Predicting Demand For Emergency Ambulance Services: A Comparative Approach

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Accurate forecasting of demand for emergency medical services (EMS) is crucial for effective healthcare management, contributing to improved response times and cost control during emergencies. Additionally, it facilitates resource allocation and the implementation of knowledge-based policies, ultimately enhancing patient care and services. This study focuses on forecasting EMS demand related to patient transportation from 25 sub-hospitals in Khon Kaen, Thailand, to the central medical center hospital for the purpose of receiving necessary medical treatment. To improve the precision of demand forecasting, we evaluated various forecasting approaches. The results indicate that ANN outperforms other models. This can be attributed to the ANN's ability to identify complex relationships and efficiently learn from observed data through nonlinear mapping. These findings underscore the potential applications of the ANN model for addressing this problem.

Keywords: Machine learning, artificial neural networks, autoregressive integrated moving averages, simple moving averages, nonlinear autoregressive, wavelet nonlinear autoregressive

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1. Introduction

Forecasting vehicle availability and optimizing response times is vital for emergency medical services (EMS). With emergency illnesses being a global health concern leading to numerous deaths and disabilities, hospitals emphasize the importance of efficient and timely medical care, where ambulances play a crucial role [1]. However, EMS services face various challenges, including call volume, ambulance availability, traffic, weather, and distance to medical facilities [2]. Adequate EMS infrastructure and resources are essential. To meet these challenges, forecasting future ambulance service demand is crucial, and accurate forecasting is essential for enhancing public health and safety and timely patient care, especially as healthcare systems evolve and demands rise [3]. To employ historical data for the purpose of making precise predictions regarding deployment plans, response times, and resource allocation is of paramount importance. Such effective forecasting endeavors are instrumental in guaranteeing that EMS are adept at fulfilling the evolving demands of the community. Moreover, they play a pivotal role in elevating the quality of patient care [4]. EMS demand forecasting enables optimal resource allocation, leading to reduced response times and operational cost savings [5]. Accurate forecasting also improves community resilience during natural disasters and other emergency scenarios.

To enhance the precision of demand forecasting, researchers have utilized a range of models based on statistical methods and machine learning techniques, which have found extensive application across numerous fields. For example, [6] employed several methods, including autoregressive integrated moving average (ARIMA), double seasonal Holt-Winters, nonlinear autoregressive neural network (NAR), and nonlinear autoregressive exogenous (NARX), to forecast electricity consumption in a smart grid environment. [7] applied artificial neural network (ANN), wavelet neural network (Wavelet-NAR), ARIMA, and Holt-Winter to predict rainfall for water management. Additionally, [8] predicted rainfall using wavelet transform (WT) and moving average (MA). [9] compared the use of ANN, ARIMA, and simple moving average (SMA) to forecast the donkey population. Previous studies have demonstrated that these forecasting models provide a high level of accuracy and offer practical results. ANN is able to capture non-linear patterns and is efficient at handling multiple variables for forecasting, such as weather, traffic, and historical call volumes [10]. NAR is designed to forecast a time series from past values as input to a neural network, offering simplicity and broad applicability [6]. Wavelet-NAR improves forecasting by combining wavelet analysis with neural networks, enabling the understanding of the feature of both temporal and spectral data [7]. Statistical methods like ARIMA and simple moving average (SMA) are valuable for discerning long-term trends in demand, especially when historical patterns are evident. Therefore, this study aims to evaluate the applications of ANN, ARIMA, SMA, NAR, and wavelet-NAR techniques to compare the accuracy of EMS demand forecasting. This comparative analysis is crucial for obtaining better results, as these five techniques are known for providing more accurate predictions and facilitating simplified implementation.

2. Materials and methods

This study aims to compare forecasting models for accurate EMS demand prediction for ambulance services using the ANN, ARIMA, SMA, NAR, and Wavelet-NAR models. The approach presented in this study focuses on the challenges associated with obtaining accurate forecasting models and determining the most efficient time series models. These models can demonstrate both non-linear and stationary behavior by specifying parameters. The entire workflow is illustrated in Fig. 1.

2.1. Data collection and preparation

The study used data on the EMS service demand from hospitals in each of the 25 districts within the province of Khon Kaen, Thailand. This data, collected from January 2012 to October 2020, was obtained from emergency medical statistics reports provided by the National Institute of Emergency Medicine. Each of the 25 datasets was divided into two sets: training and testing. Seventy percent of the samples were allocated to the training set for model fitting, while the remaining 30% were reserved for testing and validation purposes.

