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Efficient Forecasting of Economic Indicators Using Lightweight Time Series Models in Resource-Constrained Environments

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Abstract

The accurate prediction of economic indicators needs to be done correctly because it helps decision-making processes especially when organizations operate with restricted computational capabilities. The research investigates how lightweight time series forecasting models which include Naïve Forecast, Exponential Smoothing, Autoregressive Integrated Moving Average (ARIMA) and Prophet models perform when they predict important economic indicators that include exchange rate, GDP growth, inflation rate and interest rate. The assessment uses normalized data to create equal testing conditions which allow performance evaluation through forecasting accuracy and computational efficiency measurements.

The results show that simpler models, particularly Na"ive and Exponential Smoothing, achieve competitive accuracy across most indicators while maintaining significantly lower computational cost. The higher resource requirements of ARIMA and Prophet make them unsuitable for use in resource-constrained environments, even though they deliver better results in particular situations. The results demonstrate that lightweight forecasting methods work effectively, while model selection needs to consider both data characteristics and computational limitations. This study provides practical insights for deploying efficient forecasting solutions in low-resource settings.

Keywords: time series forecasting, economic indicators, ARIMA, exponential smoothing, resource-constrained computing

1. Introduction

Economists use Inflation rates, Gross Domestic Product (GDP) growth rates, Currency Exchange rates and Interest rates as essential economic indicators to assess both economic performance and economic stability. Government agencies, financial institutions, and policymakers use these indicators to shape their economic development plans and their decisions about monetary policy and their approaches to long-term investments. Economists need to forecast these economic variables because it helps them understand economic trends and predict future economic developments. Emerging and developing countries experience rapid index changes because their fiscal policies and external economic conditions and currency values undergo continuous changes. Economic planning and financial risk management processes require dependable forecasting tools because they establish essential requirements for both fields.

Time series forecasting has functioned as the basic method for forecasting economic variables through its use of past data since its inception. Researchers continue to use classical statistical models such as autoregressive integrated moving average (ARIMA) and exponential smoothing because these models effectively model historical data patterns while their processing requirements remain manageable Benidis et al. (2022). These models have been effectively used to many macroeconomic forecasting problems, including inflation, exchange rates, and economic growth Hyndman and Athanasopoulos (2021). Empirical research studies and forecasting competitions prove that statistical models maintain their competitive edge in forecasting different types of problems even when more advanced techniques become available Makridakis et al. (2022). Recent advances in machine learning have introduced new approaches for economic forecasting. According to this study, deep learning models, neural networks and ensemble learning methods successfully extract nonlinear economic data patterns. The models demonstrate strong prediction abilities but require extensive data and high computing power for their training process. The application of this technology depends on computational capabilities because it creates operational limits which restrict its use.

Multiple research institutes and government agencies and small businesses continue to use resource-constrained computing environments. Researchers create forecasting systems in these cases by using standard desktop computers instead of dedicated high-performance computing systems. The forecasting models need to achieve a balance between prediction accuracy and computational efficiency. The actual economic forecasting applications currently need lightweight time series forecasting models which function properly on limited hardware.

The research evaluates various lightweight time series forecasting models to determine their ability to predict major macroeconomic indicators. The analysis uses four indicators which include Inflation rate, GDP growth rate Exchange rate and Interest rate. This study evaluateded historical data from the World Bank Open Data portal which included information from 2000 through 2024. The research examined four forecasting models which included Naïve Forecast, Exponential Smoothing, Autoregressive Integrated Moving Average (ARIMA) and Prophet. The research evaluates two factors which include forecasting accuracy and computing efficiency to show how predictive performance and computational costs interact in resource-constrained environments.

2. Related Work

The field of economic forecasting has maintained its significance as a research discipline which helps determine both governmental policies and financial budget allocations. The forecasting methods that researchers use today depend on statistical time series models which analyze historical data to find time-based relationships. The autoregressive integrated moving average (ARIMA) and exponential smoothing models continue to be popular among users because they enable straightforward model comprehension despite their limited processing power requirements Hyndman and Athanasopoulos (2021). The researchers used these models to predict macroeconomic indicators such as inflation and exchange rates and economic growth across both developed and developing countries Benidis et al. (2022).

