Research Paper

Estimating the Demand for Ambulances in Traffic Accidents

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Citation Babanezhad M, Khorsha H, Mohajervatan A, Choori A. Estimating the Demand for Ambulances in Traffic Accidents. Health in Emergencies and Disasters Quarterly. 2025; 10(4):247-258. http://dx.doi.org/10.32598/hdq.10.4.149.8

http://dx.doi.org/10.32598/hdq.10.4.149.8

Article info:
Received: 10 Aug 2024
Accepted: 05 Jan 2025
Available Online: 01 Jul 2025

Keywords:
Time series, Estimating, Traffic accidents, Emergency medical service (EMS), Ambulance

ABSTRACT

Background: Effective Emergency medical service (EMS) delivery in road traffic accidents requires accurate resource planning that relies on operational, tactical and strategic demand forecasts. This study aims to estimate the demand for ambulances in traffic accidents using time series modeling techniques.

Materials and Methods: We conducted a retrospective cohort analysis of ambulance demands related to traffic incidents in Golestan Province, Iran. The analysis of individual time series was utilized for demand prediction. Then, we applied statistical methods to present the performance indicators.

Results: This research examined 37409 calls that led to ambulance dispatch from March 2021 to March 2023. According to the examination of traffic collision data, the demand rate is greater during the daytime compared to nighttime. Nonetheless, ambulance responses to deadly accidents take place more frequently at night compared to daytime. Our analysis indicates that demand will vary between 2400 and 800 with a 90% confidence level. Additionally, at an 80% confidence level, the demand range is expected to be between 300 and 2800.

Conclusion: By analyzing the historical data, we have identified a trend and seasonal patterns in the data, which suggests an increase in demand during the summer months. Forecasting the course of service recipients in the prehospital emergency service can increase situational awareness and help manage the challenges caused by overcrowding. By anticipating the surge in demand for services during peak periods, it is possible to plan and allocate resources effectively and minimize delays.

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Introduction

Emergency medical services (EMS) worldwide face significant challenges, mainly due to the impact of road traffic accidents [1]. These incidents include a considerable part of calls to emergency dispatch centers [2]. Providing effective EMS in these incidents requires careful resource planning, which generally relies on forecasting operational, tactical, and strategic demand. Care providers outside the hospital typically face economic and human resource limitations [3]. The primary goal of EMS in these events is to minimize emergency response time while managing operational costs [4]. Failing to match available resources with demand in EMS seriously affects patients, staff, and the entire healthcare system [5, 6]. The imbalanced demand for ambulances in terms of space and time has made EMS physicians dependent on predicting the volume of care to develop staffing and dynamic deployment plans [7]. Robust forecasting will allow sound decisions for capacity and staffing levels. Accurate forecasting of the demand and optimal management of the ambulance fleet can increase the chance of the injured's survival and the system's efficiency. An efficient medical emergency system has led to numerous studies in this field [8, 9]. Estimating the association between resources and demand in EMS is crucial to ensure timely and effective response to emergencies, such as road traffic accidents [10, 11]. In contrast to the typical methods employed by research centers that often rely on descriptive techniques and focus on presenting reports with graphs, it is crucial to establish a suitable model for predicting and assessing outcomes [12].

Nevertheless, certain potential biases may result in inaccurate predictions and inadequate resource distribution. As a result of using a faulty model, there is a risk of inaccurately estimating demand due to the failure to appropriately represent the connections between demand and resources. This may lead to improper distribution of resources and unsatisfactory results [13-18]. Various forecasting methods are used in the health system, including historical averaging, smoothing techniques, linear regression and autoregressive integrated moving average (ARIMA) modeling [19-24]. Generally, two main streams of research are related to forecasting ambulance demand in EMS. The first stream focuses on applying time series methods and regression approaches to forecasting aggregate ambulance demand [25, 26]. The second stream enables the forecasting of EMS demand using spatiotemporal forecasting methods [4]. There are many studies on applying time series forecasting (TSF) in EMS [27, 28]. The TSF predicts system behavior by utilizing both current and past data. TSF addresses real-world issues, including traffic systems, oil market dynamics, weather predictions and financial markets [29]. The examination and prediction of time series typically rely on ARIMA models and their different variations [30]. However, research highlights that utilizing suitable time series models is the best option for prediction [31]. The time series methods give users better results than other statistical methods for seasonal forecasts in EMS [5]. This outcome may be because time series models monitor key performance indicators that can be a powerful tool for organizations to gain insights and make data-driven decisions. By analyzing historical data and using time series models to predict future trends and patterns, organizations can identify potential issues before they become major problems [10]. Hence in this study, we intend to use a time series model to estimate demand ambulance in traffic accidents in the emergency medical system to help managers to optimize resource allocation and response times.

