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A Comparative Performance Analysis of ARIMA, Moving Average, and Exponential Smoothing Methods in Interest Rate Forecasting

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Abstract
Forecasting is an important function of operations management, providing a basis for decision-making in the face of uncertainty. This study aims to compare the performance of the Autoregressive Integrated Moving Average (ARIMA), Moving Average (MA), and Exponential Smoothing (ES) methods in forecasting the BI Rate, while also enriching the body of references on the application of forecasting methods in operations management. A comparative quantitative approach was employed using secondary BI Rate data in the form of a time series. The ARIMA model was developed using the Box–Jenkins procedure, while Moving Average and Exponential Smoothing were employed as comparative methods. Forecasting accuracy was evaluated using Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The results show that the three-period Moving Average (MA-3) achieved the highest forecasting accuracy, with a MAD of 0.001689, MSE of 0.0000074, and MAPE of 3.415%. Exponential Smoothing with $\alpha = 0.25$ yielded a MAD of 0.006682, MSE of 0.0000562, and MAPE of 15.101%, whereas ARIMA(1,1,0) produced a MAD of 0.008929, MSE of 0.0000797, and MAPE of 19.971%. These findings indicate that a more complex method does not necessarily produce greater forecasting accuracy. Given the relatively stable characteristics of the BI Rate data, the Moving Average method provided more accurate forecasts than Exponential Smoothing and ARIMA. This study also demonstrates that the application of ARIMA can serve as an alternative approach for enriching the teaching and study of forecasting in the field of operations management.

Keywords: forecasting, BI rate, arima, moving average, exponential smoothing, forecasting accuracy

Introduction

Forecasting constitutes a vital function within operations management, serving as the cornerstone for production planning, inventory control, workforce scheduling, budgeting, and a broad spectrum of strategic and operational decisions. The accuracy of forecast outcomes profoundly impacts decision-making quality; thus, the selection of an appropriate forecasting methodology represents a crucial aspect in both the advancement of operations management literature and practical business applications. An optimal forecasting method enables organizations to mitigate uncertainty, enhance resource utilization efficiency, and support the formulation of more robust strategic initiatives.

Within operations management literature, the Moving Average (MA) and Exponential Smoothing (ES) methods remain two of the most widely adopted forecasting techniques due to their inherent simplicity, ease of implementation, and minimal computational requirements (Siregar & Riskamora, 2016; Rahman et al., 2018). Both techniques have been extensively applied to facilitate production planning, inventory management, and Material Requirements Planning (MRP) systems. Nevertheless, their capacity remains relatively constrained when confronted with time-series data exhibiting complex characteristics, such as autocorrelation, pronounced trends, or evolving structural patterns over time.

A prominent technique extensively utilized in time-series analysis is the Autoregressive Integrated Moving Average (ARIMA) model (Rezaldi, 2021). Developed through the rigorous Box–Jenkins methodology encompassing model identification, parameter estimation, diagnostic checking, and forecasting ARIMA systematically captures underlying data dynamics. Unlike MA and simple ES, ARIMA explicitly models serial dependence and can accommodate non-stationary series through differencing, making it theoretically more flexible when past observations contain systematic temporal information. However, greater model flexibility does not necessarily translate into consistently lower forecasting errors.

Recent comparative evidence illustrates this unresolved issue. Chandra and Rohmaniah (2022), for example, found Single Exponential Smoothing to outperform Moving Average in forecasting inflation based on MAD, MSD, and MAPE. In contrast, Fahmuddin et al. (2023) reported that ARIMA generated a lower MAPE than Single Exponential Smoothing when forecasting Indonesian cocoa export values. A broader comparison by Khan et al. (2024), which included Moving Average, several Exponential Smoothing specifications, and ARIMA-family models across multiple univariate series, further demonstrated that the best-performing method varied according to the underlying series: ARIMA-family models performed better for several datasets, whereas Triple Exponential Smoothing was superior for another. More recently, Syahputra et al. (2025) similarly showed that the relative ranking of ARIMA and Exponential Smoothing models may differ according to the forecasting error criterion used. Collectively, these findings suggest that the unresolved question is not whether one forecasting family is generally more sophisticated, but under what data characteristics a simpler smoothing method can outperform a structurally richer ARIMA model.

The execution of ARIMA modeling necessitates adequate historical data to ensure optimal model identification and parameter estimation. In organizational practice, operational data is frequently constrained by limited observation windows, which hinders the construction of reliable ARIMA models. Consequently, this study utilizes the BI Rate dataset as its research object, given its extended time horizon, open accessibility, and compliance with time-series analytical requirements (Salwa, 2018). The BI Rate also provides a useful empirical setting because its historical movements exhibit periods of relative stability interrupted by discrete adjustments, creating a structure in which the responsiveness of MA, ES, and ARIMA can be meaningfully contrasted. Accordingly, the methodological gap addressed in this study concerns the relative ability of these three forecasting approaches to capture a comparatively stable but periodically adjusting time series under a common evaluation framework. This comparison is particularly relevant because existing studies demonstrate context-dependent model rankings rather than a universally dominant forecasting method.

The BI Rate represents a pivotal economic indicator intrinsically linked to business activity, investment decisions, corporate financing, and operational strategy, thereby offering strong relevance as an empirical case study for evaluating forecasting methodologies. Its relevance in this study therefore lies not in explaining the determinants of monetary policy, but in providing an observable real-world series through which alternative forecasting mechanisms can be evaluated under identical data conditions.

