Comparing the Predictive Accuracy of Traditional Linear (ARIMA) and Nonlinear Recurrent Neural Network (LSTM) Models for Inflation Forecasting in Zimbabwe

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ABSTRACT

The study compared the forecasting performance of a univariate ARIMA model (traditional econometric model) and a univariate LSTM model (artificial neural network model) in predicting inflation. The purpose was to determine a more appropriate model for forecasting inflation in Zimbabwe, a country that is beset by episodes of high inflation. The research utilized monthly inflation rates of Zimbabwe spanning the time from November 2019 to November 2022. In forecasting inflation, the univariate ARIMA model and the LSTM model were each used separately. The performance of the models was evaluated by using the root mean square error (RMSE) metric. Univariate LSTM outperformed univariate ARIMA by a big margin, having an RSME of 0.14 compared to 6.7 for univariate ARIMA. The findings confirm the hypothesis that the nonlinearity in inflation data is more accurately explained by LSTM. The study contributes to the growing body of evidence that nonlinear neural network models are superior to traditional linear models in terms of predicting time series data with non-linearity.

Key Words: Forecasting, Inflation, ARIMA, LSTM and Predictive Accuracy.

INTRODUCTION

Accurate inflation forecasts are important for shaping sound monetary policies and guiding investment decisions. This is especially most relevant for Zimbabwe, where the economy has faced prolonged periods of inflation instability. Zimbabwe has experienced high inflation levels since 2000, which culminated into hyperinflation in March 2007 (Masiyandima et al. 2018). Annual inflation peaked at 231 million percent in July 2008 (Masiyandima et al. 2018; ZimStat 2024).

Traditional econometric models, notably the Autoregressive Integrated Moving Average (ARIMA), have long been used for inflation forecasting by the Reserve Bank of Zimbabwe (RBZ) due to their computational simplicity and interpretability. Latest developments in artificial intelligence through the application of recurrent neural network architectures such as univariate Long Short-Term Memory (LSTM) networks present promising solutions that can capture intricate nonlinear relations in real economic data that traditional methods fail to exploit (Taslim and Murwantara 2024).

This study investigates how well univariate ARIMA and LSTM models predict inflation in Zimbabwe. It aims to establish the approach with the best predictive performance in an economy characterized by hyperinflation episodes. The peculiar nature of Zimbabwe makes it worthwhile as a case study, particularly considering that models with superior performance in stable economies can present different performances when applied in unstable economic environments. The motivation behind this study is driven by the growing application of artificial intelligence in economic predictions, along with the limited empirical evidence available on its success in African economies, particularly Zimbabwe.

The literature review indicates that there have been two significant gaps: first, no direct comparison was made between univariate LSTM and ARIMA models for inflation forecasting with data from Zimbabwe; secondly, research from other countries has yielded mixed findings. This creates uncertainty regarding the comparative advantages of the models in question. This research seeks to close these gaps by coming up with knowledge that can assist policymakers and researchers to select a suitable forecasting model for inflation prediction in any given economic context.

The organization of the paper is as follows: the introduction section states the research question and its importance; the literature review covers previous research on inflation forecasting with econometric and neural network approaches; the methodology section explains the data and models used; the results section reports and compares forecasting outcomes; and the conclusion summarizes major findings and implications for policy and future research.

Role Of Inflation Forecasting In Economic Stability

(Simionescu 2025) highlighted that accurate inflation forecasts help monetary authorities make better decisions about how to deal with inflation. Similarly, decisions about how to respond to inflation are usually based on both inflation forecasts and inflation targets (IMF 2025; Kalish and Gibbard 2025). The Bank of Canada emphasizes the importance of inflation forecasts in directing inflation-related policy-making (Bank of Canada 2024). Majority of recent forecasts by the United States Federal Reserve show that they employ forecasts of inflation to regulate inflationary pressures, with a view to keeping it in line with a long-run target of 2 percent (Carlson 2025; Federal Reserve 2025). The Reserve Bank of Zimbabwe (RBZ) has also currently established an inflation target of 20% to 30% per annum by December 2025, whereas the monthly inflation target is expected to remain below an average of 3% in 2025 (RBZ 2025). These practices demonstrate how inflation forecasting is integrated into real-world policy frameworks to enhance economic stability.

Structural Framework Of The Arima Model

ARIMA is a univariate time series model. Being a univariate model means it models and forecasts a single time series variable based only on its own past values and past errors. The ARIMA model uses the philosophy that “let the variable speak for itself”. This means that the variable is regressed on its own past values. The ARIMA model combines three components represented by the parameters p, d and q. These components are: AR (AutoRegressive) with parameter p; I (Integrated) with parameter d and MA (Moving Average) with parameter q. “AR” captures the dependency of the current value on its past values. “I” indicates the number of times the data is differenced to achieve stationarity. Then “MA” captures the dependency of the present value on past forecast errors. Together AR (p), I (d) and MA (q) form the ARIMA (p, d, q) model.

