OJ-TP

JOURNAL OF SCIENCE AND TECHNOLOGY
ISSN: 2229-8460 e-ISSN: 2600-7924

Vol. 18 No. 1 (2026) 41-57
https://publisher.uthm.edu.my/ojs/index.php/jst

Forecast of Municipal Solid Waste Generation in Shah Alam Using Linear Trendline, Moving Average, Seasonal Naive, and Holt-Winters Additive Methods

Jamilah Mohd Ghazali[1]*, Adibah Shuib[2], Rossidah Wan Abdul Aziz[3]

[1] *Science and Mathematics Department, Centre for Diploma Studies, Universiti Tun Hussein Onn Malaysia UTHM), Pagoh Campus, 84600 Panchor, Muar, Johor, MALAYSIA*
[2] *College of Computing, Informatics and Mathematics, Universiti Teknologi MARA (UiTM), 40450 Shah Alam, Selangor, MALAYSIA*
[3] *School of Mathematical Sciences, College of Computing, Informatics and Mathematics (KPPIM), Universiti Teknologi MARA (UiTM), Seremban Campus, 70300 Seremban, Negeri Sembilan, MALAYSIA*

*Corresponding Author: jamilahg@uthm.edu.my
DOI: https://doi.org/10.30880/jst.2026.18.01.005

Article Info

Received: 2 October 2025
Accepted: 22 May 2026
Available online: 30 June 2026

Keywords

Municipal solid waste, forecasting, linear trendline, simple moving average, seasonal naive, holt-winters, mean absolute error, root mean square error, and mean absolute percentage error

Abstract

Shah Alam, a rapidly growing city in Selangor is experiencing a rise in municipal solid waste (MSW) generation, which poses challenges to sustainable urban management. This study analyses MSW generation patterns in Shah Alam for 2024 and 2025. This study forecast the MSW using four forecasting approaches, Linear Trendline, three-month Simple Moving Average (SMA), Seasonal Naive and the Holt-Winters Additive method, to forecast MSW generation in 2026. Monthly MSW data spanning 24 months (January 2024 to December 2025) from 56 collection zones in Shah Alam range from a minimum of 17,165 tons to a maximum of 22,328 tons. All four models were implemented in MATLAB. Forecast accuracy was assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results show that among the seasonal models, the Holt-Winters Additive method achieved a MAPE of 2.79%, representing a 14.41% improvement over the Seasonal Naive baseline. The Holt-Winters method is therefore selected as the most suitable forecasting approach, with a total MSW generation of approximately 281,710 tons forecasted for 2026. These results provide actionable insights for local authorities in strengthening MSW management infrastructure and developing long-term reduction strategies.

1. Introduction

Solid waste management is one of the major challenges influencing both the economic progress of a country and the well-being of its people. In Shah Alam, as one of the highest domestic waste producing cities in Selangor, municipal solid waste (MSW) generation is forecasted to rise due to population growth, yet challenges such as inefficient source separation and limited sustainable management practices persist [1]. The sector continues to face pressing issues such as inefficient collection systems, limited recycling practices, and growing environmental concerns [2]. Daily human activities remain the primary source of solid waste, which is classified by regulations into municipal, industrial, agricultural, and mining categories, and further categorized as hazardous or non-hazardous.

For this study, monthly MSW collection data from 56 zones in Shah Alam for the year 2024 and 2025 were obtained directly from KDEB Waste Management Sdn. Bhd. (KDEBWM) through their appointed officers. These official records provide a reliable basis for analysing MSW generation patterns at the local level. The data show the actual amounts of MSW collected across different zones, thereby reflecting real MSW generation trends in Shah Alam, one of the fastest developing cities in Selangor. Such volumes put increasing pressure on landfills, reducing their expected lifespan of 25 years [3], and contributing to issues such as soil and water contamination, air pollution, and general environmental degradation. For example, [4] reported that 29 rivers, or 4% of the national total, were polluted. Moreover, the location of landfills near residential areas exposes communities to health risks such as odour problems and the spread of vector-borne diseases from pests including rats, flies, and cockroaches [5].

Accurate forecasting of MSW growth has therefore become essential for sustainable MSW management in Malaysia. Reliable forecasts support infrastructure development, long-term planning, and resource allocation, while minimizing environmental impacts and ensuring public health. However, forecasting future MSW volumes is difficult, as the process involves dynamic variables such as urbanization, consumption patterns, and demographic changes [6]. Poor forecasts may result in under or over investment in facilities such as landfills, recycling centres, and treatment plants, leading to inefficiency and wasted resources.

Recent studies have shown an increasing application of sophisticated and hybrid forecasting techniques, especially machine learning [7] and artificial intelligence models. This is due to their potential to improve forecast accuracy [8]. However, such approaches often involve complex structures and high computational requirements, which may limit their interpretability and practical implementation [9]. Furthermore, evidence suggests that these complex models do not always yield significantly better performance than simpler statistical methods [10]. Therefore, there is still a need to re-examine the effectiveness of simple and interpretable time series methods, such as the Linear Trendline, three-month Simple Moving Average (SMA), Seasonal Naive and Holt-Winters models, especially when applied to real-world MSW data in Malaysia. Addressing this gap, the present study seeks to generate practical and reliable forecasts for 2026 using actual monthly MSW collection data from Shah Alam. The objectives of this study are threefold: to identify and understand patterns in MSW generation in Shah Alam over a 24-month period by using trend analysis with descriptive statistics, to predict MSW generation in Shah Alam for 2026 using Linear Trendline, three-month SMA, Seasonal Naive and Holt-Winters Additive methods, and to evaluate the accuracy of these forecasts through Mean Absolute Error (MAE) , Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), thereby enabling a comparison of forecasting performance. The remainder of this paper is structured as follows: The next section describes the data sources and forecasting methods employed. This is followed by the presentation and discussion of results. The paper concludes with a summary of the key findings and recommendations.

2. Methodology

In this study, a quantitative forecasting approach is applied to analyse MSW generation trends in Malaysia. The analysis begins with data collection, utilized 24 months of data collected from 56 zones in Shah Alam to forecast MSW generation for 2026. A longer and more reliable dataset generally reduces prediction errors, as past information provides better insights into future trends. This approach aligns with previous research, such as [11], who also employed historical time-series data spanning from 1987 to 1998. The author used parameter estimates from each preceding year to generate predictions through both quarterly and annual data analysis.

In line with the first objective, trend analysis using descriptive statistics is applied to identify and understand patterns in MSW generation over the 24-month period using Microsoft Excel. The analysis examined monthly fluctuations relative to the annual mean, deviations from the mean, percentage variation, and classification of MSW generation levels to detect temporal and seasonal patterns. In addition, a Linear Trendline and coefficient of determination (R^2) are used to assess the presence or absence of long-term growth trends in MSW generation. Subsequently, four forecasting methods, the Linear Trendline, three month-SMA, Seasonal Naive and Holt-Winters Additive, are employed to forecast MSW generation up to 2026. All models are implemented in MATLAB, where the Linear Trendline model estimates future values based on the overall upward trend in the data, while the three-month SMA model generates forecasts by averaging the three most recent observations. The Holt-Winters Additive model produces smoothed components of level, trend, and seasonality to generate forecasted MSW values, whereas the Seasonal Naive method serves as a benchmark by repeating observed values from the corresponding month in the previous year [12]. To evaluate the reliability of the forecasts, the MAE, RMSE, and MAPE are calculated, providing a quantitative measure of model accuracy. Finally, the results of the descriptive trend analysis and the forecasting analysis, including the identified MSW patterns, the forecasted MSW values, and the accuracy of each model, are synthesized and interpreted in relation to the research objectives.

