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Mode of Arrival Aware Models for Forecasting Flow of Patient and Length of Stay in Emergency Departments

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Aim: Flow of patients to emergency departments (EDs) and their stays in EDs (ED-LOS) depend significantly on their arrival modes. In this study, developing effective models for forecasting patient flow and LOS in EDs by considering arrival modes is aimed to lead better planning of ED operations.
Materials and Methods: In this study, by categorizing mode of arrival into two, self-arrived in and by ambulance, autoregressive integrative moving average (ARIMA) models are applied for forecasting four time series: daily number of patients self arrived/arrived by an ambulance and average LOS of patients self-arrived/ arrived by an ambulance. The models are validated with real-life data received from a large-scaled urban ED in Izmir, Turkey.
Results: While seasonal ARIMA is proper for forecasting daily number of patients on both modes, non-seasonal models are proper for forecasting average LOS. The mean absolute percentage errors (MAPE) for the models of four time series are respectively as 5.432%, 13.085%, 9.955% and 10.984%. Thus, daily arrivals to EDs show seasonality patterns.
Conclusion: By emphasizing the impact of mode of arrival in ED context, this study can be used to aid strategic decision making in EDs for capacity planning to enable efficient use of ED resources.

Keywords: emergency department, forecasting, patient flow, length of stay, ARIMA
Short Title in English: Patient Flow and LOS in EDs

Introduction

Emergency departments (EDs), which provide prompt and essential medical care for patients, are an important component of health systems. However, patients in many countries often suffer from the overcrowded environment of EDs that causes increase in length of stay (LOS), intensive stress among ED personnel, increase in costs, and decrease in patient satisfaction (1). Although increasing resources is a possible solution to deal with such problems, it is not always efficient since it requires high budgets. Thus, efficient management of patient flow/demand in EDs has become an urgent issue and currently significant attention is paid for planning ED operations and improving management strategies. To this end, forecasting has becoming a prominent subject for researchers and practitioners, since ability to generate real-like forecasts has substantial implications for EDs in improving strategic planning.

In this context, the first thing comes to mind is forecasting the patient flow. However, in planning and managing ED operations, forecasting not only the flow of patient but also the LOS, time from registration of patient in ED to final disposition, has a great importance (2). Nonetheless, both the daily flow of patients and their LOS values depend highly on how they arrived to ED. Mode of arrival of patients is mainly grouped into two as those arrived by an ambulance and by walking. While LOS of patients arrived by an ambulance is generally higher than those arrived by walking, the opposite comparison holds for daily demand (3). Undoubtedly, generating mode of arrival aware models for forecasting daily demand and LOS, which mainly consider differences in the values for the patients who arrived by an ambulance and by walking, has a significant impact in ED operations management.

Many different forecasting models such as regression models, time series analyses, queueing theory-based models, neural network models and simulation models have been proposed in ED literature (4). Since daily patient flow, LOS and many other ED related data have a time series structure, time series models are most widely used among all these forecasting models both in theory and practice. Time series analysis is defined as a branch of statistics that provides methods for making numerical predictions about future events by using past observations collected at regular intervals. Generated long and/or short term forecasts are used to make current decisions and plans in EDs.

The main objective of this work is to propose statistical models based on univariate time series of daily patient flow and LOS which can be used in generating forecasts for short and/or long term planning. Although, modelling with ED based time series have frequently studied in literature, previous studies have been limited to generate models for either daily flow of patient or LOS by considering all types of patient arrivals; effect of mode of arrival is not considered. Thus, this study contributes to literature by developing mode of arrival aware models for two main time series of EDs, both daily flow of patient and LOS, and by analyzing the impact of mode of arrival in performance of forecasting models.

The remainder of this paper is organized as follows: In Section related studies are summarized. In Section 3 data of this study and the used forecasting model are presented. The results on data analysis and validation of the models on the data set are shown in Section 4. Main findings, practical implications and limitations of this study are discussed in Section 5. Finally, sixth section presents the conclusion of this study.

1. Literature Review

Existing studies vary in target time series data of ED to be forecasted and the used forecasting methods. In this section, studies on forecasting patient flow, forecasting LOS and different methods used for forecasting in ED context are respectively summarized.

1.1. ED patient flow forecasting

Many of the existing studies focus on forecasting demand in EDs. These studies differ based on their objectives, methods and type of forecasting intervals. Although some of these studies aim to predict flow of patients in different time-intervals such as hourly (5-8), periodically (9,10), weekly (11), or monthly (12-16), many of them focus on generating forecasts on the daily basis. A few of those studies generating forecasts for daily demand are presented here.

Batal et al. (17) formed a mathematical equation which forecasts daily number of patients seeking for urgent care by considering the calendar variables. Jones et al. (18) aimed to forecast daily patient volumes in the emergency department. Sun et al. (19) developed forecasts for daily ED attendances to aid resource planning for micro and macro level. Kam, Sung and Park (20) developed models for forecasting daily number of arrivals of a Korean regional hospital's ED. Higginson, Whyatt and Silvester (21) proposed that analysis of ED demand was the first step towards effective workforce planning and process redesign. Boyle et al. (22) developed and validated models to predict ED presentations for day of the year. Cote et al. (23) proposed a tutorial for ED practitioners for forecasting patient volumes in support of strategic, tactical and operational planning. With the aim of modelling daily number of patients and assess the relative importance of contributing variables, Xu, Wong and Chin (24) applied forecasting models. By using calender variables and ambient temperature readings, Marcilio, Hajat and Gouveia (25) forecasted daily visits of an ED. Kadri et al. (26) aimed to model and forecast ED overcrowding. Considering the seasonality of time series, Luo et al. (27) focused on forecasting daily arrivals to a hospital. Carvalho-Silva et al. (28) evaluated various forecasting models for daily arrivals of a Portuguese ED. Besides generating periodical forecasts, Sariyer (10) used techniques to forecast daily demand of EDs, and compared the performances of periodical and daily forecasting. In order to present a baseline to ED management for allocating human resources and medical equipment efficiently, Yucesan, Gul and Celik (29) proposed methods for patient arrival forecasting. By using the previous arrival and departure times of all patients and exogenous variables, Whitt and Zhang (30) focused on forecasting future daily arrivals in an ED. With the objective of creating a tool that accurately predicts daily arrivals at EDs to support optimal planning of resources, Jilani et al. (31) applied models for both short and long term levels. In order to provide an insight for researchers and practitioners on forecasting in EDs to show current state and potential areas for future researches, Gul and Celik (32) presented exhaustive review in the context of forecasting ED arrivals.

