Forecasting Patients Admitted to Emergency Departments with the Diagnosis of Upper Respiratory Tract Infection Using Time Series and Artificial Neural Network Modelling

Üst Solunum Yolu Enfeksiyonu Tanısıyla Acil Servise Başvuran Hastaların Zaman Serisi ve Yapay Sinir Ağı Modelleri Kullanılarak Tahmin Edilmesi

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ABSTRACT

Emergency departments are vital units that operate 24/7, care for critically ill patients, and provide immediate emergency care in accordance with the triage code for admitted patients. The efficient operation of emergency services depends on adequate human and medical resources and on early planning. The increase in the intensity of emergency services due to COVID-19, a biological disaster, has limited the effective use of resources and planning efforts. Overcrowding in emergency rooms can disrupt services and endanger patients' lives. For this reason, it is essential to organize emergency service units according to patient estimates, provide service at an optimal level, facilitate planning and management, use medical and human resources effectively, and ensure patient satisfaction. This study was conducted to predict emergency department patient arrivals using meteorological data. In this study, hourly forecasting results are obtained using estimation methods, including the seasonal autoregressive integrated moving average (SARIMAX), an artificial neural network (ANN), and a nonlinear autoregressive with exogenous inputs (NARX) model. For the study, patient arrival data from a training and research hospital for December 2021 and meteorological data, including temperature, humidity, and wind, were used. Methods for predicting emergency department patient admissions were compared, and the SARIMAX model performed best. It is thought that predictions based on meteorological data will contribute to emergency department planning.

Keywords: Patient Forecast, Emergency Service, SARIMAX, ANN, NARX

ÖZ

Acil servisler tam zamanlı çalışan, kritik hastalara hizmet veren ve hastalara triyaj koduna göre acil bakım sağlayan hayati birimlerdir. Acil servislerin verimli çalışması, yeterli insan ve tıbbi kaynaklara ve erken planlama çalışmalarına bağlıdır. Biyolojik bir afet olan COVID-19 nedeniyle acil servislerin yoğunluğunun artması, kaynakların etkin kullanımını ve planlama çalışmalarını sınırladı. Acil servislerde hasta yoğunluğu, hizmetin aksamasına neden olarak hastaların hayatını tehlikeye atabilir. Bu nedenle acil servis birimlerinin hasta tahminlerine göre düzenlenmesi, hizmetin optimum düzeyde sağlanması, planlama ve yönetim kolaylığı sağlanması, tıbbi ve insan kaynaklarının etkin kullanılması, hasta memnuniyeti ve hastalara yeterli hizmet verilmesi açısından önemlidir. Bu çalışma acil servise hasta gelişlerini meteorolojik veriler ışığında tahmin etmek amacıyla yapılmıştır. Çalışmada, mevsimsel Otoregresif Entegre Hareketli Ortalama (SARIMAX), yapay sinir ağı (ANN), dışsal girdili doğrusal olmayan otoregresif modeller ve dışsal regresyonistlerle (NARX) tahmin yöntemleri kullanılarak saatlik tahmin sonuçları elde edilmiştir. Çalışma kapsamında, Aralık 2021 dönemine ait bir eğitim ve araştırma hastanesinin acil servisine başvuran hasta verileri ile sıcaklık, nem ve rüzgâr gibi meteorolojik veriler kullanılmıştır. Karşılaştırılan yöntemler arasında SARIMAX modelinin en iyi performansı gösterdiği saptanmıştır. Meteorolojik verilere dayalı tahminlerin, acil servis planlamasına katkı sağlayacağı düşünülmektedir.

Anahtar Kelimeler: Hasta Tahmini, Acil Servis, SARIMAX, ANN, NARX

Highlights

* There is a need for estimation of patient arrivals to recognize the deteriorating conditions in the emergency department as soon as possible and to take appropriate measures in a timely manner.
* Since studies on hourly patient arrival estimations are limited, SARIMAX, ANN, and NARX methods were used.
* The analysis revealed that the epidemic trend is related to meteorological factors.

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INTRODUCTION

The emergency department of a hospital is one of the most essential parts of the medical response (1). Sudden waves that cause significant problems in emergency departments, which are critical components of hospitals, usually occur due to human or natural events (2). Inadequate emergency services due to overcrowding from various causes can lead to worsening symptoms or adverse patient outcomes such as death (3).

Emergency services worldwide, including in Turkey, have faced increasing demand, especially in recent years (4). Sudden and overcrowding in the volume of patients in emergency departments due to the pandemic has increased the burden of emergency services and created concerns about the adequacy of resources. With the rapid spread of COVID-19, which first appeared in Wuhan, China, on December 31, 2019, there has been a significant increase in patients presenting to hospital emergency departments (2).