J. of Science and Technology Vol. 18 No. 1 (2026) p. 41-57

2.1 Trend Analysis Using Descriptive Statistics

Descriptive statistical techniques are employed to analyse the MSW generation patterns in Shah Alam over a 24-month period. Measures such as the mean, deviation from the mean, percentage variation, and coefficient of determination (R^2) are used to summarize the monthly MSW generation data and identify temporal trends, fluctuations, and seasonal variations. Descriptive statistics are widely used to summarize datasets and facilitate the observation of patterns and trends in MSW generation [13]. The analysis is conducted using Microsoft Excel, which is a practical and reliable tool for data organization, computation, statistical analysis, and data visualization [14].

For each month, the actual MSW collected (in tons) is compared with the overall mean value for each respective year. The deviation from the mean is calculated to measure the magnitude of difference, while the percentage variation is used to standardize comparisons across months. These values are then categorized into three classifications: Above Average, Below Average, and Normal. This classification framework helps in identifying temporal MSW generation patterns, such as months with significantly higher or lower MSW volumes than the average. Such descriptive insights are important to complement forecasting analysis, as they reveal short-term fluctuations and provide a clearer understanding of seasonal or irregular waste generation behaviour [15].

2.2 Forecasting Methods

This section introduces the forecasting techniques applied in the study. Four methods are selected: Linear Trend, three-month SMA, Seasonal Naive and the Holt-Winters Additive. Linear Trend and the three-month SMA approaches belong to the class of classical time series forecasting methods often cited for their simplicity and effectiveness in capturing growth or trend behaviour [16]. The Seasonal Naive method is a classical benchmark approach, while the Holt-Winters Additive belongs to the exponential smoothing family of time series forecasting methods [17]. The methods are detailed in the following subsections.

2.2.1 Linear Trendline

The Linear Trendline method was employed as a non-seasonal benchmark to forecast monthly MSW generation for 2026. In the model, the independent variable x represents the month index ($1-24$ for training), while the dependent variable y denotes the total MSW collected in tons. A linear regression line was fitted to the training data. The fitted model takes the general form shown in Equation 1.

$$y = mx + b \tag{1}$$

In this equation, the parameter m indicates the average monthly rate of change in MSW generation, which shows the rate of change in y with respect to x, as expressed in Equation 2.

$$m = \frac{n\,(\sum xy) - (\sum x)(\sum y)}{n(\sum x^2) - (\sum x)^2} \tag{2}$$

The parameter b represents the y - intercept, which is the value of y when $x = 0$. It is computed using the formula shown in Equation 3.

$$b = \frac{\sum y - m(\sum x)}{n} \tag{3}$$

In this expression, n denotes the number of data points, while the summation symbol Σ indicates the total of all values. Here, x and y represent the individual observations in the dataset. The model equation was then used to forecast MSW generation for subsequent months beyond the observed period, corresponding to $x = 25-36$ (January - December 2026).

2.2.2 Simple Moving Average

The SMA technique smooths fluctuations in historical data by averaging values over a fixed period [18]. A three-month SMA is applied as a non-seasonal benchmark. For this research, this method is applied to highlight the general direction of MSW growth while minimizing the effect of irregular variations. The use of SMA helps to present a clearer trend of long-term waste generation patterns in Malaysia. The SMA serves as a common technique for smoothing data trends. It is obtained by computing the arithmetic mean of a sequence of values across a specified interval. Equation 4 illustrates the formula used for the SMA in this study.

$$SMA = \frac{\sum_{i=1}^{n} x_i}{n} \tag{4}$$

In this context, n represents the number of periods, refers to the 24 monthly intervals of MSW collection data from Shah Alam in 2024 and 2025, as expressed in Equation 5.

$$SMA = \frac{x_{t-2} + x_{t-1} + x_t}{3} \tag{5}$$

x_t denotes the observed value of the time series corresponding to period t.

2.2.3 Seasonal Naive

The Seasonal Naive method serves as a simple seasonal baseline. This method generates forecasts by repeating the observed value from the same month in the previous seasonal cycle, making it a straightforward benchmark for seasonal time series data. This method is widely used as a benchmark model for seasonal time series due to its simplicity and transparency [19]. A similar formulation has also been applied in recent empirical studies such as [20], where monthly forecasts are based on observations from the same month in the previous year. The forecast equation is expressed as shown in Equation 6.

$$\hat{y}_{T+h} = y_{T+h-s} \tag{6}$$

where $\hat{y}_{T+h}$ denotes the forecasted MSW value (in tons) at forecast horizon h, y_{T+h-s} is the actual observed MSW value (in tons) from the same month in the previous year, T is the last time point in the training data, h is the forecast horizon (number of months ahead being forecast, where $h = 1, 2, 3, \ldots, 12$ for January to December 2026), and s is the seasonal period, which is set to $s = 12$ for monthly data. For the out-of-sample test period (September - December 2025), the forecast for each test month h was computed directly from the training data as shown in Equation 7. A four-month sample was used to maintain adequate training data while enabling independent out-of-sample forecast validation, consistent with practices in short time series forecasting evaluation [17].

$$\hat{y}_{n+h} = y_{n_{\text{train}}-s+h} \tag{7}$$

where $y_{n_{\text{train}}-s+h}$ is the observed value from the same month one year prior within the training set, and $n_{\text{train}} = 20$ is the number of months in the training period. For the 2026 forecast, the model was applied to the full 24-month dataset, where each monthly forecast repeats the corresponding observed value from 2025, as expressed in Equation 8.

$$\hat{y}_{n+h} = y_{n-s+h} \tag{8}$$

where y_{n-s+h} is the observed MSW value (in tons) from the same month in 2025, $n = 24$ is the total number of observed data points, and $h = 1, 2, 3, \ldots, 12$ corresponds to January through December 2026. This approach requires no parameter estimation and serves as a practical baseline for evaluating the performance of more sophisticated forecasting methods.

2.2.4 Holt-Winters Additive

The Holt-Winters Additive method is an exponential smoothing technique designed for time series data exhibiting both trend and seasonal components [19]. The model decomposes the series into three components: level (L_t),

J. of Science and Technology Vol. 18 No. 1 (2026) p. 41-57

trend (T_t), and seasonal index (S_t), updated recursively using three smoothing parameters: α (level), β (trend), and γ (seasonal). The equations are as shown in Equation (9) - (11).

$$L_t = \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{9}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{10}$$

$$S_t = \gamma(y_t - L_t) + (1-\gamma)S_{t-s} \tag{11}$$

Equation (9) updates the level component by combining the current observation after removing seasonal effects with the previous level adjusted by the trend. The parameter α determines the weight assigned to the most recent observation, where a higher value places greater emphasis on recent data. Equation (10) updates the trend component based on the change between the current and previous level values. The smoothing parameter β controls how quickly the trend adapts to changes, with smaller values producing a smoother trend. Equation (11) updates the seasonal component by capturing repeating patterns within each seasonal cycle. The parameter γ regulates the rate at which the seasonal pattern is updated over time. The h-step-ahead forecast is given in Equation (12).

$$\hat{y}_{T+h} = L_T + hT_T + S_{T+h-s} \tag{12}$$

where s denotes the seasonal period (12 months in this study). This equation shows that the future value is obtained by combining the final estimated level, the projected trend over h periods, and the corresponding seasonal effect. The level provides the baseline at time T, the trend extends this baseline into the future, and the seasonal component adjusts the forecast according to the recurring monthly pattern. In this study, the smoothing parameters were set as $\alpha = 0.2$, $\beta = 0.1$, and $\gamma = 0.2$. According to [19], the Holt-Winters model employs these three smoothing parameters, which are constrained within the interval [0,1]. The initial values were determined using a standard approach, where the initial level was estimated as the mean of the first seasonal cycle. The initial trend was computed based on the difference between successive cycle averages, while the initial seasonal indices were obtained as deviations from the initial level. The model was first fitted using a 20-month training dataset (January 2024 - August 2025) with a seasonal period of $s = 12$ months, to generate out-of-sample forecasts over a 4-month test period (September - December 2025) for model validation. Upon confirming satisfactory forecast accuracy, the model was subsequently refitted using the full 24-month dataset (January 2024 - December 2025) to produce a 12-month ahead forecast for the year 2026.

