Hybrid ARIMA-SVR-MLP Model for Forecasting Nigeria's Gross Domestic Product (GDP)

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Abstract

This paper proposes a novel hybrid ARIMA-SVR-MLP model that integrates Autoregressive Integrated Moving Average (ARIMA), Support Vector Regression (SVR), and Multilayer Perceptron (MLP) neural network to forecast Nigeria's Gross Domestic Product (GDP). The models were fitted on yearly GDP data from 1960-2022. The series was tested for stationarity using the Augmented Dickey-Fuller (ADF) test and found to be stationary at the first differencing. Based on model selection criteria, ARIMA (1, 1, 0) was identified as the appropriate ARIMA model. Support Vector Regression (SVR) was also applied to the original series to capture the nonlinearity that might not have been accounted for by ARIMA. The predictions of the best ARIMA and SVR models were then used as inputs for the MLP neural network to form the hybrid model. Out-of-sample forecasts demonstrate that the hybrid model outperforms individual models in terms of accuracy

Keywords: Forecasting, GDP, Hybrid ARIMA-SVR-MLP, Modelling

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1. Introduction

Economic forecasting plays a crucial role in shaping policy decisions, financial planning, and strategic initiatives across various sectors. Among the most significant economic indicators is Gross Domestic Product (GDP), which measures the total value of goods and services produced within a country over a specific period. For Nigeria, a developing market economy, accurate GDP forecasting is essential for informed decision-making. However, the inherent volatility, structural complexities, and frequent economic shocks make GDP forecasting challenging (World Bank, 2024).

Traditional time series models like AutoRegressive Integrated Moving Average (ARIMA) have been widely used due to their simplicity and effectiveness in capturing linear relationships. For example, for example, Adebayo (2016) applied the ARIMA model to forecast Nigeria's GDP for the period 1960-2015, concluding that the ARIMA(1, 2, 2) configuration was optimal for GDP predictions. Abonazel and Abd-Elftah (2019) found that the appropriate statistical model for forecasting the Egyptian GDP is ARIMA (1, 2, 1), this model was used forecast the GDP of Egypt until 2026. Atanu *et al.* (2020) also use ARIMA model to forecast Gross Domestic Product using the annual data of Nigeria's GDP from 1981 to 2019. They identified ARIMA (1, 2, 1) as an appropriate model for modeling of Nigeria's GDP. Ghazo (2021) applies the ARIMA model to the process of forecasting GDP and CPI in the Jordanian economy. The study of Yao (2024) used ARIMA model to analyse and forecast China's GDP from 1978 to 2022. The results show that ARIMA (0, 2, 0) model's predictions are in good agreement with the actual values. However, ARIMA struggles with non-linear patterns, which are prevalent in economic data, especially in developing economies like Nigeria. Recent studies have highlighted the limitations of ARIMA models and called for integrating more sophisticated methods to improve forecasting accuracy.

Moreover, hybrid models that combine ARIMA with machine learning techniques have shown great potential in improving forecasting performance, as they address both linear and non-linear components of the time series data (Zhang, *et al.*, 2019). The combination of ARIMA and SVR into a hybrid model leverages the strengths of both: ARIMA captures linear trends, while SVR handles non-linear patterns. Recent research has demonstrated the effectiveness of ARIMA-SVR models in various contexts, including economic forecasting (Pai and Lin, 2020; Qiu et al., 2022). Additionally, the integration of MLP into this hybrid framework further refines the forecasting process by addressing residual patterns not captured by ARIMA or SVR (Zhang and Zhou, 2021). Hua (2022) applies hybrid ARIMA-BPNN model to forecast China's H province GDP data for the period 2010 to 2020. The results reveal that the hybrid model outperform the single models. Syahab *et al.* (2023) conduct a study on hybrid ARIMA-MLP using ARIMA and MLP to improve estimation model performance in solar radiation sensor data. The research shows that the ARIMA-MLP hybrid model is able to increase the accuracy value in RMSE compared to the ARIMA and MLP individual models. Borrero and Mariscal (2023) apply the NAR–SVR hybrid model in three scenarios: Spanish berry daily yield data from 2018 to 2021, daily COVID-19 cases in three countries during 2020, and the daily Bitcoin price time series from 2015 to 2020. Their results show that the hybrid model consistently outperforms its counterparts. Ali and Mohammed (2023) suggest employing hybrids ARIMA-ANN and ARIMA-SVR to forecast daily crude oil prices between January 2010 to June 2021. The proposed hybrid model gives more accurate and efficient results and predict crude oil prices better than the single models.

