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Forecasting Light Rail Transit Passenger Demand Using Parameter-Tuned Exponential Smoothing Models

Rendra Gustriansyah[1*], Shinta Puspasari[2], Ahmad Sanmorino[3], Nazori Suhandi[4]
[1,2,4] Department of Informatics Engineering, Faculty of Computer and Natural Science, Universitas Indo Global Mandiri, Palembang, Indonesia
[3] Department of Information Systems, Faculty of Computer and Natural Science, Universitas Indo Global Mandiri, Palembang, Indonesia

Corresponding author: rendra@uigm.ac.id

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ABSTRACT

Accurate passenger demand forecasting is essential for optimising the operational efficiency and sustainability of urban rail systems. This study aims to forecast monthly passenger numbers for the Palembang Light Rail Transit (LRT) system using optimised Exponential Smoothing (ES) models with parameter tuning to improve predictive accuracy. Three variants of the ES method are examined: Simple Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Brown's Exponential Smoothing (BES). Furthermore, Seasonal ARIMA (SARIMA) is used as a benchmark to evaluate whether simpler ES models can match or outperform complex statistical approaches. Data from August 2018 to December 2023 are analysed and split into training and test sets (ratio 80:20). Model performance is evaluated using the Mean Absolute Percentage Error (MAPE), the Diebold–Mariano (DM) test, and the Ljung–Box Q (LBQ) test. The results show that the SES model with $\alpha = 0.9$ achieves the best forecasting accuracy on the test data (MAPE = 8.6%), outperforming other ES variants and previous SARIMA-based models. These findings highlight that simpler ES-based models can effectively capture short-term transportation demand patterns in developing urban transit systems. Practically, the results of this study can provide valuable insights for LRT operators and municipal planners in designing responsive, data-driven operational strategies.

INTRODUCTION

Light Rail Transit (LRT) systems have become an essential mode of urban transportation due to their punctuality, speed, and passenger comfort (Zhang et al., 2020). Accurate passenger demand forecasting is fundamental for ensuring efficient operations, optimising resource allocation, and improving service quality (Solikhin et al., 2022). Reliable forecasts support not only the planning of future railway network expansions (Cao et al., 2021) but also investment decisions, facility performance evaluation (Tian et al., 2019), and operational cost control (Fuquan et al., 2019). In practice, passenger forecasts enable operators to determine train frequencies (Widiyaningtyas et al., 2019), enhance traffic safety (Chuwang et al., 2022), and regulate ticket distribution (Qin et al., 2019). Consequently, forecasting accuracy plays a critical role in improving the overall quality of railway services (Hoppe et al., 2023).

In recent years, various forecasting approaches have been developed to predict passenger demand in the transportation sector. Machine learning techniques such as Neural Networks (Jankowitz et al., 2022; Wei et al., 2023) and Support Vector Machines (Mariñas-Collado et al., 2022; Wei et al., 2023) Have demonstrated strong predictive capabilities but often require large datasets and high computational costs. Traditional statistical models, including Holt–Winters and Autoregressive Integrated Moving Average (ARIMA) (Chuwang et al., 2022; Djakaria, 2019; Kochkina et al., 2021; Mariñas-Collado et al., 2022; Safitri et al., 2020; Sai et al., 2019; Saputra et al., 2024; Su et al., 2020; Wei et al., 2023; Widiyaningtyas et al., 2019), remain widely used due to their interpretability and robustness—some studies, such as Solikhin et al. (Solikhin et al., 2022) And Sharma et al. (Sharma et al., 2018)We have employed the DES. However, these works mainly focus on more complex models and rarely examine the effectiveness of simpler yet efficient methods, such as the ES, in the context of short-term LRT passenger forecasting.

This research addresses that gap by evaluating the performance of three ES variants (SES, DES, and BES) in forecasting monthly passenger numbers from the Palembang LRT system. Unlike previous studies, this work emphasises parameter optimisation to enhance forecasting accuracy and compares the ES models with SARIMA as a benchmark. The Palembang LRT, as Indonesia's first operational LRT system, provides a unique case for studying demand forecasting in a developing urban transportation environment characterised by moderate variability and stable growth.

