

Forecasting the Jakarta Composite Index (IHSG) Using the Moving Average Method

Heru Ismanto*¹

¹Department Informatics Engineering, Universitas Musamus Merauke, Indonesia

e-mail: *heru@unmus.ac.id

Abstrak

Indeks pasar keuangan memiliki peran penting dalam mencerminkan kondisi ekonomi dan mendukung pengambilan keputusan investasi. Di Indonesia, Indeks Harga Saham Gabungan (IHSG) berfungsi sebagai tolok ukur utama untuk menilai kinerja pasar saham secara keseluruhan. Namun, karakteristik IHSG yang dinamis dan volatil menjadikan proses peramalan pergerakannya sebagai tantangan dalam analisis deret waktu keuangan. Banyak penelitian terkini menggunakan model machine learning dan deep learning yang kompleks, tetapi pendekatan tersebut umumnya membutuhkan sumber daya komputasi yang besar serta memiliki tingkat interpretabilitas yang rendah, sehingga membatasi penerapannya secara praktis. Penelitian ini dimotivasi oleh kebutuhan akan metode peramalan yang transparan dan mudah diimplementasikan. Oleh karena itu, penelitian ini mengkaji penggunaan metode Simple Moving Average (SMA) sebagai model dasar untuk meramalkan IHSG. Kontribusi utama penelitian ini adalah penyajian evaluasi sistematis terhadap metode moving average dengan menggunakan berbagai ukuran jendela dan metrik kesalahan standar. Data historis IHSG dipra-pemrosesan, dianalisis secara deskriptif, dan dibagi ke dalam data pelatihan serta data pengujian. Peramalan jangka pendek kemudian dihasilkan melalui penerapan model SMA dengan beberapa konfigurasi jendela. Kinerja metode yang diusulkan dievaluasi menggunakan Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), dan Mean Absolute Percentage Error (MAPE). Hasil penelitian menunjukkan bahwa metode moving average mampu menangkap tren umum IHSG, dengan tingkat akurasi peramalan yang sangat dipengaruhi oleh pemilihan ukuran jendela. Penelitian selanjutnya disarankan untuk mengintegrasikan metode peramalan tambahan, memasukkan variabel eksogen, serta mengembangkan model hibrida atau adaptif guna meningkatkan akurasi dan ketahanan peramalan.

Kata kunci: Peramalan pasar saham, Indeks Harga Saham Gabungan (IHSG), analisis deret waktu, moving average, peramalan keuangan

Abstract

Financial market indices play a crucial role in reflecting economic conditions and supporting investment decision-making. In Indonesia, the Jakarta Composite Index (IHSG) serves as a key benchmark for evaluating overall stock market performance. Due to its dynamic and volatile nature, accurate forecasting of IHSG movements remains a challenging task in financial time series analysis. Many recent studies employ complex machine learning and deep learning models, which often require substantial computational resources and lack interpretability, limiting their practical adoption. Motivated by the need for transparent and easily implementable forecasting approaches, this study investigates the use of the Simple Moving Average (SMA) method as a baseline model for forecasting the IHSG. The main contribution of this research lies in providing a systematic evaluation of the moving average method using different window sizes and standard error metrics. Historical IHSG data are preprocessed, analyzed descriptively, and divided into training and testing datasets. Short-term forecasts are generated by applying the SMA model with varying window configurations. The

performance of the proposed approach is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results demonstrate that the moving average method is capable of capturing the general trend of the IHSG, with forecasting accuracy strongly influenced by the choice of window size. Future work may focus on integrating additional forecasting techniques, incorporating exogenous variables, and developing hybrid or adaptive models to further enhance prediction accuracy and robustness.

