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Forecasting the Iraqi Exchange Rate for the Years (2024 to 2026) by Using BAT-Exponential Trend Model

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Abstract: This study examines the performance and forecasting of the Iraqi Exchange Rate (ER) using an Exponential Trend Model and optimization techniques. To identify patterns and trends in the Iraqi exchange rate over the past years and establish a baseline for forecasting. The data, sourced from the World Bank, covers the annual average index values of the ER from 2009 to 2023. The optimization process is performed using the BAT Optimizer Algorithm, which minimizes prediction errors by adjusting parameters over multiple iterations. As shown in Table (1), the algorithm successfully reduces MSE and RMSE, with significant improvements in model efficiency, as reflected in the decreasing AIC and BIC values. Table (2) provides the optimized parameters of the Exponential Trend Model, with both parameters, A and B, found to be highly statistically significant (p-value < 0.0001), indicating a reliable model. Table (3) compares the predicted and actual values for the ER, highlighting the residuals between the two, which indicate how well the model fits the data. Finally, Table (5) presents the forecasted ER values for 2024 to 2026, providing predictions with 95% confidence intervals, and suggesting a stable but slightly fluctuating market outlook. The results indicate that the BAT Optimizer and the Exponential Trend Model can effectively forecast and track the performance of the Iraqi exchange rate.

Keywords: Iraqi exchange rate, BAT Optimizer Algorithm, Exponential Trend Model, and Forecasting.

التنبؤ بسعر الصرف العراقية للسنوات (٢٠٢٤-٢٠٢٦) باستخدام نموذج الاتجاه الأسي الخفاش المحسن

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المستخلص: تتناول هذه الدراسة تنبؤات سعر الصرف العراقية باستخدام نموذج الاتجاه الأسي وتقنيات التحسين. بهدف التعرف على أنماط واتجاهات سعر الصرف العراقي خلال السنوات الماضية ووضع قاعدة أساسية للتنبؤ بها. والبيانات قيد الدراسة تم أخذها من البنك الدولي، و هي متوسط قيم المؤشر السنوية لسعر الصرف العراقية من عام ٢٠٠٩ إلى عام ٢٠٢٣. وتم عملية التحسين باستخدام خوارزمية محسن BAT، التي تقلل من أخطاء التنبؤ عن طريق تعديل المعلمات على مدار تكرارات متعددة. وكما هو موضح في الجدول (١)، نجحت الخوارزمية في تقليل MSE وRMSE بنجاح، مع تحسينات كبيرة في كفاءة النموذج، كما ينعكس في انخفاض قيم AIC وBIC. يوفر الجدول (٢) المعلمات المحسنة لنموذج الاتجاه الأسي، حيث وجد أن كل من المعلمتين A وB ذات دلالة إحصائية عالية قيمة ($p < 0.0001$) ، مما يشير إلى نموذج معنوية. يقارن الجدول (٣) القيم المتوقعة والفعلية لسعر الصرف العراقية، مع تسليط الضوء على المتبقيات بين الاثنين، والتي تشير إلى مدى ملاءمة النموذج للبيانات. وأخيرًا، يعرض الجدول (٥) قيم ER المتوقعة للفترة من ٢٠٢٤ إلى ٢٠٢٦، مما يوفر تنبؤات بحدود الثقة ٩٥٪، مما يشير إلى تنبؤات سوق مستقرة ولكنها متقلبة قليلاً. تشير النتائج إلى أن BAT Optimizer ونموذج الاتجاه الأسي يمكنهما التنبؤ بأداء سعر الصرف العراقية وتتبعه بشكل فعال.

الكلمات المفتاحية: سعر الصرف العراقية، خوارزمية خفاش المحسن، نموذج الاتجاه الأسي، التنبؤ.

