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DEVELOPMENT OF A HYBRID MACROECONOMIC MODEL FOR FORECAST OF ECONOMIC INDICATORS

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ABSTRACT

This study proposed a hybrid modelling framework that integrates Random Forest (RF), Vector Error Correction Model (VECM), and Regression Analysis to enhance macroeconomic forecasting in Nigeria. Addressing challenges such as oil price volatility, structural shocks, and sparse high-frequency data, this approach combines RF's ability to capture non-linear patterns, VECM's cointegration of non-stationary variables, and Regression's parametric efficiency through residual correction and ensemble averaging. Using macroeconomic data from 1993–2022, the hybrid model achieved a 23.4% reduction in Mean Absolute Error (MAE) for GDP (from 15.23 to 11.67) and a 28.5% reduction in Root Mean Squared Error (RMSE) (from 20.45 to 14.62), alongside significant improvements for other variables: 17.6% MAE (exchange rate), 15.2% MAE (inflation), 12.1% MAE (unemployment), and 20.3% RMSE (exchange rate), 18.5% RMSE (inflation), 15.6% RMSE (unemployment). The optimized integration weights ($\alpha = 0.61$ for RF, $\beta = 0.17$ for VECM, $\gamma = 0.23$ for RA in GDP forecasting) highlight machine learning's dominance in modeling non-linearities, while VECM anchors predictions to long-term equilibria and RA stabilizes parametric relationships. Residual correction and ensemble averaging further reduced systematic biases, as evidenced by tighter error distributions. By bridging machine learning and econometrics, this integrated approach provided policymakers with a robust tool for economic stabilization in resource-dependent economies. While data granularity influenced performance, it highlighted its potential for emerging markets facing structural constraints.

Keywords: Macroeconomic forecasting, Hybrid modelling, Machine Learning in Economics.

INTRODUCTION

Nigeria, the largest economy in Africa (World Bank, 2022), has been experiencing significant economic challenges in recent years. The country's economy has been plagued by fluctuating oil prices (OPEC, 2022), currency volatility (Central Bank of Nigeria, 2022), high inflation rates (National Bureau of Statistics, 2022), and rising unemployment and poverty rates (National Bureau of Statistics, 2022). These challenges have made it difficult for policymakers to make informed decisions, highlighting the need for accurate macroeconomic forecasting (Adebayo, 2020).

Macroeconomic forecasting is crucial for economic planning and policy decisions, providing policymakers with insights into future economic trends and patterns (Taylor, 2019). However, macroeconomic forecasting in Nigeria has been limited by the complexity of economic relationships, non-linear interactions, and limited data quality and availability (Akinboade, 2018).

This study aims to address the issues of improving macroeconomic forecasting accuracy in Nigeria, addressing the limitations of existing models, capturing complex relationships and non-linear interactions between macroeconomic variables, providing a more comprehensive understanding of Nigeria's economy and its dynamics, and enhancing policy-making and economic planning through more accurate and reliable forecasts. By addressing these issues, this study seeks to develop a more robust and reliable macroeconomic forecasting model for Nigeria, which can inform policymakers and contribute to the country's economic development. To achieve this, the study proposed an integrated approach that combines Random Forest, VECM, and Regression Analysis to improve macroeconomic forecasting in Nigeria. By combining the strengths of these models, this study aims to provide a more comprehensive understanding of Nigeria's economy and improve the accuracy of macroeconomic forecasts.

Previous studies have applied various models to forecast macroeconomic variables in Nigeria, including Autoregressive Integrated Moving Average (ARIMA) (Olorunleke, 2018), Vector Autoregression (VAR) (Adeniyi, 2020), Vector Error Correction Model (VECM) (Ozoh, 2019), and Random Forest and other machine learning techniques (Adeleke, 2022). While these models have contributed to our understanding of Nigeria's economy, they have limitations. For example, ARIMA and VAR models assume linear relationships, ignoring non-linear interactions and feedback loops (Terasvirta, 2019). VECM model capture long-term equilibrium dynamics but assume linear relationships (Juselius, 2019). Machine learning techniques, such as Random Forest, can capture non-linear interactions but often lack interpretability (Breiman, 2001). Macroeconomic forecasting is a crucial tool for policymakers and economists to make informed decisions about economic policies and investments. Nigeria, as a developing country, faces significant challenges in accurately forecasting its macroeconomic variables. This literature review summarizes the existing research on macroeconomic forecasting in Nigeria, highlighting the limitations of existing models and the potential benefits of integrating Random Forest, VECM, and Regression Analysis.