This study does not aim to analyze Bank Indonesia’s monetary policy; rather, it utilizes the BI Rate as a practical baseline to evaluate the performance of diverse forecasting techniques applied to real-world time-series data. This approach is intended to elucidate the distinct characteristics of each method while expanding the empirical literature regarding forecasting application within operations management.

Building upon these premises, this research aims to comparatively evaluate the predictive performance of ARIMA, Moving Average, and Exponential Smoothing models in forecasting the BI Rate, using Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute

Percentage Error (MAPE) as accuracy metrics. In this study, forecasting accuracy refers specifically to one-step-ahead historical predictive performance within the available observation sample, where forecasts generated from preceding information are compared with the corresponding actual BI Rate values over a common evaluation period; no separate holdout sample is used. This common evaluation basis ensures that differences in MAD, MSE, and MAPE reflect the relative forecasting performance of the three methods under the same historical data conditions. The findings are expected not only to identify the optimal forecasting model for the analyzed dataset, but also to provide valuable insights that contribute to the broader literature on operational forecasting techniques.

Method

This study employs a quantitative approach utilizing a comparative design to evaluate the predictive performance of three forecasting methodologies: Autoregressive Integrated Moving Average (ARIMA), Moving Average (MA), and Exponential Smoothing (ES) in projecting the BI Rate. A comparative framework is applied to discern the technique that yields superior accuracy based on standardized forecast error metrics (Hudaningsih et al., 2020). Each method embodies distinct computational dynamics: MA relies on the unweighted average of historical observations, ES assigns exponentially decreasing weights to older observations while prioritizing recent data, and ARIMA integrates autoregressive processes, differencing, and moving average components to model time-series structures (Windi, 2025).

Research Data

This research utilizes secondary time-series data comprising the monthly BI Rate retrieved from official Bank Indonesia publications. The dataset is structured chronologically at a monthly frequency across the observation period. Utilizing monthly intervals ensures structural consistency in the observation period, thereby satisfying the necessary empirical prerequisites for time-series forecasting models.

The selection of the BI Rate as the analytical object is grounded in the availability of an adequate historical time horizon required for robust time-series analysis—particularly ARIMA modeling—as well as data characteristics that allow for the systematic observation of longitudinal fluctuations.

Research Procedures

This study was conducted through a series of systematic stages, beginning with a literature review and followed by data collection, descriptive analysis, predictive modeling, forecast accuracy evaluation, and the determination of the best-performing forecasting model. The literature review was undertaken to establish the theoretical foundation of the study and to synthesize previous research related to time-series forecasting, the BI Rate, and the application of ARIMA, Moving Average, and Exponential Smoothing methods. The reviewed literature also provided the basis for developing the analytical framework and selecting the appropriate indicators of forecasting accuracy. Historical BI Rate data were subsequently collected from official Bank Indonesia publications, verified for consistency, and arranged chronologically to form a time-series dataset suitable for forecasting analysis. Descriptive analysis was then performed to identify the main characteristics of the data by examining the minimum, maximum, mean, standard deviation, and temporal variability of the BI Rate. In addition, the historical movement of the series was visually examined to obtain an initial understanding of its pattern before the forecasting models were developed.

The forecasting stage involved the application of three methods, namely Moving Average (MA), Exponential Smoothing (ES), and Autoregressive Integrated Moving Average (ARIMA). The Moving Average method generated forecasts by calculating the unweighted average of observations from a predetermined number of preceding periods, with the moving-average window selected according to the analytical requirements and subsequently evaluated using forecast error measures. The Exponential Smoothing method assigned progressively lower weights to older observations while giving greater emphasis to more recent data. Several smoothing constant values were evaluated, and the specification producing the most favorable forecasting accuracy was selected (Alfarisi, 2017). Meanwhile, ARIMA modeling followed the Box–Jenkins procedure, beginning with stationarity testing using the Augmented Dickey–Fuller (ADF) test, followed by model identification through the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), parameter estimation, and residual diagnostic checking to assess whether the residuals exhibited white-noise characteristics. The ARIMA specification that satisfied the relevant statistical and diagnostic criteria was then selected for forecasting and subsequently compared with the Moving Average and Exponential Smoothing models using the designated forecast accuracy measures.

Forecast Accuracy Evaluation

The predictive performance across all three methods was evaluated using Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). MAD measures the average absolute deviation, MSE measures the average squared error, and MAPE quantifies the mean error in percentage terms. Lower error values indicate higher forecasting precision (Ardiansah, 2017).

Determination of the Optimal Model

The relative performance of the three techniques was compared against their MAD, MSE, and MAPE metrics. The model demonstrating the lowest error values across these metrics was selected as the optimal forecasting methodology for the BI Rate dataset (Marlina, 2024).

Data Analysis Techniques

Data analysis was executed using Microsoft Excel for the implementation of the Moving Average and Exponential Smoothing models, including the calculation of forecast values and error metrics. Meanwhile, EViews software was utilized for ARIMA modeling, encompassing stationarity testing, model identification via ACF and PACF plots, parameter estimation, diagnostic residual checking, and forecast generation.
Subsequently, the forecasting outputs from all three methodologies were comparatively evaluated based on their MAD, MSE, and MAPE metrics to determine the model exhibiting superior predictive accuracy (Alfarizi, 2017).

Results and Discussion

Descriptive Statistics of BI Rate Data

Prior to executing predictive modeling via ARIMA, Moving Average, and Exponential Smoothing methodologies, a descriptive statistical analysis was conducted to establish a comprehensive overview of the structural properties of the BI Rate dataset. This preliminary analysis aims to characterize the central tendency, dispersion, and overall range of the interest rate across the designated observation period.

