Journal of Power and Energy Engineering, 2025, 13(10), 75-86
https://www.scirp.org/journal/jpee
ISSN Online: 2327-5901
ISSN Print: 2327-588X

Comparative Performance of Exponential Smoothing Approach in Forecasting RON 97 Fuel Price in Malaysia

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How to cite this paper: Hussin, N.H., Said, R.M., Anuar, S.H.H. and Azahari, N.B. (2025) Comparative Performance of Exponential Smoothing Approach in Forecasting RON 97 Fuel Price in Malaysia. *Journal of Power and Energy Engineering*, **13**, 75-86.
https://doi.org/10.4236/jpee.2025.1310006

Received: September 24, 2025
Accepted: October 24, 2025
Published: October 27, 2025

Abstract

Forecasting fuel prices is a critical endeavor in energy economics, with significant implications for policy formulation, market regulation, and consumer decision-making. This study investigates the comparative efficacy of three exponential smoothing techniques: Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Holt-Winters Exponential Smoothing (TES), in modeling and predicting weekly RON97 fuel prices in Malaysia over the period from January 2020 to May 2025. The models were evaluated based on their predictive accuracy using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) across both in-sample and out-of-sample forecasts. The empirical results demonstrate that DES consistently yields superior performance, achieving the lowest error metrics and effectively capturing the underlying trend dynamics without the added complexity of seasonal adjustments. While TES offers a more comprehensive structure, its benefits are marginal in the absence of pronounced seasonality. SES, by contrast, exhibits limited responsiveness to trend variations. The findings underscore the suitability of DES as a robust and parsimonious forecasting tool for trend-dominated fuel price series, offering practical utility for analysts and policymakers in Malaysia's regulated energy market. Future research may extend this framework by integrating hybrid models or exogenous economic indicators to enhance forecasting precision.

Keywords

Fuel Price, Exponential Smoothings, Time Series Forecasting, RON97 Malaysia

1. Introduction

Fuel price forecasting is an essential analytical tool in modern energy economics, with implications for national policy, retail management, and consumer behavior. In Malaysia, fuel prices such as RON97 are subject to weekly fluctuations under the Managed Float System, reflecting global oil prices, currency exchange rates, and internal cost structures [1]. These frequent adjustments create uncertainty, making short-term forecasts vital for decision-making by regulators, suppliers, and individual consumers alike.

Time series forecasting techniques offer a range of tools to capture patterns and project future values based on historical data. Among these, Exponential Smoothing (ES) models have gained prominence due to their simplicity, interpretability, and adaptability. The family of ES models includes Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Triple Exponential Smoothing (TES) or commonly known as Holt-Winters, which collectively address time series with varying degrees of complexity in level, trend, and seasonal components [2]. These models are particularly useful when transparency and computational efficiency are prioritized over algorithmic sophistication.

SES is the most basic form of the ES family and is suitable for series without trend or seasonality like stationary data fluctuating around a constant mean. It applies a smoothing constant α that constrained within the interval (0, 1), determining the influence of the latest observation on the forecast [3]. Ostertagová and Ostertag [4] demonstrated that SES provides stable forecasts when data are randomly distributed around a fixed level, although performance deteriorates when trends are present.

In a comparative study on Malaysian electricity consumption forecasting, research in [5] found that SES was outperformed by more complex variants like DES, where SES was more suitable to model stable consumption patterns and demonstrated practical value for short-term forecasting. Their results reinforce the limitation of SES for trending data, making it less suitable for the RON97 fuel series considered in this study.

DES, also known as Holt's linear method, extends SES by incorporating a trend component, making it suitable for data with steady growth or decline. DES uses two smoothing parameters: α for level and β for trend. It has been successfully applied in various financial and energy domains where pattern shifts occur, but seasonality is minimal. Shafie *et al*. [6] show that DES outperformed SES and TES in forecasting gold prices by providing the lowest RMSE, making it the most suitable model for gold price forecasting in Malaysia. Similarly, Liantoni and Agusti [7] employed DES for Bitcoin price forecasting and the best α was selected based on the lowest MAPE, highlighting its robustness for data with consistent directional movement.

