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COMPARISON OF ARIMA, EXPONENTIAL SMOOTHING, AND CHEN-SINGH FUZZY MODELS FOR INFLATION FORECASTING IN ASEAN COUNTRIES

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ABSTRACT

This study aims to (i) develop predictive models using statistical and fuzzy approaches, and (ii) evaluate their forecasting performance. The data were obtained from www.investing.com for the period 1961 to 2017 and focus on five ASEAN countries: Indonesia, Malaysia, the Philippines, Singapore, and Thailand. The statistical models used are Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing, while the fuzzy approaches include Chen and Singh fuzzy time series models. The dataset was divided into training and test sets in a 75%-25% proportion. ARIMA models capture trends and autocorrelations in time series data, while Exponential Smoothing uses exponentially weighted averages. Fuzzy models are designed to handle uncertainty and linguistic patterns in data. The results show that Singh's fuzzy model yields the lowest error for Indonesia, while exponential smoothing and Chen fuzzy time series model demonstrate the same lowest error for Malaysia. For the Philippines, exponential smoothing is most accurate, whereas ARIMA and Singh fuzzy time series achieve the smallest error for Singapore. For Thailand, exponential smoothing and ARIMA perform equally well. However, the robustness of the forecasting model cannot be determined from either statistical or fuzzy methods, highlighting the challenge in determining the most robust model for inflation in the ASEAN region. The 75%-25% data split may also limit the generalizability of the findings. This study contributes a rare cross-country comparison of statistical and fuzzy forecasting methods in the ASEAN context. It highlights the importance of model selection based on country-specific inflation behavior and provides insights for improving forecasting strategies in macroeconomic applications.

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1. INTRODUCTION

Inflation in economics refers to the increase in the overall price level of goods and services during a certain period [1], [2]. Each country aims to achieve sustainable economic growth, and inflation is viewed as a key factor in shaping future economic situations [3]. If the price level of goods and services increases, then each unit of currency purchases fewer goods and services. In other words, inflation continuously raises the overall price level. The overall price level represents the total price level for goods and services in an economy at a specific moment [4]. In the context of ASEAN, inflation management is especially vital due to region's diverse economic structures and varying monetary policies. For example, member countries like Indonesia, Thailand, and the Philippines often face inflationary pressures stemming from energy prices, food supply issues, and exchange rate volatility. A high inflation rate will boost the daily expenses and affect the living standards of people in a given country.

The inflation rate is known as a crucial component in evaluating the performance of a central bank [5]. Inflation forecasting is a necessary unit in the set of variables used for strategic thinking in the monetary policy [6]. This study considers inflation trends for the group of five ASEAN member states consisting of Indonesia, Malaysia, the Philippines, Singapore, and Thailand. According to Robiyanto et al. [7], the emerging market economies of ASEAN-5 countries share similarities in various financial aspects, the real sector, and are exposed to common regional shocks. For instance, Indonesia and the Philippines have historically experienced higher inflation volatility due to external shocks and supply-side constraints. Malaysia maintains a relatively moderate inflation rate under a managed float exchange rate system. Singapore, with its unique exchange rate-based monetary policy framework, has one of the lowest inflation volatilities in the region. Thailand operates under an inflation-targeting regime, balancing domestic demand and external factors. The five ASEAN countries have undergone substantial financial and industrial expansion over the last four decades at different times.

According to [8], [9], [10], [11], forecasting future events is necessary for effective planning and decision-making. Financial forecasting stands as one of the most extensively explored subjects within the field of time series analysis [12], [13]. Forecasting is highly beneficial for investors, stockholders, and individuals with a strong interest in finance, as they can apply the forecasting results when making policy decisions for the future [12], [14]. Based on [15], [16], technical analysis in economic forecasting has a positive impact on tracking transformations in the global market. Moreover, time series data consist of observations systematically recorded at consecutive points in time within a specified period [17], [18]. Time series methods are fundamental in statistical analysis, enabling the identification of data patterns and facilitating forecasting future values by analyzing past trends [9], [18], [19]. As central banks strive to implement forecast-based monetary policies, it goes without saying that inflation forecasting is crucial for designing effective monetary strategies.

In addition, forecasting inflation has been approached in many different methods. Researchers strive to improve the model's performance. The wide implementation of models has been proposed in order to enhance the improvement in the financial time series forecasting. A study combines feature selection and Shapley values to explain inflation predictions. Tests in volatile Turkey show that tree-based ensemble models improve both accuracy and interpretability [20]. Furthermore, Long Short-Term Memory (LSTM) performs similarly to Seasonal Autoregressive Integrated Moving Average (SARIMA); it surpasses Autoregressive (AR), Neural Network (NN), and Markov-switching models by a little margin. A unique layer-wise relevance propagation technique is used to provide a qualitative interpretation of network learning, and hyperparameter sensitivity analysis is performed to forecast nonlinear inflation [21]. Using a large US Consumer Price Index (CPI)-U dataset, the evaluation shows that the Hierarchical Recurrent Neural Network (HRNN) model outperforms various established inflation prediction baselines and offers new forecasting tools for policymakers and market participants focused on sectoral and component-specific price changes [22]. A study offers an extensive review of research that compares Autoregressive Integrated Moving Average (ARIMA) combined with machine learning techniques for forecasting time series data. It also explores their integration into hybrid statistical-AI models, applied across various fields including finance, healthcare, weather, utilities, and network traffic [23].

Although various advanced forecasting models have been applied globally, including ensemble trees, LSTM, and hybrid ARIMA-ML models [20], [21], [22], [23], such approaches remain limited in the ASEAN context. Most studies in the region focus on single models or individual countries without comparing multiple forecasting approaches. This lack of comparative studies across both statistical and fuzzy models reduces the insight available for regional inflation forecasting. Therefore, this study fills the gap by evaluating and comparing ARIMA, Exponential Smoothing, and Chen-Singh fuzzy models for inflation forecasting across multiple ASEAN countries. The fuzzy time series approach has been adopted as a notable technique within the fields of artificial intelligence and soft computing [24]. The novelty of this research lies in the comparative evaluation of fuzzy time series models, specifically the Chen and Singh methods, against classical statistical models (ARIMA and Exponential Smoothing) for inflation forecasting across multiple ASEAN countries. Furthermore, ARIMA, Exponential Smoothing, and the Chen and Singh fuzzy time series models were selected in this research due to their widespread use, interpretability, and suitability for economic forecasting, such as inflation. ARIMA is a well-established statistical model effective for non-stationary data with autocorrelation, while Exponential Smoothing is known for its simplicity and robustness, particularly in short-term forecasting. The Chen fuzzy model serves as a foundational approach in fuzzy time series analysis, offering a structured method for handling uncertainty in economic data. Singh's model enhances Chen's by refining the fuzzification and forecasting process, improving accuracy while maintaining transparency. Moreover, Chen's is used as a foundational approach due to its simplicity, efficiency, and ability to handle uncertain or imprecise data, such as inflation rates. Singh improved Chen's model by refining the defuzzification process and logical relationship construction, making it more accurate and suitable for volatile data, such as inflation in emerging economies. Such comparisons are rarely found in the existing literature. Furthermore, this study highlights the model-specific performance differences by country, offering practical insights into the suitability of each forecasting method in diverse economic settings.

2. RESEARCH METHODS

2.1 Data Management

The data source is www.investing.com, collected from 1961 to 2017. In total, there are 57 observation data points. The data is the annual percentage of inflation. Fig.1 shows a conceptual framework of this research. The data were separated into train and test groups in order to obtain the best predicted outcome. Based on [25], [26], 75%-25% is selected as the best ratio for tuning the train and test data frames.