Table 1. Descriptive Statistics of BI Rate Data

Statistic	Value
Number of Observations (N)	117

Mean	0,0493
Median	0,0500
Minimum	0,0350
Maximum	0,0625
Range	0,0275
Standard Deviation	0,0090
Variance	0,000082

As presented in Table 1, the BI Rate across the observation period recorded a mean value of 0.0493 (approximately 4.93%) and a median of 5.00%. The close proximity between the mean and median indicates a relatively symmetric distribution that is free from severe skewness or extreme outliers.

The historical BI Rate ranged from a minimum of 3.50% to a maximum of 6.25%, yielding a overall spread (range) of 2.75 percentage points. This spread reflects multiple policy rate adjustments enacted by Bank Indonesia during the observation period in response to evolving macroeconomic dynamics and monetary policy directives.

A standard deviation of 0.0090 indicates relatively low dispersion in the BI Rate throughout the analyzed timeframe. This implies that despite intermittent policy adjustments, the interest rate generally fluctuated within a fairly stable corridor. Furthermore, these empirical characteristics suggest a stepwise adjustment pattern driven by deliberate monetary policy decisions rather than high-frequency random noise.

These baseline descriptive statistics provide a crucial foundation for the subsequent modeling stage involving ARIMA(1,1,0), Moving Average, and Exponential Smoothing methodologies. A thorough understanding of these initial data traits is essential for properly interpreting the relative predictive performance of each forecasting model.

Moving Average Modeling

Moving Average (MA) modeling was implemented to smooth random fluctuations within the historical BI Rate series by computing the unweighted average over a specified number of prior time periods (N). The initial step in this modeling framework involves identifying the optimal order length (N) to minimize forecast error metrics. Mathematically, the general formulation of the Moving Average method of order N is expressed as follows:

$$F_{t+1} = \frac{A_t + A_{t-1} + A_{t-2} + \cdots + A_{t-N+1}}{N}$$

Where F_{t+1} represents the forecast value for the subsequent period $t+1$, A_t denotes the actual observed value at time period t, and N signifies the number of periods included in the moving average window calculation. In this study, a moving average window of order $N = 3$ was selected, resulting in the following specific forecasting equation:

$$F_{t+1} = \frac{A_t + A_{t-1} + A_{t-2}}{3}$$

The forecast outcomes generated via the Moving Average method ($N = 3$) were subsequently evaluated against the actual observed values, as illustrated in Figure 1.

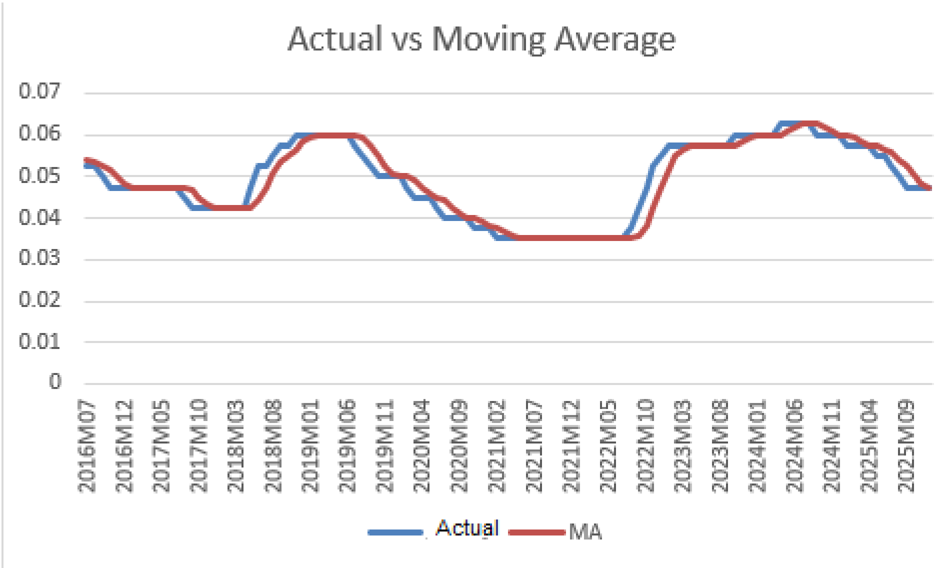

Figure 1. Comparison between actual data and moving average forecast values.

As visualized in Figure 1, the forecasting curve exhibits the quintessential characteristic of the Moving Average methodology, wherein the predicted values demonstrate a pronounced lagging effect relative to the sharp turning points in both the upward and downward trajectories of the BI Rate. This phenomenon stems from the intrinsic mechanism of moving averages, which systematically absorbs historical policy shifts in a gradual manner. Nevertheless, the method proves sufficiently robust in attenuating high-frequency noise and short-term random fluctuations, thereby yielding a smoothed trendline that effectively delineates the overarching direction of the interest rate from July 2016 through December 2025.

Exponential Smoothing Modeling

Exponential Smoothing modeling—specifically Single Exponential Smoothing—was employed to forecast the time-series data by applying exponentially decaying weights to historical observations. Unlike the Moving Average method, which assigns equal weighting across a specified window, this approach places greater emphasis on more recent observations. Mathematically, the foundational formulation of the Exponential Smoothing method is expressed as follows:

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

Where F_{t+1} represents the forecast value for the subsequent period $t+1$, A_t denotes the actual observed value at time period t, F_t signifies the forecast value for time period t, and α represents the smoothing constant, bounded by $0 < \alpha < 1$. In this study, the model was implemented using a smoothing constant of $\alpha = 0.25$. The resulting forecast values were subsequently evaluated against actual historical data, as illustrated in Figure 2.