In the Malaysian context, Abdul Rahman *et al*. [8] used DES to forecast monthly gold prices, selecting the model based on RMSE and showing that DES outperformed both SES and Holt-Winters, despite the slight presence of seasonal noise.

This validates DES as a flexible tool for regulated commodities, including fuel.

Holt-Winters Exponential Smoothing is the most comprehensive ES model, designed to handle data with both trend and seasonality. It introduces a third parameter γ to accommodate seasonal cycles. There are additive and multiplicative variants depending on the nature of the seasonal fluctuations. While powerful, Holt-Winters can overfit or perform sub-optimally when seasonality is weak or absent. In studies where seasonal patterns are prominent, such as sales or temperature data, Holt-Winters consistently outperforms simpler models [9] [10].

In a multi-model comparison, Setiawan *et al.* [11] found Holt-Winters effective for long-term forecasting of passenger volumes where seasonality was strong, but they also acknowledged the importance of parameter optimization. Their findings reinforce the need for careful consideration of data structure when selecting ES models. Another relevant contribution by Gorges and Zahra [12] evaluated gasoline consumption in Iraq using ES models and recommended TES for its robustness against noisy time series data. Although the economic context differs, fuel demand dynamics and forecasting challenges bear a resemblance to the Malaysian case.

The objective of this study is to evaluate and compare the performance of SES, DES, and Holt-Winters Exponential Smoothing methods for forecasting weekly RON97 fuel prices in Malaysia using data from January 2020 to May 2025. The selected dataset exhibits a clear trend and moderate volatility, with no apparent seasonal component, thereby providing an ideal testing ground for the three ES variants.

Model accuracy is assessed using standard error metrics, including Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), both in-sample and out-of-sample. The comparison facilitates identification of the most reliable method for operational and strategic forecasting in Malaysia's regulated fuel market. Additionally, this paper contributes to the growing body of empirical research exploring lightweight time series models in energy applications.

2. Materials and Methods

2.1. Data Description

The data of weekly RON97 fuel price in Malaysia spanning from January 2020 to May 2025 is a secondary data obtained from the official Malaysia's Official Open Data Portal. The dataset is structured as a univariate time series, comprising of 292 observations recorded at weekly intervals. For the purposes of model development, the dataset was first subjected to preprocessing to detect and address any missing values. The cleaned data were then divided into training and testing subsets according to conventional allocation schemes (90:10, 80:20, and 70:30) [13]. In this study, a ratio of 80/20 split was employed, with 80% of the observations reserved for in-sample training datasets and 20% for out-sample testing datasets. The testing dataset was subsequently used to evaluate and compare with the ron97 fuel price forecasts generated by each model.

2.2. Exponential Smoothing Model

The smoothing constants play a vital role in exponential smoothing models. For Single Exponential Smoothing (SES), the smoothing constant is denoted by alpha (α). Double Exponential Smoothing (DES) incorporates both alpha (α) and beta (β), whereas the Holt-Winters Exponential Smoothing model or Triple Exponential Smoothing (TES) utilizes alpha (α), beta (β), and gamma (γ). Selecting optimal values for these smoothing parameters is critical, as they directly influence the minimization of the error function and, consequently, the forecasting accuracy.

This study applies the Exponential Smoothing approach, specifically employing three variants: SES, DES, and Holt-Winters or TES. Model performance is assessed using the Root Mean Squared Error (RMSE), and the model with the lowest RMSE is identified as the best-fitting option.

2.3. Single Exponential Smoothing (SES) Model

The SES fitting procedure begins with the selection of an initial value, which serves as the foundation for recursive smoothing. The method for determining this initial point is outlined in Equation (1):

$$F_{t+1} = L_t = F_t + \alpha\left(v_t - F_t\right) = \alpha v_t + \left(1-\alpha\right)F_t, \tag{1}$$

where F_{t+1} represents the forecast for the upcoming period $t + 1$ which is the estimate of average level L_t at the end of period *t*. Here, v_t represents the observed data in period *t*, while α is the smoothing constant for level and constrained within the interval (0, 1), governs the degree of adjustment applied to the forecast. Conceptually, the updated forecast represents a revision of the previous estimate, moderated by a proportion of the forecast error. Alternatively, it can be interpreted as a weighted average between v_t, the most recent observation, and F_t, the prior forecasted level which thereby integrating new information with historical estimates to enhance predictive accuracy.

