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Enhancing PETRONAS share price forecasts: a hybrid Holt integrated moving average

Nurin Qistina Mohamad Fozi[1], Nurhasniza Idham Abu Hasan[1], Azlan Abdul Aziz[2], Siti Meriam Zahari[3], Mogana Darshini Ganggayah[4]
[1]College of Computing, Informatics and Mathematics, Universiti Teknologi MARA Perak Branch, Tapah, Malaysia
[2]College of Computing, Informatics and Mathematics, Universiti Teknologi MARA Perlis Branch, Arau, Malaysia
[3]College of Computing, Informatics and Mathematics, Universiti Teknologi MARA Selangor, Shah Alam, Malaysia
[4]School of Business, Monash University Malaysia, Selangor, Malaysia

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ABSTRACT

Understanding the variations in PETRONAS share price over time is important for improving the forecast accuracy of PETRONAS share prices to provide stakeholders with reliable analyses for future market predictions. Therefore, the main objective of this study is to improve the accuracy of PETRONAS share price by utilizing a hybrid Holt method with the moving average (MA) from the Box-Jenkins model. Holt's method will address linear trends for non-stationary data, while MA will analyze residual aspects of the data. This combination transforms non-stationary data into stationary by removing noise and averaging out fluctuations. The secondary data used in this study consists of daily observation from bursa Malaysia, the official national stock exchange of Malaysia, covering the period from January 3, 2000, to October 2, 2023. The study encompasses both low and high share price scenarios. The models' performance was compared using various error metrics across different training and testing splits. The findings highlight that the proposed hybrid [Holt–MA] model called Holt integrated moving average (HIMA) improves the accuracy of forecasting model with the smallest errors for both daily low and high share price. The HIMA model demonstrates significant potential, particularly in reducing residuals and improving prediction accuracy.

Corresponding Author:

Nurhasniza Idham Abu Hasan
College of Computing, Informatics and Mathematics, Universiti Teknologi MARA Perak Branch
35400, Tapah Road, Perak Darul Ridzuan, Malaysia
Email: nurhasniza@uitm.edu.my

1. INTRODUCTION

Petroliam Nasional Berhad, known as PETRONAS is Malaysia's foremost integrated oil and gas enterprise and has become a major player in the global energy sector. This sector operates within a milieu shaped by fluctuations in international oil prices, geopolitical complexities, technological advancements, and sustainability imperatives [1]. The share price of PETRONAS encapsulates the cumulative impact of these diverse factors, serving as a reflection not only of the company's financial performance but also of broader trends within the energy sector. Given its fundamental role in underpinning the nation's economic framework, the volatility of PETRONAS' share price holds significant ramifications for Malaysia's financial markets and broader economic stability [2]. The interplay of these factors, combined with the company's strategic initiatives and financial performance, contributes to the intricate mosaic of its market valuation [3]. As Malaysia positions itself as a regional energy hub, PETRONAS share price is not only reflective of its performance but is also emblematic of the broader trends and challenges facing the energy sector in the Asia-Pacific region [4]. Accurate forecasting of the share price of PETRONAS is a complex undertaking that requires a nuanced understanding of the unique dynamics at play within the energy sector, as well as the broader economic context in Malaysia [5], [6]. The objective of this study is unravelling the time series patterns inherent in PETRONAS share price, forecast future trends through time series techniques, and critically assess the accuracy of these forecasting methodologies.

Forecasting the PETRONAS share price has become increasingly important for energy planning. The primary goals include establishing appropriate pricing and taxation frameworks, assisting in potential investments and decision-making regarding oil reserves to enhance energy security, facilitating the early resolution of emission and contamination issues, enabling the provision of future energy demands, and identifying national infrastructure and energy requirements. Accurate forecasting supports strategic planning and policy-making, ensuring a stable and secure energy future [7]. Given the importance of oil to the economy, projecting PETRONAS share prices has received a lot of focus in the literature. The decision on when to drill and how much to hedge is based on forecasting, which is inherently an imperfect science. This is especially true for the oil industry, a global sector characterized by widely inconsistent data [8]. Inaccurate forecasts with upside or downside bias can affect profit loss, with downside bias causing higher losses due to lower predicted prices [9]. Past forecasting approaches are crucial for understanding why petroleum share prices are difficult to predict [10]. Therefore, a study on forecasting PETRONAS share price has become essential.

There are many methods for investigating the PETRONAS share price. The most common forecasting model is the traditional Holt method [11]. Muchayan [12] used the traditional Holt method to formulate a forecasting model, determining which method provides more accurate predictions for net asset value (NAV) price movements from January 1, 2019, to January 1, 2020. The study found that the traditional Holt method outperformed the other benchmark models, which produced the least error. Another study conducted by Bogar and Gungor [13] found that the traditional Holt method was superior to other models for forecasting the quantity of waste mobile phones (WMP) in Turkey. The study found that the Holt method can accurately predict future data points where the trend is either increasing or decreasing at a constant rate. Furthermore, Shukor *et al.* [14] discovered that the traditional Holt method is the most accurate forecasting method for the stock market prices of crude oil and platinum, utilizing monthly data from January 2000 to December 2016. It is evident that the traditional Holt method remains a relevant and widely used forecasting method today. However, due to the potential limitation of the traditional Holt method, such as sensitivity to parameter selection "α and β", the assumption of a linear trend in time series falls short when dealing with data that exhibits strong seasonal patterns, tend to overestimate or underestimate, especially in long-term forecasts and handling of structural changes [15], [16], [17].

Recognizing these shortcomings, Gardner and McKenzie [18] introduced the damped trend method (DTM) in 1985, which includes a dampening factor to reduce the impact of trends over time. However, this method still struggles to outperform other smoothing methods consistently and still falls short of achieving optimal forecast accuracy [19]. Therefore, this study is conducted to improve the accuracy performance of PETRONAS share prices by combining the traditional Holt method with the moving average (MA) from the Box-Jenkins model. The Holt method effectively captures linear trends and handles trends for non-stationary data. The purpose of MA in this hybrid model is the capability of MA to analyze residuals that exist in the data being studied. Besides that, MA helps correct errors by adjusting past forecast errors and, at the same time, improve the percentage accuracy of model predictions [20], [21]. This combination transforms non-stationary data into stationary data by removing noise and averaging out fluctuations [22]. Other than that, the other purpose of this study is to contribute to the existing body of knowledge, providing stakeholders with a robust analytical foundation for anticipating future market movements. The insights generated from this research are expected to empower investors, analysts, and policymakers with the knowledge necessary to navigate the challenges and opportunities presented by the evolving energy landscape in Malaysia.

This research article is structured as follows: section 1 provides the background of the study, its objectives, and an overview of traditional methods alongside the hybrid Holt integrated moving average (HIMA) model. Section 2 reviews previous works by other researchers in the field. Section 3 offers a detailed description of the Holt method, DTM, and autoregressive moving average (ARIMA) model, along with the construction process of the HIMA model. Section 4 discusses the results, and section 5 concludes the study.

