7 (2): 196-203 (2023)

Journal of Aviation

https://dergipark.org.tr/en/pub/jav

e-ISSN 2587-1676

Air-traffic Flow Prediction with Deep Learning: A Case Study for Diyarbakır Airport

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Article Info

Received: 31 May 2023
Revised: 22 June 2023
Accepted: 23 June 2023
Published Online: 30 June 2023

Keywords:
Aviation
Deep learning
Aircraft prediction
Long-short term memory

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RESEARCH ARTICLE

https://doi.org/10.30518/jav.1307741

Abstract

Aviation industry develops rapidly. So the continuous growth of the aviation, accurate predictions play a crucial role in managing air traffic and optimizing airport operations. The prediction process involves various factors such as weather conditions, airport traffic, flight schedules, and historical data. Advanced techniques like machine learning contribute to enhancing the accuracy of predictions. In this context, air traffic data belonging to Diyarbakır province were utilized to predict the number of arrival aircraft to the airport using both traditional Autoregressive (AR) model and deep learning architecture, specifically the stacked Long Short-Term Memory (LSTM) model. The results indicate that the stacked LSTM model outperformed the AR model in terms of air traffic estimation. The AR model had a quite poorly MSE value of 48043.35 and an RMSE value of 219.18, while the stacked LSTM model achieved a significantly higher MSE value of 0.03 and an RMSE value of 0.17. The lower MSE values obtained by the stacked LSTM model indicate its ability to make more accurate predictions compared to the AR model. The stacked LSTM model's predictions were closer to the actual values, resulting in a more realistic estimation of air traffic. Accurate predictions enable efficient resource management, passenger planning, and airport security measures. Continuous efforts in predicting aircraft landings are necessary for the effective functioning of the aviation industry. In this study highlights the importance of predicting the number of aircraft landings at airports.

1. Introduction

The aviation industry holds an increasingly significant role worldwide in today's era (Bakreen, Markovskaya, Merzlikin, & Mottaeva, 2022). Air transportation plays a vital role in swiftly, safely, and efficiently moving people and goods from one point to another. However, this rapid growth and development have led to an increase in airport traffic, posing a significant challenge for the aviation sector. In this context, predicting the number of aircraft landing at an airport has become crucial for the efficient and safe operation of the aviation industry (Jo & Chang, 2023).

Airports serve as crucial hubs for passenger and cargo transportation worldwide (Li & Zhao, 2023). Thousands of aircraft land and take off at different airports every day. Airport traffic has evolved into a complex and dense network. This situation requires meticulous coordination and regulation of flights and landings at airports. Therefore, predicting the number of aircraft landings has become a critical tool for effectively managing airport operations (Bombelli, Santos, & Tavasszy, 2020; Tanrıverdi, Ecer, & Durak, 2022).

Predicting aircraft landings is of great importance for air traffic management and airport capacity planning. Accurately forecasting the number of landings at an airport ensures the smooth flow of air traffic, enables planning of landing sequences, optimizes runway utilization, and provides the necessary gaps between flights. Additionally, airport operators, air traffic control units, and airline companies rely on these predictions for efficient resource management and personnel planning (Dalmau, 2022).

Predicting aircraft landings involves a complex process that encompasses various factors. Weather conditions, airport traffic, flight schedules, historical data, and intuitive factors are the fundamental elements of prediction models. Weather conditions significantly impact the number of landings at an airport. For example, dense fog, strong winds, or storms can reduce or even cancel landings. Moreover, airport traffic can influence the simultaneous occurrence of flights and landings at a specific airport. Particularly at major international airports, the demands of multiple airlines to land at the same time can affect the accuracy of predictions (Mondoloni & Rozen, 2020).

Accurate predictions of aircraft landings are not only essential for effectively managing airport operations but also for airline companies, travel agencies, passengers, and airport security. Precise landing predictions facilitate efficient allocation of resources utilized in flight planning and prevent the exceeding of airport facility capacities. They also assist passengers in adjusting their travel plans and provide advance notice of potential delays or cancellations. In terms of airport security, predictions enable the implementation of necessary security measures and proper allocation of resources.

Prediction models employ various methods and techniques to forecast aircraft landings. These models perform statistical analyses based on historical data and evaluate current weather conditions to generate predictions. Machine learning and artificial intelligence techniques have contributed to the development of more advanced prediction models. These technological advancements hold great potential for increasing the accuracy of predictions and enhancing the efficiency of airport operations.