Unexpected and significant fluctuations in patient volume in emergency departments lead to long waiting times, strain the service, increase the time to hospitalization, and negatively affect the clinical outcomes of many patients, including mortality (2, 5-7). In addition, it causes emergency service personnel to work under stress and significantly affects employee satisfaction (4).

Deep learning and artificial intelligence models have demonstrated strong performance in classification and forecasting across a range of fields, from agricultural disease detection (8) to health service demand prediction. These advances support the use of neural network–based approaches for modeling complex healthcare data influenced by environmental factors. Emergency services require resources to manage unexpected patient flows, but the available resources are limited (4). Accurate estimation of patient volume is crucial for the optimization of the allocation of materials and resources to use resources effectively in emergency departments (9). For this purpose, various methods have been used together with time series analyses to make predictions based on time data in emergency services (10). The general linear method (GLM), classical shallow artificial neural network (ANN), autoregressive integrated moving average (ARIMA), and seasonal autoregressive integrated moving average (SARIMA) are the most widely used methods (11). Time series analyses consist of annual, monthly, daily, weekly, or hourly forecast models (5, 10, 12). Compared to monthly and yearly forecast models, hourly forecast models provide more accurate forecasts and reduce emergency department crowding by increasing readiness and initiating rapid follow-up triage (13). However, studies on hourly occupancy prediction models in emergency departments are limited (10). For this reason, the primary aim of the study is to develop a forecast model based on time series analysis to report the hourly change in emergency services due to the COVID-19 pandemic.

It is crucial to recognize the deteriorating conditions in the emergency room as soon as possible and to take appropriate measures in a timely manner so that resource and material optimization preparations can be carried out (10). The number of patient visits to the emergency department varies seasonally, and calendar variables have significant effects on the number of emergency department admissions (11). This study aims to examine the performance of SARIMAX, NARX, and ANN models that include calendar and meteorological variables in predicting emergency department visit counts and to evaluate their usability for early detection of emergency department occupancy. Therefore, the research question of this study is how well the SARIMAX, NARX, and ANN models, developed using calendar and meteorological variables, predict the number of emergency department visits. Data from patients with upper respiratory tract infections diagnosed between December 1, 2020, and January 1, 2021, at a hospital emergency department located in the southeastern Anatolia region of Turkey, were used. The rest of the article is structured as follows: literature review, research methodology, data analysis, discussion, results, and recommendations.

Review of Previous Studies

In this section, studies on patient arrival predictions at hospital emergency departments are evaluated. Patient potentials for emergency services vary. For this reason, time is an essential factor in the performance of emergency services, affecting service quality and patient care. At a detailed level, the hourly studies examined can serve as an example (10, 13).

Some studies estimate daily patient arrivals (14-18), as well as those that estimate weekly patient arrivals (19). Some studies are hourly-daily (20-23), daily-weekly, daily-weekly-monthly, weekly-monthly, or daily-monthly-yearly patient arrivals were estimated (19, 24).

One or more variable datasets were used to build the prediction model. When these variables were examined, past emergency room arrival data were used in almost all studies. In addition, seasonal data, calendar variables such as time, day, month, and year), meteorological variables, demographic variables, patients' triage codes, and variables for special days were used (16-19, 23, 24).

In these studies, machine learning, time-series, and regression-based estimation methods were generally used. If we give examples of some of them; According to (9) ARIMA, CCMU, and GEMSA ED daily arrivals using a time series-based approach (12), short, medium, and long-term ED arrivals using regression and ANN (18), DNN, ARIMA, GLM, SARIMAX by designing and comparing a series of hybrid models, daily patient flows in an emergency department (17), Recurrent Neural Network (RNN)-LSTM with methods, daily patient arrivals (15), ED daily patient admissions with exponential smoothing and hybrid methods such as linear regression (LR), ARIMA, ANN, ARIMA–ANN, ARIMA-LR (14), patient flow to the emergency room with the hybrid-based ARIMA-SVR approach, compared it with the SARIMA, MLP, SARIMAX models in estimating the daily visits of patients in the emergency department.

Commonly used error metrics to evaluate and compare forecasting models are root mean square error (RMSE) (9), normalized mean square error (NMSE) (19), MAPE (mean absolute percent error), MAE (mean absolute error) (16), MSE (mean square error) (23), sMAPE (symmetric mean absolute percent error) (22), explained variance (EV) (20) and R-squared (12).

Various studies in the literature estimate the number of patients admitted to the emergency department. Few of these studies aim to estimate hourly patient arrivals (13). Used Holt-Winters, ARIMA, neural network, and TBATS methods. In the 2021 study, Cheng et al. used the SARIMAX method to estimate emergency room occupancy (11). The study used calendar and meteorological parameters to estimate the number of patients coming to the emergency department hourly and daily. Used week-day-hour seasonality, long-term trends, calendar events, and temperature effects to make hourly probabilistic estimations of hourly patient arrivals to the emergency department (25).

