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A Hybrid BAT-SVR Methodology for Forecasting Iraq's Interest Rates of Commercial Bank (IRCB) Time Series Data

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ABSTRACT:

Time series forecasting plays a crucial role in economics and finance, particularly in predicting interest rates that influence monetary policy and financial decision-making. While previous research has explored optimizing similar models, this study is the first to apply an optimized model to Iraq's IRCB dataset. Accurately predicting interest rates in Iraq's volatile economy remains a challenge, as traditional forecasting methods struggle with the dataset's non-linear patterns in financial data, leading to suboptimal predictions. Additionally, selecting optimal hyperparameters for SVR is time-consuming and often ineffective. To address these issues, this study used a Hybrid BAT-SVR approach, leveraging the Bat Algorithm's global search capabilities to automate and enhance SVR's hyperparameter tuning. The BA is utilized to optimize SVR's hyperparameters, enhancing its predictive accuracy and robustness in handling non-linear relationships in time series data. So that, the primary goal is to develop a reliable and accurate forecasting model for IRCB data. The proposed methodology is applied to Iraq's Commercial Bank Interest Rates (IRCB) dataset, covering the period from June 2005 to June 2024. Empirical results demonstrate that the hybrid model outperforms standalone SVR and traditional forecasting methods in terms of prediction accuracy and generalization ability. Performance metrics, including R^2, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC), confirm the efficiency of the BAT-SVR model in capturing complex financial trends. The findings provide a valuable tool for policymakers and financial institutions to enhance decision-making and economic planning. Furthermore, this study contributes to the growing field of hybrid machine learning models in financial time series forecasting, offering insights for future research in optimization-based predictive modelling.

Keywords: Bat Algorithm (BA), Hybrid BAT-SVR, Time Series Forecasting, Support Vector Regression (SVR)

1 INTRODUCTION

Time series forecasting is a critical tool in economics and finance, particularly for predicting key variables such as interest rates, which play a pivotal role in monetary policy and economic planning. Accurate forecasting of interest rates enables policymakers, financial institutions, and investors to make informed decisions, manage risks, and plan for future economic scenarios. However, time series data, such as Iraq's Commercial Bank Interest Rates (IRCB), often exhibit complex patterns, including trends, seasonality, and non-linear relationships, making traditional forecasting methods less effective. To address these challenges, this study proposes a hybrid BAT-SVR Methodology, which combines the Bat Algorithm (BA), a metaheuristic optimization algorithm, with Support Vector Regression (SVR), a machine learning technique. The Bat Algorithm is inspired by the echolocation behavior of bats and is known for its