Mathematically, the input into the ARIMA model is a univariate time series Y_t (a sequence of observations indexed by time t. The original time series Y_t is differenced d times to make it stationarity. The mathematical representation for a d-th order differencing is:

$$Y_t^{(d)} = \Delta^d Y_t = (1 - B)^d Y_t \quad \ldots\ldots (1)$$

Where B is the backshift operator (that is $BY_t = Y_{t-1}$). This step removes trends and makes the series stationary. The differenced series $Y_t^{(d)}$ is then regressed on its own past p lagged values. The mathematical representation of the AR(p) process is:

$$Y_t^{(d)} = \emptyset_1 Y_{t-1}^{(d)} + \emptyset_2 Y_{t-2}^{(d)} + \emptyset_3 Y_{t-3}^{(d)} + \cdots \emptyset_p Y_{t-p}^{(d)} + e_t \quad \ldots\ldots (2)$$

Where $Y_t^{(d)}$ is the value of the time series at time t after differencing d times, $\emptyset_i$ are AR coefficients, $Y_{t-1}^{(d)}, Y_{t-2}^{(d)}, Y_{t-3}^{(d)}, \ldots Y_{t-p}^{(d)}$ are lagged values of the differenced time series (or simply the order of the AR component), e_t is the white noise error term at time t. The error term represents the random shock or noise in the series that cannot be explained by the model. Important to note is that each $\emptyset_i$ represents the weight or

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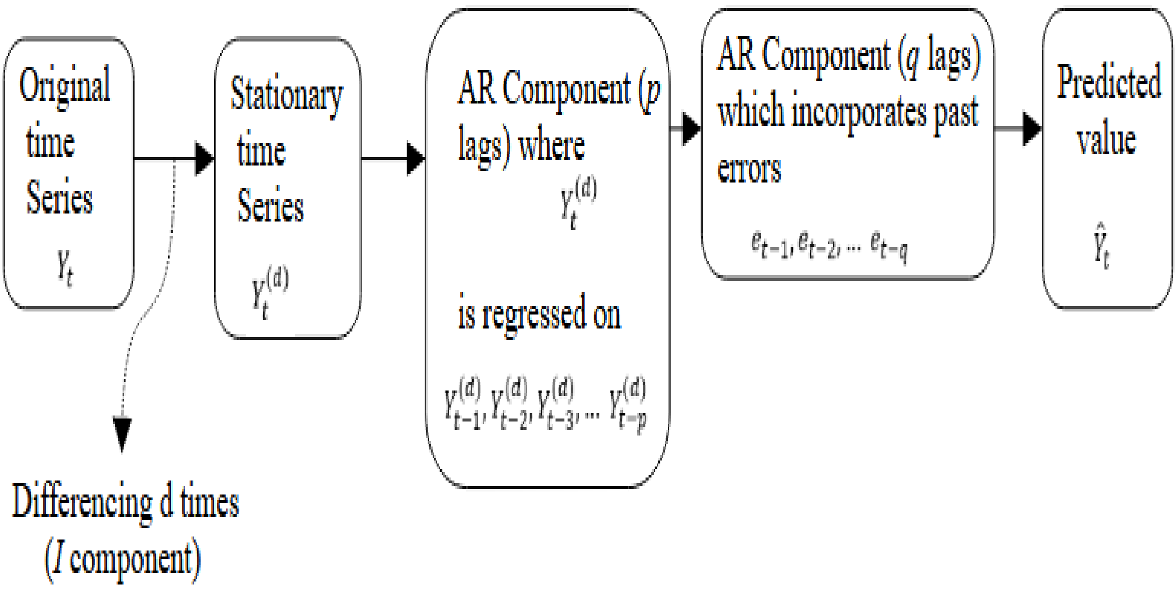
influence of the lagged value $Y_{t-i}^{(d)}$ on the current differenced value $Y_t^{(d)}$. This formulation captures the dependence of the current observation on its previous values, helping ARIMA models account for trends and patterns in time series data.

In addition, the MA component captures the dependency of the present value on past forecast errors. The mathematical representation of the MA (q) process is:

$$Y_t^{(d)} = \mu + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

Where $Y_t^{(d)}$ is the value of the time series at time t after differencing d times, μ is the mean of the series (if needed), e_t is the white noise error term at time t, $\emptyset_i$ are MA coefficients that determine the influence of past error terms and $e_{t-1} + e_{t-2} + \cdots + e_{t-q}$ are the lagged forecast errors of the differenced time serios (or simply the order of the MA component). These processes are illustrated in the conceptual diagram of the ARIMA model shown in Figure 1. Note that in the diagram, the output or the predicted value for current time step is denoted as $\widehat{Y}_t$.

