

Forecasting the Stock Price of PT Astra International Tbk on the Indonesia Stock Exchange Using the Single Exponential Smoothing Method Historical Data 2020–2025

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Abstract : This study evaluates the sensitivity of the Single Exponential Smoothing (SES) parameter in forecasting the monthly end-of-month closing prices of PT Astra International Tbk (ASII) during a period covering the COVID-19 market disruption and subsequent recovery, rather than merely applying forecasting software. The dataset comprises 72 monthly observations from January 2020 to December 2025. Data from January 2020 to December 2024 were used for model training, while January–December 2025 was reserved for out-of-sample testing. SES was initialized with $F_1 = X_1$ and evaluated using α values of 0.1, 0.3, 0.5, 0.7, and 0.9. Forecasting accuracy was assessed through rolling one-step-ahead forecasts. The recalculated results show that $\alpha = 0.9$ achieved the lowest out-of-sample errors, with a MAPE of 5.63%, MAD of Rp301.62, and MSD of Rp115,141.97. These values represent test-set accuracy, not in-sample model fit. The high α enabled the model to respond rapidly to recent price changes, but also increased its sensitivity to short-term fluctuations. After refitting the selected model using all observations through December 2025, the forecasts for January, February, and March 2026 were each Rp6,700. This constant forecast reflects the level-only structure of SES, which does not explicitly extrapolate trend or seasonality. The accuracy obtained can serve as a transparent baseline for short-term investment analysis. However, it should not be the sole basis for investment decisions, as it does not account for market volatility, fundamental information, structural changes, or other risk factors.

Keywords: stock forecasting, single exponential smoothing, time series, stock price, forecasting accuracy

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INTRODUCTION

Stocks are investment instruments that offer potential returns through capital gains and dividends, although their price movements also expose investors to considerable uncertainty (Permana, 2023). Stock prices change continuously in response to market supply and demand, investors' expectations, company-specific information, macroeconomic conditions, and broader capital market developments. These fluctuations create a need for analytical methods that can systematically process historical information and provide quantitative estimates of possible price movements in subsequent periods. Forecasting cannot eliminate market uncertainty, but it can provide

additional guidance for investors when evaluating the timing and risks of investment decisions (Makridakis et al., 2022).

PT Astra International Tbk is a diversified public company listed on the Indonesia Stock Exchange. It operates in several strategic sectors, including automotive, financial services, heavy equipment, agribusiness, infrastructure, logistics, and information technology. The diversity of its business activities makes the movement of its stock price relevant to investors who follow developments in major Indonesian companies. Previous research has also shown that ASII stock prices exhibit fluctuations that may vary across observation periods, necessitating the use of time-series methods to examine their historical movement patterns systematically (Pohan, 2022; Murfadiyah et al., 2023).

Time series forecasting methods use the temporal structure of historical observations to estimate values in subsequent periods (Petropoulos et al., 2022). One of the basic methods used for this purpose is Single Exponential Smoothing (SES), which assigns greater weight to more recent observations while progressively reducing the weight of older observations. SES has several practical advantages, including computational simplicity, ease of interpretation, limited data requirements, and the ability to update forecasts when new observations become available. These characteristics make SES a useful baseline model for evaluating whether a relatively simple forecasting procedure can achieve acceptable accuracy before more complex models are considered (Hyndman & Athanasopoulos, 2021; Svetunkov, 2022).

Nevertheless, the suitability of SES depends on the characteristics of the observed time series. SES primarily represents the level component of a series and is generally more appropriate when the data do not exhibit a strong, persistent trend or seasonal pattern. A small smoothing constant produces a smoother forecast but responds more slowly to recent changes. In contrast, a large smoothing constant makes the model more responsive to the latest observations but also more sensitive to short-term fluctuations. Therefore, the selection of the smoothing constant cannot be separated from the observed volatility and movement pattern of the stock price. When a series exhibits a persistent trend, seasonality, structural changes, or extreme fluctuations, methods such as Holt's trend method, Holt-Winters, ARIMA, or more advanced computational models may provide a more appropriate specification (Hyndman & Athanasopoulos, 2021; Kourentzes et al., 2020).