Accurate passenger forecasting is crucial amid rapid urbanisation and rising public transportation demand. Overestimation or underestimation of demand can directly affect operational efficiency, service quality, and passenger satisfaction. Therefore, this study aims to (1) evaluate and compare the forecasting performance of SES, DES, and BES methods for the Palembang LRT system; (2) determine the optimal smoothing parameters based on MAPE; and (3) statistically validate model accuracy using the DM and LBQ tests.

The novelty of this study lies in providing empirical evidence that optimised simple models, such as the ES, can outperform more complex methods like SARIMA for short-term operational forecasting. By statistically validating these results, this research contributes both academically and practically to advancing efficient, data-driven public transport management in Indonesia.

METHOD

This study employs a quantitative approach utilising monthly passenger data from the Palembang LRT system, covering the period from August 2018 to December 2023. The dataset, obtained from the Palembang City LRT management authority (Saputra et al., 2024)It consists of 65 observations, split into a training set (53 months) and a test set (12 months). The data are analysed and tested using three ES methods: SES, DES, and BES, each optimised for parameter selection. The Seasonal ARIMA (SARIMA) model is used as a benchmark to assess comparative forecasting performance.

1. Simple Exponential Smoothing (SES)

The SES method is a forecasting method that utilises historical time series data characterised by a horizontal pattern with no significant trends or seasonal variations. SES employs a single smoothing parameter, α, which ranges from 0 to 1. The SES model is formulated as in (1) (Gustriansyah et al., 2019).

$$F_{t+1} = \propto A_t + (1-\propto)F_t \tag{1}$$

Where F_{t+1} – the forecast value at period t+1, F_t – the forecast value at period t, A_t – the actual value at period t, $F_2 = A_1$, and $\alpha \in [0,1]$.

2. Brown's Exponential Smoothing (BES)

BES extends SES to accommodate trend components by applying double smoothing. It uses a single parameter (α) and recursive smoothing at two levels. The model equations are expressed as in (2) (Gustriansyah et al., 2023).

$$\begin{aligned} &S't = \alpha A_t + (1-\alpha) S't\text{-}1 \\ &S''_t = \alpha S't + (1-\alpha) S''_{t-1} \\ &L_t = 2S't - S''_t \\ &T_t = \alpha / (1-\alpha) (S't - S''_t) \\ &F_{t+m} = L_t + m\, T_t \\ &S'_1 = S''_1 = A_1 \end{aligned} \tag{2}$$

Where $S't$ and S''_t are the singly and doubly smoothed series, L_t is the estimated level, T_t is the estimated trend at period t, and F_{t+m} represents the forecast for m future periods.

3. Double Exponential Smoothing (DES)

DES, also known as Holt's linear trend method, captures both the level and trend components of a time series using two parameters: α (level) and β (trend). The formulas for DES can be found in (3) (Gustriansyah et al., 2023).

$$\begin{aligned} &F_{t+m} = L_t + m\, T_t \\ &L_t = \alpha A_t + (1-\alpha)(L_{t-1} + T_{t-1}) \\ &T_t = \beta (L_t - L_{t-1}) + (1-\beta) T_{t-1} \\ &T_1 = 0, L_1 = A_1 \end{aligned} \tag{3}$$

4. Parameter Optimisation via Grid Search

To ensure optimal model performance, the Grid Search (GS) approach is utilised to identify the best combination of smoothing parameters. GS systematically evaluates predefined parameter grids and selects the values that minimise the MAPE.

The GS procedure is summarised as follows:

- Define parameter grid: α and β ∈ [0.1, 0.2, ..., 1.0].
- Generate combinations: construct all parameter pairs (α, β) for DES and a single α for SES/BES.
- Model evaluation by fitting the ES model on training data for each parameter combination and computing MAPE.
- Select the best parameters to identify the combination with the lowest MAPE value on the validation set.

This approach enables systematic, reproducible tuning of ES parameters to maximise accuracy.

5. Model Evaluation Metrics

The models' predictive performance is evaluated using three complementary metrics: MAPE for accuracy measurement, the Diebold–Mariano test for statistical comparison, and the Ljung-Box Q test for residual adequacy.