Keywords: *Stock market forecasting, Jakarta Composite Index (IHSG), time series analysis, moving average, financial forecasting*

1. INTRODUCTION

Financial markets play a critical role in modern economies by facilitating capital allocation, supporting investment decisions, and reflecting macroeconomic conditions. Among various financial indicators, stock market indices are widely used as benchmarks to measure overall market performance and investor sentiment. In Indonesia, the Jakarta Composite Index (Indeks Harga Saham Gabungan – IHSG) represents the aggregate price movement of all listed stocks on the Indonesia Stock Exchange and serves as a primary indicator for both domestic and international investors. Due to its sensitivity to economic policies, global market dynamics, geopolitical events, and investor behavior, the IHSG exhibits complex temporal patterns characterized by volatility, trend shifts, and short-term fluctuations. Consequently, accurate forecasting of IHSG movements has become an important research topic in the fields of financial analytics, computational economics, and time series analysis. Recent advances in data-driven decision support systems have further increased the demand for reliable forecasting models that are interpretable, computationally efficient, and suitable for practical implementation in emerging markets such as Indonesia [1], [2].

Despite the availability of extensive historical data, forecasting stock market indices remains a challenging problem due to the stochastic nature of financial time series. Market prices are influenced by a combination of linear trends, seasonal effects, random shocks, and non-stationary behaviors. Many studies have attempted to address this problem using advanced machine learning and deep learning approaches, including artificial neural networks, long short-term memory networks, and hybrid models [3]–[5]. While these approaches often demonstrate strong predictive performance, they typically require large datasets, extensive parameter tuning, and significant computational resources. Moreover, the lack of interpretability and transparency in complex models can limit their acceptance among practitioners and policymakers. In contrast, traditional statistical methods such as moving averages, exponential smoothing, and autoregressive models remain widely used in financial practice due to their simplicity, robustness, and ease of interpretation [6]. However, in the context of the IHSG, systematic evaluation of simple moving average methods using recent data and standardized performance metrics is still relatively limited, creating a research gap that warrants further investigation.

The primary goal of this research is to analyze and forecast the Jakarta Composite Index using the Moving Average (MA) method as a baseline time series forecasting approach. This study aims to investigate how different moving average window sizes affect forecasting accuracy and to evaluate the suitability of the moving average method for short-term IHSG prediction. The motivation for this research is twofold. First, from a practical perspective, many individual investors, analysts, and small financial institutions rely on simple technical indicators due to their low implementation cost and real-time applicability. Second, from an academic perspective, establishing a strong baseline model is essential for benchmarking more complex forecasting techniques. By focusing on the moving average method, this study emphasizes

transparency, reproducibility, and methodological clarity, which align well with the principles of computational and cybernetic systems research. Furthermore, recent literature highlights that simple models can still provide competitive performance under certain market conditions, particularly when noise dominates structural patterns in the data [7], [8].

To address the identified research problem, this study proposes a systematic application of the moving average method to IHSG historical data, followed by a comprehensive evaluation using standard error metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The proposed approach involves preprocessing historical index data, applying multiple moving average configurations, and generating short-term forecasts for comparative analysis. The main contributions of this research are threefold. First, it provides an updated empirical analysis of IHSG forecasting using recent data, contributing to the limited body of literature focused on the Indonesian stock market. Second, it offers a structured evaluation framework that can be easily replicated or extended by future studies. Third, it establishes a transparent baseline model that can serve as a reference point for comparing advanced machine learning-based forecasting techniques. The results of this study are expected to demonstrate that, despite its simplicity, the moving average method can produce meaningful forecasts and valuable insights for short-term market analysis. In conclusion, this research reinforces the relevance of classical time series methods in modern financial forecasting and highlights their continued applicability within computational decision-support systems.

2. METHODOLOGY

Forecasting stock market indices has been extensively studied using a wide range of statistical, machine learning, and hybrid approaches. Early and contemporary studies emphasize that financial time series are inherently noisy, non-stationary, and influenced by both endogenous and exogenous factors, making accurate prediction a persistent challenge. In recent years (2020–2025), the literature has increasingly focused on comparing classical statistical models with advanced data-driven techniques to assess their relative effectiveness, robustness, and practical applicability. Despite the rapid development of deep learning-based forecasting models, several studies reaffirm the continued relevance of traditional time series methods, particularly as baseline or benchmark models [6], [7].