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Introduction

The Iraqi exchange rate (ER) has undergone a transformative journey from 2009 to 2023, adapting to the dynamic political, economic, and security challenges in Iraq. Established in 2004, the ER initially faced considerable obstacles, including low trading volumes and limited investor participation due to the unstable post-invasion environment. By 2009, Iraq had made substantial efforts to modernize its financial markets, aiming to integrate more closely with global financial systems. According to Al-Okaily (2016), the period following 2009 was marked by the implementing of several reforms, including the introduction of electronic trading systems, which were essential for boosting market efficiency and transparency. From 2009 onward, the ER saw gradual improvements, with key initiatives focusing on enhancing market infrastructure. One significant reform was the introduction of the Iraq Stock Exchange Law in 2007, which was updated in subsequent years to ensure better governance, enhance market liquidity, and attract foreign investment. As noted by Hameed (2019), these regulatory changes, along with efforts to improve corporate governance and investor protection, played a key role in encouraging both local and foreign investments, particularly in the banking and telecommunications sectors. The early 2010s saw an increase in the number of listed companies, although market activity remained volatile, heavily influenced by Iraq's political instability and reliance on oil exports. The period between 2014 and 2017 was particularly challenging for the ER due to the ISIS insurgency, which caused widespread security concerns and negatively impacted investor sentiment. Despite these challenges, the ER continued its operations, demonstrating resilience and maintaining its importance as a symbol of Iraq's potential for economic recovery and diversification. According to World Bank (2021), the period following the insurgency saw a stabilization of Iraq’s economy, which was reflected in a renewed interest in the ER, albeit with slow growth due to the underlying geopolitical and security risks. The COVID-19 pandemic in 2020 and the subsequent collapse in oil prices further complicated Iraq's economic trajectory, yet the ER managed to adapt to the situation. In response to these challenges, the ER introduced more digital and online trading platforms to accommodate investors in a socially-distanced world, while regulatory frameworks were updated to promote transparency and investor confidence. IMF (2020) notes that these adaptations helped stabilize the market during a period of global economic uncertainty, although Iraq’s reliance on oil revenues remained a persistent vulnerability. By 2023, the ER had become a more accessible and efficient marketplace, thanks in part to international partnerships and modernized trading technologies. Hameed (2019) emphasizes that Iraq’s economic diversification strategies, particularly in sectors such as banking, telecommunications, and industry, were pivotal in boosting investor interest. The exchange began to attract increasing foreign investment, particularly from regional markets seeking to capitalize on Iraq's growing economic potential. As Al-Okaily (2016) observes, the future of the ER depends on Iraq's ability to continue reforming its financial systems, reduce political instability, and build confidence among both local and international investors. The trajectory of the Iraqi exchange rate from 2009 to 2023 highlights both the challenges and opportunities faced by an emerging market in a region marked by volatility. As Iraq continues to implement reforms aimed at economic diversification and improved governance, the ER is poised to play a critical role in the country's financial development.

Literature Review

The performance and volatility of the Iraqi exchange rate (ER) have been influenced by both macroeconomic factors and geopolitical conditions. A study by Ali et al. (2017) examined the factors contributing to stock price volatility on the ER. The authors concluded that the Iraqi market exhibits high levels of volatility due to political instability, fluctuating oil prices, and other external shocks. Additionally, the study found that foreign investors tend to shy away from the market due to its perceived risks, but there has been a growing interest in the market as reforms and modernization efforts began in the early 2010s. In a related study, Al-Salman (2019) explored the role of political and economic factors in driving stock market volatility and concluded that periods of political unrest (such as the rise of ISIS in 2014) significantly impacted market performance. The study also highlighted that while the ER had been experiencing growth, its overall liquidity remained low compared to more mature markets. These findings underscore the challenges of operating in a market that is heavily influenced by extrinsic factors like oil prices and political tensions. In the context of economic forecasting, the use of optimization algorithms like BAT to fine-tune forecasting models is a growing area of research. The BAT-Exponential Trend Model has proven effective in predicting economic indicators and stock market trends by optimizing parameters to achieve better forecast accuracy. As demonstrated by Yang et al. (2010) and Zhang et al. (2016), combining the Bat Algorithm with the Exponential Trend Model enhances the model's adaptability and robustness, particularly in volatile environments such as the Iraqi stock market. This hybrid approach could be particularly beneficial for improving the forecasting capabilities for the ER, where uncertainty and volatility are prominent features.

