MEHMET AKİF ERSOY ÜNİVERSİTESİ
İKTİSADİ VE İDARİ BİLİMLER FAKÜLTESİ DERGİSİ
Mehmet Akif Ersoy University
Journal of Economics and Administrative Sciences Faculty

ISSN: 2149-1658
Cilt: 9 Sayı: 2 s.1239-1259
Volume: 8 Issue: 3 p.1239-1259
Temmuz 2022 July

A STUDY ON FORECASTING THE IMPACT OF COVID-19 ON EMERGENCY SERVICE IN A PUBLIC HOSPITAL

COVID-19'UN BİR DEVLET HASTANESİ ACİL SERVİSİ ÜZERİNDEKİ ETKİSİNİN TAHMİNİ ÜZERİNE BİR ÇALIŞMA

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Makale Türü	Article Type
Araştırma Makalesi	Research Article
Başvuru Tarihi	**Application Date**
07.12.2021	12.07.2021
Yayına Kabul Tarihi	**Admission Date**
13.07.2022	07.13.2022

DOI

https://doi.org/10.30798/makuiibf.1033816

Abstract

The COVID-19 pandemic has seriously threatened human life all over the world since the first quarter of 2020. Hospitals have fought on the frontlines against this threat. The aim of this study is to predict the number of monthly emergency service patients for a public hospital. In particular, the impact of the COVID-19 pandemic on the number of emergency service patients was examined. While the data set for the period January 2012- June 2021 (114 months) is used in the analyses, two different data sets were created for the Box- Jenkins (B-J) and Gray Prediction approaches. Then, the number of monthly emergency service patients was predicted using the SARIMA model, GM (1,1) and TGM. In the analyses, while examining the long-term trend of the number emergency services patients' using the SARIMA model, GM (1,1) and TGM were used to focus on the COVID-19 period. The findings suggest that the TGM has the most successful results in terms of evaluation criteria.

Keywords: COVID-19, Emergency Service, SARIMA, GM (1,1), TGM.

Öz

COVID-19 pandemisi, 2020 yılının ilk çeyreğinden bu yana tüm dünyada insan hayatını ciddi şekilde tehdit etmektedir. Hastaneler bu tehdide karşı ön saflarda savaşmaktadır. Bu çalışmanın amacı, bir devlet hastanesinin aylık acil servis hasta sayısının tahmin edilmesidir. Özellikle COVID-19 pandemisinin acil servis hasta sayısı üzerindeki etkisi incelenmiştir. Analizlerde Ocak 2012- Haziran 2021 (114 ay) dönemine ait veri seti kullanılırken, Box-Jenkins (B-J) ve Gri Tahminleme yaklaşımları için iki farklı veri seti oluşturulmuştur. Daha sonra SARIMA modeli, GM (1,1) ve TGM kullanılarak aylık acil servis hasta sayıları tahmin edilmiştir. Analizlerde SARIMA modeli ile hastanenin acil hasta sayısının uzun dönem trendi incelenirken, GM(1,1) ve TGM ile özellikle COVID-19 dönemine odaklanılmıştır. Elde edilen bulgular, değerlendirme kriterleri açısından en başarılı sonuçlara TGM'nin sahip olduğunu göstermektedir.

Anahtar Kelimeler: COVID-19, Acil Servis, SARIMA, GM (1,1), TGM.

GENİŞLETİLMİŞ ÖZET

Çalışmanın Amacı

Bu çalışmada, COVID-19 pandemisinin acil servis hasta sayısı üzerindeki etkisini incelemek amacıyla Türkiye'de bir devlet hastanesinin aylık acil servis hasta sayısı tahmin edilmiştir.

Araştırma Soruları

COVID-19 pandemisinin acil servis hasta sayısı üzerinde nasıl bir etkisi olmuştur? Box-Jenkins ve Gri Tahminleme yaklaşımları ile acil servis hasta sayısının tahmini için başarılı sonuçlar elde edilebilir mi?

Literatür Araştırması

COVID-19 pandemisi dünya çapında milyonlarca ölüme neden olurken, insan yaşamını yaşam kalitesi ve halk sağlığı gibi birçok yönden olumsuz etkilemektedir (WHO, 2020). Özellikle hastaneler bu dönemde yüksek talebe cevap verebilmek için normal kapasitenin üzerinde performans sergilemektedir (Pecoraro vd., 2021). Bu nedenle pandemi döneminde acil servisler her zamankinden daha önemli hale gelmiştir. Yetersiz kaynaklar ve sürekli artan talep, hastane kaynaklarının optimal kullanımı üzerinde büyük baskı oluşturmaktadır (Abraham vd., 2009). Aslına bakılırsa hasta akışı, bir hastanenin genel sağlık hizmet kalitesi ve maliyeti ile yakından ilişkilidir. Bu nedenle, hastane yöneticileri gelecekteki talebi tahmin etmeli ve tıbbi hizmetleri etkin maliyetli olacak şekilde yönetmelidir (Huang vd., 2015; Xu vd., 2016).

Yöntem

Çalışmada, bir devlet hastanesinin aylık acil servis hasta sayısı SARIMA Modeli, GM (1,1) ve TGM kullanılarak tahmin edilmiştir. Analizlerde Ocak 2012-Haziran 2021 (114 ay) dönemine ait aylık acil servis hasta sayısı kayıtları kullanılmıştır. Özellikle COVID-19 pandemisinin acil servis hasta sayılarına etkisi incelenmiştir.

Sonuç ve Değerlendirme

Analizlerde SARIMA modeli ile hastanenin acil hasta sayısının uzun dönem trendi incelenirken, GM (1,1) ve TGM ile özellikle COVID-19 dönemine odaklanılmıştır. SARIMA, GM (1,1) ve TGM ile elde edilen tahmin sonuçlarının başarısı değerlendirme kriterleri açısından incelenmiştir. Modellerin başarısı karşılaştırıldığında, TGM, hem aynı dönem için tahmin edilen GM (1,1)’e göre hem de daha uzun dönemi kapsayan SARIMA modeline göre daha başarılı sonuçlar vermiştir. TGM diğer modellere göre daha başarılı sonuçlar vermesine ve mevsimsel pik ve dipleri yakalamasına rağmen ara değerleri yakalamada yetersiz kalmaktadır. Bunun en büyük sebebinin vaka artışına bağlı olarak yönetim tarafından alınan yasak ve tedbir kararları olduğu sonucuna varılabilir.

