BAREKENG: Journal of Mathematics and Its Applications
December 2026 Volume 20 Issue 4 Page 2799-2812
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol20iss4pp2799-2812

PREDICTING HOURLY AMBULANCE USAGE FOR TWO SELECTED GOVERNMENT HOSPITALS IN MALAYSIA; COMPARISON BETWEEN SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (SARIMA) AND SEASONAL DECOMPOSITION MODELS

Loshini Thiruchelvam[1*], Nur Balqishanis Zainal Abidin[2], Uma Eswari Punchanathan[3], Nur Dayana Abdul Rahman[4], Nur Amalina Mat Jan[5], Jane Irene P. J. Antony[6]

[1,4,5]*Department of Physical and Mathematical Science, Faculty of Science, Universiti Tunku Abdul Rahman*
[3]*Department of Marketing, Teh Hong Piow Faculty of Business and Finance, Universiti Tunku Abdul Rahman*
[6]*Department of English Education, Faculty of Education, Universiti Tunku Abdul Rahman*
Jln. Universiti, Bandar Barat, Kampar, Perak, 31900, Malaysia.

[2]*Faculty of Computing & Informatics (FCI), Multimedia University*
Persiaran Multimedia, Cyberjaya, Selangor, 63100, Malaysia.

*Corresponding author's e-mail: * **loshini@utar.edu.my***

Article Info

Article History:
Received: 6th September 2025
Revised: 2nd May 2026
Accepted: 7th June 2026
Available online: 1st July 2026

Keywords:
ambulance usage;
Box-Jenksins Methodology;
RMSE;
MAE;
MASE;
SARIMA.

ABSTRACT

An ambulance is a vehicle used to transport sick or injured people, and the patient will be sent to a hospital for further treatment. This study aims to predict hourly use of ambulances in two selected government hospital, namely the Hospital Sultanah Nur Zahirah (HSNZ), located in Terengganu, a state in the East Peninsular Malaysia, and Hospital Tapah, located in Perak state, in the West Peninsular Malaysia. Data on hourly ambulance usage were obtained from the hospital's emergency department for 2010. Two distinct statistical models, namely the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Seasonal Decomposition model, were used to model the dataset. The study found that both hospitals have different best forecasting models: HSNZ uses the Seasonal Decomposition Model, whereas the SARIMA model was found to forecast better at Hospital Tapah. For example, in the HSNZ study, the study determined the best SARIMA model from a few candidate models, namely $(1,0,0)(2,1,0_{24}$*. This model showed good performance on the training dataset and performed best on the test dataset. However, when further compared with the seasonal decomposition model, the study found the latter model to perform better. When visually investigated as well, the model's forecasted values were close to the actual values, or at least relatively acceptable. So far, this study concludes that the developed model is highly localized and specific to the given dataset.*

How to cite this article:

L. Thiruchelvam, N. B. Z. Abidin, U. E. Punchanathan, N. D. A. Rahman, N. A. M. Jan and J. I. P. J. Antony, "PREDICTING HOURLY AMBULANCE USAGE FOR TWO SELECTED GOVERNMENT HOSPITALS IN MALAYSIA; COMPARISON BETWEEN SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (SARIMA) AND SEASONAL DECOMPOSITION MODELS", *BAREKENG: J. Math. & App.*, vol. 20, no. 4, pp. 2799-2812, Dec, 2026.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

The Emergency Department (ED) is known to be the busiest department, accepting many patients, including high-risk patients. ED's primary goal is to treat urgent and emergency situations that require immediate care by making a quick diagnosis and administering medical or surgical therapy as soon as possible [1]. Patients arrive at the ED mostly via the ambulatory service and by their own transport.

In Malaysia, the Malaysian Ministry of Health (MOH) is the main supplier of ambulance services. Besides MOH ambulances, clinic and private hospital ambulances are also used for emergencies and patient transfers. There are more reasons to establish a sustainable ambulance service, given the sharp rise in traffic accidents and hospital and clinic cases, which have led to a need for ambulance services. Besides, ambulances play a vital role in prehospital care and crises; thus, they should be maintained and updated to guarantee their best utilization, patient safety, and ultimately improved health outcomes [2].

According to a report, Malaysia's Ministry of Health (MOH) responded to only 31.5% to 41.8% of Priority 1 emergency calls within 15 minutes between 2017 and 2021, falling short of the goal set by the country's national audit report. Life-threatening events, such as strokes or accidents, are included in priority 1 cases. Only 443,080 of the 1.06 million such calls were answered in the allotted period. Only two hospitals, Sultanah Aminah in Johor and Tuanku Fauziah in Perlis, achieved the target. Other hospitals, particularly those in isolated locations such as Tawau in Sabah, suffered from long coverage distances and delayed team activation. Poor coordination and extended distances (up to 450 km) are causes of poor performance [3]. The lack of personnel and ambulances is making it difficult for the Malaysian Ministry of Health (MOH) to provide high-quality service. The creation of specialized ambulance teams is hindered by the need for emergency room assistant medical officers to multitask, according to Health Minister Dr. Zaliha Mustafa. Currently, the MOH only possesses 590 ambulances, even though 1,100 are needed for disaster response and patient transport. Response times are prolonged by the continued centralization of ambulance services at hospitals. Since 2019, there has been a shortage of ambulances at clinics serving high-accident areas, such as Gopeng and Gunung Rapat in Ipoh [3]. Hospitals that are short-staffed should raise their staffing issues with the Ministry of Health to secure the placement of new staff in their places. Health Minister Dr. Zaliha Mustafa claimed on 6th March 2023 that public hospital emergency rooms are overcrowded and that urgent action is required to address the acute staff and equipment shortages most public hospitals are experiencing [4].

To address the problems of staff shortages and insufficient facilities in the Emergency Unit, the first step is to estimate the staffing and facility needs at any given time. One way to do this is to predict ambulance use based on time in the hospital. This forecast shows the times when ambulance use is high or low, which indirectly indicates whether the Emergency Unit will be busy. When the Emergency Unit is predicted to be busy at a certain time, the number of staff on duty should be increased. The number of ambulances used at a certain time can also roughly reflect the number of equipment and facilities needed [5].

The importance of ambulance management has been demonstrated in many studies, focusing on optimal ambulance routing models, the number of available ambulances, and hospital preparedness. For example, [6] used mathematical modelling and an optimization-based simulation study to identify the best location for emergency medical centers and assign the ambulances to the chosen facilities, in order to reduce the overall cost of the emergency medical services (EMS) system and increase the survival rate. A case study was carried out in four regions of Isfahan city, in Iran, with the following scenario: (1) number of fixed emergency centers per neighbourhood, (2) maximum number of general ambulances, (3) number of maximum advanced ambulances, (4) allocation of mobile general ambulance at the crowded area. Another study by [7] eveloped a simulation model that accounts for hospitals, dispatching sites, and available ambulances to determine the best route for transporting patients, a dynamic process that is highly time-dependent and also depends on the patient's urgency at that time. Real data of hospital admissions for the area of Victoria, in Melbourne, has been obtained from the Australian government for this purpose. The simulation model yielded a promising optimal route with an average arrival time of 15 minutes to the incident area.