This study proposes a novel hybrid ARIMA-SVR-MLP model to improve the accuracy of Nigeria's GDP forecasts. By leveraging ARIMA for linear trends, SVR for non-linear dynamics, and MLP for further refinement, this model aims to provide a more comprehensive and reliable forecasting framework. This approach has the potential to inform policymakers and stakeholders, offering more accurate forecasts that can enhance decision-making in Nigeria's complex economic environment.

2. Materials and Methods

ARIMA Model

The ARIMA model, introduced by Box and Jenkins in 1976, is a popular method for time series forecasting. ARIMA (p, d, q) combines autoregressive terms (p), differencing (d), and moving averages (q) to make non-stationary data stationary and predict future values. It is represented as:

$$(1-\phi_1 B-\phi_2 B^2-\ldots-\phi_p B^p)(1-B)^d y_t = c+(1+\theta_1 B+\theta_2 B^2+\ldots+\theta_q B^p)\varepsilon_t \qquad (1)$$

In a more compact form is:

$$\phi_p(B)(1-B)^d y_t = c + \theta_q(B)\varepsilon_t \tag{2}$$

where, B is the backshift operator, y_t is the value of the time series at time t, ϕ_i are the autoregressive coefficients, θ_j are the moving average coefficients, d the degree of differencing and ε_t is the error term at time t.

Support Vector Regression (SVR)

SVR, proposed by Vapnik and Cortes (1995), is a supervised machine learning algorithm used for regression tasks. It fits a hyperplane in high-dimensional space, minimizing error while considering a margin of tolerance. (Bargam, et al. 2024). Given input dataset x = {x_1, x_2, x_3, ..., x_n} and the target value y = {y_1, y_2, y_3, ..., y_n} we have that:

$$f(x) = w\phi(x) + b \tag{3}$$

where w is the weight vector function and b is the offset factor, representing a non-linear mapping. In order to prevent overfitting of the calibration, data samples, Support Vector Regression (SVR) utilizes an objective function (Eq. 4) and a loss function (Eq. 5) to determine the regression parameters in equation (3):

$$\min \frac{1}{2}\|w\|^2 + C\sum_{1}^{n}(\xi_i + \xi_1^*) \tag{4}$$

subject to:

$$\begin{cases} y_i - (w\phi(x) + b) \le \varepsilon + \xi_i \\ (w\phi(x) + b) - y_i \le \varepsilon + \xi_i^* \\ \xi_i \ge 0,\ \xi_i^* \ge 0,\ i = 1, \ldots, n \end{cases} \tag{5}$$

ε represents a positive error threshold, C is a penalty coefficient set by the user, ξ_i and ξ_i^* the slack variables are used to assess the deviation of calibration data from ε. To prevent overfitting, SVR optimizes parameters using GridSearchCV and selects the best kernel (RBF, polynomial, or sigmoid).

Multilayer Perceptron (MLP)

MLP is a type of artificial neural network with an input layer, hidden layers, and an output layer. Each neuron processes weighted inputs, sums them with a bias, and applies an activation function to produce an output (Koukaras et al., 2022). The process is represented as:

$$h_t = \sum_{i=1}^{N} w_i x_{it} + b \Rightarrow Y_t = (h_t) \tag{6}$$

$$\sigma(h_t) = \frac{1}{1+e^{-h_t}} \tag{7}$$

Here, is the activation function, typically chosen as a sigmoid or another continuous function. (Al-Nefaie, *et al.* 2022).

3. Results and Discussion

Data Description

This study uses annual GDP data for Nigeria from 1960-2022, obtained from the World Bank. The data was split into a training set (51 points) and a test set (10 points). The ADF test confirmed non-stationarity with a p-value of 0.8838. After first differencing, the series became stationary (p-value: 5.97e-08).

The original data as seen in figure 1 is non-stationary. A formal Dicky Fuller test was conducted and the p-value of 0.8838 confirmed its non-stationarity. It was made stationary at the first differecing as seen in figure 2 with the p-value of 5.9683e-08 for the Dicky Fuller test. In order to make sure that the ARIMA model compete on the same level as the other models, the data was scales using python MinMaxScaler. ARIMA was first used to estimate the linear part of the stationary data. Various candidates ARIMA models were fitted using auto ARIMA in python in order to select the one with the lowest information criteria. ARIMA (1, 1, 0) gave the lowest AIC and was selected. The time series plot of this data is shown in Figure 1.below:

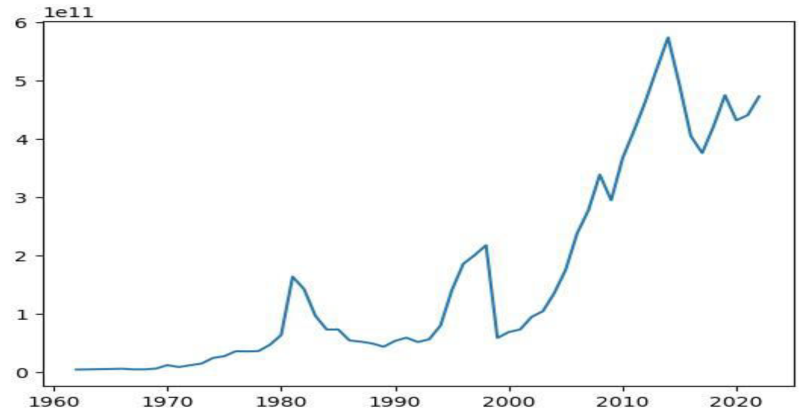

Figure 2: Time Plot of Original GDP Series

Augmented Dickey-Fuller test for GDP shows p-value of 0.8838 > 0.05 which means that the original series is non-stationary.

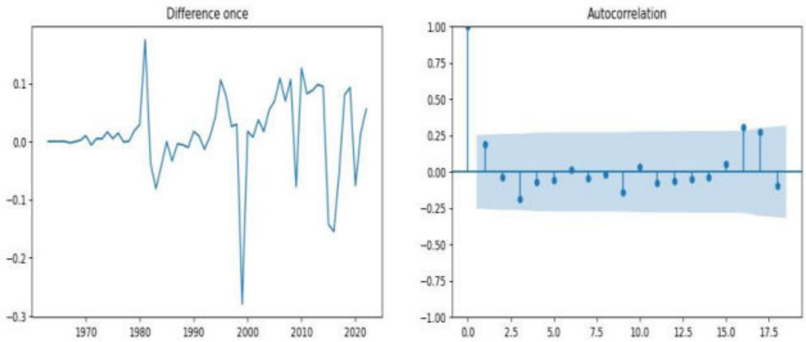

Figure 3: First Differencing and ACF Plots of GDP Series

Augmented Dickey-Fuller test for GDP shows p-value of 5.9683e-08 < 0.05 which means that the series is stationary.
Having differenced the original series once and seen being stationary, python code for auto ARIMA fitting was run. Below are the candidate models in Tablen1:

Table 1: Results of ARIMA model selection for GDP

ARIMA			
MODEL	AIC	BIC	HQIC
ARIMA (1, 1, 0)	-127.367	-123.542	-125.91
ARIMA (1, 1, 1)	-125.712	-119.976	-123.528

ARIMA (1, 1, 2)	-124.662	-117.014	-121.75
ARIMA (1, 1, 3)	-122.666	-113.106	-119.025
ARIMA (2, 1, 0)	-126.101	-120.365	-123.917
ARIMA (2, 1, 1)	-125.097	-117.448	-122.184
ARIMA (2, 1, 2)	-122.666	-113.106	-119.025
ARIMA (2, 1, 3)	-120.666	-109.194	-116.297
ARIMA (3, 1, 0)	-124.644	-116.996	-121.732
ARIMA (3, 1, 1)	-123.099	-113.538	-119.458
ARIMA (3, 1, 2)	-121.413	-109.941	-117.044
ARIMA (3, 1, 3)	-121.647	-108.263	-116.55

Source: Results of Data Processing using Microsoft Excel

Table 1 shows that ARIMA (1, 1, 0) has the lowest AIC, BIC and HQIC among the candidate ARIMA models. Hence, ARIMA (1, 1, 0) was selected.

ARIMA (1, 1, 0) Model Estimation

After the best model has been chosen, the parameters of the model are estimated. The results of this estimate are shown in Table 2 below:

Table 2: Results of ARIMA (1, 1, 0) Model Estimation for GDP

Parameter	Coefficient	Std. Error	Z	P-value
ar.L1	0.1720	0.131	1.310	0.190
sigma2	0.0042	0.000	9.865	0.000***

Source: Results of Data Processing using Microsoft Excel

Similarly, the SVR model was fixed on the scaled series using various kernel to obtain the best SVR model. The kernels used are Radial Basis Function (rbf), Polynomial Function (poly) and Sigmoid Function (sigmoid).. The results of this estimate are shown in Table 3 below:

Table 3: Results of SVR model selection for GDP

SVR			
KERNEL	MSE	RMSE	MAE
Rbf	0.0085	0.0921	0.0867
Poly	0.0095	0.0972	0.0836
sigmoid	15.1791	3.896	3.291

Source: Results of Data Processing using Microsoft Excel
Table 3 shows that rbf kernel turned out to be with the lowest metrics. Hence, it was selected and used along with ARIMA (1,1,0) for the building of the hybrid.