Materials and Methods

Sample and study design

A retrospective cohort study was conducted on ambulance demands for traffic accidents in the Golestan Province of Iran from March 2021 to March 2023. In this research, we conducted a longitudinal analysis of calls that resulted in ambulance dispatch during traffic accidents. These studies aid in creating and executing more efficient preventive strategies to enhance ambulance demand management. All individuals involved in traffic accidents who were taken to a hospital by EMS were part of the study's statistical population. All the ambulances sent out for traffic injuries were chosen using the census method. The information was derived from the prehospital care report. These data included the request time and the EMS's reaction times (RT). We used performance indicators in the form of time series data to effectively monitor prehospital emergency services. Two measurements, RT and total prehospital time (TPT), were utilized in a temporal sequence. We used statistical methods to present the performance indicators individually.

Forecasting approach

The individual forecasting time series model is a standard and straightforward method. We assume the coming days will be the same as the previous ones. In other words, we use the empirical distribution of past daily accidents to create a predictive distribution of future accidents. At first, the data were smoothed by removing flows and seasonal changes. To remove the tides or long-term changes in the average, we used the one-step differential method and to remove the seasonal changes, we used the Box-Cox transformation to create stability in the variance. Then, we fitted a suitable time series model to the smoothed data. With data availability or smoothed past events, we use it as a key to make reliable predictions. The final data results forecast the expected demand for ambulances for traffic accidents in the upcoming years. We used R statistical software, version 4.5.0 and the forecast package.

Results

Descriptive statistical analysis

Throughout the study period, 37409 requests were recorded for traffic accidents. Since it is sensitive data, it does not include personal or postcode information. Our findings indicate that, according to the chi-square test, there is a significantly higher number of injuries and deaths in men compared to women ($P<0.05$). It is noted that accidents occur more frequently during the day than at night. Nonetheless, fatal accidents are more common at night compared to daytime ($P<0.05$). After analyzing accident locations, it was discovered that urban transportation accidents result in more injuries than road accidents, yet road accidents have a higher fatality rate ($P<0.05$). The t-test analysis indicates a significant difference in EMS arrival time at accident scenes based on location (city or roads) (Table 1).

The data indicates that the TPT within the city differs from the TPT on the road. The noted distinction is statistically meaningful and can be deemed genuine ($P<0.05$). This result suggests that traffic congestion, road conditions, and infrastructure affect TPT in urban and rural areas. The research findings could help guide choices regarding transportation planning, urban design, and traffic management approaches to enhance TPT both in the city and on the highway (Table 2).

Time series analysis

In step 1, the study was conducted at a daily time-series level. Each observation represents the daily count of emergency calls that resulted in the dispatch of one or more emergency ambulances. By plotting the time series graph in Figure 1, we found flow or long-term changes in the average. The time series average has a trend or exhibits long-term changes over time. This outcome could indicate underlying factors, such as seasonality, growth, or resource decline. There were also more random fluctuations in the data during the summer months compared to other months. This result could be due to various reasons, such as changes in demand, availability of resources, or external factors. Further, more accidents occurred in the summer of 2023 than in the summer of 2021. This means that the data shows seasonal changes. We first made the data stationary to determine which time series model the accident data follows. Then, we plotted the autocorrelation and partial autocorrelation coefficients (ACF) of these data regarding delay. Autocorrelation measures the correlation between a time series and its past values, while partial autocorrelation measures the correlation between a time series and its past values after controlling for intermediate values. We

Table 1. Analysis of each ambulance's activity based on the sex of the casualty and response time

Total Injury		No. (%)/Mean±SD (MRT)		
		Overall (n=37409)	Injury	Death
		37409	36931(98.7)	478(1.3)
Sex	Men	n=29219 10.24±7.52	n=28827(98.7) 10.25±7.53	392(1.3) 9.55±7.33
	Female	n=8190 10.40±8.7	8104(98.9) 10.40±8.8	86(1.1) 9.55±6.51
Arrival time of day	Day (6 AM–6 PM)	n=20856 10.24±7.42	20618(98.9) 10.24±7.42	238(1.1) 10.20±8.12
	Night (6 PM–6 AM)	n=16553 10.32±8.13	16313(98.6) 10.33±8.14	240(1.4) 9.31±6.34
Location of accidents	City	n=15278 7.44±5.40	15151(99.2) 7.44±5.39	127(0.8) 7.33±6.37
	Road	n=22131 12.21±8.41	21780(98.4) 12.22±8.42	351(1.6) 10.47±7.33

MRT: Mean reaction time of EMS.