Previous studies have applied exponential smoothing and related time-series methods to various stock price data. Zainurrosid et al. (2023) applied SES to Indonesian banking stocks and reported an average MAPE of approximately 1.4% using a smoothing constant of 0.2. Murfadiyah et al. (2023) used the Exponential Moving Average method to examine the movement of PT Astra International Tbk stock prices, demonstrating how weighted historical data can support investment analysis. Using the same stock object, Sofiyati et al. (2024) applied Winters' exponential smoothing to monthly ASII closing prices and generated forecasts that incorporated changing price movements over the forecast horizon. Meanwhile, Muhaimin and Pamuji (2024) compared SES with an optimized Long Short-Term Memory model for Bank BRI stock prices and found that the more complex model produced lower forecasting errors. Collectively, these studies indicate that simple smoothing methods remain useful as transparent forecasting benchmarks, although their performance may be surpassed when the data contain more complex temporal dependencies.

Other studies have used different forecasting specifications for ASII stock prices. Pohan (2022) applied an ARIMA model, whereas Herlambang and Al Azies (2026) compared ARIMA and Prophet. The use of moving averages, Winters' exponential smoothing, ARIMA, Prophet, and machine learning models indicates that no single forecasting method is universally appropriate for every stock price pattern. A more complex method does not necessarily yield better performance unless its additional components align with the data's underlying characteristics. Consequently, SES remains relevant as a parsimonious baseline model whose performance can be evaluated through systematic parameter selection and comparison of forecasting errors (Makridakis et al., 2020).

The 2020–2025 observation period is analytically important because it includes the COVID-19 shock, the initial market recovery, and subsequent adjustments in capital market conditions. Evidence from the Indonesian stock market shows that the pandemic and government interventions generated different short-term responses across industrial sectors, while research covering Asia-Pacific markets demonstrates that the effects of pandemic-related developments on volatility changed over time (Sinaga et al., 2022; Vo et al., 2022). These changing market responses suggest that forecasting models estimated over the 2020–2025 period must accommodate observations generated under different levels of uncertainty and volatility. Therefore, the relevance of a traditional model such as SES should not be assessed solely from its simplicity, but also from its ability to respond to changes in the level and direction of monthly stock prices.

Although various time series methods have been applied to Indonesian stock prices, several research gaps remain. First, prior research on ASII stocks has predominantly employed moving averages, ARIMA, Prophet, or trend-and-seasonality-based exponential smoothing models. In contrast, the sensitivity of SES forecasts to different smoothing constants has received less attention. Second, limited research has evaluated how a level-based forecasting model performs when the observation period covers both the pandemic disruption and subsequent market recovery. Third, forecasting performance is often reported only through errors calculated from the same historical data used to estimate the model, without clearly distinguishing model fit from genuine forecasting accuracy on unseen data. These gaps indicate the need to evaluate SES through systematic selection of smoothing parameters, examination of the data pattern, and assessment using a holdout test period.

This study contributes to the forecasting literature in three ways. First, it evaluates the sensitivity of monthly ASII stock price forecasts to alternative smoothing constants, thereby demonstrating how parameter selection affects model responsiveness, forecasting lag, and error magnitude. Second, it examines whether SES can adequately follow monthly stock price movements over a period characterized by changing market conditions. Third, it evaluates the selected model using MAPE, MAD, and MSD and distinguishes the model's historical fit from its forecasting performance on test data. The study also interprets forecasting errors in relation to their potential economic use rather than relying exclusively on statistical classifications.

The economic relevance of a forecasting error depends on the context in which the forecast is used. An error level acceptable for monitoring general monthly price movements may not provide sufficient precision for short-term trading, portfolio rebalancing, or long-term investment planning. Investors must also consider market volatility, forecast direction, investment horizon, transaction costs, liquidity, and risk

tolerance. Accordingly, the forecasts generated in this study are intended as a quantitative decision-support tool, not as the sole basis for buying or selling ASII shares.