Machine learning and artificial intelligence have developed new methods for time series forecasting since recent advances made them accessible to researchers. Economic and financial forecasting research has adopted deep learning technologies which include recurrent neural networks and long short-term memory networks and transformer-based systems Hewamalage et al. (2021). The models can identify complicated nonlinear patterns within time series data and they demonstrate effective results in multiple forecasting tasks. The models require extensive datasets and substantial computational capability for their training process which creates obstacles to their use in settings that lack advanced computing resources Lim and Zohren (2021). Recent research studies have investigated how statistical forecasting methods perform compared to machine learning forecasting approaches. The M4 and M5 forecasting competitions showed that statistical models maintained their competitive edge against advanced machine learning techniques when tested on extensive time series datasets Makridakis et al. (2022). The research demonstrated that different forecasting models perform better with specific dataset characteristics which include data frequency and volatility and structural patternsMontero-Manso and Hyndman (2022).

The researchers have dedicated their work to developing enhanced forecasting methods which specifically address actual business requirements and economic time series data. The Prophet forecasting tool developed by Taylor and Letham has gained popularity because it enables users to decompose time series data into three components which include trend and seasonal and residual elements through a user-friendly implementation method Taylor and Letham (2020). The recent research studies demonstrate that Prophet effectively predicts economic trends because it helps researchers investigate macroeconomic data through trend analysis and irregular pattern detection Nguyen and Tran (2023).

The advanced forecasting models have become more popular yet their computational efficiency remains essential for numerous practical applications. The organizations who use forecasting systems have chosen to implement these systems on normal computing equipment instead of using specialized high-performance computing resources. The development of lightweight forecasting methods which achieve accurate predictions while using minimal computational resources remains essential for building effective forecasting systems. The research study compares multiple lightweight forecasting models which are tested on different macroeconomic indicators to assess their forecasting accuracy and computational efficiency.

3. Methodology

This section presents the forecasting models, dataset, preprocessing procedures, and experimental design adopted in this study. The study aims to test predictive performance and computational efficiency of lightweight time series models which operate in environments with limited resources.

3.1. Forecasting Models

Four forecasting models were considered: Naïve Forecast, Exponential Smoothing, Autoregressive Integrated Moving Average (ARIMA), and Prophet.

The Naïve Forecast model serves as a baseline method where the forecast for the next time step is equal to the most recent observed value:

$$\hat{y}_{t+1} = y_t$$

Exponential Smoothing assigns exponentially decreasing weights to past observations:

$$\hat{y}_{t+1} = \alpha y_t + (1 - \alpha)\hat{y}_t$$

where α is the smoothing parameter estimated from the training data.

The ARIMA model combines autoregressive, differencing, and moving average components:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t$$

In this study, an ARIMA(1,1,1) configuration was adopted, with parameters estimated using maximum likelihood estimation.

The Prophet model represents the time series as an additive combination of components:

$$y(t) = g(t) + s(t) + \epsilon_t$$

where $g(t)$ models trend, $s(t)$ captures seasonality, and ϵ_t represents the residual component.

3.2. Dataset

The World Bank Open Data platform provides access to a dataset which includes four macroeconomic indicators: inflation rate, gross domestic product (GDP) growth rate, exchange rate, and interest rate. The dataset includes univariate time series data which shows annual measurements from the year 2000 until 2024, producing 25 data points for each indicator.

3.3. Data Preparation

A complete assessment of the datasets were conducted to check for missing data and inconsistent data elements. The researchers transformed each dataset into a univariate time series which used the year as its time index.

To achieve indicator comparability which uses different numerical scales Min-Max normalization was implemented for every dataset. The transformation process rescaled data to a range that extends from 0 to 1 which decreased scale differences effect on evaluation metrics including MAE and RMSE.

The normalization parameters were calculated using only training data and applied them to test data because this method protects against data leakage and creates authentic forecasting conditions.

3.4. Experimental Design

The datasets were divided into training and testing sets based on their chronological sequence. The training set used data from 2000 to 2018 while the testing set used data from 2019 to 2024.

Sixteen forecasting experiments were conducted by using their forecasting models to predict economic indicators. Normalized training data were used to train their models which they tested through forecasting during the testing period. The researchers assessed performance by comparing predicted values with actual observations.

3.5. Evaluation Metrics and Implementation Environment

Forecasting accuracy was evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

These metrics quantify the difference between predicted and actual values.

The study evaluated computational efficiency through its assessment of training time and prediction time together with memory usage because these factors determine the suitability of the model for environments with limited resources.

The research experiments were conducted using Python together with its standard scientific libraries which include Pandas and NumPy and Statsmodels and Prophet and Scikit-learn and Matplotlib and Psutil. The experiments took place on a computer system which had restricted processing power to simulate actual deployment environments.