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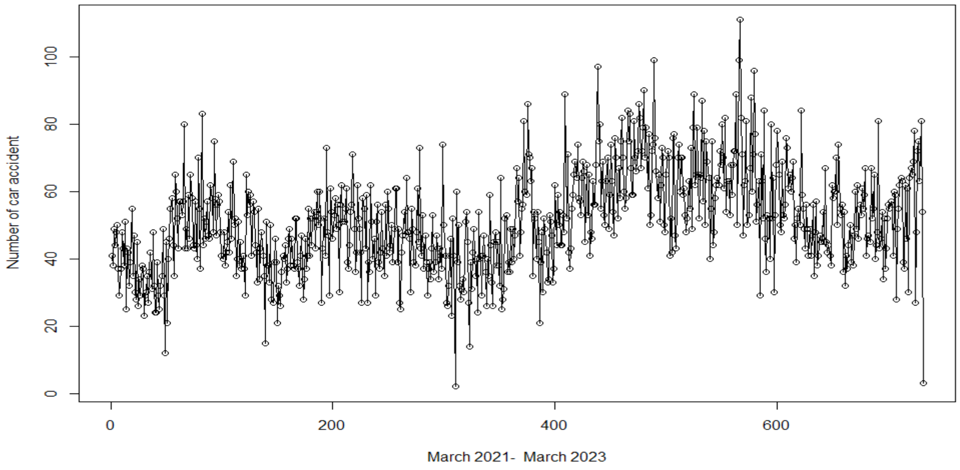

Figure 1. Time series graph of car accidents in Golestan Province from March 2021 to March 2023

used the data differentiation method to fix data stationarity. We transformed the non-stationarity of a time series into a stationary series by differentiating and stabilizing its variance by box-cox transformation (Figures 1, 2 and 3).

In step 2, we differentiated the data once and performed the augmented dickey-fuller test. The associated P is below the threshold, leading to the rejection of the null hypothesis. Consequently, evidence suggests that the one-step differentiated data is stationary. We then drew graphs of autocorrelation and partial ACF (Figures 4 and 5). We found that the data follows the ARIMA model (1, 1, 5).

In step 3, we calculated the average daily number of requests and time performance indicators at this stage. The daily mean and median of patients are 43. The explanations related to the report are based on the data of daily patients transferred to medical centers due to accidents from the beginning of March 2021 to March 2023. They followed the moving autoregressive moving average model (ARIMA) model (0, 0, 0). Using the Ljung-BOX statistical test [10], the daily residual of the data shows that the randomness of the data is significant ($P<0.05$). When differentiating the ARIMA (1, 1, 1) using the Ljung-BOX statistical test [10], it is significant ($P<0.05$). The average time of arrival of emergency services to the accident scene from March 2021 to March 2023 based on the time series functions are reported in the Table 1. It follows the ARIMA model (0, 0, 0) using the Ljung statistical test [10] daily residual of the data; the randomness of the data is significant ($P<0.05$). When differentiating the autoregressive model, the moving average (ARIMA) is (1, 1, 1), using the LJung-BOX statistical test [10], it is at a significant level ($P<0.05$) (Tables 3 and 4). An analysis of information regarding ambulance dispatch calls revealed variations in the number of requests throughout the research period, with a low of 20 and a high of 80. Throughout the study time frame, ambulances typically took 5 to 12 minutes to reach the accident location. In addition, individuals usually stay in the prehospital stage (TPT) for about 28 to 45 minutes on average (Figures 6, 7, 8 and 9).

Table 2. TPT analysis

Location		No.	Mean	Std. Deviation	Std. Error Mean
Injured	City	14432	0:27:28	0:13:38	0:00:06
	Road	20939	0:42:49	0:22:59	0:00:09
Died	City	110	0:29:25	0:14:54	0:01:25
	Road	306	0:39:50	0:21:53	0:01:15

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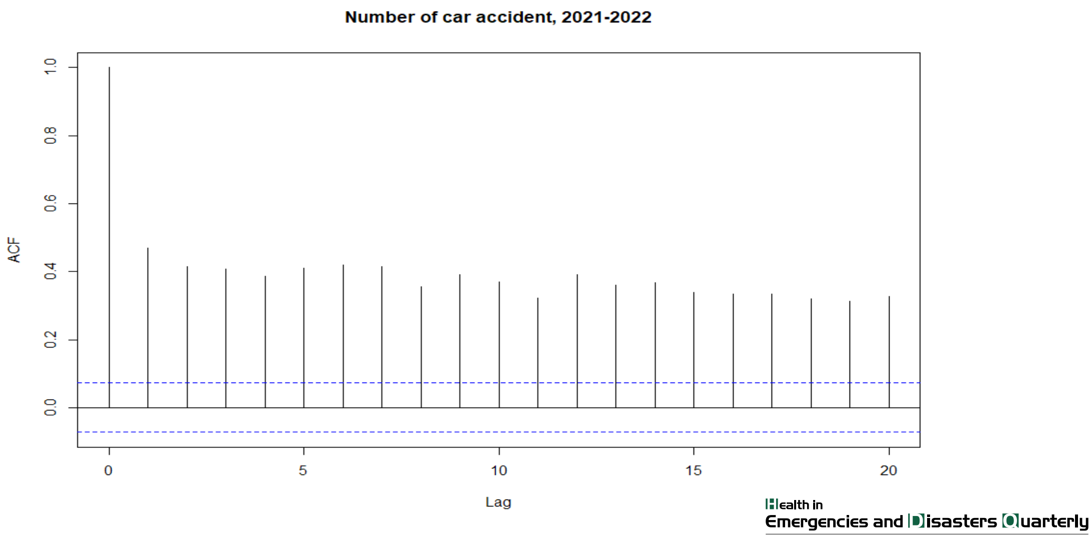