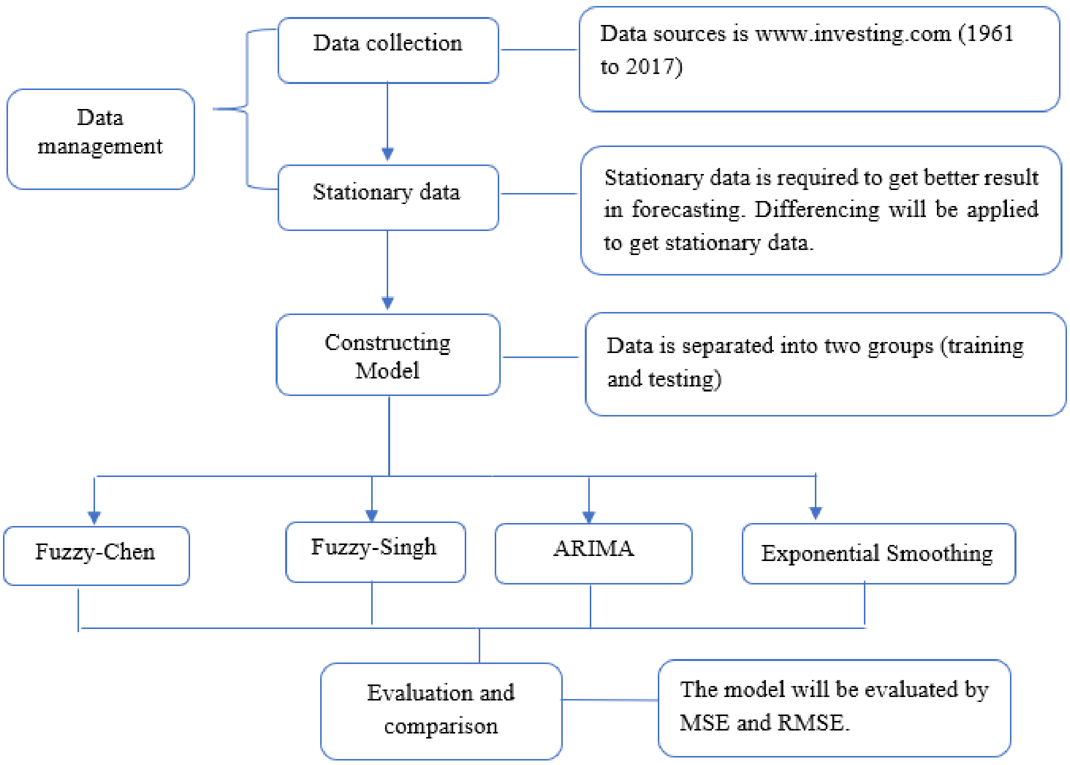
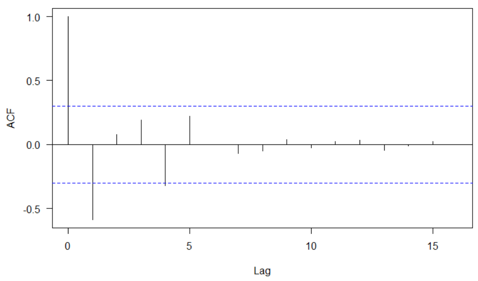
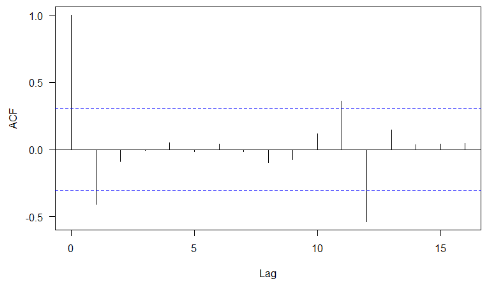


Figure 1. Conceptual Framework

Furthermore, in this study, stationary data will be implemented by differencing transformation. A stationary process is a fundamental requirement for constructing traditional forecasting approaches such as ARIMA, moving average, exponential smoothing, and others. A time series is classified as stationary when its statistical attributes, such as the mean, variance, and autocorrelation, do not vary over time. Therefore, a stationary data set can be forecasted precisely. Furthermore, the Autocorrelation Function (ACF) plot in the stationary data keeps decreasing to zero significantly. However, the exact stationary data does not exist. The researchers can only try to approach it. It can be seen in Fig. 2, the ACF plot for Indonesia, Malaysia, Philippines, Singapore, and Thailand illustrates the stationary time series data after differencing transformation. The ACF showed lean passing through the blue horizontal line.



(a)



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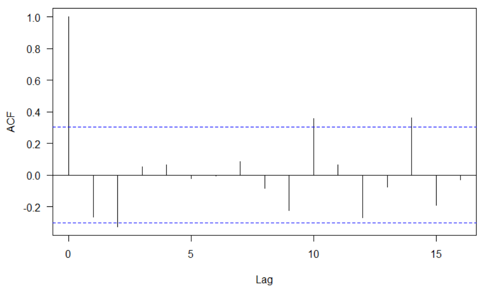

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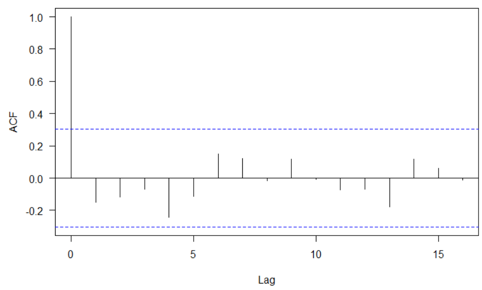
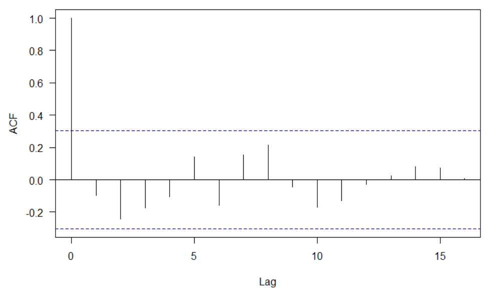


(d)



(e)

Figure 2. Plot of ACF after Differencing for (a) Indonesia, (b) Malaysia, (c) the Philippines, (d) Singapore, and (e) Thailand

2.2 Chen's Model of Fuzzy Time Series

The implementation of fuzzy time series Chen's technique [27] is represented as follows:

1. Partition.
   In this approach, the universal set is grouped into 7 same range intervals $(v_1, v_2, \dots, v_7)$. In the fuzzy time series models (Chen and Singh), the universe of discourse was partitioned into seven equal-length intervals. Seven intervals were selected as a balance between granularity and generalization; finer partitioning (more intervals) increases model complexity and sensitivity to noise, while coarser partitioning may overlook significant variation.
2. Set the fuzzy sets, which are linguistic variables.
   Let $A_1, A_2, \dots, A_7$ be fuzzy sets of intervals $v_1, v_2, \dots, v_7$. The definitions of fuzzy sets are represented as follows:

$$A_1 = \frac{1}{v_1} + \frac{0.5}{v_2} + \frac{0.5}{v_3} + \frac{0.5}{v_4} + \frac{0.5}{v_5} + \frac{0.5}{v_6} + \frac{0.5}{v_7},$$
$$A_2 = \frac{0.5}{v_1} + \frac{1}{v_2} + \frac{0.5}{v_3} + \frac{0.5}{v_4} + \frac{0.5}{v_5} + \frac{0.5}{v_6} + \frac{0.5}{v_7},$$
$$A_3 = \frac{0.5}{v_1} + \frac{0.5}{v_2} + \frac{1}{v_3} + \frac{0.5}{v_4} + \frac{0.5}{v_5} + \frac{0.5}{v_6} + \frac{0.5}{v_7},$$
$$A_4 = \frac{0.5}{v_1} + \frac{0.5}{v_2} + \frac{0.5}{v_3} + \frac{1}{v_4} + \frac{0.5}{v_5} + \frac{0.5}{v_6} + \frac{0.5}{v_7},$$
$$A_5 = \frac{0.5}{v_1} + \frac{0.5}{v_2} + \frac{0.5}{v_3} + \frac{0.5}{v_4} + \frac{1}{v_5} + \frac{0.5}{v_6} + \frac{0.5}{v_7},$$
$$A_6 = \frac{0.5}{v_1} + \frac{0.5}{v_2} + \frac{0.5}{v_3} + \frac{0.5}{v_4} + \frac{0.5}{v_5} + \frac{1}{v_6} + \frac{0.5}{v_7},$$
$$A_7 = \frac{0.5}{v_1} + \frac{0.5}{v_2} + \frac{0.5}{v_3} + \frac{0.5}{v_4} + \frac{0.5}{v_5} + \frac{0.5}{v_6} + \frac{1}{v_7}.$$