2. LITERATURE REVIEW

Most of the researchers suggest a hybrid model that produces more robust and enhanced forecasting accuracy [23]. Besides, Shetty and Ismail [24] indicated that the performance of hybrid forecasting models is better than any traditional or benchmark models. A lot of work has been conducted regarding the combination of the traditional model with other models, such as neural networks, which can be found in the literature. The ultimate focus of the development of this hybrid model is to yield a more accurate forecasting model with the least error percentage. Several hybrid models have been implemented in previous studies for Holt method. Haque *et al.* [25] proposed a modified Holt's method for short-term forecasting modification that uses time series data from 1991 to 2013 and forecasts for five consecutive years from 2014 to 2018. It incorporates recent trend values as a weight parameter and previous trends. As a result, the modified method yields forecast values closer to actual values, with forecast values slightly higher and more aligned with observed data. The study concludes the new hybrid method provides a more accurate and reliable estimate of real values. Mohammed [26] suggested a new hybrid model for time series forecasting called AR-Holt (p+5) to enhance prediction accuracy and robustness. This model combines the Holt method with the autoregressive (AR) model. The performance of the AR-Holt (p+5) model is better than other methods, which Yule-Walker, Burg, residual auto-covariance (RA), least squares, modified covariance, and least median squares (LMS) methods.

Moreover, Egrioglu and Baş [27] introduced a modified Holt's linear trend method based on particle swarm optimization (PSO) to improve forecasting accuracy. The study used simulated data sets with linear and quadratic trends, as well as real-world data from the Istanbul stock exchange, consisting of two different time series observed daily between February 1, 2009 to May 29, 2009, and April 1, 2010 to May 31, 2010. The method updates trends and values and incorporates second-order update formulas. Consequently, the study concludes that the proposed method outperforms the traditional Holt's method in terms of forecasting performance. Besides, Liu and Wu [28] introduced a modified Holt's exponential smoothing (MHES) method for predicting housing prices. This method adjusts historical data weights and smoothing parameters based on sample size. Housing price data from Kunming, Changchun, Xuzhou, and Handan spanning January 2015 to August 2019 were utilized. Comparative analysis revealed that the newly developed whale optimization algorithm - modified Holt's exponential smoothing (WOA-MHES) method exhibited superior performance over conventional models "backpropagation neural network (BPNN), (grey model (GM) (1,1)), and ARIMA," demonstrating reduced prediction errors and faster computation times. These findings highlight the applicability of the new hybrid model in forecasting for housing price market investors and policymakers.

Furthermore, some of the previous studies discussed hybrid models for ARIMA. The research by Ravichandran *et al.* [29] aimed to forecast the yield and productivity of food grains within the agricultural sector through the application of time-series analysis. The dataset in that study encompasses time series data on the production and yield of various oilseed crops spanning from 1950-51 to 2015-16. The study employs a hybrid methodology that integrates autoregressive moving average (ARIMA) models with artificial neural networks (ANN) as (ARIMA-ANN) model. The findings demonstrate that the ARIMA-ANN hybrid model outperforms the individual ARIMA and ANN models in terms of accuracy and effectiveness. Echevarria and Aranas [30] employed consumer price index (CPI) data from the Philippines and its regions for the year 2022, utilizing a hybrid ARIMA-ANN approach to enhance CPI forecasting accuracy. As a result, the hybrid ARIMA-ANN models consistently surpassed standalone ARIMA models, delivering more precise and reliable forecasts over an extended period. Overall, the results of the previous studies showed that the hybrid model was able to increase the prediction's accuracy in many applications, making it a potential candidate for time series forecasting analysis.

3. METHOD

This research aims to compare the performance of the traditional Holt method, DTM, ARIMA, and a new hybrid traditional Holt and moving average called HIMA model employing time-series analysis to forecast the low and high PETRONAS share prices. Data analysis was performed using R programming and Excel. Figure 1 presents a schematic representation of the research flow of this study.

The research methodology comprises five distinct stages. It begins with exploratory data analysis (EDA), a critical phase for summarizing the primary features of the time series data. This stage involves detecting trend patterns, outliers, and missing values in the dataset [31]. The data is then cleaned, and incomplete entries are addressed by removing missing values [32]. Subsequently, the complete dataset is divided into two subsets: training and testing. This partitioning is important for assessing the model's performance. The partitioning strategy relies on time series cross-validation to enhance the accuracy of forecast values, as illustrated in Figure 2.

Figure 2 presents the partitioning of a full dataset into five distinct sets, each with varying proportions of training and testing subsets. In set 1, 99% of the data is allocated for training and 1% for testing, while in set 2, 95% is used for training and 5% for testing. Set 3 assigns 90% to training and 10% to testing, set 4 follows with 80% for training and 20% for testing, and set 5 allocates 70% of the data to training and 30% to testing. This progressive partitioning approach supports cross-validation by allowing model evaluation across different training and testing ratios [33], [34], [35]. Table 1 presents the distribution summary of the training and testing sets for daily high and low PETRONAS share prices across five distinct sets.