Figure 2. ACF of car accidents in Golestan Province from March 2021 to March 2023 according to delay before stationary

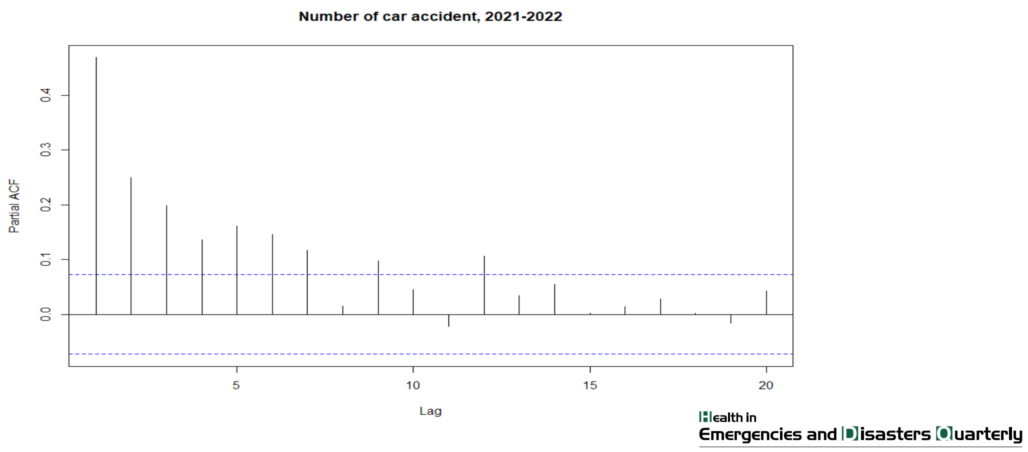

Figure 3. ACF diagram of car accidents in Golestan Province from March 2021 to March 2023 according to delay before performing stationary

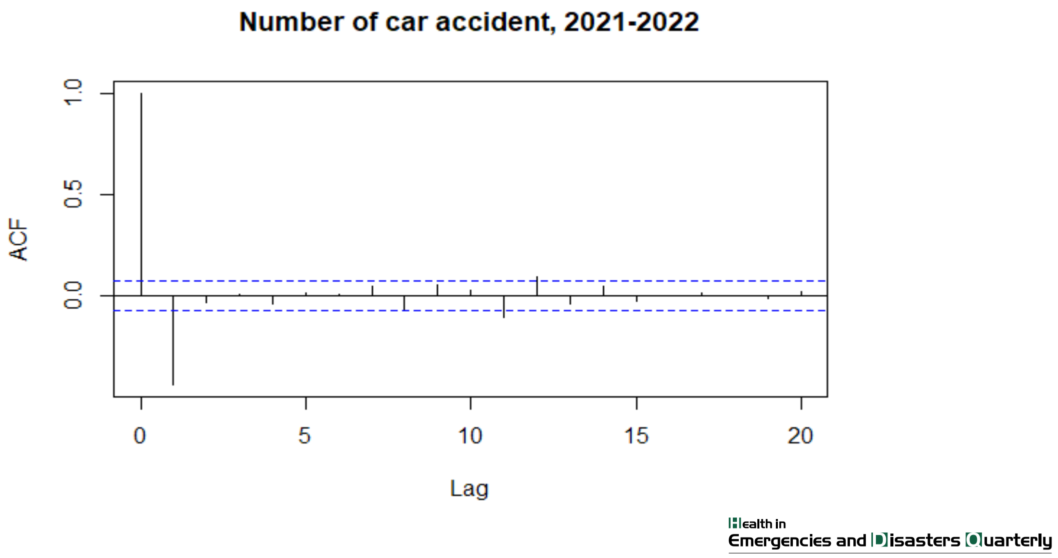

Figure 4. Chart of ACF of car accidents in Golestan Province from March 2021 to March 2023 according to delay after performing stationary