1. Methodology

A. Methodology of BAT-Exponential Trend Model

The BAT-Exponential Trend Model is a hybrid approach that combines the Bat Algorithm (BAT), a nature-inspired optimization technique, with an Exponential Trend Model for time series forecasting. The main idea behind this model is to leverage the Bat Algorithm's optimization capability to tune the parameters of the Exponential Trend Model in order to obtain better forecasting accuracy for time series data. This methodology has become popular for forecasting due to its ability to effectively model and predict complex, non-linear time series trends.

(1) Exponential Trend Model

The Exponential Trend Model is widely used for time series forecasting due to its simplicity and effectiveness in capturing the growth or decay patterns in data. The general form of the Exponential Trend Model is:

$$y_t = A \cdot e^{(B \cdot t)} \qquad (1)$$

Where:

y_t is the value of the time series at time t.

A is the initial value or the intercept parameter.

B is the rate of growth or decay (trend parameter).

t is the time step (1, 2, 3, ..., n).
e is the base of the natural logarithm.

This model assumes that the time series grows or decays exponentially over time, and the values of A and B need to be estimated based on historical data. The goal is to find the best-fitting values of A and B that minimize the error between the predicted and actual values of the time series.

(2) Bat Algorithm (BAT)

The Bat Algorithm (BAT) is a nature-inspired optimization technique based on the echolocation behavior of bats. Bats use sound waves to locate prey, and the algorithm mimics this behavior to find optimal solutions for optimization problems. The BAT algorithm can be effectively applied to search for the best parameters in a given model, such as the Exponential Trend Model's parameters. The key steps in the Bat Algorithm are as follows:

(a) nitialization: A population of bats is initialized randomly with different positions (solutions) and velocities. Each bat has a position in the search space, which corresponds to a set of potential solutions (in this case, the parameters A and B for the Exponential Trend Model).

(b) Movement and Search: Bats move through the search space based on a velocity update rule:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \qquad (2)$$

Where:
$x_i^{(t+1)}$ is the position (solution) of bat i at time t.
$v_i^{(t+1)}$ is the velocity update of bat i.

The velocity update equation is:

$$v_i^{(t+1)} = v_i^{(t)} + \alpha \ . \ (x_i^* - x_i^{(t)}) + \beta \ . \ \delta_i^{(t)} \qquad (3)$$

Where:
x_i^* is the global best solution found so far.
α is the step size.
$\delta_i^{(t)}$ is a random vector representing the randomness in bat movements.
β is a scaling factor for the randomness.

(c) Updating Solution and Exploration vs Exploitation: The bats also adjust their position according to their loudness and pulse emission rates. The loudness and pulse rates are dynamically updated during the search process. The bats with higher loudness have more influence on the search space, while those with lower loudness are more explorative. This trade-off between exploration and exploitation helps to refine the search process and escape from local optima.

(d) Convergence: The algorithm proceeds iteratively, refining the positions of the bats (i.e., the model parameters) until a convergence criterion is met, typically when the improvement in the objective function (forecasting error) becomes negligible.

(3) BAT-Exponential Trend Model Framework

The BAT-Exponential Trend Model combines the optimization power of the BAT algorithm with the Exponential Trend Model for time series forecasting. The methodology consists of the following steps:

Step 1: Data Preprocessing

The input time series data is cleaned and prepared. Missing values, if any, are handled, and the data is scaled or normalized if necessary.

Step 2: Initialize BAT Population

Initialize the population of bats, where each bat represents a potential solution (a set of values for A and B.

Step 3: Define Fitness Function

The fitness function is defined as the mean squared error (MSE) between the observed values $\mathbf{y_t}$ and the predicted values $\hat{\mathbf{y}}_t$ from the Exponential Trend Model. The objective is to minimize this error, i.e.:

$$\boldsymbol{Fitness} = \frac{1}{n}\sum_{t=1}^{n}(y_t - A.e^{(B.t)})^2 \qquad (4)$$

Where y_t are the actual values from the time series, and $\hat{y}_t = A.e^{(B.t)}$ are the predicted values from the Exponential Trend Model.