The membership function in Chen's method is the way to represent fuzzy set $A_1, A_2, \dots, A_7$. If the data belongs to intervals v_1 then the maximum degree is in the fuzzy set A_1. Otherwise, in case of data fit to intervals v_2 then the maximum degree is in the fuzzy set A_2. Once, in Chen's model, it is considered the degree of membership function within $\{0, 0.5, 1\}$. If the maximum degree of the membership function is in a fuzzy set A_k, then the fuzzified result is A_k.

3. Divide the fuzzy rules into groups.
   The fuzzy rules have been grouped by combining the right-hand sides that are identical to the left-hand side, aligning them with the right-hand side of the fuzzy logic group.
4. Compute the forecasting output
   The established rules to compute the forecast are written as follows:
   a. If the fuzzification results in a time step i are fuzzy sets A_i and appropriate with the Fuzzy Logical Relationship (FLR) as written:
   $$A_i \to \emptyset,$$
   which means that there is no right-hand side of FLRs satisfying the data in time i, then the forecasting result for the time step i is in fuzzy set A_i which the midpoint of v_i is m_i. And the defuzzified result is equal to m_i.
   b. If the fuzzification results in a time step i are fuzzy sets A_i and appropriate with the FLRs as written:
   $$A_i \to A_k,$$
   the forecasted result for the given time step i is in fuzzy set A_k which the midpoint of u_k is m_k. And the defuzzified result is equal to m_k.
   c. If the fuzzification results in a time step i are fuzzy sets A_i and appropriate with the FLRs as written:
   $$A_i \to A_1, A_2, \dots, A_n.$$
   The forecasting result for the subsequent time step i is then obtained in $A_1, A_2, \dots, A_n$ which the midpoint of $v_1, v_2, \dots, v_n$ is $m_1, m_2, \dots, m_n$. And the defuzzified result is equal to $\frac{(m_1+m_2+\cdots+m_n)}{n}$.

2.3 Singh's Model of Fuzzy Time Series

The forecasting procedure for inflation using the fuzzy time series method, as proposed by Singh [28] outlined as follows:

1. Dividing the universal set into equal intervals.
   Division of the universal set U is into the same length intervals. The intervals are similar to the previous model, which is the fuzzy time series Chen's model.

2. Establishing a fuzzy set defined by the triangular membership function
   Fuzzy sets are formed using the triangular membership function, which defines the degree of membership for each data point.

3. Fuzzification
   The process of fuzzification involves converting numerical data into fuzzy values according to the defined fuzzy sets and membership functions.

4. Forecasting
   Fuzzy time series Singh's method, applying order three, as $G(t+1)$ is obtained by $G(t-2), G(t-1)$ and $G(t)$. The third-order fuzzy time series model was adopted following the original method proposed by Singh [28]. Furthermore, $G(t+1)$ is calculated by using the following Eq. (1):

$$G(t+1) = G(t-1) * L(t, t-1, t-2), \tag{1}$$

   where $G(t+1)$ is defined as the fuzzy output (or fuzzy set) associated with the time point $t+1$, The max-min composition operator is notated by using " $*$ " and L is a value representing the gap between successive points of time t with $t-1$ and the value of $t-1$ with $t-2$. The change between the previous 3-time step t data can be measured as written in the following Eq. (2):

$$L(t, t-1, t-2) = \big||A_i - A_{i-1}| - |A_{i-1} - A_{i-2}|\big|, \tag{2}$$

   here A_i, A_{i-1}, and A_{i-2} are the original data of time $i, i-1$, and $i-2$.

2.4 Autoregressive Integrated Moving Average (ARIMA)

Box and Jenkins were the inventors of ARIMA in 1970. Based to Siami et al. in 2018 [29], one of the most well-known linear forecasting models during the past three decades is the ARIMA model. Furthermore, the future value is thought to be a linear mix of the error and the previous value. The formula of the ARIMA model can be presented in the following Eq. (3):

$$y_t = \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}. \tag{3}$$

Where y_t is called the actual data, ε_t is called the random bias at the time step t, ϕ_j and θ_k are called the coefficient, p and q are referred to as integers, these represent the model order and are designated as polynomials for autoregression and moving averages, respectively.

Some researchers [30], [31] have presented the basic steps of the ARIMA approach as follows:

1. Identification
   Autocorrelation Function (ACF) and Autocorrelation Function (PACF) are identified in this part to determine the order of the ARIMA model. Satisfying stationarity is mandatory in the ARIMA model; therefore, data transformation is needed. A stationary time series that has constant variance and mean is advantageous for forecasting techniques.

2. Estimate the parameter
   To minimize the error, a nonlinear estimation procedure will deal with the model parameter. The R program version 4.5.0 with the package Forecast has been used to estimate the ARIMA parameters for each time series data set.

3. Diagnostic checking
   Error assumptions will be examined to see if they are satisfied. The residual plot is employed to evaluate the adequacy of the model. After parameter estimation, the ACF plot and the Ljung-Box test will be utilized to assess if the forecast errors exhibit correlation. Additionally, the histogram of the forecast errors will be examined to verify if they follow a normal distribution with a mean of zero and constant variance. Moreover, 14 forecasted values from the testing data were evaluated and found to satisfy the diagnostic checking criteria, indicating that the model's assumptions were reasonably met.

The ACF plot in Fig. 3 indicates little evidence that the sample autocorrelation at lag 20 exceeds the significance threshold for the 14 forecasted values in Indonesia. The plot also suggests that the variance remains approximately constant over the time period. Furthermore, 0.9369 is the p-value in the Ljung-Box test, indicating non-zero autocorrelations for lags 1-20 in the forecasting inaccuracies. The histogram of the time series for the 14 predicted values illustrates that the residuals are close to a normal distribution with zero mean and constant variance, as depicted in Fig. 4. Therefore, it gives the conclusion that the forecasting inaccuracies for the 14 predicted values of Indonesia can be satisfying a normal distribution with zero mean and constant variance.

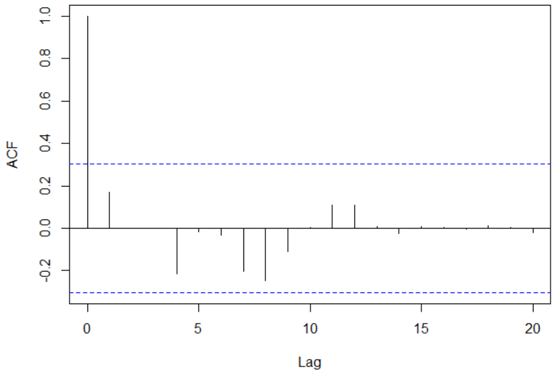


Figure 3. The ACF plot of the ARIMA Forecast Error for Indonesia

The ACF plot of the forecast residuals up to lag 20 is illustrated in Fig. 3. The autocorrelations mostly lie within the 95% confidence bounds (blue dashed lines), indicating that the residuals are largely uncorrelated over time. This suggests that the forecasting model has adequately captured the time-dependent structure of the inflation series. A slight spike at lag 2 and lag 11 is observed, but these are within acceptable bounds and do not imply significant model inadequacy.