On the other hand, some studies have also examined the cost-effectiveness of ambulance maintenance. For example, [2] compared two strategies: one with 10 years of compulsory replacement and another with replacement within 15 years, and found that 10 years of ambulance replacement is cost-effective. Although switching from a 15- to 10-year replacement method would cost an extra MYR 13.0 million, it would save an additional 1,157 people annually. Thus, the study recommends that the Ministry of Health (MoH) Malaysia consider compulsory replacement of ambulances after 10 years, taking into account the need for ambulances, their utilization, and the mortality rate of cases involving unattended ambulances. Looking into the various types of mathematical or statistical approaches used to model ambulance usage, several studies have included Autoregressive Integrated Moving Average (ARIMA), Holt-Winters, Multiple Regression, Singular Spectrum Analysis (SSA), artificial neural networks (ANNs), Seasonal ARIMA (SARIMA), and the Simple Exponential Smoothing (SES) models.

Based on the case studies conducted by [8], comparing four forecasting methods, which included Autoregressive Integrated Moving Average (ARIMA), Holt-Winters, Multiple Regression, and Singular Spectrum Analysis (SSA), to assess their accuracy in predicting ambulance call volumes across different planning horizons, the findings showed that ARIMA is most effective for weekly and monthly forecasts. In addition, a study identified a reliable method for forecasting daily ambulance calls [9] and found that a model combining Facebook's Prophet and ARIMA regression worked well. However, these forecasting methods did not involve the seasonal criteria. The improvised forecasting model that adds a seasonal trend to the SARIMA model has been shown to be effective for predicting demand for emergency medical services (EMS) and ambulances. In another study, [10] also developed a SARIMA model to forecast call volume at an emergency ambulance service call center in India, which proved useful for manpower and resource planning. Additionally, artificial neural networks (ANNs) have been shown to provide accurate ambulance demand forecasts [11]. However, ANNs are most effective for short-term time series forecasting and may have limitations for long-term predictions. Forecasting methods increasingly incorporate machine learning models to predict ambulance demand [12] and daily ambulance arrivals [13] using historical EMS data. Moreover, [14] proposed A Geographic Information System – based (GIS-based) statistical model to predict ambulance demand and optimize pre-allocation. This approach helps to improve emergency response times and patient outcomes by forecasting prehospital medical demand. Another forecasting model implemented by [15] used a hierarchical forecasting approach to generate both point and probabilistic forecasts of daily ambulance demand in EMS, which would help improve coordination and decision-making at all organizational levels within hospitals.

Moreover, a simple exponential smoothing approach with weekly seasonality, also used by [16] was found to be effective for forecasting ambulance call volumes for tactical planning. The study compared forecasting methods for EMS call volumes and found that simple models with weekly seasonality perform well, while adding complexity does not significantly improve accuracy. Hourly patient arrival and ambulance demand forecasting has been greatly enhanced by time-series models such as SARIMA and machine learning techniques, offering practical insights for controlling overcrowding and improving service effectiveness [17], [18]. Accurate forecasting facilitates proactive scheduling, enhanced equipment readiness, and dynamic resource allocation in emergency situations, when prompt action can save lives. These factors eventually improve patient outcomes and operational resilience [19]. The incorporation of predictive analytics into hospital operations is part of a larger trend in healthcare planning toward data-driven decision-making. Although there is an increasing body of research on ambulance and emergency department (ED) demand, there remains a noticeable lack of hourly forecasting models specifically designed for Malaysian hospital settings. Without using hour-by-hour forecasting at the hospital level, existing studies often concentrate on daily or monthly demand or utilize aggregated patterns and larger spatial-temporal scales [15], [19], [20]. For operational planning in emergency care, the emphasis on hourly resolution rather than daily or monthly averages is especially crucial. When patient admissions spike during peak ambulance arrival hours, emergency departments are under pressure to increase staffing, equipment, and bed capacity. Hospital managers may plan staff, including backups, during anticipated peak hours; proactively assign emergency supplies and equipment; alleviate crowding; and shorten reaction times using hourly forecasts. The study contributes both local uniqueness and methodological innovation by using this strategy in Malaysia's hospital emergency services.

To close this gap, we develop, compare, and select the optimum model using Seasonal Autoregressive Integrated Moving Average (SARIMA) and further comparing it with another statistical model, known as the Seasonal Decomposition model for two selected study hospitals, Hospital Sultanah Nur Zahirah (located in East of Malaysia) and Hospital Tapah (located in West of Malaysia), using hourly ambulance usage of year 2010. This comparison also allows for determining which model is better at predicting seasonal data. The selected optimal model is then used to provide an hourly-based ambulance demand projection for the next few hours. The novelty of our study would be to examine hourly-based estimation and prediction, which very few studies have investigated, especially in the Malaysian context, and which would be far more accurate and practical than weekly or monthly ambulance usage estimates.

2. RESEARCH METHODS

2.1 Dataset

The dataset used in this study consists of hourly ambulance usage for the whole year of 2010. The data were obtained from two selected government hospitals, namely Hospital Sultanah Nur Zahirah, located in the state of Terengganu, in the East of Peninsular Malaysia, and Hospital Tapah, located in the state of Perak, in the East of Peninsular Malaysia.

2.2 Methodology for Statistical Models

2.2.1 Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

The SARIMA model for hourly ambulance usage can be denoted as the following Eq. (1).

$$y_t = c + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{P} \gamma_i y_{t-24i} + \sum_{i=1}^{Q} \beta_i \varepsilon_{t-24i} + \varepsilon_t \tag{1}$$

where c is the constant, $\alpha_i, \theta_i, \gamma_i, \beta_i$are the coefficients to be estimated, y_{t-i} and y_{t-24i} are the number of ambulance usage at the respective time, and ε_{t-i}, ε_{t-24i} and ε_t are the computed error at the respective time. The first two coefficients to be estimated, the summation of α_i, θ_i, captures the non-seasonal effects, represented as the autoregressive with terms up to p $(AR(1), AR(2), \dots AR(p))$ and moving average terms up to q terms, $(MA(1), MA(2), \dots MA(q))$, respectively. On the other hand, the summation of γ_i, β_i, captures the seasonal effects, represented as the seasonal autoregressive with terms up to P $(SAR(1), SAR(2), \dots SAR(p))$ and seasonal moving average terms up to Q terms, $(SMA(1), SMA(2), \dots SMA(Q))$, respectively. Here, the seasonal effect of 24 hours is considered since the model is to learn the hourly dataset, thus, it is expected that similar patterns on number of usages can be seen at the same time on other days too.

