ON COMPARATIVE STUDY OF NEURAL NETWORK AND MARKOV-SWITCHING MODELS FOR INFLATION FORECASTING

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ABSTRACT

This study examines the effectiveness of forecasting inflation in Nigeria over the period 2000 to 2024 using Artificial Neural Networks (ANN) and Markov-Switching Models (MSM). It assesses the ability of each model to capture nonlinear dynamics and structural shifts in inflation behaviour during the study period. Monthly inflation data obtained from the National Bureau of Statistics, the official data source, were analysed. Model performance was evaluated using standard forecast accuracy measures, including the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Theil's U-statistic. The results show that the ANN model delivers higher forecasting accuracy by effectively capturing complex nonlinear relationships in the data. In contrast, the MSM performs better in identifying transitions between low- and high-inflation regimes, thereby providing useful insights into the structural behaviour of the economy. Overall, the findings suggest that integrating machine learning techniques with regime-switching models can enhance forecast accuracy and provide valuable support for monetary and fiscal policy formulation in Nigeria.

Keywords: Artificial Neural Network (ANN), Markov-Switching Model (MSM), Inflation, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Theil's U-statistic.

1.0 Introduction

Accurate inflation forecasting is essential for guiding monetary policy, informing investment decisions, and maintaining economic stability. As a key macroeconomic indicator, inflation influences purchasing power, interest rates, exchange rate dynamics, and overall economic performance. In Nigeria, inflation has exhibited considerable fluctuations over time, driven by factors such as currency volatility, fiscal imbalances, supply-side constraints, and global economic shocks. Understanding these dynamics and forecasting future trends is therefore critical for policymakers, investors, and researchers seeking to promote price stability and sustainable growth.

Traditional econometric models such as ARIMA and VAR have been widely used in inflation forecasting. While effective in certain contexts, these models assume linear relationships and fixed parameters, thereby limiting their ability to capture the nonlinearities and structural breaks often observed in emerging economies. To address these limitations, more advanced modelling approaches have been developed. Artificial Neural Networks (ANNs) utilise machine learning techniques to capture complex nonlinear relationships without requiring strong distributional assumptions, making them effective in identifying hidden patterns in inflation data. Markov-

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Switching Models (MSMs), on the other hand, allow model parameters to vary across distinct economic regimes, such as periods of low and high inflation, thereby capturing abrupt structural changes and policy effects.

This study evaluates and compares the forecasting performance of ANN and MSM approaches for inflation in Nigeria over the period 2000 to 2024. Using performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Theil's U-statistic, the analysis provides empirical evidence on the model that delivers more accurate and robust forecasts. The findings are intended to contribute to both academic literature and policy formulation by demonstrating the potential benefits of integrating data-driven models with regime-switching frameworks to enhance inflation forecasting and macroeconomic stability in Nigeria.

2.0 Literature Review

Inflation forecasting is a core element of macroeconomic analysis and policy design. Although conventional linear models such as ARIMA and VAR remain widely used, their performance is often limited by their inability to capture nonlinear dynamics, structural breaks, and regime shifts that characterize inflation behaviour, particularly in emerging economies. These limitations have motivated two main strands of methodological development: data-driven nonlinear techniques, notably Artificial Neural Networks (ANNs), and regime-switching econometric models, especially Markov-Switching Models (MSMs). Whereas ANNs are designed to approximate complex nonlinear relationships through flexible functional forms, MSMs explicitly model discrete transitions between latent inflation regimes, such as low- and high-inflation states. As a result, much of the empirical literature has shifted toward evaluating their relative forecasting performance and assessing whether hybrid specifications yield additional predictive gains.

Empirical evidence on inflation dynamics in Nigeria reflects this methodological evolution. Olorunfemi et al. (2025) documented weak interest rate pass-through, attributing it to structural inefficiencies in the financial system. Chiamaka and Sunday (2025) found that inflation responds with considerable delays to monetary policy actions, thereby reducing policy effectiveness. Idris and Shuyur (2024) showed that exchange rate pressures significantly reinforce inflation persistence, highlighting the importance of external shocks. Using stochastic and machine learning approaches, Nkemnole and Oyelami (2025) reported strong forecasting performance for nonlinear models such as GARCH, STAR, and SETAR. In a related contribution, Bartholomew et al. (2025) demonstrated that hybrid ANN–SARIMA frameworks outperform single-model specifications in terms of predictive accuracy.