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ability to balance exploration and exploitation in solving optimization problems [1]. Support Vector Regression (SVR) is a machine learning technique derived from Support Vector Machines (SVM) and is used for predicting continuous variables. In the context of time series analysis, SVR is a powerful tool for modeling and forecasting complex, non-linear relationships in sequential data. By mapping input features into a higher-dimensional space using kernel functions (e.g., linear, polynomial, radial basis functions), SVR captures intricate patterns that traditional linear models might miss. It operates within an ε-insensitive margin, focusing only on significant deviations while ignoring minor errors, which makes it robust against outliers. Key parameters such as the regularization constant (C), kernel coefficient (γ), and margin of tolerance (ε) allow for fine-tuning the model to balance accuracy and complexity. SVR is particularly well-suited for financial time series, such as interest rates, where fluctuations exhibit non-linearity and noise, making it an ideal choice for precise forecasting and analysis [2]. By integrating these two methods, the hybrid approach optimizes the hyperparameters of SVR, enhancing its predictive accuracy and robustness. On the other hand, Support Vector Regression (SVR) has been widely used for time series forecasting due to its ability to model non-linear relationships and handle high-dimensional data. Smola and Schölkopf (2004) [2] demonstrated that SVR outperforms traditional regression methods in capturing complex patterns in time series data. The use of kernel functions, such as the Radial Basis Function (RBF), allows SVR to map input data into a higher-dimensional space, enabling the modeling of non-linear trends and seasonality. The Bat Algorithm (BA) is a nature-inspired optimization algorithm that mimics the echolocation behavior of bats. [1] introduced BA as a robust and efficient method for solving complex optimization problems. BA's ability to balance exploration and exploitation makes it particularly suitable for optimizing the hyperparameters of machine learning models, such as SVR. Studies have shown that BA outperforms other metaheuristic algorithms, such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), in terms of convergence speed and solution quality [3]. Hybrid approaches that combine metaheuristic algorithms with machine learning techniques have gained popularity in recent years. [4] used SVR to forecast interest rates in the United States, achieving high accuracy and robustness. Their study highlighted the importance of optimizing SVR's hyperparameters to improve predictive performance. Forecasting Iraq's Commercial Bank Interest Rates (IRCB) presents unique challenges due to the country's volatile economic environment and limited historical data. Traditional forecasting methods often fail to capture the complex dynamics of IRCB data, necessitating the use of advanced techniques such as SVR and metaheuristic optimization. The Hybrid BAT-SVR Methodology proposed in this study addresses these challenges by leveraging the strengths of BA and SVR to improve forecasting accuracy and reliability. Despite of previous research has explored optimizing similar models, to the best of the researchers' knowledge, this is the first study to apply such an optimized model to this specific dataset in Iraq. This study addresses the critical challenge of accurately predicting interest rates in Iraq's volatile and complex economic environment. Traditional forecasting methods often struggle to capture the non-linear patterns, trends, and seasonality inherent in IRCB data, leading to suboptimal predictions that hinder effective economic planning and decision-making. Additionally, the selection of optimal hyperparameters for machine learning models like Support Vector Regression (SVR) remains a significant obstacle, as manual tuning is time-consuming and often yields subpar results. To overcome these limitations, this study proposes a hybrid approach that combines the Bat Algorithm (BA), a metaheuristic optimization technique, with SVR to automate and optimize hyperparameter selection. By leveraging BA's global search capabilities. So that, the primary objective of this study is to develop a reliable and accurate forecasting model for Iraq's IRCB data using the Hybrid BAT-SVR Methodology. The study introduces a novel hybrid approach that optimizes SVR's hyperparameters, such as the regularization parameter C, kernel parameter γ, and margin of tolerance ϵ, to enhance forecasting accuracy and robustness. This methodology addresses the challenges of predicting interest rates in Iraq's volatile economic environment, where traditional methods often fail to capture complex, non-linear patterns. The study demonstrates the hybrid model's superior performance over standalone methods, providing a reliable tool for policymakers and financial institutions to make data-driven decisions. Additionally, it advances the application of metaheuristic algorithms in optimizing machine learning models, offering a framework for future research in time series forecasting and other domains. Overall, the study contributes to improving forecasting techniques and supports economic planning in challenging environments.

2 Research Methodology

2.1 SUPPORT VECTOR REGRESSION (SVR)

Support Vector Regression (SVR) is an extension of Support Vector Machines (SVM) that is used for regression tasks. It is designed to predict continuous values rather than classification. SVR works by finding a hyperplane (or decision function) that best fits the given data. In contrast to linear regression, SVR introduces a margin of tolerance, within which errors are ignored. It is a robust method capable of modelling non-linear relationships in data. SVR has gained popularity in time series forecasting due to its ability to handle non-linearity and provide reliable generalization in the presence of noise [5].

For a given training set $\{(x_1, y_2), (x_2, y_2), \ldots, (x_n, y_n),\}$, where $x_i \in R^m$are the input vectors and $y_i \in R$are the corresponding outputs (targt values), to goal of SVR is to find a function $f(x)$that approximates the underlying relationship between the input $x$and output y.

The general form of the regression function is [6]:

$$f(x) = w.x + b \quad (1)$$

Where:

$w$is the weight vector,

x is the input vector, and

b is the bias term.