1.2. ED-LOS forecasting

A literature gap is identified in modelling ED-LOS despite ED-LOS remains the most commonly reported outcome measure resulting from overcrowding. A few studies aiming to model ED-LOS are summarized in this section. With the aim of identifying the factors characterizing LOS in EDs, Combes, Kadri and Chaabane (33) developed models for ED-LOS prediction. Gul and Guneri (34) aimed to forecast ED-LOS by using the predictive input factors such as age, sex, mode of arrival, treatment unit, medical tests, and inspection in the ED. By using the input variables of gender, age, triage level, mode of arrival and diagnosis Sariyer, Taşar and Cepe (2) proposed models for classifying patients of EDs based on their LOS.

Although many existing studies aimed to analyze or model the relation between ED flow of patient and ED-LOS (3,35-36), to the best of the knowledge, only a few studies provided models for forecasting both of the flow of patients and LOS in EDs (37).

1.3. Used methods in forecasting

Various forecasting techniques have been proposed in ED literature. Although some of those studies use queueing theory based models and/or simulation models (28,30), most of them employ regression models and/or time series models.

In order to predict flow of patient in EDs, many of the existing studies applied different types of regression models (6,7,9,17,18,23,25).On the other hand, as most widely used time series model, many researchers employed non-seasonal/ seasonal auto regressive integrative moving average (ARIMA / SARIMA) in ED demand prediction (10,11,13-16,19,20,26,27).

More current approach in forecasting ED demand is use of artificial neural networks (ANN). Xu, Wong and Chin (24), Menke et al. (38) can be cited as just few of those studies utilizing neural networks in this context. Besides, some researchers applied hybrid models such as regression-ANN or ARIMA-ANN hybrid models in ED patient volume forecasting (1,29,31).

For ED-LOS forecasting, although some researchers employed regression and time series modelling (3,37), most of the others used artificial neural networks or some other types of classification models (2,33.34).

In this study, in order to model two main time series in EDs, patient flow and ED-LOS, ARIMA-SARIMA models are employed. The proposed models differ from existing studies based on their arrival mode awareness. That is, while existing studies used all patient arrivals and corresponding LOS values, in this study, different time series models are proposed for patients who arrived to ED by walking or by an ambulance.

2. Methods

2.1. Study design

This is a retrospective study to model daily patient flow and average daily LOS of both walk in and ambulance patients at a single ED. The local institutional review board approved this study and waived the requirement for informed consent.

2.2. Study setting and participants

The data of this research is obtained from a large-scaled urban training hospital having an average daily number of around 1,000 patients in İzmir, Turkey. All patients registered to this ED during the study period of January 2017 to June 2017 are included in the study.

2.3. Data sources and variables

Data of all these patients are extracted from the hospital's electronic data warehouse. This database includes protocol numbers, time stamps and different demographics of registered patients. In this study, time stamps (times of arrival and departure stored in the following form "dd.mm.yyyy hh:mm:ss") and mode of arrival, which is then combined in two categories as patients who arrived by walking and by an ambulance, are used. The variables of this study are then defined as 1) daily number of patients who arrived by walking, 2) daily number of patients arrived by an ambulance, 3) average daily LOS of patients arrived by walking and 4) average daily LOS of patients arrived by an ambulance. Daily number of patients is defined as the total number of patients arrived in the single day, and counted by all days during the study period. LOS of each patient is defined as the difference between his time of departure and time of arrival and measured in minutes. Average daily LOS is calculated by taking the average LOS values of patients arrived in the single day and for each day of the study period these average LOS values are similarly obtained.

2.4. Statistical analysis

In this study, ARIMA models are used in analyzing time series data representing the study variables. These models analyze autocorrelations among the observations of the time series. The general structure of ARIMA is represented as $ARIMA(p,d,q) * (P,D,Q)_s$. While in this representation, lower case letters (p,d,q) represent the non-seasonal parameters, upper case letters (P,D,Q) represent the seasonal parameters where s denotes seasonality length. This model has two main parts as $AR(p)$ and $MA(q)$. The integrative part, $I(d)$ is used to integrate non-stationary series into stationary series. $AR(p), MA(q)$ and $ARMA(p,q)$ models are used to analyze and forecast non-seasonal and stationary time-series. $ARMA(p,q) * (P,Q)_s$ is used to analyze seasonal and stationary time series. While non-stationary and non-seasonal series are analyzed with $ARIMA(p,d,q)$, non-stationary and seasonal series are analyzed with $ARIMA(p,d,q)*(P,D,Q)_s$ (39).

In an $AR(p)$ model, an observation is mathematically modelled with previous p observations of the times series and the random error as:

$$Y_t = \sum_{i=1}^{p} \alpha_i Y_{t-i} + \varepsilon_t \qquad (1)$$

where Y_{t-i}'s show previous observations, α_i corresponding coefficients ($i = 1, \ldots, p$) and ε_t is the random error term having the standard normal distribution $\varepsilon_t \sim N(0, \sigma^2)$.

In the other main part, $MA(q)$, an observation is a linear function of past q error terms and the average of them:

$$Y_t = \varepsilon_t + \sum_{j=1}^{q} b_j \varepsilon_{t-j} \qquad (2)$$

where, ε_{t-j}'s represent past error terms of q observations and $b_j's$ are the model coefficients ($j = 1, \ldots, q$).