Based on these considerations, this study aims to identify the characteristics of the monthly stock price series of PT Astra International Tbk, evaluate alternative SES smoothing constants, determine the parameter that produces the best forecasting performance, and assess the model's accuracy using a holdout test period. The selected model is subsequently used to generate stock price forecasts for periods following December 2025. Through this procedure, the study seeks to determine not only which smoothing constant produces the smallest statistical error, but also under what data conditions SES can provide a useful and interpretable baseline forecast for short-term financial analysis.

RESEARCH METHODS

Research Type

This study uses a descriptive quantitative approach with a time series analysis method. The quantitative approach is used because this research utilizes numerical data in the form of stock prices, which are statistically analyzed to generate forecasts for the next period. Descriptive research is chosen to describe the movement pattern of stock prices based on historical data and to produce stock price estimates for future periods using a measurable forecasting method.

Research Subject and Object

The subject of this research is PT Astra International Tbk (ASII), a large company listed on the Indonesia Stock Exchange (IDX). This company was selected because it has a large market capitalization and high stock trading activity, making its stock price movement a frequent concern for investors.

The object of this research is the monthly stock price of PT Astra International Tbk (ticker: ASII; Yahoo Finance ticker: ASII.JK) from January 2020 to December 2025, comprising 72 chronological observations. Monthly stock price is defined operationally as the unadjusted closing price in Indonesian rupiah on the final trading day of each calendar month. This definition is used consistently throughout data preparation, model estimation, accuracy evaluation, and forecasting.

Data Source

This study uses secondary daily historical price data for PT Astra International Tbk (ASII.JK) obtained from the Yahoo Finance Historical Data page (<https://finance.yahoo.com/quote/ASII.JK/history/>), accessed on July 19, 2026. The Close column, rather than Adjusted Close, is used because the study analyzes the observed market closing price. The monthly series is formed by sorting the daily observations chronologically and selecting the closing price on the last available trading day of each month. Dates, duplicate records, missing months, and possible corporate actions are checked before analysis. All 72 monthly values are expressed in Indonesian rupiah.

Table 1. Stock Price Data of PT Astra International Tbk (ASII) from January 2020 to December 2025

Month	2020	2021	2022	2023	2024	2025
January	6350	6100	5475	6000	5125	4800
February	5525	5400	5800	6100	5225	4530

Month	2020	2021	2022	2023	2024	2025
March	3900	5275	6575	6000	5150	4920
April	3850	5500	7575	6750	5150	4800
May	4770	5250	7350	6450	4290	4850
June	4800	4940	6625	6775	4460	4500
July	5150	4720	6325	6850	4720	5100
August	5100	5225	6975	6450	5100	5500
September	4460	5500	6625	6225	5050	5775
October	5425	6025	6650	5775	5100	6150
November	5300	5775	6050	5400	5100	6550
December	6025	5700	5700	5650	4900	6700

Source: Yahoo Finance (2026)

Data Analysis Technique

The analysis is conducted in five stages: data preparation and preliminary time-series diagnostics, model specification and initialization, parameter estimation, out-of-sample accuracy evaluation, and final short-term forecasting. Minitab is used for model estimation, while the exported fitted values and errors are independently checked against the standard Single Exponential Smoothing equations described below.

a. Preliminary Time-Series Diagnostics

Before SES is fitted, the monthly observations are inspected for chronological completeness, missing values, duplicated dates, and unusual price movements. A time-series plot is used to identify changes in level, outliers, and possible structural breaks. Changes in annual mean prices are then compared, and a linear time-trend model ($X_t = \beta_0 + \beta_1 t + \varepsilon_t$) is estimated at a 5% significance level. A persistent trend is indicated when the estimated slope's direction is statistically meaningful and supported by sustained changes in annual means; a short, reversible movement is interpreted as a temporary fluctuation. A monthly seasonal plot and the autocorrelation function are also reviewed to assess recurring seasonal or more complex serial patterns.