Figure 1: Conceptual Diagram of the ARIMA Model



Source: Authors

Architecture of the Univariate Lstm Model

The univariate LSTM model is a sub-class of recurrent neural networks (RNNs) that are built to process sequential data through the sustenance of long-term dependencies (Kharel, Zarean, and Kaur 2024; Prabhu and Kundargi 2020). The mechanisms encapsulated in the LSTM cell enable the network to either remember or forget information for long periods (Vaswani and Mehta 2024). The design of an LSTM cell is specified by a cell state that regulates the flow of information through three basic gates which are the input gate, the forget gate, and the output gate. According to (Kharel et al. 2024), the cell state acts like long-term memory since it remembers dependencies and patterns for a long time (Kharel et al., 2024). Input data to the cell state is regulated by the input gate (Alkaabi, Shakya, and Mizouni 2023; Kharel et al. 2024). At each time step, the forget gate determines what data should be deleted from the cell (Limouni et al. 2022) and the output gate regulates what data is transmitted depending on the stored memory (Prabhu and Kundargi 2020). These gates update the state of the cell by using sigmoid and tanh functions.

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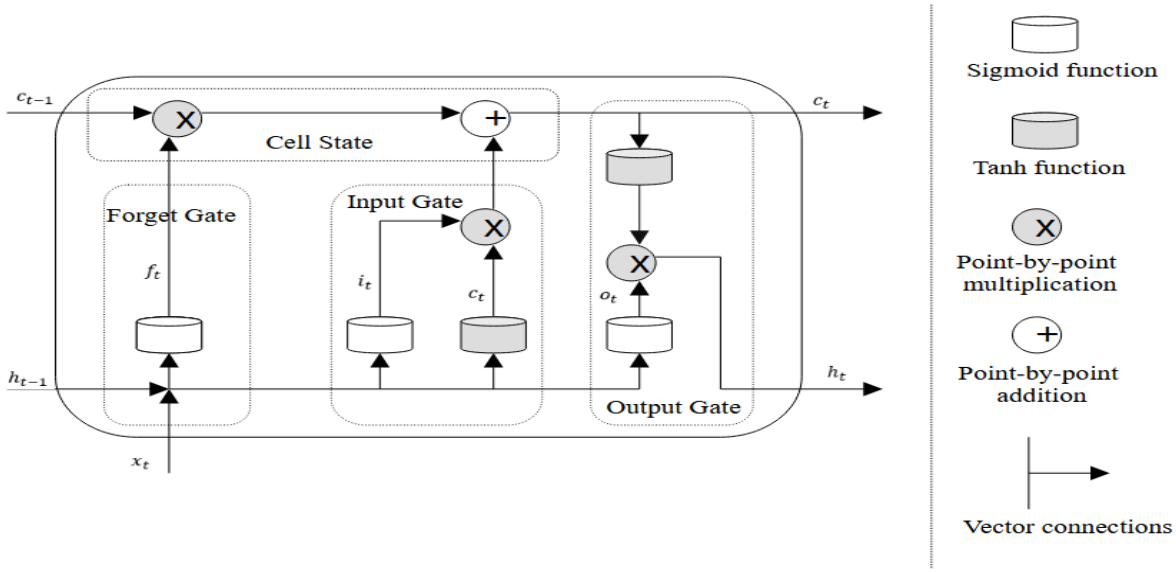
Figure 2 shows the architecture of an LSTM memory cell. The diagram illustrates that the core concept of LSTM revolves around the cell state and its various gates.

Figure 2: Architecture of an LSTM Cell



Source: Adapted from Kharel et al., (2024)

Conflicting Findings In Arima Vs. Lstm Comparisons

Recent research comparing ARIMA and LSTM models in time series prediction has had mixed findings on which one has higher predictive power. Some studies found that ARIMA is superior in multi-step prediction forecasting (Albeladi, Zafar, and Mueen 2023; Kobiela et al. 2022), while other studies established that LSTM is superior in instances where the time series data is nonlinear (Abdoli, MehrAra, and Ebrahim Ardalani 2020; García et al. 2023; Musora et al. 2024). This lack of consensus is pronounced for inflation prediction, where the literature does not offer conclusive evidence on the comparative performance of these models.

The contradictory findings appear strongly influenced by contextual factors. The most salient of these are the time range of the data and the size of the dataset. For example, Zhang et al., (2022) found that ARIMA is more accurate for monthly and weekly predictions, whereas LSTM is more accurate for daily predictions. , Taslim & Murwantara, (2024) also found dataset size to be an important determining factor, where LSTM performed better on small datasets but tended to fall behind when used on large datasets. These trends indicate that LSTM's relative predictive accuracy over ARIMA is extremely context-dependent. This necessitates a case-specific evaluation for model choice rather than a universal recommendation.

