without seasonal effects. There are level values in the "Level" chart. In the "Trend" graph, it has been determined that the time series is not in the trend effect. “Seasonality” shows the striking effect of seasonality on the time series. “Residuals” is a graph of errors, and in this graph it can be seen that the errors are random.

The Ata model is Ata (1,0,1) (A,N,A). This model is the trendless simple Ata form. It shows that the error is additive, there is no trend, seasonality is additive, and the dumped value is 1. In contrast to the 1525 Akaike criterion value in the ETS model, this criterion value was found to be 1516 in the Ata model. Since the small Akaike value in the model comparison indicates the consistency of the model, it was determined that the Ata method reached better predictive values than the ETS model, according to these results. The seven-month estimation values were obtained for both models.

Table 1. *Actual value between June 2021 and December 2021, ETS estimate, Ata estimate*

Months	Actual Value	ETS Estimate	Ata Estimate
June 2021	4825	4794	4818
July 2021	5921	5809	5826
August 2021	6206	6146	6158
September 2021	5996	5987	5983
October 2021	7687	7813	7793
November 2021	8286	8308	8296
December 2021	11528	11481	11479

According to the estimation results, while the actual number of patients admitted to the emergency department in June 2021 was 4825, it was found to be 4794 and 4818 in the ETS and Ata models, respectively. It was also determined in other months that the point estimates of the Ata model were closer to the true value than the ETS model (Table 1).

Table 2. *Performance criteria values of ETS and Ata methods*

Performance Criteria	ETS	Ata
MAE	68.282	64.167
MAPE	1.069	1.006
MASE	0.908	0.083

When the performance criteria for model comparison were examined, it was found that Ata method gave better results than ETS method according to all criteria. In addition, the fact that the MAPE value is around 1% is presented as a proof that the Ata model obtains predictive values with high accuracy (Table 2).

4. DISCUSSION

With the increasing population, the improvement and acceleration of health services has become indispensable. Studies in the literature, in which health data are processed, increase especially with the pandemic period. In particular, researches are carried out so that hospitals can be prepared in all respects (medical consumables, etc.) and provide a better health service. For this reason, the main issues in health services; estimating the number of patients admitted to hospitals, determining the patient profile quickly, and predicting serious diseases by processing the analysis results. In studies in which the number of patients is estimated, ARIMA and ETS methods are frequently used in time series analysis. In addition, the Ata model, which has just started to be used, has started to be used in different areas with its high accuracy predictions.

Irmak et al. (2012) used artificial neural networks, exponential smoothing and ARIMA methods in 8 years of hospital data and found Holt's Winters additive model to be the most appropriate model according to MAE and MAPE criteria. Likewise, Yiğit (2016) determined the Holt-Winters exponential smoothing method as the best model according to the MAPE and MAD criteria in his modeling of medical equipment demand data between 2011 and 2016 using different methods. Some researchers have used ARIMA methods for patient demand or referral estimation. Juang et al. (2017) found the ARIMA method as the most suitable model among these methods, using only ARIMA method in hospital data estimation. Sarıyer (2018) used ARIMA and SARIMA methods according to MAPE criteria to find demand estimation for patient. In the following years, patient demand was estimated using different methods and comparisons were made according to different criteria. Karakaş (2019) applied ARIMA, exponential smoothing and moving average models in her research on pediatric patient demand between 2015 and 2018, and stated the moving average model as the best model in his evaluation based on MAE, MAPE, MSE criteria. Dedeoğlu&Çetin (2021), in their study on patient demand forecasting, used many methods such as Holts Winters method, trend analysis, regression analysis, moving average and exponential smoothing models. In this study, it was determined that Holt's Winters method has the best predictive values according to MAD, MSE, MAPE criteria. Yapar et al. (2017), in their study, determined that the Ata method gave better results than the ETS method, according to the MAE, MAPE and MASE criteria. However, this method has not been applied to health data. In health data, especially patient demand gives a different design and data pattern.