Hourly forecast models provide more accurate patient arrival estimates compared to monthly and annual forecast models (13). The number of patient visits to the emergency department varies seasonally, and calendar variables have significant effects on the number of emergency department admissions (11). For this reason, it is aimed to evaluate patient arrivals to the emergency department using hourly forecast models and meteorological variables. In this context, our contributions to the literature are;

(1) Presenting hourly forecast models for epidemics such as COVID-19, which has the potential to increase the number of patient visits to the emergency department,

(2) Evaluation of the effects of metrological data (temperature, wind speed, and humidity) on the number of patients presenting to the ED with COVID-19 symptoms

(3) It has been determined that the use of SARIMAX, ANN, and NARX methods together in hourly estimation and evaluation of estimation accuracy by making comparisons.

MATERIAL AND METHODOLOGY

Two datasets were used for this study. The first is data from a hospital in a province with a population of 626,319 located in the Southeastern Anatolia Region of Türkiye, collected for December 2021. The second is weather data for the city where the hospital is located. The first variable, patient arrivals, is the number of patients admitted to the emergency department with an upper respiratory tract diagnosis. The second variable, temperature, can be expressed as the average kinetic energy of the particles (atoms or molecules) in a system. The third variable, wind speed, is the speed at which wind, air, or other gases move through the atmosphere. The last variable, humidity temperature, is the temperature at which the water vapor in your compressed air changes from vapor to liquid (condensation). December data from the selected province were used for all variables in this study. Based on hospital data, the number of patients visiting the emergency department in a month was 44,724, and the day, hour, and ICD (International Statistical Classification of Diseases and Related Health Problems) codes for these patients were recorded. Meteorological data, on the other hand, were obtained from the Weather Spark website, which provides monthly, daily, and hourly weather conditions and climate reports. Hourly data, including temperature, humidity, and wind speed, were obtained from this website.

It is known that the number of patients worldwide has increased due to the COVID-19 pandemic; accordingly, our study was conducted using regional cases exhibiting specific findings of this disease. Fever and cough are among the most common symptoms of COVID-19 (26). However, previous studies have also reported symptoms such as respiratory distress, muscle pain, fatigue, headache, general body pain, and joint pain (27, 28). In line with this information, a classification was made using the preliminary diagnoses in the patients' ICD codes, and a study was conducted on a total of 23.466 patients who exhibited one or more of these symptoms. The dataset was partitioned into training, validation, and test sets through an automated random selection process. Specifically, 70% of the data was used for training, 15% for validation, and the remaining 15% for testing to evaluate the model's generalization performance.

Figure 1 shows the distribution of the variable parameters over time. In the graph of the hourly distribution of patient admissions to the emergency department with a diagnosis of upper respiratory tract, the number of admissions increased gradually. Then it decreased gradually, reaching a maximum of 87 admissions within an hour. The temperature and humidity point graph likewise showed gradual increases and decreases. We can say that the wind speed graph gradually increases, decreases, and finally flattens.

Methodology

In this study, hourly forecast analysis was conducted using 1-month admissions and weather variables from a hospital with an average of 1400 daily emergency service admissions. The block diagram for the study on emergency room patient flow estimation is shown in Figure 2. Initially, the hospital data were preprocessed, and information that would not be used was extracted. All quantitative data were then compiled in Excel. The data were then analyzed using SARIMAX, ANN, and NARX methods to estimate the hourly number of patients arriving at the hospital emergency department. The accuracy of the results obtained in this way was evaluated and compared with real data.