In addition, the domain in which the univariate ARIMA and LSTM models are applied contributes to the divergent results. For example, research on financial markets commonly finds ARIMA to perform better especially on longer forecast horizons (Holm and Akesson 2024; Kobiela et al. 2022). Yet, LSTM is found to be superior in areas such as foreign exchange rate prediction (García et al. 2023) and epidemiological modelling (Zhang et al. 2021). Such inconsistency is even observed within inflation prediction. Jamil, (2022) found that the forecasting capability of ARIMA and LSTM models vary across nations without any discernible pattern of one model outperforming the other. This disparity of opinion highly suggests that underlying economic structures have a part to play in the prediction outcome of both the ARIMA and LSTM model.

Regardless of the noted significance of context to inflation forecasting, no study has been undertaken to directly contrast the forecast accuracy of ARIMA and LSTM models exclusively for inflation forecasting in Zimbabwe. This is a significant research gap. Zimbabwe's economic history has been marked by episodes of high inflation and extreme currency volatility which are different from those in the studied economies. Generic findings from global comparisons of the relative performance of ARIMA and LSTM are thus unlikely to be

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directly applicable to Zimbabwe. A focused investigation into the comparative performance of ARIMA and LSTM within this distinct environment is required to establish the best approach to Zimbabwean inflation forecasting.

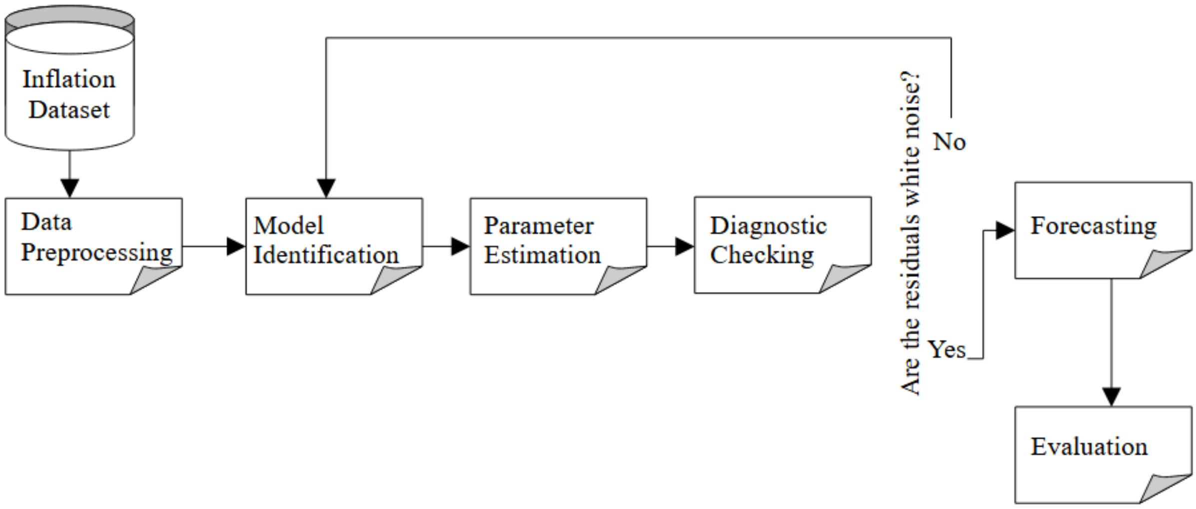
RESEARCH METHODOLOGY

The research methods applied in the prediction of inflation in this study were modified from established frameworks. The univariate ARIMA model adapted research methods from the Box-Jenkins methodology, while the research methods for the univariate LSTM model were adapted from the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology. The forecasting capability of both the ARIMA and LSTM models was compared using the Root Mean Squared Error (RMSE). A lower RMSE means predictions are closer to the actual values.

Modified Box-Jenkins methodology

The methodology adapted for forecasting inflation using ARIMA is visualised in Figure 3.

Figure 3: Flow of the adapted Box Jenkins methodology in the form of a block diagram.



