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A Machine Learning Predictive Model for Determining Daily Exchange Rate Movement in Sierra Leone

Mohamed Samba Barrie

Senior Research Economist, Economic Modelling and Forecasting Division, Research and Statistics Department, Bank of Sierra Leone, Freetown, Sierra Leone
https://orcid.org/0000-0001-7425-4896
e-mail: barriemohamedmsb@gmail.com; mbarrie@bsl.gov.sl

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Abstract: *Prophet is an advanced machine learning tool designed for accurate time series forecasting. Utilizing a Bayesian additive regression model, it employs statistical techniques to analyze historical data and capture underlying patterns, trends, seasonality, and holiday effects. With its ability to handle uncertainties, anomalies, missing data, outliers, and changes in trends or seasonality, Prophet is a versatile solution for both univariate and multivariate time series analyses. In the context of the Sierra Leone currency market, our analysis using Prophet reveals valuable insights into the nominal exchange rates between the Leones and the dollar. On an annual basis, there is an observed upward trend in the nominal exchange rates. Weekly patterns indicate that the Leones tends to experience a slight depreciation on Tuesdays, while showing marginal stabilization or appreciation on Fridays. Additionally, the model highlights a tendency for marginal appreciation in the Leones from April to June, with a slight depreciation around September to October. These findings provide crucial information for risk management, economic planning, and decision-making in the Sierra Leone currency market. By understanding the identified trends in the Leones dollar exchange rates, stakeholders can make informed decisions regarding investments, currency trading, and overall economic strategies. This knowledge contributes to improving investor confidence and enables effective measures for mitigating risks. In summary, Prophet's Bayesian-based forecasting model offers probabilistic insights into future predictions, empowering decision-makers with accurate forecasts and valuable knowledge for strategic planning and risk management.*

Keywords: *Machine Learning; Forecasting; Artificial Intelligence; Bayesian Additive Regression.*

Introduction

Foreign exchange markets play a critical role in stabilizing the global economy, with exchange rate movements influencing trade, investment, and monetary policy decisions. The ability to accurately forecast exchange rate movements is of great importance for various stakeholders, including businesses, policymakers, and investors. Traditional time series forecasting techniques have been widely used for this purpose, but they often struggle to capture the complex patterns and uncertainties inherent in financial markets. The current forecast tools for exchange rate movements have several shortcomings, including difficulties in capturing complex patterns and uncertainties inherent in financial markets, limited adaptability to handle data anomalies, uncertainties, and changing market conditions, and a lack of probabilistic predictions and confidence intervals to quantify forecast uncertainty. Additionally, traditional time series forecasting techniques often struggle to incorporate external factors such as political events, economic fluctuations, and external shocks that can significantly impact currency valuations. These limitations underscore the need for more advanced and robust forecasting tools, such as machine learning models like Prophet, specifically tailored for exchange rate forecasting in contexts like Sierra Leone. In recent years, machine learning approaches have emerged as powerful tools for time series forecasting. One such approach is Prophet, a machine learning model that utilizes a Bayesian additive regression model to forecast time series data. Prophet is designed to handle various sources of uncertainty and data anomalies, making it well-suited for predicting daily exchange rate movements in Sierra Leone. Prophet incorporates historical data and employs a range of statistical techniques to capture the underlying patterns, trends, seasonality, and holiday effects in the data. By decomposing the time series into trend, seasonality, and holiday components, Prophet can effectively model the dynamics of exchange rate movements and make accurate predictions for future values.

One of the key features of Prophet is its ability to handle missing data, outliers, changes in trend, and seasonality. This flexibility allows the model to adapt to the unique characteristics of the exchange rate data in Sierra Leone, where factors such as political events, economic fluctuations, and external shocks can significantly impact currency valuations. Moreover, Prophet utilizes Markov Chain Monte Carlo (MCMC) techniques for the estimation of posterior distributions concerning the model parameters. Bayesian inference seeks to derive the posterior distribution of parameters based on the observed data, reflecting the revised beliefs about these parameters. Nevertheless, in numerous instances, obtaining the precise posterior distribution through analytical means proves impractical, and this is where the utility of MCMC methods becomes very useful. MCMC methods provide a way to indirectly generate samples from the posterior distribution, even when direct calculation is infeasible. By utilizing MCMC methods, Prophet can estimate the posterior distributions of key parameters such as trend, seasonality, and holiday effects. These posterior distributions provide valuable information about the uncertainty associated with the forecasts, enabling the model to provide probabilistic predictions and confidence intervals.

This research paper aims to investigate the application of Prophet in predicting daily exchange rate movements in Sierra Leone. By leveraging the power of machine learning and Bayesian inference, we seek to assess the accuracy and effectiveness of Prophet in capturing the dynamics of the currency market in Sierra Leone. Additionally, we aim to evaluate the model's ability to handle data anomalies, uncertainties, and changing market conditions, ultimately contributing to the development of robust forecasting tools for financial decision-making.

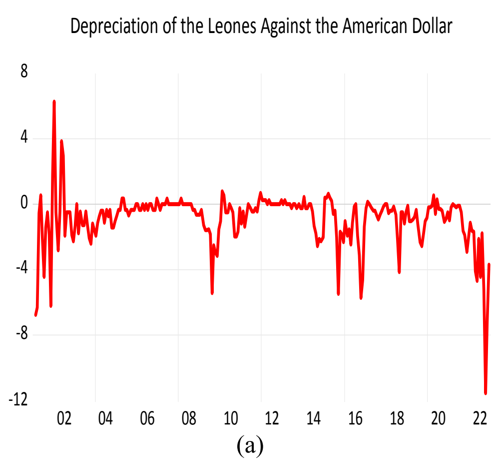
This paper explores the application of Prophet, a machine learning model, for predicting daily exchange rate movements in Sierra Leone. It assesses the accuracy and effectiveness of Prophet by comparing its predicted exchange rate movements with actual values, providing insights into its strengths and limitations. The study highlights Prophet's ability to handle data anomalies, uncertainties, and changing market conditions, including political events, economic fluctuations, and external shocks. It also explains how Prophet utilizes Bayesian inference and MCMC methods to estimate posterior distributions of model parameters, enabling probabilistic predictions and confidence intervals. Overall, this research contributes to the field of exchange rate forecasting by investigating Prophet's effectiveness in the Sierra Leone currency market and enhancing understanding of the Bayesian framework in this context.