Deep learning approaches such as artificial neural networks (ANN), long short-term memory (LSTM), and gated recurrent unit (GRU) models have been widely applied to stock index forecasting. Chen et al. [3] demonstrated that deep neural networks can capture nonlinear relationships in stock market data and outperform traditional linear models under certain conditions. Similarly, Liu et al. [4] applied LSTM models augmented with technical indicators and reported improved predictive accuracy for stock price movements. A comprehensive systematic review by Sezer et al. [5] highlighted that deep learning models generally achieve lower forecasting errors compared to classical methods, particularly when large-scale datasets and rich feature representations are available. However, these studies also noted critical limitations, including high computational complexity, sensitivity to hyperparameter selection, and limited interpretability, which may reduce their suitability for real-time decision-making and resource-constrained environments.

In contrast, classical statistical and time series methods such as moving average, exponential smoothing, and autoregressive integrated moving average (ARIMA) remain widely used due to their simplicity and transparency. Hyndman and Athanasopoulos [6] emphasized that simple forecasting methods often perform competitively, especially for short-term predictions and in scenarios dominated by random fluctuations. The findings of the M5 forecasting competition further support this perspective, showing that no single complex model consistently outperforms simpler approaches across all datasets and evaluation metrics [7]. Wang et al. [8] conducted a comparative study between statistical and machine learning

methods for stock index forecasting and found that while machine learning models generally achieved better accuracy, classical methods provided more stable performance and easier interpretability. These results suggest that simple methods such as moving averages still offer practical value, particularly as baseline models or complementary tools.

Several studies have specifically applied moving average-based techniques to financial time series forecasting. Although moving average methods are often criticized for their lagging nature, recent empirical analyses indicate that appropriate window size selection can significantly improve forecasting performance [8]. Moreover, moving average indicators remain popular among practitioners due to their low implementation cost and intuitive interpretation. However, most existing studies either focus on developed markets or incorporate moving averages only as auxiliary indicators within more complex models. Empirical research dedicated to evaluating the standalone performance of moving average methods on emerging markets, such as the Indonesian stock market, remains relatively limited. In addition, many studies do not provide a systematic comparison across multiple evaluation metrics, which is essential for assessing forecasting reliability and robustness.

Based on the reviewed literature, a clear research gap can be identified. While advanced machine learning and deep learning models dominate recent forecasting research, there is insufficient emphasis on transparent baseline models evaluated using recent data and standardized metrics, particularly in the context of the Jakarta Composite Index (IHSG). Existing studies rarely focus on the trade-off between predictive accuracy, computational efficiency, and interpretability when applied to emerging markets. Therefore, this study addresses this gap by providing a systematic evaluation of the moving average method for IHSG forecasting, using multiple error metrics and recent historical data. By doing so, this research contributes to the state-of-the-art by reinforcing the importance of classical time series approaches as reliable baselines and practical tools within modern financial forecasting systems.

2.1. Research Object and Data Source

The object of this research is the Jakarta Composite Index (Indeks Harga Saham Gabungan – IHSG), which represents the overall performance of stocks listed on the Indonesia Stock Exchange. The IHSG is widely used as a benchmark indicator to reflect market trends, investor sentiment, and macroeconomic conditions in Indonesia. The data used in this study consist of historical IHSG index values recorded over a specified observation period. This type of data is classified as univariate time series data, where each observation represents the index value at a particular time point. Time series data are particularly suitable for forecasting analysis, as they allow the identification of trends, patterns, and temporal dependencies that can be exploited for prediction purposes. The selection of IHSG as the research object is motivated by its economic importance and its frequent use in both academic research and practical investment decision-making. To provide a clear and systematic overview of the research process, a methodological workflow is designed to illustrate the sequence of steps applied in this study. The flowchart presents the logical progression from data acquisition to forecasting and performance evaluation, ensuring transparency and reproducibility of the proposed approach. Each stage in the workflow reflects the methodological framework adopted for forecasting the Jakarta Composite Index (IHSG) using the Moving Average method and serves as a conceptual guide for the implementation and analysis discussed in the subsequent sections.