1. INTRODUCTION

While the COVID-19 pandemic causes millions of deaths worldwide, it negatively affects human life in many aspects such as quality of life and public health (WHO, 2020). In particular, hospitals performed above normal capacity in order to respond to the high demand during this period (Pecoraro et al., 2021). As a result, hospitals and emergency services have made a significant contribution to the management of this process.

Emergency services are medical units that provide services to people in need of emergency medical care and have certain characteristics (Ozturk et al., 2018). The main reason for this is that only some percentages of the total patients though to the hospital emergency service, needing urgent and highly specialized treatment (Nayeri and Aghajani, 2010).

During the pandemic, emergency services have become more important than ever. Insufficient resources and ever-increasing demand put great pressure on the optimal use of hospital resources (Abraham et al., 2009). As a matter of fact, patient flow is closely related to the overall health care quality and cost of most hospitals. Future demand must be accurately forecasted by hospital executives to deal with medical services in a cost-effective way (Huang et al., 2015; Xu et al., 2016).

In general, it is possible to divide the forecasting methods into two basic categories, linear and nonlinear. Holt–Winters exponential smoothing, multiple linear regression (MLR), autoregressive integrated moving average (ARIMA) and Grey Model (GM) methods are the most frequently used linear methods in the healthcare-related studies (Xu et al., 2013). On the other hand, nonlinear forecasting methods such as Genetic Programming (GP), Artificial Neural Networks (ANN), Support Vector Regression (SVR) give more successful results in modeling the input-output relationship in any complex and dynamic system (Xiao et al., 2018).

Time series models are frequently used in different fields of studies. Time series models generally predict patient numbers based on the outcome of three components: (1) long-term trends; (2) short-term and often cyclical changes and (3) the effects of unexpected, random events (Wargon et al., 2009).

In this study, the number of monthly emergency service patients was predicted for a public hospital using the Seasonal Autoregressive Integrated Moving Average (SARIMA) Model, the Grey Model (GM) and the Trigonometric Grey Model (TGM). In analyses, monthly emergency service patient data for the period from January 2012 to June 2021 (114 months) were used. The prediction results obtained in the analyses were compared and evaluated. In particular, the effect of the COVID-19 pandemic on the number of emergency service patients was examined. The rest of this study is organized as follows: In the subsequent section a brief literature review is given. In section 3, detailed explanations are given about the B-J and Gray Prediction approaches. In section 4, the data are described and the predictive analyses are made. Finally, the prediction results were evaluated and suggestions for further studies were presented.

2. LITERATURE REVIEW

When the literature is reviewed, it is seen that there are many studies about the prediction of the number of emergency service patients using the time series. Some of the studies carried out in recent years are summarized below.

Duarte et al. (2021) applied the ARIMA, Prophet and the General Regression Neural Network (GRNN) methods for an emergency service. In the study, hourly data of a hospital in the United Kingdom were examined in four aspects; patients in department, number of attendances, unallocated patients with a decision to admit and medically fit for discharge. According to the analysis results, the best results were obtained via the GRNN method in terms of both accuracy and reliability for the pandemic period.

Vollmer et al. (2021) predicted the emergency service demand for two hospitals in the United Kingdom using traditional time series and machine learning algorithms. In the study, daily data between 2011-2019 were used and demand forecasts for 1, 3 and 7 days were made. According to the analysis results, it was indicated that linear models generally outperform machine learning methods.

Rocha and Rodrigues (2021) evaluated the hourly, four-hour, eight-hour and daily admissions to the emergency service of a hospital in Portugal. In the study, 10 years (2009-2018) data were used for analysis and Exponential Smoothing (ES), SARIMA, Autoregressive and Recurrent Neural Network (ARNN), XGBoost and Ensemble Learning methods were used for the models. In terms of efficiency, XGBoost has much better performance results than other methods.

Zhao et al. (2020) developed six rolling grey Verhulst models using 7, 8, and 9-day data sequences to predict the daily growth trend of the number of COVID-19 patients in China. In the study, daily patient data from 21 January to 20 February 2020 were used. Analysis results showed that the rolling grey Verhulst model and its derived models could accurately predict changes in patient numbers.

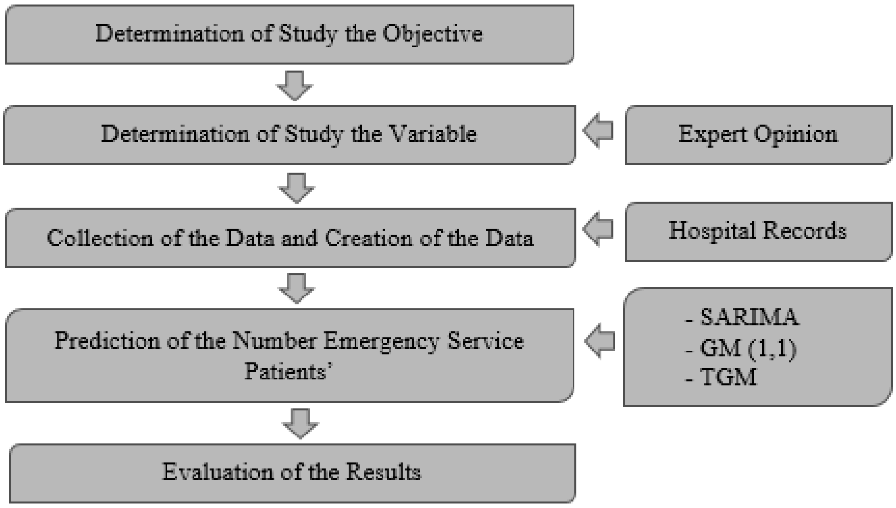
Lu et al. (2021) used ARIMA, multilayer perceptron (MLP) and long short-term memory (LSTM) models to predict the number of emergency service patients in the urban area of Beijing in China. Cheng et al. (2021) created a Seasonal Autoregressive Integrated Moving Average with External Regressor (SARIMAX) model for hourly patient estimation for an emergency service. Duwalage et al. (2020) used generalized additive (GAMs), generalized linear, MLR, SARIMA models and random forest methods for patient prediction for the emergency services of four public hospitals in Australia. Becerra et al. (2020) predicted the emergency patient admissions due to respiratory diseases for a city in Chile using Akaike Information Criteria (AIC) and SARIMA methods. Khaldi et al. (2019) made weekly patient forecasting using ANN without signal decomposition, ANN with Discrete Wavelet

Transform (DWT) decomposition and ARIMA models for all emergency services of a university hospital in Morocco and compared the results. Jilani et al. (2019) modeled the emergency services data of four hospitals in the UK using ARIMA, Neural Networks (NN) and Fuzzy Time Series methods. Zhang et al. (2019) predicted and evaluated the number of daily radiology emergency service patients using ARIMA, SVR, and a hybrid ARIMA-SVR approaches. Carvalho-Silva et al. (2018) evaluated the patient flow for the emergency service of a hospital in Portugal using the ARIMA model.