Source: Authors

Description of the adapted Box Jenkins methodology

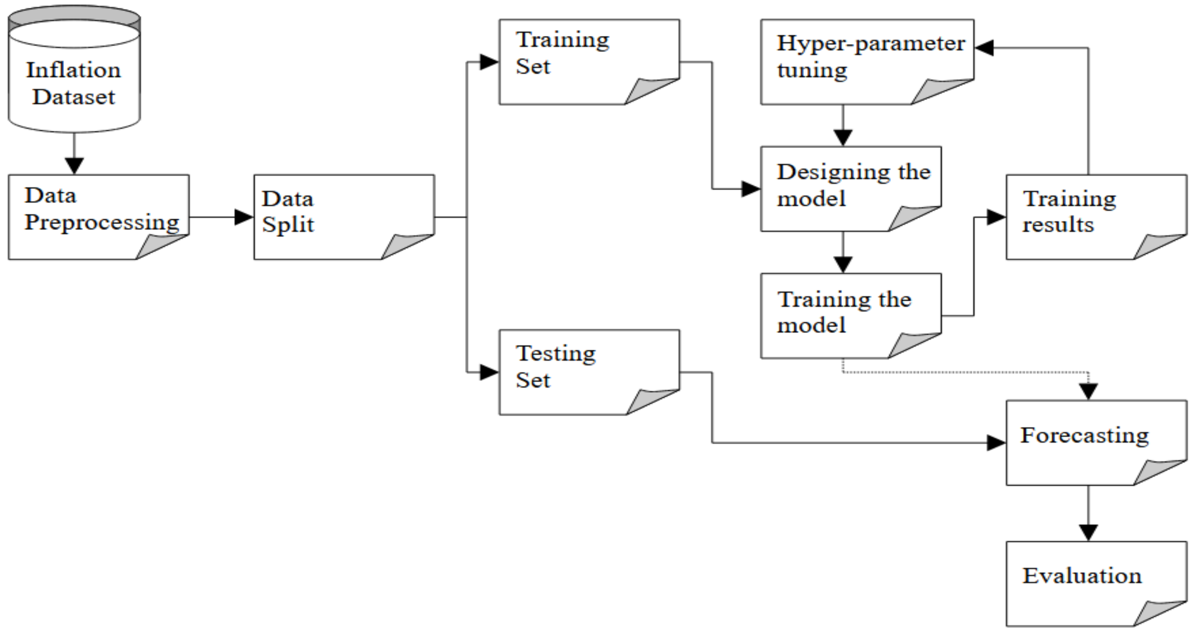
The monthly inflation series from November 2019 to November 2022 was obtained from the Zimbabwe Statistics (ZimStat) website. The data then underwent preprocessing to identify and address any missing values or inconsistencies. Stationarity testing was performed using a visual inspection of raw data plots, a correlogram of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), as well as the Augmented Dickey-Fuller (ADF) test. Model identification stage commenced after confirmation of the data as stationary. This process was done using a correlogram of ACF and PACF. Statistical significance of the lags informed the decision on the combination of the ARIMA model parameters. The plots determined the appropriate order of AR and MA components.

The identification of an appropriate ARIMA model was followed by the estimation of its parameters. Parameter estimation was done using the EViews 10 econometric software. The purpose of parameter estimation was to find the coefficients that make the model's predictions as close as possible to the actual historical inflation data. Diagnostics checks were then performed by examining a correlogram of the residuals to make sure the model captured all important patterns and did not leave any unexplained information behind. Having done the diagnostic checks and satisfied with the chosen ARIMA model, the next step was to carry out static forecasting for an 8-month period from April 2022 to November 2022. The performance of the selected ARIMA model was evaluated using the RMSE. The lower the RMSE, the greater the predictive accuracy.

Modified CRISP-DM methodology

The methodology adapted for forecasting inflation using LSTM is visualised in Figure 4.

Figure 4: Flow of the adapted Crisp-DM methodology in the form of a block diagram.



Source: Authors

Description of the adapted CRISP-DM methodology

The process began with the loading and preprocessing of monthly inflation data using Python 3.12.7 in Jupyter Notebook. The data was normalized between 0 and 1 by using MinMaxScaler as required by LSTM. Normalisation helps the model to learn better by ensuring that input features have similar scales. The LSTM models require 3D input data with the shape of [number of samples, time steps, number of features].

The inflation series was also divided into 80% training set and 20% test set. The LSTM model's architecture was built using an LSTM layer with 110 neurons, a dense layer with 110 neurons, a ReLU (Rectified Linear Unit) activation and a final dense layer with one neuron. Note that the ReLU activation function is used in neural networks to introduce nonlinearity into the model. The number of neurons were randomly selected. As soon as the validation loss stopped improving, model training was terminated using early stopping. The model was trained with a batch size of 20, learning rate of 0.018 and epochs of 100.

Hyperparameters were chosen through a combination of standard heuristics and trial and error. These hyperparameters were the tuned for best performance. The tuned hyperparameters included learning rate, batch size, verbose settings, patience, number of layers in a LSTM network and the number of neurons per layer. The RMSE was used to evaluate the LSTM's forecasting performance over the test data period. The test data covered an 8-month period from April 2022 to November 2022. Forecasts were based on this period.

FINDINGS

ARIMA Model

The inflation series was visually examined for stationarity at level values, and the inspection confirmed that the series is stationary. To be sure that this is a non-stationary series, a correlogram (ACF and PACF plot) of level values was plotted at 16 lags and it was established that the inflation series was stationary. The ADF test also confirmed stationarity, with a test statistic of -3.123409 (below the 5% critical value of -2.948404) and a p-value of 0.0339 (below 0.05). All the tests for stationarity indicated that the inflation time series did not

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exhibit a unit root and was stationary at levels. As a result, there was no need for differencing. This meant that d was equal to zero.

An analysis of a correlogram of the ACF and PACF led to the identification of ARIMA (1,0,1) model. Parameter estimation of the identified ARIMA (1,0,1) model established that the model was well-specified with statistically significant parameters as shown in table 1.