Besides, $ARMA(p,q)$ model is a linear function of past observations and error terms:

$$Y_t = \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} b_j \varepsilon_{t-j} + \varepsilon_t \qquad (3)$$

When time series is non-stationary, integrative part of these models should be active, since before constructing the forecasting models time series is needed to be stationary (29,40). By taking the differences of sequential observations, an original time-series can be integrated to new time series, and the process of taking differences in integrated time series should be repeated d times until the obtained time series becomes stationary. After the series becomes stationary, $AR(p)$ or /and $MA(q)$ parts of the model are used for forecasting time series.

If time series is seasonal, then the related seasonality part should work in a similar manner, where the models, $AR(P), MA(Q)$, use the past observations/error terms which are seasonality length, s, behind of the current observation to be modelled. Likewise, integrating the seasonal time series means taking the differences in the observations and the ones which are *s* period behind of them.

2.5. Outcome measures

In this study, mean absolute percentage error (MAPE) is used to evaluate the performances of the forecasting models. For each models of this study, MAPE values are computed as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{Y}_i - Y_i}{Y_i}\right| * 100 \qquad (4)$$

In equation (4) Y_i shows the observed value in period i and $\hat{Y}_i$ is the generated forecast value of the model for the same period, *n* represents the length of forecasting period.

Besides, in order to tentatively identify the numbers of AR or/and MA terms (p, q, P, Q), or check the appropriateness of the models with the identified numbers, autocorrelation (ACF) and partial autocorrelation (PACF) functions of the time series and the models are checked.

3. Results

Statistical tools of EViews Version 8 and Minitab Version 16 are used in obtaining the results of this study.

During the study period, average daily patient volume is 955.97 where daily average values for number of patients arrived by walking and by an ambulance are 909.33 and 46.64 respectively. While daily percentage of patients arrived by walking is 95.08%, those for arrived by an ambulance is 4.92%. While the average daily LOS of all patients is 104.67 minutes, the respective values for the patients arrived by walking and by an ambulance are 97.43 and 244.77 minutes.

Daily distributions of each variable of this study are shown in Figures 1 and 2.

Insert Figure 1: Distribution of daily patient flow

Insert Figure 2: Distribution of average daily LOS of patients

From Figures 1 and 2, it is mainly observed that both the daily number of patients and average daily LOS values significantly differ based on mode of arrival. During the study period, while the daily number of patients arrived by walking vary within the range [713-1325], range is defined as [29-66] for those arrived by an ambulance. Similarly, while the range of average daily LOS of patients arrived by walking is defined as [73.55-138.26], it is [172.54-360.59] for the ones who arrived by an ambulance. Additionally, the seasonality pattern of time series "daily number of patients who arrived by walking" can be depicted from Figure 1a.

Main descriptive statistics of the study variables are represented by box plots in Figures 3 and 4.

Insert Figure 3: Descriptive statistics on daily patient flow

Insert Figure 4: Descriptive statistics on average daily LOS of patients

According to Figures 3 and 4, it is seen that the median values for the fore-mentioned time series are 880, 47, 95.41, and 242.17 respectively. Besides, while the second, third and fourth time series of this study are symmetric (see Figures 1b, 2a, 2b), the first time series is not symmetric (see Figure 1a). Thus, while the last three time series of this study follow a normal distribution, normality fails for the first time series.

As mentioned earlier, time series should be stationary in ARIMA models. Thus before deciding on the proper ARIMA models, setting the model parameters, stationarity of the data set is checked based on Augmented Dickey-Fuller (ADF) test which is one of the most widely used technique for unit root testing. In unit root testing, null hypothesis states that the time series of interest has a unit root which is a signal for non-stationarity. Test results are shown in Table 1.

Insert Table 1: Stationarity results

The results of Table 1 show that none of the time series of this study has a unit root meaning that all of them are stationary. Thus, differencing in time series is not required; i.e. integrative parts of the ARIMA models should be inactive ($d=0$ and $D=0$). In order to decide on the other parameters, p/P

and *q/Q*, many different models are applied on the time series. Based on the model results, such as significance of model parameters and ACF-PACF of residuals, different ARIMA models are seemed to be proper for each of the time series of this study. For example, for time series of daily number of patients who arrived by walking seasonal models such as $ARIMA(1,0,0) * (1,0,0)_7, ARIMA(1,0,0) * (2,0,0)_7, ARIMA(1,0,1) * (1,0,0)_7$ are proper. For the other time series of this study, non-seasonal models are observed to be appropriate. For time series of daily number of patients arrived by an ambulance, the proper fits are $ARIMA(1,0,1) * (0,0,0)_7$ and $ARIMA(1,0,2) * (0,0,0)_7$. While $ARIMA(1,0,0) * (0,0,0)_7$ and $ARIMA(1,0,1) * (0,0,0)_7$ are good fits for average daily LOS of patients arrived by walking, $ARIMA(1,0,0) * (0,0,0)_7, ARIMA(2,0,0) * (0,0,0)_7$ and $ARIMA(1,0,1) * (0,0,0)_7$ are proper for average daily LOS of patients arrived by an ambulance.

For each of time series optimal forecasting models are decided by comparing the MAPE values of the proper models. Since minimizing the forecast error is aimed, the models with the lowest MAPE values are determined as the optimal ones. These optimal models and their performances based on MAPE values for the time series of this study are presented in Table 2.

Insert Table 2: Optimal models and their performances

Table 2 shows that ARIMA models with different parameters are best fits for different time series. For the first time series seasonal ARIMA model, considering one non-seasonal and two seasonal auto regressive lags is the best fit. Seasonal models are not proper for the other time series. While model with one non-seasonal auto regressive and moving average lags is best fit for the second and third time series, best fit for the last time series considers two non-seasonal auto regressive lags. According to MAPE values of the optimal models, which are all smaller than 15 %, it is concluded that while the performances of ARIMA models is good (41) for forecasting patient volumes and LOS in EDs, these models fit the best for time series of "Daily number of patients arrived by walking". It is additionally seen that the model performances are better for forecasting patient flow and ED-LOS for the patients who arrived by walking compared to those arrived by an ambulance.