4. Results and Discussion

The section shows the outcomes which were produced through testing selected forecasting models on economic indicators while measuring their ability to predict results and their computational performance. The analysis uses normalized data to provide equal assessment of different indicators which have varying measurement standards while the results are explained through actual data patterns and model performance. The section examines how all models function both within single indicators and across multiple indicators while demonstrating the resource efficiency trade-off which exists between accurate results and efficient operations.

4.1. Trend Analysis of Economic Indicators

The historical patterns of selected economic indicators serve as essential background information which helps to interpret the forecasting results. The study period displays different trend patterns which each indicator follows, showing two extreme outcomes of either consistent behavior or complete movement volatility. The different forecasting models demonstrate varying abilities to detect fundamental data patterns due to these data variations.

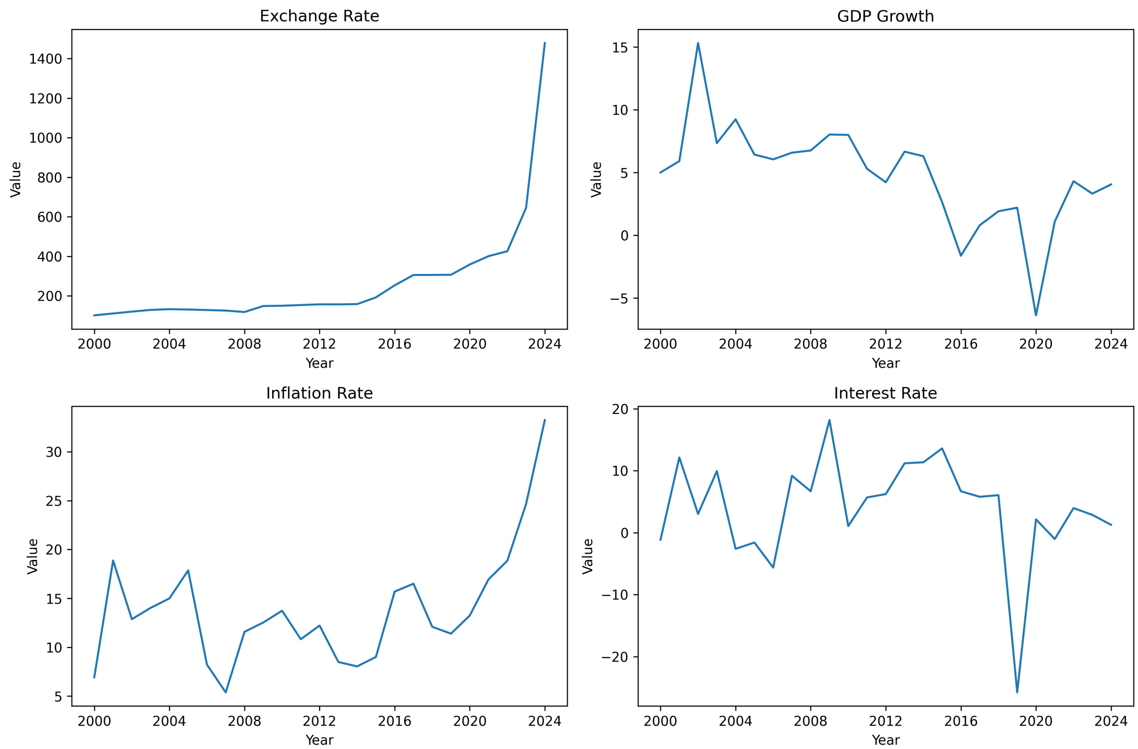

Figure 1: Historical trends of exchange rate, GDP growth, inflation rate, and interest rate from 2000 to 2024.

The exchange rate shows a permanent upward movement which begins with steady growth and ends with rapid ascension during its later years according to Figure 1. The GDP expansion shows alternating patterns of growth and decline which represent unstable economic conditions. The inflation rate shows moderate variability initially but rises significantly toward the end of the period, which indicates that price pressures throughout the period kept increasing. The interest rate shows irregular movements because it experiences both significant declines and subsequent recoveries which reflect changes in monetary policy and economic conditions. The different characteristics of the two elements require forecasting models which can handle both stable trend patterns and highly unpredictable time series data.

4.2. Overall Forecasting Results

The selected forecasting models show their complete performance results through the economic indicators assessment which includes testing their predictive accuracy and computational efficiency. The results are evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), training time, prediction time, and memory usage, all computed on normalized data to ensure fair comparison.