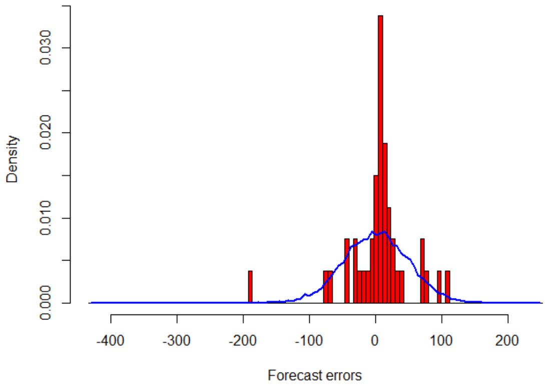


Figure 4. Histogram of the ARIMA Forecast Error for Indonesia

As seen in Fig. 5, the ACF plot illustrates that the sample autocorrelation at lag 20 exceeds the significance thresholds for the 14 predicted values of Malaysia. The plot also indicates that the variance remains approximately constant over time. Furthermore, the p-value for the Ljung-Box test is 0.2695, suggesting that there is small evidence for non-zero autocorrelations for lags 1-20 in the forecasting inaccuracies. The histogram of the time series for the 14 predicted values of Malaysia illustrates that the forecasting inaccuracies are close to a normal distribution and the mean is 0.2975, as shown in Fig. 6. Therefore, it can be concluded that the forecasting inaccuracies for the 14 predicted values of Malaysia follow a normal distribution with constant variance and a mean of zero.

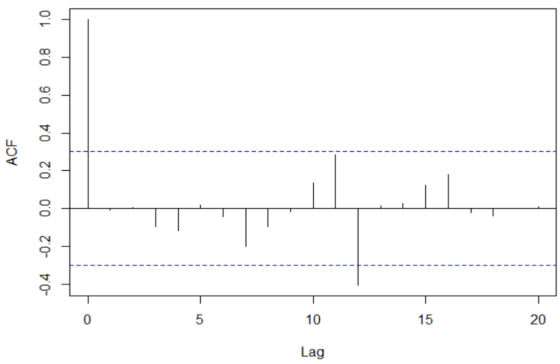


Figure 5. The ACF plot of the ARIMA Forecast Error for Malaysia

The ACF plot of the inflation time series up to lag 20 is displayed in Fig. 5. A strong positive autocorrelation at lag 1 suggests persistence in the data. Most other lags fall within the 95% confidence bounds, except for minor spikes at lags 10 and 14, possibly indicating weak cyclical effects. This pattern implies that the series is likely stationary or nearly stationary, guiding the selection of appropriate forecasting models such as ARIMA.

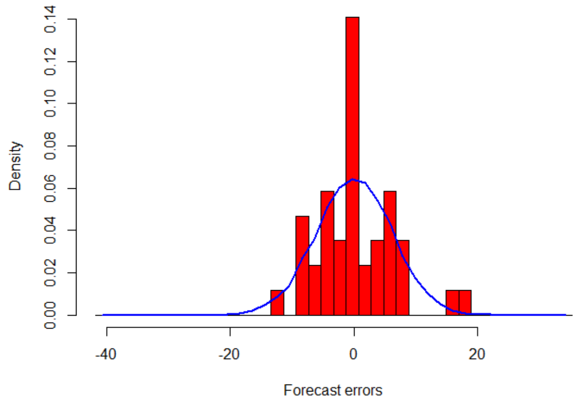


Figure 6. Histogram of the ARIMA Forecast Error for Malaysia

The histogram of forecast errors, overlaid with a kernel density curve, is presented in Fig. 6. The errors are approximately centered around zero, indicating that the forecasts are unbiased. The shape of the distribution is roughly symmetric and resembles a normal distribution, which supports the assumption of normally distributed residuals. This is important for validating the adequacy of statistical models like ARIMA or fuzzy models that assume error normality for optimal performance.

The ACF plot in Fig. 7 reveals that the sample autocorrelation at lag 20 surpasses the significance thresholds for the 14 forecasted values of the Philippines. The plot also indicates that the variance remains approximately constant over time. Furthermore, the p-value for the Ljung-Box test is 0.3312, indicating that there is small evidence for non-zero autocorrelations for lags 1-20 in the forecasting inaccuracies. Moreover, the histogram of the time series for the 14 predicted values of the Philippines represents that the forecasting inaccuracies are close to a normal distribution, and the mean is 0.2693, as shown in Fig. 8.

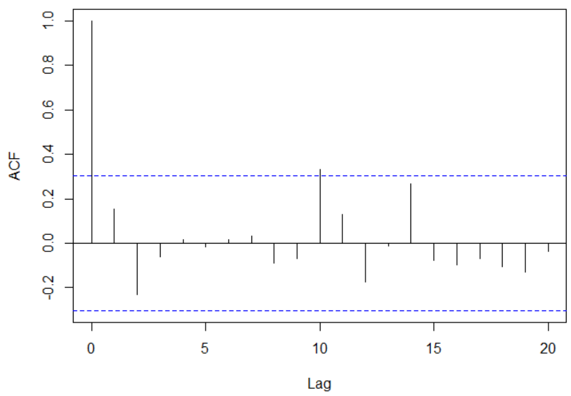


Figure 7. The ACF plot of the ARIMA Forecast Error for the Philippines

The ACF plot in Fig. 8 depicts a histogram of forecast errors (red bars) with a density curve (blue line) to evaluate the distribution of errors. Most forecast errors are centered around zero, indicating that the model performs reasonably well. However, the distribution shows a right skew, suggesting that the model tends to underestimate actual values (resulting in positive forecast errors). A few large outliers also appear in the positive range, which may reflect occasional poor predictions or model limitations. Overall, while the model is generally accurate, there is room for improvement in reducing over-predictions and outliers. Therefore, it can be concluded that the forecasting inaccuracies for the 14 predicted values of the Philippines follow a normal distribution with constant variance and a mean of zero.

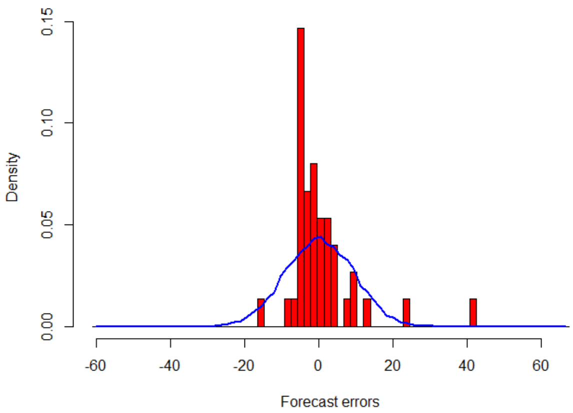


Figure 8. Histogram of the ARIMA Forecast Error for the Philippines

The ACF plot presented in Fig. 9 indicates that the sample autocorrelation at lag 20 crosses the significance thresholds for the 14 forecasted values of Singapore. The plot also indicates that the variance remains approximately constant over time. Furthermore, 0.5509 is the p-value for the Ljung-Box test, indicating that there is small evidence for non-zero autocorrelations for lags 1-20 in the forecasting inaccuracies. Moreover, the time series histogram for the 14 forecasted values depicts that the forecasting inaccuracies are close to a normal distribution and the mean seems to be close to zero, as shown in Fig. 10. Therefore, it provides evidence that the forecasting inaccuracies for the 14 forecasted values of Singapore follow a normal distribution with mean zero and constant variance.