Summary results of these optimal forecasting models of each time series are given in Table 3.

Insert Table 3: Summary results of the optimal forecasting models

Values of Table 3 show that the model parameters as well as the constants of the models are significant in 95% confidence interval for the fit ARIMA models of each time series, since the corresponding p-values are all smaller than 0.05.

In Figures 5 through 8 the ACF and PACF values of optimal forecasting model residuals are shown.

Insert Figure 5: ACF and PACF of $ARIMA(1,0,0) * (2,0,0)_7$ model for TS1

Insert Figure 6: ACF and PACF of $ARIMA(1,0,1) * (0,0,0)_7$ model for TS2

Insert Figure 7: ACF and PACF of $ARIMA(1,0,1) * (0,0,0)_7$ model for TS3

Insert Figure 8: ACF and PACF of $ARIMA(2,0,0) * (0,0,0)_7$ model for TS4

Based on the ACF and PACF of residuals shown in Figures 5-8, it is also concluded that the defined models are proper fits for time series of this study, since residuals fall within the control limits.

4. Discussion

Accurate forecasting of flow of patients in EDs is beneficial for the reasonable planning and allocation of healthcare resource to meet the emergency demands. In the mean time, predicting ED-LOS can provide useful information for both patients and service providers: it could not only improve resource allocation, but also could facilitate decision-making. In this regard, presenting forecasting models for both of the patient flow and ED-LOS is aimed in this paper. It is additionally aimed to consider differences in patient flow and ED-LOS profiles based on the mode of arrival, patients who arrived by walking or by ambulance, in order to improve the performances of the proposed models. Thus, main variables of this study are defined as daily number of patients who arrived by walking, daily number of patients arrived an ambulance, average daily LOS of patients arrived by walking and average daily

LOS of patients arrived by an ambulance, and the corresponding time series are analyzed appropriately.

First of all, it is observed that none of the time series has a unit root meaning that time series of this study is stationary which could be supported by existing studies (12,37).

It is also seen that while time series of daily number of patients who arrived by walking is seasonal, other time series of daily number of patients who arrived by an ambulance is non-seasonal. Average daily LOS time series are also non-seasonal for both of the patients arrived by walking and by ambulance. Since to do best of the knowledge, mode of arrival aware forecasting models have not been studied in ED context, these results should not be supported with literature. However, this result is consistent with real –life experiences. In EDs, for the patients who arrived by walking, these are frequently the ones who are categorized as not urgent, significant differences exist in their daily volumes between the days of the week. Indeed, in weekends flow of patients who arrived by walking significantly increases compared to weekdays, since other services or departments of the hospitals do not provide service to patients, while EDs provide 7/24 service (3). Besides, many of these patients having slight complaints and working during the weekdays, may make a visit to EDs in weekends and this also causes an increase in daily number of patients who arrived by walking in weekends. On the other hand, for the patients who arrived by an ambulance, those generally being triaged as urgent or emergent, it is unlikely to observe such a significant difference in the daily patient volumes between days of the week. This is due to the fact that, urgent or emergent situations such as myocardial infarction, cerebral bleeding, accidents and many of the others are time independent and may happen in any day and hour of the days. Besides, it is unlikely to observe a difference in daily average LOS values, since patients with similar characteristics may have similar LOS values and this is not significantly related with arrival days of them. These findings are then supported by adopted time series models. While seasonal models are proper in forecasting daily number of patients arrived by walking, non-seasonal models are more appropriate for other time series of interest.

For the performances of forecasting models, it should be stated that while forecasting performance for the time series of daily number of patients who arrived by walking is high, performances are good for other time series of this study (41). This is also interpreted with higher time dependency of daily number of patients who arrived by walking. For the other time series of this study, different models such as linear regression, in which additional inputs should be considered can improve the performance of forecasting. It is also concluded that the model performances are better for forecasting the patients who arrived by walking compared to those arrived by an ambulance. This result can be interpreted with the higher randomness of the related time series of the patients arrived by an ambulance.

This study has many implications in practice. Firstly, since the models accurately predicts the flow of patients and expected LOS values in EDs, they should be used to support optimal planning of human and physical resources. Optimal resource planning is valuable in EDs; unless they have sufficient capacity to satisfy demand, they will fail to meet performance standards and will be operating in the "coping zone" which carries high risks for not only the patients but also the ED staff (21). On the other hand, having more than required capacity is costly and leads an inefficient use of resources (42). Besides, since mode of arrival aware forecasting models are proposed in this paper, it is possible to make more specific decisions such as required number of ED staff in triage areas (urgent, emergent, not urgent) or predicating on average service times of patients for both of the arrival mode categories based on the results of these models. Thus, it is believed that results yielded by the proposed forecasting models will aid practitioners in their decision making process to utilize and allocate ED staff efficiently, by considering the variability in demand and LOS values on the system as well as the differences based on the arrival mode of patients. It is also estimated that, making better decisions on resource planning may generate solutions to one of the biggest problem in ED environment, overcrowding, which may lead to increase in quality of ED services and patient satisfaction.

There are also some limitations of this study. The main limitation is related with the study design since it is conducted using data from a unique ED. However, although structure of optimal forecasting models for time series is data dependent and may not be generalizable, the motivation behind this study, being aware on the effect of mode of arrival on forecasting models' definitions and performances, should be used by other researchers and practitioners. Other limitation is related with the lack of some other explanatory variables of patient volume and ED-LOS in the forecasting models. For future research directions, it is planned to extend the current study by presenting an ARIMA model including some other explanatory variables, namely ARIMAX, and compare the results of these models with existing models.