In this study, ETS, which is one of the time series methods, and Ata methods, which present a new time series approach to the literature, were used in patient demand forecasting. In the ETS (A,N,A) model built on error-trend-seasonality components, a model in which error has an additive effect, no trend and seasonality has an additive effect has been established. In the Ata model, the model was found as Ata(1,0,1)(A,N,A). This is the simple form where there is no trend and the dumped value is 1, and the error and seasonality are additive. In Ata model, Akaike (1516), MAE (64.127), MAPE (1.006) and MASE (0.083) values were found to have lower error values when compared to ETS. Thus, in the model comparison, it was shown that the Ata model made more consistent predictions than the ETS model.

5. CONCLUSION

The health sector is the most important sector that needs to be sustained due to the increasing population. With the pandemic experienced in the past years, the value of the health sector has been understood again. In this context; The hospital's ability to correctly adjust its resources, meet patient demands, and provide health care to patients in a short time and effectively has a vital role. Under such topics, machine learning methods are frequently used in health data in order to provide insight into the hospital. In particular, time series analyzes are used to predict the number of patients, to determine the need for medical supplies and the number of applications to operating rooms. The leading models used in the time series are algorithms such as ARIMA and ETS. Ata modeling, which has been applied in recent years, also obtains values with good performance. The Ata model, based on the exponential smoothing method, created its mathematical model and provided application results with higher consistency and in a short time.

Within the scope of this study, the ETS model, which is frequently used in many areas in the literature, was applied for health data in this study. In addition, the Ata method, which has not been applied to this field before, was also used in these data; As a result of criteria such as MAE, MAPE and MASE, it has been shown that the model with the best predictive ability can be created according to performance comparisons. The fact that the data within the scope of the study can be applied to the original data and with different methods and model comparisons can be made ensures the continuity and continuation of this study.

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REFERENCES

[1]. Akkan, B., & Çalışır, V. (2022). Klasik Zaman Serisi Yöntemleri ile Konteyner Elleçleme Tahmini. *Journal of Anatolian Environmental and Animal Sciences*. 7(3):341-349.
[2]. Arsham, H. (2000). Time Critical Decision Making for Bussiness Administration. İnternet adresi: http://home.ubalt.edu/ntsbarsh/stat-data/forecast.htm
[3]. Bağcı, B. (2020). Hareketli Ortalamalar ve Üssel Düzeltme Yöntemlerinin Tahmin Gücünün Artırılması: Türkiye'de Döviz Kuru Tahmini. *Turkuaz Uluslararası Sosyo-Ekonomik Stratejik Araştırmalar Dergisi*. 2(1):1-12.
[4]. Çapar, S, Selamlar, H.T., Yavuz, İ., Taylan, A. S., Yapar, G. (2023). Method's Performance in the M4 Competition. *Hacettepe Journal of Mathematics & Statistics.* 52(1):268-276
[5]. Dedeoğlu, T., & Çetin, O. (2021). Sağlık Sektöründe Hasta Talebinin Tahmini. *Trakya Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*. 10(1):25-38.
[6]. Duru, Ö. (2007). Zaman Serileri Analizinde ARIMA Modelleri ve Bir Uygulama. İstanbul Üniversitesi Sosyal Bilimler Enstitüsü Ekonometri Anabilim Dalı, Yüksek Lisans Tezi, 103 sayfa.
[7]. Elmunim, N. A., Abdullah, M., Hasbi, A. M. ve Bahari, S. A. (2015). Comparison of Statistical Holt-Winters Models for Forecasting the Ionospheric Delay Using GPS Observations. *Indian Journal of Radio and Space Physics.* 44(1):28-34.
[8]. Esen, H., & Kaya, Ü. (2021). Bir Eğitim Araştırma Hastanesi Acil Servis Birimine Başvuran Hasta Sayısı Tahmini. *Verimlilik Dergisi*. (3):129-145.
[9]. Gelper, S., Fried, R., & Croux, C. (2010). Robust Forecasting with Exponential and Holt–Winters Smoothing. *Journal of Forecasting*. 29(3):285-300.