b. Single Exponential Smoothing Model

Single Exponential Smoothing updates the forecast by combining the latest actual observation with the forecast from the preceding period. The standard SES recurrence is:

$$F_{t+1} = \alpha X_t + (1 - \alpha)F_t$$

where:

F_{t+1} = forecast for period $t + 1$

X_t = actual stock price in period t

F_t = forecast for period t

α = smoothing constant, with $0 \leq \alpha \leq 1$

The coefficient α assigns weight to the latest observation, whereas $1 - \alpha$ assigns weight to the preceding forecast. A small α produces stronger smoothing and slower adjustment; a large α responds more rapidly to recent movements. The boundary value $\alpha = 1.0$ assigns full weight to the most recent observation and zero weight to the preceding forecast. Under this condition, the one-step-ahead forecast becomes $F_{t+1} = X_t$, which is equivalent to a naïve forecast and performs virtually no

smoothing. Values above 1.0 are outside the classical SES parameter range and are not used in this study.

For transparent and reproducible initialization, the first forecast is set equal to the first observation ($F_1 = X_1$). This rule is appropriate for a short univariate series because it does not introduce information from future observations. The Minitab setup is configured to use the standard SES formulation, and the first fitted values are checked against this initialization rule before the output is accepted.

c. Selection of the Smoothing Constant

Parameter estimation is performed only on the training data. Minitab automatically searches for an α within the interval $0 \leq \alpha \leq 1$ that minimizes the sum of squared one-step-ahead training errors. As a sensitivity analysis, the systematic candidate values 0.1, 0.3, 0.5, 0.7, and 0.9 are also estimated. The value $\alpha = 1.0$ is retained as the upper-bound comparator because it represents the maximum responsiveness permitted in classical SES: it assigns full weight to the latest observation and zero weight to the preceding forecast, so the one-step-ahead forecast becomes identical to the naïve forecast. Including this boundary value, therefore, provides a theoretically meaningful reference for assessing whether lower α values, which impose progressively stronger smoothing, improve forecasting performance.

d. Training and Test Data

To distinguish model fit from genuine forecasting performance, the observations are divided chronologically rather than randomly. This approach is consistent with recommendations for evaluating time-series forecasting models using temporally ordered data (Bergmeir et al., 2018). January 2020–December 2024 (60 observations) constitute the training set, and January–December 2025 (12 observations) constitute the test set. Model initialization, α estimation, and all tuning decisions use only the training set. From the forecast origin at December 2024, the fitted training model produces forecasts for all 12 test months without being re-estimated or updated using the actual 2025 values. Thus, the test data remain unseen during model development.

Accuracy measures calculated from the training set are reported only as in-sample fit statistics. The principal evidence of forecasting accuracy is MAPE, MAD, and MSD calculated separately from the 12 out-of-sample errors in the 2025 test set. This separation prevents a low training error from being interpreted as sufficient evidence of forecasting ability.

e. Forecasting Accuracy Measures

For each evaluated period, the forecast error is defined as $e_t = X_t - F_t$. Let n denote the number of observations in the relevant evaluation set ($n = 12$ for the test set). The three accuracy measures are calculated as follows:

1) Mean Absolute Deviation (MAD)

Kurnia (2022) explains that MAD measures the average absolute error between actual and forecast values. The MAD formula is as follows:

$$MAD = \frac{\sum_{t=1}^n |X_t - F_t|}{n}$$

Description:

n = number of periods

The smaller the MAD value, the better the forecasting model's accuracy.

2) Mean Squared Deviation (MSD)

Muhendra (2025) explains that MSD is used to measure the average squared forecasting error, so larger errors have a stronger influence in the model evaluation.

$$MSD = \frac{\sum_{i=1}^n (X_t - F_t)^2}{n}$$

The smaller the MSD value, the more accurate the forecasting model is considered.

3) Mean Absolute Percentage Error (MAPE)

Maricar (2019) explains that MAPE measures the average percentage error relative to the actual value, making it easier to interpret the model's accuracy.