Table 1: A summary of ARIMA (1,0,1) model estimation results

Variable	Coefficient	t-Statistic	Probability
C	10.07698	2.903036	0.0065
AR (1)	0.376736	2.217347	0.0336
MA (1)	0.632761	3.372604	0.0019

Results from the ARIMA indicate that all estimated coefficients are statistically significant as evidenced by their probability values that are below the 0.05 threshold. The constant term (C) has a coefficient of 10.08, which suggests a baseline level in the data when other factors are held constant.

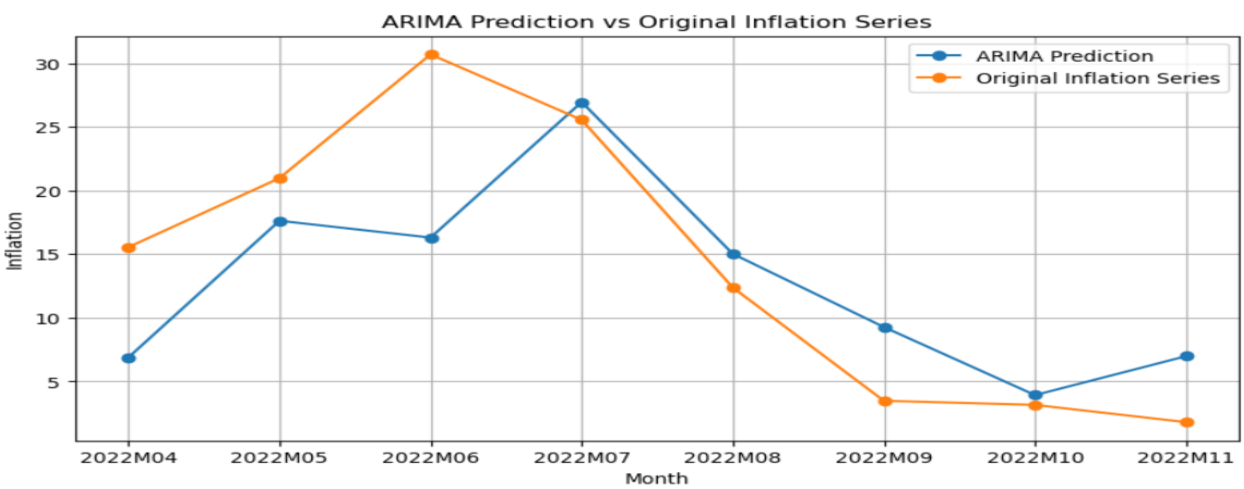
The AR (1) term has a coefficient of 0.38. This implies that a one-unit increase in the previous period's inflation rate leads to an expected increase of about 0.38 units in the current inflation rate. The AR (1) term's t-statistic of 2.22 and the p-value of 0.034 indicate that the relationship between past and current inflation values is statistically meaningful.

Similarly, the MA (1) term has a coefficient of 0.63, showing a stronger influence of past error terms on the current value. This indicates that a one-unit shock in the prior period's error term positively impacts the current value by approximately 0.63 units. The MA (1) term's higher t-statistic of 3.37 and very low p-value of 0.0019 further confirm its significance.

The diagnostic checks established that the ARIMA (1,0,1) model was well specified as the correlogram of residuals for both ACF and PACF was flat. This means that all information was captured because all the lags fell withing the 95% confidence interval. The performance evaluation of the forecasts done by the model for an 8-month period from April 2022 to November 2022 produced an RMSE of 6.7.

The line graph in Figure 7 presents a comparison between ARIMA predictions and the actual inflation values.