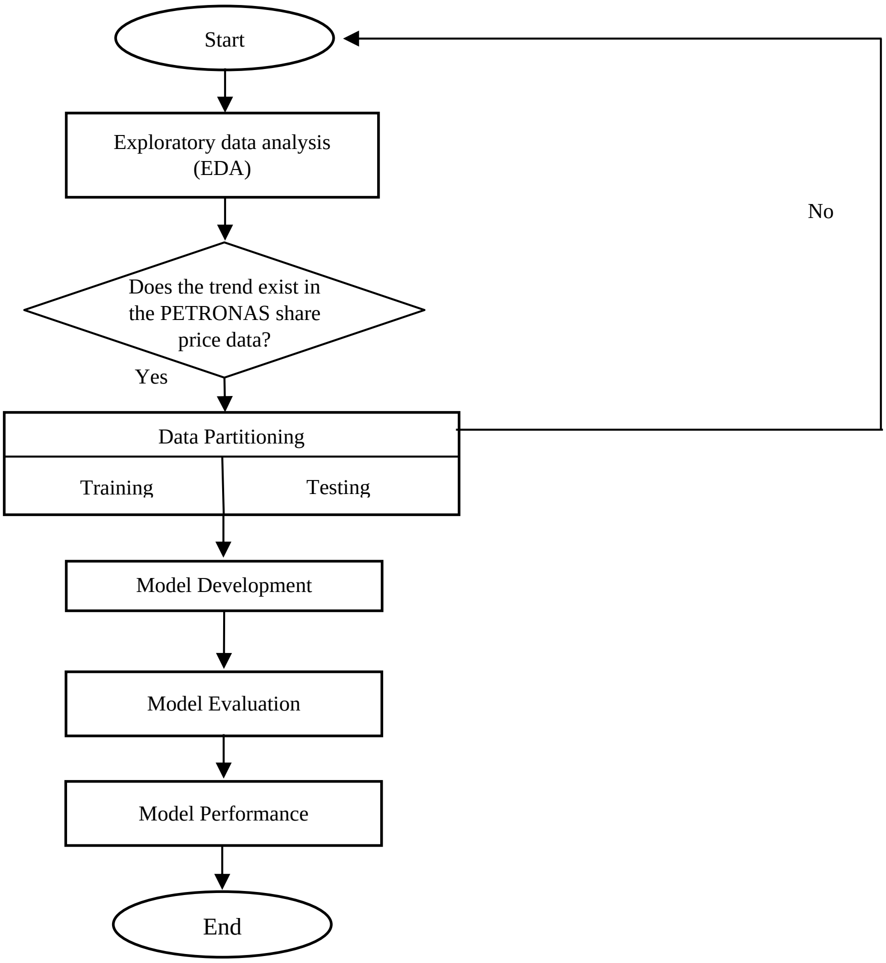


Figure 1. Research framework of this study

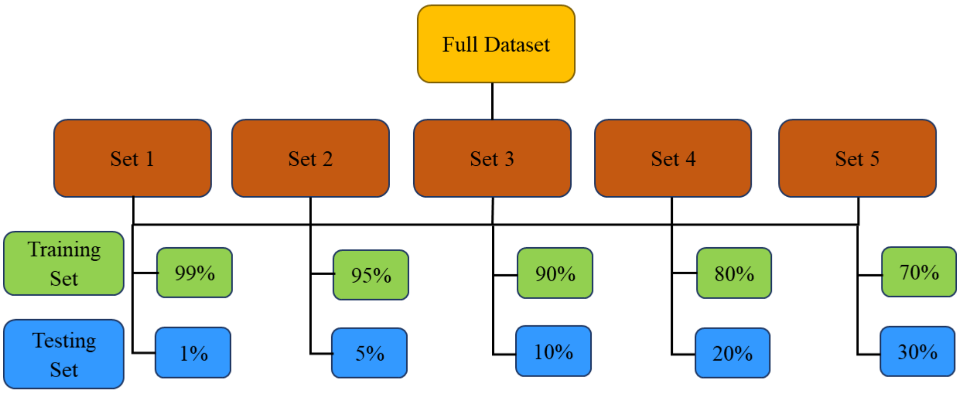


Figure 2. Data split of time series cross-validation

The dataset is divided into training and testing sets across five configurations, each varying in the proportion of data allocated for training and testing. These configurations differ in terms of duration and sample size, designed to assess the robustness and reliability of the predictive model across diverse scenarios. The secondary data utilized in this study comprises daily observations from bursa Malaysia, the national stock exchange of Malaysia, spanning the period from January 3, 2000 to October 2, 2023. The analysis includes both low and high-share price scenarios. Out of the original 5,943 datasets, two observations contain missing values, resulting in a final total of 5,941 datasets. This final dataset will be divided according to the five different configuration sets as illustrated in Table 1. The next phase involves the development of a hybrid Holt and moving average (MA) model. In this phase, five data configurations are employed to assess the accuracy of PETRONAS share price predictions by comparing the traditional model with the proposed model. Figure 3 illustrates the model development process of the HIMA model.

Table 1. Testing and training set for daily high and low

Set	Data partition	Percentage (%)	Duration	Sample size
Set 1	Training	99	January 3, 2000 – July 4, 2023	5,882
	Testing	1	July 5, 2023 – October 2, 2023	61
Set 2	Training	95	January 3, 2000 – July 8, 2022	5,644
	Testing	5	July 12, 2022 – October 2, 2023	299
Set 3	Training	90	January 3, 2000 – April 20, 2021	5,347
	Testing	10	April 21, 2021 – October 2, 2023	596
Set 4	Training	80	January 3, 2000 – November 21, 2018	4,753
	Testing	20	November 22, 2018 – October 2, 2023	1,190
Set 5	Training	70	January 3, 2000 – July 1, 2016	4,159
	Testing	30	July 4, 2016 – October 2, 2023	1,784

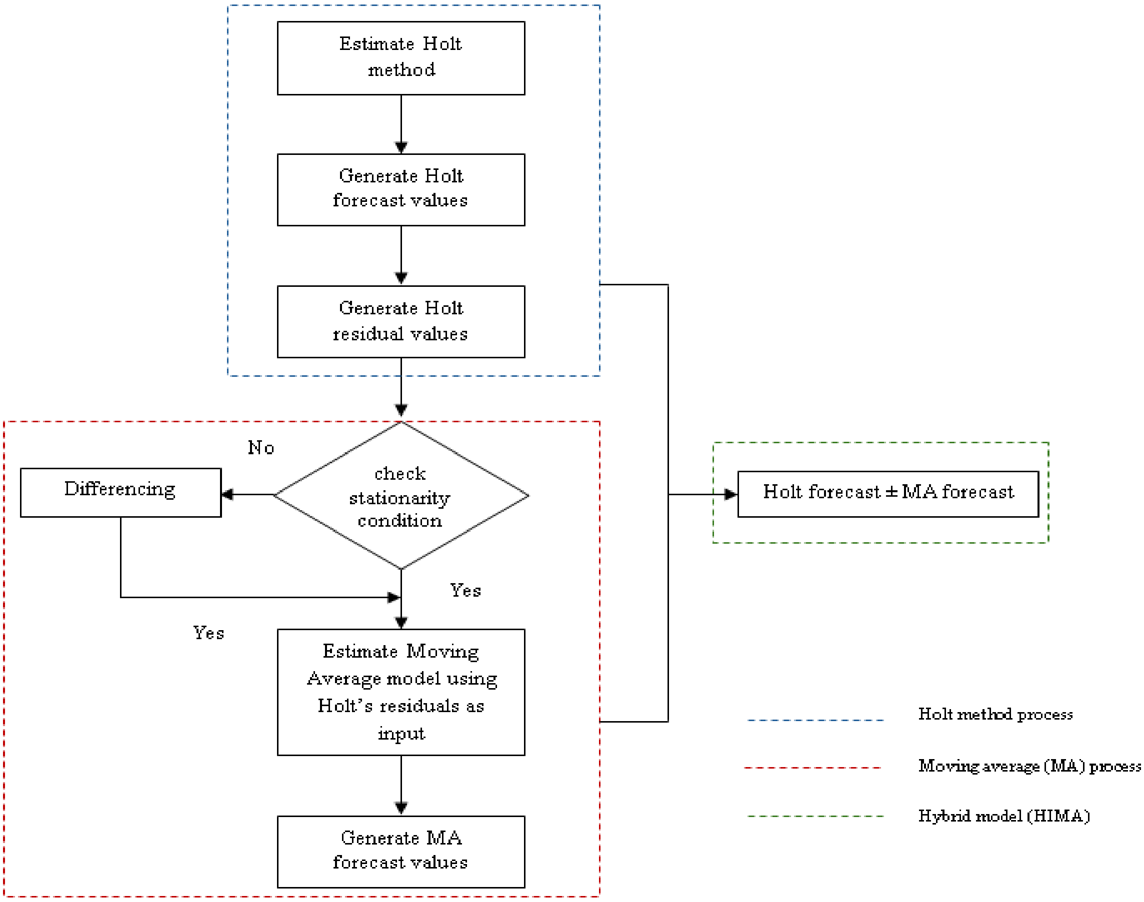


Figure 3. Model development of HIMA

The proposed model development starts with estimating two equations, which are level and trend as stated in (2) and (3), respectively. Then, the forecast value in (1) will be generated. The Holt residual values, which represent the differences between the actual data and the forecasted values, are also calculated as represented in (12). Later, the Holt residual will be used in the MA process. To ensure the residual can be used for the MA process, the assumption of the stationary needs to be checked. A stationary series is a series that fluctuates randomly around some fixed values (mean variance or any constant value) [36]. If the assumption is violated, a differencing process will be applied [37]. The MA model is estimated using the Holt residuals as input. The MA forecast values are then generated as in (11). Finally, the hybrid model combines the Holt and MA forecasts to produce the final output, either by adding or subtracting to produce the final forecasted values [Holt ± MA] as in (13).