SVR uses an ϵ -insensitive loss function to define the margin of tolerance. This means that errors within a range ϵ are not penalized. The optimization problem for SVR is formulated as:

$$min \frac{1}{2}\|w\|^2 + c\sum_{i=1}^{n}(\varepsilon_i + \varepsilon_i^{¿}) \quad (2)$$

Subject to the constraints:

$$y_i - (w.x_i + b) \leq \in + \varepsilon_i$$

$$(w.x_i + b) - y_i \leq \in + \varepsilon_i$$

$$\varepsilon_i \varepsilon_i^{¿} \geq 0$$

Where:

$\varepsilon_i \wedge \varepsilon_i^{¿}$are slack variables that allow for some error outside the margin,

C is a regularization parameter that controls the trade–off between maximizing the margin and minimizing the error.

2.2 SVR FOR TIME SERIES FORECASTING

For time series data, the goal is to predict future values based on historical data. Time series data often exhibit temporal dependencies (short dependency) that are difficult to capture with traditional methods. SVR is well-suited for this task, as it can handle non-linear patterns and adapt to complex time short dependencies. Time series forecasting using SVR involves the following steps [7][8]:

1- Data Preparation: The time series data is divided into training and testing sets. The data points are transformed into lag-based feature vectors, where the past observations are used to predict future values.

2- Model Training: SVR is trained on the transformed feature vectors to minimize the error while fitting the hyperplane. The model learns the complex relationship between past observations and future predictions, then forecasting.

3- Prediction: The trained model is used to predict values based on the test data.

Let the input time series be represented by {y1,y2,…,yT}. To forecast future values, the data can be reformulated into lagged form. For instance, the data at time *t* can be represented as:

$$X_t = [y_{t-1}, y_{t-2}, \ldots, y_{t-p}] \quad (3)$$

Where:

- $X_t$is the feature vector at time t,
- p is the number of lags used as features.

The goal is to predict Y_t, the value of the time series at time *t*, using the trained SVR model.

2.3 CHOOSING KERNEL FUNCTIONS AND HYPERPARAMETER TUNING IN SVR

SVR can handle both linear and non-linear data, and this is achieved by using kernel functions. The most common kernel functions used in SVR are [9]:

1- Linear Kernel: $K\left(x, x^{'}\right) = x . x^{'}$

2- Polynomial Kernel: $K\left(x, x^{'}\right) = ¿$

3- Radial Basis Function (RBF) Kernel: $K\left(x, x^{'}\right) = \exp\left(-\gamma \left\|x - x^{'}\right\|^{2}\right)$

4- Sigmoid Kernel: $K ¿$

The choice of kernel depends on the nature of the data. The RBF kernel is often used for non-linear relationships because it allows the model to capture complex patterns in the data. SVR performance is sensitive to the choice of hyperparameters [10] [11]:

- **C**: The regularization parameter that controls the trade-off between model complexity and training error.
- **ϵ**: The margin of error within which no penalty is exist.
- **Kernel parameters (e.g., γ for RBF)**: The parameters that define the shape of the decision boundary.

  Hyperparameter tuning is typically done using techniques like Grid Search or Random Search, which systematically test different combinations of parameters to find the optimal configuration for the model. Once the SVR model is trained, its performance is evaluated using various metrics:

- Mean Absolute Error (MAE):

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| y_i - y_i^{¿} \right|$$

- Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i - y_i^{¿} \right)^2}$$

- Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - y_i^{¿}}{y_i} \right| \times 100$$

These metrics help evaluate the accuracy of the forecasts and the model's ability to generalize to unseen data [13].