However, despite the growing popularity of machine learning models for exchange rate forecasting, there is a lack of research investigating the specific application of Prophet in predicting daily exchange rate movements in Sierra Leone and assessing its accuracy, effectiveness, and ability to handle data anomalies, uncertainties, and changing market conditions, highlighting the need for this study.

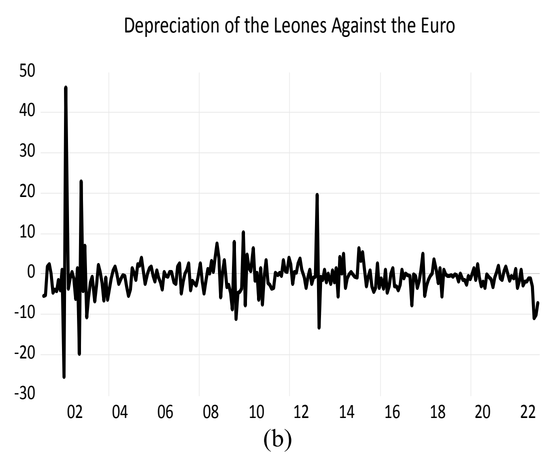
In the subsequent sections of this paper, we will provide stylized facts of exchange rate movement in Sierra Leone in the major currency basket, review the relevant literature, provide a comprehensive overview of the methodology employed by Prophet, discuss the implementation details, present experimental results, and discuss the implications and potential applications of our findings. Through this research, we aim to advance the understanding of machine learning-based exchange rate forecasting and provide valuable insights for financial practitioners, policymakers, and researchers in Sierra Leone and beyond.

Stylized Fact

Exchange rate movements in Sierra Leone exhibit significant volatility and are influenced by various factors, including political events, economic indicators, and external shocks. Figure 1 shows the evolution of the depreciation of Leones against the US Dollar (a), Euro (b), British Pounds (c), SDR (d), and WAUA (c) basket of currencies. The daily exchange rate movements in Sierra Leone demonstrate a notable degree of volatility, indicating a dynamic and rapidly changing currency market. This volatility can be attributed to multiple factors that impact the value of the country's currency. Political events play a crucial role in influencing exchange rate movements. Changes in government policies, elections, political stability, and geopolitical developments can have a substantial impact on the market sentiment towards Sierra Leone's currency. Political uncertainty may lead to heightened volatility and increased exchange rate fluctuations, as market participants adjust their positions based on perceived risks and opportunities. Economic indicators and macroeconomic factors also significantly influence exchange rate movements in Sierra Leone. Factors such as inflation, interest rates, gross domestic product (GDP) growth, trade balances, and fiscal policies can affect the supply and demand dynamics of the currency. Positive economic indicators and stable economic conditions often attract foreign investors, leading to an appreciation of the currency, while negative economic developments can lead to currency depreciation.



(a)



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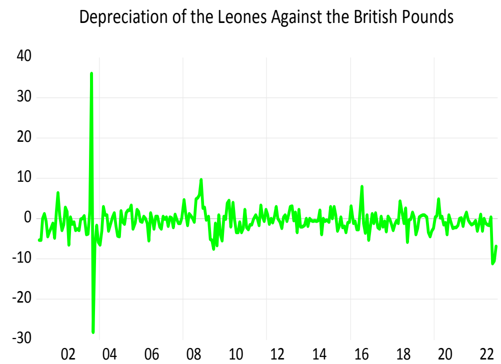

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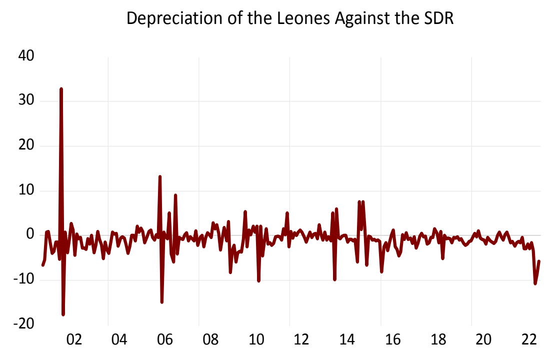
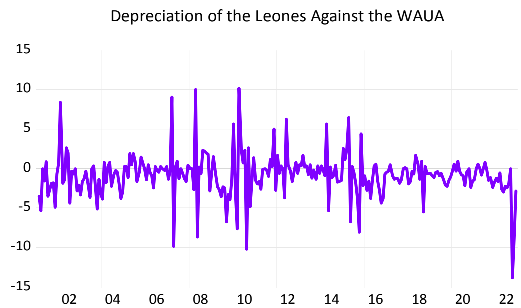


(d)



(e)

Fig. 1. Depreciation of the Leones in the Various Market Segment

Source: Authors own computation using nominal exchange rate of the Leone against the selected basket of currencies.