(1) Mean Absolute Percentage Error (MAPE)

MAPE quantifies the average deviation between forecasted and actual values in percentage form, as defined in (4) (Gustriansyah et al., 2019).

$$MAPE\ (\%) = \frac{100}{n}\sum_{t=1}^{n}\frac{|A_t - F_t|}{A_t} \tag{4}$$

Lower MAPE values indicate better model accuracy.

(2) Diebold-Mariano (DM) Test

The DM test statistically compares the forecast accuracy of two competing models by comparing their prediction errors. The DM test statistic is given by (5) (Hyndman et al., 2025).

$$DM = \frac{\bar{d}}{\sqrt{\frac{\gamma_0 + 2\sum_{k=1}^{M-1}\gamma_k}{T}}} \tag{5}$$

where $\bar{d}$ Is the mean loss differential between the models, γ_k is the autocovariance at lag k, T is the number of test observations, and M is the truncation lag (typically $M \approx T^{1/3}$).

H_0: No significant difference in forecast accuracy between models.

H_1: A significant difference exists in forecast accuracy.

(3) Ljung-Box Q (LBQ) Test

The LBQ test assesses the independence of residuals to verify the model's adequacy. The LBQ test is defined as (6).

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{r}_k^2}{n-k} \tag{6}$$

Where Q is the LBQ statistic, n is the number of residuals, $\hat{r}_k$ is the sample autocorrelation at lag k, and h denotes the number of lags tested (commonly $10 \leq h \leq 20$).
H_0: No autocorrelation (model residuals are white noise).
H_1: Residual autocorrelation exists (model is inadequate).
Both DM and LBQ tests were implemented in R using the forecast and tseries packages to ensure reliable statistical evaluation. (Hyndman et al., 2025).

RESULTS

The monthly passenger data for the Palembang LRT system from August 2018 to December 2023 recorded an average of 13,401,472 passengers. (Saputra et al., 2024). The lowest monthly value occurred during the COVID-19 lockdown in April 2020 (14,759 passengers), while the highest number was observed in December 2023 (417,513 passengers). These fluctuations, illustrated in Figure 1, reflect both the pandemic's impact and the gradual recovery in LRT ridership.

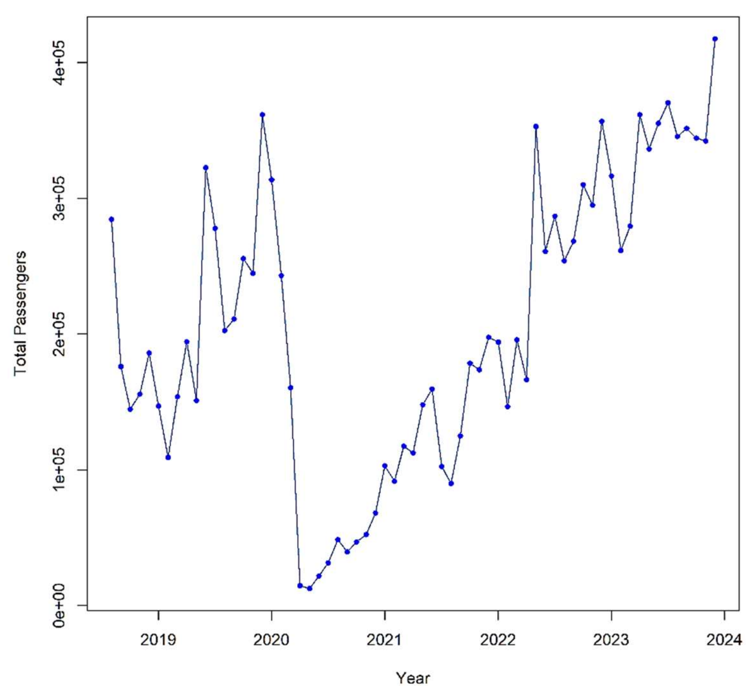

Figure 1. Time series plot of monthly LRT passenger numbers (Aug 2018-Dec 2023).