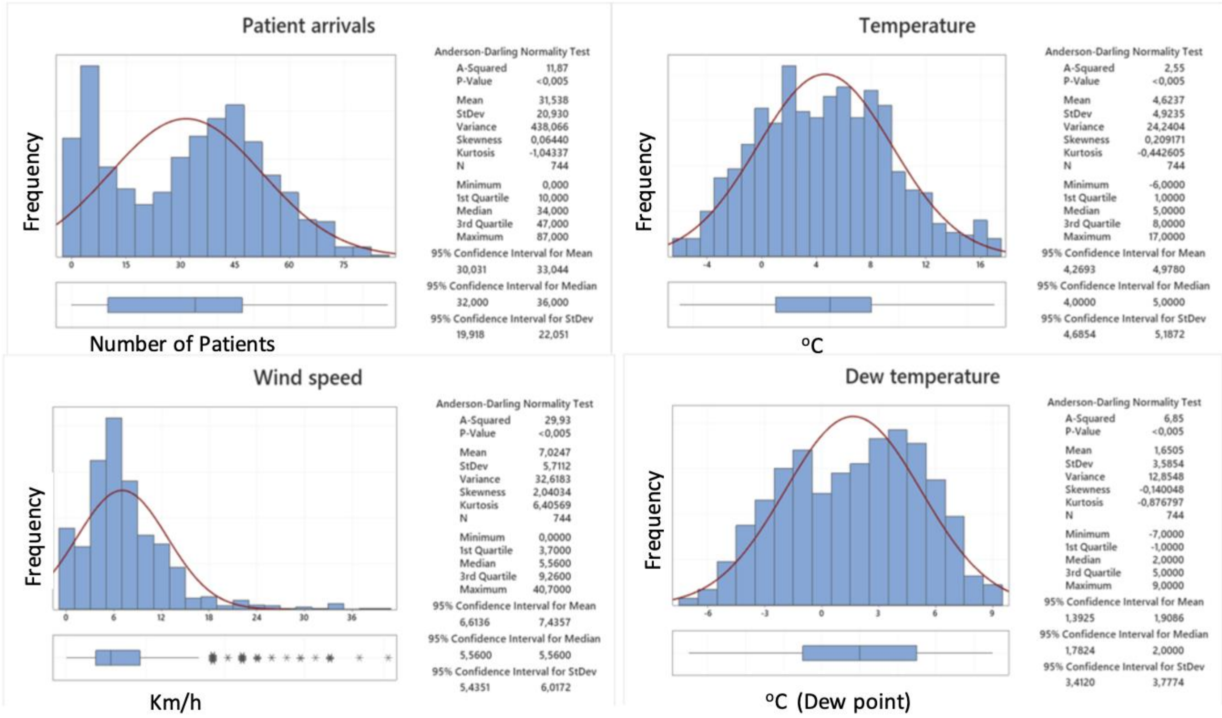

Figure 1. Descriptive Parameters of Variables

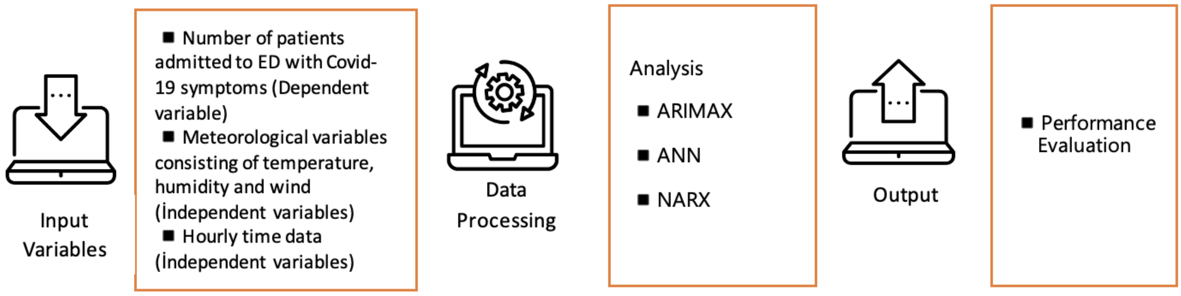

Figure 2. Flow Chart of the Work Carried Out

A time series consists of observations applied and recorded in different time periods (29). In addition, since the time factor is an essential variable across all areas of life, its application is also quite wide (29). Health care is one area where time is critical. Time series forecasting models help healthcare managers plan, make decisions, and prevent and control disease.

Overview of the SARIMAX model

The ARIMA (AutoRegressive Integrated Moving Average) model proposed by Box and Jenkins is widely used for nonstationary time series (30, 31). The ARIMA model includes three components, Autoregressive- (AR), Integrated- (I), and Moving Average- (MA), and analyzes stochastic time series with one variable (32). ARIMA models are frequently used to estimate patient arrivals in the emergency department (15). The ARIMAX model, on the other hand, is an ARIMA used to make predictions with very different input variables (33).

The time series comprises different models for each component. SARIMA is the ARIMA model extension that includes seasonal data. The SARIMAX model, on the other hand, is expanded according to the seasonal component it contains, together with the exogenous variables (34). SARIMAX, a statistical model, predicts future values using linear relationships, error terms, and side information from previously observed sequential data (35).

The SARIMA model can be expressed as

$$\phi_p(B)\phi_p(B^S)(1-B)^d(1-B^S)^D Z_t = \Theta_q(B)\Theta_Q(B^S)\varepsilon_t$$

Where, $\phi_p(B)$ seasonal autoregressive operator with p-order, $\Theta_q(B)$, seasonal moving average operator with q-order, $(1-B)^D$ seasonal differencing operator of order D, $(1-B)^d$and S - Seasonal length (15).

The SARIMAX model is an advanced version of the SARIMA model. In addition to the SARIMA model, there are explanatory variables (36).