Despite the rise of advanced forecasting techniques, classical linear models continue to serve as important benchmarks. Studies by Stockton and Glassman (1987) and Meyler et al. (1998) show that simple univariate ARIMA models can outperform more structurally complex alternatives, including Phillips-curve-based models, particularly at short forecasting horizons. Their robustness, ease of implementation, and interpretability explain their continued relevance in empirical forecasting exercises.

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To capture interdependencies among macroeconomic variables, multivariate frameworks such as Vector Autoregressive (VAR) models are commonly employed. VAR models are particularly useful for joint dynamic analysis and forecasting. Evidence from central bank studies indicates that model performance is horizon-dependent: ARIMA models typically perform better in the short run, while VAR models tend to dominate at medium horizons (Fritzer, 2002; Moser et al., 2007). Consistent findings by Robinson et al. (1987) further show that VAR models outperform ARMA models at intermediate horizons, whereas error-correction models become more effective over longer horizons.

More recently, the expansion of computational capacity has accelerated the adoption of machine learning and deep learning methods in macroeconomic forecasting. Central banks and research institutions increasingly apply these techniques to inflation prediction tasks (Sebastian et al., 2021). Although deep learning models are effective at capturing nonlinear relationships, their empirical superiority over well-specified econometric models remains inconsistent.

Within this context, neural networks—an established class of artificial intelligence models—have demonstrated strong performance in pattern recognition and forecasting applications (LeCun et al., 1989). Their use in economic forecasting has produced results broadly comparable to traditional autoregressive models (Nakamura, 2005; James et al., 1998). However, their effectiveness is often constrained by limited sample sizes and low-frequency macroeconomic data. Large-scale forecasting evidence from Makridakis et al. (2018) suggests that classical statistical models frequently outperform machine learning approaches in such environments, while Sezer et al. (2019) report that deep learning performs better in high-frequency financial markets than in macroeconomic contexts.

Nevertheless, more recent contributions present a more favourable view. Theoharidis et al. (2023) show that advanced deep learning architectures can outperform both traditional econometric and standard machine learning models by effectively capturing nonlinearities and nonstationary behaviour in inflation data. Despite these advances, methodological limitations and data constraints continue to shape performance outcomes.

Against this backdrop, a growing strand of literature has focused on inflation forecasting using either neural network models or Markov-switching frameworks in isolation. However, direct comparative evidence between the two approaches remains limited, particularly in developing economies such as Nigeria. Moreover, most existing studies emphasize in-sample performance, with relatively less attention given to out-of-sample evaluation, which is more relevant for real-time forecasting and policy application. This study addresses this gap by jointly evaluating ANN and Markov-switching models using both in-sample and out-of-sample forecasting criteria, thereby providing more robust evidence for inflation forecasting and macroeconomic policy formulation in Nigeria.

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3.0 Mathematical frame work

3.1 Markov Switching Autoregressive (MS-AR) Model

A Markov-switching autoregressive model is used to capture possible changes in regimes within the time series. Hamilton (1989) proposed this approach as a way of modelling structural changes over time. It extends the standard autoregressive model by allowing its parameters to vary across different states of the economy, with transitions between these states driven by an unobserved Markov process (Kim and Nelson, 1999). The general form of the model, as presented by Durbin and Koopman (2012), is given as follows:

$$X_t = C_{st} + \phi_1, \phi_{i,st} - 1 + \phi_2, \phi_{i,st} - 2 + \cdots + \phi_{p,i,st} - p + e_t,$$

where, C_{st} represents the intercept of the AR process in regime S_t, ϕ_t, S_t are the autoregressive coefficients of lag i in regime S_t. Furthermore, S_t is an unobserved Markov state variable at time t indicating the regime at that time and, e_t is the white noise error term at time t. The Markov state variable S_t follows a discrete-time Markov process with transition probabilities and initial probabilities that determine the switching behaviour between different regimes. A two regime transition probability matrix is then given by

$$P_{ij} = \begin{bmatrix} P_{11} & 1\text{-}P_{11} \\ 1-P_{22} & P_{22} \end{bmatrix}$$

$$X_t = \begin{cases} \phi_1 + \sum_{i=1}^{p} \phi_1 X_{t-1} e_{1j} S_t = 1 \\ \phi_2 + \sum_{i=1}^{p} \phi_2 X_{t-1} e_{2j} S_t = 2 \end{cases}$$