This SARIMA model is developed using the Box-Jenkins approach, consisting of four steps. Step 1: Model Identification. This step involves first ensuring the dataset is stationary (performing first-, second-, or seasonal differences wherever needed) and then performing preliminary model identification using plots of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to determine a suitable model structure.

Step 2: Parameter Estimation. Once a preliminary model has been identified, parameter estimation is performed to determine the parameter values. This study used the Maximum Likelihood Estimation method. Step 3: Diagnostic Checking. This step assesses whether the selected model is adequate. Diagnostic tests are conducted to examine residuals and model performance. If the model is found to be inadequate, modifications are applied. In this study, a few candidate models that fulfill the model identification, parameter estimation, and diagnostic check are selected. The most accurate model will then be selected from the candidate models using three metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Scaled Error (MASE). The RMSE, MAE, and MASE can be computed as follows Eqs. (2), (3), and (4).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}, \tag{2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|, \tag{3}$$

$$MASE = \frac{\frac{1}{n} \sum_{j=1}^{n} |e_j|}{\frac{1}{T-m} \sum_{t=m+1}^{T} |y_t - y_{t-m}|}, \tag{4}$$

where for RMSE and MAE, y_i, $\hat{y}_i$ refers to the actual and predicted value at time i, with n refers to the number of observations. Whereas for the MASE, e_j represents the jth error in testing dataset T refers to the number of observations in the training set and m refers to the seasonal period.

Step 4: Forecasting. Once a well-fitted model has been established through the preceding steps, it can be used to generate forecasts for future time series data. This study forecasts ambulance usage over the next 12 hours. The obtained result is plotted against the actual data to visually compare them.

2.2.2 Seasonal Decomposition Model

Seasonal variation refers to repetitive, predictable movements that occur within a period of 1 year or less. To identify seasonal variation, time intervals must be measured in small units such as days, weeks, months, or quarters. There are several important reasons for studying seasonal variation, such as its ability to identify patterns of changes in the past and to forecast the future.

This study uses the classical decomposition forecasting method, consisting of a linear trend component and the multiplicative seasonal component. First, the linear trend line is computed by using the following Eq. (5):

$$\widehat{T}_t = a + b_t, \tag{5}$$

where a is the intercept-value, b is the slope value and t is the time index.

Next, the seasonal index for each hour is computed. This is done by first grouping the dataset by hour, then computing the average for each hour, and finally computing the overall average. Eq. (6) shows the formula for Seasonal Index.

$$Seasonal\ Index_h = \frac{Average\ Usage_h}{Overall\ Average} \tag{6}$$

A seasonal index above 1 indicates that usage at that hour is above the overall usage, and vice versa. Finally, the next step is to multiply the trend and seasonal index value at time image.png, and thus obtain the trend-adjusted seasonal forecast. This is also known as the multiplicative decomposition forecasting method. Thus, the forecast can be computed using Eq. (7).

$$Forecast = Trend\ \times Seasonal\ Index \tag{7}$$

Once the forecast is obtained, its performance can be measured by computing the RMSE, MAE, and MASE using the formulas in Eqs. (2), (3) and (4). Finally, the forecast can be plotted against actual observations for visual analysis.

3. RESULTS AND DISCUSSION

This section discusses the research findings from the SARIMA and seasonal decomposition models applied to the two selected government hospitals.

3.1 Modelling the Hourly Ambulance Usage using SARIMA Model

3.1.1 Development of SARIMA Model for Hourly Ambulance Usage at Hospital Sultanah Nur Zahirah (HSNZ).

The following shows the time series plot of hourly ambulance usage at Kuala Terengganu Hospital in 2010. This plot shows a seasonal pattern: ambulance usage is highest in the middle of the day, whereas during midnight (12am to 4am), it is at a minimum. This pattern is consistent throughout the week. Next, the entire dataset is split into training and test sets. The first 132 observations are used as the training dataset, where a model is developed by learning the pattern in the dataset. The remaining half of the dataset is then used to assess how well the model performs on the new dataset. Using the training dataset, first, it is checked whether the dataset is stationary by differencing at both seasonal and non-seasonal orders. The study found a need for seasonal differencing of order one.

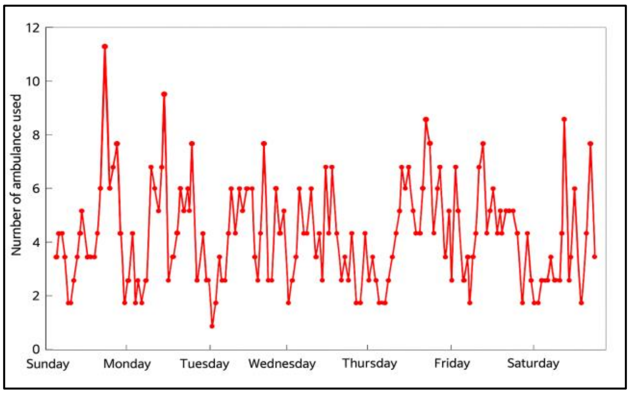

Figure 1. Time Series Plot of Ambulance Usage Data at Hospital Sultanah Nur Zahirah (HSNZ), located at East Peninsular of Malaysia, for year 2010

Next, the orders of the autoregressive and moving-average parameters for both seasonal and non-seasonal effects are examined through plots of the autocorrelation and partial autocorrelation functions. These plots are described in the following Figs. 2 and 3.

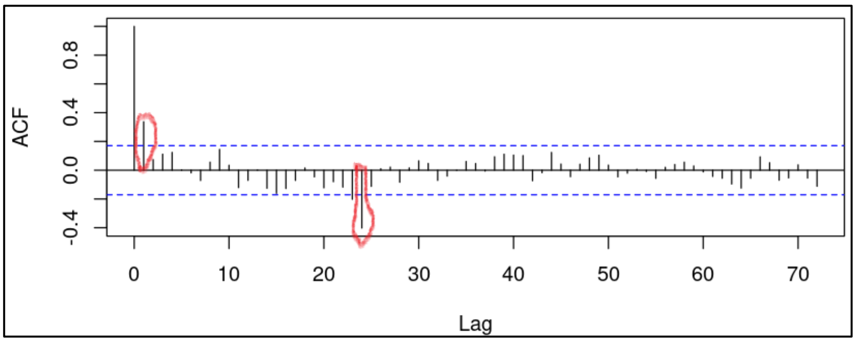

Figure 2. Autocorrelation Function Plot for Ambulance Usage Data at Hospital Kuala Terengganu, located at East of Peninsular of Malaysia, for year 2010

