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Integrating Genetic Algorithms with LSTM for Improved Public Transportation Passenger Forecasting in Thailand

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Abstract: This study presents a novel forecasting framework that integrates Genetic Algorithms (GA) with Long Short-Term Memory (LSTM) networks to enhance the prediction accuracy of passenger volumes in Thailand's public transportation systems. The unique contribution of this research lies in leveraging GA for automatic hyperparameter optimization of LSTM models, improving performance over conventional methods. The dataset comprises weekly aggregated passenger counts from road and rail modes between January 2020 and August 2023. The proposed GA-enhanced LSTM model (LSTM+GA) is evaluated using four metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Median Absolute Percentage Error (MdAPE). Results demonstrate that LSTM+GA outperforms baseline models including Autoregressive Integrated Moving Average (ARIMA), Facebook Prophet (FBProphet), and standard LSTM, achieving a MAPE of 4.04 for road and 5.86 for rail datasets. These findings suggest that the proposed model offers a practical and scalable tool for transport planners and public agencies seeking to optimize forecasting strategies and decision-making.

Keywords: Forecasting, forecasting passenger numbers, public transportation systems, long short-term memory, genetic algorithms

1. Introduction

Public transportation has become a vital component in the daily lives of people worldwide, including Thailand, where continuous efforts have been made to enhance and expand its infrastructure [1]. The development of an efficient public transport system, incorporating road, water, rail, and air transport, is key to promoting economic growth and improving social connectivity. Accurate ridership forecasting is critical for optimizing public transport operations, reducing costs, and improving passenger satisfaction. It also facilitates better long-term structural planning to meet future demands.

Despite the advancements in time-series forecasting, each method possesses inherent limitations. Traditional statistical models like Autoregressive Integrated Moving Average (ARIMA), while effective for linear and stationary data, often fail to capture complex temporal dependencies and nonlinear patterns prevalent in public transport data. Similarly, models like Facebook Prophet (FBProphet), though robust in handling seasonality and holidays, rely on additive regressions that may not sufficiently model long-term dependencies. Deep learning models, particularly Long Short-Term Memory (LSTM), have shown superior capabilities in learning temporal dynamics but are sensitive to hyperparameter selection, which can significantly affect performance. To address these gaps, recent studies have proposed hybrid models that combine optimization techniques such as Genetic Algorithms (GA) with neural networks to automate hyperparameter tuning and improve forecasting accuracy [2-5]. This study builds upon such hybridization efforts and seeks to enhance model robustness and generalizability within the context of Thailand's dynamic transportation environment.

This study proposes a novel approach that integrates LSTM networks with GA for public transport ridership forecasting. By combining the time-series processing strength of LSTM with the optimization capabilities of GA, a model is developed to outperform existing methods. To evaluate its effectiveness, we compare it with three established models: FBProphet, ARIMA, and traditional LSTM. FBProphet is known for handling seasonal data effectively, ARIMA offers a robust statistical framework, and LSTM provides deep learning benefits. The results of our study indicate that the LSTM+GA model significantly improves forecasting accuracy and reliability, outperforming the other methods. Several studies have explored similar approaches to forecasting in various fields. For example, Shobhit Chaturvedi et al. [6] compared SARIMA, LSTM, FBProphet, and trend-based models for forecasting energy demand in India, concluding that FBProphet was the most effective model. Gopi Battineni and Nalini Chintalapudi [7] used FBProphet to predict COVID-19 infections in multiple countries, highlighting its predictive accuracy despite some limitations. Additionally, Fanoon Raheem and Nihla Iqbal [8] applied FBProphet to predict currency exchange rates, demonstrating the model's robustness.

Furthermore, advanced forecasting techniques have been applied to transportation systems. For instance, Sergey Khalil et al. [9] utilized a spatiotemporal framework combining CNN and LSTM models to forecast public transport ridership, while Halyal et al. [10] compared LSTM and SARIMA models for forecasting bus passenger demand using APC data, finding that LSTM outperformed SARIMA. Additionally, Dan Yang et al. [11] developed an enhanced LSTM model that improved urban rail transit predictions. These studies reinforce the potential of integrating deep learning models with optimization algorithms to achieve more accurate and efficient forecasting outcomes in public transport systems. By integrating LSTM and GA, our research aims to contribute to the growing body of knowledge on improving public transport ridership forecasting, leveraging state-of-the-art techniques for enhanced accuracy and operational efficiency.