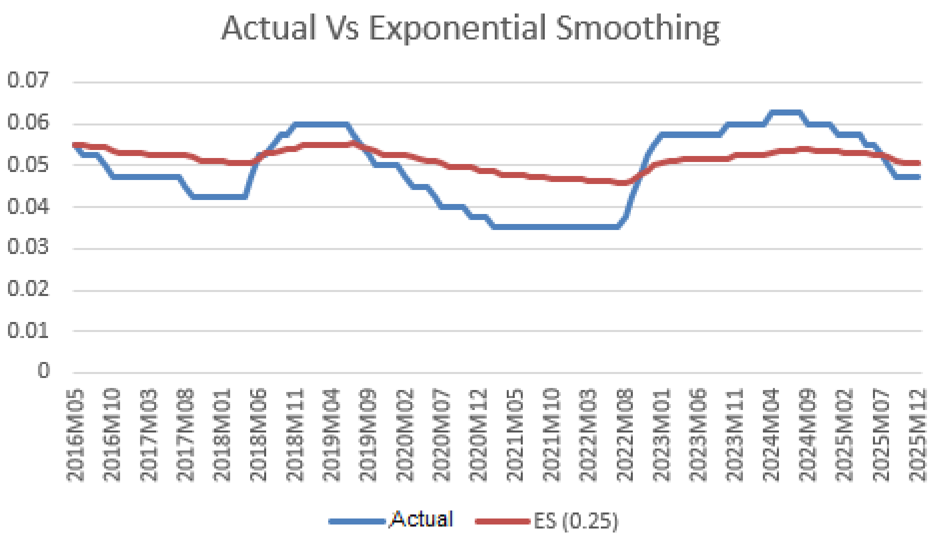

Figure 2. Comparison graph between actual data and Exponential Smoothing forecast values ($\alpha = 0.25$).

As visualized in Figure 2, employing a smoothing constant of $\alpha = 0.25$ generates a remarkably smooth and stable forecast trajectory. Because the assigned α value is relatively conservative, historical observations retain substantial weighting within the algorithm; consequently, the model absorbs abrupt shifts in the actual BI Rate in a measured, incremental manner rather than mirroring raw volatility. This characteristic proves highly effective in attenuating stochastic noise inherent in monetary policy fluctuations.

ARIMA Modeling

Autoregressive Integrated Moving Average (ARIMA) modeling was executed in accordance with the canonical Box–Jenkins methodology, encompassing four sequential phases: model identification, parameter estimation, diagnostic checking, and forecasting. This framework aims to derive an optimal parsimonious model that accurately captures the structural dynamics of the BI Rate series to yield robust predictive capabilities.

Stationarity Test

The foundational requirement in ARIMA modeling necessitates evaluating series stationarity via the Augmented Dickey-Fuller (ADF) test. This preliminary diagnostic ensures the absence of a unit root, thereby satisfying the fundamental stationarity assumption underlying time-series inference. Following first differencing (ΔY_t), the ADF test statistic yielded -5.725210 with an associated p-value of 0.0000. The test statistic easily surpasses the 5% significance threshold and lies well beyond the MacKinnon critical value of -2.886732 at the $\alpha = 0.05$ level. Consequently, the null hypothesis asserting the presence of a unit root is decisively rejected.

These empirical results confirm that the BI Rate series achieves stationarity after a single order of differencing (first differencing), thereby establishing the integration parameter at $d = 1$.

Table 2. ADF Stationarity Test Results

Parameter	Nilai
Augmented Dickey-Fuller test statistic	-5.725210
Prob.	0.0000

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1% level	-3.488063
5% level	-2.886732
10% level	-2.580281
Decision	Stationary Data at First Difference

Model Identification

Once the series achieved stationarity, the subsequent phase involved identifying the candidate model order through the evaluation of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Based on the correlogram depicted in Figure 3, the ACF pattern displays a gradual decay (*tailing off*), whereas the PACF exhibits a prominent spike at the first lag before dampening across subsequent lags. This structural behavior signifies that the autoregressive component exerts a dominant influence over the moving average component. In accordance with these empirical characteristics, the ARIMA(1,1,0) specification was selected for model estimation—comprising a first-order autoregressive parameter ($p = 1$), a single order of non-seasonal differencing ($d = 1$), and zero moving average terms ($q = 0$).