2.2. Methods

The five algorithms used in this study are as follows. Artificial neural network (ANN) is brain-inspired machine learning models used in image recognition, natural language processing, and recommendation [11]. Autoregressive integrated moving averages (ARIMA) is a popular time series forecast model, combining autoregressive and moving average components with differencing to make time series data stationary [12]. Simple moving average (SMA) is a basic time series tool for data smoothing and trend spotting. It can lag behind data changes and is sensitive to window choice. Nonlinear autoregressive neural network (NAR) is an extension of autoregressive models, introducing nonlinear relationships between current and past time series values [13]. Wavelet neural network (Wavelet-NAR) combines wavelet analysis with NAR to capture complex patterns in time series data [14]. This study employs Mean Absolute Percentage Error (MAPE), often used in time series and demand forecasting, to measure forecast accuracy by calculating the average percentage difference between predicted and actual values [15].

3. Application

3.1. Case study

At present, EMS services transport patients from 25 sub-hospitals, each situated in the 25 districts of Khon Kaen, to receive treatment at the main hospitals located in Mueang Khon Kaen District, serving as the central medical center in Khon Kaen (Fig. 2). The demand for EMS service depends on the requirements of the patient, which may not always align with the available EMS resources. Efficiently managing EMS provision is therefore crucial for optimal patient care. A key aspect of this management involves having an accurate forecast of the expected EMS demand, enabling the allocation of appropriate resources at the operational level.

This study evaluates and compares different forecasting models to determine the most accurate time series forecasting model for EMS service demand. The analysis includes five distinct forecasting models. The methodology presented in this study considers the challenges associated with achieving accurate forecasting models and identifies the inherent characteristics of time series demand, such as non-linearity and stationarity.

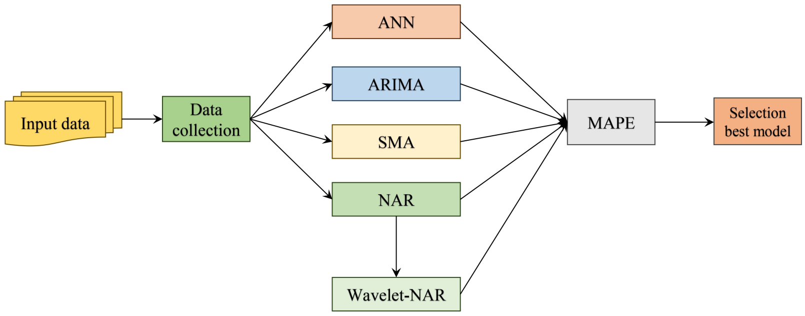

Fig. 1. EMS forecasting utilizing time series forecasting techniques.

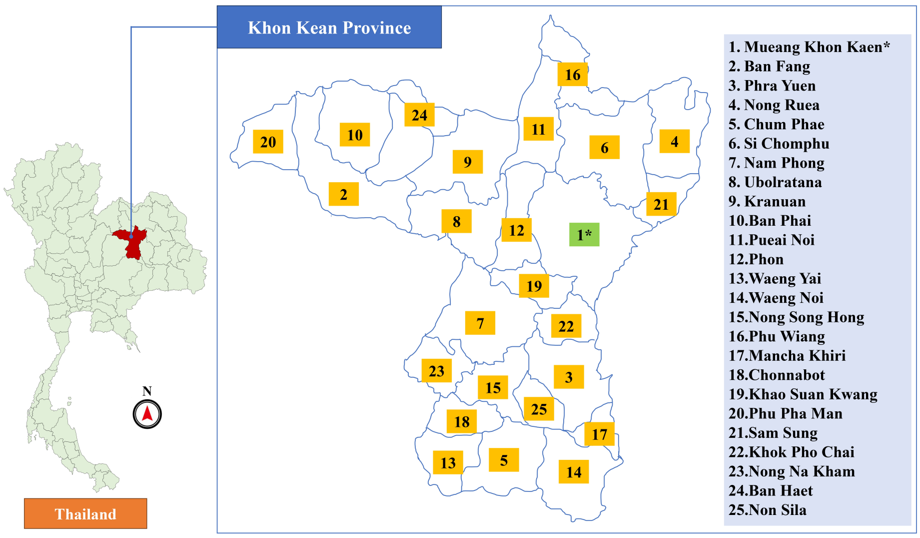

Fig. 2. Study area – Khon Kaen Province, Thailand.