Step 4: Apply BAT to Optimize A and B

Use the Bat Algorithm to optimize the parameters A and B by minimizing the fitness function (MSE). The best values of A and B found by the BAT algorithm correspond to the best-fitting Exponential Trend Model.

Step 5: Forecast Future Values

Once the optimal values for A and B are determined, use the Exponential Trend Model to forecast future values of the time series:

$$\hat{y}_t = A_{opt} \,.\, e^{(Bopt\,.t)} \qquad (5)$$

Where A_{opt} and B_{opt} are the optimized parameters.

Step 6: Model Evaluation

Evaluate the model's forecasting performance using standard metrics such as Mean Absolute Error (**MAE**), Mean Squared Error (**MSE**), and R-squared.

B. Dickey-Fuller Test

The **Dickey-Fuller test** (or **Augmented Dickey-Fuller test**) is a statistical test used to determine whether a time series is **random** or not. The basic form of the Dickey-Fuller test involves estimating the following regression:

$$\Delta y_t = \alpha + \beta_t + \gamma y_t - 1 + \sum i = 1p\ \delta_i \Delta y_{t-I} + \epsilon_t \qquad (6)$$

Where:

- Δy_t is the first difference of the time series.
- α is a constant (intercept).
- β_t is a time trend.
- y_{t-1} is the lagged value of the series.
- γ is the coefficient of the lagged dependent variable.
- Δy_{t-i} are the lags of the differenced series.
- ϵ_t is the error term.

Evaluate Precision of Forecasting Models

Evaluating the precision of forecasting models is a critical step in determining how well a model predicts future values. The precision of a forecasting model refers to its ability to generate accurate, reliable, and consistent predictions. There are various statistical measures and methods used to assess the precision of forecasting models, depending on the type of model being used (e.g., time series, regression, machine learning). Below is an overview of some common methods and metrics used to evaluate the precision of forecasting models:

(1) Mean Squared Error (MSE)

MSE is a metric that is used to evaluate how well a model's predictions match the actual data. It calculates the average of the squared differences between the predicted values and the actual values.

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2 \qquad (7)$$

where:

- n is the number of observations.
- y_t is the actual value.
- $\hat{y}_t$ is the predicted value.

(2) Root Mean Squared Error (RMSE)

The **Root Mean Squared Error (RMSE)** is another commonly used metric to evaluate forecasting accuracy. RMSE penalizes large errors more heavily than MAE because it squares the differences between actual and forecasted values before averaging them. This makes RMSE particularly sensitive to outliers and large deviations in forecasts.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \qquad (8)$$

(3) Akaike Information Criterion (AIC)

AIC is a model selection criterion that helps evaluate how well a statistical model fits the data while penalizing the model for having too many parameters (complexity). It is widely used to compare different models.

$$\text{AIC} = 2\,k - 2\ln(\mathscr{L}) \qquad (9)$$

Where:

- n: is the number of observations.
- $\mathscr{L}$: is the log-likelyhood.

(4) Bayesian Information Criterion (BIC)

BIC is very similar to AIC in that it also balances model fit with model complexity, but it applies a stronger penalty for complexity. It is based on Bayesian principles and is often used in statistical model selection.

$$\text{BIC} = k\,.\,\ln(n) - 2\ln(\mathscr{L}) \qquad (10)$$

Where:

- n: is the number of observations.
- $\mathscr{L}$: is the log-likelyhood.
- k: is the number of explanatory variables in the model.

2. Applications

A. Data Description

The data provides the annual values of the **Iraqi exchange rate** from **2009** to **2023**, with values presented as the **average index** for each year. These values are taken from the **World Bank website**, which provides international financial and economic data.