Overview of the ANN model

The hyperparameters used in ANN models were selected based on ranges suggested in the literature to optimize model performance. The number of hidden neurons in the MATLAB program was tested. The model with the lowest MSE was selected. Artificial neural networks are used to model complex, nonlinear relationships between inputs and outputs (37). ANNs, also called neural networks, mimic the architecture and operation of the human brain and perform computational operations through a series of interconnected components (38). The advantage of ANNs is that they can be used without relying on the assumption of a relationship between input variables (38). Advantage is that they can process data that is too complex to be generated by a conventional computer and can include uncertainty in each dataset. ANNs are used in fields such as engineering, agriculture, medicine, education, physics, biology, and chemistry (39). It is also frequently used for emergency services to make patient admission times, length of stay, and patient arrival estimations (40).

Overview of the NARX model

NARX neural network models are a popular subclass of recurrent networks used in many applications (41). NARX, a type of dynamic ANN, iterates and describes the modeled process based on lagged input-output variables and prediction errors. At the same time, NARX has become a preferred model because of the positive results it has shown in the estimation of time series with seasonal components (42).

The expression for the NARX model is given by:

$$Y(t) = f(x(t-1), \dots x(x-d), y(t-1), \dots y(t-d)$$

In this equation, x (t) represents the inputs, y (t) f represents the outputs of the nonlinear uncertainty function, and d represents the feedback. Hourly patient arrivals, temperature, humidity, wind, and time of day were used as target variables. Similarly, in the NARX model, different numbers of neurons and input-feedback delays were tested, and the structure with the lowest MSE error was selected as the final model.

RESULTS AND DISCUSSION

Various methods were used within the scope of the study to obtain the best results. These are methods: SARIMAX, ANN, and NARX. To test the models' accuracy, MSE, R2, and MAPE were evaluated. According to the results, the optimal solution was achieved in neuron 3 using the ANN method.

NARX results were analyzed for neuron count and latency according to MSE and R2. The best solution is obtained when the number of neurons is 1, and the number of delays is 2. It is used in the SARIMAX model to estimate future values and predict errors. The best ARMA model chosen was determined as (4,2) (0,1).

Parameter Estimation

The primary mechanism by which climatic factors drive disease transmission is the virus's ability to survive in the external environment before entering a host. In other words, the environment can mediate the transmission of SARS-CoV-2 or destabilize the virus, reducing its epidemic capacity (42). When determining the epidemic trend, the combination of several meteorological factors performs better than using a single factor (43). Because these factors can affect droplet stability, the survivability of viruses, and may change the number of hospital admissions by affecting transmission. Analyses of the meteorological aspects of COVID-19 outbreaks, a biological disaster, reveal an essential link between the incidence of positive cases and climatic conditions (43). Therefore, in this study, various meteorological factors were used to determine the effect on the number of patient visits in the hospital emergency department. The study's date range covers a period when COVID-19 patient numbers were high. It is thought that this situation will allow a more qualified assessment.

First, we created an appropriate LR-based forecast model based on clock changes and the data's trend over the 1-month period of January 2021. Values related to the significance of the estimated model are given in Table 1.

Table 1. Results of the estimated LR model. Patient = 0.371 + 0.0214*Temperature- 0.0142*Wind + 0.0475* Humidity + 0.0277*Monday + 0.020*Tuesday + 0.0382* Wednesday + 0.0311* Thursday + 0.0131* Friday- 0.004* Saturday

Predictor	Coef	Predictor	Coef
Patient	0.3716	*SA8*	-0.343
Temperature	0.0214	*SA9*	-0.246
Wınd	- 0.0142	*SA10*	-0.108
Humidity	0.0475	*SA11*	0.017
Monday	0.0277	*SA12*	0.084
Tuesday	0.0204	*SA13*	0.029
Wednesday	0.0382	*SA14*	0.115
Thursday	0.0311	*SA15*	0.154
Frıday	0.0131	*SA16*	0.160
Saturday	- 0.004	*SA17*	0.081
SA1	-0.111	*SA18*	0.026
SA2	-0.258	*SA19*	0.094
SA3	-0.337	*SA20*	0.222
SA4	-0.369	*SA21*	0.241
SA5	-0.382	*SA22*	0.140
SA6	-0.399	*SA23*	0.099
SA7	-0.382		

The wind coefficient value of-0.014, one of the independent variables in the table, indicates an effect on the number of patients coming to the emergency department at an average rate of 0.014 per day. A decrease in wind speed has been associated with an increase in emergency department visits. It is thought that wind speed is associated with COVID-19 cases, with lower wind speed being associated with more cases (44). This may be due to the virus being diluted and removed by high wind speeds while remaining in the air for a shorter time, reducing transmission (45). However, the effect of wind on droplet transport and accumulation is complex, and the rate of viral transmission may increase with coughing in an environment with insufficient social distancing (46). The variables SA1–SA23 represent time periods within the day. The coefficients for these variables show how the number of emergency room visits in the relevant time period differs from the reference time period; negative coefficients indicate a tendency toward fewer visits, while positive coefficients indicate a tendency toward more visits.