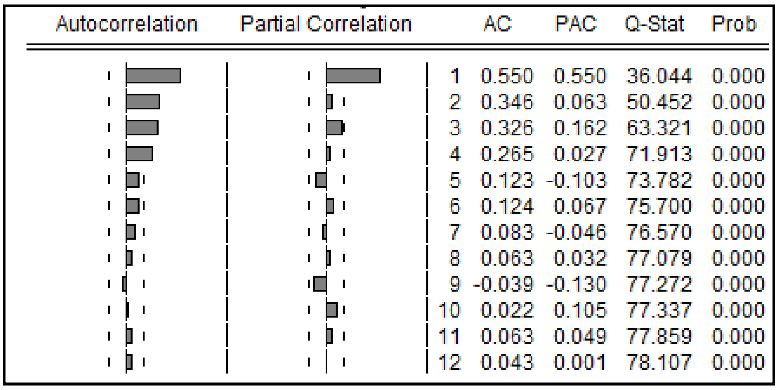


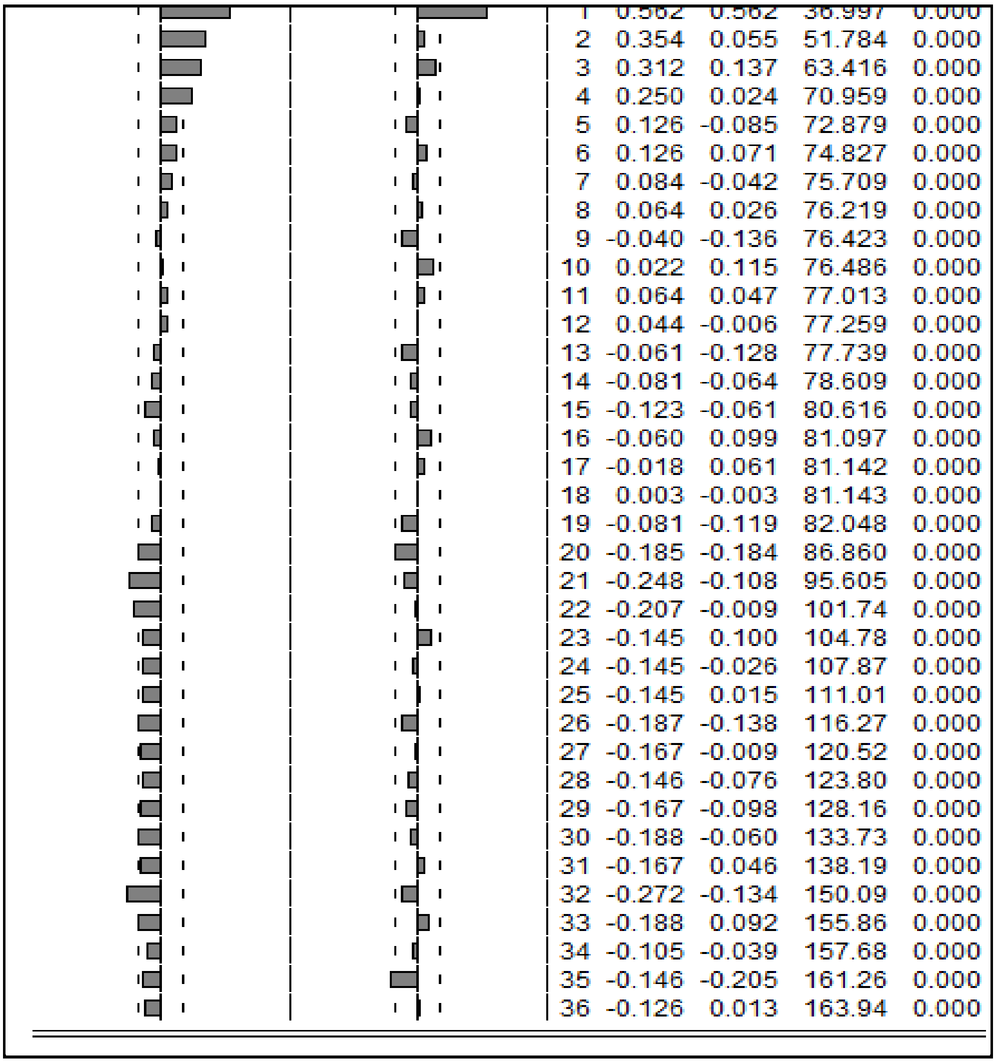
Figure 3. Correlogram ACF and PACF after Differentiation

Model Estimation

Parameter estimation was executed via the Maximum Likelihood Estimation (MLE) method. The optimization algorithm for the candidate ARIMA(1,1,0) specification successfully achieved convergence after 13 iterations. The estimated AR(1) coefficient yielded a value of 0.545640 with an associated p-value of 0.0000, confirming statistical significance at the 1% level. This demonstrates that past rate adjustments exert a persistent, positive impact on subsequent BI Rate dynamics. Conversely, the constant term proved statistically insignificant ($p = 0.8294$), implying that time-series variations are overwhelmingly driven by the autoregressive process rather than a deterministic drift component. The estimated model registered an Akaike Information Criterion (AIC) of -10.31433 and a Schwarz Criterion (SC) of -10.24312, serving as model selection benchmarks. Additionally, a Durbin-Watson statistic of 2.058589 indicates the absence of severe first-order serial correlation among the residuals.

Model Diagnostic Checking

To confirm model adequacy, diagnostic checking of the residual series was performed using the Ljung–Box Q-statistic. Based on the residual correlogram shown in Figure 4, the calculated p-values across all examined lag orders consistently exceed the standard 5% significance threshold. This confirms that the residual sequence closely resembles a white noise process with no remaining serial autocorrelation. Consequently, the ARIMA(1,1,0) model satisfies all required diagnostic criteria and is validated for forecasting the BI Rate.



1	0.562	0.562	36.997	0.000
2	0.354	0.055	51.784	0.000
3	0.312	0.137	63.416	0.000
4	0.250	0.024	70.959	0.000
5	0.126	-0.085	72.879	0.000
6	0.126	0.071	74.827	0.000
7	0.084	-0.042	75.709	0.000
8	0.064	0.026	76.219	0.000
9	-0.040	-0.136	76.423	0.000
10	0.022	0.115	76.486	0.000
11	0.064	0.047	77.013	0.000
12	0.044	-0.006	77.259	0.000
13	-0.061	-0.128	77.739	0.000
14	-0.081	-0.064	78.609	0.000
15	-0.123	-0.061	80.616	0.000
16	-0.060	0.099	81.097	0.000
17	-0.018	0.061	81.142	0.000
18	0.003	-0.003	81.143	0.000
19	-0.081	-0.119	82.048	0.000
20	-0.185	-0.184	86.860	0.000
21	-0.248	-0.108	95.605	0.000
22	-0.207	-0.009	101.74	0.000
23	-0.145	0.100	104.78	0.000
24	-0.145	-0.026	107.87	0.000
25	-0.145	0.015	111.01	0.000
26	-0.187	-0.138	116.27	0.000
27	-0.167	-0.009	120.52	0.000
28	-0.146	-0.076	123.80	0.000
29	-0.167	-0.098	128.16	0.000
30	-0.188	-0.060	133.73	0.000
31	-0.167	0.046	138.19	0.000
32	-0.272	-0.134	150.09	0.000
33	-0.188	0.092	155.86	0.000
34	-0.105	-0.039	157.68	0.000
35	-0.146	-0.205	161.26	0.000
36	-0.126	0.013	163.94	0.000