3.2. Result

This section presents the results of forecasting using five different models: ANN, ARIMA, SMA, NAR, and Wavelet-NAR. These models were fine-tuned using the scikit-learn package in Python [16], utilizing both historical and current data to predict future EMS service demand. The evaluation of these models was based on their accuracy and efficiency, quantified using the MAPE, covering all 25 districts in Khon Kaen Province, Thailand. Table 1 provides a performance ranking based on the average MAPE values obtained during testing. ANN demonstrates the highest efficiency with the lowest average MAPE, followed by Wavelet-NAR, NAR, ARIMA, and SMA in descending order.

Fig. 3 complements these findings by illustrating the accuracy of EMS service demand forecasting across the 25 districts in Khon Kaen Province, with MAPE as a critical metric for accuracy assessment. ANN consistently outperforms other models in terms of MAPE, indicating their superior accuracy in predicting EMS service demand. A lower MAPE value indicates that a model's predictions closely align with the actual values, making ANN a robust choice for precise forecasting. However, additional data could significantly enhance the development of a prediction model, ensuring both greater precision and reliability, thereby enabling practitioners to improve their decision-making and management practices.

Table 1. Comparison of average MAPE values across all districts in Khon Kaen Province, Thailand, for five models: ANN, ARIMA, SMA, NAR, and Wavelet-NAR.

No.	District	MAPE				
		ANN	ARIMA	SMA	NAR	Wavelet-NAR
1	Mueang Khon Kaen	0.297	6.394	6.950	4.9613	0.796
2	Chum Phae	0.500	7.635	10.040	7.0870	2.031
3	Ban Phai	0.209	6.903	8.720	6.3968	1.428
4	Kranuan	0.634	6.995	8.750	8.9751	2.581
5	Phon	0.377	8.786	20.530	10.4896	1.799
6	Nam Phong	0.447	13.661	15.950	6.5135	1.576
7	Mancha Khiri	0.635	11.504	12.200	8.9800	2.044
8	Nong Ruea	0.996	9.610	10.540	5.9326	1.357
9	Phu Wiang	1.502	11.760	18.520	11.8391	5.227
10	Si Chomphu	0.630	10.497	12.810	7.6442	1.693
11	Ubolratana	0.167	10.528	11.180	9.0499	2.378
12	Ban Fang	0.672	8.712	10.670	9.9382	2.379
13	Waeng Noi	0.372	11.493	16.000	10.1130	2.217
14	Nong Song Hong	1.854	24.684	33.190	13.4601	1.884
15	Chonnabot	0.769	15.132	18.130	9.2343	2.081
16	Khao Suan Kwang	0.506	19.229	21.850	9.5077	2.302
17	Pueai Noi	2.017	18.684	21.090	12.9017	3.171
18	Waeng Yai	0.864	10.921	14.510	13.2945	2.658
19	Phra Yuen	1.003	15.413	16.210	14.6132	3.090
20	Phu Pha Man	0.197	14.296	15.280	11.9957	3.060
21	Sam Sung	0.973	14.071	18.730	12.6721	2.213
22	Ban Haet	0.314	12.647	12.320	10.9070	3.017
23	Khok Pho Chai	0.687	23.236	34.450	20.7727	5.310
24	Nong Na Kham	2.442	19.219	20.160	20.7727	2.985
25	Non Sila	3.343	31.385	77.890	38.2856	17.237

3.3. Discussion

The results show that SMA model exhibits lower accuracy, attributed to its data smoothing nature, which can lead to lagged or delayed data points and higher forecasting errors, especially in complex or rapidly changing data. ARIMA, NAR, and Wavelet-NAR models have their advantages but also limitations. ARIMA models can be complex to parameterize and require specific data sets, making them unsuitable for very complex data or long-term predictions. NAR models can be computationally intensive and challenging to interpret, demanding larger datasets. Wavelet-NAR models, while useful for non-linear data, add complexity and computational demands.

As depicted in Fig. 4, the ANN provides accurate forecasts for the EMS demand volume, showing its highly effective and superior forecasting efficiency. This highlights the potential of ANN in predicting EMS service demand, not limited to healthcare but applicable in various fields. These findings align with previous studies highlighting the capacity of ANN to effectively learn from observed data through nonlinear mapping [6-9]. In summary, ANN emerges as a powerful tool for accurate EMS service demand prediction, capable of addressing forecasting challenges across a broad spectrum of applications.