2.4 BAT ALGORITHM METHODOLOGY

The Bat Algorithm (BA) is a nature-inspired optimization algorithm that is based on the echolocation behaviour of bats. It was introduced by Xin-She [12]. The algorithm is a metaheuristic optimization method used to solve complex optimization problems by mimicking the natural behaviour of bats in locating prey via echolocation. The BA is particularly effective for continuous, combinatorial, and multi-objective optimization problems. The basic principle behind BA is that bats use echolocation to navigate, and in the context of optimization, this behaviour is modelled mathematically. The BA uses the following principles [10]:

1- Echolocation: Bats emit a series of pulses that can vary in frequency and intensity. They use the return time of these pulses to determine the distance to objects and potential prey. In BA, the position of the bat in the solution space corresponds to the potential solution, and the pulse rate corresponds to the exploration of the search space.

2- Pulse Emission and Velocity: Bats update their positions and velocities based on three key parameters:

- **Frequency**: This influences the exploration and exploitation process. Higher frequency leads to exploration of new areas, while lower frequency leads to exploitation of the best solutions found.
- **Pulse Rate**: Determines how fast the bats fly through the search space.
- **Loudness**: Refers to the intensity of the pulse emission. High loudness means the bat can search broadly, while low loudness signifies a local search, focusing on exploitation.

The BA is particularly effective for global optimization problems due to its ability to explore the search space efficiently while exploiting promising regions [1]. The Bat Algorithm is governed by the following equations:

3- Frequency Update:

The frequency f_i of the i-th bat is updates as:

$$f_i = f_{min} + ¿$$

Where:

f_{max} and f_{min} are the minimum and maximum frequencies,

β is a random vector uniformly distributed in [0,1].

1- Velocity Update:

The velocity υ_i of the i-th bat is updates as:

$$\upsilon_i^{t+1} = \upsilon_i^t + \left(x_i^t - x_{¿}\right) f_i (5)$$

Where:

x_i^t is the current position of the i-th bat at iteration t,

$x_{¿}$ is the current global best solution,

f_i is the frequency of the i-th bat.

2- Position Update:

The position x_i of the i-th bat is updated as:

$$x_i^{t+1} = x_i^t + \upsilon_i^{t+1} (6)$$

3- Loudness and Pulse Emission:

The loudness A_i and pulse emission rate r_i are update as:

$$A_i^{t+1} = \alpha A_i^t$$

$$\gamma_i^{t+1} = \gamma_i^0 \left[1 - \exp(-\gamma t)\right] (7)$$

Where:

α and γ are constants (typically $\alpha = \gamma = 0.9 ¿$,

A_i^0 and γ_i^0 are the initial loudness and pulse emission rate.

The performance of the Bat Algorithm depends on the following parameters key:

1- Frequency Range (f_{min}, f_{max}**)**: Controls the exploration and exploitation of the search space.

2- Loudness (A_i**)**: Determines the acceptance of new solutions. As iterations progress, loudness decreases to focus on exploitation.

3- Pulse Emission Rate (γ_i**)**: Controls the frequency of local searches. As iterations progress, the pulse emission rate increases to enhance exploitation.

4- Population Size: The number of bats (solutions) in the population.

5- Stopping Criteria: The maximum number of iterations or a convergence threshold.

2.5 HYBRID BAT-SVR METHODOLOGY FOR TIME SERIES DATA

The **Hybrid BAT-SVR Methodology** combines the Bat Algorithm (BA) for optimization and Support Vector Regression (SVR) for time series forecasting. This hybrid approach leverages the strengths of both techniques, using the Bat Algorithm for efficient optimization of SVR parameters, such as the regularization parameter C, the kernel parameters, and the epsilon parameter ϵ, while SVR is used as the forecasting tool for time series data. In the Hybrid BAT-SVR approach,

The process involves using the **Bat Algorithm** to optimize the hyperparameters of the **SVR** model for time series prediction. **Steps:**

1- Parameter Initialization:

Define the parameter space for SVR hyperparameters, such as the regularization parameter C, epsilon ϵ, and kernel parameters like σ. Initialize a population of bats, each representing a set of SVR parameters.