3.1. Traditional methods

The implementation and evaluation of forecasting techniques, including the traditional or existing methods such as the Holt method, DTM, and ARIMA model. Further details are discussed in the next subsections

3.1.1. Holt method

Holt [38], [39] developed the Holt method in 1957, which enhanced simple exponential smoothing to predict data with a trend.

$$\text{Forecast: } F_{t+m} = S_t + T_t \times m \tag{1}$$

$$\text{Level: } S_t = \alpha y_t + (1-\alpha)(S_{t-1} + T_{t-1}) \tag{2}$$

$$\text{Trend: } T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1} \tag{3}$$

where S_t denotes an estimate of the level of the series at time t, T_t denotes an estimate of the trend "slope" of the series at time t. Two smoothing constants, α and β, with values between 0 and 1, are used in this method, α is the smoothing parameter for the level, and β is the smoothing parameter for the trend.

3.1.2. Damped trend method (DTM)

Gardner and Mckenzie [39] introduced the DTM, which effectively reduces the impact of the trend, causing it to level off at a specific point in the future. This approach contains a damping factor to mitigate the influence of older data. In addition to the α and β parameters, there is a damping parameter (ϕ) that varies from 0 to 1.

$$\text{Forecast: } F_{t+m} = S_t + (\phi + \phi^2 + \cdots + \phi^m)T_t \tag{4}$$

$$\text{Level: } S_t = \alpha y_t + (1-\alpha)(S_{t-1} + T_{t-1}) \tag{5}$$

$$\text{Trend: } T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1} \tag{6}$$

3.1.3 Autoregressive integrated moving average (ARIMA)

ARIMA models find applications in the prediction of time series data, which encompass sequential data points gathered or documented at regular time intervals. These models comprise three primary models: autoregressive (AR), integrated (I), and MA, and time series do not require an integrated part to decline the seasonality represented as mixed autoregressive and moving average (ARMA) models, all designed to capture the fundamental patterns and trends inherent in time series data [40].

a. Autoregressive (AR), the equation for AR of order p can be written as (7):

$$y_t = \mu + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t \tag{7}$$

b. Moving average (MA), the equation for MA of order q can be written as (8):

$$y_t = \mu - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_p \varepsilon_{t-q} + \varepsilon_t \tag{8}$$

c. Mixed autoregressive and moving average (ARMA), the equation for ARMA (p, q) can be written as (9):

$$y_t = \mu + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_p \varepsilon_{t-q} + \varepsilon_t \tag{9}$$

d. Autoregressive integrated moving average (ARIMA), the equation for ARIMA (p, d, q) can be written as (10):

$$y_t = y_{t-1} + \emptyset_1 y_{t-1} - \emptyset_2 y_{t-2} + \varepsilon_t - \theta_1 \varepsilon_{t-1} \quad (10)$$

where y_t is the actual value and ε_t is the random error. μ is the mean about which the series fluctuates. Then, $\emptyset$ is parameters of autoregressive and θ is the moving average parameters to be estimated. ε_{t-q} is the error terms ($q = 1,2,3$ ...) assumed to be independently distributed over time. p^{th} order of the lagged lagged dependent or current value.

3.2. Proposed method

The formulation of model development for the HIMA involves the traditional Holt method and moving average from Box-Jenkins methodology.

3.2.1 Moving average (MA) from Box-Jenkins methodology

The MA model in the Box-Jenkins methodology is a past forecast error (multiplied by a coefficient) in a regression-like model.

$$\text{MA: } y_t = \mu - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_p \varepsilon_{t-q} + \varepsilon_t = (\mu - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t) \quad (11)$$

where y_t is the actual value and ε_t is the random error, assumed to be identically, independently distributed, with a mean equal to zero and the same variance.

3.2.2. Holt integrated moving average (HIMA)

In reality, time series data consists of linear and non-linear components that make up the movement trends [41], [42]. HIMA model is the combination of the Holt method and the MA from Box-Jenkins methodology. The proposed new hybrid model is developed to enhance forecast accuracy by incorporating the residual values from Holt method into a MA model. A new strategy is introduced where the residual value e_t in (12) is resulting from the estimated residual value were obtain from traditional Holt method that used as an input variable to the MA model.

$$\text{Holt residual: } e_t = y_t - \hat{F}_t \quad (12)$$

$$\text{HIMA model: } F^*{}_{t+m} = (S_t + T_t \times m) \pm (\mu - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t) \quad (13)$$

where e_t as error values, which are the difference between actual data y_t and the fitted values $\hat{F}_t$ and $F_{t+m}{}^*$ is the forecast value that will be generated from the addition or subtraction of the forecast values generated from traditional Holt's method.

There are three reasons for combining with MA: i) error correction, which means MA works to correct any errors produced by the AR model in producing forecast values. For the HIMA model, the MA model will fix any errors made by Holt method; ii) improve accuracy prediction by taking past error terms into account, Holt method can readjust its predictions accordingly to improve the value of forecast accuracy; and iii) reduce residuals or differences between predicted and actual values. This leads to more efficient and effective models for predicting future values [43].

3.3. Model evaluation

Once the model is developed, it is evaluated using the testing data. This evaluation involves applying error metrics to assess the model's accuracy. Error measures are used to differentiate between a poor and a good forecast model. In other words, the error measure was used to find the best model which fits the data. A model that has the smallest error is said to be the best model. The evaluation measures calculated include the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) values for each model. The formulas used to calculate the errors are: $e_t = y_t - \hat{y}_t$, where y_t is the actual value in time (*t*) and $\hat{y}_t$ refers to fitted value in time (*t*). Root mean square error (RMSE) is a statistical metric employed to gauge the degree of error in predictions by computing the square root of the average of the squared differences between predicted and actual values.

$$\text{RMSE} = \sqrt{\frac{\sum e_t^2}{n}} \quad (14)$$

Mean absolute error (MAE) is another metric used for error assessment, focusing on the average absolute differences between predicted and actual values, making it less influenced by extreme outliers when compared to RMSE.

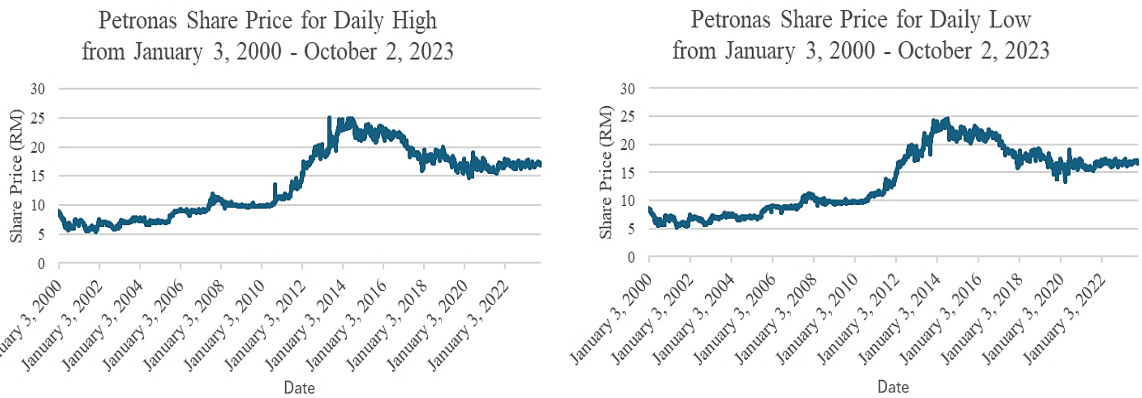
$$\text{MAE} = \sum \frac{|e_t|}{n} \tag{15}$$