2. Methodology

Figure 1 illustrates the conceptual methodology framework guiding this research, outlining the key stages of data processing, model development, and evaluation. The framework begins with data sourcing from statistical information on the transportation network, covering the period from January 2020 to August 2023. [12] This is followed by a data preprocessing step where daily data is aggregated and resampled on a weekly basis to prepare it for analysis. Next, the dataset is divided into two portions: 85% for training and 15% for testing. Various forecasting models are applied to the data, including Fbprophet, ARIMA, LSTM, and a combination of LSTM with a GA. The performance of these models is then evaluated using multiple metrics such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Median Absolute Percentage Error (MdAPE), and Root Mean Square Error (RMSE) allowing for conclusions to be drawn on model accuracy and effectiveness. This structured approach provides a comprehensive overview of how the research is conducted, from data handling to model validation.

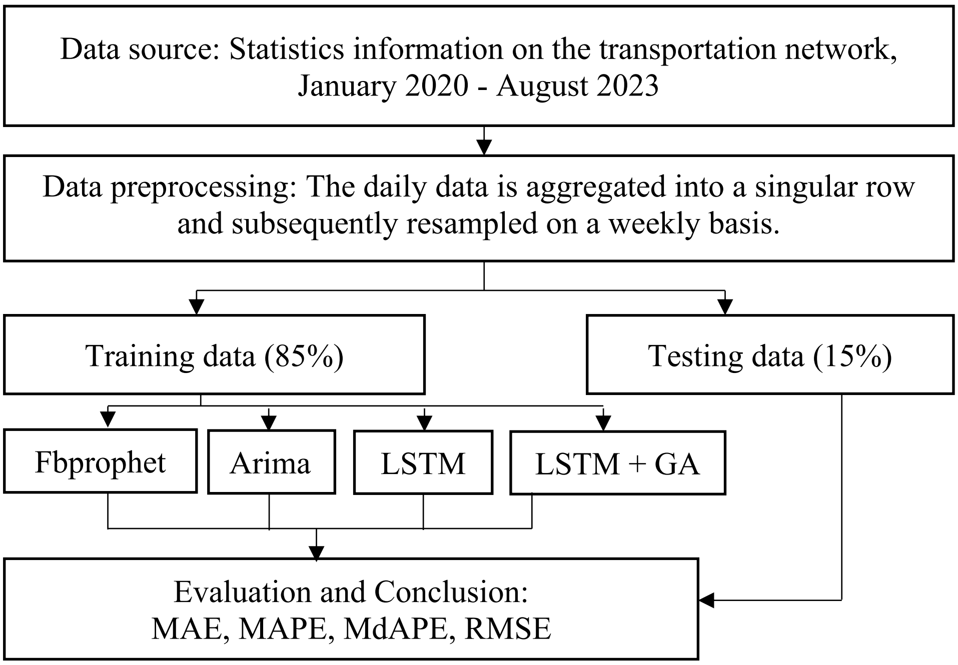

Fig. 1 Conceptual methodology framework. Source: authors

The entire implementation of this research was conducted in Python 3.9. The LSTM model was built using the TensorFlow and Keras libraries, while the Genetic Algorithm was implemented using the DEAP framework. FBProphet and ARIMA models were implemented using the Prophet and statsmodels libraries respectively. A simplified pseudocode illustrating the integration of GA with LSTM is provided in the methodology section.

2.1 Data Source and Preprocessing

The dataset comprises weekly aggregated passenger counts for road and rail transportation in Thailand, derived from daily records provided by the Ministry of Transport [12] and resampled to weekly intervals to reduce noise and highlight broader trends. It contains 192 time-indexed observations per mode from January 2020 to August 2023, representing univariate numerical data suitable for time-series forecasting. Descriptive statistics (Table 1) indicate slightly higher average weekly passengers for road (874,069) compared to rail (854,068), while rail exhibits greater variability (std = 358,562 vs. 292,170). Passenger volumes range from approximately 300,000 to 1.66 million for road and 187,000 to 1.62 million for rail, reflecting notable fluctuations throughout the study period.

Table 1 Statistics of passenger numbers resampled weekly. Source [12].