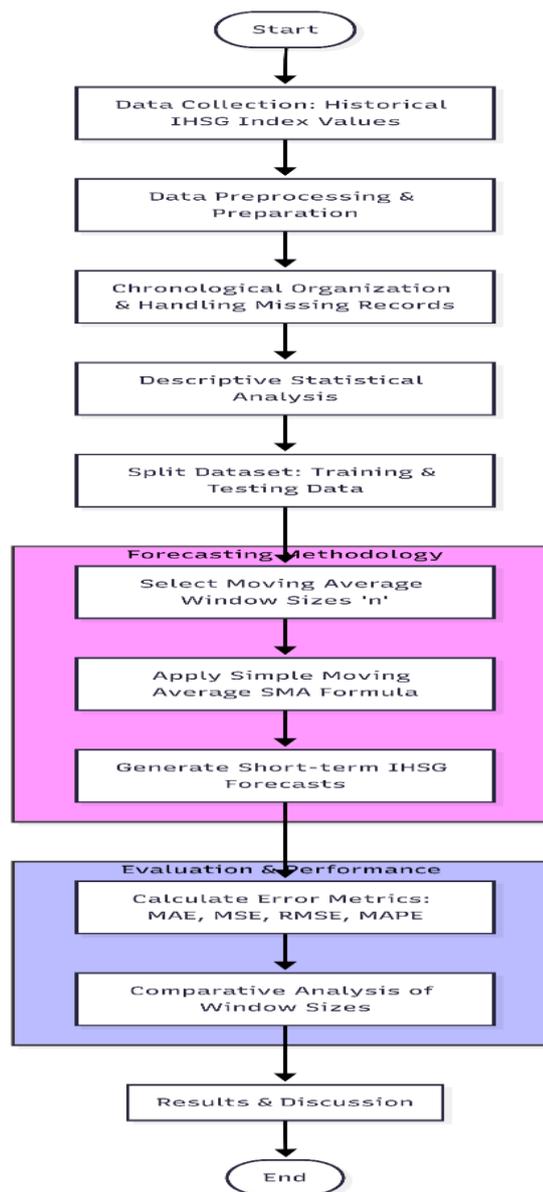


Figure 1. Research Methodology Flowchart for IHSG Forecasting Using the Moving Average Method

Figure 1 illustrates the overall research methodology employed in this study for forecasting the Jakarta Composite Index (IHSG) using the Moving Average approach. The process begins with the collection of historical IHSG index values, which serve as the primary data source for the analysis. The collected data then undergo preprocessing and preparation, including chronological organization and handling of missing records, to ensure data consistency and reliability. Descriptive statistical analysis is subsequently performed to obtain an initial understanding of the data characteristics and underlying patterns. Afterward, the dataset is divided into training and testing subsets to support model development and performance evaluation. The core forecasting stage involves selecting appropriate moving average window sizes and applying the Simple Moving Average (SMA) formula to generate short-term IHSG forecasts. Finally, the forecasting results are evaluated using standard error metrics, namely MAE, MSE, RMSE, and MAPE, followed by a comparative analysis of different window sizes. The workflow concludes with the presentation of results and discussion,

providing insights into the effectiveness of the proposed methodology and its applicability to short-term stock index forecasting.

2.2. Data Preparation and Preprocessing

Before applying the forecasting model, the raw IHSG data undergo a data preparation process to ensure consistency and reliability. Data preprocessing is an essential step in time series analysis, as irregularities such as missing values, outliers, or inconsistent time intervals can negatively affect forecasting accuracy. In this study, the data are first organized chronologically to preserve the temporal order of observations. Any missing or incomplete records are handled to maintain continuity in the time series. Furthermore, descriptive statistical analysis is conducted to gain an initial understanding of the data distribution, central tendency, and variability. This step also facilitates the identification of overall trends and short-term fluctuations in the IHSG. The prepared dataset is then divided into two subsets, namely the training data and the testing data. The training dataset is used to construct the forecasting model, while the testing dataset is reserved for evaluating the predictive performance of the proposed method.