3. METHODOLOGY

During the pandemic period, the records of those who applied to the hospital with the suspicion of COVID-19 in Turkey were taken by the emergency services. For this reason, the importance of emergency services has increased more in this process. The aim of this study is to predict the number of monthly emergency service patients for a public hospital. In addition, it is also aimed to evaluate the impact of the COVID-19 pandemic on emergency service. The methodological framework of the study is shown in Figure 1.

Figure 1. Methodological Framework



3.1. Box- Jenkins Method

The Box- Jenkins (B-J) method was developed by George Box and Gwilym Jenkins in 1976 (Goh and Law, 2002). The prerequisite for this method, which is used for modeling and predicting time series, is the stationarity of the series (Meciarova, 2007). The stationarity is the collection of values in the series around a certain mean and variance. (Makridakis and Hibon, 1997). In the method, stationarity of time series is determined by Correlogram and Unit Root Tests. If the series is not stationary, the difference of the series is taken until the stationary series is obtained. Then, the appropriate model is determined from the stationary series obtained. Thus, the determined model provides forecasting of near-term values. In addition, future values can be predicted by means of past values.

The purpose of the B-J method is to identify and predict a statistical model that can derive sample data. For this purpose, every model derived has to provide the assumption that it is stationary and stable (Gujarati and Porter, 1995). The B-J method has many model structures. For this reason, it is often preferred and used in many studies. Information about Seasonal Autoregressive Integrated Moving Average (SARIMA), one of the most used B-J models, is given below.

- SARIMA (P, D, Q) Model

The SARIMA (P, D, Q)/ ARIMA (p, d, q) x (P, D, Q) model produces solutions by considering seasonal factors. The general representation of the model is as shown in equation [1] (Halim and Bisono, 2008):

$$\beta_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D y_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t \quad [1]$$

In the equation, the expression $(1\text{-}B)^d$ is equal to the operator Δ^d, and the expression $(1\text{-}B^S)^D$ is equal to the operator Δ_s^D .

$$\beta_p(B)\Phi_P(B^S)\Delta^d\Delta_S^D y_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t \quad [2]$$

The model is shown as in equation [4] by adding equation [3], which expresses the differenced series (*wt*), to equation [2] (Li et al., 2003).

$$w_t = (1-B)^d(1-B^S)^D y_t = \Delta^d\Delta_S^D y_t \quad [3]$$

$$\beta_p(B)\Phi_P(B^S)w_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t \quad [4]$$

Where;

p, d, q: order of non-seasonal AR, differencing and MA respectively.

P, D, Q: order of seasonal AR, differencing and MA respectively.

yt: data set at period t.

εt: normally distributed error at period t.

B: backward shift, where $\left(B^m y_t = y_t - m\right)$.

S: seasonal order.

3.2. Grey System Theory and Grey Prediction

The Gray System Theory was developed in 1982 by Deng Julong (Liu and Forrest, 2007). The main focus of the theory is uncertain systems that work via partially known and partially unknown information (Lim et al., 2008). The system takes its name from the color of the researched subjects according to the type of information. In this context, the darkness of the colors is generally used to indicate the degree of clarity of the information (Liu and Lin, 2006). In theory, the color "gray" means information is incomplete or missing in a system, the color "white" means information is available, and the color "black" means information is not available (Chang et al., 2013). The advantage of the theory over other methods is that it can provide solutions to problems via fewer data sets (min. four observation values) and incomplete information (Awouda and Mamat; 2010).

The grey forecasting is a part of the Grey System Theory (GST) and includes many forecasting models. In this respect, studies have been carried out in many areas (electrical energy consumption, stock price, earthquake, natural gas consumption, container, etc.) using gray prediction models (Wang, 2009). The GM (1,1) model, which represents the first-order univariate grey model, is the most frequently used among the grey prediction models.

Because the GM (1,1) model always generates an exponentially increasing or decreasing time series, the residual values of the series may become gradually larger. This situation may reduce the reliability in terms of predictive values (Zhou et al., 2006). Therefore, in time series analysis, the trigonometric models are capable of modeling cyclic variations via a linear trend. Detailed explanations about GM (1,1) and Trigonometric Gray Estimation Model (TGM) are given below.

- GM (1,1) Model

The GM (1,1) model is the most classical forecasting model for modeling and forecasting small fluctuation time series (Wang et al., 2020:3). The model was developed by Julong (1989). The GM (1,1) model consists of the following basic steps (Liu and Lin, 2006):

Step 1: The time series with a sample size of n is defined as $X^{(0)}$ and is shown in equation [5].

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots\ldots, x^{(0)}(n))\,; \quad n \geq 4 \qquad [5]$$

Step 2: This series is transformed into a new $X^{(1)}$ series by the accumulated generating operation (AGO). The new series is shown in equations [6] and [7].

$$X^{(1)}(k) = (x^{(1)}(1), x^{(1)}(2), \ldots\ldots, x^{(1)}(n))\,; \quad n \geq 4 \qquad [6]$$

$$X^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \qquad k = 1, 2, 3, \ldots\ldots.., n \qquad [7]$$

Step 3: From the generated $X^{(1)}$ sequence, the sequential mean $Z^{(1)}$ series of this sequence is generated. In Equation 9, the series expressing the mean of two consecutive data is shown.

$$Z^{(1)} = (\mathrm{z}^{(1)}(1), \mathrm{z}^{(1)}(2), \ldots\ldots, \mathrm{z}^{(1)}(n)) \qquad [8]$$

$$Z^{(1)}(k) = 0.5\, x^{(1)}(k) + 0.5\, x^{(1)}(k-1) \qquad \mathrm{k}=2,3,\ldots\ldots..,\mathrm{n} \qquad [9]$$

Step 4: In Equation [10], the gray differential equation of the GM (1,1) model is created:

$$x^{(0)}(k) + az^{(1)}(k) = b \qquad k = 2, 3, \ldots\ldots.., n \qquad [10]$$

where, α is the development coefficient and b represent grey action quantity.