2.3 Accuracy Metrics

To evaluate the reliability of the forecasting results, three accuracy metrics are employed: MAE, RMSE, and MAPE. These metrics are widely used in time series forecasting to measure the deviation between observed and forecasted values, with lower values indicating higher accuracy [21]. The formulae are presented in Equations (13), (14), and (15) respectively.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{13}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{14}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \quad (15)$$

where y_i represents the actual MSW value (in tons) collected from KDEBWM for each month of the test period, $\hat{y}_i$ is the forecasted MSW value generated by the Seasonal Naive and Holt-Winters Additive methods, and n is the number of observations in the test set ($n = 4$). MAE measures the average magnitude of errors in the same unit as the data. RMSE assigns greater penalty to larger errors due to the squaring of residuals. MAPE expresses the error as a percentage of the actual value, enabling intuitive interpretation of model accuracy regardless of data scale. The method with the lowest values across all three metrics is considered the most accurate for forecasting MSW generation in 2026.

3. Results and Discussion

In this section, the outcomes of the forecasting analysis are presented, focusing on three key aspects. First, the results of the descriptive statistical trend analysis are presented. The second segment highlights the Linear Trendline, three-month SMA, Seasonal Naive and Holt-Winters Additive forecast results, as well as the predictive performance of these techniques in estimating MSW generation based on historical data. The third segment evaluates the MAE, RMSE, and MAPE results of all forecasting approaches to determine their accuracy and reliability for future MSW generation predictions.

3.1 Trend Analysis of Municipal Solid Waste Generation

The descriptive statistical analysis of MSW generation in Shah Alam for 2024 reveals distinct temporal patterns characterized by interspersed with seasonal deviations. As presented in Table 1, the annual mean MSW generation stood at 18,070.21 tons per month, with monthly values ranging from 17,164.83 tons in September to 19,100.93 tons in January, yielding a variation range of 1,936.10 tons. Monthly deviations from the mean exhibited three distinct classification patterns. Seven months fell within the normal classification range of ±3% variation, including March, April, July, August, October, November and December. However, significant positive deviations were recorded in January and May. January's peak can be attributed to post new year disposal activities, when households typically generate more MSW from packaging materials, decorations, and food residues, while May's elevation aligns with Hari Raya Aidilfitri celebrations, which result in substantial increases in food waste, packaging materials, and household discards. These patterns are consistent with [22], who highlighted that temporal factors such as festive and holiday periods significantly influence variations in MSW generation.

Conversely, three months demonstrated negative deviations: February, June, and September marking the lowest monthly MSW generation. These troughs may reflect post festive recovery periods or shifts in domestic consumption during school holidays. The presence of such seasonal variations aligns with findings in prior studies by [23], where the authors mentioned that the timing of seasons and temporal factors significantly impact waste generation.

Table 1 *Monthly MSW generation data, deviations, and classification for Shah Alam, 2024*

Month	Actual Data (tons)	Deviation from Mean	Percentage Variation (%)	Classification
January	19,100.93	1030.72	5.70	Above Average
February	17,385.29	-684.92	-3.79	Below Average
March	18,253.29	183.08	1.01	Normal
April	17,806.10	-264.11	-1.46	Normal
May	18,926.55	856.34	4.74	Above Average
June	17,354.55	-715.66	-3.96	Below Average
July	18,504.11	433.90	2.40	Normal
August	17,804.25	-265.96	-1.47	Normal
September	17,164.83	-905.38	-5.01	Below Average

Month	Actual Data (tons)	Deviation from Mean	Percentage Variation (%)	Classification
October	18,153.08	82.87	0.46	Normal
November	17,910.20	-160.01	-0.89	Normal
December	18,479.36	409.15	2.26	Normal

The low coefficient of determination (R^2 = 0.0285) indicates the absence of significant long-term growth, suggesting that MSW generation in this municipality remains relatively stable across the annual cycle, where low R^2 values in environmental and social datasets reflect high variability rather than a complete lack of significance [24],[25]. The MSW generation pattern demonstrates that above average months constitute only 16.67% of the annual cycle, while below average months represent 25%, with the majority maintaining normal generation levels. This characteristic is typical of mature urban areas with stable populations, where MSW generation responds primarily to consumption patterns driven by festive calendars and holiday cycles rather than population growth or economic expansion [26].

Table 2 *Monthly MSW generation data, deviations, and classification for Shah Alam, 2025*

Month	Actual Data (tons)	Deviation from Mean	Percentage Variation (%)	Classification
January	19892.76	-1082.42	-5.16	Below Average
February	17872.33	-3102.85	-14.79	Below Average
March	21528.34	553.16	2.64	Normal
April	21054.53	79.35	0.38	Normal
May	21569.77	594.59	2.83	Normal
June	20550.55	-424.63	-2.02	Normal
July	21963.83	988.65	4.71	Above Average
August	20638.32	-336.86	-1.61	Normal
September	21027.3	52.12	0.25	Normal
October	22327.75	1352.57	6.45	Above Average
November	21010.14	34.96	0.17	Normal
December	22266.57	1291.39	6.16	Above Average

The descriptive statistical analysis of MSW generation in Shah Alam for 2025 indicates an increase compared to 2024, reflecting the continued effects of urbanisation and rising consumption patterns. As shown in Table 2, the monthly average in 2025 was 20,975.18 tons, with values ranging from 17,872.33 tons in February to 22,327.75 tons in October, resulting in a wider variation range of 4,455.42 tons than in 2024. Monthly deviations from the mean show three patterns. Seven months (March, April, May, June, August, September, and November) fall within the normal range. Three months, July (4.71%), October (6.45%), and December (6.16%) are classified as above average, likely due to increased household activity during school holidays and higher consumption during year-end festive periods. These patterns are consistent with [22], who emphasised the role of seasonal factors in MSW variation. In contrast, January (-5.16%) and February (-14.79%) fall under below average, with February showing the largest deviation across both years, possibly due to reduced post-festive consumption [23]. The coefficient of determination for 2025 (R^2 = 0.3676) is higher than in 2024 (R^2 = 0.0285), indicating a stronger linear relationship in the 2025 data. The positive slope of the trendline suggests a moderate upward trend. This observation is consistent with findings by [27] and [28], which associate MSW growth with urban expansion.