The level estimate, L_t (and the subsequent forecast F_{t+1}) can be expressed recursively as a function of all preceding demand observations, thereby capturing the evolving trend based on historical data. Consequently, F_{t+1} can be interpreted as a weighted average of all preceding demand values, where the weight assigned to each v_i is given by $\alpha\left(1-\alpha\right)^{t-i}$ with *t* representing the most recent time period. As *t* increases, the cumulative sum of these weights asymptotically approaches 1, ensuring the stability and consistency of the forecasting model. The formula for L_t can be expressed as Equation (2):

$$L_t = \sum_{i=1}^{t} \alpha\left(1-\alpha\right)^{t-i} v_i . \tag{2}$$

2.4. Double Exponential Smoothing (DES) Model

The Double Exponential Smoothing (DES) method enhances forecasting by directly smoothing both the level and the trend components using distinct smoothing parameters. In this context, the time series demonstrates a discernible trend, necessitating the estimation of both the level and the trend components. The forecast for the subsequent period in Equation (3), $t + 1$ can be expressed as follows:

$$F_{t+1} = L_t + T_t \,. \tag{3}$$

This approach offers greater flexibility in determining how rapidly changes in trend and slope are captured. Equation (4) presents the exponentially smoothed series, which resembles the formulation of Single Exponential Smoothing (SES), but includes an additional term for the trend component, T_{t-1}.

$$L_t = \alpha v_t + (1-\alpha)(L_{t-1} + T_{t-1}) \,. \tag{4}$$

The trend estimate, T_t, is derived from the difference between two consecutive smoothed values, specifically ($S_t - S_{t-1}$). Equation (5) presents the trend estimation process, where the difference between two successive smoothed values, ($L_t - L_{t-1}$) is scaled by the smoothing constant for trend estimate, *β*, that constrained within the interval (0, 1). This scaled value is then incorporated into the previous trend estimate, adjusted by the factor (1 − *β*).

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \,. \tag{5}$$

Since the smoothing is applied to the trend component rather than directly to the raw data, and in the absence of random fluctuations, the result is a more stable and smoothed representation of the underlying trend.

2.5. Holt-Winters Exponential Smoothing (TES) Model

The Holt-Winters method adheres to the structural framework of Holt's model, maintaining similar relationships between level and trend components. Equation (6) shows the forecast for the subsequent period, $t + 1$ that can be expressed as follows:

$$F_{t+1} = (L_t + T_t) S_{t-s+1} \,, \tag{6}$$

where L_t, T_t, and S_t are the level estimate, trend estimate and length of seasonality, respectively.

The level estimate in Holt-Winters presented in Equation (7) is now derived from the deseasonalized demand observed in period *t*, alongside the level estimate for the same period.

$$L_t = \alpha \frac{v_t}{S_{t-s}} + (1-\alpha)(L_t + T_{t-1}) \,. \tag{7}$$

The trend estimate is similar to DES method in Equation (5). While the seasonal index corresponding to the most recent period is updated based on the actual demand and the latest level estimate, shown in Equation (8). This revised index is subsequently utilized when the corresponding season recurs.

$$S_t = \gamma \frac{v_t}{L_t} + (1-\gamma) S_{t-s} \,. \tag{8}$$

Here, v_t are the observed values that include seasonality, while smoothing constant for level estimate, *α*, smoothing constant for trend estimate, *β*, and smoothing constant for seasonality estimate, *γ*, are all constrained within the interval (0, 1) respectively.

2.6. Forecasting Performance Evaluation

The evaluation of model performance is conducted using error metrics derived from out-of-sample data. To identify the most suitable forecasting model among Simple Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Holt-Winters Exponential Smoothing, the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) are employed as the primary criteria. Commonly utilized forecast error measures serve to assess the predictive accuracy of various methods and facilitate the selection of the optimal forecasting approach.