2- Fitness Evaluation:

The fitness of each bat is calculated by training an SVR model with its respective set of parameters and evaluating its performance using a fitness function, typically **Mean Squared Error (MSE)** or **Root Mean Squared Error (RMSE)**.

$$\text{Fitness ¿}\frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2 (8)$$

where:

y_i are the actual values,

$\hat{y}_i$ are the predicted values by the SVR model.

3- Bat Algorithm Update:

Bats explore the parameter space by adjusting their positions based on the fitness value, optimizing the parameters iteratively. The Bat Algorithm updates the bats' velocities and positions using the equations above, gradually converging to the optimal SVR parameters.

4- Forecasting:

Once the Bat Algorithm converges to the optimal SVR parameters, the best parameter set is used to train an SVR model, which then forecasts future values in the time series. In addition, mathematically can be summarize these steps as follows:

- **SVR Prediction**:

$$\hat{y}_i=w^T x_i+b$$

- **Optimization Goal (Fitness Function - MSE):**

$$\text{Fitness ¿}\frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2$$

- **BAT Position and Velocity Update:**

$$x_i(t+1)=x_i(t)+\upsilon_i(t+1)$$

$$\upsilon_i(t+1)=\upsilon_i(t)+\alpha.(x_i(t)-x^{¿}(t))+\beta.(\gamma_1(t)-0.5).x_{i,best}(t)$$

- **Update of Loudness and Frequency:**

$$f_i(t+1)=f_{min}+(f_{max}-f_{min}).r_2(t)$$

$$A_i(t+1)=A_0.(1-\gamma.t)$$

3 Application and Results

3.1 DATA DESCRIPTION

In this paper, monthly observations are used of Interest Rate of Commercial bank (IRCB), the sample period is Jun 2005 to Jun 2024. The **Iraq Commercial Bank Interest Rates (IRCB)** refers to the historical data collected from commercial banks operating in Iraq, and the researchers used R-language software to analysing their data, whereas it is focusing on the interest rates they offer on various financial products such as loans, deposits, and other banking services. These interest rates are crucial indicators of the economic environment in Iraq, influencing not only the banking sector but also the broader economy, including consumer behaviour, investment decisions, and macroeconomic policies. Interest rates play a significant role in shaping financial and economic trends, and in a developing economy like Iraq, they are heavily influenced by both domestic factors (e.g., inflation, monetary policy) and external factors (e.g., international trade, global economic conditions). Thus, the IRCB Time Series Data provides valuable insights into the economic health and stability of Iraq, making it an important dataset for researchers, policymakers, financial analysts, and economists.

Table 1. Represents the stationary test of the series

Models	Test	t-Statistic	P-value
Level	ADF	-7.30984	0.000

The test results indicate the Augmented Dickey-Fuller (ADF) test applied to the IRCB time series at the level (original form) of the data. The t-statistic of -7.30984 and the p-value of 0.000 strongly reject the null hypothesis of a unit root, meaning the time series is stationary at its level. This suggests that the IRCB data does not require differencing to achieve stationarity, making it suitable for time series modelling without additional transformations.