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{X_t - F_t}{X_t} \right|$$

The interpretation of MAPE values can be explained as follows:

Table 2. Criteria for Interpreting MAPE Values

MAPE Value	Accuracy Interpretation
MAPE < 10%	Very accurate
10% ≤ MAPE ≤ 20%	Good
20% < MAPE ≤ 50%	Reasonable
MAPE > 50%	Inaccurate or low forecasting ability

Source: Sharma et al. (2021).

The classification in Table 2 supports interpretation but does not replace direct comparison of the three out-of-sample measures. The conclusion considers MAPE, MAD, and MSD together, with particular attention to whether a few large errors dominate MSD.

f. Forecast Horizon and Interpretation

After out-of-sample evaluation, the selected SES specification is re-estimated using the complete January 2020–December 2025 series. The final forecast horizon is three months—January, February, and March 2026—because the study is intended to provide a short-term illustration and because uncertainty generally increases as the horizon expands. Since SES contains no trend component, all multi-step point forecasts beyond December 2025 are equal to the final smoothed level. Thus, the January, February, and March 2026 point forecasts will be constant. This property is an inherent characteristic of SES and must not be interpreted as evidence that the actual stock price will remain unchanged.

RESULTS AND DISCUSSION

This section jointly presents and discusses the recalculated Single Exponential Smoothing (SES) results for 72 monthly end-of-month closing prices of PT Astra International Tbk (ASII) from January 2020 to December 2025. January 2020–December 2024 is used as the training period, while January–December 2025 is reserved as the test period. SES is initialized with $F_1 = X_1$ and estimated for systematic candidate values of $\alpha = 0.1, 0.3, 0.5, 0.7$, and 0.9 . The Test accuracy is evaluated through rolling one-step forecasts. Each forecast uses only information available before the target month, and the level is updated after that month's actual price becomes available.



Figure 1. Monthly End-of-Month Closing Prices of PT Astra International Tbk (ASII), January 2020–December 2025

Figure 1 shows a sharp pandemic-period decline from Rp6,350 in January 2020 to the sample minimum of Rp3,850 in April 2020, followed by recovery and a peak of Rp7,575 in April 2022. The annual average then declined from approximately Rp6,477 in 2022 to Rp6,202 in 2023 and Rp4,948 in 2024, before rising to Rp5,348 in 2025; within 2025, the price increased from Rp4,800 in January to Rp6,700 in December. Thus, the full series does not exhibit a stable monotonic trend or a clearly repeated seasonal pattern, which supports the use of SES as a parsimonious level-only benchmark. However, the multi-period decline during 2022–2024 and the sustained increase in 2025 also indicate level changes and temporary directional movement that may cause a level-only model to lag (Hyndman & Athanasopoulos, 2021).