In this study, the number of arriving aircraft at Diyarbakir Airport was estimated for air traffic flow. The total number of arrival flights at Diyarbakir Airport between 2008 and 2023 was taken into account. Since the data were collected on a monthly basis, they exhibit a time-dependent pattern. Consequently, time series estimation was performed using both traditional autoregressive (AR) models and a deep learning architecture called Stacked Long Short Term Memory (LSTM). Both of models were compared in terms of prediciton accuracy.

This study examined the process of predicting aircraft landings and emphasized the importance of such predictions. Detailed information was provided about the methods and techniques used in prediction models, along with their impact on airport operations and potential future developments. Recognizing the significance of accurate predictions in managing aircraft traffic and ensuring the efficiency of airport operations, continuous efforts in the field of aircraft landing prediction are crucial.

The study is organized as follows. The second part provides a comprehensive literature review. The third section covers the data utilized in the study, the data normalization process, and the models employed. In the fourth, the estimation results obtained from the AR and Stacked LSTM models are compared and analyzed. The final section presents the overall conclusion of the study.

2. Literature Review

Jiang and Luo (2022) conducted a comprehensive examination of the utilization of graph neural networks in various traffic forecasting problems, including road traffic flow, speed forecasting, passenger flow forecasting in urban rail transportation systems, and demand forecasting in passenger transportation platforms. They also provided an extensive list of available open data and source codes for each problem and identified future research directions (Jiang & Luo, 2022).

Mendez et al. (2023) presented a hybrid model that combines a Convolutional Neural Network (CNN) and a Bidirectional Long-Short-Term Memory (BiLSTM) network. The model was applied for long-term traffic flow prediction on urban routes. The hybrid model leverages the CNN's capability to extract hidden-value features from the input model and the BiLSTM's ability to understand the temporal context. To assess the effectiveness of the model, four streets in the city of Madrid with distinct characteristics were selected, and the performance of the proposed model was compared to eight commonly used baseline models (Méndez, Merayo, & Núñez, 2023).

Gravio et al. (2015) aimed to improve the safety assessment of Air Traffic Management (ATM) and create proactive safety indicators. They utilized the Aviation Performance Factor and the Analytical Hierarchy Process to develop a statistical model for safety events and used Monte Carlo simulation, along with analytical models based on historical data, to estimate safety performance (Di Gravio, Mancini, Patriarca, & Costantino, 2015).

Kotegawa et al. (2010) developed and compared three algorithms based on the node characteristics of airports to improve existing air traffic forecasting methods used by the United States Federal Aviation Administration and to add new routes to air traffic. They utilized artificial neural networks and logistic regression algorithms for estimation. Each algorithm was fed with historical data and validated by comparing the accuracy and precision of the predicted new city pairs using the knowledge of actual new city pairs that emerged (Kotegawa, DeLaurentis, & Sengstacken, 2010).

Tascon and Olariaga (2021) conducted a medium-term traffic forecast for Bogotá-El Dorado International Airport in Colombia and assessed the impact of future demand on the airport's runway capacity. Due to the complexity of aviation forecasting, they employed System Dynamics (SD) as the analysis approach. The results indicated the necessity of expanding the airport's runway system after mid-2019, as the current capacity utilization rate reaches approximately 100%, requiring two to three runways for normal operations. Starting from October 2022, it was determined that three runways will be needed, and this trend is projected to continue until the final simulation period in 2023 (Tascón & Díaz Olariaga, 2021).

Solvoll et al. (2020) examined and compared traffic forecasting methods for a Norwegian airport using various quantitative approaches. They specifically focused on two estimation methods: changes in infrastructure and traffic forecasting (Solvoll, Mathisen, & Welde, 2020).

Standfuss et al. (2021) investigated the impact of the disparity between predicted and actual traffic on established performance indicators in European Air Traffic Management. They conducted regression models using cross-sectional and panel data to analyze the correlation between prediction quality and ANSP performance. The study revealed that the actual traffic counts often fell outside the STATFOR confidence intervals. Consequently, many ANSPs faced unreliable forecasts. Additionally, the research demonstrated a statistically significant relationship between forecast quality and air traffic punctuality as well as service provider productivity (Standfuss, Fricke, & Whittome, 2022).