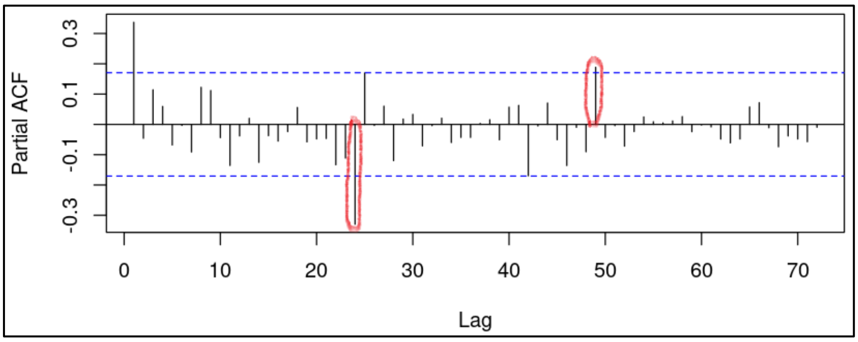

Figure 3. Partial Autocorrelation Function Plot for Ambulance Usage Data at Hospital Kuala Terengganu, located at East of Peninsular of Malaysia, for year 2010

The ACF and PACF plots, as in Figs. 2 and 3 describe the candidate SARIMA models to be considered: (0,0,1)(1,1,1)24, (0,0,1)(1,1,0)24, (0,0,1)(0,1,1)24, (0,0,1)(2,1,1)24, and (0,0,1)(2,1,0)24; thus, SARIMA models of these orders are developed. Table 1 describes the RMSE, MAE, and MASE values for the test data obtained for each model. The results show that the best model fit is the SARIMA (0,0,1)(2,1,0)24, as it learns the data well and, more importantly, performs best on a new dataset compared to other models.

Table 1. Candidate SARIMA models and their Performance Results for HSNZ

Measurement Tool	**Type of Dataset**	**(0,0,1)(1,1,1)$_{24}$**	**(0,0,1)(1,1,0)$_{24}$**	**(0,0,1)(0,1,1)$_{24}$**	**(0,0,1)(2,1,1)$_{24}$**	**(0,0,1)(2,1,0)$_{24}$**
RMSE	Training	**2.81179**	3.438446	2.820890	2.812820	3.365548
	Testing	3.86254	3.543416	3.835655	3.860549	**3.519176**
MAE	Training	2.198138	2.634172	**2.197880**	2.199034	2.591232
	Testing	3.368235	3.176197	3.324381	3.365732	**3.100874**
MASE	Training	**0.5569749**	0.6674594	0.5569097	0.5572021	0.6565792
	Testing	0.8534600	0.8048005	0.8423480	0.8528257	**0.7857147**

Next, the residuals from the developed SARIMA model are checked to ensure they are random, have a mean of zero, and are normally distributed. The following Fig. 4 explains that the residual has all the previously mentioned properties: (a) mean of zero, (b) residuals are random or there is no autocorrelation among them, (c) residuals are normally distributed.

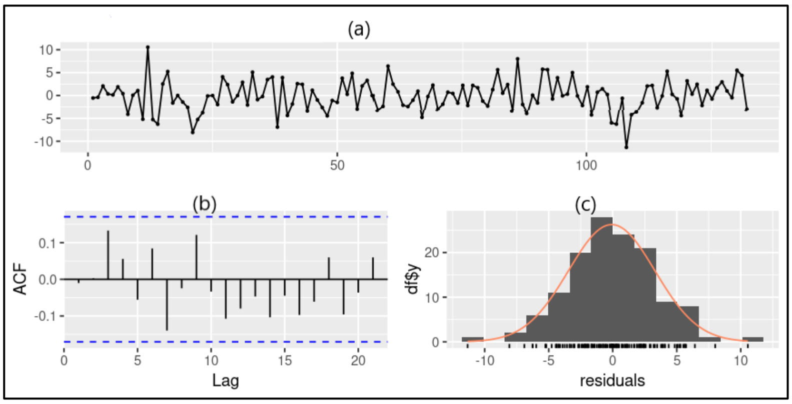

Figure 4. Residuals for SARIMA $(0,0,1)(2,1,0)_{24}$ Model for Hourly Ambulance Usage at Kuala Terengganu Hospital, year 2010

Fig. 5 also presents the next 12-hour forecast using the best-fit SARIMA $(0,0,1)(2,1,0)_{24}$ model. This forecast is plotted against the actual observations, and it is seen that the forecasted values are close to the actual observations.

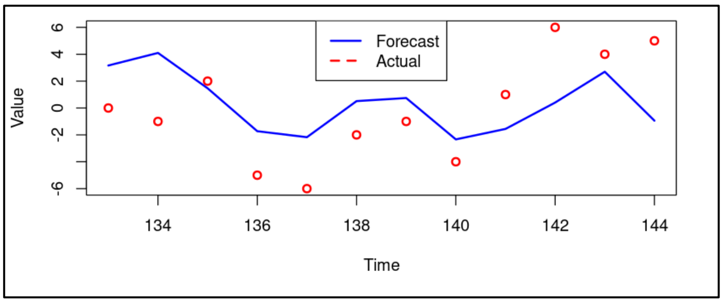

Figure 5. Plot of the Forecasted Values Against Actual Observation for Hourly Ambulance Usage in HSNZ, Year of 2010

3.1.2 Development of SARIMA Model for Hospital Tapah.

The following Fig. 6 shows the time series plot of hourly ambulance usage at Hospital Tapah in 2010. This plot shows a seasonal pattern: ambulance usage is highest in the middle of the day or evening, whereas at midnight (12am to 4am) it is at a minimum or at least moderate. This pattern is consistent throughout the week, though with different numbers of usages on different days. Next, the entire dataset is split into training and test sets. The first 134 observations are used as the training dataset, where a model is developed by learning the pattern in the dataset. The remaining half of the dataset is then used to assess how well the model performs on the new dataset. Using the training dataset, first, it is checked whether the dataset is stationary by differencing at both seasonal and non-seasonal orders. The study found there is no need for both types of differencing.