5. Conclusion

In this study, ARIMA models with optimal parameters are proposed to forecast four main time series in ED context; daily number of patients arrived by walking/ by an ambulance, average daily LOS of patients arrived by walking/ by an ambulance. While forecasting daily numbers and average daily LOS values, since patients are categorized based on how they arrived to ED, the proposed models are labelled as mode of arrival aware forecasting models in EDs. The model results show that, while seasonal ARIMA models are proper for forecasting the first time series of interest (daily number of patients arrived by walking), non-seasonal models are best fits for the other time series of this study. Another main result of this study is that models perform better for forecasting walk in patients.

Although, this study presents an application of a unique ED, the proposed approach of generating mode of arrival aware forecasting models can be used in many of other EDs both in Turkey and other countries. It is believed that utilizing such models help ED practitioners and decision makers to generate better plans and decision strategies in ED setting to improve quality of the emergency services.

The author declares that there is no conflict of interest

References

1. Xu Q, Tsui KL, Jiang W, Guo, H. A hybrid approach for forecasting patient visits in emergency department. Qual Reliab Eng Int. 2016; 32(8): 2751-2759.
2. Sariyer G, Taşar CÖ, Cepe, GE. Use of data mining techniques to classify length of stay of emergency department patients. Bio-Algorithms and Med-Systems 2019; 15(1).
3. Sariyer G, Ataman MG, Kızıloğlu, İ. Factors affecting length of stay in the emergency department: a research from an operational viewpoint. Int J Healthc Manag. 2018; 1-10
4. Wiler JL, Griffey RT, Olsen, T. Review of modeling approaches for emergency department patient flow and crowding research. Acad Emerg Med. 2011; 18(12): 1371-1379.
5. Chase VJ, Cohn AE, Peterson TA, Lavieri, MS. Predicting emergency department volume using forecasting methods to create a "surge response" for noncrisis events. Acad Emerg Med. 2012; 19(5): 569-576.
6. Hertzum M. Forecasting hourly patient visits in the emergency department to counteract crowding. The Ergonomics Open Journal 2017; 10(1).
7. Jones SS, Evans RS, Allen TL, Thomas A, Haug PJ, Welch SJ, et al. multivariate time series approach to modeling and forecasting demand in the emergency department. J Biomed İnform. 2009; 42(1): 123-139.
8. McCarthy ML, Zeger SL, Ding R, Aronsky D, Hoot NR, Kelen, GD. The challenge of predicting demand for emergency department services. Acad Emerg Med. 2008; 15(4): 337-346.
9. Peck JS, Benneyan JC, Nightingale DJ, Gaehde SA. Predicting emergency department inpatient admissions to improve same-day patient flow. Acad Emerg Med. 2012; 19(9): E1045-E1054.
10. Sariyer G. Time series modelling for forecasting demand in the emergency department. IJERAD. 2018(a); 10(1): 66-77
11. Butler MB, Gu H, Kenney T, Campbell SG. Does a busy day predict another busy day? A time-series analysis of multi-centre emergency department volumes. CJEM. 2016; 18(S1): S83-S84.

12. Bergs J, Heerinckx P, Verelst S. Knowing what to expect, forecasting monthly emergency department visits: A time-series analysis. Int Emerg Nurs. 2014; 22(2): 112-115.
13. Mai Q, Aboagye-Sarfo P, Sanfilippo FM, Preen DB, Fatovich DM. Predicting the number of emergency department presentations in W estern A ustralia: A population-based time series analysis. Emerg Med Australas. 2015; 27(1): 16-21.
14. Petrou P. An interrupted time-series analysis to assess impact of introduction of co-payment on emergency room visits in Cyprus. Appl Health Econ Hea. 2015; 13(5): 515-523.
15. Rosychuk RJ, Klassen TP, Voaklander DC, Senthilselvan A, Rowe BH. Seasonality patterns in croup presentations to emergency departments in Alberta, Canada: a time series analysis. Pediatr Emerg Care. 2011; 27(4): 256-260.
16. Rosychuk RJ, Youngson E, Rowe BH. Presentations to emergency departments for COPD: a time series analysis. Can Respir J. 2016.
17. Batal H, Tench J, McMillan S, Adams J, Mehler PS. Predicting patient visits to an urgent care clinic using calendar variables. Acad Emerg Med. 2001; 8(1): 48-53.
18. Jones SS, Thomas A, Evans RS, Welch SJ, Haug PJ, Snow GL. Forecasting daily patient volumes in the emergency department. Acad Emerg Med. 2008; 15(2): 159-170.
19. Sun Y, Heng BH, Seow YT, Seow E. Forecasting daily attendances at an emergency department to aid resource planning. BMC Emerg Med. 2009; 9(1): 1.
20. Kam HJ, Sung JO, Park RW. Prediction of daily patient numbers for a regional emergency medical center using time series analysis. Health Inform Res. 2010; 16(3): 158-165.
21. Higginson I, Whyatt J, Silvester K. Demand and capacity planning in the emergency department: how to do it. Emerg Med J. 2011; 28(2): 128-135.
22. Boyle J, Jessup M, Crilly J, Green D, Lind J, Wallis M, et al. Predicting emergency department admissions. Emerg Med J. 2012; 29(5): 358-365.
23. Cote MJ, Smith MA, Eitel DR, Akçali E. Forecasting emergency department arrivals: a tutorial for emergency department directors. Hosp Top. 2013; 91(1): 9-19.