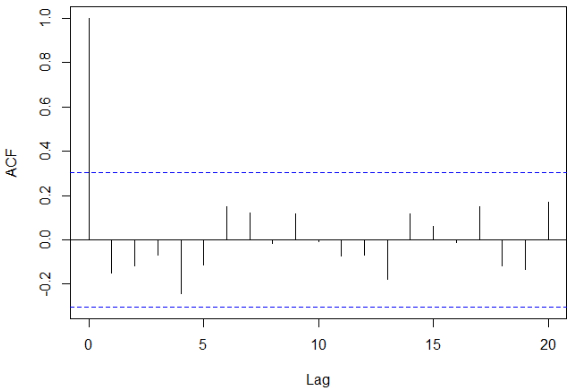


Figure 9. The ACF plot of the ARIMA Forecast Error for Singapore

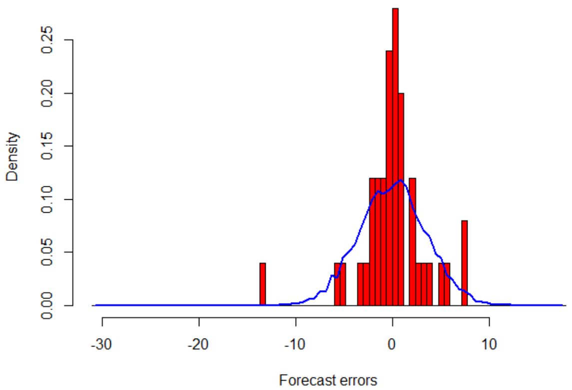


Figure 10. Histogram of the ARIMA Forecast Error for Singapore

The ACF plot, in which the sample autocorrelation at lag 20 crosses the significance lines for 14 forecasted values of Thailand, is presented in Fig. 11. The plot also indicates that the variance remains approximately constant over time. Furthermore, the p-value for the Ljung-Box test is 0.7775, indicating weak evidence for non-zero autocorrelations for lags 1-20 in the forecasting inaccuracies. Moreover, the histogram of the time series for 14 forecasted values of Thailand represents that the forecasting inaccuracies are close to a normal distribution with zero mean, as shown in Fig. 12. Therefore, it is evident that the forecast errors for 14 forecasted values of Thailand are a normal distribution with mean zero and constant variance.

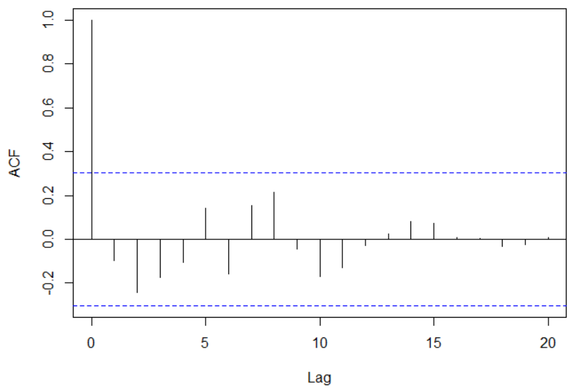


Figure 11. The ACF plot of the ARIMA Forecast Errors for Thailand

A histogram of forecast errors (in red) with an overlaid density curve (in blue) is presented in Fig.12. The distribution of errors is sharply centered around zero, indicating that the forecasting model performs well and is relatively unbiased. The shape of the density curve is approximately symmetric, with shorter and more balanced tails compared to the previous plot. This suggests that the forecast errors are closer to being normally distributed, and there are fewer extreme outliers. Overall, the ARIMA model for Thailand shows better forecasting consistency and accuracy, with reduced bias and variance in the prediction errors.

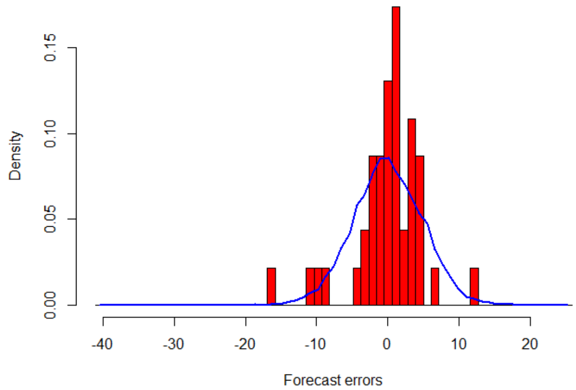


Figure 12. Histogram of the ARIMA Forecast Error for Thailand

As the successive forecasting errors do not appear to be correlated and the forecasting inaccuracies exhibit a distribution close to normal with a mean of zero and constant variance, the prediction model for all anticipated values is supported by the constructed ARIMA model.

2.5 Exponential Smoothing

Based on studies [10], [32], signal and noise are the components of the data set. The signal refers to the underlying pattern or trend that the model aims to estimate, while noise represents random fluctuations or irregularities that obscure the true structure of the data. Exponential Smoothing operates by applying exponentially decreasing weights to past observations, allowing recent data to contribute more heavily to the forecast. This process effectively smooths out the noise and produces a clearer estimate of the signal, making it particularly suitable for datasets with short-term fluctuations but stable underlying trends. Exponential smoothing can be defined as a separation process between the signal (data set) and noise in order to gain signal estimation smoothly. Obtaining the smoother separation of the simple exponential smoothing method can be done by calculating the discount factor θ. It can be presented in the following Eq. (4).

$$\tilde{y}_T = (1-\delta)y_T + \theta\tilde{y}_{T-1}. \quad (4)$$

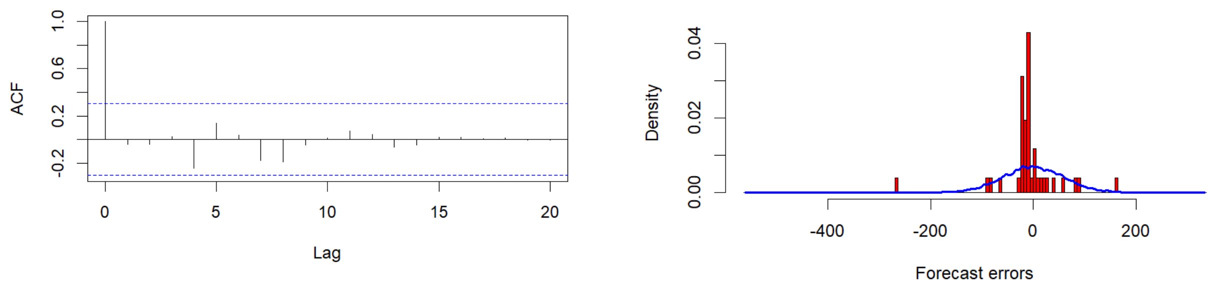
Where $\tilde{y}_T$ is called the forecasted value of y_T,δ is called the discount factor, y_T is called the actual value.

The equations for simple exponential smoothing can also be expressed in an alternative form by defining $\gamma = 1-\delta$ in the following Eq. (5),

$$\tilde{y}_T = \gamma\, y_T + (1-\gamma)\tilde{y}_{T-1} \quad (5)$$

where α symbolizes the weight assigned to the last actual data and $(1-\gamma)$ represents the weight assigned to the smoothed value of the previous actual data $(0 \leq \gamma \leq 1)$. A parameter (γ) needs to be estimated for 75% training data. The smoothing parameter (γ) in the Exponential Smoothing method was estimated automatically using the built-in optimization function in R, which minimizes the sum of squared errors (SSE). The model was applied separately for each ASEAN country to capture the unique characteristics of their respective inflation time series.