Additionally, external shocks and global market trends play a crucial role in determining exchange rate movements. Sierra Leone's economy is susceptible to external factors such as changes in global commodity prices (particularly for key exports like diamonds), fluctuations in international capital flows, and shifts in investor sentiment towards emerging markets. These external influences can amplify the volatility of exchange rates and create unpredictable movements in the currency market. Understanding and incorporating these stylized facts into the machine learning-based prediction of daily exchange rate movements in Sierra Leone using Prophet is essential for developing accurate forecasting models. By considering the impact of political events, economic indicators, and external shocks, the Prophet model can effectively capture the underlying patterns and dynamics of the currency market in Sierra Leone, enabling improved predictions and informed decision-making for various stakeholders. In the subsequent sections of this research paper, we will delve deeper into the analysis of these stylized facts and investigate how Prophet, with its robust capabilities and Bayesian additive regression model, can effectively incorporate these factors to enhance the accuracy of daily exchange rate predictions in Sierra Leone.

Literature Review

Exchange rate forecasting is a critical area of research in international finance, as accurate predictions can greatly impact investment decisions and economic outcomes. Over the years, researchers have explored various approaches and techniques to improve the accuracy of exchange rate forecasts. In this literature review, a thorough and all-encompassing examination of research conducted in this field is provided, centering around four primary themes: the significance of technical analysis in predicting exchange rates, the constraints and market conditions affecting technical analysis, alternative methods for forecasting exchange rates, and the utilization of outlier detection in the realm of finance. By examining the findings and insights from these studies, we gain valuable insights into the factors influencing exchange rate movements and the effectiveness of different forecasting methods. Understanding these themes can help investors, policymakers, and researchers make informed decisions in the dynamic and complex world of international finance.

Based on the provided literature review, we can identify several themes:

1. *Importance of Technical Analysis in Exchange Rate Forecasting:*

Taylor and Allen (1992) and Lui and Mole (1998) found that foreign exchange dealers place importance on technical analysis, relying more on it than fundamental analysis. Epley and Gilovich (2006) suggest that investors prefer technical analysis tools due to their hesitance to make adjustments and their preference for sticking to established beliefs. Pruitt and White (1988) proposed a trading system based on technical indicators that outperformed the market, while Wong, Manzur, and Chew (2003) found positive returns using specific technical indicators.

2. *Market Conditions and Limitations of Technical Analysis:*

Neely, Weller, and Ulrich (2009) highlighted that widely used technical analysis techniques are subject to various assumptions and that both market conditions and profitability change over time. Gurrib and Kamalov (2019) pointed out limitations of using the Relative Strength Index (RSI) and its interpretation across differently priced securities. Menkhoff (2010) discovered that most fund managers in five countries use technical analysis in their trading decisions.

3. *Alternative Approaches to Exchange Rate Forecasting:*

Meese and Rogoff's (1983) investigation revealed that conventional econometric models failed to outperform a random walk model when it came to forecasting exchange rates. As a result, this prompted researchers to explore innovative and alternative approaches in the field of exchange rate prediction. Machine learning techniques, such as artificial neural networks (ANN) and LSTM architectures, have gained popularity for exchange rate prediction. Hybrid forecasting models combining different techniques, such as empirical mode decomposition and support vector regression, have been proposed to account for non-linearities in time series data. Plakandaras et al. (2015) applied machine learning algorithms, including support vector machines (SVM) and random forest, to predict exchange rate direction based on market sentiment.

4. *Outlier Detection in Finance and its Application:*

Outlier detection has been widely used in diverse fields, including finance for fraud detection, risk modeling, and customer behavior analytics. Nian et al. (2016) proposed spectral ranking for outlier detection, successfully applied to fraud detection in auto insurance claim data. Ram and Gray (2018) used density estimation trees for outlier detection in fraudulent financial transactions. However, outlier detection has not been extensively utilized for forecasting exchange rates. These themes highlight the significance of technical analysis, the impact of market conditions, the exploration of alternative approaches, and the application of outlier detection in the field of exchange rate forecasting.

Machine learning approaches, including Prophet, have emerged as powerful tools for forecasting exchange rate movements. Prophet's utilization of Bayesian additive regression, coupled with its ability to handle data anomalies and uncertainties, makes it well-suited for predicting daily exchange rate movements in Sierra Leone. By incorporating historical data and employing statistical techniques, Prophet accurately models the dynamics of exchange rate movements and provides probabilistic predictions and confidence intervals. This research contributes to the advancement of forecasting methodologies for financial decision-making and offers insights into the practical application at the Bank of Sierra Leone.

Methodology

Prophet is a forecasting methodology that shares similarities with a generalized additive model (GAM) since it also utilizes time as a regressor. However, Prophet goes beyond the standard GAM framework by incorporating extra features and advanced techniques to significantly improve its forecasting capabilities. In its most basic form, Prophet provides a powerful and flexible tool for time series forecasting, enabling users to make more accurate predictions based on time-related data. In its simplest form;

$$Y_{(\mathrm{t})} = \mathrm{P_t} + \mathrm{Q_t} + \mathrm{R_t} + \mathrm{e_t} \tag{1}$$

Let's define the components of the procedure's equation as follows:

$\mathrm{P_t}$: This component represents non-periodic changes in the trend, reflecting the overall growth or decline over time.

$\mathrm{Q_t}$: Accounts for periodic changes, such as weekly, monthly, or yearly seasonality, which cause repetitive patterns in the data.

R_{t}: Incorporates the effects of holidays, taking into account the impact of irregularly occurring special events.

e_{t}: This component captures idiosyncratic changes that are not accounted for by the model, representing the random or unpredictable fluctuations in the data.