3. Materials and Methods

The study utilized air traffic data that represents the total number of domestic and international flights related to Diyarbakır province. The next step involved applying the normalization process to the obtained passenger data. The air traffic prediction was conducted by modeling the normalized data using the Autoregressive (AR) and stacked LSTM methods. Fig. 1 presents the flowchart of the study.

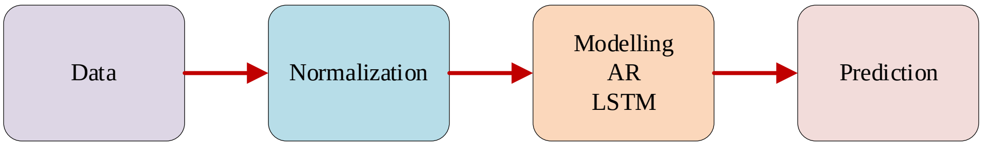

Figure 1. Flowchart of the study

3.1. Data

The data on the number of planes in the air traffic at Diyarbakır Airport from January 2008 to the end of May 2023 was obtained from the General Directorate of State Airports Authority. The passenger data was collected on a monthly basis throughout the years. The total number of aircraft was calculated by summing the number of domestic and international arrival aircraft at Diyarbakır Airport on a monthly basis (DHMİ, n.d.). For the training of the AR and stacked LSTM models, 80% of the total 185 data points were utilized, while the remaining 20% was reserved for testing (Guo, Lao, Hou, Li, & Zhang, 2021; Song et al., 2020).

The Fig. 2 shows the domestic, international, and total air traffic for Diyarbakır Airport. Upon examining the figure, it can be observed that the domestic air traffic varies between 0 and 1600, while the international air traffic is limited to a range of 0-100 aircraft. Additionally, when the period between 2019 and 2021, which coincides with the pandemic, is examined, a significant decrease in domestic air traffic is evident, along with a slight decrease in international air traffic. However, after the pandemic period, specifically after 2021, it can be noticed that there is a surge in both domestic and international air traffic.

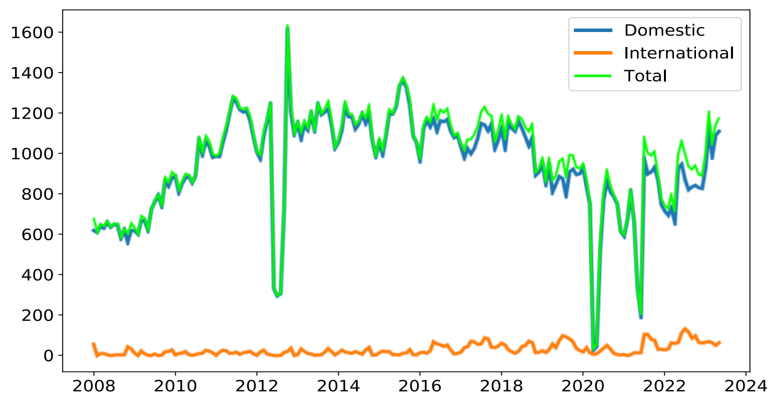

Figure 2. Air traffic of Diyarbakır Airport by year

3.2. Normalization

Normalization enables the handling and comparison of data with different data distributions on a unified scale. In this study, the min-max normalization method was utilized. The original dataset undergoes a linear transformation using the min-max normalization method, resulting in the dataset being scaled to the range of [0-1]. The mathematical expression for the min-max normalization method is shown in Equation 1.

$$x' = \frac{x_t - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

Here, x' represents the normalized data, x_t represents the input value at time t, x_{max} is the largest number in the dataset, and x_{min} is the smallest number in the dataset (Song et al., 2020). By subtracting the minimum value and dividing it by the range (maximum minus minimum), the data is transformed to a normalized scale between 0 and 1.

3.3. Auto regressive model

Auto regressive model (AR) is one of the statistical methods used for time series prediction. The AR model investigates a linear relationship with the past values of the variable. It tries to predict future values based on the relationships it has developed. The AR model is represented by Equation 2.

$$x_t = c + \varphi_1 x_{(t-1)} + \varphi_2 x_{(t-2)} + \cdots + \varphi_p x_{(t-p)} + \varepsilon_t \qquad (2)$$

Here:

- x_t represents the value of the time series at time t.
- c is the constant term.
- ϕ_1, ϕ_2, ..., ϕ_p are the auto-regression coefficients representing the relationships with past values.
- $x_{(t-1)}$, $x_{(t-2)}$, ..., $x_{(t-p)}$ are the values at p time steps before $x_{(t)}$.
- ε_t is the error term of the time series, indicating the deviation from the expected value.