Step 5: The whitenization equation of the GM (1,1) model is shown in equation [11].

$$\frac{dx^{1}(\mathrm{k})}{dt} + ax^{(1)}(\mathrm{k}) = b \qquad [11]$$

Step 6: The method of ordinary least squares (OLS) or parametric method is used to calculate the a and b parameters in the gray differential equation. The equation is solved below using the more commonly used the method of OLS.

$$x^{(0)}(k) = -az^{(1)}(k) + b \qquad k = 2,3,........,n \qquad [12]$$

$$Y = \begin{pmatrix} x^{(0)}(1) \\ x^{(0)}(2) \\ \vdots \\ x^{(0)}(n) \end{pmatrix} \quad B = \begin{pmatrix} -z^{(1)}(1) & 1 \\ -z^{(1)}(2) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{pmatrix} \quad \hat{a} = \begin{pmatrix} a \\ b \end{pmatrix} \qquad [13]$$

$$Y = B\hat{a} \qquad [14]$$

$$B^{T}Y = B^{T}B\hat{a} \qquad [15]$$

$$(B^{T}B)^{-1}B^{T}Y = \hat{a} \qquad [16]$$

$$\hat{a} = \begin{pmatrix} a \\ b \end{pmatrix}; \; \begin{pmatrix} a \\ b \end{pmatrix} = (B^{T}B)^{-1}B^{T}Y \qquad [17]$$

Step 7: According to the whitenization equation, the expression $x^{(1)}(\mathrm{k})$ can be solved for a time k. Considering the values of a and b, the gray models in equations [18] and [19] can be created.

$$x_{p}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} \qquad [18]$$

In equation [18], $x_{p}^{(1)}(k+1)$ is the cumulative value of x predicted for time k+1.

$$x_{p}^{(0)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a} \right] e^{-ak}(1\text{-}e^{a}) \qquad [19]$$

In Equation [19], the inverse- accumulated generating operation is applied for the non-accumulative values of the forecast values.

- Trigonometric Grey Prediction Model

The Trigonometric Gray Prediction Model (TGM) approach was developed by Zhou et al. (2006). This model has a more efficient modeling capability that considers the seasonal effect for seasonal time series analysis (Wang et al., 2018). In this respect, the TGM provides more successful results than the GM (1,1).

The steps of TGM are shown below (Zhou et al., 2006; Wang et al., 2019):

Step 1: In order to create TGM, firstly, the original data set must be predicted using the GM (1,1) model. Therefore, according to the GM (1,1) model, the predictive value $\hat{X}^{(0)}$ of the original $X^{(0)}$ data set can be obtained.

$$\hat{X}^{(0)} = \left\{\hat{x}^{(0)}(2), \hat{x}^{(0)}(3), ..., \hat{x}^{(0)}(n)\right\}; \qquad n \geq 4 \qquad [20]$$

Step 2: In this step, the residuals of the model are calculated. The $r^{(0)}$ residual is shown in equations [21] and [22].

$$r^{(0)} = \left\{r^{(0)}(2), r^{(0)}(3), ..., r^{(0)}(n)\right\}; \qquad n \geq 4 \qquad [21]$$

$$r^{(0)}\left(k\right) = \left\{x^{(0)}(k) - \hat{x}^{(0)}(k)\right\}; \qquad \mathrm{k} = 2, 3, ..., n \qquad [22]$$

Step 3: The residual values are evaluated as a combination of the periodic changes and a linear trend. In this respect, the residual values can be modeled via Trigonometric Model (TM):

$$r^{(0)}\left(k+1\right) = b_0 + b_1 k + b_2 \sin\frac{2\pi k}{L} + b_3 \cos\frac{2\pi k}{L} + \varepsilon_k \qquad [23]$$

Where, L is the periodic change period (subjective) and ε_k denotes the random component.

Step 4: The coefficients of Equation [23] can be predicted using the OLS.

$$\left[\hat{b}_0,\ \hat{b}_1,\ \hat{b}_2,\ \hat{b}_3\right]^T = \left(B^T B\right)^{-1} B^T R_n \qquad [24]$$

$$R_n = \left[r^{(0)}(2), r^{(0)}(3), ..., r^{(0)}(n)\right]^T \qquad [25]$$

$$B = \begin{bmatrix} 1 & 1 & \sin\frac{2\pi}{L} & \cos\frac{2\pi}{L} \\ 1 & 2 & \sin\frac{2\pi}{L} & \cos\frac{2\pi}{L} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \text{n-1} & \sin\frac{2\left(n-1\right)\pi}{L} & \cos\frac{2\left(n-1\right)\pi}{L} \end{bmatrix} \qquad [26]$$

Step 5: The prediction value of the residual is shown in equation [27].

$$\hat{r}^{(0)}\left(k+1\right) = \hat{b}_0 + \hat{b}_1 k + \hat{b}_2 \sin\frac{2\pi k}{L} + \hat{b}_3 \cos\frac{2\pi k}{L} + \varepsilon_k \qquad [27]$$

Thus:

$$\hat{r}^{(0)} = \left[\hat{r}^{(0)}(2),\ \hat{r}^{(0)}(3), \ldots\ldots\ldots, \hat{r}^{(0)}(n)\right]^T \quad [28]$$

Step 6: TGM is created based on the TM obtained by the trigonometric residual modification technique.

$$\hat{x}_{tr}^{(0)}(1) = x^{(0)}(1) \quad [29]$$

$$\hat{x}_{tr}^{(0)}(\mathrm{k}) = \hat{x}^{(0)}(k) + \hat{r}^{(0)}(k) \quad [30]$$

Where $\hat{x}_{tr}^{(0)}(\mathrm{k})$ represents the trigonometric predicted value, $\hat{x}^{(0)}(k)$ is output of GM (1,1) model.