	Road	**Rail**
count	192.00	192.00
mean	874,068.65	854,067.50
std	292,169.98	358,562.03
min	300,118.71	187,378.14
25%	646,698.50	583,587.46
50%	936,495.00	895,746.71
75%	1,063,281.46	1,156,074.07
max	1,661,955.00	1,619,166.00

2.2 Forecasting Models

FBProphet, developed by Facebook's data science team in 2018 [13], is a fast, scalable forecasting tool used for various applications like weather and e-commerce forecasting. It decomposes time series data into trend, seasonality, and noise components, enabling accurate forecasts. Its analyst-in-the-loop approach combines human expertise with automation for effective large-scale forecasting.

The ARIMA Model [14-16] reduces "Noise" in time series data to improve forecasting accuracy. Its components—autoregression, integration, and moving averaging—work together to capture essential patterns and trends. The model is represented as ARIMA (p, d, q), where each parameter reflects a specific aspect of the model's structure. In the ARIMA model, p represents the number of lag observations (Auto-Regressive part), d is the degree of differencing required to make the series stationary (Integrated part), and q is the order of the moving average, which models the forecast error as a combination of past errors (Moving Average part).

The general formula for an ARIMA model can be written as:

$$Y'_t = c + \emptyset_1 Y'_{t-1} + \emptyset_2 Y'_{t-2} + \cdots + \emptyset_p Y'_{t-p} + \emptyset_1 \in_{t-1} + \emptyset_2 \in_{t-2} + \cdots + \emptyset_q \in_{t-q} + \in_t \quad [-] \qquad (1)$$

where: Y'_t is the differenced series, obtained after differencing the original series d times to achieve stationarity [Passengers]; c is constant term (intercept) [Passengers]; $\emptyset_1, \emptyset_2 \ldots \emptyset_p$ are the coefficients of the autoregressive terms [-]; $\theta_1, \theta_2 \ldots \theta_p$ are the coefficients of the moving average terms [-]; $\in_t$ is represents white noise error terms [Passengers]. p is autoregressive order (number of lagged observations) [Weeks]; d is degree of differencing (number of differencing operations applied to the series) [Weeks]; q is moving average order (number of lagged forecast errors) [Weeks].

LSTM networks [17-19], a variant of Recurrent Neural Networks (RNNs), are designed to capture long-term dependencies, making them highly effective for sequential prediction tasks. Unlike traditional RNNs, which struggle with long-range dependencies and the vanishing gradient problem, LSTMs use gating mechanisms to retain relevant information over extended sequences. During predictions, the output is fed back into the model to predict the next value, with activation functions helping to normalize values and reduce errors like gradient explosions.

In this study, a GA is applied to the hyperparameter optimization of LSTM neural network models [20–24] designed for time series forecasting. The collaborative process between LSTM and GA is summarized in the following pseudocode (Table 2), which is presented here to clearly illustrate the proposed methodology.

Table 2 summarizes the GA operations used to tune LSTM hyperparameters. Source: authors.

Pseudocode: GA to optimize the number of neurons in the LSTM layer and the learning rate.
Input: Training dataset, Testing dataset
Output: Final GA-optimized LSTM model

*1: **SETUP** Genetic Algorithm*
1.1 DEFINE fitness function and individual structure.
1.2 CREATE a toolbox for genetic operators.
*2: **FUNCTION** evaluates individual*
2.1 EXTRACT hyperparameters from individual
2.2 CREATE LSTM with specified number of neurons.
2.3 COMPILE model loss and adam optimizer
2.4 TRAIN model
2.5 EVALUATE model and RETURN loss as fitness.
*3: **REGISTER** evaluation function to GA toolbox*
*4: **RUN** Genetic Algorithm*
4.1 INITIALIZE a population with a predefined number of individuals.
4.2 SET the number of generations for the evolution.
4.3 RUN the genetic algorithm using population, toolbox, and defined probabilities for crossover and mutation.
*5: **ASSEMBLE** and **TRAIN** final LSTM model using best hyperparameters found by GA*

To optimize LSTM hyperparameters, GA was applied to search for the best combination of neuron count (10–100) and learning rate (0.001–0.1). A population of 10 individuals evolved over 5 generations, with everyone evaluated by training an LSTM on 85% of the data and measuring MAE on the 15% test set. The process used two-point crossover (0.5), Gaussian mutation (0.2), and tournament selection (size = 3). The best-performing individual was selected to retrain the final LSTM model.