This is the mathematical representation of the AR model. It tries to predict the current value using weighted combinations of past values. The predictive abilities of auto regressive models vary depending on how the past values are utilized. Generally, a higher auto regression order (p) relies on a longer history. Higher order models can capture more complex relationships, but they require more data and increase the complexity of the model (Shakeel, Tanaka, & Kitajo, 2020).

3.4. Long short term memory

Long Short-Term Memory (LSTM) is a type of artificial neural network that is particularly useful in dealing with sequential data, such as time series data and natural language processing. It is an extension of traditional Recurrent Neural Networks (RNNs) designed to address the issue of capturing long-term dependencies (Dursun & Toraman, 2021).

LSTM introduces a memory cell as its basic building block, which allows it to remember and access information over long periods of time. The memory cell consists of three main components: an input gate, a forget gate, and an output gate. These gates regulate the flow of information into and out of the memory cell.

The input gate determines how much of the incoming information should be stored in the memory cell. It takes into account the current input x_t and the previous hidden state h_t of the LSTM to decide which information is relevant and should be stored. The input gate is computed using the sigmoid (σ) activation function. Input gate formulation is shown in Equation 3.

$$i_t = \sigma(W[h_{t-1}, c_{t-1}, x_t] + b_i) \quad (3)$$

The forget gate controls the extent to which the previous memory content should be retained or forgotten. It considers the current input x_t and the previous hidden state h_{t-1} to determine which information is no longer useful and should be discarded from the memory cell. The forget gate is also computed using the sigmoid (σ) activation function. Equation 4 represents the forget gate.

$$f_t = \sigma(W[x_t, c_{t-1}, h_{t-1}] + b_f) \quad (4)$$

The output gate determines how much of the memory cell's content should be exposed to the next hidden state and used for making predictions. It considers the current input x_t and the updated memory cell content c_t to decide which information is relevant for the current time step. The output gate is computed using the sigmoid (σ) activation function. The output gate is given in Equation 5.

$$o_t = \sigma(W[h_{t-1}, c_t, x_t] + b_o) \quad (5)$$

The memory cell is updated based on the input gate, forget gate, and the current input x_t and previous hidden state h_{t-1}. The cell state update equation is stated in Equation 6.

$$c_t = i_t \times \tanh(W[h_{t-1}, c_{t-1}, x_t] + b_c) + f_t \times c_{t-1} \quad (6)$$

Here, c_t represents the updated cell state at time step t, c_{t-1} is the previous cell state, and tanh is the hyperbolic tangent activation function.
Finally, the hidden state h_{t-1} is computed based on the output gate and the updated cell state. The hidden state represents the output of the LSTM at each time step and can be used for making predictions or passed on to subsequent layers. The equation for the hidden state is denoted as in Equation 7 (Aygun, Dursun, & Toraman, 2023). The structure of LSTM is shown in Fig. 3.

$$h_t = o_t * \tanh(c_t) \quad (7)$$

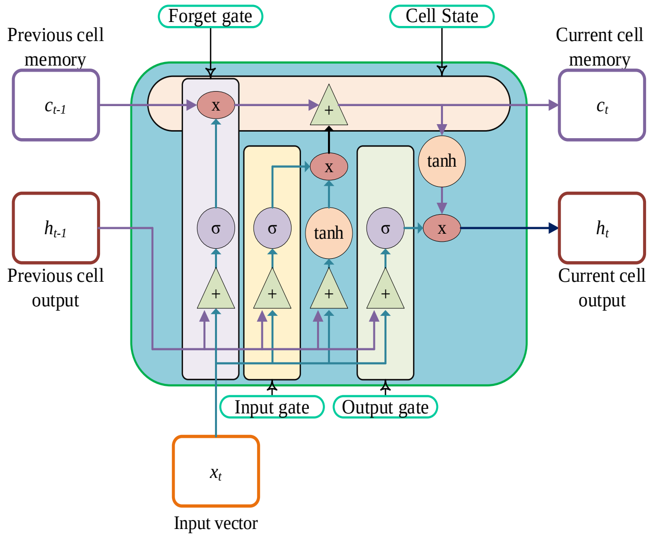

Figure 3. LSTM architecture

3.5. The evaluation criteria

In the recommended study, the performance measurement considered Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), and they were evaluated. The equations for MSE and RMSE, which are performance metrics, can be seen in Equations 8-9. MSE serves as a function that measures the error rate and performance of the model. It calculates how different the model's prediction is from the actual value. The lower the difference between the actual and predicted values, the better the prediction. If the MSE value approaches 0, it indicates a good prediction (Kızrak & Bolat, 2019; Shakeel et al., 2020).