Hence, the equation describing the procedure can be represented as follows:

$$Y_{\mathrm{t}} = \mathrm{Trend_t} + \mathrm{Seasonality_t} + \mathrm{Festive\ Periods_t} + \mathrm{i.i.d.Error\ term} \tag{2}$$

In this equation, Y_{t} refers to the time series data at time t. The components include trend(t) for the trend model, seasonality(t) for the seasonal component, holiday effects(t) for the impact of holidays, and i.i.d. error term representing independent and identically distributed random errors. This comprehensive equation encompasses the various components considered in the forecasting methodology, providing a holistic representation of the time series forecasting process. Prophet employs a similar approach to exponential smoothing by modeling seasonality as an additive component. One notable advantage of the Generalized Additive Model (GAM) formulation used in Prophet is its ease of decomposition and ability to incorporate new components as needed, such as when identifying new sources of seasonality. Instead of explicitly analyzing the time-based relationship of each individual observation, Prophet approaches the forecasting problem as an exercise in curve-fitting. The model utilizes a Bayesian approach to estimate its parameters, employing Markov Chain Monte Carlo (MCMC) methods to sample from the posterior distribution of these parameters. This is particularly beneficial because obtaining an exact analytical solution is often impractical. MCMC methods generate a Markov chain that eventually converges to the target posterior distribution, enabling the quantification of uncertainty and the generation of probabilistic forecasts. Prophet's methodology effectively combines the strengths of generalized additive models, Bayesian inference, and MCMC techniques, resulting in a robust and flexible approach to time series forecasting. By incorporating both linear and non-linear functions of time, capturing seasonality and holiday effects, and considering uncertainty in model estimation, Prophet emerges as a powerful tool for accurate and probabilistic forecasting in a variety of applications.

Trend

Prophet captures the overall direction or long-term behavior of the time series through the estimation of the trend component. It employs a piecewise linear or logistic function to model the trend. This function divides the time series into small intervals and fits a linear or logistic curve within each interval, allowing for flexibility in capturing non-linear trends. The procedure provides two potential trend models for the component P_t: a saturating growth model and a piecewise linear model. These models are used to describe the overall trend or pattern in the data over time.

Saturating Growth Model

When the data indicates the possibility of saturation, which implies the existence of constraints such as limited space, processing power, or growth rate that must be considered, the preferable approach is to utilize a logistic growth model. This model is recommended as it can effectively capture and accommodate the saturating behavior observed in the data. This type of modeling effectively captures and represents nonlinear trends that reach a saturation point;

$$P_t = \frac{C}{1+\exp(-k(t-m))} \tag{3}$$

In this simplified equation, we have the following variables:

C: Represents the carrying capacity.

k: Stands for the growth rate.

m: Denotes an offset parameter.

Nevertheless, it is crucial to highlight that the mentioned equation does not encompass two critical factors influencing growth at Meta. These factors include the variations in carrying capacity and the erratic rate of change, both of which are not adequately addressed within this simplified model. Therefore, additional considerations and modifications are necessary to better account for these essential aspects in Meta's growth analysis.

- *Time-Varying Carrying Capacity: Adapting Growth Ceilings to Changing Circumstances*

In economic models, understanding the concept of carrying capacity is essential for predicting growth trends accurately. Traditionally, carrying capacity is often treated as a fixed value, assuming a static limitation on growth. However, as real-world dynamics evolve, this assumption may not hold true. To address this limitation, a more nuanced approach involves considering the carrying capacity as a time-varying factor. In this variant, the growth ceiling (C) is no longer treated as a constant but rather a function of time$C_{(t)}$. This modification allows economic models to adapt to changing circumstances, reflecting shifts in resources, technological advancements, market developments, and other factors influencing growth potential. By incorporating a time-varying carrying capacity, economic models become more flexible and responsive, better capturing the complex interactions between growth and the evolving environment. This approach provides a more realistic representation of economic dynamics and enables more accurate forecasting of future trends in various industries and markets.

- *Dynamic Rate of Change in Time Series Analysis: Accounting for Market Evolution and Trend Shifts*

In the ever-evolving market landscape, technological advancements and innovations continually drive changes in growth rates. The substantial progress witnessed in handheld devices, app development, and global connectivity over the past decade exemplifies this dynamic nature. As a result, growth rates are far from constant, and any forecasting model must be capable of accommodating these variations to accurately fit historical data. To address this challenge, Prophet introduces a concept of specific change points in time where the growth rate can shift. Let's assume there are S change points occurring at times sj, where j = 1, ..., S. To adapt to these changes, Prophet incorporates a vector of rate adjustments, denoted as $\delta \epsilon \mathbb{R}^S$. To clarify the calculation of the rate at any specific time t, we consider a base rate k and then sum up all the adjustments until that time, which can be represented as $k + \sum_{j:t>s_j} \delta_j$. This approach allows for a more concise representation of the varying growth rates over time. In summary, the incorporation of these rate adjustments and change points enables Prophet to capture the dynamic nature of growth rates in time series analysis effectively. By accounting for market evolution and trend shifts, the model becomes better equipped to make accurate forecasts and adapt to the changing conditions of the market.

To present this more clearly and concisely, we define a vector as follows:

$\mathrm{a(t)} \epsilon \{0,1\}^{\mathrm{S}}$

Such that; $\mathrm{a_j(t)} = \begin{cases} 1, & \text{if } \mathrm{t} \geq \mathrm{s_j} \\ 0, & \text{otherwise} \end{cases}$

At any given time t, the rate can be calculated as the sum of the base rate k and the dot product of the vector a(t) and the vector of rate adjustments δ, i.e., $k + a(t)^T\delta$.

When adjusting the rate k at a change point, it is essential to modify the offset parameter m as well. This adjustment ensures a smooth connection of endpoints for each segment. To achieve this, the correct adjustment at change point j can be easily computed using the following formula:

$$\gamma_j = \left(s_j - m - \sum_{l<j} \gamma_j\right)\left(1 - \frac{k+\sum_{l<j}\gamma_j}{k+\sum_{l\leq j}\gamma_j}\right) \tag{4}$$

At last, the piecewise growth='logistic' model is reached;

$$P_t = \frac{C_{(t)}}{1+exp\left(-(k+a_t{}^T\delta)\left(t-(m+a_{(t)}{}^T\gamma)\right)\right)} \tag{5}$$

By incorporating these adjustments, Prophet ensures that the growth rate and offset parameters are appropriately updated at change points, enabling seamless connections between segments and enhancing the accuracy of the forecasting model.