3.3. The Evaluation Criteria

Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) criteria were used to evaluate the success level of the models used in the study. These criteria are shown in equations [30], [31], [32] and [33] (Sallehuddin et al., 2007):

$$MSE = \frac{1}{n} * \sum_{t=1}^{n} (\mathrm{y}_t - \mathrm{y}_t)^2 \quad [31]$$

$$RMSE = \sqrt{\frac{1}{n} * \sum_{t=1}^{n} (\mathrm{y}_t - \mathrm{y}_t)^2} \quad [32]$$

$$MAPE = \sum_{t=1}^{n} \left| \frac{\mathrm{y}_t - \mathrm{y}_t}{\mathrm{y}_t} \right| * \frac{100}{n} \quad [33]$$

$$MAE - MAD = \sum_{t=1}^{n} \frac{\left|\mathrm{y}_t - \mathrm{y}_t\right|}{n} \quad [34]$$

where y_t is the actual series values, y_t is the predicted series values, n is the number of predicted period.

4. PREDICTING THE NUMBER OF EMERGENCY SERVICE PATIENTS

In this section, explanations and evaluations will be made about the data set used in the study and the prediction results for the emergency service.

4.1. The Data Set

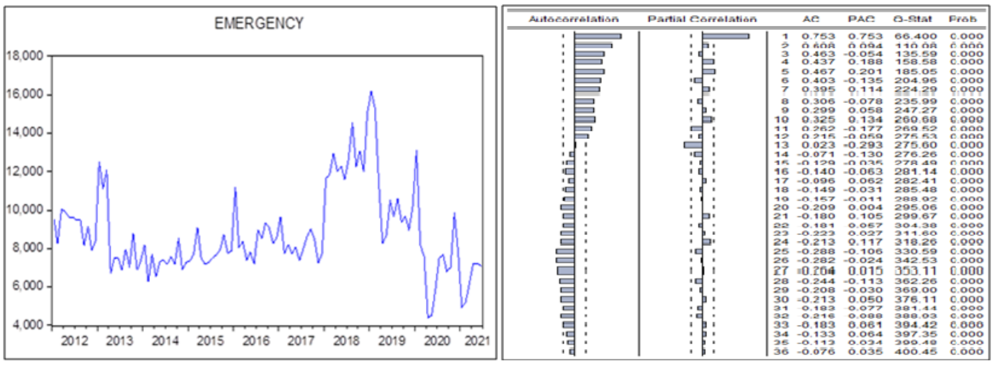
In the study, the records of emergency service for the period of January 2012- June 2021 (114 months) of a public hospital were used as a data set. Two different data sets were created for the B-J and

Grey Prediction approaches. In addition, both approaches were evaluated in terms of model success criteria using their own sample data set.

4.2. Predicting the Number of Emergency Service Patients using the SARIMA Model

For the SARIMA(p,d,q)x(P,D,Q) model, the number of monthly emergency service patients were predicted using a time series of 114 months (January 2012-June 2021). From the dataset, the predictions for the period of July 2021-December 2022 (18 months) have been calculated. The number of emergency service patients was expressed as the EMERGENCY time series. Figure 2 shows the line and correlogram charts of the number of emergency service patients for the 114-month period.

Figure 2. The Line and Correlogram Charts for the EMERGENCY Sequence



As seen in Figure 2, the sequence values are almost stationary but contain periodic fluctuations. The correlogram graph also supports this situation. It is determined that the values in the sequence generally peak in the first quarter of each year, however, they are the lowest in the summer months. The seasonal effect is observed more clearly in the correlogram graph. Seasonal (12-month) fluctuations and overflows from the confidence interval observed in both AR and MA processes support this result.

However, the line chart shows a sudden decrease in the first quarter of 2020. The reason for this decline can be attributed to the COVID-19 pandemic, which has affected the whole world. Boserup et al. (2020) stated that patients may be less likely to benefit from hospital emergency services because of fears about COVID-19. In addition, there are reports showing that patients who would normally require emergency services may ignore this condition. For example, in the US, the number of emergency service patients decreased by 42% in the period of March 29–April 25, 2020 compared to the same period of the previous year. (Hartnett et al. 2020:1). Tschaikowski et al. (2020) found that the number of emergency service patients decreased by 40% in a clinic in Munich between 01 February 2020 and 30 April 2020 compared to the same period of the previous year.

In addition to the graphs in Figure 2, the stationarity tests were carried out using unit root tests for the EMERGENCY sequence. The test results are shown in Figure 3.

Figure 3. The Unit Root Test Results for EMERGENCY Sequence

Null Hypothesis: EMERGENCY has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.896546	0.0028
Test critical values:	1% level	-3.489117	
	5% level	-2.887190	
	10% level	-2.580525	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: EMERGENCY has a unit root
Exogenous: Constant
Bandwidth: 7 (Newey-West automatic) using Bartlett kernel

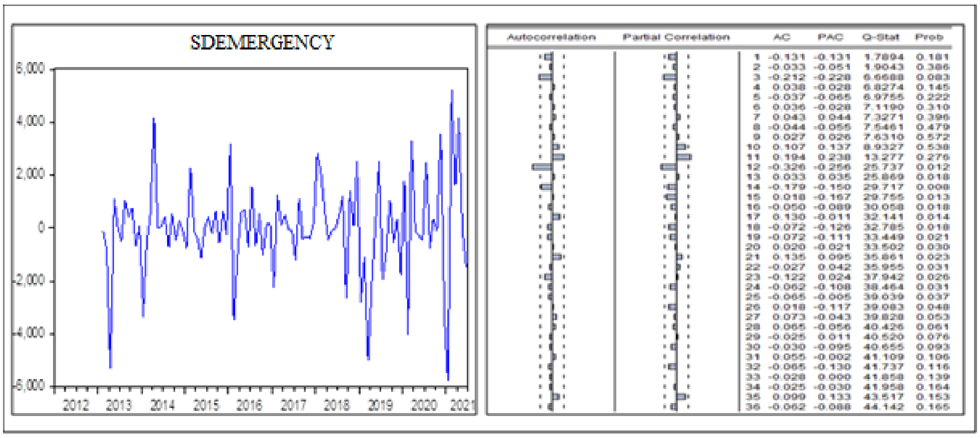
		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.872981	0.0031
Test critical values:	1% level	-3.489117	
	5% level	-2.887190	
	10% level	-2.580525	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	2105944.
HAC corrected variance (Bartlett kernel)	2073824.