3.2 Structure of Artificial Neural Network Used in this Study

This study implements a feedforward back-propagation artificial neural network (FFBP-ANN) structure, with the learning and parameter estimation procedure derived from the framework proposed by Ermis et al. (2007) and later modified through the extensions introduced by Akintunde (2013). The resulting specification offers an improved computational formulation for representing complex nonlinear relationships among variables, thereby enhancing forecasting accuracy, improving convergence behaviour during training, and strengthening the model's ability to generalise to unseen multivariate data.

STEP I: Evaluation of net input to the j^{th} node and k^{th} node in the hidden layer as below:

$$net_j = \sum_{i=1}^{n} w_{ij} x_i - \theta_j$$

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$$net_k = \sum_{j=1}^{n} w_{jk} x_j - \theta_k$$

Where

i is the input node, j is the hidden layer node, k is the output layer, w_{ij} is the weights connecting the i^{th} input node to the j^{th} hidden layer node, w_{jk} is the weights connecting the j^{th} hidden layer node to the k^{th} output layer, θ_j is the threshold between the input and hidden layers θ_k the threshold connecting the hidden and output layers.

STEP II: Evaluation of the j^{th} node in the hidden layer and the output of the k^{th} node in the output layer as:

$$h_j = f_h\left\{\sum_{i=1}^{n} w_{ij} x_i - \theta_j\right\}, \text{ and } y_k = f_k\left\{\sum_{j=1}^{n} w_{jk} x_j - \theta_k\right\}$$

Where

and $f_k(x) = \dfrac{1}{(1+\exp(-\lambda_k x))}$,

Where:

h_j is the vector of hidden neurons,

y_k is the output-layer of neurons

$f_h(x)$ and $f_k(x)$ are logistic sigmoid activation function from input layer to the hidden layer and from hidden layer to output layer respectively and λ_h and λ_k are the variables which control the slope of the sigmoid function.

The output of each neurons is obtained by applying an activation functions $f_h(x)$ and $f_k(x)$. The nodes are used to perform the non-linear input/output transformation using a sigmoid activation function.

STEP III: The calculations of errors in the output and hidden layers can be expressed as follows:

The output layer error between the target and the observed output is expressed as:

$$\delta_k = -(d_k - y_k) f_k^1$$

$f_k^1 = y_k(1-y_k)$ for sigmoid function

Where

δ_k is the vector of errors for each output neurons y_k and d_k are the target activation of output layer. The term δ_k depends only on the error $(d_k - y_k)$ and f_k^1 is the local slope of the node activation function for output nodes. The hidden layer error term is expressed as

$$\delta_j = f_h^1 \sum_{h=1}^{n} w_{kj}\delta_k,$$

$$f_h^1 = h_j\left(1 - h_j\right),$$ for sigmoid function

δ_j is the vector of errors for each hidden layer neurons, δ_k is a weighted sum of all nodes and f_h^1 is the local slope of the node activation for hidden nodes.

STEP IV: The adjustment of weights and thresholds in the output layer and hidden layer is obtained as follows:

$$w_{kj}^{t+1} = w_{kj}^{t} + \alpha\delta_k h_j + \eta\left(w_{kj}^{t} - w_{kj}^{(t-1)}\right),$$

$$w_{ji}^{t+1} = w_{ji}^{t} + \alpha\delta_j h_i + \eta\left(w_{ji}^{t} - w_{ji}^{(t-1)}\right),$$

$$\theta_k^{t+1} = \theta_k^{t} + \alpha\delta_k, \theta_j^{t+1} = \theta_j^{t} + \alpha\delta_j$$

Where α is the learning rate, η is the momentum factor, and t the time period.

3.3 Network Training

The specification of an appropriate stopping criterion represents a fundamental aspect of artificial neural network training, particularly in ensuring convergence efficiency and predictive robustness. In the neural network literature, two major approaches are commonly adopted for determining the termination point of the learning process. The first approach advocates iterative training until successive epochs no longer produce statistically meaningful reductions in the objective function across multiple randomly initialized weight vectors. Under this framework, convergence is considered to have been attained when further iterations fail to improve the network error beyond a tolerable threshold. The underlying objective of this procedure is to approximate the global optimum of the error surface while minimizing the possibility of entrapment within suboptimal local minima.