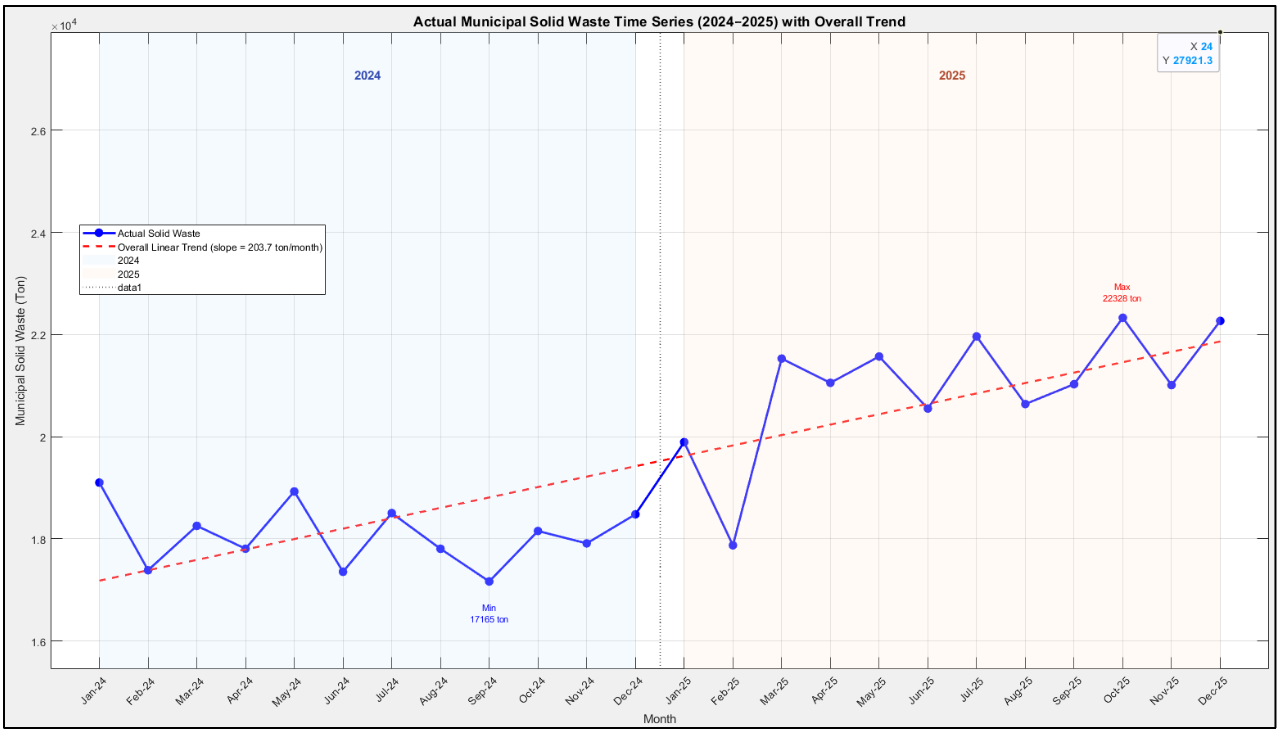

Fig. 1 *Actual municipal solid waste time series (2024–2025) with overall trend*

Fig. 1 provides a visual representation of the 24-month MSW time series for Shah Alam. The figure illustrates the upward shift in MSW generation from 2024 to 2025, with 2025 monthly values consistently exceeding those of the corresponding months in 2024 from March onward. The total MSW in 2025 reached 251,703 tons, an increase of 16.1% from 216,841 tons in 2024, highlighting the need for accurate multi-year forecasting in MSW management planning.

3.2 Linear Trendline Forecasting Results

The linear trend model fitted to the full 24-month training dataset data produced the regression equation shown in Equation 16.

$$y = 203.7x + 16{,}976.46 \tag{16}$$

where y represents the monthly MSW in tons and x is the month index (1 – 24). The slope of 203.70 tons per month indicates that MSW generation in Shah Alam increased at an average rate of approximately 203.70 tons per month over the two-year observation period. The intercept b = 16,976.46 represents the baseline level of MSW when x = 0. Using this equation, monthly forecasts for 2026 (January – December; x = 25 – 36) were generated. Table 2 presents the monthly Linear Trendline forecasts for 2026.

Table 3 *Linear trendline forecast for MSW generation*

Month	Linear Trendline Forecast (tons)
December	22,069
February	22,273
March	22,476
April	22,680
May	22,884
June	23,087
July	23,291
August	23,495
September	23,699
October	23,902
November	24,106
December	24,310
Annual Total	**278,271**

The forecasted values ranged from 22,069 tons in January 2026 to 24,310 tons in December 2026, indicating an increasing pattern of MSW generation. This progressive increase reflects the positive slope of the model and produces an increasing forecast trend. For visualization of the trend, Fig. 2 illustrates the comparison between the actual MSW data and the Linear Trendline forecasts.

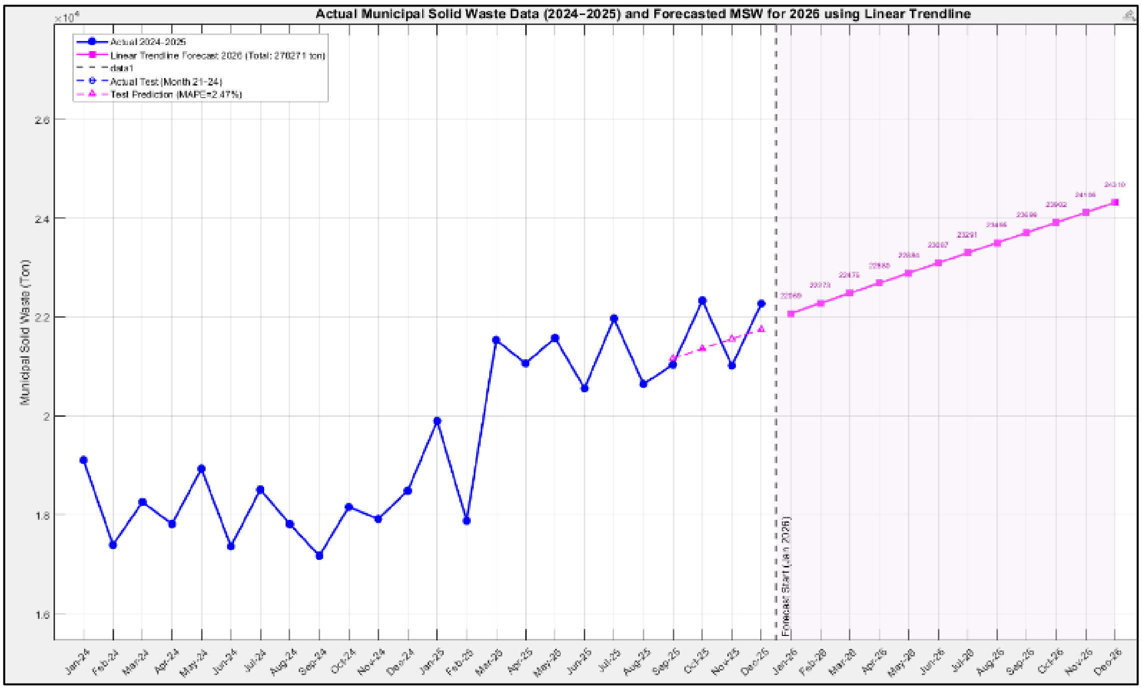

Fig. 2 *Actual municipal solid waste data (2024–2025) and forecasted MSW for 2026 using linear trendline*

The results suggest that the Linear Trendline method provides a simplified forecast of MSW generation. As shown in Fig. 2, the Linear Trendline produces a uniformly rising forecast that follows direction of the historical data. The comparison between the 2024-2025 actual data and the 2026 forecast highlights the actual MSW values showed wide variations that were likely influenced by seasonal, operational, or behavioral factors such as festive seasons, changes in collection efficiency, and population behavior [29]. By contrast, the Linear Trendline used in the forecasting process smooths out these fluctuations, producing more stable estimates. This makes the forecast useful as a benchmark reference, although it tends to underestimate peak months and overestimate low months [30]. In summary, while the Linear Trendline method provides a straightforward forecast of MSW generation, showing a stable pattern around 23,189 tons per month in 2026 with an upward slope, it may oversimplify the dynamics of MSW generation, since traditional forecasting methods often struggle to capture the complex patterns and fluctuations inherent in real-world time series data [16].