A vital group of parameters in our model is denoted as C(t), which represents the expected capacities of the system at any given time. Analysts often possess valuable insights into market sizes, allowing them to set these capacities accordingly. Furthermore, external data sources, such as population forecasts from the World Bank, can provide valuable information that helps in determining the carrying capacities. In practical applications, the logistic growth model presented in our framework is a specific example of generalized logistic growth curves, which is just one type of sigmoid curve. As a result, this trend model can be easily extended to accommodate other families of curves without much complexity. This flexibility enables us to capture a broader range of growth patterns and adapt the model to various scenarios, making it more versatile and applicable in diverse forecasting situations.

Adapting Linear Trends with Change Points

The second trend model provided by Prophet is the default and much simpler Piecewise Linear Model, which assumes a constant rate of growth. This model is particularly well-suited for situations where there are no apparent market limitations or constraints. By setting the growth parameter to 'linear', this straightforward model can be implemented. When dealing with forecasting scenarios that do not exhibit saturating growth, choosing the piece-wise constant rate of growth offers a parsimonious yet effective modeling approach. It provides a practical solution without unnecessary complexity. Implementing the linear trend in Prophet is a straightforward process, and in many cases, no further adjustments are required. The default setting typically suffices to capture the linear growth pattern effectively. This ease of implementation makes it a convenient and practical choice for various forecasting applications.

$$P_t = (k + a_t{}^T\delta)t + \left(m + a_{(t)}{}^T\gamma\right) \tag{6}$$

In the context of equation (6), the variables are defined as follows: k: Represents the growth rate, δ: Signifies the rate adjustments, m: Denotes the offset parameter. To maintain continuity in the function, the variable γj is set as: γj $=-s_j\delta_j$. With these definitions, equation (6) expresses the trend P_t as a linear combination of the growth rate (k) and the rate adjustments (δ) over time (t), and also accounts for the offset parameter (m) and additional adjustments represented by γ. This formulation ensures a smooth and seamless representation of the growth pattern, enabling the model to effectively capture changes and fluctuations in the underlying data.

Automatic Change Point Selection

In scenarios where users possess prior knowledge of specific change points (sj) that significantly impact growth, such as product launches or significant events, they can explicitly specify these points in the model. However, the Prophet model also offers the option of automatic change point selection from a set of candidate points. To achieve automatic selection, the model incorporates a sparse prior on the rate adjustments (δ), which can be naturally implemented in either the logistic growth or linear growth model. When automatic selection is preferred, it is beneficial to include a substantial number of candidate change points, such as one per month for several years of historical data. A commonly used prior for controlling the model's flexibility in adjusting its rate is the Laplace prior, represented as $\delta_j \backsim Laplace(O,\tau)$. Importantly, applying a sparse prior on the adjustments (δ) does not affect the primary growth rate (k). As the τ parameter approaches zero, the model fit simplifies to a standard logistic or linear growth without the piecewise adjustments. By allowing for automated change point selection and incorporating sparse priors, the Prophet model becomes more adaptable and capable of identifying relevant shifts in growth patterns automatically. This flexibility enhances its forecasting accuracy and makes it a valuable tool for a wide range of applications in time series analysis.

Trend Forecast Uncertainty

When employing the model for forecasting beyond the historical data (extrapolation), the trend g(t) assumes a constant rate. To estimate the uncertainty in the forecasted trend, the generative model is extended forward. This extension takes into account the existence of S change points observed over a history of T data points, with each change point having a rate change$\delta_j \backsim Laplace(O,\tau)$. To simulate future rate changes that resemble those observed in the past, the τ parameter is replaced with a variance inferred from the available data. In a fully Bayesian framework, this can be accomplished by utilizing a hierarchical prior on τ to obtain its posterior distribution. Alternatively, we can use the maximum likelihood estimate of the rate scale parameter to estimate τ. By adopting this approach, the model enables the generation of realistic simulations of future rate changes, allowing for meaningful forecasts with associated uncertainties. This consideration of uncertainty is crucial for making more informed decisions and effectively managing risks associated with the forecasted trends. Thus, the model's capability to generate forecasts along with the quantification of their uncertainties enhances its utility in various predictive applications as shown in equation 7 below:

$$\lambda = \frac{1}{S}\sum_{j=1}^{S}\left|\delta_j\right| \tag{7}$$

To quantify the uncertainty in the forecasted trend, Prophet adopts a random sampling technique for future change points. This method ensures that the average frequency of change points in the forecast aligns with that observed in the historical data. The procedure is represented by equation 8 below:

$$\forall_j > T, \begin{cases} \delta_j = 0 \; w.p. \frac{T-S}{T}, \\ \delta_j \sim Laplace(0, \lambda) \; w.p. \frac{S}{T} \end{cases} \tag{8}$$

By incorporating this random sampling approach, Prophet can effectively capture the variability and potential shifts in the growth pattern, offering more reliable forecasts with a realistic representation of uncertainties. This approach enhances the model's forecasting capabilities, making it a valuable tool for generating probabilistic predictions in various time series analysis tasks. Prophet employs a generative process to estimate uncertainty in future trends, considering change points beyond the historical range (j > T). For such change points, the rate change δj is assigned a value of 0 with a probability of (T-S)/T, or it is sampled from a Laplace distribution with mean 0 and scale parameter λ with a probability of S/T. By assuming that the future will exhibit a similar average frequency and magnitude of rate changes as observed in the historical data, the model generates possible future trends using this approach. The uncertainty intervals are then calculated based on these simulated trends. However, it's essential to recognize that Prophet's assumption regarding the continuity of trend changes at the same frequency and magnitude as historical data is quite strong. As a result, the uncertainty intervals may not precisely capture the actual coverage. As the rate scale parameter (τ) increases, the model becomes more flexible in fitting the historical data, leading to lower training error. Nonetheless, this increased flexibility can result in wider uncertainty intervals when projecting forward. Despite this limitation, the uncertainty intervals remain valuable indicators of the level of uncertainty and serve as useful tools to assess the potential for overfitting. By providing a measure of the model's uncertainty, these intervals enable users to make more informed decisions and gain insights into the range of possible future outcomes.