Mean absolute percentage error (MAPE) provides a percentage-based assessment of error between predicted and actual values. It proves particularly valuable when expressing error as a proportion of the actual values, facilitating comparisons across diverse datasets and models. Where n is sample size.

$$\text{MAPE} = \sum \frac{\left(\frac{e_t}{y_t}\right)*100}{n} \tag{16}$$

4. RESULTS AND DISCUSSION

Figure 4 illustrates the original time series plot daily PETRONAS for high share price in Figure 4(a) and low share price in Figure 4(b). The time series plot for daily PETRONAS high share price in Figure 4(a) and low share price in Figure 4(b) from January 3, 2000 to October 2, 2023, reveals upward and downward trend movement. Initially, the share price experienced a decline until approximately January 1, 2004, then after which it stabilized with minimal fluctuations. A significant upward trend is observed from January 3, 2007 to December 31, 2013, culminating in a peak around 2014 to 2015. Following this peak, the share price declined and then entered a phase of stabilization, which began around January 4, 2016. From January 3, 2020 to October 2, 2023, the share price remained relatively stable. This initial analysis suggests that the Holt method is effective in capturing the trend patterns present in the data.



(a) (b)

Figure 4. Time series plot for daily (a) high and (b) low

4.1. Model performance

The final step is to interpret the model's performance, highlighting its effectiveness in reducing residuals and improving prediction accuracy. Table 2 shows the error measures and forecast accuracy percentage for daily highs. The [Holt+MA] and HIMA [Holt–MA] models present the best performances based on the lowest error measures and the highest forecast accuracy percentage. MA model or value of *q* is the number of significant spikes in the autocorrelation function (ACF). The best MA model for the [Holt+MA] between set 1 to set 5 is MA(1), MA(4), MA(4), MA(3), and MA(1). Meanwhile, MA(1) for set 1 to set 4 and MA(6) for set 5 had the best MA model. The forecast accuracy percentage ranged from 56.76% to 99.68%, demonstrating significant variability in predictive performance among the models. The best model performance for each model (Holt method, DTM, ARIMA, HIMA [Holt+MA], and HIMA [Holt–MA]) is set 1 with the train-test split of 99:1.

Table 3 shows the error measures and percentage of forecast accuracy for daily lows. The best MA model for the [Holt+MA] is MA(2), MA(1), MA(3), MA(5), and MA(4) for set 1 to set 5, respectively. Meanwhile, the HIMA [Holt–MA] model shows that all sets of MA(1) are the best MA models, excluding set 2, which is MA(7). The forecast accuracy percentage ranged from 56.99% to 98.88%, demonstrating significant variability in predictive performance among the models. For the daily lows, the best performance for each model (Holt method, DTM, ARIMA, HIMA [Holt+MA], and HIMA [Holt–MA]) is also set 1 with the train-test split of 99:1. For the HIMA model, both daily high and low do not require differencing because the p-values are less than 0.05.

Table 2. Error measures and percentage of forecast accuracy for each model (daily high)

Model	Set	MA (q)	Training: testing	RMSE (testing)	MAE (testing)	MAPE (testing)	Percentage of forecast accuracy (testing)
Holt's method	1	-	99:1	**0.2064**	**0.1805**	**1.0465**	**99.68**
	2	-	95:5	0.5259	0.4560	2.6582	97.34
	3	-	90:10	0.7036	0.6091	3.5721	96.43
	4	-	80:20	3.5416	3.3721	20.2060	79.79
	5	-	70:30	7.9834	7.3726	43.2406	56.76
DTM	1	-	99:1	**0.2438**	**0.2163**	**1.2540**	**99.59**
	2	-	95:5	0.6775	0.6258	3.6544	96.35
	3	-	90:10	1.0416	0.9531	5.5944	94.41
	4	-	80:20	2.2477	2.1310	12.8222	87.18
	5	-	70:30	4.6942	4.4167	25.8606	74.14
ARIMA	1	-	99:1	**0.2492**	**0.2219**	**1.2870**	**99.58**
	2	-	95:5	0.6634	0.6108	3.5667	96.43
	3	-	90:10	1.0317	0.9437	5.5391	94.46
	4	-	80:20	2.2170	2.0997	12.6357	87.36
	5	-	70:30	7.8622	7.2635	42.6008	57.40
HIMA [Holt+MA]	1	MA(1)	99:1	**0.2065**	**0.1806**	**1.0473**	**99.68**
	2	MA(4)	95:5	0.5259	0.4559	2.6580	97.34
	3	MA(4)	90:10	0.7037	0.6093	3.5730	96.43
	4	MA(3)	80:20	3.5418	3.3723	20.2074	79.79
	5	MA(1)	70:30	7.9841	7.3733	43.2445	56.76
HIMA [Holt−MA]	1	MA(1)	99:1	**0.2063**	**0.1803**	**1.0457**	**99.68**
	2	MA(1)	95:5	0.5260	0.4560	2.6583	97.34
	3	MA(1)	90:10	0.7034	0.6089	3.5710	96.43
	4	MA(1)	80:20	3.5413	3.3718	20.2045	79.80
	5	MA(6)	70:30	7.9827	7.3719	43.2366	56.76

Table 3. Error measures and percentage of forecast accuracy for each model (daily low)

Model	Set	MA (q)	Training: testing	RMSE (testing)	MAE (testing)	MAPE (testing)	Percentage of forecast accuracy (testing)
Holt's method	1	-	99:1	**0.2061**	**0.1906**	**1.1189**	**98.88**
	2	-	95:5	0.3978	0.3320	1.9651	98.04
	3	-	90:10	0.6162	0.5286	3.1496	96.85
	4	-	80:20	3.1409	2.9806	18.2031	81.80
	5	-	70:30	7.6805	7.1143	42.5040	57.50
DTM	1	-	99:1	**0.2443**	**0.2239**	**1.3140**	**98.69**
	2	-	95:5	0.5622	0.5041	2.9848	97.02
	3	-	90:10	0.9672	0.8808	5.2506	94.75
	4	-	80:20	1.9381	1.8127	11.1344	88.87
	5	-	70:30	4.7115	4.4365	26.4712	73.53
ARIMA	1	-	99:1	**0.2436**	**0.2233**	**1.3104**	**98.69**
	2	-	95:5	0.5586	0.5004	2.9623	97.04
	3	-	90:10	0.9614	0.8754	5.2180	94.78
	4	-	80:20	1.9639	1.8392	11.2959	88.70
	5	-	70:30	7.7823	7.1984	43.0135	56.99
HIMA [Holt+MA]	1	MA(2)	99:1	**0.2062**	**0.1906**	**1.1191**	**98.88**
	2	MA(1)	95:5	0.3980	0.3323	1.9663	98.03
	3	MA(3)	90:10	0.6164	0.5287	3.1502	96.85
	4	MA(5)	80:20	3.1410	2.9807	18.2037	81.80
	5	MA(4)	70:30	7.6810	7.1149	42.5075	57.49
HIMA [Holt−MA]	1	MA(1)	99:1	**0.2060**	**0.1905**	**1.1182**	**98.88**
	2	MA(7)	95:5	0.3980	0.3323	1.9664	98.04
	3	MA(1)	90:10	0.6161	0.5285	3.1489	96.85
	4	MA(1)	80:20	3.1407	2.9805	18.2024	81.80
	5	MA(1)	70:30	7.6799	7.1137	42.5005	57.50

In summary, all models achieve their best performance with a 99:1 training/testing ratio. Among the models, the traditional Holt method and the proposed HIMA [Holt+MA] model demonstrate the highest accuracy and lowest error rates, particularly in the 99:1 scenario. The performance of all models deteriorates as the proportion of training data decreases, emphasizing the importance of a larger training dataset for accurate forecasting. The previous study by Cerqueira *et al.* [44] indicates that the size of the training set greatly impacts the accuracy of forecasting models. Larger training sets tend to improve performance, especially when dealing with data that is not stationary. Tables 4 and 5 display the model comparison for each model with the best set of data partitioning for daily high and low, respectively. This testing phase is designed to rigorously evaluate the model's performance on a substantial testing set, ensuring the comparison model can generalize well to new data, helping to maximize predictive accuracy in predicting share prices for different periods.