When Figure 3 is examined, it is seen that the probabilistic (p) values of the Agumented Dickey Fuller (ADF) and Phillips Perron (PP) unit root tests are less than the critical value of 0.05. In addition, it is seen that t-Statistic test values are bigger than different critical values (1-5-10%). This means that the stationarity of the EMERGENCY sequence is acceptable. However, the first difference of the series was taken in order to obtain more successful results and to make the series more stationary. In addition, the first seasonal difference of the series was taken to reduce the seasonal factor effect. The first order non-seasonal and seasonally different series is called SDEMERGENCY. The time path and correlogram graph of this series are shown in Figure 4.

Figure 4. The Line and Correlogram Charts for the SDEMERGENCY Sequence



	AC	PAC	Q-Stat	Prob
1	-0.131	-0.131	1.7894	0.181
2	-0.033	-0.051	1.9043	0.386
3	-0.212	-0.228	6.6688	0.083
4	0.038	-0.028	6.8274	0.145
5	-0.037	-0.065	6.9755	0.222
6	0.036	-0.028	7.1190	0.310
7	0.043	0.044	7.3271	0.396
8	-0.044	-0.055	7.5461	0.479
9	0.027	0.026	7.6310	0.572
10	0.107	0.137	8.9327	0.538
11	0.194	0.238	13.277	0.276
12	-0.326	-0.256	25.737	0.012
13	0.033	0.035	25.869	0.018
14	-0.179	-0.150	29.717	0.008
15	0.018	-0.167	29.755	0.013
16	-0.050	-0.089	30.058	0.018
17	0.130	-0.011	32.141	0.014
18	-0.072	-0.126	32.785	0.018
19	-0.072	-0.111	33.449	0.021
20	0.020	-0.021	33.502	0.030
21	0.135	0.095	35.861	0.023
22	-0.027	0.042	35.955	0.031
23	-0.122	0.024	37.942	0.026
24	-0.062	-0.108	38.464	0.031
25	-0.065	-0.005	39.039	0.037
26	0.018	-0.117	39.083	0.048
27	0.073	-0.043	39.828	0.053
28	0.065	-0.056	40.426	0.061
29	-0.025	0.011	40.520	0.076
30	-0.030	-0.095	40.655	0.093
31	0.055	-0.002	41.109	0.106
32	-0.065	-0.130	41.737	0.116
33	-0.028	0.000	41.858	0.139
34	-0.025	-0.030	41.958	0.164
35	0.099	0.133	43.517	0.153
36	-0.062	-0.088	44.142	0.165

When Figure 4 is examined, it is seen that the series has got rid of the unit root and has no seasonal effect. This shows that the series is ready for the model determination phase. In order to determine the model that gives correct prediction results, first of all, seasonal and non-seasonal AR and MA degrees of the model (seasonal P, D, Q and non-seasonal p, d, q) must be determined. SDEMERGENCY series correlogram was used to determine the model degrees. Lag values in the ACF (Autocorrelation) and PACF (Partial Correlation) graphics were evaluated according to the confidence limits. The lag values outside the confidence limit give an idea about the model degrees and alternatives. In this context, P and Q degrees are determined using the PACF chart, while p and q degrees are determined using the ACF chart.

Among the 15 alternative SARIMA models determined, it was concluded that 4 models were significant as a result of the analysis of the parameter estimation values of the models. The parameter estimation value, Adjusted R^2, AIC (Akaike Information Criteria) and SIC (Schwarz Information Criteria) results for the 4 models are shown in Table 1.

Table 1. The Significance Values of SARIMA Models

Model No	Model	AR	MA	SAR	SMA	Ayarlı R^2	AIC	SIC
		B_1 (prob.)	θ (prob.)	Φ (prob.)	Θ (prob.)			
1	**ARIMA(1,1,1)x(1,1,0)$_{12}$**	0,81 0,00	-0,97 0,00	-0,44 0,00		0,21	17,66	17,78
2	**ARIMA(1,1,1)x(0,1,0)$_{12}$**	0,77 0,00	-0,98 0,00			0,08	17,83	17,91
3	**ARIMA(0,1,0)x(1,1,0)$_{12}$**			-0,49 0,00		0,17	17,69	17,74
4	**ARIMA(0,1,0)x(0,1,1)$_{12}$**		-		-0,86 0,00	0,42	17,35	17,40

In the analysis results, it is observed that the adjusted R^2, AIC and SIC values of all 4 models are in suitable ranges. However, since the results of the analysis are close to each other, the success of the 4 models must also be evaluated in terms of evaluation criteria. The predictive success evaluation criteria (MAPE, MAE-MAD, RMSE and MSE) results of 4 models calculated using the January 2017-December 2019 (36 months) sample data set are shown in Table 2.

Table 2. The Evaluation Criteria Results of SARIMA Models

Model No	Model	MAPE	MAE-MAD	RMSE	MSE
1	**SARIMA(1,1,1)x(1,1,0)**	28.81	3,380.09	4,221.45	17,820,640.10
2	**SARIMA(1,1,1)x(0,1,0)**	25.71	3,030.39	3,835.80	14,713,361.64
3	**SARIMA(0,1,0)x(1,1,0)**	**17.40**	**1,870.89**	**2,177.47**	**4,741,375.60**
4	**SARIMA(0,1,0)x(0,1,1)**	21.29	2,530.29	3,246.59	10,540,346.63