In this study, the model that yields the lowest RMSE and MAPE value on out-of-sample data is considered the most effective for forecasting RON 97 fuel price in Malaysia. The central objective is to generate fitted values corresponding to each value of the smoothing parameter α, and to compare these fitted values against the actual observations. Consequently, identifying the value of α that minimizes forecast error is essential for enhancing the accuracy of fuel price forecasting. The general formula for RMSE and MAPE are presented in Equation (9) and (10), respectively.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\hat{v}_t - v_t\right)^2}, \tag{9}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|\hat{v}_t - v_t\right|}{v_t}, \tag{10}$$

where v_t and $\hat{v}_t$ represent the empirical and theoretical value in time, while n denotes the number of forecast error terms.

3. Results and Discussion

Figure 1 shows a time series with trend analysis plot for the RON97 fuel price in Malaysia spanning from January 2020 to May 2025 with a total observation of 292 weekly data. The data are divided into 80% of training data and 20% of testing data for the in-sample and out-sample performance measure.

The graph demonstrates a downward trend in RON97 fuel prices, indicating a long-term decrease over the observed period. However, it does not exhibit any noticeable seasonal patterns or cyclical behaviour. To quantitatively confirm the absence of seasonality, the Seasonal Trend decomposition using Loess (STL) was performed and applied the Ljung-Box test on seasonal lags. The STL decomposition revealed a dominant trend component with minimal seasonal variation, and the Ljung-Box test yielded p-values > 0.05, indicating no significant autocorrelation due to seasonality.

This suggests that the price changes are not influenced by recurring time-based factors such as quarters, months, or seasons. Instead, the variations appear to be driven by external economic and geopolitical influences, such as currency exchange rates or policy decisions. The absence of seasonality implies that forecasting future prices would rely more on trend analysis and external variables rather than seasonal decomposition or time series models.

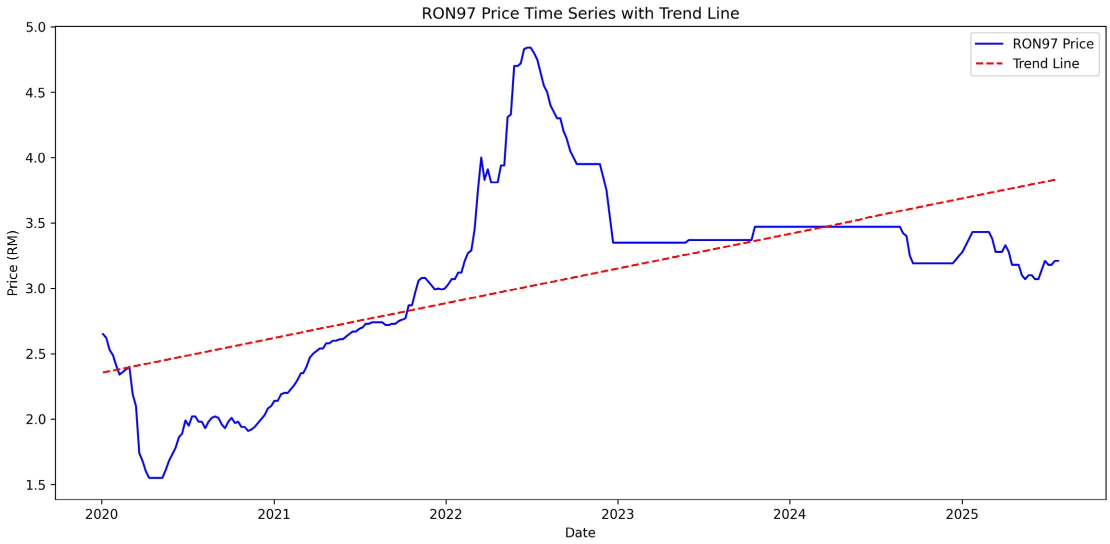

Figure 1. The time series and trend line plot of RON97 fuel price in Malaysia.