The value of 0.021 for temperature indicates that the number of patients decreases as temperature increases. Exposure to low environmental temperatures increases the risk of upper and lower respiratory tract infections and of death. According to data from many clinical studies, the body surface cools when exposed to cold air, and cold stress occurs as body temperature decreases. This increases susceptibility to infection by narrowing the blood vessels in the respiratory tract and suppressing immune responses (47). On the other hand, coronavirus can maintain its infectivity for up to 2 weeks in an environment with low humidity and low-temperature components, which is a factor that facilitates its transmission (48). As a matter of fact, the value of 0.047 belonging to the humidity indicates that the number of patients decreased with an increase in the rate of the amount of moisture by 0.047. In other words, cold, dry climatic conditions are thought to be a factor in the virus's spread, while hot, humid climates reduce its spread.

[45] It is also known that humidity influences the dynamics of change in the droplet size of the viruses (46). However, it can be argued that summer weather alone cannot replace prevention and mitigation policies; if lower temperatures and inappropriate policy interventions are not implemented, transmission intensity will increase (49).

A value of 0.027 for one of the other independent variables indicates that there are 0.027 more visits to the emergency room on a typical Monday than on a typical Sunday. It can be said that this is related to increased interaction among people due to the workload and curfew measures applied on the weekend. This shows that not only meteorological variables but also social and political measures and behaviors are effective in the spread of contagion.

Forecasting results

In this study, SARIMAX, ANN, and NARX models were used to predict patient arrivals. In Figure 3, the hourly forecast intervals for 28 days in the test set are shown for these models. The blue lines represent the observed occupancy, while the red lines represent the estimated patient count. The predictive performance of time series models can be compared via error statistics (criteria). In this study, one of the essential criteria, MAPE, was used.

As can be seen in Figure 3, the deviations observed in the ANN and NARX models increase, especially during peak hours (18:00–23:00), while the SARIMAX model produces more stable predictions during these hours.