3.3 Simple Moving Average Forecasting Results

The SMA method is an approach for smoothing out short-term fluctuations and highlighting longer-term trends in a time series [31]. A three-month period SMA was selected for this forecast. The selection of a three-month window is common for monthly data as it effectively captures recent trends without over-smoothing, thus providing a responsive yet stable forecast [32]. The resulting forecasts are presented in Table 4, with an annual total of approximately 262,233 tons.

Table 4 *Three-month SMA forecast for MSW generation*

Month	SMA Forecast (tons)
January	21,868
February	21,715
March	21,950
April	21,844
May	21,836
June	21,877
July	21,853
August	21,855
September	21,862
October	21,856
November	21,858
December	21,859
Annual Total	**262,233**

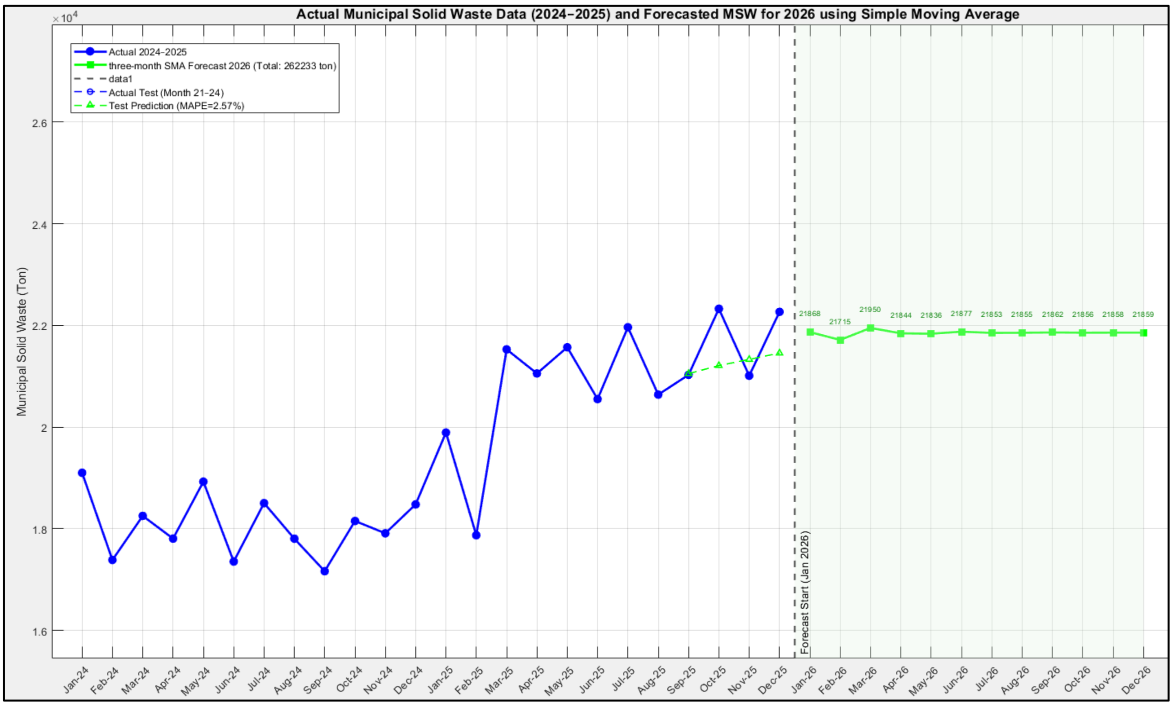

Fig. 3 *Actual municipal solid waste data (2024–2025) and forecasted MSW for 2026 using SMA*

J. of Science and Technology Vol. 18 No. 1 (2026) p. 41-57

Fig. 3 illustrates the application of the SMA method to forecast MSW generation in 2026 produced values that are consistent, with forecasts clustering around 21,853 tons per month. This outcome reflects the inherent nature of SMA, which smooths short-term variability by averaging recent observations [33]. Unlike the Linear Trendline method, which imposes a directional trend across time, the SMA approach prioritizes local patterns, effectively reducing the "noise" observed in the 2024-2025 dataset [34]. As a result, the forecasts present a stable pattern that is easy to interpret and apply for short-term planning purposes. However, the SMA technique, which is based solely on recent observations and excludes seasonal effects, often fails to reflect actual fluctuations in waste generation. As a result, temporary surges during festive periods or reductions arising from operational changes in collection practices are not adequately represented. While the SMA method provides ease of application and short-term stability, it remains limited in capturing long-term structural changes or pronounced seasonal variations in municipal solid waste generation [35]. Overall, the SMA provides a practical and straightforward forecasting tool that balances simplicity with moderate accuracy.

3.4 Seasonal Naive Forecasting Results

The Seasonal Naive forecast for 2026, presented in Table 5, was constructed by carrying forward the corresponding monthly values from 2025 in accordance with Equation 8.

Table 5 *Seasonal naive forecast for MSW generation*

Month	Seasonal Naive Forecast (tons)
January	19,893
February	17,872
March	21,528
April	21,055
May	21,570
June	20,551
July	21,964
August	20,638
September	21,027
October	22,328
November	21,010
December	22,267
Annual Total	**251,702**