The second approach is predicated on a fixed train–validation or train–test learning framework, in which network training is terminated after a predetermined number of epochs, followed by performance evaluation using an independent validation dataset. This procedure is primarily intended to assess the out-of-sample predictive capability and generalization performance of the network. In the context of artificial neural network modelling, generalization refers to the capacity of an estimated model to capture the underlying nonlinear data-generating mechanism and maintain predictive accuracy when exposed to previously unseen observations. The adoption of

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this strategy is particularly important in mitigating overfitting, thereby enhancing the stability and external validity of the forecasting model.

The learning mechanism of the network is implemented through a gradient-based optimisation procedure, in which synaptic connection weights are iteratively updated in the direction opposite to the gradient of the predefined loss function. More formally, the back-propagation learning algorithm recursively propagates the prediction error backward through the hidden and output layers, enabling systematic adjustment of network parameters in accordance with the steepest descent criterion. This iterative optimisation process facilitates continuous minimisation of the training error function, improves convergence properties, and enhances the overall forecasting accuracy and computational efficiency of the neural network architecture.

$$w_{ij}(t+1) = w_{ij}(t) - \eta \frac{\partial E}{\partial w_{ij}}$$
$$v_{jk}(t+1) = v_{jk}(t) - \eta \frac{\partial E}{\partial w_{ij}}$$

Where η is the learning rate controlling convergence speed

Using the delta rule, the error signal for the output layer and is defined as

$$\partial_k = (y_k - \hat{y}_k) f'(\bullet)$$

For the hidden layer, the error is propagated backward as

$$\partial_j = f'(\bullet)\sum_k \partial_k v_{jk} \quad \Delta w_{ij} = \eta \partial_j x_i, \Delta v_{jk} = \eta \partial_k h_j$$

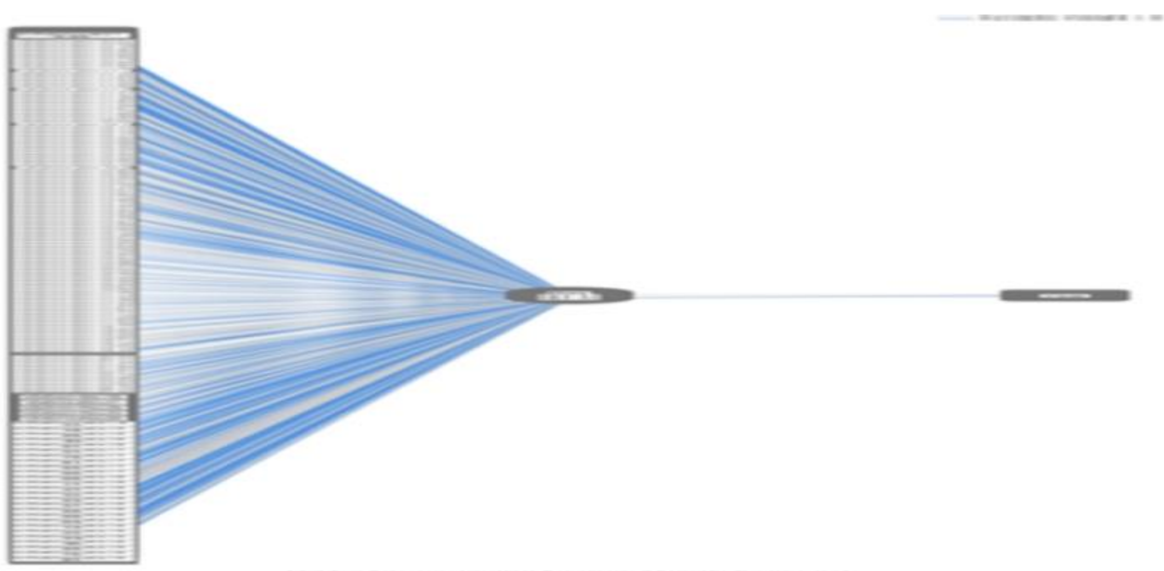

Figure 1: Inflation rate data architecture used for the study **Source** Authors Computation