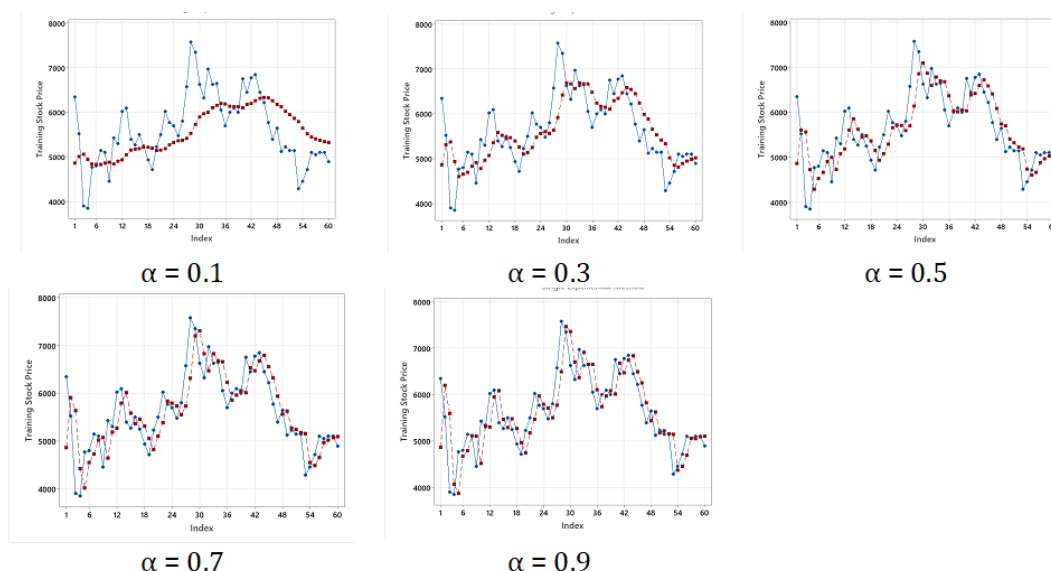


Figure 2. Sensitivity of SES One-Step Fitted Values to the Smoothing Constant on the Training Data, January 2020–December 2024

Figure 2 summarizes the effect of α without repeating every upward and downward movement in the plots. At $\alpha = 0.9$, the fitted line is highly smoothed and responds slowly

to changes in the observed level, resulting in substantial lag following abrupt price movements. Increasing α progressively reduces smoothing and lag because more weight is assigned to the newest price.

Table 3. Model Fit Measures on the Training Data, January 2020–December 2024

α	MAPE (%)	MAD (Rp)	MSD (Rp ²)
0.1	11.48	603.85	622,902.40
0.3	8.53	454.64	381,692.28
0.5	7.76	416.04	302,589.04
0.7	7.21	388.19	263,033.65
0.9	6.80	369.95	241,183.49

Table 3 presents the model-fit measures calculated using the training data from January 2020 to December 2024 for smoothing constants of 0.3, 0.5, 0.7, and 0.9. The results show that the in-sample MAPE, MAD, and MSD consistently decrease as the smoothing constant increases. Among the evaluated candidates, $\alpha = 0.3$ yields the largest errors, with a MAPE of 8.53%, a MAD of Rp454.64, and an MSD of Rp381,692.28. This indicates that the stronger smoothing associated with a lower α causes the model to respond more slowly to changes in ASII's stock price. In contrast, $\alpha = 0.9$ produces the smallest training errors, with a MAPE of 6.80%, MAD of Rp369.95, and MSD of Rp241,183.49, followed by $\alpha = 0.7$. Therefore, within the evaluated range, higher α values provide a better fit to the training data by assigning greater weight to recent observations and reducing forecasting lag. Nevertheless, these measures represent only the in-sample model fit and cannot independently establish forecasting accuracy for observations not used in model estimation.

Table 4. SES Sensitivity and Out-of-Sample One-Step Forecast Accuracy on the Test Data, January–December 2025

α	MAPE (%)	MAD (Rp)	MSD (Rp)
0.1	11.16	623.54	539,541.92
0.3	8.21	468.81	333,854.80
0.5	7.02	391.24	206,695.54
0.7	6.17	336.91	144,582.60
0.9	5.63	301.62	115,141.97

Table 4 presents the sensitivity characteristics and out-of-sample one-step forecasting accuracy for the January–December 2025 test period. The $\alpha = 0.9$ MAPE was 5.63%, the MAD was Rp301.62, and the MSD was Rp115,141.97. This result suggests that ASII's price movements during 2025 were strongly influenced by the most recent observations, allowing highly responsive models to reduce the lag experienced by more heavily smoothed specifications. Although the use of a separate test period provides stronger evidence than in-sample evaluation alone, the result should still be interpreted cautiously because highly responsive models are more sensitive to random disturbances and short-term market volatility.