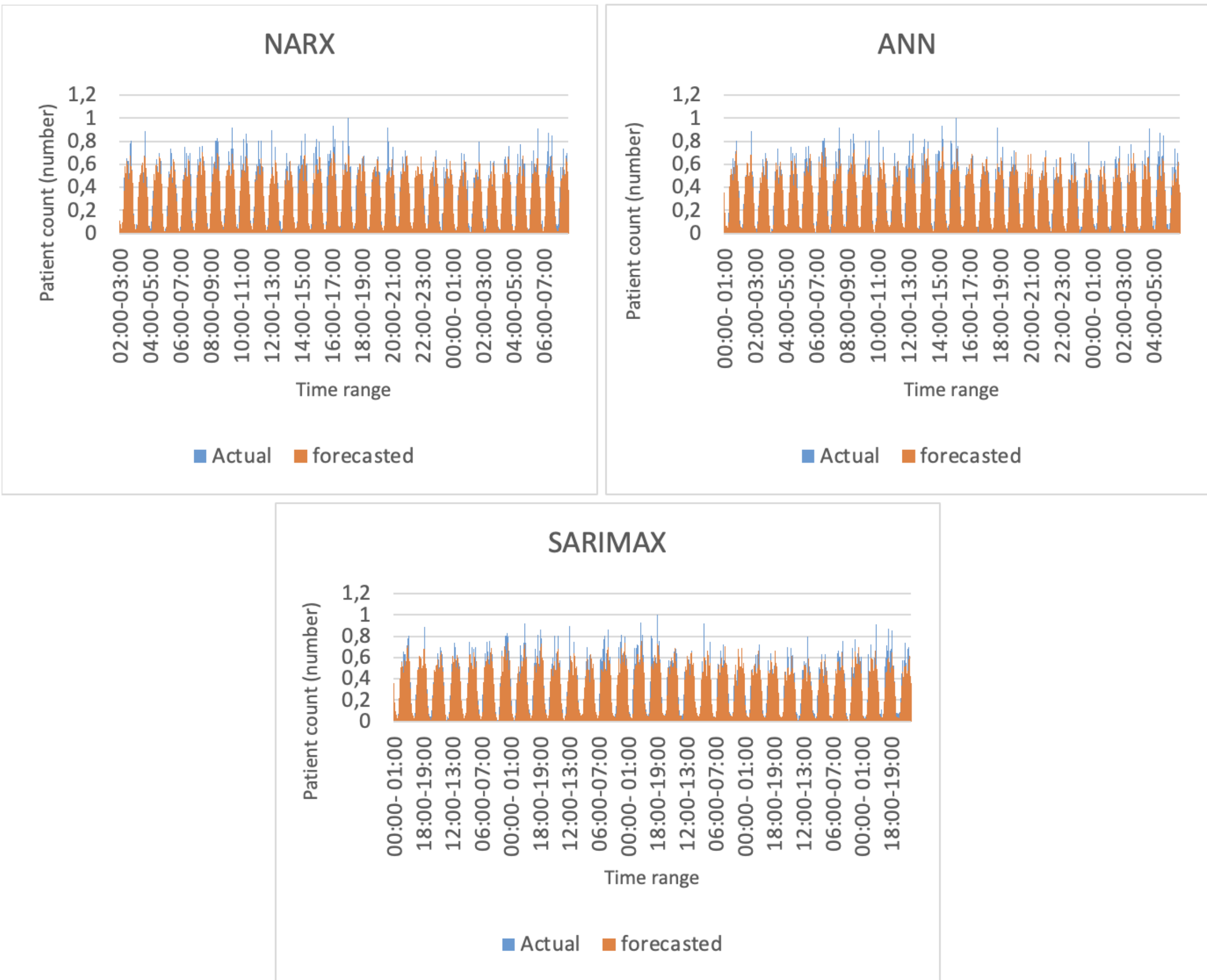

Figure 3. Hourly Actual and Estimated Number of Patients Graphs of the Applied Models

After applying the models to predict hourly patient arrivals, comparisons and evaluations were made with performance measures. Figure 4 shows the comparative evaluation results of the methods. As shown in this figure, SARIMAX is the method that comes closest to the actual estimation results.

The comparative results presented in Figure 4 show that the SARIMAX model exhibits more stable performance, particularly at night and during periods of low application density, whereas the ANN and NARX models are more sensitive to weekday fluctuations.

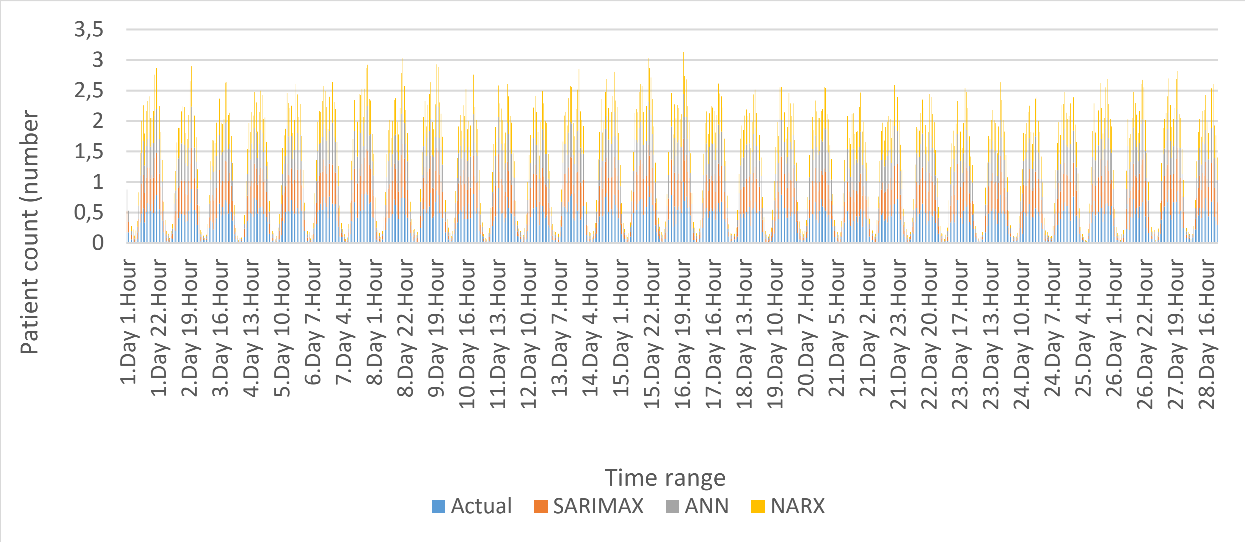

Figure 4. Comparative Estimation Results of the Models

The reports provided for the SARIMAX model are as follows (Table 2). R^2 determination coefficient value is 0.83%. This value indicates that the model explains the prediction at 83%. The standard regression error of 0.09 represents the difference between the actual number of patients arriving at the emergency service and the estimated number per hour. The fact that the F test is 0.0 indicates that the independent variables in the proposed model cannot be discarded.

Model Accuracy Results

Compared with previous studies, a good MAPE is obtained for hourly forecasts (21). Estimated hourly and daily patient arrivals using ARIMA and Naïve methods, and obtained the best MAPE value of 47%. The present study attempted to predict daily and hourly patient arrivals using calendar and meteorological variables, achieving an MAPE of 40%. On the other hand, they found the best MAPE value to be 23% in their study of hourly and daily estimates of patient arrivals (11, 22).