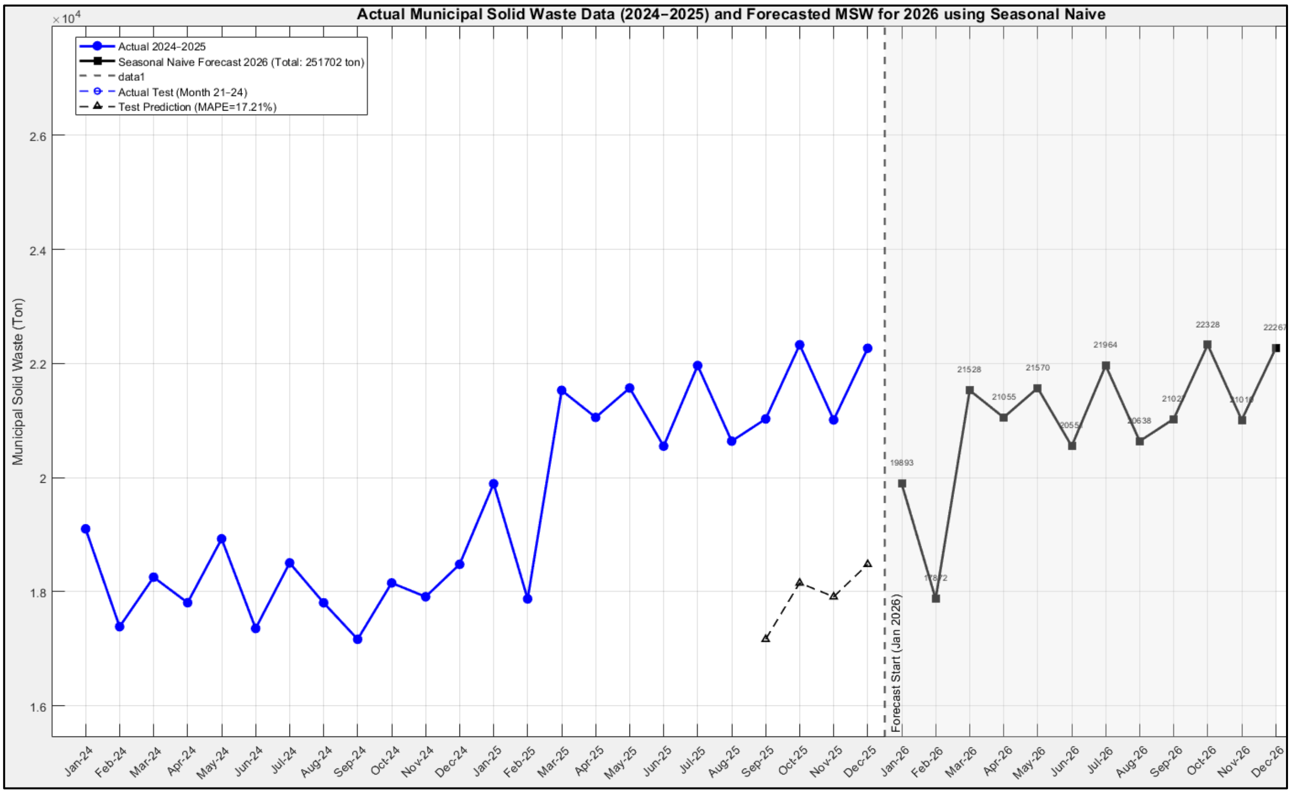

Fig. 4 *Actual municipal solid waste data (2024–2025) and forecasted MSW for 2026 using seasonal naive*

As illustrated in Fig. 4, the Seasonal Naive forecast replicates the seasonal shape observed in 2025, preserving month-to-month peaks. However, since the method carries forward the 2025 values without any trend correction, it systematically underestimates 2026 MSW generation. Given that the data exhibit a consistent monthly growth rate of approximately 203.70 tons per month, forecasting 2025 values directly into 2026 ignores one full year of accumulated growth. Seasonal Naive forecasts are useful for benchmarking models and are commonly employed as baseline methods for evaluating forecasting performance [36].

3.5 Holt-Winters Additive Forecasting Results

The Holt-Winters Additive model was trained on months 1–20 with smoothing parameters $\alpha = 0.2$, $\beta = 0.1$, and $\gamma = 0.2$ [19]. The 2026 monthly forecasts generated by this model are presented in Table 6, with an annual total of approximately 281,710 tons.

Table 6 *Holt-winters additive forecast for MSW generation*

Month	Holt-Winters Additive Forecast (tons)
January	23,286
February	21,712
March	23,231
April	22,888
May	24,036
June	22,711
July	24,052
August	23,402
September	23,112
October	24,305
November	24,046
December	24,930
Annual Total	**281,710**

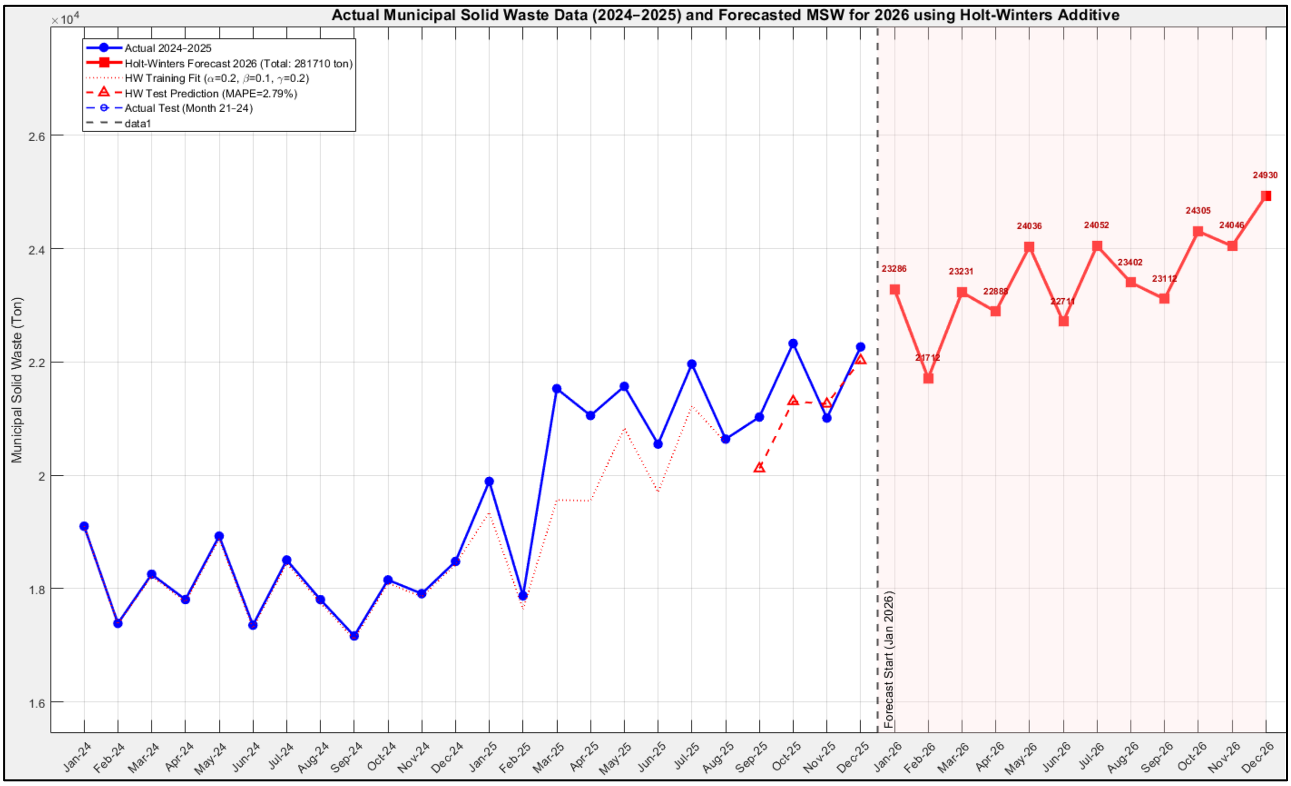

Fig. 5 *Actual municipal solid waste data (2024–2025) and forecasted MSW for 2026 using Holt-Winters additive*

The Holt-Winters Additive forecast, illustrated in Fig. 5, produces a 2026 forecast that reflects both the upward trajectory of the data and the recurring seasonal pattern. February 2026 records the lowest forecasted monthly volume at 21,712 tons, reflecting the lower MSW generation period prior to the festive season, consistent with the seasonal variation characteristics commonly observed in MSW generation patterns [37]. December 2026 yields the highest forecasted volume at 24,930 tons, reflecting accumulated trend growth combined with the seasonal elevation characteristic of the year-end period. Festive-related months such as May 2026 (24,036 tons), July 2026 (24,052 tons), and October 2026 (24,305 tons) also record elevated forecasted values, mirroring the seasonal peaks identified in the historical data and reflecting increased consumption activities during holiday periods [38]. The annual total of 281,710 tons represents an increase of approximately 30,007 tons (11.9%) over the 2025 actual total of 251,703 tons, reflecting the sustained growth trajectory of MSW generation in Shah Alam, which is consistent with the increasing MSW generation trend reported in Malaysia due to urbanisation, population growth, and changing consumption patterns [39].