Table 5. Out-of-Sample Rolling One-Step Forecasts for ASII in 2025 Using SES with $\alpha = 0.9$

Period	Actual price (Rp)	Forecast (Rp)	Absolute percentage error (%)
January 2025	4,800	4,900	2.08
February 2025	4,530	4,800	5.96
March 2025	4,920	4,530	7.93
April 2025	4,800	4,920	2.50
May 2025	4,850	4,800	1.03
June 2025	4,500	4,850	7.78
July 2025	5,100	4,500	11.76
August 2025	5,500	5,100	7.27
September 2025	5,775	5,500	4.76
October 2025	6,150	5,775	6.10
November 2025	6,550	6,150	6.11
December 2025	6,700	6,550	2.24

Table 5 presents the rolling one-step forecasts for the January–December 2025 test period using SES with $\alpha = 0.9$. Under this specification, the forecast for each month equals the actual price observed in the immediately preceding month. The forecast errors are relatively small when monthly price changes are limited, as shown in May 2025, which records the lowest absolute percentage error of 1.03%. Conversely, the model produces larger errors when the price changes abruptly. The highest error occurs in July 2025, when the actual price increases to Rp5,100 while the forecast remains at the June price of Rp4,500, resulting in an absolute percentage error of 11.76%. The errors observed from August to November 2025 also reflect the model's one-period delay in following the sustained price increase. Overall, the test-period MAPE of 5.46% indicates relatively strong one-step forecasting performance.

Table 6. Three-Month ASII Forecasts after December 2025 Using SES with $\alpha = 0.9$

Forecast period	Point forecast (Rp)	Approx. 95% lower bound (Rp)	Approx. 95% upper bound (Rp)
January 2026	6,700	5,749	7,651
February 2026	6,700	5,356	8,044
March 2026	6,700	5,053	8,347

Table 6 presents the ASII forecasts for January–March 2026, following model updates using all observations through December 2025. The point forecast remains constant at Rp6,700 for all three months because SES does not contain a trend or seasonal component. Therefore, every multi-step forecast equals the final estimated level, which, at $\alpha = 0.9$, is identical to the December 2025 closing price. Although the point forecasts are constant, the approximate 95% prediction intervals widen as the forecast horizon increases. The interval extends from Rp5,749–Rp7,651 in January 2026 to Rp5,053–

Rp8,347 in March 2026, indicating greater uncertainty for more distant forecasts. These intervals should be interpreted with caution because they are based on historical one-step errors and do not account for unexpected market shocks, changes in volatility, structural changes, or parameter uncertainty.



Figure 3. ASII Training Data, Test Data, Rolling One-Step Forecasts, and Forecasts after December 2025

Figure 3 visually distinguishes the training data, the 2025 test data, the rolling one-step test forecasts, and the forecasts after December 2025. During the training period, ASII prices exhibit substantial fluctuations, including a decline in 2020, a peak in 2022, and a downward trend during 2023–2024. In the 2025 test period, the rolling forecasts generally track actual price movements but lag by 1 period because $\alpha = 0.9$ uses the preceding month's price as the current forecast. This lag is particularly visible during the sustained increase from July to December 2025. After December 2025, the forecast line becomes horizontal at Rp6,700 for January–March 2026. The flat forecast path illustrates the principal limitation of SES for multi-step forecasting: without an explicit trend component, the model cannot extrapolate the upward movement observed toward the end of 2025.

Murfadiah et al. (2023) also analyzed the pandemic and recovery period. However, they used moving-average windows on quarterly observations and did not report an error table equivalent to the present train/test evaluation. Sofiyati et al. (2024) analyzed monthly average closing prices and obtained a 6.29% MAPE from multiplicative Holt–Winters, with forecasts that fluctuated and tended to increase. The present test MAPE of 5.46% is numerically lower. However, it must not be interpreted as proof of superiority because the target price definition, period, horizon, model components, and evaluation sample differ. The contrast is nevertheless conceptually informative: Holt–Winters can generate changing multi-step paths through trend and seasonal components, whereas the selected SES/naïve specification produces a constant path after the final observation.