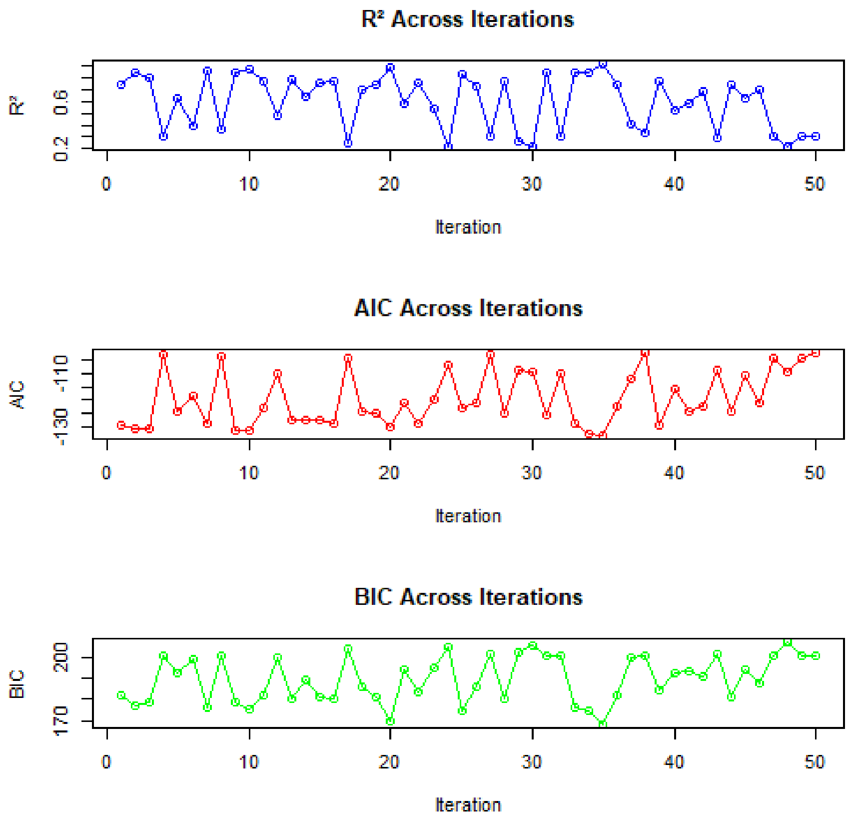

Figure 1. Shows the performance metrics of a BAT-SVR model second

Figure 1 shows the performance metrics of a BAT-SVR model applied to a time series dataset over 50 iterations. The top panel illustrates the R^2 values, fluctuating between 0.20 and 0.91, representing the model's ability to explain variance in the data, with variability reflecting the Bat Algorithm's stochastic exploration. The middle panel tracks the Akaike Information Criterion (AIC), where lower values (-133.51) indicate a better balance between model fit and complexity, while the bottom panel shows the Bayesian Information Criterion (BIC), which also penalizes complexity and fluctuates between 168 and 208. The oscillations across all metrics reflect the optimization process, where the algorithm balances exploration and exploitation to improve model performance. The best iteration is identified by combining the highest R^2 and lowest AIC/BIC values, which are gained at iteration 35 representing an optimal trade-off between fit and simplicity.

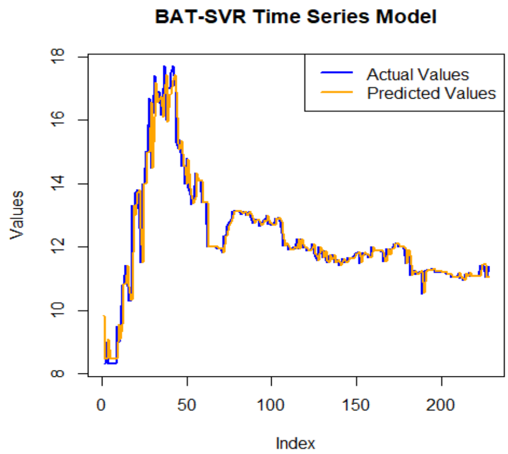

Figure 1. Shows the performance of the BAT-SVR between actual and predicted values for variable IRCB

Figure 2 shows the performance of the BAT-SVR (Bat Algorithm optimized Support Vector Regression) model in predicting the time series variable IRCB. The x-axis represents the index (time), while the y-axis represents the values of IRCB. The blue line corresponds to the actual values of IRCB, while the orange line represents the predicted values generated by the BAT-SVR model. The model effectively tracks the trends and patterns of the actual data, particularly during periods of sharp increases and stabilization. Minor deviations between actual and predicted values may occur, indicating areas where the model could be further refined. Overall, the close alignment of the two lines demonstrates the model's ability to capture and predict the time series behavior of IRCB accurately.