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(x_t - \bar{x}_t)^2 \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(x_t - \bar{x}_t)^2} \quad (9)$$

Here, n is the number of samples, x_t is the number of aircraft in t time, $\bar{x}_t$ is the estimated number of aircraft number in t time.

4. Result and Discussion

In this section, the performance evaluation criteria for both the AR and LSTM models, the hyperparameter tuning of the stacked LSTM model, and the evaluation of prediction results have been discussed.
In this study, no parameter settings were applied for the AR model. However, in the newly proposed stacked LSTM model, the following parameter configurations were used:

- Optimization Algorithm: Adam
- Loss Function: Mean Squared Error (MSE)

The hyperparameters of the LSTM model were determined using the brute force method. The model architecture consists of a three-layer stacked LSTM structure.

The hyperparameter values were tested as follows:

- Number of Cycles: 100, 200, 400 (The best result was obtained at 100 cycles).
- Cluster Size: 2, 4, 8 (The best result was obtained with a cluster size of 4).
- Output Layer Number: 1 (The LSTM model has a single output layer).

For each layer of the model, the following values were tried as memory blocks:

- First LSTM Layer: 16
- Second LSTM Layer: 32
- Last LSTM Layer: 64

The best performance was achieved with these memory block values.

The learning rate (*lr*) was explored in the range of [10^{-1}, ..., 10^{-4}]. The best learning rate was found to be $lr = 10^{-3}$. When the learning rate was set to 10^{-4}, the model started to memorize instead of learning.

In the air traffic estimation using the AR model, the MSE value was found to be 48043.35 and the RMSE value was 219.18. On the other hand, the stacked LSTM model yielded an MSE value of 0.03 and an RMSE value of 0.17. When comparing the two models based on the MSE values, it is evident that the stacked LSTM model, with an MSE value close to zero, provided more accurate predictions than the AR model. This indicates that the stacked LSTM model achieved a more realistic estimation compared to the AR model. A comprehensive overview of the performance evaluations for both models can be seen in Table 1.

Table 1. Performance evaluation of the models

AR		Stacked LSTM	
MSE	RMSE	MSE	RMSE
48043.35	219.18	0.03	0.17

80% of the 185 air traffic data for Diyarbakır province from 2008 to 2023, a total of 148 data points, were used for training the AR and stacked LSTM models. The remaining 20% of the data, 37 data points, were reserved for testing.

After the training process, the models were evaluated using the test data. The estimated values and actual values are presented in Table 2. Considering the first row of Table 2, the actual air traffic data for Diyarbakır was recorded as 1173. The AR model predicted this value as 987.6, while the stacked LSTM model predicted it as 1029.1.

Table 2. Actual and forecast results

Actual	Predicted	
	AR	Stacked LSTM
1173	987.6	1029.1
1140	987.3	1004.7
1047	987	1099.4
1202	986.6	1071
992	986.2	973.2
889	985.6	981.9
896	984.9	962.8
940	984.1	1004.7
920	983.2	920.2
937	982.1	1034.9

Loss values are used to measure the error between the model's predicted output and the actual output. The validation loss (Val loss) specifically indicates the error during the training phase. It is desirable for both the loss and validation loss values to approach zero as the training progresses. A decreasing loss and validation loss signify that the model is learning and improving its predictions. However, it's important to strike a balance and avoid overfitting, where the model becomes too specialized to the training data and performs poorly on new, unseen data.

The line chart in Fig. 4 illustrates the variation of the loss function for the proposed stacked LSTM model based on the number of epoch. Upon analyzing the graph, it becomes evident that the loss value for both the training and test data decreases as the iterations progress.

In this study, MSE was utilized as the loss function. The small value of MSE indicates that the proposed model provides accurate estimations. Throughout the learning process, both the training and test data values gradually approached zero. The loss graph depicted in Fig. 4 demonstrates that the model did not suffer from overfitting or memorization.