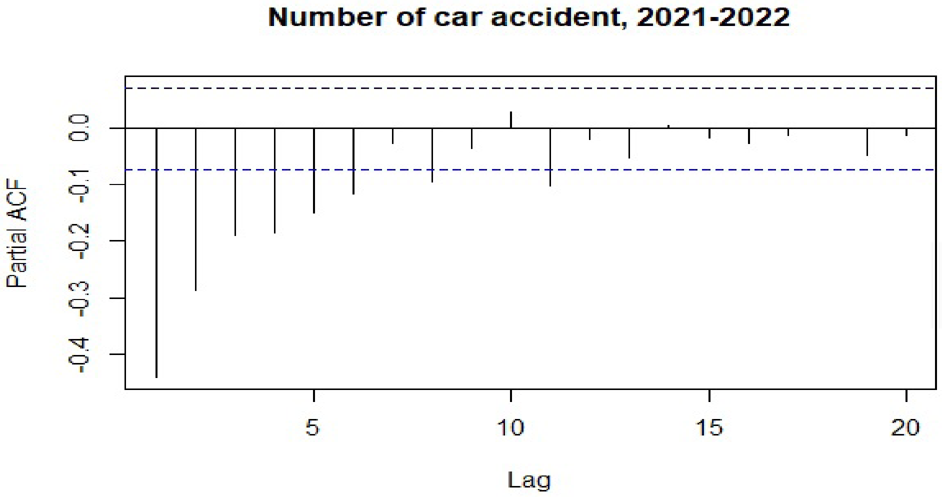

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Figure 5. Chart of partial ACF of car accidents in Golestan Province from March 2021 to March 2023 according to delay after performing stationary

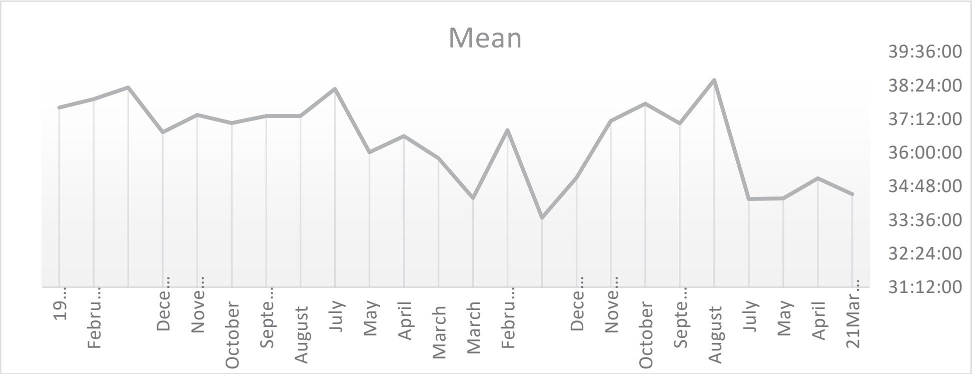

Figure 6. TPT trend

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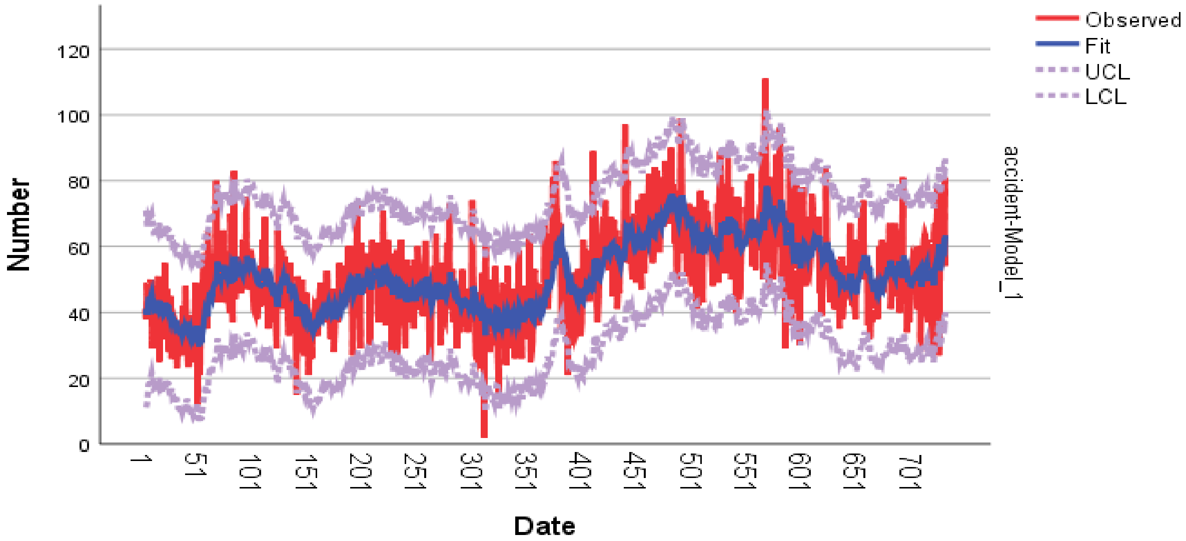