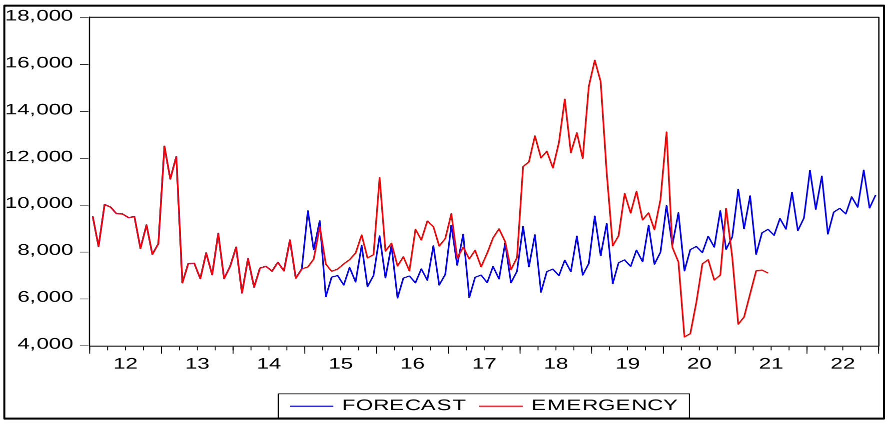
As seen in Table 2 the Model 3 (SARIMA(0,1,0)x(1,1,0)) provides the lowest results in terms of all evaluation criteria. Therefore, it can be said that the most successful model in terms of evaluation criteria is SARIMA(0,1,0)x(1,1,0). Thus, the number of emergency patients for the period of July 2021-December 2022 (18 months) is predicted for model number 3. The series expressing the predicted data set values are named PRETICTED. The predictive values obtained in the analyzes for the SARIMA(0,1,0)x(1,1,0) model using the E-Views 7 program are shown in Table 2.

Table 3. PRETICTED Sequence Values

Date		PRETICTED Sequence Values
Year	**Month**	
2021	**July**	8,713.97
2021	**August**	9,431.92
2021	**September**	8,976.27
2021	**October**	10,545.49
2021	**November**	8,913.60
2021	**December**	9,450.17
2022	**January**	11,483.75
2022	**February**	9,825.13
2022	**March**	11,239.67
2022	**April**	8,766.85
2022	**May**	9,696.64
2022	**June**	9,863.68
2022	**July**	9,624.94
2022	**August**	10,354.11
2022	**September**	9,913.96
2022	**October**	11,495.32
2022	**November**	9,878.02
2022	**December**	10,427.81

The raw data set (EMERGENCY) and the values of the predicted (FORECAST) series obtained by applying Model 3 to the entire data set are shown in Figure 5.

Figure 5. Line Charts of the EMERGENCY and FORECAST Series



When Figure 5 is examined, it can be said that Model 3, which gives very successful results in terms of evaluation criteria, has caught the serial trend. However, it is seen that the predictive values (FORECAST) do not fully capture the seasonal rises and falls in the raw data set (EMERGENCY).

4.3. Predicting the Number of Emergency Service Patients using the GM (1,1) and TGM

The Grey Prediction models give more successful results with fewer data sets. For this reason, in this part of the study focused on the pandemic process and used the data set for the period of January 2019-June 2021 (30 months) for GM (1,1) and TGM. The predicted values consist of the period from July 2021 to December 2022 (18 months) for both models. In addition, the prediction results of both models were evaluated in terms of success criteria.

The coefficient values calculated using the GM (1,1) differential equation [19] were found as α=0.0282 and b=12662.59. Then, the obtained GM (1,1) equation is given in [35].

$$x_p^{(0)}(k+1)=\left[16184-\frac{12662,59}{0,0282}\right]e^{-(0,0282)*k}(1\text{-}e^{0,0282}) \qquad [35]$$

The $\hat{x}^{(0)}(k)$ series, which shows the predictive values of GM (1,1), is used to find the residual values , which is the first step of TM. The $r^{(0)}$ series is obtained by taking the difference of observed values (raw data set values) $x^{(0)}(k)$, and prediction values $\hat{x}^{(0)}(k)$. The model coefficients were determined by using the OLS method of the TM model. The model coefficient values were calculated as $\hat{b}_0=-538,023$, $\hat{b}_1=40,58349$, $\hat{b}_2=-863,173$ and $\hat{b}_3=732,5444$ respectively. Then, the obtained TM equation is given in [36].

$$\hat{r}^{(0)}(k+1)=(-538,023)+(40,58349*k)+\left((-863,173)*\sin\frac{2\pi k}{12}\right)+\left(732,5444*\cos\frac{2\pi k}{12}\right)+\varepsilon_k \qquad [36]$$

As a result of the sum of the TM and GM (1,1) forecasted values, the TGM forecasted values $\hat{x}_{tr}^{(0)}(\mathrm{k})$ is obtained [30]. The forecasted and relative errors values of GM (1,1) and TGM obtained as a result of the analyzes are shown in Table 4.

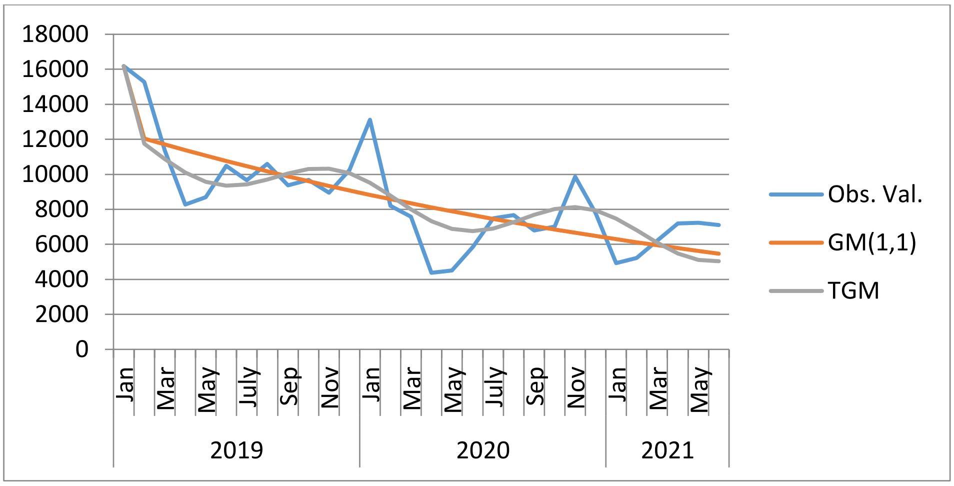
Table 4. Forecasted and Relative Errors Values of GM (1,1) and TGM