3.1. Optimal Smoothing Parameters

The determination of optimal parameters in exponential smoothing models is achieved through a sophisticated optimization process. This procedure systematically evaluates various parameter combinations by fitting the model to historical data and computing the resulting forecast errors. The smoothing parameters α, β, and γ were optimized using a grid search method implemented via Microsoft Excel Solver, while the search space was set between a range from 0.01 to 1.00 with a step size of 0.01. The set of parameters that collectively minimizes a specified error metric, which is the Root Mean Squared Error (RMSE), is then selected. This approach is to ensure that the model is calibrated to provide the most accurate forecasts possible for the given time series.

Table 1 listed the best-performing parameter values for three forecasting model, Single Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Holt-Winters Exponential Smoothing (TES). The parameters α, β, and γ represent the smoothing levels for level, trend, and seasonality, respectively. For SES, only α is used, and its optimal value is 0.01, indicating a very stable model that heavily relies on historical data. DES incorporates both α and β, with values of 0.1142 and 0.89, respectively, suggesting a model that moderately adapts to level changes but quickly adjusts to trend shifts. Holt-Winters includes all three parameters: $\alpha = 0.1142$, $\beta = 0.67$, and $\gamma = 0.505$, allowing it to capture level, trend, and seasonal patterns.

Despite Holt-Winters having the most comprehensive structure, performance metrics show that DES achieves a strong balance between responsiveness and accuracy, especially in trend-dominated data like fuel prices. Its high β value enables it to track rapid changes effectively, while the moderate α ensures stability. These parameter choices make DES a compelling model for forecasting RON97 prices, outperforming Holt-Winters in terms of simplicity and generalization, and SES in terms of trend sensitivity.

Table 1. Optimal smoothing parameters.

Model	Smoothing parameters			RMSE
	α	β	γ	
SES	0.0100	-	-	0.1313
DES	0.1142	0.89	-	0.1147
TES	0.1142	0.67	0.505	0.1240

3.2. Forecasting Performance Evaluation

The comparative evaluation of exponential smoothing models: SES, DES and Holt-Winters exponential smoothing listed in Table 2 reveals a significant difference in forecasting accuracy across in-sample and Table 3 across the out-sample datasets.

Table 2. Performance measure for in-sample data.

Model	In-sample data		
	RMSE	MAPE	Rank
SES	0.692	17.25	3
DES	0.200	4.93	1
TES	0.340	9.19	2

Table 3. Performance measure for out-sample data.

Model	Out-sample data		
	RMSE	MAPE	Rank
SES	0.1313	3.52	3
DES	0.1147	2.84	1
TES	0.1240	2.94	2

The DES model consistently outperforms the others, achieving the lowest RMSE and MAPE values in both data categories, which is 0.200 for in-sample RMSE and 0.1147 for out-sample RMSE, with 4.93 in-sample MAPE and 2.84 out-sample MAPE. This indicates the superior predictive capability and robustness of DES model. The Holt-Winters model follows closely, with RMSE values of 0.340 for in-sample and 0.1240 for out-sample, and MAPE values of 9.19 and 2.94 respectively, earning it the second rank. In contrast, the SES model demonstrates the highest error rates in both in-sample and out-sample RMSE and MAPE placing it third in both evaluations, suggesting limited effectiveness in capturing data trends.

To validate the robustness of the 80/20 train-test split, this study also tested a 70/30 configuration. The DES model maintained superior performance under this alternative split, achieving the lowest RMSE and MAPE values, thereby confirming its reliability across different data partitions.

The results highlight the effectiveness of the Double exponential smoothing model in capturing trend components without the complexity of seasonal adjustments. While Holt-Winters incorporates seasonality and performs better than the Single model, it does not surpass the Double model in this dataset context. These findings suggest that for datasets with minimal seasonal variation, the Double exponential smoothing model offers a more efficient and accurate forecasting approach. The consistent ranking across both in-sample and out-sample data further reinforces the reliability of the DES model for practical forecasting applications.

Figure 2 illustrates the in-sample and out-of-sample forecasts from 2020 to 2025, while Figure 3 presents the out-sample forecast comparisons for all three exponential smoothing models. Each method is evaluated based on its ability to track actual data trends. In Figure 2, the SES model shows limited responsiveness to changes, resulting in forecasts that lag behind actual data. The Holt-Winters or TES model, which incorporates seasonality, appears more dynamic but may introduce unnecessary complexity if seasonal patterns are not present. The model is overfitting as compared to the actual data. While DES model on the other hand, which accounts for trend but not seasonality, provides a balanced and accurate fit, closely aligning with actual data across both in-sample and out-of-sample periods.