Figure 7. By the number of daily incidents in the maximum and minimum range

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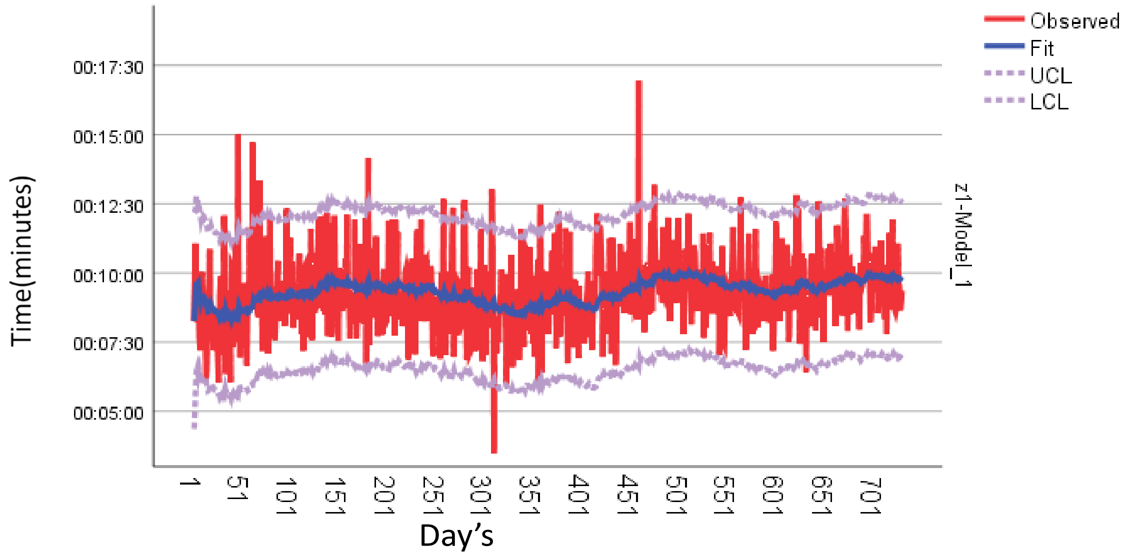

Figure 8. Average daily and monthly response times in a two-year period

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In step 4, we utilized the R software and the forecast package to estimate the future monthly demand for ambulances. We calculated the demand with confidence coefficients of 80% and 95%, reflecting the uncertainty range surrounding the forecasts. The blue line symbolizes the forecasted count of demands, while the shaded region around it indicates the likelihood of events happening within that distance. This provides a sense of the uncertainty associated with our predictions. Our analysis suggests that demand will vary between 2400 and 800 with a 90% confidence level. Additionally, at an 80% confidence level, the demand range is expected to be between 300 and 2800 (Figure 10).

Discussion

This study focuses on forecasting the ambulance demand in traffic accidents in Golestan Province through time series modeling analysis. Predicting how many service recipients will arrive in the prehospital emergency enhances understanding of the situation and helps manage issues related to overcrowding. In Iran, this research was among the preliminary studies to utilize the time series model for forecasting ambulance needs during traffic accidents in prehospital emergencies. Other studies emphasize that using time series in prehospital emergencies is vital [5, 32, 33]. Our research findings revealed a rising trend in the future use of EMS for traffic accidents. Using ARIMA modeling, we successfully