Table 1: Performance Comparison of Forecasting Models

Ind.	Model	MAE	RMSE	Train(s)	Pred(s)	Mem(MB)
Exch.	Naive	1.4519	2.4600	0.0004	0.0042	0.00
	Exp. Sm.	1.4519	2.4600	0.1024	0.0226	2.00
	ARIMA	1.5109	2.4990	0.6368	0.0174	3.91
	Prophet	1.6657	2.5487	6.7820	0.2058	27.74
GDP	Naive	0.1508	0.2179	0.0003	0.0001	0.00
	Exp. Sm.	0.1539	0.2169	0.0301	0.0072	0.00
	ARIMA	0.1482	0.2190	0.8491	0.0125	0.01
	Prophet	0.3377	0.3819	0.2890	0.1001	0.20
Infl.	Naive	0.5830	0.7871	0.0003	0.0001	0.00
	Exp. Sm.	0.5826	0.7867	0.0090	0.0030	0.00
	ARIMA	0.5859	0.7902	0.6868	0.0129	0.00
	Prophet	0.8602	1.0317	0.2129	0.1627	0.24
Int.	Naive	0.3702	0.5729	0.0003	0.0001	0.00
	Exp. Sm.	0.3719	0.5740	0.0170	0.0071	0.00
	ARIMA	0.4129	0.6172	0.9295	0.0102	0.06
	Prophet	0.3565	0.5527	0.1676	0.0771	0.44

The results in Table 1 show different levels of forecasting accuracy for each model and indicator tested. The Naïve and Exponential Smoothing models delivered equal results for exchange rate prediction while they exceeded the performance of ARIMA and Prophet forecasts because the simple models could handle the exchange rate's ongoing upward movement. The ARIMA model produced its best results through the MAE metric while Exponential Smoothing delivered its best outcomes through the RMSE metric, which demonstrated that both models show equal performance for different evaluation tests. The inflation rate results showed Exponential Smoothing as the best model, although Naïve, ARIMA, and Exponential Smoothing showed only minor differences which indicated that the data exhibited moderate variability.

Prophet demonstrated its best performance for interest rates through its lowest MAE and RMSE results which enabled the model to capture both irregular patterns and nonlinear trends more effectively. The accuracy improvement does not apply to all indicators because Prophet showed its weakest performance for GDP growth and inflation rate tests. The study results demonstrate that more advanced models do provide benefits in some situations but less complicated models deliver similar performance results when used for stable and trend-based data.

4.3. Model Comparison Across Indicators

The assessment of model performance in this section uses RMSE to evaluate economic indicators because it enables comparison of accuracy between different forecasting methods.

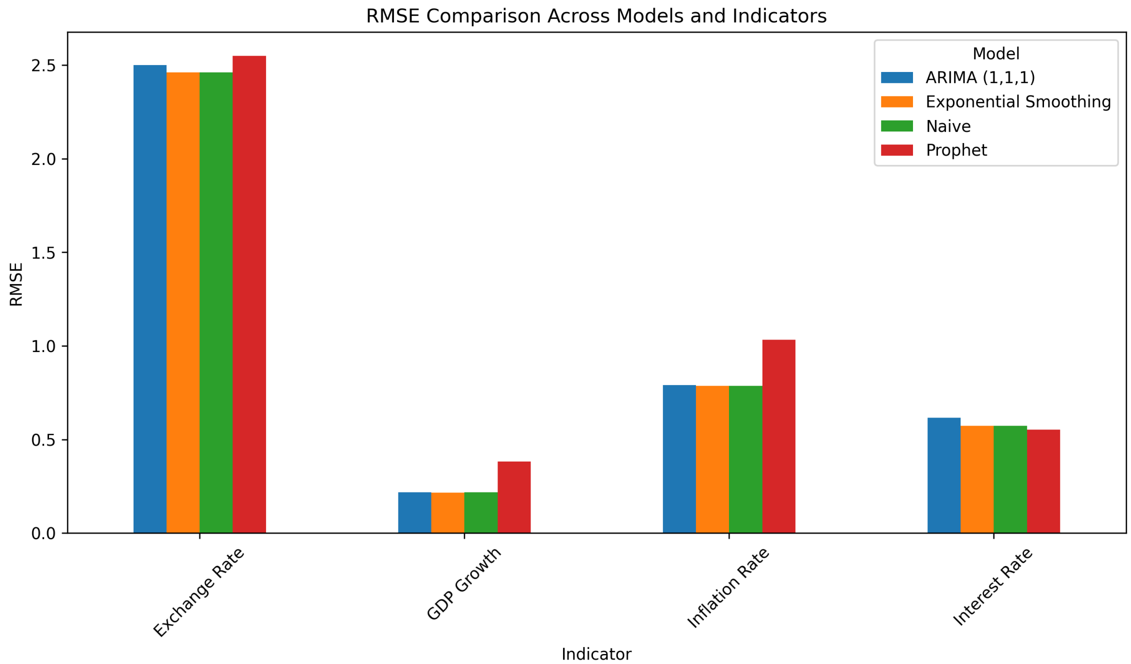

Figure 2: RMSE comparison of forecasting models across economic indicators.