1. Model Selection and Parameter Optimisation

To determine the optimal parameters for each ES variant, several α (and β, for DES) values were tested using the training dataset. The SES model achieved the lowest MAPE (44.5%) when α = 0.9, as shown in Table 1. It indicates that higher weighting on recent observations enhanced model responsiveness.

Table 1. MAPE for the SES model with different α parameters.

α	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	**0.9**
MAPE (%)	128.6	106.8	90.5	77.3	67.4	59	52.6	47.8	**44.5**

A similar tuning procedure was conducted for the BES. The optimal α value was 0.5, yielding a MAPE of 59.7% (Table 2).

Table 2. MAPE for the BES model with variations in α.

α	0.1	0.2	0.3	0.4	**0.5**	0.6	0.7	0.8	0.9
MAPE (%)	107.1	88.6	71.9	62	**59.7**	60.6	61.4	62	62

For the Double Exponential Smoothing (DES) model, α and β parameters were simultaneously optimised. The lowest MAPE (47.4%) was achieved when α = 0.9 and β = 0.1 (Table 3).

Table 3. MAPE results for the DES model with variations in α and β.

α	β	MAPE (%)
0.1	0.1	119.1
	0.5	163.5
	0.9	192.5
0.3	0.1	93.0
	0.5	96.2
	0.9	89.4
0.6	0.1	61.9
	0.5	64.3
	0.9	73.0
0.9	**0.1**	**47.4**
	0.5	60.1
	0.9	60.9

Table 4 compares the error rates from the three exponential smoothing forecasting models. The smallest MAPE value is 44.5%. Therefore, the SES model (α = 0.9) is considered the most appropriate for forecasting the number of LRT passengers in Palembang City, which tends to be stable and exhibits minimal seasonality.

Table 4. Summary of ES model evaluation results.

Model	Parameters	MAPE (%)
SES	α = 0.9	44.5
BES	α = 0.5	59.7
DES	α = 0.9, β = 0.1	47.4

2. Forecasting Results and Model Performance

The next step is to use the SES model with α = 0.9 to forecast the number of LRT passengers for the test period (January-December 2023). The test dataset consists of 12 monthly data points for this period. After generating forecasts, the model's error level is evaluated using the MAPE metric. The model's performance, evaluated using MAPE, is summarised in Table 5.

Table 5. Comparison between actual and forecasted passenger numbers (January-December 2023)

Month	Actual	Forecasting	MAPE (%)

1	316,521	350,614	10.8
2	261,581	319,930	22.3
3	279,621	267,416	4.4
4	361,765	278,400	23.0
5	336,260	353,429	5.1
6	355,364	337,977	4.9
7	370,468	353,625	4.5
8	345,592	368,784	6.7
9	351,418	347,911	1.0
10	344,388	351,067	1.9
11	342,228	345,056	0.8
12	417,513	342,511	18.0
Average			**8.6**

The evaluation reveals a MAPE value of 8.6%, indicating a forecasting error of less than 10% and demonstrating excellent model accuracy. This performance surpasses that of the SARIMA model utilised in previous research. (Saputra et al., 2024). Figure 2 depicts a time series plot of the forecasting results generated by the SES model using a smoothing parameter (α) of 0.9, illustrating the model's effectiveness in forecasting the fluctuating patterns of the time series. However, it also highlights the lag values inherent in the time series, as the SES model relies solely on actual values and previous forecasts without incorporating any trends.