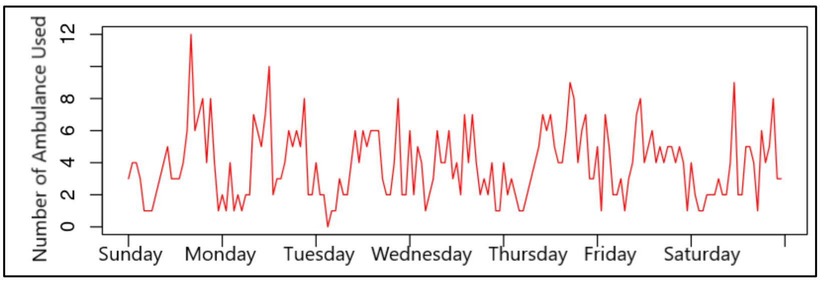

Figure 6. Time Series Plot of Ambulance Usage Data at Hospital Tapah, located at West Peninsular of Malaysia, for Year 2010

Next the orders of the autoregressive and moving-average parameters for both seasonal and non-seasonal effects are examined through plots of the autocorrelation and partial autocorrelation functions. These plots are described in the following Figs. 7 and 8.

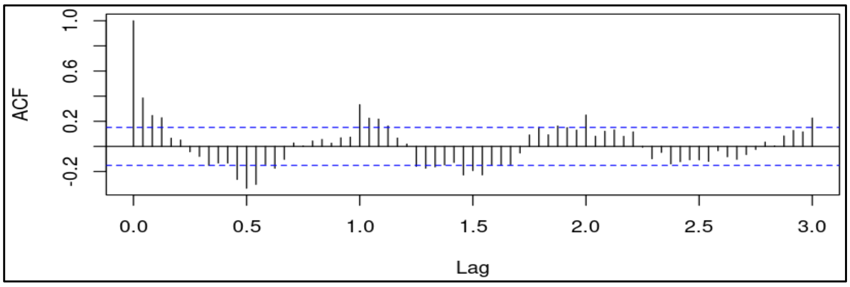

Figure 7. Autocorrelation Function Plot for Ambulance Usage Data at Hospital Tapah, located at West of Peninsular of Malaysia, for year 2010

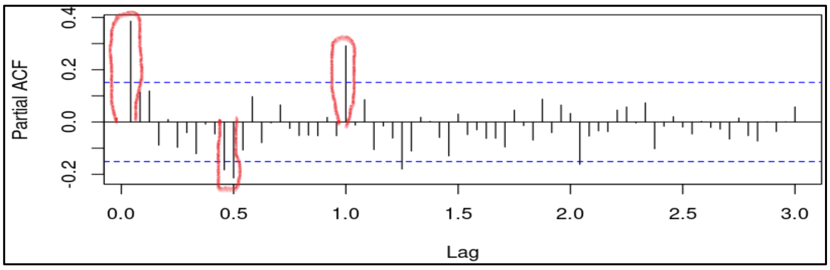

Figure 8. Autocorrelation Function Plot for Ambulance Usage Data at Hospital Tapah, located at West of Peninsular of Malaysia, for year 2010

Referring to prior Fig. 7, the ACF plot shows a repeated exponential and sinusoidal pattern throughout the lags. For this scenario, the model order shall be selected based on the PACF plot instead. Referring to Fig. 8, it is obvious that there are non-significant spikes at both the non-seasonal and seasonal lags. There are three non-significant spikes for the non-seasonal lags, which are the first, 11^{th} and 12^{th} lags. To check for the seasonal lags, spikes that appear to be non-significant after one whole cycle of 24 lags are examined. Here, only the first lag appears to be non-significant; that is, it lies above the confidence band, illustrated as blue dotted lines in the figure above. Thus, the suggested SARIMA model orders are $(1,0,0)(1,0,0)_{24}$, $(1,0,0)(11,0,0)_{24}$ and $(12,0,0)(1,0,0)_{24}$ models. However, a check of the residuals using the Ljung-Box test showed p-values less than 0.05 for the second and third models, indicating that the residuals are correlated and not white noise. The SARIMA $(1,0,0)(1,0,0)_{24}$ model has all its parameters estimated well, and its residuals are not correlated, as indicated by the Ljung-Box test with p-value 0.4829 (bigger than 0.05). Thus, only SARIMA model $(1,0,0)(1,0,0)_{24}$ is finalized. This also explains that the non-significant spikes at lags 11 and 12 for the non-seasonal order might get canceled off with the inclusion of order 1 itself (AR 1). The SARIMA $(1,0,0)(1,0,0)_{24}$ model's performance is described in the following Table 2.

Table 2. SARIMA Model and Its Performance Results for Hospital Tapah

Measurement Tool	Type of Dataset	SARIMA $(1,0,0)(1,0,0)_{24}$
RMSE	Training	1.867
	Testing	1.834
MAE	Training	1.492
	Testing	1.434
MASE	Training	0.8068
	Testing	0.7755

Fig. 9 also further explains that the residuals have all the required properties: (a) mean of zero, (b) residuals are random, or there is no autocorrelation among them, and (c) residuals are normally distributed.

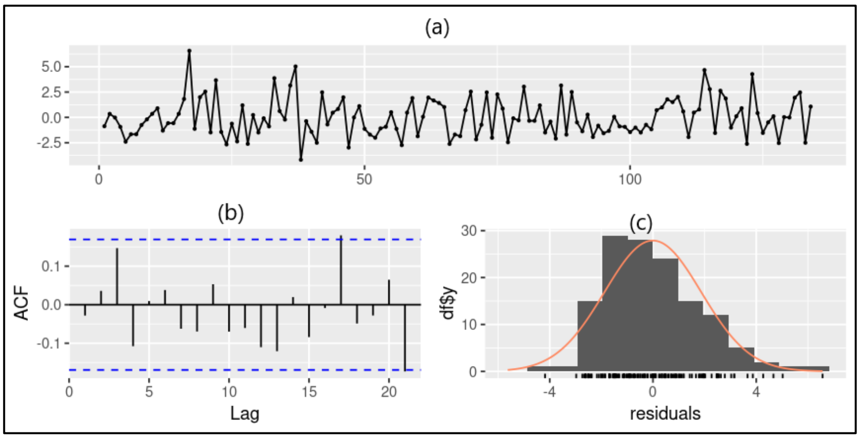

Figure 9. Residuals for SARIMA $(1,0,0)(1,0,0)_{24}$ Model for Hourly Ambulance usage at Hospital Tapah, year 2010

To measure the performance of this SARIMA $(1,0,0)(1,0,0)_{24}$ model on a new dataset, the model is used to forecast the next 12 observations, which are then compared with the actual observations. Fig. 10 explains the results obtained. This figure shows that some observations were correctly or very closely forecast, although a few forecasts differ from the actual observations.