2.3. Proposed Forecasting Method: Moving Average

The primary forecasting approach employed in this study is the Moving Average (MA) method, which is one of the most commonly used techniques in time series analysis and technical forecasting. The moving average method aims to smooth short-term fluctuations and highlight underlying trends by averaging a fixed number of past observations. Conceptually, this method assumes that future values can be approximated by the average of recent historical values. The simplicity and interpretability of the moving average method make it particularly suitable as a baseline forecasting model, as emphasized in prior studies [6], [7].

Mathematically, the simple moving average (SMA) of order n at time t is defined as:

$$MA_t = \frac{1}{n} \sum_{i=0}^{n-1} X_{t-i} \quad (1)$$

where MA_t represents the moving average value at time t , X_{t-i} denotes the actual IHSG value at time $t-i$, and n is the window size or the number of past observations included in the calculation. By adjusting the window size n , different levels of smoothing can be achieved. A smaller window size reacts more quickly to recent changes, while a larger window size produces smoother forecasts but may introduce a lag effect. In this research, the moving average method is applied systematically to generate short-term forecasts of the IHSG based on historical index values.

2.4. Supporting Techniques and Model Configuration

To enhance the robustness of the forecasting results, this study considers the effect of different moving average window sizes on prediction performance [8], [9]. The use of multiple window configurations allows for a comparative analysis of how responsiveness and smoothing influence forecast accuracy [8], [10]. This approach is consistent with findings in the literature, which suggest that the choice of window size plays a critical role in determining the effectiveness of moving average-based forecasting models [8], [11]. Although no complex hybrid or machine learning-based enhancements are introduced, this configuration strategy provides valuable insights into the trade-offs between sensitivity to market changes and noise reduction [9], [10]. By maintaining a simple model structure, the study prioritizes transparency

and reproducibility, which are important considerations for practical financial forecasting and academic benchmarking [11].

2.5. Evaluation and Performance Assessment

The performance of the proposed moving average forecasting model is evaluated using standard error metrics commonly applied in time series forecasting studies. These metrics provide quantitative measures of the deviation between the predicted IHSG values and the actual observed values in the testing dataset. The evaluation metrics used in this research include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Each metric captures different aspects of forecasting accuracy and error magnitude. The use of multiple evaluation metrics is intended to ensure a comprehensive and reliable assessment of model performance, as recommended in forecasting literature [6], [7]. The evaluation results serve as the basis for analyzing the effectiveness of the moving average method and for drawing conclusions regarding its applicability to short-term IHSG forecasting.

3. RESULTS AND DISCUSSION

This section presents and discusses the results obtained from the application of the Simple Moving Average (SMA) method to forecast the Jakarta Composite Index (IHSG). The discussion begins with a visual analysis of the forecasting outcomes to illustrate the behavior of the proposed model in capturing market trends and price movements. Subsequently, the results are interpreted to highlight the relationship between different moving average window sizes and their impact on trend representation, smoothing effects, and forecasting reliability.

3.1 Visualization of IHSG Forecasting Using the Simple Moving Average Model

Figure 2 presents a visual comparison between the actual IHSG closing prices and the Simple Moving Average (SMA) models with window sizes of 20 and 50 over the period 2010–2018. The figure demonstrates how the SMA method smooths short-term fluctuations in the IHSG time series while capturing the overall market trend. The SMA20 curve responds more quickly to price changes, reflecting higher sensitivity to short-term movements, whereas the SMA50 curve exhibits a smoother trajectory with a noticeable lag, indicating stronger noise reduction but reduced responsiveness. This behavior highlights the inherent trade-off between sensitivity and stability in moving average forecasting. During periods of strong upward or downward trends, both SMA models are able to follow the general direction of the IHSG, although deviations are more evident during high-volatility intervals. The visualization confirms that smaller window sizes are more suitable for short-term trend detection, while larger window sizes provide better smoothing for long-term trend analysis. These findings support the use of multiple window configurations to assess forecasting behavior and serve as a basis for the quantitative evaluation discussed in the subsequent sections.