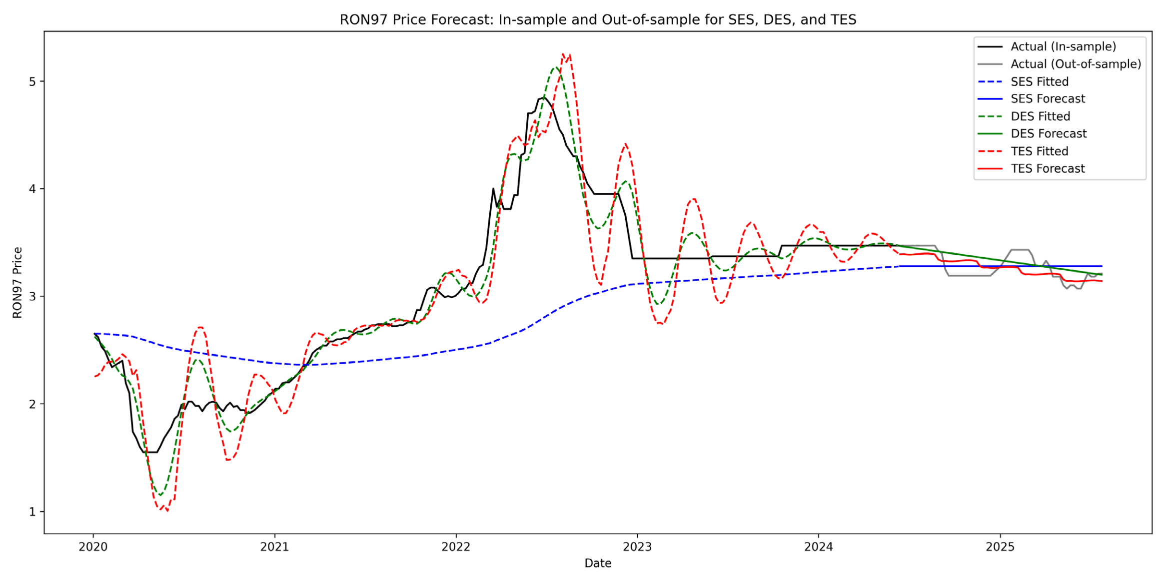

Figure 2. Comparisons of actual and in-sample and out-sample forecast using exponential smoothing models.