Table 4. Model comparison for each model with the best set of data partitioning (daily high)

Model	Set	Training: testing	RMSE (testing)	MAE (testing)	MAPE (testing)	Percentage of forecast accuracy (testing)
Holt's method	1	99:1	0.2064	0.1805	1.0465	99.68
Damped trend method	1	99:1	0.2438	0.2163	1.2540	99.59
ARIMA	1	99:1	0.2492	0.2219	1.2870	99.58
HIMA [Holt+MA]	1	99:1	0.2065	0.1806	1.0473	99.68
HIMA [Holt–MA]	1	99:1	**0.2063**	**0.1803**	**1.0457**	**99.68**

Table 5. Model comparison for each model with the best set of data partitioning (daily low)

Model	Set	Training: testing	RMSE (testing)	MAE (testing)	MAPE (testing)	Percentage of forecast accuracy (testing)
Holt's Method	1	99:1	0.2061	0.1906	1.1189	98.88
Damped Trend Method	1	99:1	0.2443	0.2239	1.3140	98.69
ARIMA	1	99:1	0.2436	0.2233	1.3104	98.69
HIMA [Holt + MA]	1	99:1	0.2062	0.1906	1.1191	98.88
HIMA [Holt – MA]	1	99:1	**0.2060**	**0.1905**	**1.1182**	**98.88**

The result of this study shows that proposed HIMA models had lower error rates and highest accuracy than DTM, ARIMA models, and traditional Holt methods for both daily high and low PETRONAS share prices. Although traditional Holt and proposed HIMA models show similar accuracy rates, the proposed HIMA [Holt–MA] model outperforms other forecasting methods. This result is consistent with what has been reported by Hansun and Subanar [45] in their work on a new hybrid model called hybrid-weighted exponential moving average (H-WEMA), which merges the calculation of the weighting factor in weighted MA with the Holt method for Jakarta stock exchange composite index. The current finding shows that the hybrid H-WEMA provides more accurate and robust forecasting results compared to the traditional weighted moving average (WMA) and Holt method. This result further reinforces most findings that hybrid models capture complex patterns in time series data, leading to more accurate and dependable forecasts [46].

The study showcases a hybrid approach that leverages the strengths of the traditional Holt method and the MA model, yielding improved predictive performance, particularly for PETRONAS share price dataset. This combination harnesses the Holt method's capability to capture linear trends and the MA model's ability to smooth out short-term fluctuations, resulting in more accurate and reliable forecasts. By integrating these techniques, the hybrid model addresses the limitations inherent in using either method alone, thus providing a more robust forecasting tool for financial time series data. The application of this model to PETRONAS share price highlights its practical relevance and potential for enhancing decision-making processes in financial analysis and investment strategies.

Contrary to what has been reported by Airlangga *et al.* [47], the results indicate the backpropagation neural networks algorithm outperforms compared to the traditional single, double, and triple exponential smoothing models in terms of accuracy, achieving lower error rates for rice production in Indonesia. Therefore, for future research, this study suggests the application of other hybrid models that combine various machine-learning techniques with traditional statistical methods. For instance, integrating backpropagation neural networks with methods like ARIMA, Holt-Winters, or exponential smoothing could yield even more accurate and robust forecasting models. Additionally, advanced machine learning algorithms such as support vector machines (SVM), random forests, or Gradient Boosting could be incorporated to capture complex non-linear patterns and interactions within the data.

Future research should focus on refining these hybrid models by optimizing their parameters and improving their computational efficiency. Comparative studies could be conducted to evaluate the performance of different hybrid models across various datasets, including those with different temporal resolutions (daily, weekly, monthly) and characteristics (linear and non-linear trends). Moreover, it would be beneficial to explore the applicability of these models to other financial markets, commodities, and economic indicators to validate their effectiveness and generalizability under diverse conditions. Furthermore, incorporating domain-specific knowledge and external factors, such as macroeconomic indicators, geopolitical events, or industry-specific variables, could enhance the forecasting accuracy of these hybrid models. Investigating the integration of real-time data streams and adaptive learning mechanisms would also be valuable for developing models that can dynamically adjust to changing market conditions. Ultimately, the goal of future research should be to create versatile and robust forecasting tools that can provide valuable insights and support decision-making across various domains.

However, the study is subject to several limitations that warrant consideration. Firstly, there is a noticeable gap in existing research specifically focused on improving the forecast accuracy of PETRONAS share price, making it challenging to benchmark the results against prior studies. Secondly, the analysis is confined to daily share price data, which may not capture the different dynamics present in weekly or monthly datasets. Future research could explore these different temporal resolutions to validate the model's effectiveness across various time frames. Lastly, the study predominantly deals with data exhibiting a linear trend component, which may limit its applicability to datasets with more complex, non-linear trends. Addressing these limitations in future studies could further enhance the robustness and generalizability of the hybrid forecasting approach.

5. CONCLUSION

The study revealed that the HIMA model, which integrates the Holt method with the MA from the Box-Jenkins methodology, presents a reliable approach for forecasting PETRONAS share prices, consistently maintaining accuracy across both high and low daily data. The HIMA model further shows considerable promise in minimizing residuals and enhancing predictive precision. The findings of this study indicate that while traditional models such as the Holt method and ARIMA are effective, hybrid models like HIMA may offer more dependable predictions in the context of volatile financial markets.

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REFERENCES

[1] M. E. Hoque, S.-W. Low, and M. A. S. Zaidi, "The effects of oil and gas risk factors on Malaysian oil and gas stock returns: do they vary?," *Energies*, vol. 13, no. 15, pp. 1–22, Jul. 2020, doi: 10.3390/en13153901.

[2] O. K. T. Fong, Y. P. Lee, and F. K. Qi, "Export business plan for PETRONAS company," *International Research Journal of Modernization in Engineering Technology and Science*, vol. 5, no. 9, pp. 1736–1745, Sep. 2023, doi: 10.56726/IRJMETS44877.

[3] Y. Shen, "The impact of environmental, social, and governance factor on the financial performance of China's companies," in *Proceedings of the 2nd International Conference on Financial Technology and Business Analysis*, EWA Publishing, Jan. 2024, pp. 129–137. doi: 10.54254/2754-1169/57/20230693.