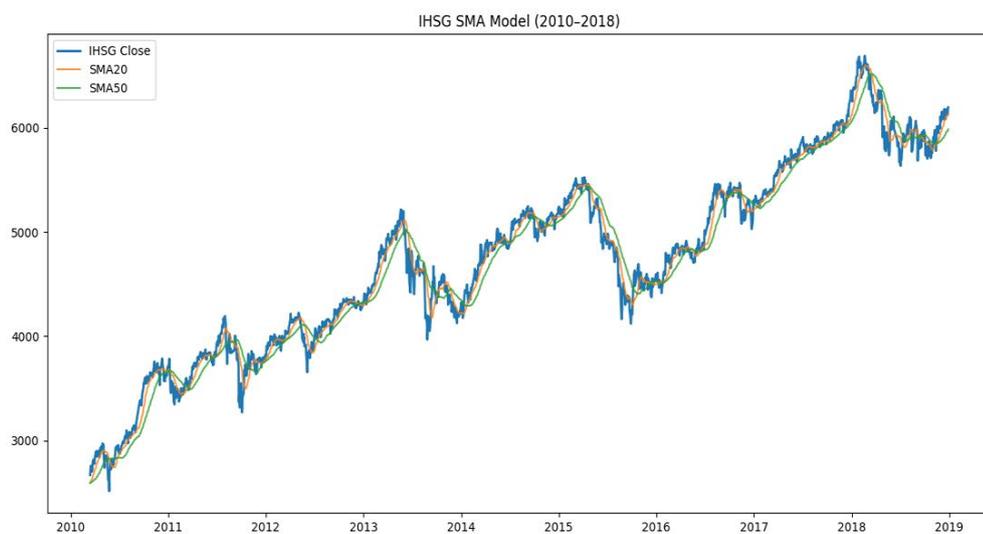


Figure 2. IHSG Closing Price and Simple Moving Average (SMA) Models with Different Window Sizes (2010–2018)

4. CONCLUSIONS

This study investigated the application of the Simple Moving Average (SMA) method for forecasting the Jakarta Composite Index (IHSG) using historical time series data. The research focused on establishing a transparent and interpretable baseline forecasting model by systematically applying different moving average window sizes and evaluating their performance using standard error metrics. The methodological framework included data preprocessing, descriptive statistical analysis, model construction, and performance evaluation, ensuring a structured and reproducible research process.

The results demonstrate that the SMA method is capable of capturing the general trend of the IHSG, particularly for short-term forecasting purposes. Smaller window sizes exhibit higher responsiveness to recent market movements, while larger window sizes provide smoother forecasts with reduced sensitivity to short-term volatility. The evaluation results indicate that the choice of window size significantly influences forecasting accuracy, highlighting the trade-off between trend sensitivity and noise reduction. Despite its simplicity, the SMA approach yields meaningful insights into IHSG behavior and serves as a reliable baseline for comparative forecasting studies.

For future work, this research can be extended by incorporating additional forecasting techniques, such as exponential smoothing, autoregressive models, or machine learning-based approaches, to improve predictive accuracy. Further improvements may also include the integration of exogenous variables, such as macroeconomic indicators or trading volume, to capture broader market dynamics. Additionally, applying adaptive or hybrid moving average models and evaluating their performance over different market regimes may provide deeper insights into the robustness and applicability of the proposed approach.

5. SUGGESTION

Future research may extend this study by exploring more advanced forecasting techniques to improve predictive accuracy and robustness. Comparative analyses involving exponential smoothing, autoregressive integrated moving average (ARIMA), and machine learning-based models such as support vector regression or recurrent neural networks could

provide deeper insights into the relative performance of classical and modern approaches. Additionally, incorporating exogenous variables, including macroeconomic indicators, trading volume, or global market indices, may enhance the model's ability to capture broader market dynamics. Further studies may also investigate adaptive or hybrid moving average models that dynamically adjust window sizes in response to changing market conditions. Finally, evaluating the proposed approach across different time horizons and market regimes would contribute to a more comprehensive understanding of its generalizability and practical applicability in real-world financial forecasting scenarios.

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