3.3 Selection of error metrics for assessment

Mean Squared Error (MSE): MSE is a fundamental and extensively employed error metric in the realm of predictive modelling. It serves as a robust measure to quantify the overall quality of predictions by assessing the magnitude of the discrepancies between predicted values and actual observations. Mathematically, the Mean Squared Error is given by

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_t\right)^2$$

Root Mean Squared Error (RMSE): RMSE is the square root of the MSE and provides an error measure in the same units as the original data. Mathematically, the Root Mean Squared Error is given by

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

Mean Absolute Error (MAE): MAE measures the average absolute difference between predicted and actual values. The equation of MAE is

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

Mean Absolute Percentage Error (MAPE): MAPE emerges as a crucial error metric that operates on the foundation of calculating the average percentage discrepancy between predicted values and actual observations, in relation to the actual values themselves. It is expressed as

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_t}{y_t}\right|$$

Theil's U Statistic: Theil's U Statistic combines measures of accuracy and bias to provide an overall assessment of prediction performance.

The Theil's U Statistic formula is given by:

$$U = \sqrt{\frac{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - \hat{y}_t\right)^2}{\frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right|}}$$

4.0 Application to Nigerian Inflation Rates

The data used for the study is Nigerian monthly inflation rates data spanning between 2000 and 2024.To improve the accuracy of predicting inflation rates for Nigerian, we used a Markov-Switching autoregressive (MS-AR) model and an artificial neural network (ANN).

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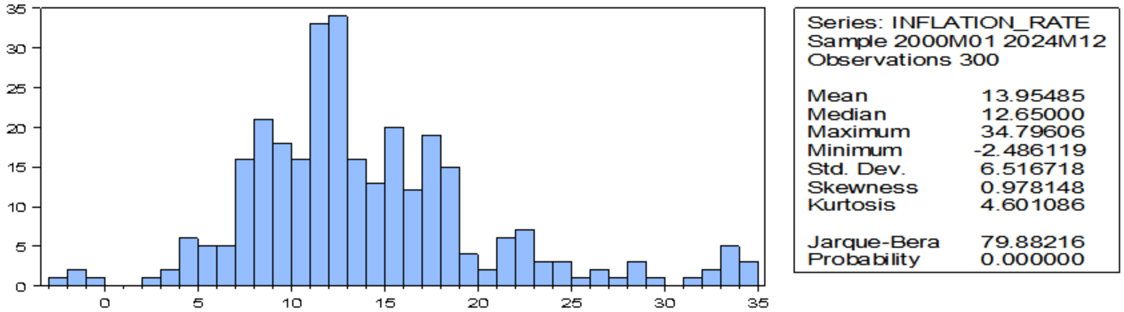

Figure 2: Descriptive Statistics

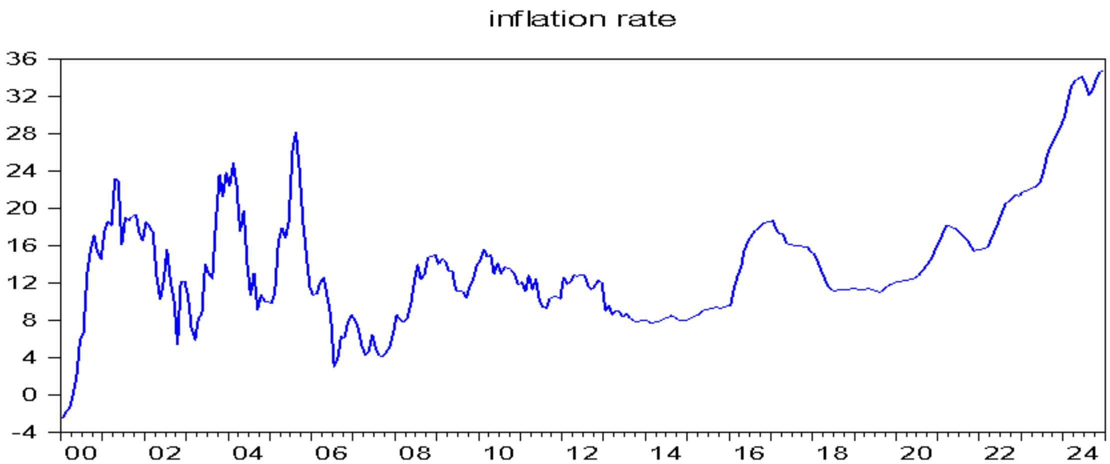

Figure 3: Level graph of inflation data

The graph above is the original data of inflation series where it is shown that the series was stable at first difference