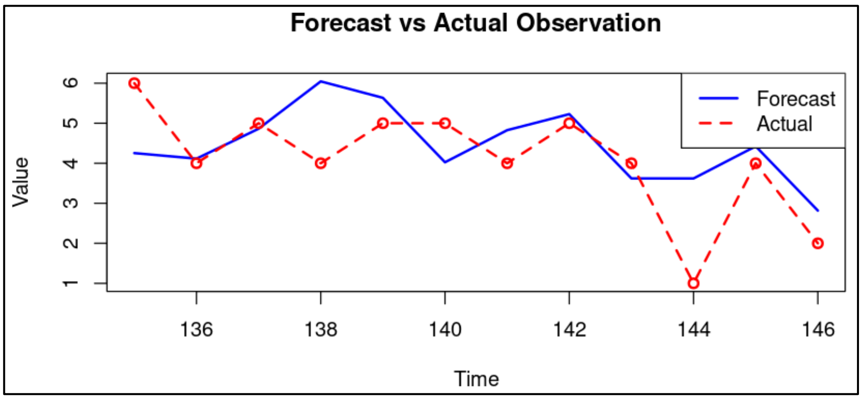

Figure 10. Plot of the Forecasted Values Against Actual Observation for hourly Ambulance usage in Hospital Tapah, Year of 2010

3.2 Modelling the Hourly Ambulance Usage using Seasonal Decomposition Model

3.2.1 Development of Seasonal Decomposition Model for Hourly Ambulance Usage at Hospital Sultanah Nur Zahirah (HSNZ)

The seasonal decomposition model is developed based on the steps discussed in Section 2.2. The following Table 3 describes a section of the analysis.

Table 3. Some Section of the Data Analysis for Hourly Ambulance Usage at HSNZ using Seasonal Decomposition Model

Index	Hour	Usage	Average Hourly Usage	Seasonal Index	Intercept Value	Slope Value	Linear Trend Forecast (LTF)	Seasonal Trend Forecast (STF)
1	0	7	6	0.6502	9.792208	-0.01025	9.782	6.360
2	1	7	4.333	0.4696			9.772	4.589
3	2	1	4	0.4334			9.761	4.213
4	3	1	3	0.3251			9.751	3.170
5	4	3	3.5	0.3793			9.741	3.695
6	5	2	2.333	0.2529			9.730	2.460

The results of the measurement tools, RMSE, MAE, and MASE, for both the training and testing datasets are tabulated in Table 4. These results are compared with the previously selected optimum SARIMA model, and the study found that the latter seasonal decomposition model outperformed the SARIMA model, with lower RMSE and MAE and comparably good MASE values.

Table 4. Performance Results for the developed Seasonal Decomposition model for Hourly Ambulance Usage at HSNZ.

Measurement Tools	Type of Data	Type of Model: Seasonal Decomposition	Type of Model: SARIMA
RMSE	Training	2.747	3.366
	Testing	3.196	3.520
MAE	Training	2.124	2.591
	Testing	2.542	3.101
MASE	Training	0.6729	0.6566
	Testing	0.7875	0.7857

The following Fig. 11 shows the plotted graphs of the actual usage (represented in red colour) against forecasted usage (represented in blue color) across the timeline. From the figure, it is clear that actual usage exhibits a distinct daily cyclic pattern. For all days of the week, ambulance usage is very low till at least 7am; then the number starts to increase, reaching its peak at noon by 1pm, and after that it reduces slightly and remains moderate till night. The number of usages starts to drop again as the time nears midnight. Only a slight difference in pattern was seen on day six, which was a Friday; the number of usages remained moderate till 1am, perhaps due to many public users still using the road since it was a holiday in this state. These findings are consistent with previous studies which highlighted that emergency demand is often aligned with traffic patterns and public activity hours [24], [25]. Looking into the forecasted graph, this graph managed to follow the pattern of actual usage most of the time, except for having some overestimates and underestimates at times. This shows the developed seasonal decomposition model is reliable.

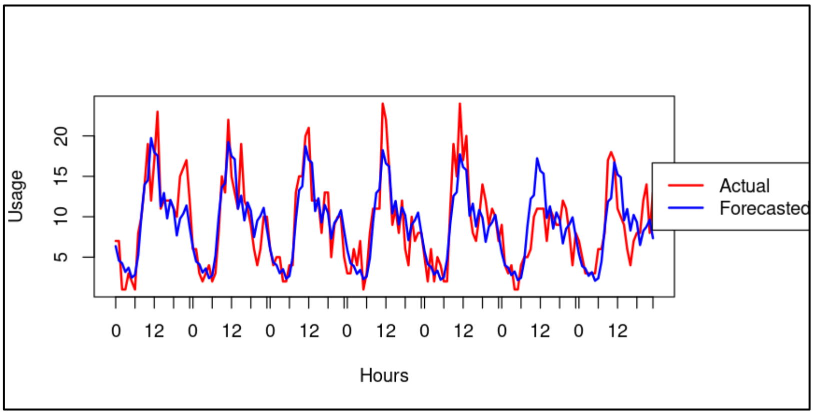

Figure 11. Comparison between Actual Usage and Forecasted values using Seasonal Decomposition Model for Hourly Ambulance Usage in HSNZ, 2010.

3.2.1 Development of Seasonal Decomposition Model for Hourly Ambulance Usage at Hospital Tapah.

The seasonal decomposition model is developed based on the steps discussed in Section 2.2. Table 5 below describes a section of the analysis.

Table 5. Some Section of the Data Analysis for Hourly Ambulance Usage at Hospital Tapah using Seasonal Decomposition Model

Index	Hour	Usage	Average Hourly Usage	Seasonal Index	Intercept Value:	Slope Value:	Linear Trend Forecast (LTF)	Seasonal Trend Forecast (STF)
1	0	3	4	1.000	3.679	0.003983	3.683	3.684
2	1	4	2	0.5000			3.687	1.844
3	2	4	4.167	1.042			3.691	3.846
4	3	3	2.5	0.6252			3.694	2.310
5	4	1	1.333	0.3334			3.699	1.233
6	5	1	1.333	0.3334			3.703	1.235

The results of the measurement tools (RMSE, MAE, and MASE) for both the training and testing datasets are described in Table 6. These results are compared with the prior finalized SARIMA model, and a mixed result is found: a better model. However, when selecting the optimal forecasting model, priority should be given to the model that performed best on the test dataset, even though it is trained on a new dataset. Thus, for this comparison, the study selected the SARIMA $(1,0,0)(1,0,0)_{24}$ model as the best forecasting model. This is because, when comparing performance on the testing dataset, this model has the lowest RMSE, a comparably low MAE, and a better MASE value than the developed Seasonal Decomposition model.

Table 6. Performance Results for the developed Seasonal Decomposition model for Hourly Ambulance Usage at Hospital Tapah.