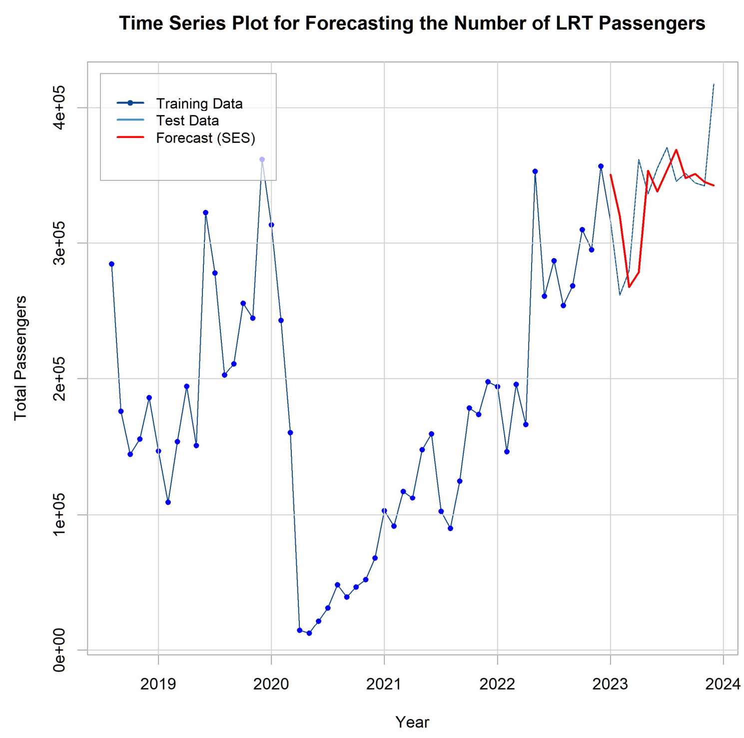

Figure 2. Forecasted and actual LRT passenger numbers (January–December 2023, SES model, α = 0.9).

The results of this study indicate that the SES model with α = 0.9 yields the lowest MAPE, making it the most accurate for forecasting LRT passenger numbers in Palembang City. This figure reflects quite good performance, especially when compared to other forecasting methods, such as

BES and DES. The strength of SES lies in its ability to identify stable data patterns with minimal fluctuations, making it effective for short-term forecasting in the transportation sector.

However, although the SES MAPE is lower, there is still potential for errors that could affect operational decisions. For example, the MAPE of the modelling results (44.5%) indicates a considerable uncertainty in the estimation of the number of passengers. In this context, it is crucial to consider external factors that can affect demand, such as changes in transportation policies, social events, and economic conditions. For example, during the COVID-19 pandemic, passenger numbers declined sharply, reflecting the significant impact of the extraordinary situation. Therefore, although SES successfully captured the basic trend, more complex modelling may be needed to handle more dramatic fluctuations.

Furthermore, the analysis of the forecasting results shows that this model has high accuracy for short-term forecasting, with an average MAPE of 8.6% on the test data from January to December 2023. It demonstrates that the model can accurately forecast over a shorter period, which is crucial for daily operational decision-making. While some months, like February and April, exhibit higher MAPE, the model maintains relatively stable performance.

3. Comparative and Statistical Validation

In comparison with the SARIMA model applied in previous research (Saputra et al., 2024)The SES model demonstrates an improvement of approximately 8% in forecasting accuracy on the same dataset, reflected in an MAPE of 8.6%. Despite its simplicity, the SES model achieved comparable or superior accuracy, emphasising that optimised simple models can outperform complex ones under stable data conditions.

The DM test produced a p-value of 0.40 (>0.05), indicating no statistically significant difference in accuracy between SES and SARIMA. This result suggests that SES performs as well as SARIMA in predictive reliability. Moreover, the LBQ test yielded a p-value of 0.58 (>0.05), confirming the absence of autocorrelation in SES residuals. These findings emphasise the importance of selecting a forecasting model that balances data behaviour and complexity, rather than focusing solely on model sophistication.

Figure 3 illustrates that all LBQ test p-values exceed the 0.05 significance level for most lags, indicating no significant autocorrelation in the SES residuals. The average p-value (≈ 0.58) further supports that the residuals behave as white noise, confirming the statistical adequacy of the SES model.