3.6 Accuracy Evaluation

The forecasting performance of all four models was evaluated using the four-month out-of-sample testing period (September to December 2025). Three error metrics were used: MAE, RMSE, and MAPE. The results are summarised in Table 7.

Table 7 *Forecast accuracy metrics for out-of-sample testing (September-December 2025)*

Model	MAE (tons)	RMSE (tons)	MAPE (%)	Seasonal
Linear Trendline	541.053	618.086	2.47	No
Three month-SMA	568.506	709.208	2.57	No
Seasonal Naive	3,731.07	3,751.64	17.21	Yes
Holt-Winters Additive	605.358	705.974	2.79	Yes

The Holt-Winters Additive model achieved a MAE of 605.358 tons, an RMSE of 705.974 tons, and a MAPE of 2.79%, while the Seasonal Naive model recorded larger errors, with a MAE of 3731.072 tons, an RMSE of 3751.637 tons, and a MAPE of 17.21%. The Linear Trendline model produced the lowest overall errors, with a MAE of 541.053 tons, an RMSE of 618.086 tons, and a MAPE of 2.47%, followed closely by the three-month SMA model with a MAE of 568.506 tons, an RMSE of 709.208 tons, and a MAPE of 2.57%. Although the Linear Trendline model recorded the smallest forecasting errors, it does not account for seasonal fluctuations in the MSW data. Similarly, the three-month SMA model produced relatively low errors but tends to smooth the data excessively, causing the forecasts to react more slowly to changes in the data pattern. In addition, the SMA model does not explicitly incorporate seasonality [40],[41].

Based on the guideline by [21], a MAPE value below 10% indicates high forecasting accuracy. Therefore, the Holt-Winters model can be considered accurate, whereas the Seasonal Naive model demonstrates relatively poor predictive performance. The large difference in error values can be explained by the limitations of the Seasonal Naive approach. Since each forecast is based solely on the value from the same month in the previous year, the model is unable to capture the upward trend observed between 2024 and 2025. As a result, all forecasts for the testing period underestimate the actual observed values. In contrast, the Holt-Winters model updates its level and trend components throughout the training process. This allows the model to adapt to the increasing pattern in the data and produce forecasts that are closer to the observed values. The RMSE results further support this finding. The lower RMSE value for the Holt-Winters model indicates not only smaller average errors but also fewer large deviations. This is particularly important in MSW management planning, where large forecasting errors may lead to inefficient resource allocation, insufficient capacity planning, and suboptimal collection operations [42]. Overall, based on all three-evaluation metrics, the Holt-Winters Additive model is identified as the more reliable approach for forecasting MSW generation in Shah Alam. Its forecasts for 2026 are therefore more suitable for supporting future MSW management planning decisions.

4. Conclusion

This study analysed MSW generation in Shah Alam and applied four forecasting methods, the Linear Trendline, three month-SMA, Seasonal Naive and Holt-Winters Additive, using 2024 and 2025 data from 56 collection zones. Results showed that the Linear Trendline and three-month SMA models produced relatively low forecasting errors but were limited in capturing seasonal variation in the data. Results showed that the Holt-Winters Additive model provided significantly higher accuracy, making it suitable for forecasting under seasonal variation with an upward trend. The findings indicate that simple models like Seasonal Naive cannot capture trend and thus produce poor forecasts when the data shows consistent growth. This research provides a baseline reference for Shah Alam's MSW management and underlines the need for integrating advanced time-series approaches in future studies to improve forecasting precision and sustainability outcomes.

Acknowledgement

The authors would like to express sincere gratitude to the Centre for Diploma Studies, Universiti Tun Hussein Onn Malaysia (UTHM), for providing the necessary facilities and support to conduct this research. The authors also acknowledge KDEBWM for their valuable contribution in providing the data used in this study.

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Jamilah Mohd Ghazali;* ***data collection:*** *Jamilah Mohd Ghazali, Adibah Shuib, Rossidah Wan Abdul Aziz;* ***analysis and interpretation of results:*** *Jamilah Mohd Ghazali, Adibah Shuib, Rossidah Wan Abdul Aziz;* ***draft manuscript preparation:*** *Jamilah Mohd Ghazali;* ***revision of manuscript****: Jamilah Mohd Ghazali*

References

[1] Bazrbachi, A., Sidique, S. F., Adam, S. U., Ismail, N. W. B., & Sheng, T. Y. (2023). Assessing the measurement model for source-separating waste for recycling under a proposed smart waste management scheme in shah alam, Malaysia. *Recycling*, *8(4)*, 58, https://doi.org/10.3390/recycling8040058

[2] Abd Manaf, L., Samah, M. A. A., & Zukki, N. I. M. (2009). Municipal solid waste management in Malaysia: Practices and challenges. *Waste Management, 29(11)*, 2902-2906, https://doi.org/10.1016/j.wasman.2008.07.015

[3] Bernama (2023). Cultivate recycling practices from a young age. New Straits Times. Retrieved on 15 March 2026 from https://www.nst.com.my/amp/news/nation/2023/03/889326/cultivate-recycling-practices-young-age

[4] Department of Environment Malaysia. (2023). 29 polluted rivers identified in 2022. *MalaysiaNow*. Retrieved on 25 September 2025 from https://www.malaysianow.com/news/2023/06/13/29-polluted-rivers-identified-in-2022

[5] Norsa'adah, B., Salinah, O., Naing, N. N., & Sarimah, A. (2020). Community health survey of residents living near a solid waste open dumpsite in Sabak, Kelantan, Malaysia. *International journal of environmental research and public health, 17(1)*, 311, https://doi.org/10.3390/ijerph17010311

[6] Chen, F., Zhang, S., Liang, Y., & Yin, A. (2023). Spatiotemporal Variability in Municipal Solid Waste Production and the Determinants in Hefei's Core Urban Districts. *Sustainability, 15(22)*, 16058, https://doi.org/10.3390 /su152216058

[7] Latif, S. D., Hazrin, N. A. B., Younes, M. K., Ahmed, A. N., & Elshafie, A. (2024). Evaluating different machine learning models for predicting municipal solid waste generation: a case study of Malaysia. *Environment, Development and Sustainability, 26(5)*, 12489-12512.

[8] Hasri, H., Aris, S. A. M., Ahmad, R., & Shahnaz, C. (2023). COVID-19 Confirmed Cases Forecasting in Malaysia Using Linear Regression and Holt's Winter Algorithm. *International Journal of Integrated Engineering*, *15*(3), 64-72.

[9] Sawalha, S., & Al-Naymat, G. (2025). An Adaptive Holt-Winters Model for Seasonal Forecasting of Internet of Things (IoT) Data Streams. *IoT*, *6*(3), 39.

[10] Trull, O., García-Díaz, J. C., & Peiró-Signes, A. (2024). Msf, a forecasting library to predict short-term electricity demand based on multiple seasonal time series. *Journal of Computational Science*, *78*, 102280.