4. Conclusions

Accurate forecasting of EMS demand is essential for informed decision-making, enabling precise resource allocation, and improving overall operational efficiency. It provides crucial insights into staffing, equipment needs, and resource utilization patterns, enhancing proactive planning and collaboration with other emergency response and healthcare agencies. This study emphasizes the reliability of ANN in predicting EMS demand, demonstrating their superior accuracy compared to conventional models like ARIMA, SMA, NAR, and Wavelet-NAR in various fields. ANN offers a dependable means of forecasting ambulance service requirements, benefiting healthcare administrators, physicians, and nurses. The study encourages exploring innovative models and methods for EMS demand prediction, supporting improved patient care and outcomes through enhanced responsiveness and resource allocation.

Acknowledgements

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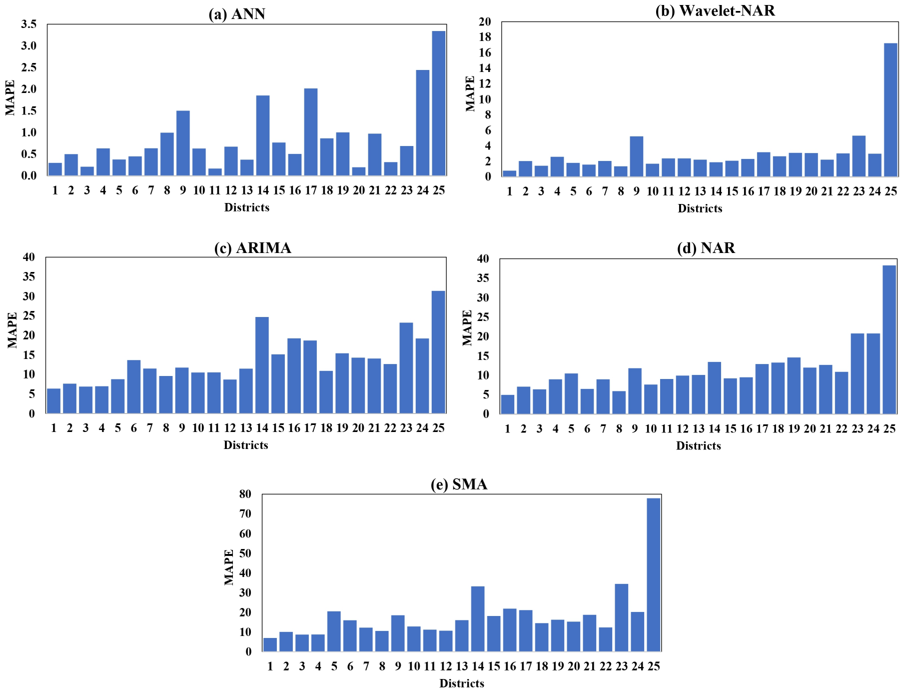

Fig. 3. MAPE values for the 25 districts of Khon Kaen Province, Thailand.

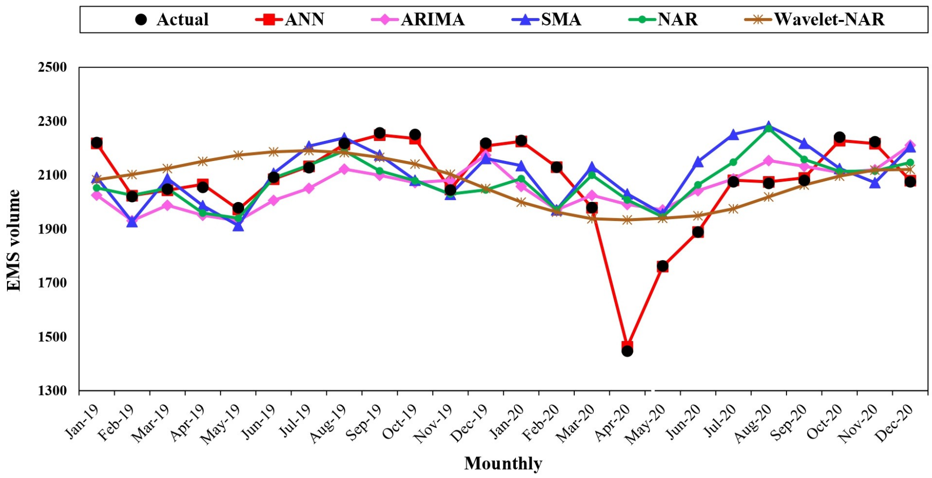

Fig. 4. Comparison of EMS demand volume curves for the five forecasting models with actual volume in the test data for the Mueang Khon Kaen dataset.

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