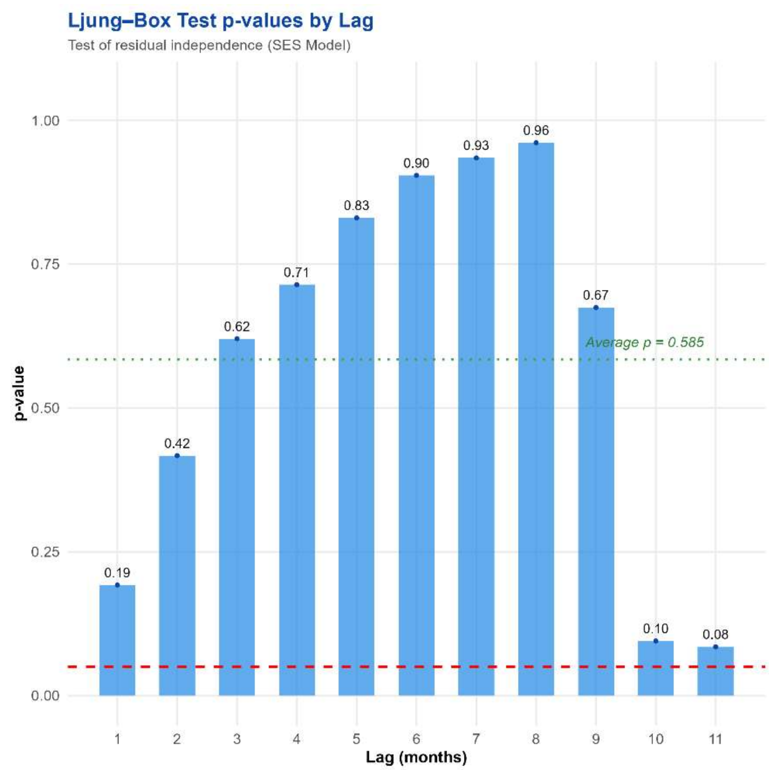

Figure 3. The Ljung–Box test p-values by lag (SES model, α = 0.9).

DISCUSSION AND IMPLICATIONS

The empirical results indicate that the SES model (α = 0.9) is the most suitable approach for forecasting LRT passenger demand in Palembang. Its parsimony and robustness make it particularly effective for operational decision-making in contexts with minimal seasonality. Although some months (e.g., February and April) exhibit higher forecast errors, the overall accuracy remains high, with MAPE consistently below 10% for most periods.

From an operational perspective, the model's simplicity allows for rapid updates and easy integration into real-time decision-support systems. However, residual fluctuations observed in extreme cases (e.g., COVID-19 disruptions) highlight the need to incorporate exogenous factors, such as economic indicators, policy changes, or special events, into future forecast models.

To enhance responsiveness, rolling forecast updates or hybrid ES-based approaches (e.g., ES-ARIMA, ES-MLP) could be adopted. Such techniques can dynamically adjust to changes in ridership behaviour. Furthermore, the proposed SES model can serve as a baseline forecasting framework for the Palembang City Government and LRT operators, enabling effective resource allocation, scheduling, and capacity planning.

Overall, this study reinforces the idea that model simplicity, when properly optimised, can yield accuracy comparable to or exceeding that of complex statistical models. These findings contribute both theoretically to the discourse on parsimonious time-series modelling and practically to the management of sustainable urban transit systems.

CONCLUSION

This study confirms that the SES model with α = 0.9 is the most effective approach for forecasting monthly passenger demand in the Palembang LRT system. The optimised SES model achieved a low MAPE of 8.6% on the 2023 test data, reflecting a forecasting accuracy of 91.4%. These results confirm that the SES model, despite its simplicity, can outperform more complex approaches such as SARIMA under conditions of relatively stable and non-seasonal data. Statistical validation using the DM and LBQ tests further confirmed the adequacy and reliability of the SES model. The DM test (p = 0.40) showed no significant difference in predictive performance between SES and SARIMA. Meanwhile, the LBQ test (p = 0.58) confirmed that the SES residuals were independent, validating the model's statistical robustness. From a practical perspective, the SES model offers a lightweight, efficient, and easily implementable forecasting tool that supports short-term operational planning and decision-making for the Palembang City Regional Government and LRT management authorities. Its interpretability and minimal data requirements make it particularly suitable for regular use in operational scheduling, resource allocation, and performance monitoring. Nevertheless, variability in passenger demand suggests the need to consider external influences such as economic conditions, weather, and social activities. Future research should therefore focus on integrating these external variables into hybrid or multivariate forecasting frameworks to enhance responsiveness and support the sustainable development of urban public transportation.

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