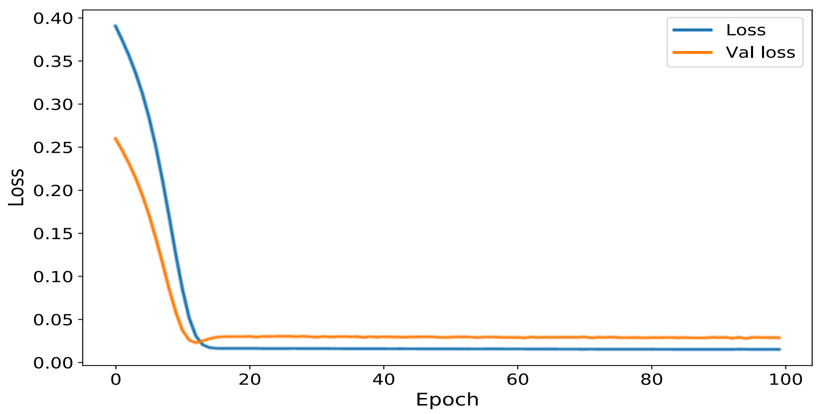

Figure 4. Stacked LSTM loss function

In addition, when comparing the estimations of the test data from both the AR and stacked LSTM models with the original data, it is observed that the estimation of the AR model deviates significantly from the original data, whereas the estimation of the stacked LSTM model closely aligns with the original data. This indicates that the stacked LSTM model provides better air traffic estimation for Diyarbakir province compared to the AR model.

Fig. 5a displays the estimation of the AR model, while Fig. 5b showcases the estimation of the stacked LSTM model. Both figures present the raw passenger data, which is divided into training and test datasets. The divergence between the AR model's estimation and the original data is apparent in Fig. 4a, whereas the estimation of the stacked LSTM model in Fig. 4b exhibits a closer match to the original data.

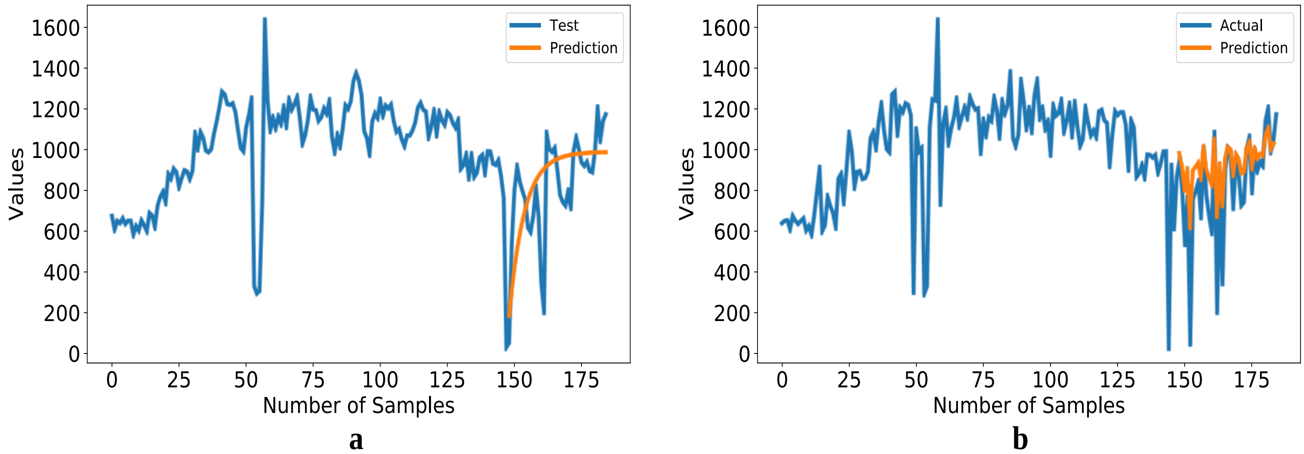

Figure 5. a) Prediction values of AR model **b)** Prediction values of Stacked LSTM model

First, we employed the AR method, which aimed to establish a linear model by considering associated with aircraft numbers. Through AR analysis, we sought to identify the relationships between these time series and accurately predict the number of aircraft. The results of AR model showed promising performance in capturing the overall trend and providing reasonable estimates of aircraft numbers. However, it is important to note that the AR approach assumes a linear relationship between the time series and the target variable, which may limit its ability to capture nonlinear dynamics and intricate patterns in the data.