24. Xu M, Wong TC, Chin KS. Modeling daily patient arrivals at Emergency Department and quantifying the relative importance of contributing variables using artificial neural network. Decis Support Syst. 2013; 54(3): 1488-1498.
25. Marcilio I, Hajat S, Gouveia N. Forecasting daily emergency department visits using calendar variables and ambient temperature readings. Acad Emerg Med. 2013; 20(8): 769-777.
26. Kadri F, Harrou F, Chaabane S, Tahon C. Time series modelling and forecasting of emergency department overcrowding. J Med Syst. 2014; 38(9): 107.
27. Luo L, Luo L, Zhang X, He X. Hospital daily outpatient visits forecasting using a combinatorial model based on ARIMA and SES models. BMC Health Serv Res 2017; 17(1): 469.
28. Carvalho-Silva M, Monteiro MTT, de Sá-Soares F, Dória-Nóbrega S. Assessment of forecasting models for patients arrival at Emergency Department. Oper Res Health Care. 2018; 18: 112-118.
29. Yucesan M, Gul M, Celik EA. Multi-method patient arrival forecasting outline for hospital emergency departments. Int J Healthc Manag. 2018; 1-13
30. Whitt W, Zhang X. Forecasting arrivals and occupancy levels in an emergency department. Oper Res Health Care 2019; 21: 1-18.
31. Jilani T, Housley G, Figueredo G, Tang PS, Hatton J, Shaw D. Short and Long Term Predictions of Hospital Emergency Department Attendances. Int J Med Inform. 2019
32. Gul M, Celik E. An exhaustive review and analysis on applications of statistical forecasting in hospital emergency departments. Health Syst. 2018; 1-22.
33. Combes C, Kadri F, Chaabane S. Predicting hospital length of stay using regression models: application to emergency department.
34. Gul M, Guneri AF. Forecasting patient length of stay in an emergency department by artificial neural networks. Journal of Aeronautics and Space Technologies, 2015; 8(2): 43-48.
35. Kolker A. Process modeling of emergency department patient flow: Effect of patient length of stay on ED diversion. J Med Syst. 2008; 32(5): 389-401.

36. Derose SF, Gabayan GZ, Chiu VY, Yiu SC, Sun BC. Emergency department crowding predicts admission length-of-stay but not mortality in a large health system. Med Care. 2014; 52(7), 602.

37. Tandberg D, Qualls C. Time series forecasts of emergency department patient volume, length of stay, and acuity. Ann Emerg Med. 1994; 23(2): 299-306.

38. Menke NB, Caputo N, Fraser R, Haber J, Shields C, Menke MN. A retrospective analysis of the utility of an artificial neural network to predict ED volume. Am J Emerg Med. 2014; 32(6): 614-617.

39. Box GE, Jenkins GM. Time series analysis, control, and forecasting. San Francisco, CA: Holden Day, 1976; 3226(3228), 10.

40. Aladeemy M, Chou CA, Shan X, Khasawneh M, Srihari K, Poranki S. Forecasting daily patient arrivals at emergency department: a comparative study. In Proceedings of the 2016 Industrial and Systems Engineering Research Conference, 2016

41. Lewis CD. Industrial and business forecasting methods: A practical guide to exponential smoothing and curve fitting. Butterworth-Heinemann 1982

42. Sariyer G. Sizing capacity levels in emergency medical services dispatch centers: Using the newsvendor approach. Am J Emerg Med. 2018b; 36(5): 804-815.

Table 1. Stationarity results

Variable /time series	t-statistic	p value	Result
TS1: Daily number of patients arrived by walking	-3.696	0.005	Reject H_0
TS2: Daily number of patients arrived by an ambulance	-11.753	0.000	Reject H_0
TS3: Average daily LOS of patients arrived by walking	-11.553	0.000	Reject H_0
TS4: Average daily LOS of patients arrived by ambulance	-11.128	0.000	Reject H_0

Table 2. Optimal models and their performances

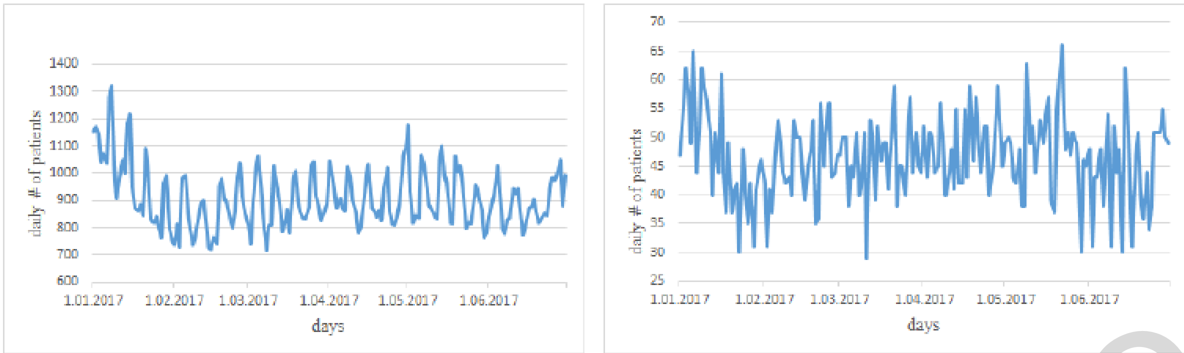
Variable /time series	Optimal model	MAPE
TS1: Daily number of patients arrived by walking	$ARIMA(1,0,0) * (2,0,0)_7$	5.432 %
TS2: Daily number of patients arrived by an ambulance	$ARIMA(1,0,1) * (0,0,0)_7$	13.085%
TS3: Average daily LOS of patients arrived by walking	$ARIMA(1,0,1) * (0,0,0)_7$	8.955%
TS4: Average daily LOS of patients arrived by ambulance	$ARIMA(2,0,0) * (0,0,0)_7$	11.984%

Table 3. Summary results of the optimal forecasting models

Variable /time series and optimal models	Final estimates on model parameters
TS1: Daily number of patients arrived by walking, $ARIMA(1,0,0) * (2,0,0)_7$	Type Coef SE Coef T P AR 1 0,5564 0,0654 8,51 0,000 SAR 7 0,4963 0,0758 6,55 0,000 SAR 14 0,2946 0,0743 3,97 0,000 Constant 87,553 4,930 17,76 0,000 Mean 943,63 53,13
TS2: Daily number of patients arrived by an ambulance $ARIMA(1,0,1) * (0,0,0)_7$	Type Coef SE Coef T P AR 1 0,8870 0,1058 8,39 0,000 MA 1 0,7803 0,1426 5,47 0,000 Constant 5,2918 0,1192 44,38 0,000 Mean 46,831 1,055
TS3: Average daily LOS of patients arrived by walking $ARIMA(1,0,1) * (0,0,0)_7$	Type Coef SE Coef T P AR 1 0,8824 0,0963 9,16 0,000 MA 1 0,7547 0,1342 5,63 0,000 Constant 11,5036 0,2211 52,03 0,000