The results for exchange rate prediction showed that the Naïve and Exponential Smoothing methods produced results that exceeded the performance of both ARIMA and Prophet, which demonstrates that basic models successfully identify the main trend. The GDP growth prediction showed that ARIMA and Exponential Smoothing methods outperformed Prophet because their RMSE results showed better performance at handling moderate market movements. The three forecasting methods Naïve, Exponential Smoothing, and ARIMA show only slight differences in their ability to predict inflation rates. The Prophet method shows weaker performance for this time series because it produces higher RMSE results than other methods.

The Prophet model demonstrates superior performance because it produces the lowest RMSE for interest rate forecasting, which shows its capability to handle both irregular patterns and non-linear patterns. The results show that no single model shows better performance across all indicators because forecasting results depend on the specific structural features of each time series.

4.4. Computational Efficiency Analysis

This subsection assesses the computational efficiency of forecasting models through an analysis of their predictive accuracy results and the resources required for their operation which includes training time, prediction time, and memory usage.

Figure 3: Model efficiency trade-off showing the relationship between RMSE and training time across forecasting models.

The Naïve model achieves minimal training time according to Figure 3 while maintaining competitive RMSE results through all assessed indicators which makes it ideal for use in systems that need to operate under tight computational constraints. Exponential Smoothing provides an affordable solution which delivers identical accuracy results for analytical work while allowing researchers to use slightly different modeling approaches.

The ARIMA model requires more time for training because it achieves only minor improvements in forecasting performance for some indicators which results in decreased efficiency gains for the process. Prophet shows the highest computational cost because its training time requirements exceed other costs yet it fails to produce superior accuracy results for all performance metrics. The results indicate that raising model complexity does not automatically lead to better performance improvements. The research shows that lightweight models which include Naïve and Exponential Smoothing methods provide optimal accuracy and efficiency results for use in resource-limited settings.

5. Conclusion

The study evaluated how lightweight time series forecasting models which used Naïve Forecast and Exponential Smoothing and ARIMA and Prophet studied economic indicators in resource-constrained settings. The results demonstrate that Naïve and Exponential Smoothing as simple models achieved forecasting accuracy which competed with other models across most indicators. The study found that ARIMA improved some indicators especially GDP growth while Prophet showed better results for irregular indicators such as interest rate. The study results demonstrate that model performance depends more on data characteristics than on the complexity of the modeling technique.

The study results show that lightweight models need less time and less memory resources than complex models for both training and prediction tasks. Prophet, despite its flexibility, showed both high computational expenses and inconsistent accuracy results which made it the most expensive option to use. The study demonstrates that organizations must choose forecasting models which achieve both precise results and efficient performance when their systems face restricted computing capabilities. Future work can explore hybrid approaches and adaptive model selection strategies that dynamically adjust to the properties of different time series to further improve forecasting performance.

Code and Data Availability

The dataset and source code used in this study are available at:
https://github.com/Oladahmad/Economic_Indicator_IndadaX2026.git

References

Konstantinos Benidis, Syama Rangapuram, Valentin Flunkert, et al. Neural forecasting: Introduction and literature overview. *International Journal of Forecasting*, 2022.

Hansika Hewamalage, Christoph Bergmeir, and Kasun Bandara. Recurrent neural networks for time series forecasting: Current status and future directions. *International Journal of Forecasting*, 2021.

Rob J. Hyndman and George Athanasopoulos. *Forecasting: Principles and Practice*. OTexts, 2021.

Bryan Lim and Stefan Zohren. Temporal fusion transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting*, 2021.

Spyros Makridakis, Evangelos Spiliotis, and Vassilios Assimakopoulos. The m5 accuracy competition: Results, findings and conclusions. *International Journal of Forecasting*, 2022.

Pablo Montero-Manso and Rob Hyndman. A review of machine learning methods for time series forecasting. *International Journal of Forecasting*, 2022.

Thanh Nguyen and Minh Tran. Economic time series forecasting using hybrid statistical and machine learning models. *Applied Economics*, 2023.

Sean Taylor and Benjamin Letham. Forecasting at scale using prophet. *The American Statistician*, 2020.