To overcome the limitations of AR, we also explored the stacked LSTM method, which is specifically designed to handle sequential data and capture long-term dependencies. LSTM introduces memory cells and gating mechanisms that enable the model to retain and selectively utilize information over extended periods. By incorporating these mechanisms, LSTM can effectively capture temporal dynamics and complex patterns in aircraft traffic.

In our experiments, we trained an LSTM model using historical data on aircraft numbers and their corresponding time series. The stacked LSTM model exhibited superior performance compared to AR in capturing the intricate patterns and nonlinear relationships present in the data. By leveraging its ability to retain memory and propagate information over time, the stacked LSTM model was able to make more accurate predictions of aircraft numbers, even when faced with fluctuations and seasonality in the data.

Furthermore, the stacked LSTM model's capability to handle input sequences of varying lengths proved advantageous when dealing with different time intervals and temporal resolutions. This flexibility allows the model to adapt to different forecasting horizons and capture short-term as well as long-term trends in aircraft traffic.

However, it is important to note that the effectiveness of the stacked LSTM method is highly dependent on the availability and quality of training data. A sufficient amount of high-quality historical data is necessary to train the model effectively and capture the underlying patterns and dynamics in aircraft traffic.

In summary, our findings indicate that stacked LSTM outperformed AR in predicting aircraft numbers, showcasing its ability to capture complex temporal dependencies and nonlinear relationships. The stacked LSTM model's flexibility, memory retention, and adaptability to varying input sequences make it a powerful tool for forecasting aircraft traffic. Nonetheless, it is crucial to consider the specific characteristics of the dataset and the problem context when choosing between AR and LSTM, as the performance of each method may vary depending on the specific scenario.

In this study will help aviation authorities and policymakers make informed decisions. Additionally, the study will provide several advantages in addressing various challenges in the future planning of the aviation industry.

Advantages:

- By estimating air traffic, the adequacy of airport infrastructure and facilities such as runways, aprons, and passenger waiting areas can be evaluated.
- Air traffic estimation can determine whether an airport will be sufficient in the future or if there is a need for an additional airport in a specific location.
- Predicting air traffic enables airline companies to plan their flights and manage their crew effectively.

However, the study has some limitations. It relies on monthly temporal data from a relatively short time period spanning from 2008 to 2023, and it does not utilize various other features. Nevertheless, this research contributes to the utilization of deep learning models in the aviation industry, which remains largely unexplored from both industrial and academic perspectives.

5. Conclusion

In this study, an analysis was conducted on predicting air traffic using AR and stacked LSTM (Long Short-Term Memory) methods. Various features and datasets were experimented with to compare the performance of both methods and evaluate their abilities to capture the complexities of aircraft traffic.

AR method aimed to build a linear model by considering different features associated with aircraft counts. Through AR analysis, we aimed to determine the relationships between these features and accurately predict aircraft counts. The results obtained demonstrated that the AR model performed quite poorly in predicting aircraft counts. However, the AR method may have limitations in capturing time dependencies and complex relationships present in the data.

On the other hand, the LSTM method offers a more complex and flexible approach. LSTM is known for its ability to capture long-term dependencies and complex relationships over time. We attempted to predict aircraft counts using this method, and the results were quite promising. LSTM can better capture temporal changes and handle dynamic patterns, which can lead to more accurate predictions in aircraft traffic.

Our comparative analysis indicated that LSTM outperformed AR method in terms of performance. Its more complex architecture and ability to capture dependencies in time series data demonstrated the effectiveness of LSTM in predicting aircraft numbers. However, the LSTM method may require more data and involve a more intricate modeling process.

In conclusion, deep learning methods such as LSTM show superior performance compared to traditional methods as AR in predicting aircraft counts. However, both methods have their own advantages and limitations, and the choice of method may depend on the dataset and problem context.

This study serves as a starting point to compare AR and LSTM methods in predicting aircraft counts. Further research can explore advanced variations of LSTM or other deep learning techniques to enhance the accuracy of air traffic predictions. Additionally, incorporating more diverse and comprehensive datasets can provide further insights into the performance and limitations of these methods in real-world scenarios.

Ethical approval

Not applicable.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Cite this article: Dursun, O.O. (2023). Air-traffic Flow Prediction with Deep Learning: A Case Study for Diyarbakır Airport. Journal of Aviation, 7(2), 196-203.