[4] S. Yacob, "PETRONAS, oil money, and Malaysia's national sovereignty," *Journal of the Malaysian Branch of the Royal Asiatic Society*, vol. 94, no. 1, pp. 119–144, Jun. 2021, doi: 10.1353/ras.2021.0014.

[5] M. R. Ab. Khalil and A. A. Bakar, "A comparative study of deep learning algorithms in univariate and multivariate forecasting of the Malaysian stock market," *Sains Malaysiana*, vol. 52, no. 3, pp. 993–1009, Mar. 2023, doi: 10.17576/jsm-2023-5203-22.

[6] N. I. Hasan, A. A. Aziz, M. D. Ganggayah, N. F. Jamal, and N. M. Ghafar, "Projection of infant mortality rate in Malaysia using R," *Jurnal Sains Kesihatan Malaysia*, vol. 20, no. 1, pp. 23–36, Jan. 2022, doi: 10.17576/JSKM-2022-2001-03.

[7] A. Ghazanfari, "Regional patterns for the retail petrol prices," *International Journal of Energy Economics and Policy*, vol. 11, no. 4, pp. 383–397, Jun. 2021, doi: 10.32479/ijeep.10132.

[8] M. F. Olayiwola and S. M. Seeletse, "Statistical forecasting of petrol price in South Africa," *Journal of Engineering and Applied Sciences*, vol. 15, no. 2, pp. 602–606, Oct. 2019, doi: 10.36478/jeasci.2020.602.606.

[9] X. Gong and B. Lin, "Effects of structural changes on the prediction of downside volatility in futures markets," *Journal of Futures Markets*, vol. 41, no. 7, pp. 1124–1153, Jul. 2021, doi: 10.1002/fut.22207.

[10] S. Khan and H. Alghulaiakh, "ARIMA model for accurate time series stocks forecasting," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 7, pp. 524–528, 2020, doi: 10.14569/IJACSA.2020.0110765.

[11] F. Petropoulos *et al.*, *Forecasting: theory and practice*, vol. 38, no. 3. Elsevier B.V., 2022. doi: 10.1016/j.ijforecast.2021.11.001.

[12] A. Muchayan, "Comparison of Holt and brown's double exponential smoothing methods in the forecast of moving price for mutual funds," *Journal of Applied Science, Engineering, Technology, and Education*, vol. 1, no. 2, pp. 183–192, Dec. 2019, doi: 10.35877/454RI.asci1167.

[13] Z. O. Bogar and A. Gungor, "Forecasting waste mobile phone (WMP) quantity and evaluating the potential contribution to the circular economy: a case study of Turkey," *Sustainability*, vol. 15, no. 4, pp. 1–38, Feb. 2023, doi: 10.3390/su15043104.

[14] S. A. Shukor *et al.*, "Forecasting stock market price of gold, silver, crude oil and platinum by using double exponential smoothing, Holt's linear trend and random walk," in *Journal of Physics: Conference Series*, IOP Publishing Ltd, May 2021, pp. 1–12. doi: 10.1088/1742-6596/1874/1/012087.

[15] A. L. S. Maia and F. de A. T. de Carvalho, "Holt's exponential smoothing and neural network models for forecasting interval-valued time series," *International Journal of Forecasting*, vol. 27, no. 3, pp. 740–759, Jul. 2011, doi: 10.1016/j.ijforecast.2010.02.012.

[16] N. A. M. Noor and N. H. A. Rahman, "Exponential smoothing constant determination to minimize the forecast error," *Mathematical Modeling and Computing*, vol. 9, no. 1, pp. 50–56, 2022, doi: 10.23939/mmc2022.01.050.

[17] R. J. Hyndman and G. Athanasopoulos, *Forecasting: principles and practice*, 3rd ed. Melbourne, Australia: OTexts, 2021.

[18] E. S. Gardner and E. McKenzie, "Why the damped trend works," *Journal of the Operational Research Society*, vol. 62, no. 6, pp. 1177–1180, Jun. 2011, doi: 10.1057/jors.2010.37.

[19] E. S. Gardner and Y. Acar, “Fitting the damped trend method of exponential smoothing,” *Journal of the Operational Research Society*, vol. 70, no. 6, pp. 926–930, Jun. 2019, doi: 10.1080/01605682.2018.1469457.

[20] S. Makridakis, S. C. Wheelwright, and R. J. Hyndman, *Forecasting: methods and applications*, 3rd ed. New York: John Wiley & Sons Inc., 1997.

[21] R. J. Hyndman and G. Athanasopoulos, *Forecasting: principles and practice*, 2nd ed. Melbourne, Australia: OTexts, 2018.

[22] B. Alhnaity and M. Abbod, “A new hybrid financial time series prediction model,” *Engineering Applications of Artificial Intelligence*, vol. 95, Oct. 2020, doi: 10.1016/j.engappai.2020.103873.

[23] H. Yu, L. J. Ming, R. Sumei, and Z. Shuping, “A hybrid model for financial time series forecasting-integration of EWT, ARIMA with the improved ABC optimized ELM,” *IEEE Access*, vol. 8, pp. 84501–84518, 2020, doi: 10.1109/ACCESS.2020.2987547.

[24] D. K. Shetty and B. Ismail, “Hybrid model approach for accuracy in forecasting,” *Journal of the Indian Society for Probability and Statistics*, vol. 19, no. 2, pp. 417–435, Dec. 2018, doi: 10.1007/s41096-018-0051-2.

[25] M. H. Haque, A. R. M. J. U. Jamali, and M. B. Hasan, “Proposed modification of Holt’s method for short term forecasting,” *International Journal of Engineering Research & Technology (IJERT)*, vol. 6, no. 11, pp. 496–499, 2017.

[26] F. A. Mohammed, “Proposed hybrid model AR-Holt (P+5) for time series forecasting by employing new robust methodology,” *Journal of Mechanics of Continua and Mathematical Sciences*, vol. 14, no. 6, pp. 413–425, Dec. 2019, doi: 10.26782/jmcms.2019.12.00029.

[27] E. E and B. W, “Modified Holt’s linear trend method based on particle swarm optimization,” *COJ Robotics & Artificial Intelligence*, vol. 1, no. 3, Dec. 2020, doi: 10.31031/cojra.2020.01.000512.

[28] L. Liu and L. Wu, “Predicting housing prices in China based on modified Holt’s exponential smoothing incorporating whale optimization algorithm,” *Socio-Economic Planning Sciences*, vol. 72, Dec. 2020, doi: 10.1016/j.seps.2020.100916.

[29] S. Ravichandran, B. S. Yashavanth, and K. Kareemulla, “Oilseeds production and yield forecasting using ARIMA-ANN modelling,” *Journal of Oilseeds Research*, vol. 35, no. 1, pp. 57–62, Jul. 2018, doi: 10.56739/jor.v35i1.137369.

[30] J. P. O. Echevarria and P. J. B. Aranas, “Forecasting the consumer price index in the regions of the Philippines using machine learning for time series models,” *Journal of Artificial Intelligence, Machine Learning and Neural Network*, no. 36, pp. 11–22, Sep. 2023, doi: 10.55529/jaimlnn.36.11.22.

[31] M. Barsalou, P. M. Saraiva, and R. Henriques, “Exploring exploratory data analysis: An empirical test of run chart utility,” *Management Systems in Production Engineering*, vol. 31, no. 4, pp. 442–448, Dec. 2023, doi: 10.2478/mspe-2023-0050.