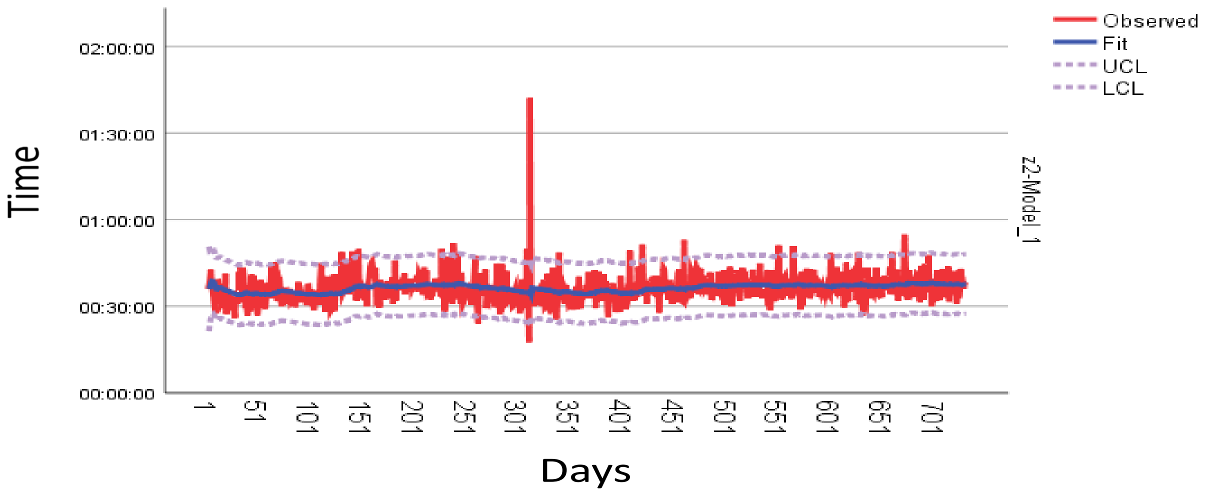

Figure 9. Average daily TPTs

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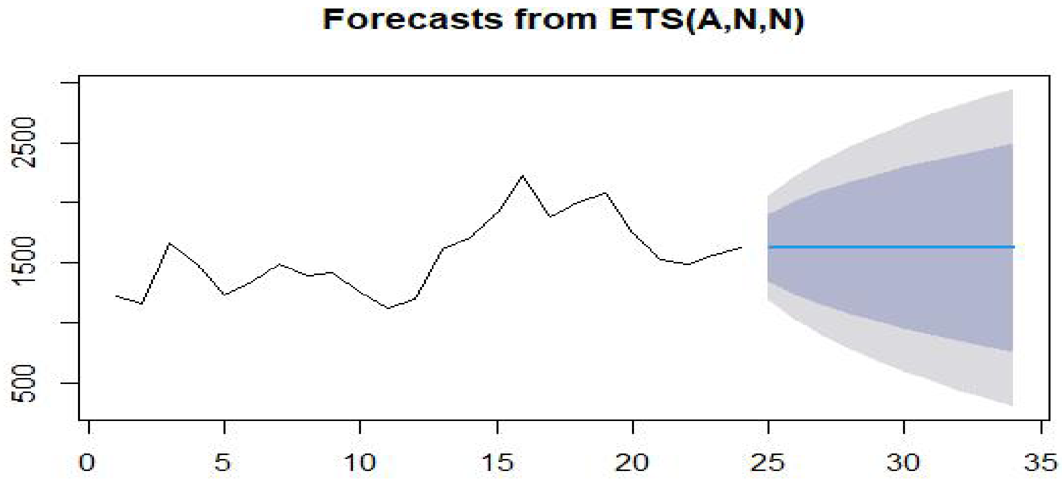

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Figure 10. Forecasting the number of accidents per month with a confidence interval of 80% and 95%

created a precise model for the monthly frequency of prehospital incidents and forecasted the rise in mission volume shortly. Different research highlights that ARIMA models are the best prediction option [31, 34, 35]. This method gives users better results than other seasonal forecasting methods [5, 35]. Our research showed significant fluctuations in the need for ambulances for individuals in traffic accidents throughout the year. During the summer, we noticed an increase in the number of people using our services. Mohammadi et al. study supports our results that summer experiences more injuries than other seasons [13]. One significant result from this research is the ongoing rise in the requests for ambulances following traffic accidents over the two-year study period, indicating a steady upward pattern in the graph. Our analysis shows that ambulance demands for traffic accident injuries may increase from 1500 to 2400 per month in the worst-case scenario and decrease to 800 with preventative measures in the best-case scenario (with a 95% confidence level). Muguro et al. reviewed 5-year data (2015-2020) in Kenya. They found that fatalities and injuries increased by 26% and 46.5%, respectively, from January 2015 to January 2020 [36]. A mortality review in some countries shows a downward trend

Table 3. Daily analysis of time series indicators of the number of patients from March 2021 to March 2023

ARIMA (0, 0, 0)				ARIMA (1, 1, 1)			
Fit Statistic	**Mean**	**Statistics**	**Sig.**	**Fit Statistic**	**Mean**	**Statistics.**	**Sig.**
Stationary R-squared	1.443E-15	Statistics	Sig.	Stationary R-squared	384	14.806	539
R-squared	1.443E-15	1944.277	000	R-squared	.357		
RMSE	14.902			RMSE	11.974		
MAPE	31.595			MAPE	25.274		
MaxAPE	2437.415			MaxAPE	1918.144		
MaxAE	60.252			MAE	9.328		
MaxAE	60.252			MaxAE	56.631		
Normalized BIC	5.412			Normalized BIC	4.993		

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Abbreviations: ARIMA: Autoregressive integrated moving average; RMSE: Root mean squared error; MAPE: Mean absolute percent error; MaxAE: Maximum absolute error; MAE: Mean absolute error; BIC: Bayesian-Schwarz criterion.