Table 2. Represents the diagnostic tests of residuals

Tests	Statistic	P-value
ADF	-8.68	0.000
BP	0.318	0.628
D-W	1.90	0.742

The residuals tests evaluate the quality of the BAT-SVR model for the IRCB time series data. The **Augmented Dickey-Fuller (ADF) test** shows a test statistic of **-8.68** with a **P-value of 0.000**, indicating strong evidence against the null hypothesis of a unit root, meaning the residuals are stationary. The **Breusch-Pagan (BP) test** yields a statistic of **0.318** and a **P-value of 0.628**, suggesting no significant heteroscedasticity (constant variance of residuals). The **Durbin-Watson (D-W) test** statistic of **1.90** with a **P-value of 0.742** indicates that the residuals exhibit little to no autocorrelation, meaning the model does not suffer from serious serial correlation issues. Overall, these results suggest that the BAT-SVR model is well-specified, with stationary and homoscedastic residuals and no strong autocorrelation (level of significant).

Table 3. Shows a forecast value of the variable IRCB

Periods	Forecasted	Confidence interval 95%	
		Low	High
Feb,2024	11.0478	9.6453	13.7410
Mar,2024	11.0478	8.7774	12.7082
Apr,2024	11.0478	9.1368	13.7758
May,2024	11.0478	9.7866	11.8995
Jun,2024	11.1860	8.9588	11.3678
Jul,2024	11.0085	9.3303	12.6105
Aug,2024	11.0085	8.6849	10.7808
Sep,2024	10.9494	8.7116	11.2958
Oct,2024	11.1563	9.3042	12.4687

Nov,2024	11.0774	9.1137	11.7620
Dec,2024	11.1860	9.7470	10.6476
Jan,2025	11.0774	9.2481	13.4002
Feb,2025	11.0774	8.7086	12.3429
Mar,2025	11.0774	9.2859	11.5081
Apr,2025	11.0774	9.5433	12.2948
May,2025	11.0774	9.7893	12.6015
Jun,2025	11.0774	9.3169	10.9948
Jul,2025	11.4336	9.7358	12.6232
Aug,2026	11.4336	8.6663	12.1668
Sep,2026	11.4336	8.9710	10.8395
Oct,2026	11.0380	9.0201	12.8315
Nov,2026	11.0380	9.7785	12.8026
Dec,2026	11.3939	9.4210	12.9238

Table 3 provides a forecast of the variable IRCB for the specified periods, including February 2024 through December 2026. The second column contains the forecasted IRCB values, while the third and fourth columns represent the 95% confidence interval's lower and upper bounds, respectively. These intervals indicate the range within which the actual IRCB values are expected to fall with 95% confidence. For instance, the forecasted IRCB value for February 2024 is 11.0478, with a confidence interval ranging from 9.6453 (low) to 13.7410 (high). Similarly, in December 2026, the forecasted value is 11.3939, with a confidence interval of 9.4210 to 12.9238. The forecasts exhibit minor fluctuations, suggesting stability in the IRCB variable over time, with narrow confidence intervals indicating a relatively high degree of certainty in the predictions.

CONCLUSION

This study analyzed the Iraq Commercial Bank Interest Rates (IRCB) time series data from June 2005 to June 2024 using the Hybrid BAT-SVR methodology. The findings indicate that the IRCB time series is stationary at its level, allowing for effective forecasting without additional transformations. The BAT-SVR model demonstrated strong predictive capabilities, with performance metrics such as R^2, AIC, and BIC confirming the model's efficiency in capturing time series patterns. The residual diagnostic tests further validated the model's adequacy, showing no significant issues of autocorrelation or heteroscedasticity. The forecasted values for IRCB suggest stability in interest rates over the next few years, providing valuable insights for policymakers, financial analysts, and banking institutions. Overall, the Hybrid BAT-SVR approach proves to be a robust method for forecasting financial time series, offering a balance between accuracy and computational efficiency. Future research could explore alternative hybrid models or incorporate external economic variables to enhance predictive performance.

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