Table (1): BAT Optimizer Algorithm

Iterations	MSE	RMSE	AIC	BIC
10	1899.113	43.57882	-13.0983	-12.39023
20	2096.096	45.78314	-13.2957	-12.58761
30	1952.1	44.18258	-13.1533	-12.44527
40	2294.114	47.89691	-13.4762	-12.76815
50	2496.07	49.96068	-13.6449	-12.9369
60	1908.114	43.68196	-13.1077	-12.39969
70	1903.089	43.62441	-13.1025	-12.39442
80	1892.09	43.49816	-13.0909	-12.38282
90	1798.131	42.40437	-12.989	-12.28096
100	**1706.177**	**41.3059**	**-12.884**	**-12.17597**

This table illustrates the performance of the BAT Optimizer Algorithm over 100 iterations, showing the changes in MSE, RMSE, AIC, and BIC at each step. As the algorithm progresses through the iterations, both MSE and RMSE decrease, indicating that the optimization is improving, with prediction errors getting smaller. Specifically, MSE decreases from 1899.11 at iteration 10 to 1706.18 at iteration 100, and RMSE similarly falls from 43.58 to 41.31. In addition to error metrics, both AIC and BIC values also improve as the algorithm advances. AIC and BIC are used to assess model quality, balancing fit and complexity, and both show a trend toward lower values over time, indicating that the model is becoming more efficient. AIC decreases from -13.0983 to -12.884, and BIC drops from -12.39023 to -12.17597 by the 100th iteration. These trends suggest that the BAT Optimizer is progressively refining the model, achieving a balance between minimizing prediction error and avoiding overfitting, as evidenced by the improvements in all metrics.

Table (2): Best optimized parameter of Exponential Trend Model

Parameters	value	S.E	t-test	p-value
A	470.2208	12.0672	38.96685	0.0000
B	0.08498	0.003209324	26.4791	0.0000

Table (2) presents the best-optimized parameters for the Exponential Trend Model, along with their associated statistical measures. The table shows the parameter values, standard errors (S.E.), t-tests, and p-values for two parameters, A and B. The parameter A has a value of 470.2208, with a standard error of 12.0672, a t-test value of 38.96685, and a p-value of 0.0000, indicating that A is statistically significant and strongly different from zero. Similarly, the parameter B has a value of 0.08498, a standard error of 0.0032, a t-test value of 26.4791, and a p-value of 0.0000, also showing high statistical significance. Both parameters are highly significant, as their p-values are well below the common threshold of 0.05, meaning the model is highly reliable and the parameters are important in explaining the exponential trend.

Table (3): Demonstrates the actual, predicted and residuals

Years	Iraqi exchange rate	Predicted	Residuals
2009	1170	1202.502	-32.502
2010	1170	1142.44	27.56
2011	1170	1123.224	46.776
2012	1166.166667	1117.069	49.098
2013	1166	1202.789	-36.789
2014	1166	1145.244	20.7564
2015	1167.333333	1197.973	-30.64
2016	1182	1233.456	-51.456
2017	1184	1123.335	60.665
2018	1182.75	1139.982	42.768
2019	1182	1198.897	-16.897
2020	1192.166667	1232.265	-40.0987
2021	1450	1395.125	54.875
2022	1450	1422.014	27.986
2023	1315.75	1345.815	-30.065

Table (4): Shows the randomness test of the residuals

Test	t-Statistic	P-value
ADF	-6.7341	0.000

Table (4) explains that the p-value of the Dickey-Fuller test equals 0.000 and it is less than 0.05, which means the residuals of the model are random, then we can use the model to make the forecast.

Table (5): shows the Forecasted values of Iraqi exchange rate

Year	Forecast	Lower 95% Limit	Upper 95% Limit
2024	1,384.911	1190.928	1616.645
2025	1,418.502	1224.519	1650.236
2026	1,397.641	1203.658	1629.375

Table (5) presents the forecasted values of the Iraqi exchange rate for the years 2024 to 2026, along with their corresponding 95% confidence intervals (Lower and Upper limits). The forecast for 2024 is 1,384.911, with a lower bound of 1,190.928 and an upper bound of 1,616.645, suggesting that the Iraqi exchange rate index is expected to be within this range with 95% confidence. Similarly, the forecast for 2025 is 1,418.502, with a lower limit of 1,224.519 and an upper limit of 1,650.236, indicating a slight upward trend. For 2026, the forecast is 1,397.641, with the lower and upper limits ranging from 1,203.658 to 1,629.375. These forecasts suggest a stable but slightly fluctuating outlook for the Iraqi exchange rate over the next three years, with the values expected to remain within the specified confidence intervals. The confidence intervals reflect the degree of uncertainty in the predictions, offering a range of plausible outcomes.