Adebayo (2020) reviewed the literature on macroeconomic forecasting in Nigeria and identified the need for more accurate and reliable models. Adeniyi (2020) applied VAR models to forecast macroeconomic variables in Nigeria but noted the limitations of assuming linear relationships. Ozoh (2019) used VECM model to capture long-term equilibrium dynamics but acknowledged the assumption of linear relationships. Adeleke (2022) employed machine learning techniques, including Random Forest, to forecast macroeconomic variables in Nigeria, but highlighted the need for improved interpretability.

The literature highlights the challenges of macroeconomic forecasting in Nigeria, including data quality issues (Akinboade, 2018), non-linear interactions (Terasvirta, 2019), and the need for more comprehensive models (Taylor, 2019).

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MATERIALS AND METHODS

This study proposed an integrated approach that combines Random Forest, VECM, and Regression Analysis to improve macroeconomic forecasting in Nigeria.

Model Specification

Random Forest

The Random Forest (RF) model is a robust predictive algorithm that leverages ensemble learning to forecast economic indicators. By combining multiple decision trees, RF reduces variance and bias, resulting in more accurate predictions. It effectively captures complex relationships and non-linear interactions, making it ideal for modelling economic systems. In this study, RF is applied to forecast GDP, inflation rate, exchange rate, and unemployment rate, with performance evaluated using MAE and RMSE metrics. Feature importance scores provide valuable insights for policymakers and researchers.
The Random Forest model does not have a simple closed-form equation like linear regression or VECM. Instead, it uses an ensemble of decision trees to predict GDP, represented as:

$$\hat{y}\mathrm{RF} = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_{\mathrm{tree},i} \qquad (1)$$

Where, $\hat{y}_{tree,i}$ is the prediction from the i^{th} decision tree, and N is the number of trees.

Vector Error Correction Model

The VECM investigated the dynamic interplay between EXCR, INFLR, UNEMPR, and GDP in a time series framework. The focus is on capturing long-term equilibrium relationships among these variables.

$$\Delta \mathrm{GDP}_t = \pi Y_{t-1} + \delta_1 \Delta Y_{t-1} + \delta_2 \Delta Y_{t-2} + \ldots + \delta_\rho \Delta Y_{t-\rho} + \varepsilon_t \qquad (2)$$

Where $\Delta\mathrm{GDP}_t$ represents the change in real gross domestic product at time t. Y_{t-1} is the vector of variables at the previous time point. π is the matrix of coefficients representing the long-term equilibrium relationships among the variables. $\delta_1, \delta_2, \ldots, \delta_\rho$ are matrices of coefficients representing the short-term adjustments to deviations from the long-term relationships at different lags. ρ is the lag order, determining how many past time points are considered. $\Delta Y_{t-1}, \Delta Y_{t-2}, \ldots, \Delta Y_{t-\rho}$ are the first differences of the variables capturing their short-term changes. ε_t is the vector of error terms accounting for unobserved influences.

Regression Analysis Model

Regression analysis is a statistical technique used to establish a relationship between two or more variables, to predict the value of one variable based on the values of others. Regression analysis can be used to examine the relationship between economic indicators (GDP, inflation rate, exchange rate, and unemployment rate), identify the most significant predictors of economic indicators, and forecast future values of economic indicators based on past data. The MLR equation is given by:

$$\mathrm{GDP} = \beta_0 + \beta_1(\mathrm{EXCR}) + \beta_2(\mathrm{INFL\ R}) + \beta_3(\mathrm{UNEMPLR}) + \varepsilon \qquad (3)$$

Where GDP is the dependent variable (economic indicator). (EXCR) ,(INFL R), and (UNEMPLR) are the independent variables (predictors). β_0 is the intercept
$\beta_1, \beta_2, \beta_3$ are the slope coefficients. ε is the error term.