The 2020 collapse, 2022 recovery peak, 2023–2024 decline, and 2025 rebound place the findings within post-pandemic market dynamics. A high α enabled the model to follow the latest recovery more quickly, demonstrating the practical advantage of a

simple, transparent method for short-horizon updating. At the same time, the same episodes expose its limitations: SES does not explicitly model persistent trend, seasonality, changing volatility, structural breaks, market shocks, or company fundamentals. A sustained downward or upward movement can therefore leave SES behind until new observations update the level.

More complex alternatives should be tested when diagnostics support their additional structure rather than selected merely because they are more sophisticated. Holt's method is appropriate when a persistent trend is present; Holt-Winters is appropriate when trend and recurring seasonality coexist; and ARIMA is appropriate when differencing and autoregressive or moving-average terms are needed to represent residual autocorrelation (Hyndman & Athanasopoulos, 2021). Volatility-aware or break-aware specifications are needed when changes in variance or structural shifts are material. Machine-learning models become more defensible when a larger sample, multiple explanatory variables, and nonlinear relationships are available, although rigorous out-of-sample validation remains essential (Lim & Zohren, 2021). Future research should therefore compare SES and the naïve benchmark with Holt and ARIMA, test residual autocorrelation and trend persistence, and incorporate relevant market, macroeconomic, and company-level predictors where justified.

CONCLUSION AND RECOMMENDATIONS

This study evaluated the performance of Single Exponential Smoothing (SES) in forecasting PT Astra International Tbk's (ASII) end-of-month closing price on a monthly basis, using data from January 2020 to December 2025. The data from January 2020 to December 2024 were used for model training, while the observations from January to December 2025 were used for out-of-sample rolling one-step validation. Among the smoothing constants evaluated, SES with $\alpha = 0.9$ produced the highest forecasting accuracy on the test data, with a MAPE of 5.63%, MAD of Rp301.62, and MSD of Rp115,141.97. The relatively high smoothing constant enabled the model to respond quickly to recent price movements and reduce the forecasting lag found in models with lower α values. However, this responsiveness also makes the model more sensitive to short-term fluctuations and random market disturbances.

After the selected SES model was updated using all observations through December 2025, the point forecasts for January, February, and March 2026 were Rp6,700 per month. The constant multi-step forecast is consistent with the level-only structure of SES, as the method does not include explicit trend or seasonal components. Therefore, the forecast should be interpreted as a short-term estimate based on the latest smoothed level rather than evidence that the ASII share price will remain unchanged. SES can consequently be used as a transparent forecasting aid or baseline model for short-term price analysis. However, it should not be used as the sole basis for portfolio allocation, trading, or long-term investment decisions. Investment decisions should also consider company fundamentals, macroeconomic conditions, market sentiment, risk, volatility, and transaction costs.

This study has several limitations. It analyzes only one stock, namely ASII, so the findings cannot be directly generalized to other companies or market sectors. The model uses only historical stock prices and does not incorporate fundamental variables, macroeconomic indicators, trading volume, market indices, or other explanatory factors that may influence stock-price movements. In addition, SES cannot explicitly model

persistent trends, recurring seasonality, changing volatility, structural breaks, or sudden market shocks. Out-of-sample validation is also limited to 12 monthly observations in 2025 and uses a rolling one-step evaluation procedure. Consequently, the estimated accuracy may be affected by the specific upward price movement during the test period. It may not fully represent model performance under different market conditions or over longer forecasting horizons.

Future research should compare SES with a naïve benchmark, Holt's trend method, ARIMA, and machine-learning models using the same training and test periods, the same forecast horizon, and consistent accuracy measures such as MAPE, MAD, and MSD. The naïve model is needed to determine whether SES provides an actual improvement over simply using the most recent observation. Holt's method should be examined when the series exhibits a persistent trend, while ARIMA should be considered when significant autocorrelation remains in the data. Machine-learning models may be evaluated when larger datasets and relevant explanatory variables are available to capture nonlinear relationships. Future studies should also employ longer or repeated out-of-sample evaluation periods, such as rolling-origin validation, and incorporate fundamental, macroeconomic, volatility, and market-related variables to obtain more robust and comprehensive forecasting results.

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