Measurement Tools	Type of Data	Type of Model	
		Seasonal Decomposition	SARIMA $(1,0,0)(1,0,0)_{24}$
RMSE	Training	**1.542**	1.867
	Testing	1.942	**1.834**
MAE	Training	**1.179**	1.492
	Testing	**1.431**	1.434
MASE	Training	**0.6585**	0.8068
	Testing	0.7974	**0.7755**

3.3 Comparison between SARIMA and Seasonal Decomposition Models.

Both the SARIMA and seasonal decomposition models have their own strengths and drawbacks. Additionally, the performance of these models varies across datasets. The Seasonal Decomposition model's strength lies in its ability to isolate trend and seasonal components, making it particularly effective for data like ambulance usage, which exhibits strong hourly seasonality. This aligns with the findings of [26], who observed that Seasonal Decomposition models often provide better interpretability and comparable accuracy in structured time series data within the healthcare sector. On the other hand, SARIMA is more flexible in capturing complex autoregressive and moving average patterns but may be less transparent in interpreting seasonal effects. Besides, another drawback of the SARIMA model is that the number of observations is reduced by the differencing step, here involving the seasonal with a length of 24. Thus, the balanced test dataset is reduced.

3.4 Discussion

Based on the findings and forecast patterns observed in this study, it is recommended that hospital administrators (particularly at the selected hospitals) strategically schedule Emergency Unit staff to align with peak ambulance usage periods. Additionally, hospital management should ensure that adequate emergency equipment is available, especially during predicted peak hours where usage may reach up to 20 cases per hour. This data-driven scheduling approach can improve response times and patient recoverability. These recommendations are supported by previous research emphasizing demand-based workforce optimization in emergency services [27]. Future studies are encouraged to expand the scope by including more hospitals and evaluating a wider range of forecasting models to better understand national ambulance usage trends and optimize healthcare resource planning across Malaysia.

4. CONCLUSION

This study developed and finalized the optimal Seasonal Autoregressive Integrated Moving Average (SARIMA) model to predict the time of day with the highest ambulance usage at the selected study hospitals. The study also further compared with another seasonal-based model, known as the seasonal decomposition model. Two study hospitals' hourly ambulance usage data are applied here, and the study found that each hospital has a distinct best forecasting model. In general, the forecasts indicate a higher demand for services during the midday and evening hours, suggesting that more personnel should be allocated to the second and third shifts. Both hospitals are advised to ensure there is sufficient emergency equipment on hand, particularly during anticipated peak hours when utilization could reach up to 20 cases per hour. Response times and patient recoverability can both be enhanced by this data-driven scheduling strategy. To better understand national ambulance demand trends and maximize healthcare resource allocation throughout Malaysia, future research is encouraged to broaden its scope by including additional hospitals and assessing a greater variety of forecasting models.

Author Contributions

Loshini Thiruchelvam: Conceptualization, methodology, software, validation. Nur Balqishanis Zainal Abidin: writing for the Introduction section and Formatting. Uma Eswari Punchanathan: writing for the Introduction section; Nur Dayana Abdul Rahman: write-up for methodology. Nur Amalina Mat Jan: write-up for Results and Discussion sections and software. Jane Irene P J Antony: writing and editing. All authors discussed the results and contributed to the final manuscript.

Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Acknowledgment

The authors would like to thank the selected government hospitals for providing the dataset for this study. The authors would also like to thank Universiti Tunku Abdul Rahman (UTAR) for providing funding for the publication process.

Declarations

The authors declare that they have no conflicts of interest in reporting the study.

Declaration of Generative AI and AI-assisted technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement (grammar, spelling, and clarity). The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. The authors reviewed and approved all final text.

REFERENCES

[1] M. Sartini *et al.*, "OVERCROWDING IN EMERGENCY DEPARTMENT: CAUSES, CONSEQUENCES, AND SOLUTIONS—A NARRATIVE REVIEW," *Healthcare*, vol. 10, no. 9, p. 1625, Aug. 2022, doi: https://doi.org/10.3390/healthcare10091625.

[2] N. Z. A. Mohd Hassan *et al.*, "MODELLING COST-EFFECTIVENESS OF REPLACEMENT STRATEGIES FOR AMBULANCE SERVICES IN THE MINISTRY OF HEALTH MALAYSIA," *BMC Health Serv. Res.*, vol. 24, no. 1, p. 168, Feb. 2024, doi: https://doi.org/10.1186/s12913-024-10557-4.

[3] CodeBlue, "AUDIT: MOH FALLS SHORT OF 50% TARGET FOR PRIORITY 1 AMBULANCE RESPONSE TIME." [Online]. Available: https://codeblue.galencentre.org/2023/03/audit-moh-falls-short-of-50-target-for-priority-1-ambulance-response-time/

[4] S. J. Zahiid, "HEALTH MINISTER ADMITS SCALE OF PROBLEM FACING EMERGENCY DEPARTMENTS AT PUBLIC HOSPITALS," Kuala Lumpur, Jun. 02, 2023. [Online]. Available: https://www.malaymail.com/news/malaysia/2023/02/06/health-minister-admits-scale-of-problem-facing-emergency-departments-at-public-hospitals/53624

[5] "TWO-DAY WAIT FOR A BED IN MALAYSIAN GOVERNMENT HOSPITALS," Nov. 22, 2024. [Online]. Available: https://www.straitstimes.com/asia/se-asia/a-two-day-wait-for-a-bed-in-malaysian-government-hospitals

[6] A. Hatami-Marbini, N. Varzgani, S. M. Sajadi, and A. Kamali, "AN EMERGENCY MEDICAL SERVICES SYSTEM DESIGN USING MATHEMATICAL MODELING AND SIMULATION-BASED OPTIMIZATION APPROACHES," *Decis. Anal. J.*, vol. 3, p. 100059, Jun. 2022, doi: https://doi.org/10.1016/j.dajour.2022.100059

[7] M. Sutherland and R. K. Chakrabortty, "AN OPTIMAL AMBULANCE ROUTING MODEL USING SIMULATION BASED ON PATIENT MEDICAL SEVERITY," *Healthc. Anal.*, vol. 4, p. 100256, Dec. 2023, doi: https://doi.org/10.1016/j.health.2023.100256.

[8] M. A. K. Al-Azzani, S. Davari, and T. J. England, "AN EMPIRICAL INVESTIGATION OF FORECASTING METHODS FOR AMBULANCE CALLS - A CASE STUDY," *Health Syst.*, vol. 10, no. 4, pp. 268–285, Oct. 2021, doi: https://doi.org/10.1080/20476965.2020.1783190.

[9] T. Monks, A. Harper, M. Allen, L. Collins, and A. Mayne, "FORECASTING THE DAILY DEMAND FOR EMERGENCY MEDICAL AMBULANCES IN ENGLAND AND WALES: A BENCHMARK MODEL AND EXTERNAL VALIDATION," *BMC Med. Inform. Decis. Mak.*, vol. 23, no. 1, p. 117, Jul. 2023, doi: https://doi.org/10.1186/s12911-023-02218-z.