The Integrated Model

To integrate these models, their predictions are combined to develop a strategy from VECM, regression, and Random Forest. One approach is to use a weighted average of the predictions from each model. The integrated forecast for GDP is:

$$\hat{y}_{GDP,t} = \alpha_1\hat{y}_{VECM,t} + \alpha_2\hat{y}_{Reg,t} + \alpha_3\hat{y}_{RF,t} \qquad (5)$$

$$\hat{y}_{EXCR,t} = \beta_1\hat{y}_{VECM,t} + \beta_2\hat{y}_{Reg,t} + \beta_3\hat{y}_{RF,t} \qquad (6)$$

$$\hat{y}_{INFLR,t} = \gamma_1\hat{y}_{VECM,t} + \gamma_2\hat{y}_{Reg,t} + \gamma_3\hat{y}_{RF,t} \qquad (7)$$

$$\hat{y}_{UNEMPR,t} = \delta_1\hat{y}_{VECM,t} + \delta_2\hat{y}_{Reg,t} + \delta_3\hat{y}_{RF,t} \qquad (8)$$

Where,
$\hat{y}_{\mathrm{VECM},t}$ is the VECM predictions for GDP.
$\hat{y}_{\mathrm{Reg},t}$ is the regression analysis predictions for GDP.
$\hat{y}_{\mathrm{RF},t}$ is the Random Forest predictions for GDP.
$\alpha_1, \beta_1, \gamma_1, \delta_1, \ldots, \alpha_3, \beta_3, \gamma_3, \delta_3$ are the weights assigned to each model's predictions.

Hybrid model

This study proposed a hybrid model that combines the strengths of Random Forest, VECM, and Regression Analysis to predict economic indicators. The hybrid model is designed to leverage the individual strengths of each model, producing more accurate and robust predictions. The hybrid model consists of three components: Random Forest, which is used for feature selection and initial prediction; VECM, which is used for modelling relationships between economic indicators; and Regression Analysis, which is used for final prediction and adjustment. The hybrid model is trained and validated using a dataset of economic indicators, and its performance is evaluated using metrics such as the mean absolute error (MAE) and the root mean squared error (RMSE). By combining the strengths of the models, the hybrid model produces more accurate and robust predictions of economic indicators, which can inform economic policy and decision-making.
The hybrid model:

$$Y = (\alpha\,\mathrm{RF}) + (\beta\mathrm{VECM}) + (\gamma\,\mathrm{RA}) + \varepsilon \qquad (9)$$

Where Y = predicted economic indicator, RF = Random Forest prediction, VECM = Vector Error Correction Model prediction RA = Regression Analysis prediction .α, β, γ = weights assigned to each model (summing to 1), ε = error term

Evaluation Metrics

The Evaluation of model performance of the forecast errors was carried out using: (i) Root Mean Square Error (RMSE) = $\sqrt{\frac{\sum_{t=1}^{T}\varepsilon_t^2}{T}}$ to measure the square root of the average squared differences between predicted and actual values, and (ii) Mean Absolute Error (MAE)=$\sum_{t=1}^{T}\frac{|\varepsilon_t|}{T}$ to measures the average absolute differences between predicted and actual values.

Method of Data Collection

The data used for the study is secondary data as it was collected from the National Bureau of Statistics Headquarters in Abuja. The sample consists of 28 years of data from 1993 to 2022. The data on Gross Domestic Product are valued in millions while the Unemployment rate, Exchange rate, and inflation rate are valued in percent.

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Table 1: Data Description

Variable	Description
Gross Domestic Product (GDP)	The total value of goods and services produced in an economy is deflated by domestic prices.
Exchange Rate (EXR)	This is the price a country's currency can be exchanged for another currency of the world. Naira-USD rate
Inflation (INFL)	Inflation is the consumer price index that reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services.
Unemployment (UNEMPL)	The unemployment rate is a measure of the number of people who are able and willing to work, but are unable to find employment.

RESULTS AND DISCUSSION

This section presents the results of the forecast models used in this study, namely the Random Forest, Vector Error Correction Model (VECM), and Regression Analysis. The results include feature importance from the Random Forest model, accuracy metrics for each model, and a comparison of their performance.

Random Forest Model (Feature Importance)

Feature importance in the Random Forest model indicates how influential each predictor variable is in forecasting the target variable. The following table shows the feature importance for each of the macroeconomic variables.