Table 1. Regime Switching

Parameter	Coefficient	Std	t-value	p-value
Regime 1				
$\hat{\mu}_1$	0.1252	0.1342	1.4321	0.0040
$\hat{\phi}_1$	0.0976	0.1178	0.3129	0.0007
$\hat{\sigma}_1$	0.1328	0.0057	3.4531	0.0002
Regime 2				
$\hat{\mu}_2$	-0.3214	0.1876	-1.2376	0.0002
$\hat{\phi}_2$	-0.1234	0.2110	-0.3421	0.0002
$\hat{\sigma}_2$	0.2341	0.01237	3.7623	0.0003

Table 2 Transition probabilities

	$P_{11} = 0.8711$	$P_{12} = 0.3421$
	$P_{22} = 0.3875$	$P_{22} = 0.8941$

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Evidence from Table 1 indicates that the two estimated states of inflation possess distinct and economically meaningful characteristics. The first state is associated with substantially lower variability, with its variance falling short of that of the second state by approximately 17.18 percent. This disparity confirms that inflation in Nigeria exhibits pronounced instability and frequently alternates between different volatility phases, with an average monthly inflation level of about 6.92 percent during turbulent periods. In contrast, when inflation evolves under the low-volatility state, the mean monthly rate declines markedly to approximately 0.1871 percent. Under this calmer state, the likelihood of moving into the higher-volatility state is given by $\boxed{pr\left(S_t = 2 \middle| S_t = 1\right) = 0.3875}$. Additional insights from Table 2 show that persistence differs across the two states. The probability of remaining in the low-volatility regime $\boxed{P_{11} = 0.8711}$ is smaller than the probability of staying in the high-volatility regime $\boxed{P_{22} = 0.8941}$.

4.2 Fitting Artificial Neural Network Model

The neural network component of this study is constructed using the innovation terms derived from both volatility states identified by the MS(2)-AR(1) process. These innovation series serve as the explanatory inputs for the learning algorithm. A broad range of network topologies was explored to determine an effective structure, with most designs comprising two intermediate processing layers. Among the tested configurations were multiple node combinations, including ANN(1,2), ANN(1,3), ANN(2,4), ANN (3,2), and ANN(4,3) arrangements, in addition to several other alternatives. Comparative assessment of these network designs shows that none achieved a forecasting error below 0.3412.

4.3 Combined Forecast Model

An examination of forecast-error sensitivity across MS(2)-AR(1), ANN(1,3), and the hybrid MS(2)-ANN(1,3) reveals that model performance is contingent on the choice of evaluation metric. Forecast accuracy is evaluated using MSE, RMSE, MAE, MAPE, Theil's U statistic, and MFE. The MS(2)-AR(1) model captures regime dynamics effectively and yields reasonable average forecast errors, whereas the ANN(1,3) specification records the lowest RMSE and Theil's U, indicating stronger performance in modelling nonlinear relationships and reducing short-run prediction bias. These results are reported in Table 4.

The evidence further indicates that forecast accuracy measures respond differently to model structure, implying that comparative rankings are sensitive to the selected evaluation criteria. The hybrid MS(2)-ANN(1,3) model outperforms the competing specifications across most metrics, suggesting superior robustness in volatile economic conditions. Overall, the results highlight the importance of employing multiple evaluation criteria to ensure a reliable and comprehensive assessment of forecasting performance.