2.3 Evaluation

MAE [10,25] is a metric used to measure the accuracy of predictive models, particularly in regression. It calculates the average of the absolute differences between predicted and actual values. Mathematically, it is expressed as:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|, \quad \text{[Passengers]} \tag{2}$$

where: n is the number of observations [-]; y_i is the actual observed value [Passengers]; $\hat{y}_i$ is the forecasted or predicted value [Passengers]; $|y_i - \hat{y}_i|$ is the absolute error for each observation [Passengers].

Root Mean Square Error (RMSE) [6,10,25] is a common metric for measuring prediction errors in forecasting and regression. It calculates the square root of the average squared differences between predicted and actual values. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}\ , \quad \text{[Passengers]} \tag{3}$$

where: n is the number of observations [-]; y_i is the actual observed value [Passengers]; $\hat{y}_i$ is the forecasted or predicted value [Passengers];.

MAPE [6] constitutes a statistical metric extensively utilized for evaluating the precision of forecast models. By quantifying accuracy in terms of a percentage, MAPE facilitates straightforward interpretation and is especially beneficial for comparative analyses of diverse forecasting models across varying scales of data. The formula for calculating MAPE is:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right|, \quad [\%] \tag{4}$$

where: n is the number of observations [-]; y_i is the actual observed value [Passengers]; $\hat{y}_i$ is the forecasted or predicted value [Passengers].

MAPE calculates the absolute difference between the actual and forecasted values, divided by the actual value, for each data point. This result is then averaged over all data points and multiplied by 100 to express it as a percentage.

MdAPE [26], used in forecasting and regression, is similar to MAPE but calculates the median of absolute percentage errors. This makes MdAPE more robust against outliers and skewed data. The formula for MdAPE is:

$$MdAPE = median\left(\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\%\right), \quad [\%] \tag{5}$$

where: y_i is the actual observed value [Passengers]; $\hat{y}_i$ is the forecasted or predicted value [Passengers].

MdAPE is particularly useful in situations where the data contains outliers or is not symmetrically distributed, as it provides a more representative measure of the typical error rate. By focusing on the median, MdAPE offers a more robust measure of central tendency in the error distribution.

3. Results and Discussion

This section presents the results of the data analysis and the comparative evaluation of forecasting models, followed by a discussion of their implications. First, descriptive statistics of the passenger datasets are summarized. Then, the performance of each forecasting model (FBProphet, ARIMA, LSTM, and LSTM+GA) is evaluated using MAE, RMSE, MAPE, and MdAPE. Finally, the findings are discussed in relation to previous studies and their practical relevance for public transportation planning in Thailand.

This research elucidates the application of GA in conjunction with LSTM networks for forecasting public passenger numbers. The study involves comparative analysis with other forecasting models, specifically FBProphet, ARIMA, and LSTM [6,9,27] The performance evaluation of each model is conducted using statistical measures such as MAE, RMSE, MAPE, and MdAPE. The outcomes of the road and rail passenger forecast experiment are systematically presented in Table 3. The computed values of MAE and RMSE are scaled by a factor of 10^5 in this analysis.

Table 3 Comparison results of models of passenger Source: authors.

Models	**Road**				**Rail**			
	MAE	**RMSE**	**MAPE**	**MdAPE**	**MAE**	**RMSE**	**MAPE**	**MdAPE**
FBProphet	1.41E5	.72E5	13.34	9.87	0.72E5	**0.91E5**	14.43	13.24
ARIMA	1.19E5	.30E5	10.45	12.13	1.33E5	1.60E5	11.12	9.54
LSTM	0.70 E5	.98E5	5.73	3.59	0.91E5	1.15E5	7.16	5.95
LSTM + GA	**0.44E5**	**0.64E5**	**4.04**	**2.31**	**0.71E5**	1.01E5	**5.86**	**4.85**

The model proposed in this study, which utilizes GA for optimizing the hyperparameters of LSTM networks, demonstrated superior performance in forecasting road passenger numbers compared to other models. This enhanced performance is evidenced by the following evaluation metrics: a MAE of 0.44E5, a RMSE of 0.64E5, a MAPE of 4.04, and a MdAPE of 2.31.