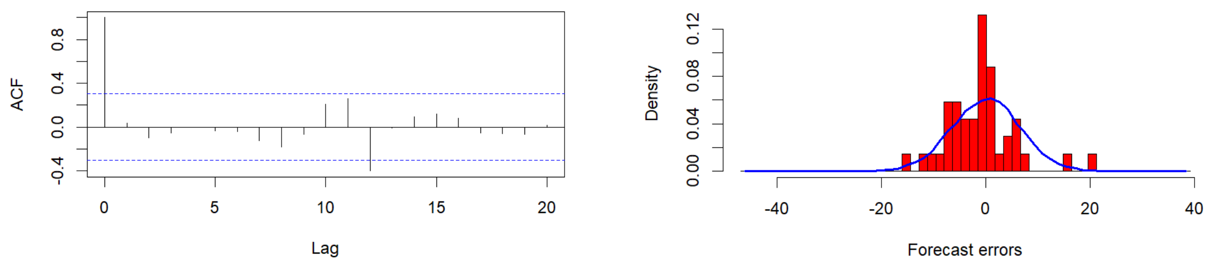
The model's error assumptions will be evaluated to ensure they are adequately met. A residual plot will be used to assess the model's overall adequacy. Following parameter estimation, both the ACF plot and the Ljung–Box test will be applied to determine whether the residuals exhibit any significant autocorrelation. Furthermore, a histogram of the residuals will be analyzed to check for normality, specifically whether they have a mean of zero and constant variance. In addition, 14 forecasted values from the testing dataset were examined and found to meet the diagnostic criteria, suggesting that the model assumptions were reasonably satisfied.



(a) (b)

Figure 13. Residual Plots for Indonesia using Exponential Smoothing (a) ACF (b), Histogram

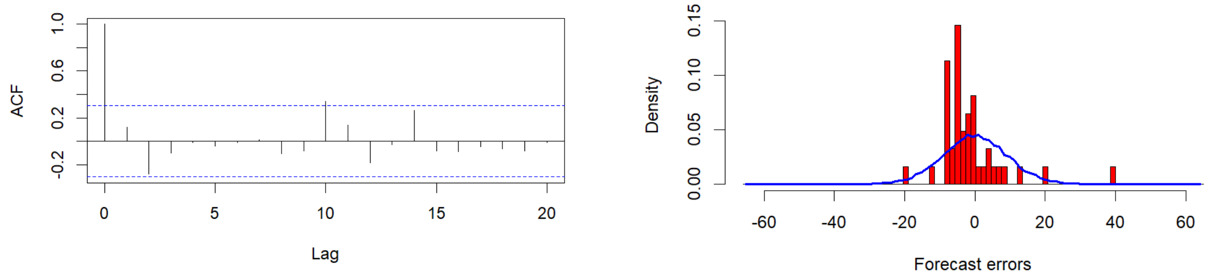
The ACF plot in Fig. 13 shows little evidence that the sample autocorrelation at lag 20 exceeds the significance threshold for the 14 forecasted values in Indonesia, indicating that the variance remains stable over time. Additionally, the Ljung–Box test yields a p-value of 0.9863, suggesting weak evidence of significant autocorrelation across lags 1 to 20 in the residuals. The histogram of the residuals from the 14 predicted values, shown in Fig. 13, indicates that they are approximately normally distributed with a mean close to zero and constant variance. These results collectively support the conclusion that the residuals from the 14 forecasted values in Indonesia satisfy the assumptions of normality, zero mean, and homoscedasticity.



(a) (b)

Figure 14. Residual Plots for Malaysia using exponential smoothing (a) ACF, (b) Histogram

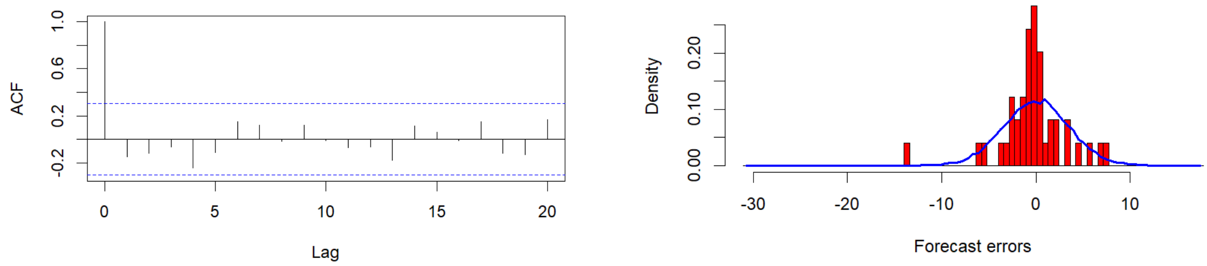
The ACF plot in Fig. 14 indicates no significant evidence that the sample autocorrelation at lag 20 exceeds the significance threshold for the 14 forecasted values in Malaysia. The plot also indicates that the variance remains approximately constant over time. Furthermore, the p-value in the Ljung-Box test is 0.3019, indicating weak evidence of non-zero autocorrelations for lags 1-20 in the forecasting inaccuracies. The histogram of the time series for 14 predicted values illustrates that the forecasting errors residuals are close to a normal distribution with zero mean and constant variance, as depicted in Fig. 14. Therefore, it gives the conclusion that the forecasting inaccuracies for 14 predicted values of Indonesia can be satisfying a normal distribution with zero mean and constant variance.



(a) **(b)**

Figure 15. Residual Plots for the Philippines using Exponential Smoothing (a) ACF, (b) Histogram

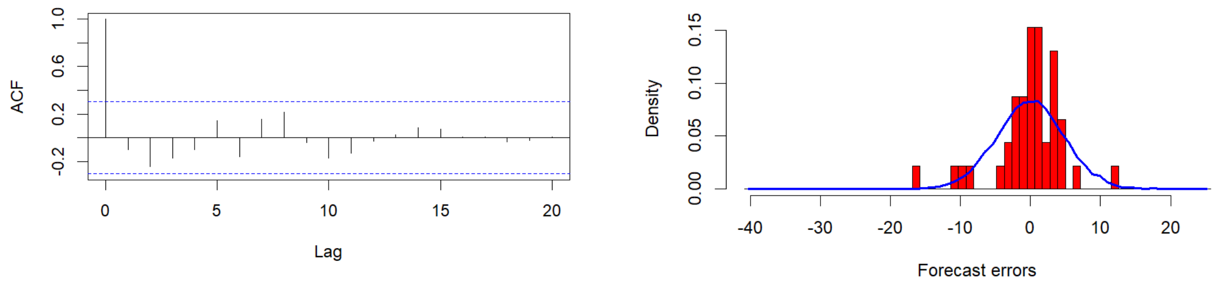
The ACF plot in Figure 15 shows no significant evidence that the sample autocorrelation at lag 20 exceeds the significance threshold for the 14 forecasted values in the Philippines, indicating that the variance remains stable over the observed period. Additionally, the Ljung–Box test yields a p-value of 0.3202, providing weak evidence of autocorrelation in the residuals across lags 1 to 20. The histogram of the residuals for the 14 predicted values, also shown in Fig. 15, indicates an approximately normal distribution with a mean close to zero and constant variance. These findings support the conclusion that the residuals from the 14 forecasted values for the Philippines satisfy the assumptions of normality, zero mean, and homoscedasticity.



(a) **(b)**

Figure 16. Residual Plots for Singapore using Exponential Smoothing (a) ACF, (b) Histogram

Based on Fig. 16, which illustrates the ACF plot for the 14 forecasted values in Singapore, there is no indication that the sample autocorrelation at lag 20 exceeds the critical significance level, suggesting that the variance remains stable throughout the period. Moreover, the Ljung–Box test yields a p-value of 0.5595, indicating minimal evidence of residual autocorrelation across lags 1 to 20. The corresponding histogram, also presented in Fig. 16, reveals that the residuals are approximately normally distributed, centered near zero, and exhibit constant variance. These results confirm that the residuals for the Philippines meet the key assumptions of normality, zero mean, and homoscedasticity.