[10]. Holt, C. C. (1957). *Forecasting Seasonals and Trends by Exponentially Weighted Averages* (O.N.R. Memorandum No. 52). Carnegie Institute of Technology, Pittsburgh USA.

[11]. Hyndman, R., Koehler, A. B., Ord, J. K., & Snyder, R. D. (2008). *Forecasting with Exponential Smoothing: The State Space Approach*. Springer Science & Business Media.

[12]. Irmak, S., Köksal, C. D., & Asilkan, Ö. (2012). Hastanelerin Gelecekteki Hasta Yoğunluklarının Veri Madenciliği Yöntemleri ile Tahmin Edilmesi. *Uluslararası Alanya İşletme Fakültesi Dergisi*. 4(1):101-114.

[13]. Juang, W. C., Huang, S. J., Huang, F. D., Cheng, P. W., & Wann, S. R. (2017). Application of Time Series Analysis in Modelling and Forecasting Emergency Department Visits in a Medical Centre in Southern Taiwan. *BMJ open*. 7(11).

[14]. Karakaş, E. (2019). Çocuk Yoğun Bakım Ünitesine Olan Talebin Zaman Serisi Yöntemleri ile Tahmin Edilmesi. *Avrupa Bilim ve Teknoloji Dergisi*. (17):454-462.

[15]. Kavuncubaşı, Ş. ve Yıldırım, S. (2015). *Hastane ve Sağlık Kurumları Yönetimi.* Siyasal Kitapevi.

[16]. Pegels, C.C. (1969). Exponential Forecasting: Some New Variations. *Management Science.* 15(5):311–315. https://www.jstor.org/stable/2628137.

[17]. Sarıyer, G. (2018). Acil Servislerde Talebin Zaman Serileri Modelleri Iie Tahmin Edilmesi. *International Journal of Engineering Research and Development*. 10(1): 66-77.

[18]. Sarıyer, G., Ataman, M. G., Akay, S., Sofuoglu, T., & Sofuoglu, Z. (2017). An Analysis of Emergency Medical Services Demand: Time of Day, Day of the Week, and Location in The City. *Turkish Journal of Emergency Medicine*. 17(2):42-47.

[19]. Şahin, S., & Kocadağ, D. (2020). Sağlik Sektöründe Talep Tahmini Üzerine Literatür Araştirmasi. *Düzce Üniversitesi Sosyal Bilimler Dergisi*. 10(1):99-113.

[20]. Üreten, S. (2005). *Üretim/İşlemler Yönetimi, Stratejik Kararlar ve Karar Modelleri*. Ankara:Gazi Kitabevi.

[21]. Yapar, G., Capar, S., Selamlar, H. T., & Yavuz, I. (2018). Modified holt's linear trend method. *Hacettepe Journal of Mathematics and Statistics*. 47(5):1394-1403.

[22]. Yapar, G., Selamlar, H. T., Capar, S., & Yavuz, I. (2019). ATA method. *Hacettepe Journal of Mathematics and Statistics*. 1-7.

[23]. Yiğit, V. (2016). Hastanelerde Tibbi Malzeme Talep Tahmini: Serum Seti Tüketimi Üzerinde Örnek Bir Uygulama. *Manas Sosyal Araştırmalar Dergisi*. 5(4): 207-222.

[24]. Yılmaz, M. B., & Çilengiroğlu, Ö. V. (2022). Talep Tahminleme Değişkenlerinin Üssel Düzeltme Yöntemi ile Belirlenmesi. *Euroasia Journal of Mathematics, Engineering, Natural & Medical Sciences*. 9(22): 92-103.