Table 4. Daily analysis of the indicators of the time series of the average time of arrival of emergency services to the accident scene from March 2021 to March 2023

ARIMA (0, 0, 0)				ARIMA (1, 1, 1)			
Fit Statistic	Mean	Statistics	Sig	Fit Statistic	Mean	Statistics.	Sig.
Stationary R-squared	1.746E-13	65.361	0.000	Stationary R-squared	0.468	12.437	713
R-squared	1.746E-13			R-squared	037		
RMSE	89.185			RMSE	87.672		
MAPE	12.760			MAPE	12.435		
MaxAPE	168.241			MAE	160.042		
MAE	69.344			MAPE	68.081		
MaxAF	457.727			MaxAPE	452.106.		
Normalized BIC	8.990			Normalized BIC	8.974		

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Abbreviations: ARIMA: Autoregressive integrated moving average; RMSE: Root mean squared error; MAPE: Mean absolute percent error; MaxAE: Maximum absolute error; MAE: Mean absolute error; BIC: Bayesian-Schwarz criterion.

[37]. Predicting worldwide road traffic injury fatalities for 2030 indicated 1.225 million deaths and 14.3 fatalities per 100000 people in 2030, reflecting a decrease of 1% and 12% compared to the figures from 2017 reported in the global burden of disease study, respectively [38]. In this study, we investigated the prognosis of trauma victims and its relationship with the time intervals before the hospital. We found that longer time intervals were directly related to death in traffic accident victims (Table 2). There is little empirical information on this topic [15]. Several studies reported various associations (negative, neutral, and positive) of the association of mortality with shorter pre-hospital time [14, 16-18]. Our study shows that TPT is longer in July, August, September and October compared to other months, corresponding with the seasonal increase in ambulance demands (Figure 6).

Additionally, the fatality rate among road accident victims is notably higher when the TPT is significantly longer than for urban accident victims (Table 1). Our study aligns with the findings of Fatovich et al. as well. During their research on trauma patients in urban and rural areas of Western Australia, they discovered that the rural population had double the risk of death compared to urban trauma patients. The average time to definitive care was longer for the rural population [16]. On the other hand, the study of Baqher et al. showed that the time at the scene (average of 17 minutes) and the total time before the hospital (average of 35 minutes) do not affect mortality among urban prehospital transport in Scandinavia [17]. Brown et al. found an association between a long time at the scene and mortality, regardless of the mode of transport (air or ground) [18]. Harmsen et al. found that rapid transportation is advantageous for individuals experiencing neurotrauma and those hemodynamically unstable due to penetrating injuries. For hemodynamically stable trauma patients without a specific diagnosis, longer on-scene and TPT do not raise the likelihood of death. For trauma patients without differentiation, the emphasis should be on prehospital care rather than quick transportation [15]. It appears that the primary aim of efforts to lower traffic accident deaths should concentrate on efficiently handling the heightened demands for ambulances during periods with longer total pre-hospital time. Due to limitations in this study, we lack data on the distribution of trauma centers, and patient flow at receiving hospitals, waiting times for services, trauma mechanisms, and air ambulance participation in road incidents. All these factors can impact the prognosis of patients, which could be enhanced by additional research.

Conclusion

We have employed a TSF approach to predict the demand for ambulances for injured individuals in traffic accidents, which can help with resource allocation and planning. By analyzing the historical data, we identified a trend and seasonal patterns in the data, which suggests that there may be an increase in demand during the summer months (associated with increased TPT). Using an 80% and 95% confidence coefficient, we accounted for the uncertainty in our predictions, which is essential for making informed decisions. According to our estimate, demand is expected to fluctuate between 300 and 2800. Predicting the trend of service recipients in the prehospital emergency room can increase situational awareness and help manage the challenges caused by overcrowding. By anticipating the surge in demand for services during peak periods, you can plan to allocate resources effectively and minimize delays.

Ethical Considerations

Compliance with ethical guidelines

This study was approved by the Ethics Committee of Golestan University of Medical Sciences, Gorgan, Iran (Code: IR.GOUMS.REC.1402.127). Informed consent was obtained from all participants included in the study.

Funding

This study was derived from a research project that received approval from Golestan University of Medical Sciences, Gorgan, Iran (Code: 113683).

Authors' contributions

All authors contributed equally to the conception and design of the study, data collection and analysis, interpretation of the results, and drafting of the manuscript. Each author approved the final version of the manuscript for submission.

Conflict of interest

The authors declared no conflict of interest.

Acknowledgments

The researcher would like to thank all the managers and staff from the EMS system who participated in the study.

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