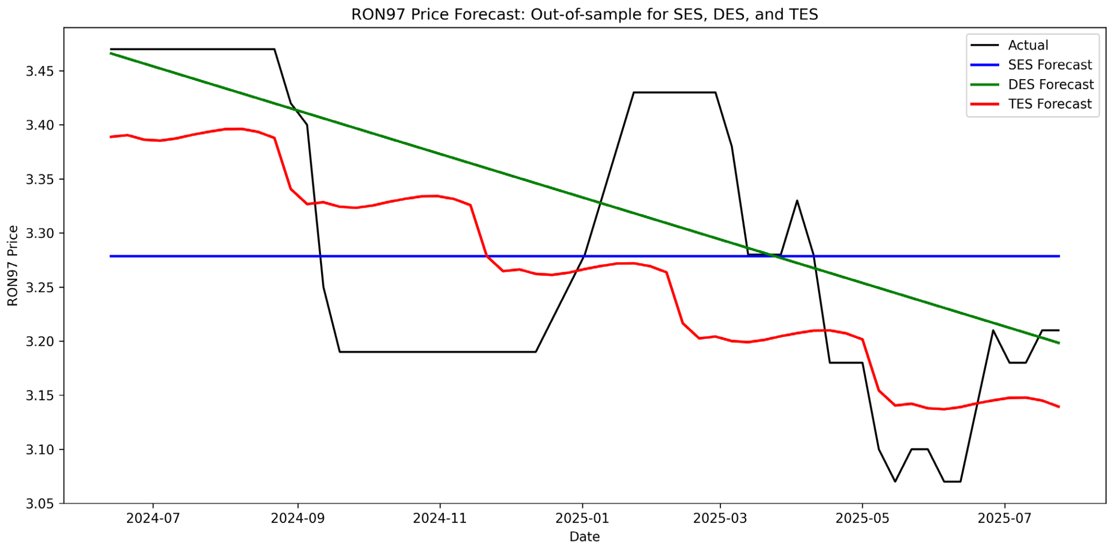

Figure 3. Performance comparison of exponential smoothing model for out-sample forecast.

Figure 3 depicted the performance comparison of out-sample forecasting for all the exponential smoothing models. The DES model forecast closely follows the actual data decreasing trend, outperforming SES model and matching the Holt-Winters or TES model in accuracy. However, since the dataset does not exhibit strong seasonal fluctuations, the added complexity of Holt-Winters or TES model does not yield significant improvements over DES model. This suggests that DES model is the most reliable model for this context, offering accurate forecasts without overfitting.

To evaluate the stability of the forecasting models, structural break tests were conducted using the Chow and Bai-Perron methodologies. Breakpoints were tested around key events such as the COVID-19 lockdown (March 2020) and major fuel subsidy policy changes (2022). A statistically significant breakpoint was identified around March 2020, corresponding with the onset of the COVID-19 lockdown. Despite this, the Double Exponential Smoothing (DES) model demonstrated consistent predictive accuracy across both pre- and post-break periods.

Furthermore, an ARIMA (1,1,0) model was employed as a benchmark model, selected based on the lowest AIC values. Although the ARIMA model effectively captured the underlying trend, its performance metrics, specifically RMSE and MAPE were relatively higher than the DES model, which is 0.3760 for RMSE and 17.49 for MAPE. This comparison thereby affirms the robustness and suitability of exponential smoothing for this dataset, specifically the DES model for short-term fuel price forecasting in trend dominated series.

In conclusion, the visual evidence supports the selection of Double Exponential Smoothing (DES) model as the most suitable and reliable forecasting method for datasets with trend but no seasonality. It strikes an optimal balance between simplicity and accuracy, making it ideal for short to medium-term forecasting in stable environments.

4. Conclusions

The primary objective of this study was to evaluate the effectiveness of exponential smoothing models in forecasting RON97 fuel prices, with a focus on identifying the most accurate model based on performance metrics. Scientific forecasting techniques were applied to ensure high precision in predicted values, aligning them closely with actual observations. Three exponential smoothing models: Simple Exponential Smoothing (SES), Double Exponential Smoothing (DES), and Holt-Winters or Triple Exponential Smoothing (TES) model were employed to capture different characteristics of the time series data, including level, trend, and seasonality.

A comparative analysis was conducted using RMSE and MAPE to determine the model that best represents the underlying structure of RON97 price movements. SES model was used to model stable price levels, DES model to capture linear trends, and Holt-Winters or TES model to incorporate seasonal fluctuations. The selection of these models was based on their proven applicability in time series forecasting.

This study contributes to the development of a reliable forecasting framework for fuel pricing in Malaysia. The presence of trend components in the data justified the use of DES and Holt-Winters models. The findings show that DES model, with optimized parameters ($\alpha = 0.1142$, $\beta = 0.89$), demonstrated strong performance, balancing simplicity and accuracy. Overall, DES is recommended as the most practical model for forecasting RON97 prices, offering reliable performance with minimal complexity. Holt-Winters model may be preferred in scenarios where seasonal patterns are prominent.

These findings provide valuable insights for policymakers and analysts in selecting appropriate forecasting techniques for fuel price modelling. Future research may explore hybrid models or incorporate external economic indicators to further enhance forecasting precision and support strategic decision-making in energy policy and pricing for fuel price in Malaysia.

Acknowledgements

The authors would like to acknowledge Centre for Research and Innovation Management of Universiti Teknikal Malaysia Melaka (UTeM) for financial funding under the Grant Tabung Insentif Penerbitan 2025 CRIM UTeM.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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