[32] Abhinav N D, Sevanthi M, and S. Y. G. Tilak, “Exploratory data analysis (EDA) and data visualization,” *International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering*, vol. 12, no. 6, pp. 61–64, May 2024, doi: 10.17148/IJIREEICE.2024.12608.

[33] N. A. M. Nor, A. A. Aziz, W. N. Wan Shahidan, W. N. Wan Shahidan, and S. N. N. Muhamad, “Short term forecast of COVID-19 cases in Japan using time series analysis models,” *Journal of Computing Research and Innovation*, vol. 7, no. 2, pp. 165–174, Sep. 2022, doi: 10.24191/jcrinn.v7i2.301.

[34] N. Q. M. Fozi and A. A. Aziz, “A novel hybrid Holt integrated moving average (HIMA) for consumer price index prediction,” *International Journal of Entrepreneurship and Management Practices*, vol. 7, no. 25, pp. 367–378, Jun. 2024, doi: 10.35631/IJEMP.725030.

[35] A. A. Aziz, M. Yusoff, W. F. W. Yaacob, and Z. Mustaffa, “Repeated time-series cross-validation: a new method to improved COVID-19 forecast accuracy in Malaysia,” *MethodsX*, vol. 13, pp. 1–9, Dec. 2024, doi: 10.1016/j.mex.2024.103013.

[36] M. A. Lazim, *Introductory business forecasting a practical approach*, 3rd ed. Malasysia: Press Universiti Teknologi MARA, 2017.

[37] A. Aieb, A. Liotta, A. Jacob, and M. A. Yaqub, “Short-term forecasting of non-stationary time series,” in *Engineering Proceedings*, Basel Switzerland: MDPI, Jul. 2024, pp. 1–14. doi: 10.3390/engproc2024068034.

[38] C. C. Holt, “Forecasting seasonals and trends by exponentially weighted moving averages,” *International Journal of Forecasting*, vol. 20, no. 1, pp. 5–10, Jan. 2004, doi: 10.1016/j.ijforecast.2003.09.015.

[39] E. S. Gardner and E. Mckenzie, “Forecasting trends in time series,” *Management Science*, vol. 31, no. 10, pp. 1237–1246, Oct. 1985, doi: 10.1287/mnsc.31.10.1237.

[40] B. Momin and G. Chavan, “Univariate time series models for forecasting stationary and non-stationary data: a brief review,” in *Smart Innovation, Systems and Technologies*, Springer Science and Business Media Deutschland GmbH, 2018, pp. 219–226. doi: 10.1007/978-3-319-63645-0_24.

[41] R. L. Andrews, “Forecasting performance of structural time series models,” *Journal of Business & Economic Statistics*, vol. 12, no. 1, pp. 129–133, Jan. 1994, doi: 10.2307/1391929.

[42] M. Guo, J. Zhang, H. Chen, X. Li, P. Sun, and C. Yu, “Railway project application of a time series data analysis and prediction algorithm,” in *2023 IEEE International Conference on Image Processing and Computer Applications (ICIPCA)*, IEEE, Aug. 2023, pp. 1493–1496. doi: 10.1109/ICIPCA59209.2023.10257976.

[43] H. Iftitah and D. Murni, “Application of time series Box-Jenkins method (ARIMA) to forecast the highest and lowest stock prices of PT. Semen Indonesia, Tbk.,” in *Proceedings of the 2nd International Conference on Mathematics and Mathematics Education 2018 (ICM2E 2018)*, Paris, France: Atlantis Press, 2018, pp. 328–333. doi: 10.2991/icm2e-18.2018.75.

[44] V. Cerqueira, L. Torgo, and I. Mozetič, “Evaluating time series forecasting models: an empirical study on performance estimation methods,” *Machine Learning*, vol. 109, no. 11, pp. 1997–2028, Nov. 2020, doi: 10.1007/s10994-020-05910-7.

[45] S. Hansun and Subanar, “H-WEMA: a new approach of double exponential smoothing method,” *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 14, no. 2, pp. 772–777, 2016, doi: 10.12928/TELKOMNIKA.v14i1.3096.

[46] S. Smyl, “A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting,” *International Journal of Forecasting*, vol. 36, no. 1, pp. 75–85, Jan. 2020, doi: 10.1016/j.ijforecast.2019.03.017.

[47] G. Airlangga, A. Rachmat, and D. Lapihu, “Comparison of exponential smoothing and neural network method to forecast rice production in Indonesia,” *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 17, no. 3, pp. 1367–1375, Jun. 2019, doi: 10.12928/telkomnika.v17i3.11768.

BIOGRAPHIES OF AUTHORS

Nurin Qistina Mohamad Fozi currently pursuing her MSc of science in statistics at Universiti Teknologi MARA (UiTM) Cawangan Perak, Seri Iskandar Campus, Malaysia, having commenced her postgraduate studies in March 2022. At the same time, she is a research assistant at UiTM Cawangan Perlis, Arau Campus. Her academic journey in the field of statistics began with a diploma in statistics from UiTM Cawangan Perak, Tapah Campus, followed by a BSc of Science (Hons.) Statistics from UiTM Cawangan Kelantan, Kota Bharu Campus, marking a consistent path of excellence and a deepening engagement with the discipline. She can be contacted at email: 2022968169@student.uitm.edu.my.

Nurhasniza Idham Abu Hasan a senior lecturer at Universiti Teknologi MARA (UiTM) Cawangan Perak, Tapah Campus, Perak, Malaysia, stands out in the field of statistics with her broad research interests spanning survival analysis, business statistics, predictive modeling, and public health, among others. With a strong foundation laid by her academic journey, which culminated in a diploma in statistics, BSc of Science (Hons.) statistics, Master of Science (Hons.) statistics, and PhD in statistics from UiTM Shah Alam. She has devoted her career to advancing statistical methodologies and their application in various domains. She can be contacted at email: nurhasniza@uitm.edu.my.

Azlan Abdul Aziz a senior lecturer at the Universiti Teknologi MARA (UiTM) Cawangan Perlis, Arau Campus, Perlis, Malaysia, is an esteemed figure in the field of statistics and mathematics, with a focus on statistical modeling, time series analysis and forecasting, statistical education through mobile learning, and econometrics. His academic journey is deeply rooted in UiTM, where he progressed from a diploma in statistics to a BSc of science (Hons.) statistics and then to a MSc of science (applied statistics) at UiTM Shah Alam. He can be contacted at email: azlan172@uitm.edu.my.

Siti Meriam Zahari a senior lecturer at Universiti Teknologi MARA (UiTM), Shah Alam, Selangor, Malaysia, specializing in time series and forecasting, econometrics, and decision analysis. Her academic journey includes a BSc of applied science (Hons.) mathematics and economics and a MSc of economics and management from Universiti Sains Malaysia, followed by a PhD in science (econometrics) from UiTM Shah Alam. She can be contacted at email: sitimeriam@uitm.edu.my.

Mogana Darshini Ganggayah earned a BSc of science in bioinformatics with distinction from Universiti Malaya, Kuala Lumpur, Malaysia, in 2018 and completed a fast-track PhD program in data science by February 2021. Currently, she is a lecturer at the School of Business, Monash University Malaysia, teaching business analytics. Her research also focuses on data literacy, visualizations, and predictive analytics in the business domain. She can be contacted at email: moganadarshini.ganggayah@monash.edu.