Table 2. SARIMAX forecasting models reporting details

Forecasting model for SARIMAX	
AR1	1.8312
AR2	-1.1867
AR3	0.0582
AR4	0.0477
MA1	-1.6894
MA2	0.9999
SMA6	0.1086
R-squared	0.839380
Adjusted R-squared	0.830241
S.E. of regression	0.099121
Sum squared resid	6.907002
Log likelihood	682.9473
F-statistic	91.84470
Prob (F-statistic)	0.000000

As shown in Table 3, the SARIMAX model performed better, with an MAPE of 31%, compared to the ANN and NARX models. The ANN model achieved the second-best performance, with a MAPE of 31.54%. The NARX model, on the other hand, was the worst, with an MAPE of 33.4%.

Table 3. The comparison of the methods

Method	Structure of the method	MAPE (%)	Rank
SARIMAX	(4,2) (0,1)	31	1
ANN	3 Neuron	31.54	2
NARX	1 neuron, 2 delay	33.4	3

Table 3 shows that the SARIMAX model provides higher accuracy in predicting hourly patient admissions compared to the ANN and NARX models. The superior performance of the SARIMAX model can be attributed to its ability to model significant seasonality in hourly data and to integrate exogenous variables such as temperature, humidity, and wind within a linear framework. In contrast, the sensitivity of the ANN and NARX models to neuron number and delay structure in hourly datasets covering a limited time interval may have increased the risk of overfitting, thus relatively reducing prediction accuracy.

The results show that the SARIMAX model performs more consistently in predicting hourly patient admissions than the ANN and NARX models. The superiority of the SARIMAX model can be attributed to its ability to directly model intraday seasonality components that are evident in hourly time series and to use exogenous variables such as temperature, humidity, and wind as explanatory variables within the same framework (10, 11, 24). In particular, the signs of the meteorological variables indicate that respiratory tract infections tend to increase under cold, dry conditions, as highlighted in the literatüre (45, 47, 48). In contrast, while the ANN and NARX models are strong at capturing nonlinear relationships, they may be more sensitive to parameter selection (number of neurons and lag structure) because of the limited number of hourly fluctuations and peak admission counts in a one-month data window (17, 21, 41).

Although numerous studies in the literature predict emergency department admissions, hourly prediction studies are reported to be limited (13, 21, 25). The error values obtained in this study are similar to those in studies that make hourly predictions (10, 11, 24). In particular, the use of the SARIMAX approach by Cheng et al. to predict hourly emergency department occupancy and the demonstration that calendar and environmental variables significantly contribute to the model shows a strong parallel with the method of this study (10). However, differences in error levels can be explained by factors such as sample size, diagnostic group selection (upper respiratory tract infection and COVID-like symptoms), data collection period (pandemic-wave effects), and the scope of the exogenous variable set included in the model (22, 23, 25). In this context, considering the findings alongside the literature indicates that hourly forecast models based on meteorological variables are applicable to emergency department resource planning. This is consistent with current developments in deep learning performance and diagnostic modeling (50).

CONCLUSION AND RECOMMENDATIONS

Faced with unexpected patient demands, emergency services have been further challenged by the COVID-19 outbreak, a global pandemic. The most essential factor in improving the quality of care through better planning in emergency services is estimating patient demand. In this context, the aim of the study is to estimate the hourly admission rate of patients to an emergency service in Turkey. Hourly forecasting models were developed for patients presenting to emergency departments in the relevant province using time-series analysis. SARIMAX, ANN, and NARX methods were used to estimate the number of patients admitted to the emergency service.

Wind speed, humidity, and temperature data were used to evaluate the impact of meteorological conditions on the spread of the epidemic and the number of patients seeking emergency care. It was concluded that the variables used in the study were related to the number of patients presenting to the emergency department and that none of the variables could be removed from the analyses. The study results show that low wind speeds, combined with low temperature and humidity, increase the persistence and spread of the virus in the air, thereby raising the risk of transmission, whereas hot, humid weather reduces its spread.

As a result of performance evaluations, the SARIMAX method emerged as the most successful prediction model. This success contributes to the availability of resources and materials for emergency services. Although the study focuses on COVID-19, the proposed prediction approach and methodology are not limited to this disease and apply to future public health crises of similar duration.

The study has some limitations. Firstly, although the data were collected from patients who presented to the emergency room with COVID-19 symptoms, it is not known whether these patients were diagnosed. Second, the meteorological variables used may be insufficient to capture variability in disease transmission. Apart from meteorological variables, the health policies implemented in the region and the society's exposure and vulnerability rates are also of great importance. Finally, the study focused on only one area, and a limited data set was used because there was no information about many features affecting the spread in the region. In future studies, new prediction models can be developed using different variables and methods with longer-term datasets. In addition, the inclusion of the effects of the precautionary policies taken for the epidemic in the region on the forecast models in the evaluation process may be the subject of future studies. Again, results may vary by country**.**

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All authors equally contributed to this paper.

Data Availability

The data set used cannot be published due to data protection restrictions.

Ethics Statement

Not applicable.

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