Seasonality

The seasonal component, denoted as s(t), plays a crucial role in enhancing the adaptability of the Prophet forecasting model. It allows the model to accommodate and forecast periodic changes that occur at sub-daily, daily, weekly, and yearly intervals, which are commonly observed in economic time series influenced by human behaviors. In economic data, multiple periods of seasonality often arise due to various factors. For instance, a 5-day work week can generate weekly repeating effects, while vacation schedules and school breaks can lead to yearly repeating effects. To effectively capture and predict these seasonal patterns, Prophet employs seasonality models represented by periodic functions of time, denoted as t. To achieve this, Fourier series is used, providing a flexible approach for modeling periodic effects. The regular period, denoted as P, corresponds to the cycle of the time series (e.g., P = 365.25 for yearly data or P = 7 for weekly data, when time is scaled in days). With the use of standard Fourier series, Prophet can efficiently approximate and handle smooth seasonal effects, making it capable of modeling various arbitrary periodic patterns in the data. By incorporating this Fourier-based seasonality modeling, Prophet significantly enhances its capacity to capture and forecast seasonal variations, contributing to more accurate and adaptable predictions for diverse time series data. This is shown in the equation below:

$$s_{(t)} = \sum_{n=1}^{N} \left(\left(a_n Cos \frac{2\pi nt}{P} \right) + b_n sin \left(\frac{2\pi nt}{P} \right) \right) \tag{9}$$

The seasonal component, denoted as s(t), is mathematically represented by equation (9). It involves a summation of N terms, consisting of sine and cosine functions, each associated with coefficients $\beta = [a1, b1, ..., aN, bN]^T$. Estimating these 2N parameters (a's and b's) is crucial for accurately fitting the seasonality pattern. To accomplish this parameter estimation, a matrix of seasonality vectors is constructed for each time value t, encompassing both historical and future data. For example, in the case of yearly seasonality and N = 10, the matrix X(t) can be expressed as shown in equation (10):

$$X_{(t)} = \left[cos\left(\frac{2\pi(1)t}{365.25}\right), \dots, sin\left(\frac{2\pi(10)t}{365.25}\right)\right] \quad (10)$$

By forming this matrix, the model captures the periodic patterns in the data, allowing for efficient estimation of the seasonality parameters. This approach empowers Prophet to effectively model and forecast seasonal effects, making it a powerful tool for time series analysis with varying periodic patterns.

Using the constructed matrix X(t) as defined in equation (10), we can express the seasonal component s(t) as shown in equation (11):

$$s_{(t)} = X_{(t)}\beta \quad (11)$$

In the generative model, Prophet assumes that the vector of coefficients β follows a normal distribution (β ~ Normal(0, σ^2)), which imposes a smoothing prior on the seasonality. Truncating the series at N effectively applies a low-pass filter to the seasonality, which helps prevent excessive complexity and overfitting in the model. Choosing an appropriate value for N is essential, as it determines the model's ability to capture seasonal patterns that may change at different rates. Although larger values of N increase the risk of overfitting, they allow the model to capture more rapid changes in the seasonal patterns. On the other hand, smaller values of N provide smoother seasonal trends but might miss capturing certain intricacies in the data. For practical purposes, specific values of N have been found to work well for common seasonal patterns. For instance, N = 10 is commonly used for yearly seasonality, while N = 3 is often applied for weekly seasonality. These values serve as good starting points, but the selection of the optimal parameters can be automated using model selection techniques like the Akaike Information Criterion (AIC), which helps find the most suitable values for N for a given forecasting problem.

Holidays and Events

In time series forecasting, specific holidays often exhibit similar impacts year after year, necessitating their incorporation into the forecast. This effect is captured by the component denoted as h(t), representing predictable events occurring throughout the year, including those on irregular schedules (e.g., Hajj Period and other festive periods). To utilize this feature, the user must provide a custom list of events. To incorporate the list of holidays into the model, Prophet assumes that the effects of holidays are independent. For each holiday i, let Di be the set of past and future dates for that holiday. To account for holidays, an indicator function is introduced, representing whether time t falls during holiday i. Additionally, a parameter κi is assigned to each holiday, denoting the corresponding change in the forecast due to that holiday's effect.

To incorporate the effects of holidays into the forecast, Prophet employs a matrix of regressors denoted as Z(t), which is generated as shown in equation (12):

$$Z_{(t)} = [1(t\epsilon D_1), \dots, 11(t\epsilon D_L)] \quad (12)$$

The component h(t) is then calculated as the dot product of Z(t) and the vector of parameters κ, denoted as h(t) = Z(t)κ (or simply h(t) = Z(t)k).

By applying this approach, Prophet effectively captures the impact of holidays on the time series data, providing a more comprehensive and accurate representation of holiday-related patterns. The model assigns a prior κ ~ Normal(0, ν^2) for the parameters κ, similar to how seasonality is handled. To ensure a more robust representation of holiday effects, the model considers a window of days around each holiday, such as weekends or national holidays. Additional parameters are included for these surrounding days, treating each of them as a separate holiday. This enables the model to better capture the influence of holidays and their associated effects on the time series forecast, enhancing the overall accuracy and adaptability of the model for various holiday-related patterns.