Figure 7: ARIMA predicted inflation rates and actual inflation rates



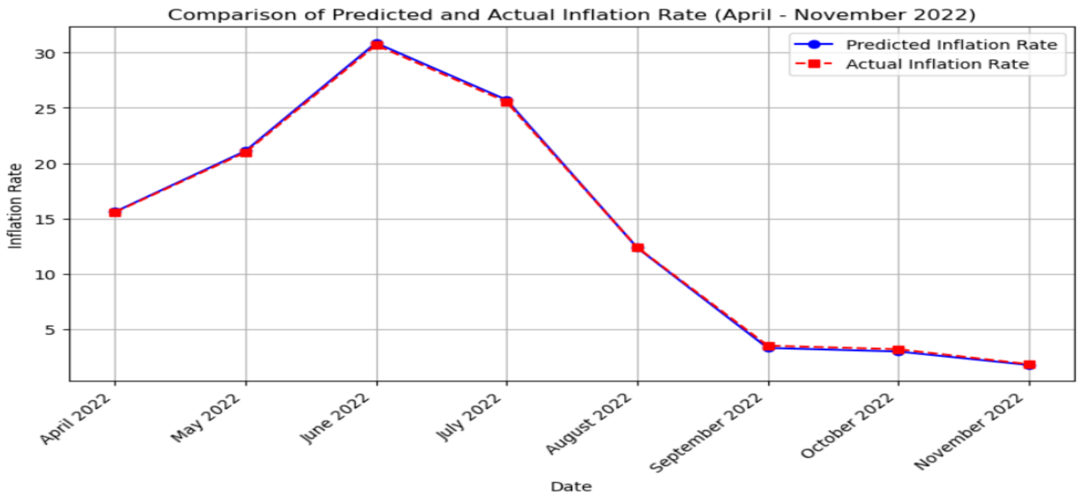
Source: Authors

LSTM Model

The performance evaluation results indicate that the RMSE values for training and testing were 0.15 and 0.14, respectively. There was a minimal deviation between the training and test RMSE scores. These values suggest that the model maintained strong generalization, as the test error was only marginally lower than the training error. The close alignment between train and test RMSE scores implies that the model avoided overfitting and was able to produce reliable forecasts across unseen data. This level of precision signifies that the chosen hyperparameters were highly effective in capturing inflation dynamics without significant residual errors.

Figure 5 presents a line graph showing a comparison of predicted inflation rates with the actual inflation rates over an 8-month testing period. There is a close match between the predicted and actual values. This indicates that the LSTM model successfully captured the inflation trends. Any differences between the two lines are very small. This demonstrates that the LSTM model provided more accurate forecasts.

Figure 5: LSTM predicted inflation rates and actual inflation rates



Source: Authors

Comparative Analysis between ARIMA and LSTM results

Figure 8 presents a graphical comparison of ARIMA and LSTM model predictions.

Figure 8: ARIMA predicted inflation rates and actual inflation rates

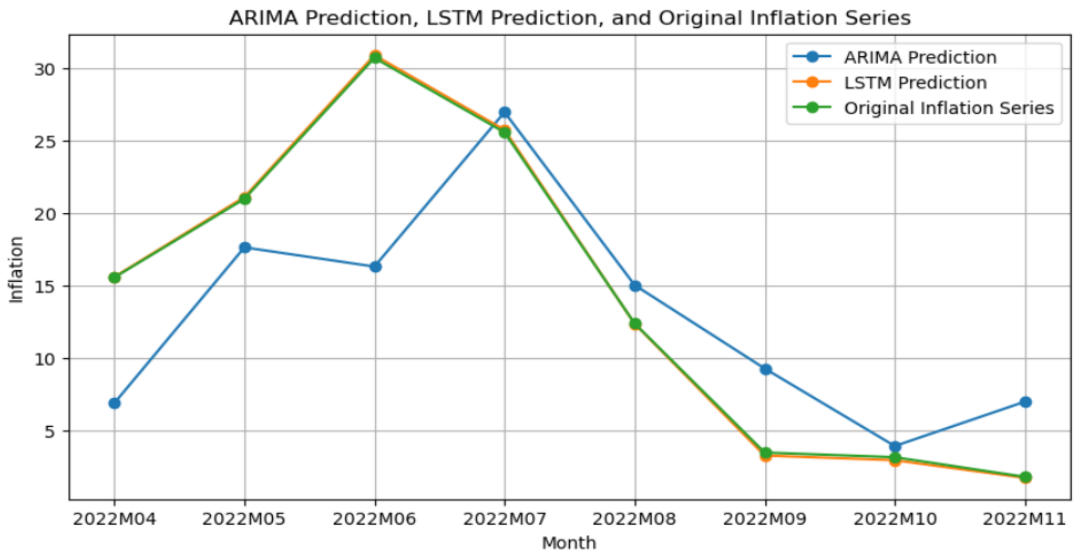


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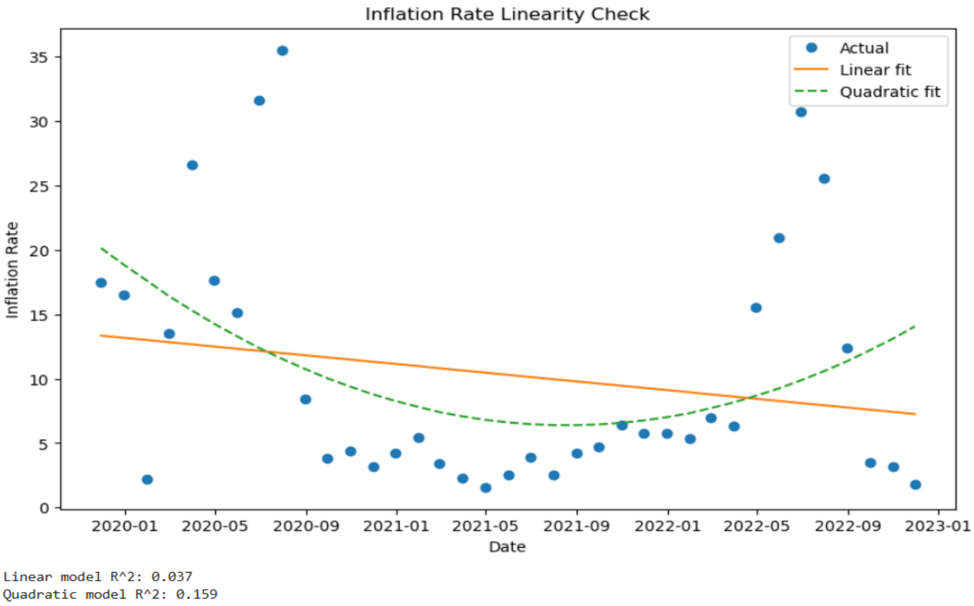
Figure 8 clearly indicates that the LSTM model provides better predictive performance than the ARIMA model. The RMSE for the ARIMA model was 6.7, while the LSTM model achieved a significantly lower RMSE of 0.14.