(a) **(b)**

Figure 17. Residual Plots for Thailand using Exponential Smoothing (a) ACF, (b) Histogram

The ACF plot for the 14 forecasted values in Thailand is presented in Fig.17, which shows no significant autocorrelation at lag 20, suggesting that the variance remains stable over time. In addition, the Ljung–Box test yields a p-value of 0.7777, providing weak evidence of autocorrelation in the residuals across lags 1 to 20. The histogram of residuals, also shown in Fig. 17, demonstrates an approximately normal distribution, with values centered around zero and displaying constant variance. These findings indicate that the residuals for Singapore satisfy the assumptions of normality, zero mean, and homoscedasticity.

The R program version 4.5.0 has been used to examine all models with the goal of obtaining the least MSE and RMSE, and the equation is written below in the following Eqs. (6) and (7) [33]:

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(x_i - y_i)^2 \tag{6}$$

$$RMSE = \sqrt{MSE} \tag{7}$$

Where:

x_i : the forecasted i^{th} value.
y_i : the actual i^{th} value.
m : the number of data points.

3. RESULTS AND DISCUSSION

A time series plot of Indonesian inflation rates, along with the forecast results from four models: Exponential Smoothing (ES), ARIMA, Fuzzy Time Series (FTS) Chen, and FTS Singh is presented in Fig. 18 . The black line represents the actual inflation data, which shows high volatility in the early years and stabilizes in the later period, where forecasting is applied. Each colored line corresponds to a model's prediction, with associated RMSE values shown in the legend. Among the models, FTS Singh (cyan line) achieves the lowest RMSE (5.00), indicating the most accurate forecast, followed by Exponential Smoothing (5.68), FTS Chen (7.08), and ARIMA (8.51). The plot highlights that fuzzy logic-based models, particularly FTS Singh, offer superior performance in forecasting inflation during stable periods in Indonesia.

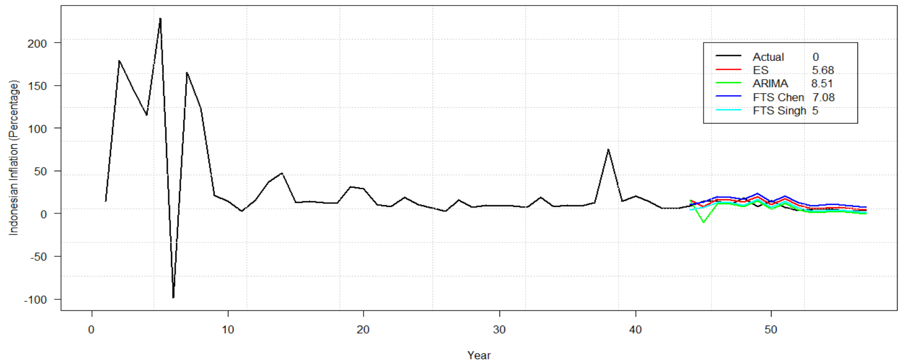


Figure 18. The Plot of Forecasting Results for Indonesia

The 14 forecasted values for Malaysia are presented in Fig. 19, which displays the time series plot of Malaysian inflation data along with forecasts from four models: Exponential Smoothing (ES), ARIMA, Fuzzy Time Series (FTS) Chen, and FTS Singh. The black line represents the actual inflation values, which remain relatively stable over time. Forecasting is applied in the latter part of the series, where the predicted lines from each model are shown. The RMSE values displayed in the legend indicate that Exponential Smoothing and FTS Chen achieved the lowest error (4.84), followed closely by FTS Singh (4.87) and ARIMA (4.97). Overall, the results suggest that all models performed comparably well on Malaysia's relatively stable inflation data, with slight differences in forecasting accuracy.

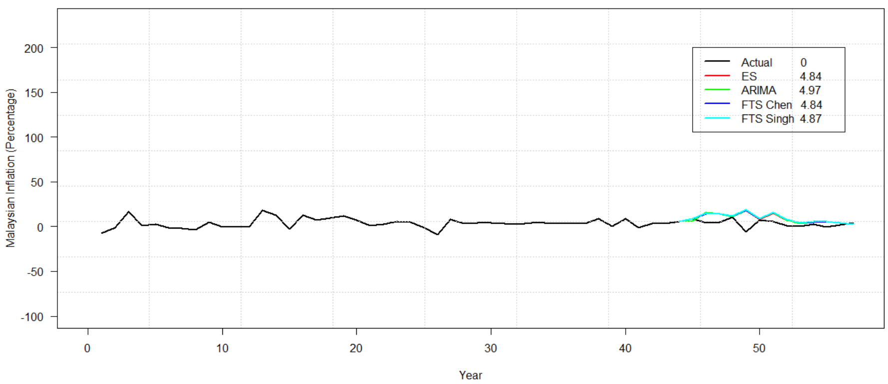


Figure 19. The Plot of Forecasting Results for Malaysia

A time series plot of inflation in the Philippines, along with forecast results from four models: Exponential Smoothing (ES), ARIMA, Fuzzy Time Series (FTS) Chen, and FTS Singh, is presented in Fig. 20. The black line represents the actual inflation data, which shows moderate fluctuations over time. Forecasts begin in the later part of the series, where the colored lines represent model predictions. Based on the RMSE values shown in the legend, Exponential Smoothing achieved the best forecasting performance (4.75), closely followed by ARIMA (4.78), FTS Singh (4.86), and FTS Chen (5.18). These results suggest that traditional statistical models slightly outperform fuzzy models in forecasting inflation in the Philippines, although all models perform reasonably well on the relatively stable data.

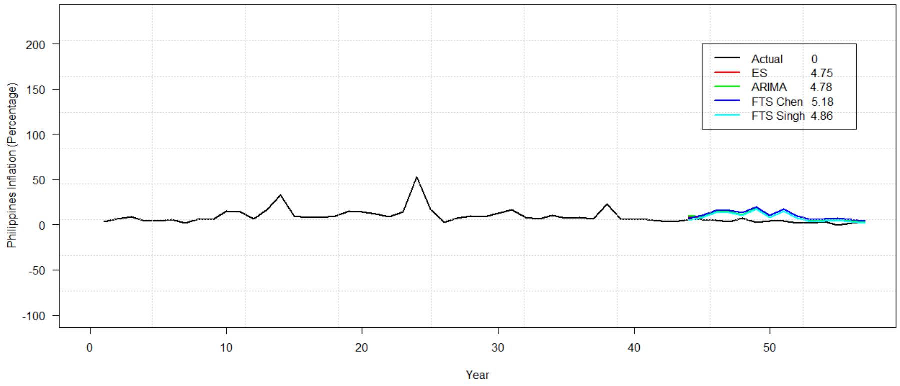


Figure 20. The Plot of Forecasting Results for the Philippines

A time series plot of Singapore's inflation rates along with forecasts from four models: Exponential Smoothing (ES), ARIMA, Fuzzy Time Series (FTS) Chen, and FTS Singh, is presented in Fig. 21. The black line represents the actual inflation data, which shows minimal fluctuations and remains highly stable throughout the observed period. Forecasting is conducted in the latter portion of the series, where predicted values from each model are illustrated. Based on the RMSE values presented in the legend, ARIMA and FTS Singh yield the most accurate forecasts (both 4.83), followed closely by Exponential Smoothing (4.85) and FTS Chen (4.92). These results indicate that all models perform similarly in forecasting Singapore's stable inflation pattern, with ARIMA and FTS Singh providing slightly better accuracy.