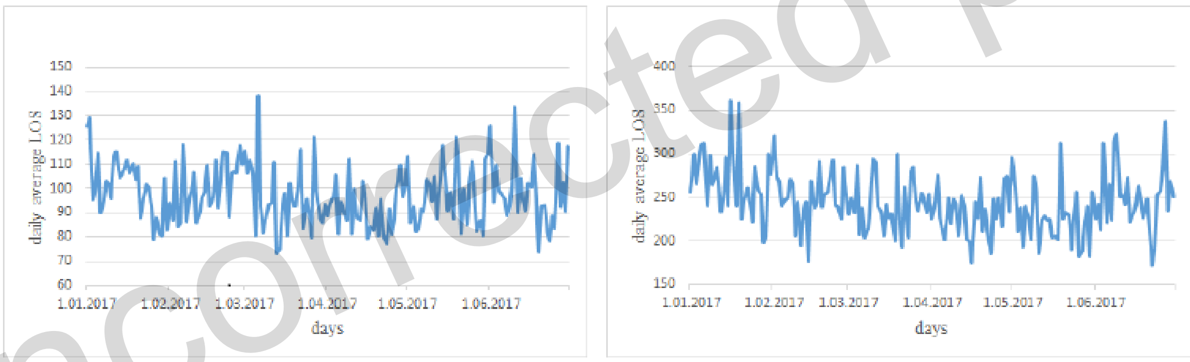
	Mean	97,835	1,880		
TS4: Average daily LOS of patients arrived by ambulance	Type	Coef	SE Coef	T	P
$ARIMA(2,0,0) * (0,0,0)_7$	AR 1	0,1480	0,0737	2,01	0,046
	AR 2	0,1806	0,0738	2,45	0,015
	Constant	164,456	2,526	65,10	0,000
	Mean	244,935	3,762		

Fig 1.



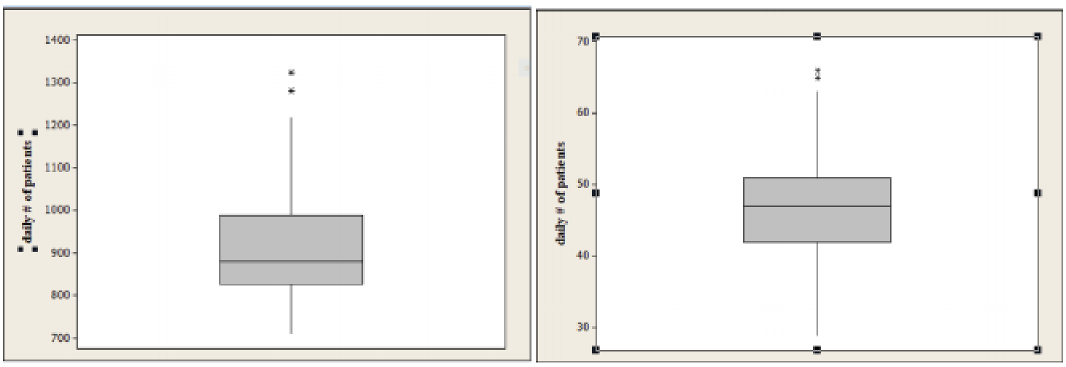
(a) arrived by walking **(b)** arrived by ambulance

Fig 2.



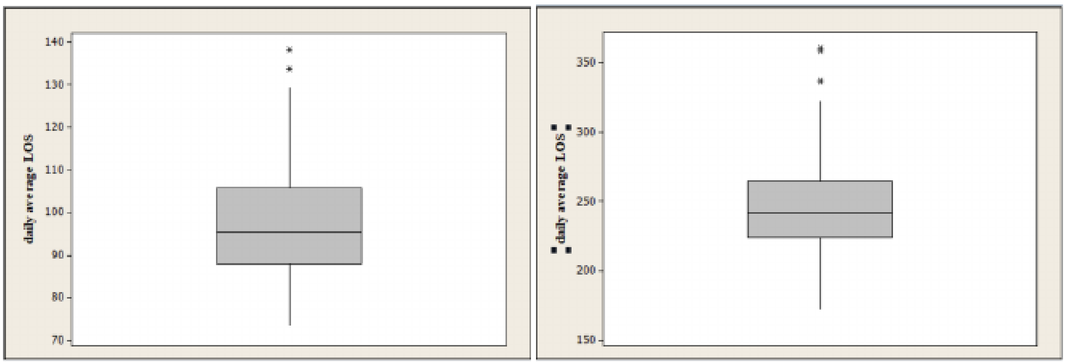
(a) arrived by walking **(b)** arrived by ambulance

Fig 3.