[10] E. V. Gijo and N. Balakrishna, "SARIMA MODELS FOR FORECASTING CALL VOLUME IN EMERGENCY SERVICES," *Int. J. Bus. Excell.*, vol. 10, no. 4, p. 545, 2016, doi: https://doi.org/10.1504/IJBEX.2016.079252.

[11] T. W. Mapuwei, O. Bodhlyera, and H. Mwambi, "UNIVARIATE TIME SERIES ANALYSIS OF SHORT-TERM FORECASTING HORIZONS USING ARTIFICIAL NEURAL NETWORKS: THE CASE OF PUBLIC AMBULANCE

EMERGENCY PREPAREDNESS,” *J. Appl. Math.*, vol. 2020, pp. 1–11, May 2020, doi: https://doi.org/10.1155/2020/2408698

[12] A. Haugsbo Hermansen and O. J. Mengshoel, “FORECASTING AMBULANCE DEMAND USING MACHINE LEARNING: A CASE STUDY FROM OSLO, NORWAY,” in *2021 IEEE Symposium Series on Computational Intelligence (SSCI)*, Orlando, FL, USA: IEEE, Dec. 2021, pp. 01–10. doi: https://doi.org/10.1109/SSCI50451.2021.9659837.

[13] E.-E. Etu *et al.*, “313 LEVERAGING DECISION TREES TO FORECAST AMBULANCE TRAFFIC IN EMERGENCY DEPARTMENTS,” *Ann. Emerg. Med.*, vol. 82, no. 4, pp. S136–S137, Oct. 2023, doi: https://doi.org/10.1016/j.annemergmed.2023.08.338.

[14] A. Y. Chen, T.-Y. Lu, M. H.-M. Ma, and W.-Z. Sun, “DEMAND FORECAST USING DATA ANALYTICS FOR THE PREALLOCATION OF AMBULANCES,” *IEEE J. Biomed. Health Inform.*, vol. 20, no. 4, pp. 1178–1187, Jul. 2016, doi: https://doi.org/10.1109/JBHI.2015.2443799.

[15] B. Rostami-Tabar and R. J. Hyndman, “HIERARCHICAL TIME SERIES FORECASTING IN EMERGENCY MEDICAL SERVICES,” *J. Serv. Res.*, vol. 28, no. 2, pp. 278–295, May 2025, doi: https://doi.org/10.1177/10946705241232169

[16] M. Rezaei and A. Ingolfsson, “FORECASTING TO SUPPORT EMS TACTICAL PLANNING: WHAT IS IMPORTANT AND WHAT IS NOT,” *Springer*, vol. 27, pp. 604–630.doi: https://doi.org/10.1007/s10729-024-09690-7

[17] B. M. Porto and F. S. Fogliatto, “ENHANCED FORECASTING OF EMERGENCY DEPARTMENT PATIENT ARRIVALS USING FEATURE ENGINEERING APPROACH AND MACHINE LEARNING,” *BMC Med. Inform. Decis. Mak.*, vol. 24, no. 1, p. 377, Dec. 2024, doi: https://doi.org/10.1186/s12911-024-02788-6.

[18] H. Farhat *et al.*, “PREDICTIVE MODELLING OF TRANSPORT DECISIONS AND RESOURCES OPTIMISATION IN PRE-HOSPITAL SETTING USING MACHINE LEARNING TECHNIQUES,” *PLOS ONE*, vol. 19, no. 5, p. e0301472, May 2024, doi: https://doi.org/10.1371/journal.pone.0301472.

[19] B. Rostami-Tabar, J. Browell, and I. Svetunkov, “PROBABILISTIC FORECASTING OF HOURLY EMERGENCY DEPARTMENT ARRIVALS,” *Health Syst.*, vol. 13, no. 2, pp. 133–149, Apr. 2024, doi: https://doi.org/10.1080/20476965.2023.2200526.

[20] J. Tuominen, T. Koivistoinen, J. Kanniainen, N. Oksala, A. Palomäki, and A. Roine, “EARLY WARNING SOFTWARE FOR EMERGENCY DEPARTMENT CROWDING,” *J. Med. Syst.*, vol. 47, no. 1, p. 66, May 2023, doi: https://doi.org/10.1007/s10916-023-01958-9

[21] C. Kasemset, N. Sae-Haew, and A. Sopadang, “MULTIPLE REGRESSION MODEL FOR FORECASTING QUANTITY OF SUPPLY OF OFF-SEASON LONGAN,” *Chiang Mai Univ. J. Nat. Sci.*, vol. 13, no. 3, 2014, doi: https://doi.org/10.12982/CMUJNS.2014.0044.

[22] C. D. Lewis, *InDUSTRIAL AND BUSINESS FORECASTING METHODS: A PRACTICAL GUIDE TO EXPONENTIAL SMOOTHING AND CURVE FITTING*. London: Butterworth Scientific, 1982.

[23] J. Montaño Moreno, A. Palmer Pol, A. Sesé Abad, and B. Cajal Blasco, “USING THE R-MAPE INDEX AS A RESISTANT MEASURE OF FORECAST ACCURACY,” *Psicothema*, vol. 4, no. 25, pp. 500–506, Nov. 2013, doi: https://doi.org/10.7334/psicothema2013.23.

[24] M. E. Helander, M. K. Formica, and D. K. Bergen-Cico, “THE DAILY PATTERNS OF EMERGENCY MEDICAL EVENTS,” *J. Biol. Rhythms*, vol. 39, no. 1, pp. 79–99, Feb. 2024, doi: https://doi.org/10.1177/07487304231193876

[25] R. J. Martin, R. Mousavi, and C. Saydam, “PREDICTING EMERGENCY MEDICAL SERVICE CALL DEMAND: A MODERN SPATIOTEMPORAL MACHINE LEARNING APPROACH,” *Oper. Res. Health Care*, vol. 28, p. 100285, Mar. 2021, doi: https://doi.org/10.1016/j.orhc.2021.100285.

[26] H. Shibayama, A. Ishigaki, T. Kobe, T. Ueda, D. Arimizu, and T. Nakamura, “DESIGN OF A FRAMEWORK FOR DEMAND FORECASTING USING TIME SERIES DECOMPOSITION-BASED APPROACH,” *PHM Soc. Asia-Pac. Conf.*, vol. 4, no. 1, Sep. 2023, doi: https://doi.org/10.36001/phmap.2023.v4i1.3696.

[27] S. M. Algfari *et al.*, “DATA-DRIVEN APPROACHES TO IMPROVING EMERGENCY RESPONSE TIMES AND PATIENT OUTCOMES,” *Int. J. Health Sci.*, vol. 6, no. S10, pp. 1833–1849, Jan. 2022, doi: https://doi.org/10.53730/ijhs.v6nS10.15151.