Similarly, the performance evaluation for rail passenger forecasting using the proposed model also surpasses that of other models. The results demonstrate superior efficacy, as indicated by a MAE of 0.71E5, a MAPE of 5.86, and a MdAPE of 4.85. However, it is noteworthy that the RMSE value of the FBProphet model marginally outperforms the proposed model, at 0.91E5. The superior performance of the FBProphet model in this context is attributable to its proficiency in handling datasets that demonstrate pronounced seasonal effects [6,13]. This is particularly relevant in the case of the rail passenger dataset, which exhibits greater variability compared to the road passenger dataset. This variance is further elucidated upon examining the standard deviation of the seasonal components, underscoring the differing characteristics of these datasets and the suitability of the FBProphet model for such analyses.

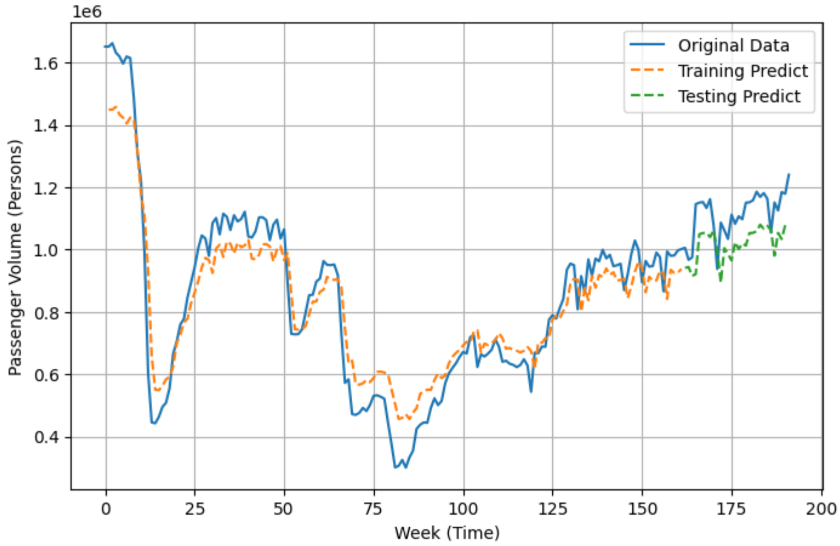

Fig. 2 Actual data with predictive outcomes (Road passenger numbers). Source: authors.

Figure 2 shows that the LSTM+GA model accurately predicts road passenger volumes, with forecasts closely matching actual data over time.

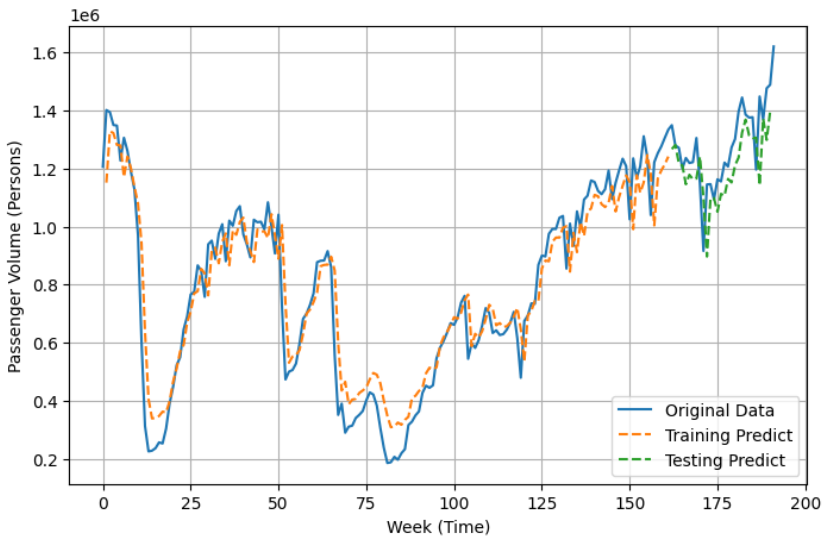

Fig. 3 Actual data with predictive outcomes (Rail passenger numbers). Source: authors.