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Table 4: Forecasting Performance of the Models

Metric	MS(2)-AR(1)	ANN(1,3)	MS(2)-ANN(1,3)
MSE	1.73614	1.06978	0.12469
MAPE	1.73456	1.06076	-7.12919E-17
MAE	6.51672	4.85604	5.11591E-15
Theil U	5.98019	4.6182	6.02777E-15
RMSE	2.05332	1.27097	0.184806

Table 5: Forecasting Performance of the Models

Metric	MS(2)-AR(1)	ANN(1,3)	MS(2)-ANN(1,3)
AIC	1.10333	1.10333	1.10333
HQC	1.10817	1.11311	1.12052
SBIC	3.75541	3.76035	3.76775

The evaluation of forecasting models has important implications for economic analysis, particularly when predictive accuracy guides policy and financial decision-making. The results show that assessments of model performance are highly sensitive to the choice of error metric. Models that perform well under scale-dependent measures such as RMSE or MAE may exhibit weaker performance when evaluated using relative measures such as MAPE or Theil's U statistic. This sensitivity raises concerns about potential model misclassification when evaluation is based on a single criterion.

Moreover, each error metric embeds specific evaluation biases. RMSE disproportionately penalizes large forecast deviations, while MAPE becomes unreliable when actual values are close to zero, a common feature in low-inflation environments. Beyond accuracy measures, model selection criteria provide additional evidence, with the Akaike Information Criterion (AIC) consistently favouring the MS(2)-AR(1) specification due to its lower information loss.

Overall, the findings highlight the importance of a multi-criteria evaluation framework to ensure robust, reliable, and policy-relevant forecasting conclusions.

5 Discussion, conclusion and Recommendations

Monetary policy effectiveness is fundamentally forward-looking, relying on the accurate formation of expectations regarding future macroeconomic conditions rather than backward-looking adjustments. Within this framework, inflation forecasting constitutes a central input into policy design. Price stability remains the dominant mandate of central banks, including the Central Bank of Nigeria (CBN), and its attainment depends critically on an accurate characterization of inflation dynamics and the ability to anticipate regime-dependent behaviour under varying macroeconomic conditions. This is particularly relevant during periods of heightened uncertainty, such as the COVID-19 shock, where forecast accuracy directly influences the timeliness and effectiveness of policy responses as well as the anchoring of inflation expectations.

This study examines inflation dynamics in Nigeria within a comparative and hybrid forecasting framework that combines a Markov-Switching Autoregressive (MS-AR) specification and an Artificial Neural Network (ANN) model. The MS-AR model captures discrete regime changes by allowing the data-generating process to alternate between latent states, while the ANN serves as a flexible nonlinear approximator capable of capturing complex functional relationships without parametric restrictions. The hybrid specification integrates information extracted from MS-AR residual dynamics into the ANN architecture, thereby embedding regime-dependent structure within a nonlinear learning framework. This design permits simultaneous modelling of structural breaks and nonlinear dependencies, enhancing robustness under time-varying economic conditions.

Forecast performance is evaluated using a suite of loss functions, including MSE, RMSE, MAE, MAPE, and Theil's inequality coefficient. The empirical evidence indicates that relative model rankings are not invariant to the choice of loss function, implying that forecast evaluation is metric-dependent rather than absolute. Complementary model selection diagnostics—Akaike Information Criterion (AIC), Hannan–Quinn Criterion (HQC), and Schwarz Information Criterion (SIC)—consistently identify the MS(2)-AR(1) specification as the most parsimonious representation of inflation dynamics. These results highlight the econometric importance of jointly considering predictive accuracy measures and information-based criteria in model evaluation.

From a structural perspective, the findings provide evidence of pronounced regime dependence in Nigerian inflation, characterized by alternating low- and high-volatility states rather than smooth adjustment paths. This behaviour implies that inflation dynamics are governed by state-contingent processes, necessitating policy frameworks that account for endogenous regime transitions induced by domestic policy actions, external shocks, and global disturbances. In parallel, the ANN model demonstrates superior performance in capturing latent nonlinearities, particularly in short-horizon prediction, where functional flexibility is most consequential. The combined framework therefore, yields a more comprehensive representation of inflation dynamics by integrating structural switching behaviour with nonlinear approximation capacity.

In sum, the results support the use of hybrid econometric–machine learning frameworks in macroeconomic forecasting environments characterized by nonlinearity and structural instability. Future extensions may incorporate extreme value theory to model tail risk behaviour in inflation distributions or adopt multivariate dependence structures—such as copula-based approaches—to capture nonlinear co-movements between inflation and key macroeconomic variables, including interest rates, output growth, and policy shocks. Such extensions would further strengthen the modelling of distributional extremes and dependence under macroeconomic stress conditions.

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