Figure 4. Correlogram Residual Model ARIMA(1,1,0)

Comparative Evaluation of Forecasting Models

Upon validating the diagnostic adequacy of the ARIMA(1,1,0) specification, the subsequent phase entailed evaluating the comparative predictive performance among the ARIMA(1,1,0), Moving Average (MA), and Exponential Smoothing (ES) frameworks in forecasting the BI Rate. This comparative assessment aims to identify the optimal model yielding the highest forecast accuracy over the investigation period. Model performance was benchmarked using three standard error metrics commonly employed in time-series analysis: Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE).

The MAD statistic quantifies the average absolute deviation between actual and predicted values, whereas MSE imposes a heavier penalty on large forecast errors by squaring the residuals. Meanwhile, MAPE expresses forecast accuracy as a scale-independent percentage, facilitating intuitive interpretation and direct comparison across different methods. Generally, lower values across MAD, MSE, and MAPE indicate superior forecasting accuracy. The empirical error metrics across all evaluated frameworks are presented in Table 3.

Table 3. Accuracy Comparison of BI Rate Forecasting Models

Metode	MAD	MSE	MAPE	Peringkat
ARIMA (1,1,0)	0.008929228	0.0000797	19.97105997	3
Moving Average (N = 3)	0.001688596	0.0000074	3.414967332	1
Exponential Smoothing (α = 0.25)	0.006682057	0.0000562	15.10071636	2

As indicated in Table 3, clear performance disparities emerge across the three evaluated methodologies. The model yielding the lowest MAD, MSE, and MAPE metrics demonstrates superior efficacy in capturing the empirical dynamics of the BI Rate throughout the observation period. Conversely, higher error magnitudes reflect greater divergence between the forecasted trajectory and actual realizations. To provide a clearer visual assessment of each model's capacity to mirror the historical trajectory of the BI Rate, the individual forecast outputs are evaluated alongside actual observed values in Figure 5.

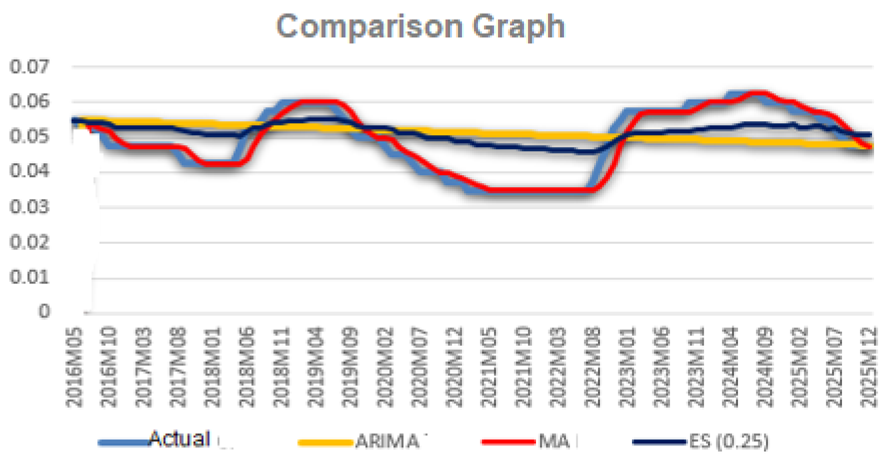


Figure 5. Comparison of BI Rate Forecast Results Using ARIMA, Moving Average, and Exponential Smoothing

As depicted in Figure 5, distinct forecasting trajectories emerge across the three methodologies in capturing the historical movements of the BI Rate. Each model exhibits unique behavioral characteristics in responding to policy rate adjustments. These structural discrepancies directly govern how closely the predicted paths align with actual realizations, which is subsequently reflected in their respective MAD, MSE, and MAPE metrics.

Visually, the framework whose forecasting line most closely tracks actual observation points achieves lower overall error rates. Conversely, methodologies that yield flatter or less responsive trajectories relative to rate shifts exhibit broader deviations from observed values. These empirical findings demonstrate that the underlying properties of the BI Rate series exert a substantial influence on the relative performance of each forecasting model.

Discussion

Empirical results indicate notable performance disparities among the Moving Average, Exponential Smoothing, and ARIMA(1,1,0) specifications in forecasting the BI Rate. Based on the calculated Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute

Percentage Error (MAPE) metrics, the three-month Moving Average method yielded the lowest error rates relative to Exponential Smoothing and ARIMA(1,1,0). These findings highlight that model selection must be closely aligned with the underlying properties of the data under analysis, as structurally complex methodologies do not inherently guarantee superior predictive accuracy. This result is particularly relevant in the context of macroeconomic and interest-rate forecasting, where predictive performance is often influenced by the degree of persistence, stability, structural adjustment, and short-term variation contained in the observed series.