Date		Observed Value	GM (1,1)		TGM	
			Forecasted Value	RE (%)	Forecasted Value	RE (%)
2019	January	16,184	16,184	0	16184	0
	February	15,277	12,043.327	-21.167	11,748.999	-23.094
	March	11,367	11,708.311	3.003	10,870.763	-4.366
	April	8,265	11,382.613	37.721	10,103.752	22.247
	May	8,692	11,065.976	27.312	9,576.701	10.178
	June	10,490	10,758.147	2.556	9,356.548	-10.805
	July	9,664	10,458.881	8.225	9,430.441	-2.417
	August	10,593	10,167.940	-4.013	9,709.116	-8.344
	September	9,371	9,885.092	5.486	10,050.730	7.254
	October	9,675	9,610.112	-0.671	10,298.761	6.447
	November	8,954	9,342.781	4.342	10,323.853	15.299
	December	10,243	9,082.887	-11.326	10,058.380	-1.802
2020	January	13,124	8,830.223	-32.717	9,514.492	-27.503
	February	8,206	8,584.587	4.614	8,780.808	7.005
	March	7,575	8,345.784	10.175	7,998.637	5.593
	April	4,374	8,113.625	85.497	7,324.105	67.446
	May	4,514	7,887.923	74.744	6,886.305	52.554
	June	5,850	7,668.500	31.085	6,752.698	15.431
	July	7,494	7,455.180	-0.518	6,911.000	-7.780

	August	7,672	7,247.795	-5.529	7,272.428	-5.208
	September	6,801	7,046.178	3.605	7,695.418	13.151
	October	7,018	6,850.170	-2.391	8,023.477	14.327
	November	9,857	6,659.615	-32.438	8,127.027	-17.551
	December	7,780	6,474.360	-16.782	7,938.054	2.032
2021	**January**	4,921	6,294.259	27.906	7,468.268	51.763
	February	5,227	6,119.168	17.068	6,805.934	30.207
	March	6,215	5,948.947	-4.281	6,092.203	-1.976
	April	7,195	5,783.461	-19.618	5,483.292	-23.790
	May	7,232	5,622.579	-22.254	5,108.631	-29.361
	June	7,101	5,466.172	-23.022	5,036.179	-29.078

The forecasted and observed (raw data set) values obtained using GM (1,1) and TGM are shown in Figure 6.

Figure 6. Line Charts of Observed and Forecasted Values



The predicted values obtained by using GM (1,1) and TGM models and the evaluation criteria results of the models are given in Table 5.

Table 5. Predicted Values of GM (1,1) and TGM models and Evaluation Criteria Results

Date		**Predicted Values of GM (1,1)**	**Predicted Values of TGM**
2021	**July**	5,314.12	4,776.09
	August	5,166.29	4,628.27
	September	5,022.58	4,484.55
	October	4,882.86	4,344.84
	November	4,747.03	4,209.01
	December	4,614.98	4,076.96
2022	**January**	4,486.60	3,948.58
	February	4,361.80	3,823.77
	March	4,240.46	3,702.44
	April	4,122.50	3,584.48
	May	4,007.82	3,469.80
	June	3,896.34	3,358.31

	July	3,787.95	3,249.93
	August	3,682.58	3,144.55
	September	3,580.14	3,042.11
	October	3,480.55	2,942.52
	November	3,383.72	2,845.70
	December	3,289.60	2,751.57
MAPE		18.00	14.69
MSE		3,287,766.86	2,184,294.30
RMSE		1,813.22	1,477.94
MAD-MAE		1,320.80	1,074.54

When the results of the evaluation criteria (MAPE, MSE, RMSE and MAD-MAE) in Table 5 are examined, it is seen that the TGM gives better results than the GM (1,1). In Figure 6, it can be said that although the forecast values of GM (1,1) are in line with the trend, it could not catch the rises and falls. It has been determined that the TGM forecast values capture both the trend and the seasonal peaks and troughs better than the GM (1,1).

5. CONCLUSION

The COVID-19 pandemic threatens the health and life of millions of people. For this reason, the common belief is that COVID-19 pandemic would significantly affect the health sector. Especially the emergency services of hospitals are one of the units most affected by this issue. In this study, the number of monthly emergency service patients was predicted for a public hospital. In particular, it was aimed to investigate the effect of the pandemic on the emergency service. For this purpose, records for the period of January 2012- June 2021 (114 months) of a hospital were selected as a data set.

In the analysis, two different sample data sets were created for the B-J and GST approaches. While examining the long-term trend of the number emergency services patients' using the SARIMA model, GM (1,1) and TGM were used to focus on the COVID-19 period. The success of the estimation results obtained via SARIMA model, GM (1,1) and TGM were examined in terms of the evaluation criteria. GM (1,1) and TGM were examined in terms of evaluation criteria. When the success of the models is compared, TGM provided more successful results than both the GM (1,1) predicted for the same period and the SARIMA model, which covers the longer period. The MAPE value of the SARIMA model, which was created with the 36-month sample data set (January 2017-December 2019), which did not include the COVID-19 period, was calculated as 17.40%. Calculated with the January 2019-June 2021 sample dataset (30 months), most of which (18 months) covers the COVID-19 period, the MAPE value of GM (1.1) was 18% and the MAPE value of TGM was 14.67%.

The TGM, which gives more successful results than the other models, is insufficient in catching other fluctuations, although it catches seasonal peaks and troughs. It can be concluded that the reason for this situation is the prohibition and precautionary decisions taken by the government depending on the increase in cases. Because the prohibition and injunction decisions do not include a periodical process. This situation especially reduces the prediction success of the models used in the study. However, when the time series used in the study shown in Figure 2 is examined, it is seen that the number of emergency patients decreased significantly during the pandemic period. Therefore, in this process, it is possible to say that people avoid going to the emergency services except in very urgent situations.

On the other hand, it is predicted that the COVID-19 pandemic may continue in the coming year or years. Therefore, it should be taken into account that the emergency services, which are one of the most crowded units of hospitals, are more affected by this situation. For this reason, forecasting models can be created with different time series such as weekly, daily or hourly instead of monthly in order to increase the success of forecasting in future studies. On the other hand, new approaches can be developed by using fuzzy or grey numbers to increase the efficiency of the models. In addition, more detailed studies can be done by classifying the reasons for patients to apply to the emergency services.

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