Figure 3 shows that the model effectively forecasts rail passenger volumes, with predicted values closely matching actual data

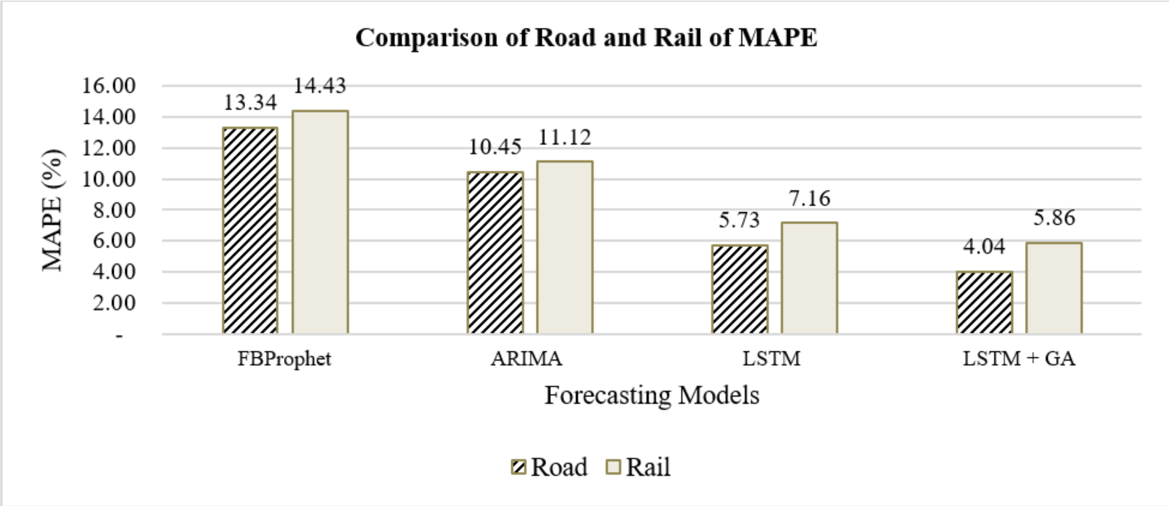

Fig. 4 Comparison of Road and Rail of MAPE. Source: authors.

Figure 4 compares MAPE values of the proposed LSTM+GA model with other models using road and rail passenger data, showing the LSTM+GA model's superior performance.

Analyzing passenger behavior during the COVID-19 pandemic presents a complex and challenging endeavor due to the unprecedented impact on travel patterns and mobility choices [27,28]. This complexity is further reflected in recent studies that explore the integration of optimization algorithms with artificial neural networks to better understand and predict such behaviors. The use of GA has been particularly prevalent in enhancing the performance of LSTM networks [6,9]. Prior research has demonstrated the effectiveness of GA in improving the efficiency of LSTM models [20,21,24], and our empirical findings align with this perspective, showing that the application of GA-optimized LSTM models yields superior outcomes compared to conventional LSTM approaches.

In our research, the LSTM enhanced with GA evidenced a significant improvement in performance metrics. For the road dataset, the MAPE was recorded at 4.04 for the LSTM+GA model, in contrast to a MAPE of 5.73 for the traditional LSTM. Similarly, for the rail dataset, the LSTM+GA model achieved a MAPE of 5.86, while the traditional LSTM registered a MAPE of 7.16. These results align with previous studies, affirming the assertion that the implementation of GA markedly improves the results of LSTM models. Such findings underscore the efficacy of GA in fine-tuning the predictive accuracy of LSTM networks, thereby reinforcing the value of this approach in forecasting endeavors.

Although the results demonstrate improved forecasting performance, statistical significance tests (e.g., paired t-test or Wilcoxon signed-rank test) were not conducted in this study. Future research should incorporate such tests to confirm whether the improvements are statistically significant.

4. Conclusions

In this study, the forecasting of passenger numbers was investigated within Thailand's public transportation networks, focusing on road and rail modes. The dataset spans from January 2020 to August 2023, and a methodology was introduced that utilizes a Genetic Algorithm (GA) to optimize the hyperparameters of an LSTM network. The proposed LSTM+GA model was compared against FBProphet, ARIMA, and traditional LSTM using metrics such as MAE, RMSE, MAPE, and MdAPE. Experimental results indicated that our approach outperformed the baseline models in terms of forecasting accuracy.

The findings offer practical value for transportation agencies in Thailand, particularly in planning vehicle allocation and service scheduling. The model's ability to anticipate passenger demand with high accuracy can support more efficient decision-making during peak seasons or holidays. However, the dataset used includes only weekly aggregated counts and lacks contextual variables such as holidays, weather conditions, or policy interventions, which may further improve forecasting accuracy and generalizability. Thus, the transferability of the model should be explored further through additional experiments. Future research should consider expanding the input features with multivariate data and testing the model across different geographical areas or transportation systems. Investigating advanced hybrid models such as attention-based LSTM or Transformer networks could also further enhance forecasting robustness and adaptability in dynamic environments.

Acknowledgments

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