The efficacy of the Moving Average approach observed in this study aligns with existing literature applying the technique to demand and sales forecasting. Prior empirical works demonstrate that moving average models effectively generate baseline forecasts from historical patterns, providing a robust benchmark when evaluated against alternative frameworks via standard error metrics (Rachman, 2018). Furthermore, previous studies confirm that moving average models achieve optimal predictive accuracy when calibrated to series exhibiting specific structural characteristics (Nurlifa, 2017). Consequently, these empirical results reinforce the utility of the Moving Average method as a viable predictive framework within operations management applications (Heizer, 2015; Irawan, 2024). More importantly, the finding extends the relevance of this relatively simple forecasting approach beyond conventional demand and inventory applications by demonstrating its effectiveness on a macroeconomic time series represented by the BI Rate.

The superior performance of the Moving Average model in this setting is intrinsically linked to the specified three-month window. A three-period rolling average enables the forecast curve to capture historical adjustments without overreacting to single-period shocks. Given that the BI Rate series analyzed in this study exhibits relatively gradual shifts, this smoothing approach successfully minimizes forecasting errors. The descriptive characteristics of the series support this interpretation: the BI Rate fluctuates within a relatively narrow range and exhibits a stepwise adjustment pattern rather than continuous high-frequency variation. Under these conditions, averaging the most recent three observations allows the model to remain sufficiently responsive to policy-rate changes while avoiding excessive sensitivity to individual monthly movements. Thus, while these findings do not imply the absolute superiority of the Moving Average method over alternative techniques, they demonstrate its contextual suitability for the specific structural dynamics of the analyzed BI Rate series.

The result can also be positioned alongside previous research specifically examining the BI Rate. Hasanah (2023) identified ARIMA(1,1,0) as an appropriate specification for forecasting the Indonesian BI Rate based on model-selection criteria such as AIC, SIC, and HQC. The present study does not contradict the statistical adequacy of ARIMA(1,1,0); rather, it adds an important comparative perspective. Once ARIMA is evaluated against simpler alternatives using common forecast-error measures, statistical model adequacy alone does not ensure the lowest predictive error. In the present dataset, MA-3 produces smaller MAD, MSE, and MAPE values, indicating that the relatively stable and stepwise movement of the BI Rate can be captured more efficiently by a short rolling window.

In this study, the Exponential Smoothing method generated higher error metrics compared to the Moving Average approach. Nevertheless, it remains highly relevant in predictive modeling, as Exponential Smoothing is widely applied in forecasting sales and demand based on historical observations (Winny, 2024). Empirical literature demonstrates that this method effectively yields next-period forecasts, with accuracy evaluated through standard metrics such as MAD, MSE, and MAPE (Hudaningsih, 2017). Evidence from macroeconomic forecasting also confirms that smoothing models can outperform ARIMA under particular data structures. Saragih and Sembiring (2022), for example, found Brown's Double Exponential Smoothing to provide more accurate short-term forecasts of Indonesian inflation than ARIMA, demonstrating that smoothing-based methods may be particularly competitive when recent movements and trend information can be captured without a more elaborate autoregressive structure. Similarly, Salfina et al. (2024) reported that Double Exponential Smoothing achieved the lowest RMSE among ARIMA, Double Exponential Smoothing, and Trend Projection models for Indonesian inflation.

The calibration of the smoothing parameter **(α)** necessitates careful consideration of the underlying data dynamics and the model's desired responsiveness to recent innovations. A smaller **α** value assigns lower weight to the most recent observation, producing stronger smoothing suited for relatively stable series. Conversely, a larger **α** enhances sensitivity to recent shifts; as **α approaches 1**, forecasting behavior increasingly converges toward a naïve model because the most recent observation assumes dominant weight. In this study, Single Exponential Smoothing with $\alpha = 0.25$ generates a comparatively smooth forecast path. Although such smoothing can be useful for representing the general level of a relatively stable interest-rate series, it may respond more slowly to discrete changes in the BI Rate. This delayed adjustment offers a plausible explanation for why its forecast errors remain higher than those of the three-period Moving Average.

This behavior is consistent with the broader insight from macroeconomic forecasting that the relative performance of smoothing and autoregressive models is data-dependent rather than universal. For example, Wu (2026) found ARIMA(1,0,0) to outperform Exponential Smoothing in forecasting China's inflation, attributing the advantage to ARIMA's ability to capture short-term persistence and lag dependence. In contrast, Indonesian inflation studies have reported better performance from Exponential Smoothing than ARIMA (Saragih & Sembiring, 2022; Salfina et al., 2024). These contrasting results reinforce the argument that the forecasting method should be selected according to the empirical structure of the series rather than according to an assumed hierarchy of methodological sophistication.

Meanwhile, the ARIMA(1,1,0) specification yielded higher error metrics than the Moving Average method. Incorporating ARIMA into this study remains critical, as it constitutes a foundational econometric approach for modeling and forecasting time-series data. Empirical studies frequently employ ARIMA models for price forecasting, demonstrating that model development often necessitates differencing to achieve series stationarity (Rezaldi, 2021). Its relevance is even more evident in financial and macroeconomic forecasting because ARIMA explicitly models temporal dependence and can accommodate non-stationarity through differencing. In the present study, first differencing successfully produced a stationary series and ARIMA(1,1,0) satisfied the required diagnostic procedure; nevertheless, the model generated higher predictive errors than MA-3. This distinction is important because a statistically adequate time-series specification is not necessarily the model that minimizes forecast error when competing approaches are evaluated on the same series.

Similar context dependence has been observed in interest-rate forecasting. Research comparing alternative models for interest rates in Pakistan found that conventional ARIMA was not uniformly superior and that models capable of incorporating additional dynamics could produce better forecasts (Zafar et al., 2025). More generally, interest-rate forecasting research has shown that forecasting performance varies with the horizon and the dynamic characteristics of the rate being modeled. These findings provide a useful perspective for interpreting the present result: ARIMA's ability to model autocorrelation does not automatically give it an advantage when the target series is characterized by long periods of stability interrupted by discrete policy adjustments.