Data Sources

The official daily exchange rate data used in this study was acquired from two departments at the Bank of Sierra Leone, namely the Financial Market Department and the Research and Statistics Department. The dataset covers a time span from 1st January 2020 -15th June 2023, encompassing a total of 1,261 Days recorded instances. As the recognized source of financial information in the country, the Bank of Sierra Leone ensures the dataset's reliability and precision. The collected data includes various aspects typically associated with compiling exchange rates, including the following:

1. Weekends: As weekends are commonly non-working days for financial markets, there are gaps in the data for those particular days.
2. Holidays: The dataset contains missing values for holidays when the financial markets remain closed.
3. Lockdowns: Periods of lockdown, such as during the Ebola outbreak and the COVID-19 pandemic, often result in financial markets being closed or operating differently, leading to missing values.
4. Actual missing values: Apart from weekends, holidays, and lockdowns, there are genuine instances of missing data in the dataset due to issues with data collection or other factors.

Results and Discussions

The paper highlights the importance of accurate exchange rate forecasting and the limitations of traditional time series forecasting techniques. It introduces Prophet as a powerful tool that uses a Bayesian additive regression model and can handle uncertainties, data anomalies, and changing market conditions. Prophet incorporates historical data and employs statistical techniques to capture underlying patterns, trends, seasonality, and holiday effects in the exchange rate data. It decomposes the time series into trend, seasonality, and holiday components, allowing it to effectively model the dynamics of exchange rate movements and make accurate predictions for future values. One key feature of Prophet is its ability to handle missing data, outliers, changes in trend, and seasonality. This flexibility allows the model to adapt to the unique characteristics of the exchange rate data in Sierra Leone, which can be influenced by factors such as political events, economic fluctuations, and external shocks.

Figure 2 displays the output of a forecast, presenting both the actual and predicted values of the official exchange rate. This forecast encompasses two components: the in-sample forecast and the out-of-sample forecast. The model has been designed to generate a daily exchange rate for a duration of six months, specifically from June 16, 2023, to November 30, 2023.

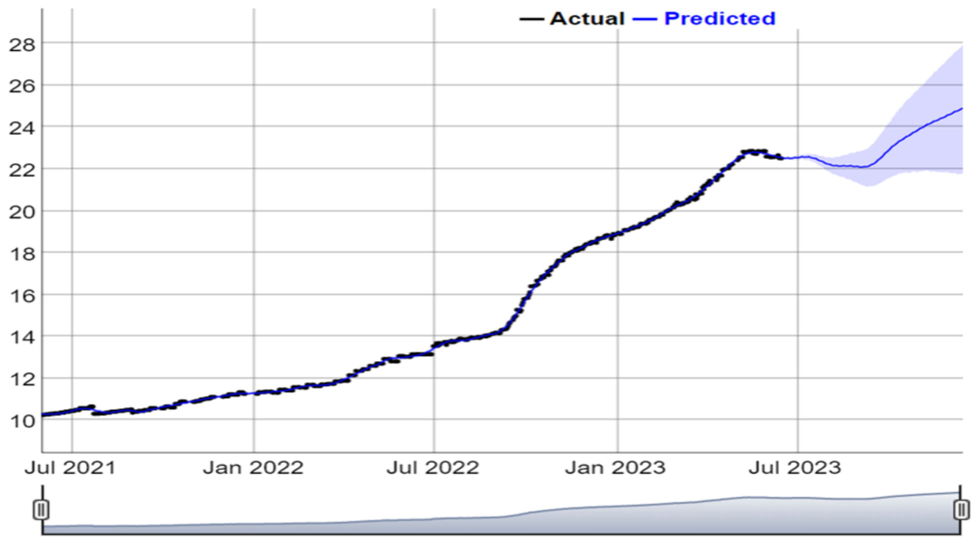


Fig. 2. Prophet Machine Leaning Model Predictions

Source: Model's computation using R programming Language using daily nominal LE/USD exchange rate.

In addition to the forecasted values, the analysis also incorporates a forecast fan chart, which is generated using a machine learning model with the MCMC (Markov Chain Monte Carlo) approach. Prophet, the utilized framework, employs MCMC methods to estimate the posterior distributions of various model parameters. By employing Bayesian inference, the model obtains the posterior distribution of parameters based on the available observed data, effectively representing updated beliefs regarding those parameters. MCMC methods serve as a means to indirectly generate samples from the posterior distribution when direct calculation is impractical. Through the application of MCMC methods, Prophet can estimate the posterior distributions of significant parameters such as trend, seasonality, and holiday effects. These posterior distributions provide crucial information about the uncertainty associated with the forecasts, enabling the model to provide probabilistic predictions and confidence intervals.

Upon analyzing the results, it becomes evident that the forecast of the exchange rate is highly accurate. This conclusion is drawn from the observation that the in-sample forecast closely aligns with the actual observations, practically overlapping with them. Consequently, the forecast appears to mirror the actual data within the in-sample period. The accuracy of the in-sample forecast serves as a promising indication that the out-of-sample forecast will likely exhibit minimal forecast error, as it is based on the same reliable model and methodology.

Therefore, these findings suggest that the forecasted exchange rate values for the upcoming period are expected to be highly accurate, with a low margin of forecast error. The utilization of the MCMC approach in conjunction with Bayesian inference and the consideration of posterior distributions allows the model to provide reliable probabilistic predictions and confidence intervals, accounting for the associated uncertainty.

Figure 3 presents evidence supporting the existence of a consistent upward trend in the nominal exchange rates between the Leones and the dollar on an annual basis from January 2021 to May 2023. This upward trend suggests that, over this period, the Leones has generally weakened against the dollar.