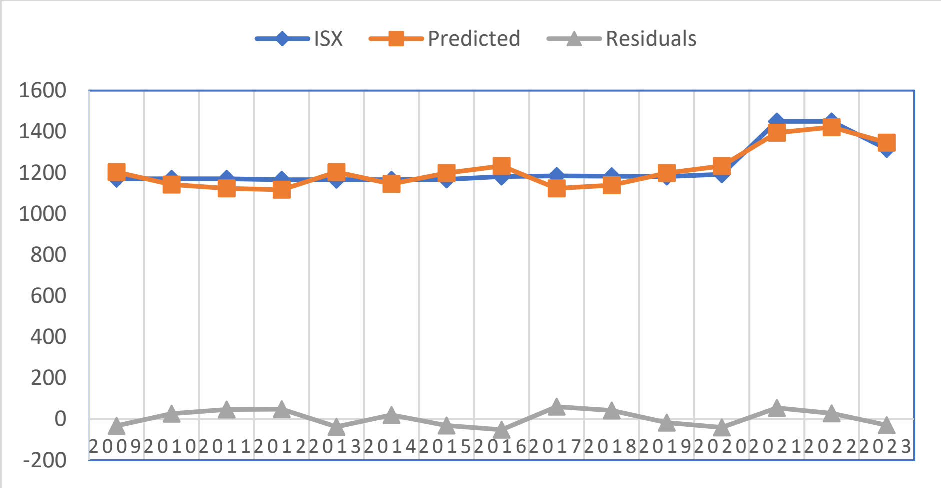

Figure (1): Represents the actual and predicted values of Iraqi exchange rate

3. Conclusions

The results of this study suggest that the Iraqi exchange rate (ER) is experiencing a phase of gradual stabilization, despite the ongoing political and economic challenges faced by Iraq. The forecasted values for the years 2024 to 2026 indicate a slight upward trend in market performance, reflecting growing investor confidence and the impact of financial reforms. The stability observed in the ER's performance, as highlighted by the confidence intervals, offers a promising outlook for both local and foreign investors. This trend aligns with Iraq's broader economic diversification strategies, which aim to reduce dependence on oil revenues and promote sectors like banking, telecommunications, and industry. The use of advanced forecasting models like the BAT-Exponential Trend Model proves to be an effective tool in managing the inherent volatility of emerging markets, providing decision-makers with reliable projections that can guide investment strategies and policy reforms.

The Iraqi exchange rate's performance has been heavily influenced by both internal reforms and external geopolitical factors. The optimization of the Exponential Trend Model using the BAT Optimizer Algorithm indicates a strong relationship between improved market performance and ongoing economic and regulatory reforms. The significant role of reforms in enhancing governance, market transparency, and investor protection is evident in the growth of foreign investment, particularly from regional markets. However, the persistent geopolitical risks, such as fluctuating oil prices and security concerns, continue to create challenges for the market. The forecast suggests that while the ER will likely see moderate growth in the short term, Iraq's ability to further stabilize its political environment and diversify its economy will be crucial for sustaining long-term market resilience and attracting sustained foreign capital.

4. Limitations

This study's focus on forecasting the performance of the Iraqi exchange rate (ER) using the BAT-Exponential Trend Model offers valuable insights but also has several limitations. The analysis is constrained by the relatively short data range (2009–2023), which may not capture long-term market dynamics, particularly during periods of extreme geopolitical instability or sudden market shocks. Additionally, the model assumes an exponential growth trend, which may not always reflect the complex, non-linear behaviors of emerging markets like the ER, especially under unpredictable political and economic conditions. Furthermore, while the BAT Optimizer improves forecast accuracy, there is still a potential risk of overfitting the model, which could limit its generalizability.

5. Future Study

Future research could expand the dataset, integrate external factors such as oil price fluctuations and geopolitical risks, and test alternative forecasting models like machine learning algorithms or hybrid approaches that incorporate more diverse market influences. Exploring longer time frames and incorporating more comprehensive external variables could enhance the robustness of market predictions for the ER, offering a more comprehensive understanding of its volatility and potential for growth.

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