The divergent performance across these three methodologies underscores that underlying data characteristics serve as a pivotal determinant in model selection. In this investigation, the three-month Moving Average yielded the optimal forecasting performance based on MAD, MSE, and MAPE metrics, whereas Exponential Smoothing and ARIMA generated comparatively higher error rates. Specifically, MA-3 recorded a MAD of 0.001689, MSE of 0.0000074, and MAPE of 3.415%, substantially below the corresponding errors produced by Exponential Smoothing (MAD = 0.006682; MSE = 0.0000562; MAPE = 15.101%) and ARIMA(1,1,0) (MAD = 0.008929; MSE = 0.0000797; MAPE = 19.971%). The consistency of this ranking across all three error measures strengthens the conclusion that MA-3 is not superior merely under a single evaluation criterion, but provides the closest overall approximation to actual BI Rate movements in the evaluation framework used in this study.

These findings resonate with existing literature demonstrating that predictive performance varies across methodological frameworks, thereby underscoring the necessity of empirical error evaluations to identify the most suitable forecasting approach (Windi, 2025). Taken together with macroeconomic forecasting evidence showing that ARIMA may outperform Exponential Smoothing in some settings while smoothing methods outperform ARIMA in others (Saragih & Sembiring, 2022; Salfina et al., 2024; Wu, 2026), the present findings further reject the assumption of a universally dominant forecasting method. Instead, forecast accuracy emerges from the interaction between model structure and the statistical behavior of the target series.

From an operations management perspective, these insights reveal that model selection need not inherently gravitate toward maximum structural complexity. Relatively straightforward techniques, such as the Moving Average, can deliver superior accuracy when aligned with the intrinsic characteristics of the underlying data. For managerial decision-making, this finding is relevant because interest-rate expectations may affect financing costs, investment timing, budgeting, working-capital decisions, and other operational plans. A forecasting approach that is transparent, computationally efficient, and empirically accurate can therefore provide greater practical value than a more complex specification when the latter does not offer a corresponding improvement in predictive performance**.**

Within the framework of this study, the BI Rate serves as an empirical time-series dataset to illustrate the practical implementation of predictive modeling, while the core focus remains evaluating the comparative performance among Moving Average, Exponential Smoothing, and ARIMA methodologies. Overall, the empirical evidence demonstrates that the three-month Moving Average framework provides optimal forecasting accuracy for the analyzed BI Rate series. The contribution of this finding lies not in establishing Moving Average as universally superior, but in demonstrating that for a relatively stable policy-rate series characterized by gradual and discrete adjustments, a short-window smoothing mechanism may outperform both recursively weighted smoothing and an autoregressive integrated specification**.** This finding further enriches the operations management literature by emphasizing that model selection should be dictated by data dynamics and predictive error metrics rather than methodological complexity alone.

Conclusion

This study evaluated the comparative predictive performance of the ARIMA(1,1,0), Moving Average, and Exponential Smoothing methodologies in forecasting the BI Rate, using Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) as primary accuracy metrics. While all three frameworks successfully generated time-series forecasts, their predictive precision varied significantly. Empirical evaluations demonstrate that the Moving Average framework yielded the lowest forecast error metrics relative to Exponential Smoothing and ARIMA(1,1,0). This indicates that the structural dynamics of the BI Rate over the observation period are most effectively captured via a rolling average mechanism, which tracked underlying rate adjustments more faithfully than the alternative models.

Although the ARIMA(1,1,0) specification fully satisfied the rigorous Box–Jenkins diagnostic workflow, including stationarity testing, model identification, parameter estimation, and residual diagnostic checking, it did not achieve superior predictive accuracy. This outcome highlights that statistical adequacy does not automatically translate into lower forecasting errors within a given evaluation period. Consequently, model selection in predictive analytics should not be dictated solely by structural complexity, but rather by the intrinsic properties of the data and empirical accuracy evaluations. Beyond evaluating comparative model performance, this research contributes to the operations management literature by introducing ARIMA modeling alongside conventional Moving Average and Exponential Smoothing techniques. Accordingly, these findings serve as a useful reference for academics, researchers, and practitioners in selecting forecasting methods tailored to specific data characteristics and analytical objectives.

Several limitations should nevertheless be considered when interpreting these findings. First, the analysis is based on a single macroeconomic time series, namely the BI Rate, so the superior performance of the three-period Moving Average should not be generalized to other financial, macroeconomic, or operational datasets. Second, the BI Rate may be affected by structural changes associated with shifts in monetary-policy regimes, economic conditions, or discrete policy adjustments, whereas the present comparison does not explicitly incorporate structural-break modeling. Third, the relative performance of the models may depend on the parameter-selection procedure, including the Moving Average window length, the smoothing constant used in Exponential Smoothing, and the selected ARIMA order. Fourth, the analysis is restricted to three conventional forecasting families and therefore does not establish their superiority over alternative models such as Holt–Winters, state-space approaches, machine-learning methods, or hybrid forecasting models. Finally, model rankings are inherently sensitive to the forecast horizon and validation period; therefore, the finding that MA-3 provides the lowest forecasting error should be interpreted as specific to the data structure, forecasting configuration, and evaluation period examined in this study. Future research could address these limitations by employing multiple financial or macroeconomic series, testing alternative forecast horizons and rolling or holdout validation schemes, explicitly accounting for structural breaks, and comparing a broader range of statistical and computational forecasting models.

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