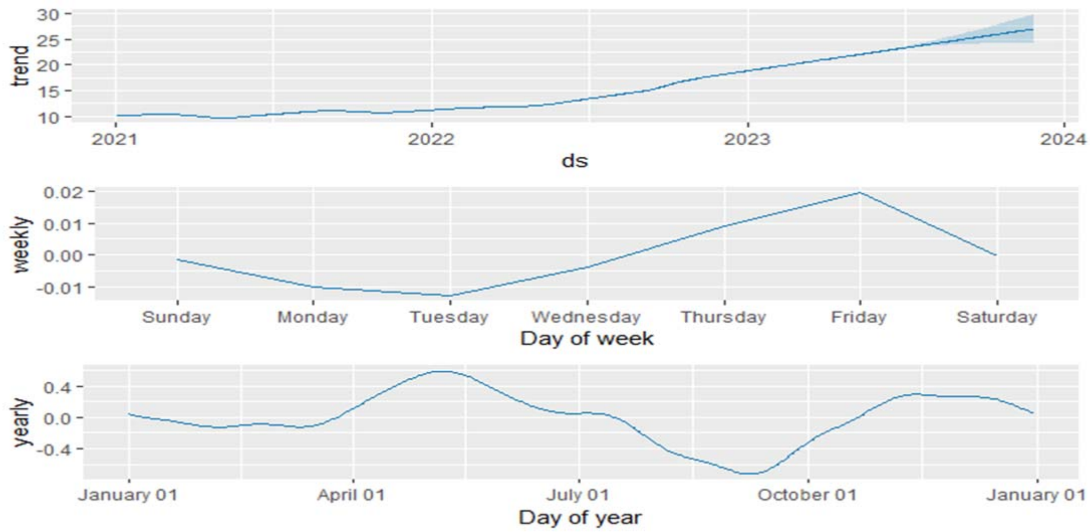


Fig. 3. Model Predictions, of annual Trend, Weekly and Monthly Movements

Source: Model's computation using R programming Language using daily nominal LE/USD exchange rate.

Additionally, when analyzing the exchange rates on a weekly basis, the model reveals interesting patterns. It shows that the Leones tends to experience marginal depreciation on Tuesdays, meaning that the exchange rate against the dollar tends to slightly decline compared to other days of the week. However, on Friday's, the model suggests a higher likelihood of a marginal appreciation, indicating that the Leones is more likely to strengthen considerably against the dollar on these specific days.

Zooming out to examine the yearly trends between January 2021 and May 2023, we observe that the Leones experiences it's most substantial appreciation starting in April, with peak appreciation occurring around May and June. During this period, the exchange rate against the dollar tends to strengthened more rapidly, suggesting that the Leones gains more value relative to the dollar.

Conversely, the model also demonstrates that the Leones tends to depreciate the most against the dollar starting in September, reaching its peak appreciation in October. This implies that the Leones loses significant value compared to the dollar during these months, indicating a weakening of the local currency against the dollar.

Conclusion

This research paper focuses on the application of the Prophet Machine learning model in predicting daily exchange rate movements in Sierra Leone. The study highlights the limitations of traditional time series forecasting techniques and emphasizes the need for more accurate and robust methods to capture the complexities and uncertainties of financial markets. Prophet, with its Bayesian additive regression model and ability to handle data anomalies, provides a suitable solution for forecasting exchange rate movements in Sierra Leone. The research aims to assess the accuracy and effectiveness of Prophet in capturing the dynamics of the currency market, evaluating its ability to handle data anomalies and changing market conditions. Additionally, the study explores the utilization of Bayesian inference and MCMC methods within Prophet to estimate posterior distributions and generate probabilistic predictions. The research paper provides valuable insights for financial decision-making, guiding stakeholders in making informed choices related to exchange rate movements. The following are the major implications of the Study:

1. Exchange Rate Management: The observed weekly patterns in the exchange rates, such as marginal depreciation on Tuesdays and minimal appreciation on Fridays, can be valuable for market participants and policymakers involved in exchange rate management. Policymakers can consider these patterns when timing interventions or designing policies related to foreign exchange operations. Market participants, including exporters and importers, can leverage these patterns to optimize their currency transactions and mitigate potential losses or maximize gains.
2. Improved Exchange Rate Forecasting: This research highlights the potential of employing machine learning models, such as Prophet, to enhance the accuracy and effectiveness of exchange rate forecasting. By examining how Prophet performs in predicting the daily exchange rate movements' specific to Sierra Leone, the central bank can strengthen its forecasting capabilities. These enhanced forecasting abilities enable the bank to make more informed decisions concerning exchange rate management, leading to improved outcomes in the context of the Sierra Leone currency market.
3. Enhanced Data-driven Decision-making: The utilization of machine learning models, such as Prophet, enables the Bank to adopt a data-driven approach in decision-making processes. The study's investigation into Prophet's capability to handle the unique characteristics of the Sierra Leone currency market sheds light on the model's adaptability to real-time data and changing market conditions. This understanding empowers the central bank to make more informed and precise decisions, utilizing the most up-to-date information available. By incorporating data-driven methodologies, the Bank can enhance its decision-making processes and improve overall outcomes in the context of the Sierra Leone currency market.
4. Investor Confidence and Economic Planning: The identified trends in the Leones dollar exchange rates can impact investor confidence and economic planning. Policymakers can use this information to communicate the currency trends effectively, manage expectations, and encourage investor confidence. Additionally, businesses and investors can factor in these trends when making long-term investment decisions and developing business strategies, ensuring they consider the potential impacts of currency fluctuations on profitability and financial performance.
5. Risk Management: The findings provide valuable insights for risk management strategies. Businesses and individuals engaged in foreign currency transactions can utilize the identified patterns to develop effective risk management plans. For instance, businesses may choose to time their currency conversions or hedging activities based on the observed patterns to mitigate potential losses or optimize gains.

Disclaimer

Opinions and viewpoints presented in this research paper are the exclusive responsibility of the author and do not necessarily represent the stance or beliefs of the author's employer.

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