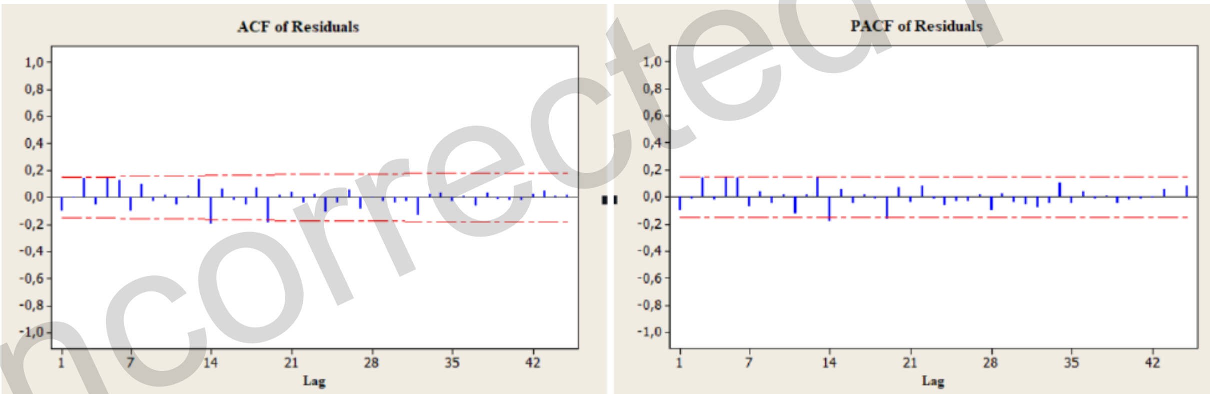
(a) arrived by walking **(b)** arrived by ambulance

Fig 4.



(a) arrived by walking **(b)** arrived by ambulance

Fig 5.



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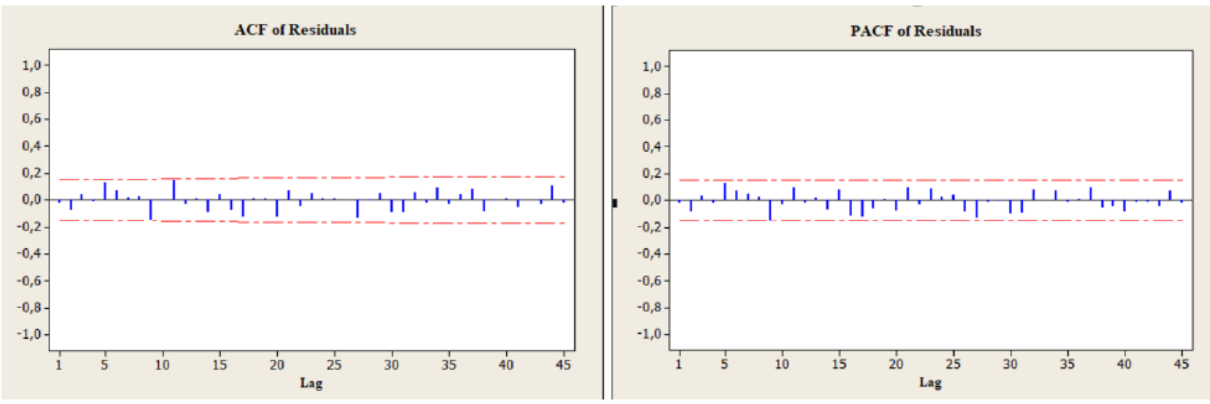

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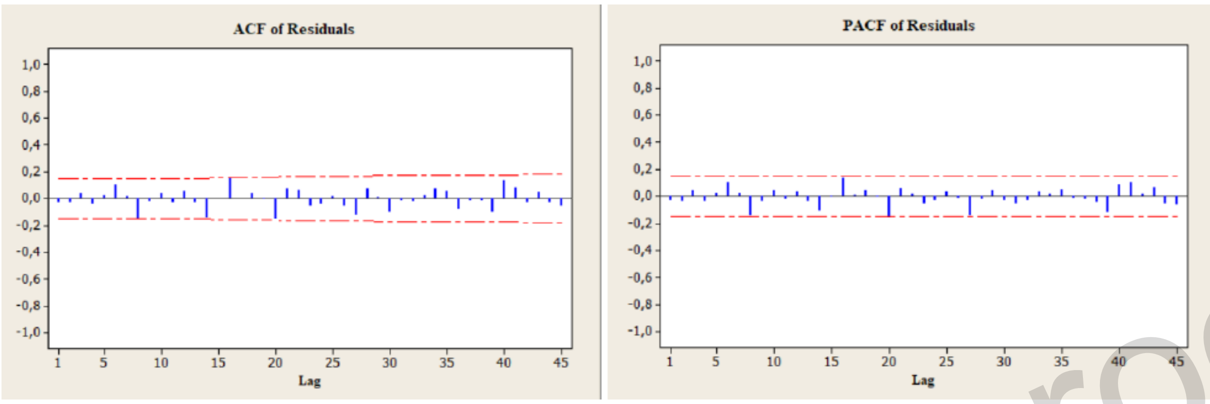
ACF of Residuals
PACF of Residuals
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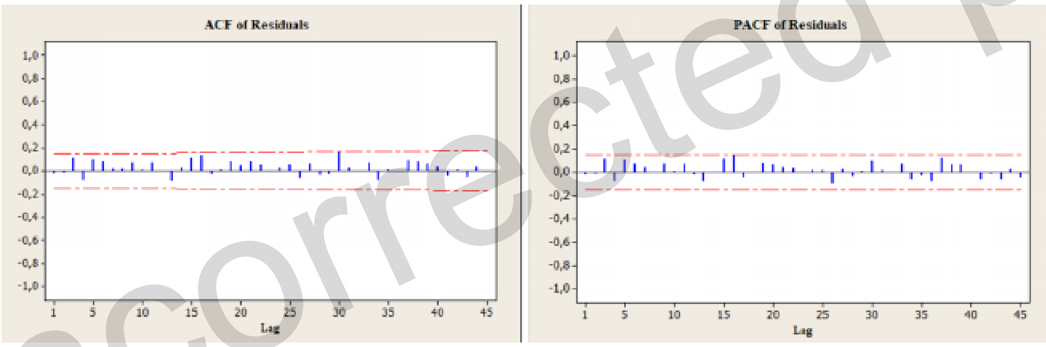
-0,4
-0,6
-0,8
-1,0
1 5 10 15 20 25 30 35 40 45
Lag

Fig 8.


ACF of Residuals
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-0,8
-1,0
1 5 10 15 20 25 30 35 40 45
Lag