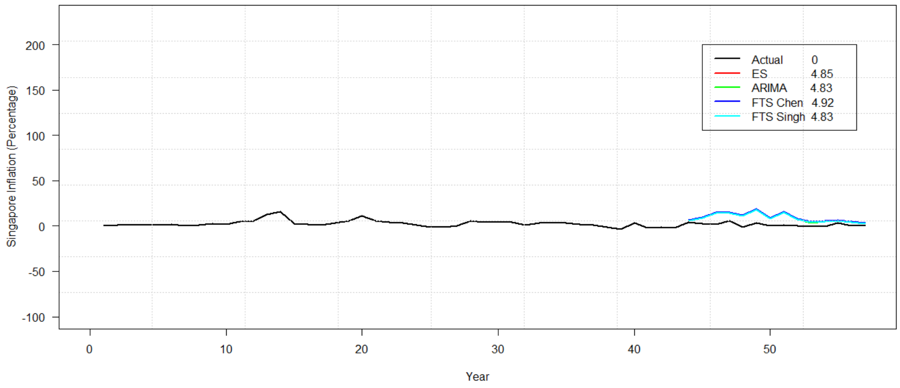


Figure 21. The Plot of Forecasting Results for Singapore

A time series plot of Thailand's inflation data alongside forecast outputs from four models: Exponential Smoothing (ES), ARIMA, Fuzzy Time Series (FTS) Chen, and FTS Singh is presented in Fig. 22 . The actual inflation trend, depicted by the black line, appears relatively stable throughout the time period with modest fluctuations. Forecasting is applied in the latter portion of the data, where the predictions from each model are compared. According to the RMSE values shown in the legend, both ES and ARIMA produced the most accurate forecasts (RMSE = 4.83), followed closely by FTS Singh (4.84) and FTS Chen (4.91). These results indicate that all models performed similarly well for Thailand's stable inflation trend, with traditional statistical methods slightly outperforming fuzzy models.

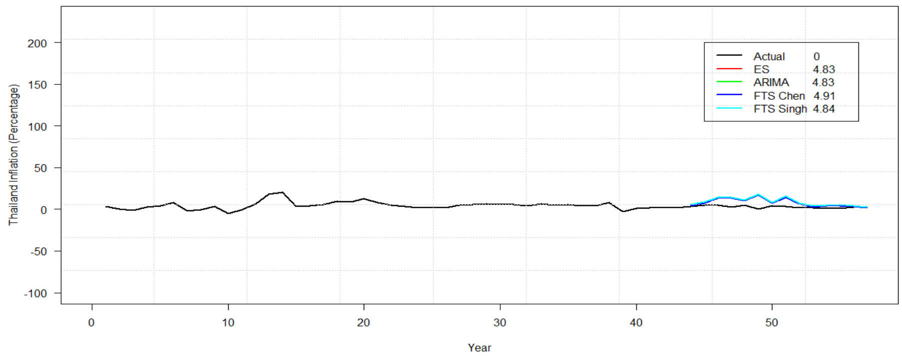


Figure 22. The Plot of Forecasting Results for Thailand

Regarding model performance as presented in Table 1, for Indonesia, the Fuzzy Singh model achieved the lowest error, with a root mean square error (RMSE) of 4.995. For Malaysia, the exponential smoothing model produced the smallest error, with an RMSE of 4.835. Similarly, exponential smoothing also demonstrated the best performance for forecasting inflation in the Philippines, with an RMSE of 4.753. In the case of Singapore, the ARIMA model recorded the lowest error, with an RMSE of 4.832, and the same model also yielded the smallest error for Thailand, with an RMSE of 4.832. Notably, the RMSE values for inflation forecasts in Malaysia, Singapore, and Thailand were relatively similar.

The results show variations in model performance across countries, which can be attributed to differences in inflation volatility. In Indonesia, where inflation data is relatively volatile, the Fuzzy Singh model demonstrates the best performance (lowest RMSE), suggesting that its higher-order fuzzy logic structure is better suited for capturing nonlinear and uncertain patterns in complex time series. In contrast, Exponential Smoothing performs best in Malaysia and the Philippines, where inflation trends are more stable and linear, making simpler models more effective. In Singapore and Thailand, all models show comparable accuracy due to the consistently stable inflation patterns. These findings imply that model selection for inflation forecasting should consider the nature of the data—particularly volatility—when guiding economic policy. For policymakers, using models like Fuzzy Singh in volatile economies can improve the accuracy of inflation projections, which are critical for setting interest rates, controlling money supply, and ensuring economic stability.

Table 1. The Evaluation for All Models

Country Method	RMSE	MSE
Indonesia		
Exponential smoothing	5.676	32.216
ARIMA	8.513	72.470
Fuzzy Chen	7.080	50.121
Fuzzy Singh	4.995	24.951
Malaysia		
Exponential smoothing	4.835	23.380
ARIMA	4.967	24.675
Fuzzy Chen	4.842	23.445
Fuzzy Singh	4.865	23.672
The Philippines		
Exponential smoothing	4.753	22.594
ARIMA	4.779	22.838
Fuzzy Chen	5.175	26.785
Fuzzy Singh	4.857	23.593
Singapore		
Exponential smoothing	4.850	23.521

Country	Method	RMSE	MSE
	ARIMA	4.832	23.346
	Fuzzy Chen	4.918	24.188
	Fuzzy Singh	4.833	23.358
Thailand			
	Exponential smoothing	4.833	23.355
	ARIMA	4.832	23.347
	Fuzzy Chen	4.910	24.110
	Fuzzy Singh	4.836	23.387

The study provides a comprehensive comparison between traditional statistical models (ARIMA, Exponential Smoothing) and fuzzy logic-based approaches (Chen and Singh FTS), which is valuable given the complexity of inflation forecasting. However, modern methods cannot guarantee to perform better than the classical method. And the classical method also cannot guarantee to perform better than the modern method. Thus, it is necessary to manage and examine the dataset to get a forecasting method properly. The use of RMSE and MSE ensures an objective evaluation of model performance. The train-test split (75%-25%) helps assess generalization capability, reducing overfitting risks. The results indicate that no single approach consistently outperforms others across the five ASEAN countries. These findings are consistent with recent studies such as Makridakis et al. in 2018 [34] and Jiang et al. in 2019 [35], which emphasize the importance of context in model performance for forecasting tasks, and that fuzzy time series models can outperform traditional ones in cases of uncertainty and nonlinear patterns. In addition, the competitive performance of fuzzy time series and hybridization, particularly [36], reinforces the study’s conclusion that no universal best model exists for some time series data. This suggests that hybrid or context-sensitive model selection may be more effective than relying solely on a single forecasting paradigm.

4. CONCLUSION

Statistical models often outperformed fuzzy models in four ASEAN countries, except Indonesia, where Fuzzy Singh excelled (RMSE 4.995 vs. ARIMA 8.513) when applied to the ASEAN inflation dataset. The fuzzy time series model outperformed others only in the case of Indonesia’s inflation data, while the statistical models generally achieved better accuracy in the remaining countries. However, each time series dataset exhibits unique characteristics that require careful examination. It is important to note that the findings of this study are based on a 75%-25% training-testing data split, which may limit the generalizability of the results and affect model robustness. Future research could investigate the impact of different training and testing data splits—such as 80%–20% or 60%–40%—on forecasting accuracy. Alternative data splits, such as 80%-20%, help evaluate model robustness across different sample sizes. Testing models on varying splits ensures that performance is not overly dependent on a specific data partition. In this study, such variations support the reliability of findings, especially given the differences in model accuracy across countries. Additionally, the development of novel fuzzy time series models incorporating alternative optimization techniques, such as genetic algorithms or simulated annealing, could be a promising direction. In recent years, various machine learning-based forecasting approaches, including decision trees and neural networks, have gained prominence. Therefore, machine learning models may serve as valuable benchmarks for comparison with fuzzy time series models in future studies.

Author Contributions

Tri Wijayanti Septiarini: Data Curation, Literature Review, Methodology, Resources Conceptualization, Writing – Original Draft. Selly Anastassia Amellia Kharis: Formal Analysis, Investigation, Writing - Review and Editing. Anuraga Jayanegara: Supervision, Validation, Writing- Review and Editing. Sahidan Abdulmana: Project Administration, Software, Visualization. All authors discussed the results and contributed to the final manuscript.

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DECLARATIONS

The authors declare no competing interests.

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