[11] Brown, L. D. (2001). How important is past analyst forecast accuracy? *Financial Analysts Journal, 57(6)*, 44-49, https://doi.org/10.2469/faj.v57.n6.2492

[12] Beck, N., Dovern, J., & Vogl, S. (2025). Mind the naive forecast! A rigorous evaluation of forecasting models for time series with low predictability. *Applied Intelligence, 55*, 395. https://doi.org/10.1007/s10489-025-06268-w

[13] Omotayo, A. O. (2024). Investigating the drivers of solid waste generation and disposal: evidence from South Africa. *Environment, Development and Sustainability*, 1-33, https://doi.org/10.1007/s10668-024-04987-7

[14] Divisi, D., Di Leonardo, G., Zaccagna, G., & Crisci, R. (2017). Basic statistics with Microsoft Excel: a review. *Journal of thoracic disease, 9(6)*, 1734, http://dx.doi.org/10.21037/jtd.2

[15] Fontaine, L., Morau, D., & Praene, J. P. (2022). Analysis and Estimation of Short-Term Residual Household Waste Production: Case Study Reunion Island. *Sustainability, 15(1)*, 348, https://doi.org/10.3390/su15010348

[16] Kolambe, M., & Arora, S. (2024). Forecasting the future: A comprehensive review of time series prediction techniques. *Journal of Electrical Systems, 20(2s)*, 575-586.

[17] Svetunkov, I., & Boylan, J. E. (2024). Local and global trend Bayesian exponential smoothing models. *International Journal of Forecasting*, https://doi.org/10.1016/j.ijforecast.2024.03.002

[18] Wibawa, A. P., Utama, A. B. P., Elmunsyah, H., Pujianto, U., Dwiyanto, F. A., & Hernandez, L. (2022). Time-series analysis with smoothed Convolutional Neural Network. *Journal of big Data, 9(1)*, 44, https://doi.org/ 10.1186/ s40537-022-00599-y

[19] Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and practice* (3rd ed.). OTexts. Retrieved on 17 March 2026 from https://otexts.com/fpp3/

[20] Athanasopoulos, G., Hyndman, R. J., Kourentzes, N., & O'Hara-Wild, M. (2023). Probabilistic forecasts using expert judgment: The road to recovery from COVID-19. *Journal of Travel Research, 62(1),* 233-258.

[21] Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting, 22*(4), 679–688. https://doi.org/10.1016/j.ijforecast.2006.03.001

[22] Firmansyah, F., Park, I., Corona, M., Aphale, O., Ahuja, A., Johnston, M., & Tonjes, D. J. (2024). Variation in municipal solid waste generation and management across time and space. *Resources, Conservation and Recycling, 204*, 107472, https://doi.org/10.1016/j.resconrec.2024.107472

[23] Lan, Q., Guo, H., & Cai, T. (2025). Modeling municipal solid waste generation in Macao: A synthetic approach. *Chinese Journal of Sociology, 11(1)*, 101-120, https://doi.org/10.1177/2057150X241312987

[24] Effrosynidis, D., Spiliotis, E., Sylaios, G., & Arampatzis, A. (2023). Time series and regression methods for univariate environmental forecasting: An empirical evaluation. *Science of The Total Environment, 875*, 162580, https://doi.org/10.1016/j.scitotenv.2023.162580

[25] Ozili, P. K. (2023). The acceptable R-square in empirical modelling for social science research. *In Social research methodology and publishing results: A guide to non-native English speakers*, 134-143, http://dx. doi.org /10.2139/ssrn.4128165

[26] Villanueva, I. A., Ibáñez, J. L., & Palmer, J. R. M. (2013). Municipal solid waste generation in mature destinations: An IPAT-type model for Mallorca. *Economía agraria y recursos naturales, 13(1)*, 69-93, https: //doi.org/10.22004/ag.econ.152823

[27] Voukkali, I., Papamichael, I., Loizia, P., & Zorpas, A. A. (2024). Urbanization and solid waste production: prospects and challenges. *Environmental Science and Pollution Research, 31*, 17678-17689. https://doi.org/10.1007/s11356-023-27670-2

[28] Lu, M., & Kempes, C. P. (2024). Worldwide scaling of waste generation in urban systems. *Nature Cities, 1*, 126-135, https://doi.org/10.1038/s44284-023-00021-5

[29] Firmansyah, F., Park, I., Corona, M., Aphale, O., Ahuja, A., Johnston, M., & Tonjes, D. J. (2024). Variation in municipal solid waste generation and management across time and space. *Resources, Conservation and Recycling, 204*, 107472, https://doi.org/10.1016/j.resconrec.2024.107472

[30] Anichebe, I. B., Ekwue, A. O., & Obe, E. S. (2024). Time-series trendline and curve-fitting-based approach to short-term electricity demand forecasting. *International Journal of Applied Power Engineering (IJAPE), 13(1)*, 81-90, https://doi.org/10.11591/IJAPE.V13.I1.PP81-90

[31] Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: principles and practice. *OTexts*.

[32] Nau, R. (2014). Forecasting with moving averages. *Fuqua School of Business, Duke University,* 1-3.

[33] Šomplák, R., Smejkalová, V., Rosecký, M., Szásziová, L., Nevrlý, V., Hrabec, D., & Pavlas, M. (2023). Comprehensive review on waste generation modelling. *Sustainability, 15(4)*, 3278, https://doi.org /10.3390/su15043278

[34] Hasan, M. M., Ng, K. T. W., Ray, S., Assuah, A., & Mahmud, T. S. (2024). Prophet time series modelling of waste disposal rates in four North American cities. *Environmental Science and Pollution Research, 31(21)*, 31343-31354, https://doi.org/10.1007/s11356-024-33335-5

[35] Cruz-Nájera, M. A., Treviño-Berrones, M. G., Ponce-Flores, M. P., Terán-Villanueva, J. D., Castán-Rocha, J. A., Ibarra-Martínez, S., & Laria-Menchaca, J. (2022). Short time series forecasting: Recommended methods and techniques. *Symmetry, 14(6)*, 1231, https://doi.org/10.3390/sym14061231

[36] Strøm, E., & Gundersen, O. E. (2024). Performance metrics for multi-step forecasting measuring win-loss, seasonal variance and forecast stability: an empirical study: E. Strøm and OE Gundersen. *Applied Intelligence, 54*(21), 10490-10515.

[37] Ooi, J. K., Woon, K. S., & Hashim, H. (2021). A multi-objective model to optimize country-scale municipal solid waste management with economic and environmental objectives: A case study in Malaysia. *Journal of Cleaner Production, 316*, 128366.

[38] Ooi, J. K., & Woon, K. S. (2021). Simultaneous Greenhouse Gas Reduction and Cost Optimisation of Municipal Solid Waste Management System in Malaysia. *CET Journal-Chemical Engineering Transactions, 83.*

[39] Devadoss, P. M., Agamuthu, P., Mehran, S. B., Santha, C., & Fauziah, S. H. (2021). Implications of municipal solid waste management on greenhouse gas emissions in Malaysia and the way forward. *Waste Management*, *119*, 135-144.

[40] Haeri, H., Beal, C. E., & Jerath, K. (2020). Near-optimal moving average estimation at characteristic timescales: An allan variance approach. *IEEE Control Systems Letters*, *5*(5), 1531-1536.

[41] Puindi, A. C., & Silva, M. E. (2021). Dynamic structural models with covariates for short-term forecasting of time series with complex seasonal patterns. *Journal of Applied Statistics, 48*(5), 804-826.

[42] Alhathlaul, N., Lakhouit, A., Abdalla, G. M., Alghamdi, A., Shaban, M., Alshahir, A., & Mutlaq Alshammari, F. (2025). Assessing Waste Management Using Machine Learning Forecasting for Sustainable Development Goal Driven. *Sustainability*, *17*(19), 8654.