Out-of-Sample Forecasts
The outputs of ARIMA and SVR were used as the inputs for the MLP. Their fitted values were first used for the selection of the best MLP. After several times of tuning the hyperparameters, model with two hidden layers of nine neurons of the first and five neurons of the second gave the lowest metrics. This best MLP model was thereafter used to make out-of-sample forecast.

Table 4: Comparison of Actual GDP and Model Forecasts for Nigeria GDP

Year	Actual GDP	ARIMA	SVR	ARIMA-SVR-MLP
2013	5.20E+11	4.73E+11	4.12E+11	4.85E+11
2014	5.74E+11	4.74E+11	4.31E+11	4.79E+11
2015	4.93E+11	4.74E+11	4.46E+11	4.74E+11
2016	4.05E+11	4.74E+11	4.57E+11	4.70E+11
2017	3.76E+11	4.74E+11	4.63E+11	4.68E+11
2018	4.22E+11	4.74E+11	4.66E+11	4.67E+11
2019	4.75E+11	4.74E+11	4.64E+11	4.68E+11
2020	4.32E+11	4.74E+11	4.58E+11	4.70E+11
2021	4.41E+11	4.74E+11	4.48E+11	4.73E+11
2022	4.73E+11	4.74E+11	4.36E+11	4.77E+11

Source: Results of Data Processing using Microsoft Excel

Table 4 compares the actual GDP values with forecasts from the three models: ARIMA, SVR, and ARIMA-SVR-MLP from 2013 to 2022. The ARIMA model provides approximately consistent forecasts of 4.74E+11 across all years, suggesting it may not be capturing year-to-year variations effectively. The SVR model shows gradually increasing forecasts from 2013 to 2018, then slightly decreasing afterwards. It seems to capture some trends but often underestimates the actual GDP. The Hybrid model appears to balance between ARIMA and SVR predictions, generally providing forecasts closer to the actual GDP than either model alone. Actual GDP fluctuates more than any of the model predictions, with significant drops in 2015-2017 that none of the models accurately captured. Overall, while no model perfectly predicts the actual GDP, the Hybrid model seems to provide the most balanced forecasts across the years.

Table 5: Error Metrics for Out-of-Sample GDP Forecasting Models

Forecast Evaluation Statistics	**ARIMA**	**SVR**	**ARIMA-SVR-MLP**
Mean Square Error	0.0101	0.0151	0.0086
Root Mean Square Error	0.1005	0.1229	0.093
Mean Absolute Error	0.0815	0.0989	0.0762

Source: Results of Data Processing using Microsoft Excel

Table 5 compares the performance of the three forecasting models in this study using three different error metrics. The Hybrid model consistently outperforms both ARIMA and SVR across all three-error metrics, having the lowest values for Mean Square Error (0.0086), Root Mean Square Error (0.093), and Mean Absolute Error (0.0762). The relatively low error values for all models suggest that they all provide reasonably accurate forecasts, with the hybrid model being the most accurate overall. These results indicate that combining the strengths of ARIMA and SVR in the Hybrid model using the MLP leads to improved forecasting performance for Nigeria's GDP.

4. Conclusion

This study presented a novel hybrid model combining ARIMA, SVR, and MLP techniques for forecasting Nigeria's GDP. The hybrid ARIMA-SVR-MLP model was designed to leverage the strengths of each individual model—ARIMA's linear forecasting capabilities, SVR's non-linear modeling power, and MLP's ability to combine the outputs of both ARIMA and SVR for more accurate forecasting. By integrating these approaches, the hybrid model outperformed the individual models in terms of forecast accuracy, particularly in the out-of-sample period.

The findings of this research demonstrate that the hybrid model is more robust in capturing the complexities and volatilities inherent in Nigeria's economic data compared to traditional methods. The successful application of this model offers a promising framework for improving economic forecasts, particularly in developing countries like Nigeria where economic dynamics are complex and challenging to predict.

Furthermore, this study contributes to the growing body of literature on hybrid models in economic forecasting. It underscores the importance of adopting advanced modeling techniques that combine both linear and non-linear approaches to capture the full range of patterns present in time series data. Future research could extend this work by incorporating additional data sources and exploring real-time forecasting capabilities, further enhancing the model's applicability to other emerging economies.

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