Linearity Check

Figure 9 below shows the results of a linearity check.

Figure 9: Linearity Check



Source: Authors

The linearity test result in Figure 9 shows that the inflation time series is non-linear. The linear fit (orange line) fails to track the trend of actual data points. In contrast, the quadratic fit (green dashed line) follows the turning points in the data more closely. This shows that the quadratic fit can better accommodate shifts in the inflation rate. Statistically, the R^2 value of the linear model is very low at 0.037. This shows that the linear model explains only 3.7% of the variation in the inflation data. The quadratic model, while still modest with an R^2 of 0.159, is a definite improvement to account for approximately 16% of the variation. This difference in the two R^2 values serves to support the finding that the inflation series is nonlinear through time.

DISCUSSIONS

In this study, the univariate LSTM model outperformed the univariate ARIMA model in terms of forecasting inflation in Zimbabwe. The LSTM model had a lower RMSE of 0.14 than the ARIMA model, which had an RMSE of 6.7. This difference in RMSEs indicates how much more accurate the LSTM model is at predicting inflation.

One reason for this result lies in the nature of the inflation data, which was confirmed to be non-linear through a linearity test. ARIMA models work well with linear and stationary time series but struggle with non-linear patterns because they are based on linear assumptions (Taslim and Murwantara 2024). LSTM models are built to handle nonlinear relationships in the data (Abdoli et al. 2020). This explains why the LSTM performed better in this study where the inflation data was confirmed to be nonlinear.

Past studies have given mixed results when comparing how well ARIMA and LSTM models predict outcomes. However, there is no study that has directly compared these models using Zimbabwe's inflation data. This study fills that gap and establishes that LSTM is superior for this context. The highly non-linear and volatile nature of Zimbabwe's inflation data makes LSTM a better fit.

The RMSE results clearly show that LSTM predicts better than ARIMA and also highlight how important it is to pick a model that fits the nature of the data. Since the inflation data in Zimbabwe is non-linear, LSTM is a better choice for this kind of forecasting.

Nevertheless, it is crucial to consider the trade-off of interpretability in policy making between ARIMA and LSTM models. The choice between ARIMA and LSTM is a trade-off between how easy the model's decision-making process can be understood (interpretability) and the ability to capture complex patterns in data. ARIMA models are more parsimonious and more interpretable and thus easier for humans to understand and believe, which is important in decision making when explanations matter. On the other hand, LSTM models are deeper and complex nonlinear deep learning models that perform better in volatile and nonlinear environments but work as a "black box" model because their internal workings are harder to explain. Therefore, the policy makers need to trade off the improvement in understanding as a result of increased transparency and the accuracy of forecasting especially under unfold economic conditions. Therefore, the policy makers need to trade off the benefit of deeper insight into the model's predictions against the need for accurate forecasting in complex economic contexts.

CONCLUSIONS, RECOMMENDATIONS AND IMPLICATIONS

This study set out to compare the predictive performance of ARIMA and LSTM models in forecasting inflation in Zimbabwe, using a time series dataset characterized by nonlinear behaviour. The results provide compelling evidence that the LSTM model significantly outperformed the ARIMA model, as indicated by a remarkably lower RMSE of 0.14 compared to 6.7 for ARIMA. The LSTM model proved to be superior in forecasting nonlinear inflation time series. Based on these findings, researchers and policy makers should focus on nonlinear models like LSTM when dealing with nonlinear economic data. In addition, a test for linearity must be conducted before choosing a model to ensure a good fit. This study emphasises the practical and methodological implications. In terms of methodological implication, the study shows how important it is to choose a model that fits the nature of the data. With regards to practical implication, the paper highlights how reliable forecasts from LSTM models can support better economic planning and policymaking.

Future Research

Future research would be to extend this univariate analysis by pursuing multivariate ARIMA and LSTM models with other economic variables such as exchange rates, interest rates, or fiscal policy variables that may further enhance forecast precision as well as contextual interpretability. Further investigation into hybrid modelling paradigms that integrate statistical and deep learning techniques may also yield productive opportunities for trading off interpretability and predictive power.

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