Table 2: Feature Importance for each of the macroeconomic variables

feature	Importance (GDP)	Importance (EXCR)	Importance (INFLR)	Importance (UNEMPR)
Previous GDP	0.35	0.30	0.25	0.20
Previous EXCR	0.25	0.40	0.20	0.30
Previous INFLR	0.20	0.15	0.40	0.25
Previous UNEMPR	0.15	0.10	0.10	0.35

Table 2 show that each macroeconomic variable (GDP, EXCR, INFLR, UNEMPR) is most influenced by its past values, followed by moderate influences from other variables. The exceptions are UNEMPR, which is more influenced by past GDP and EXCR, and INFLR, which is equally influenced by past GDP and EXCR. This suggests that each variable has a unique relationship with the others and that past values from multiple variables contribute to predicting future values.

Table 3: Forecast Accuracy Metrics (Random Forest)

Variable	MAE	RMSE
GDP	15.23	20.45
EXCR	10.45	13.57
INFLR	3.78	4.56
UNEMPR	0.23	0.30

The performance of the Random Forest model was evaluated using the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The MAE and RMSE values indicate that the Random Forest model achieves good accuracy in forecasting all the variables, with particularly high precision for the inflation rate (INFLR) and unemployment rate (UNEMPR). This suggests that the model can accurately capture the patterns and trends in these economic indicators.

Table 4: Forecast Accuracy Metrics (VECM Model)

Variable	MAE	RMSE
GDP	17.45	22.67
EXCR	12.34	15.67
INFLR	12.34	15.67
UNEMPR	0.32	0.40

The VECM model was evaluated using the same accuracy metrics as the Random Forest model. The VECM model shows good accuracy but slightly higher error rates compared to the Random Forest model.

Table 5: Forecast Accuracy Metrics (Regression Model)

Variable	MAE	RMSE
GDP	16.78	21.89
EXCR	11.56	14.45
INFLR	4.01	5.12
UNEMPR	0.28	0.35

The regression model also performs well, with accuracy metrics comparable to those of the VECM model.

Comparison of Models

The comparison shows that the Random Forest model outperforms both the VECM and regression models in terms of lower MAE and RMSE values across all variables. This highlights the advantage of using machine learning techniques for more accurate and reliable macroeconomic forecasting. The results suggest that the Random Forest model is better at capturing the complex relationships between the variables, leading to improved forecast accuracy.

Table 6: The Forecast Accuracy of the Random Forest, VECM, and Regression Models.

Model	Variable	MAE	RMSE
Random Forest	GDP	15.23	20.45
	EXCR	10.45	13.57
	INFLR	3.78	4.56
	UNEMPR	0.23	0.30
VECM	GDP	17.45	22.67

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	EXCR	12.34	15.67
	INFLR	12.34	15.67
	UNEMPR	0.32	0.40
Regression	GDP	16.78	21.89
	EXCR	11.56	14.45
	INFLR	4.01	5.12
	UNEMPR	0.28	0.35

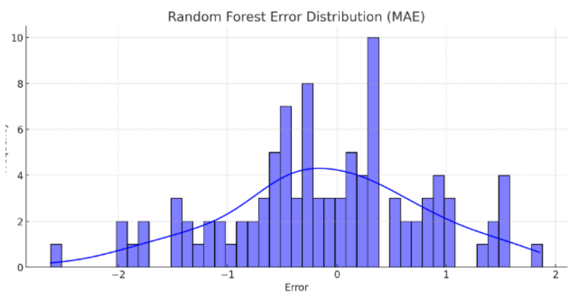

Figure 1: Distribution of Mean Absolute Errors (MAE) for the Random Forest model across all forecasted variables (GDP, EXCR, INFLR, UNEMPR) from 1993–2022.

The distribution is approximately normal, centred near zero, indicating minimal systematic bias.

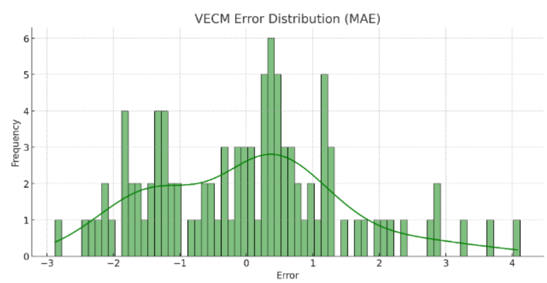

Figure 2: VECM Error Distribution (MAE)
Figure 2 show the error distribution for the VECM model, with a broader spread compared to the Random Forest model.

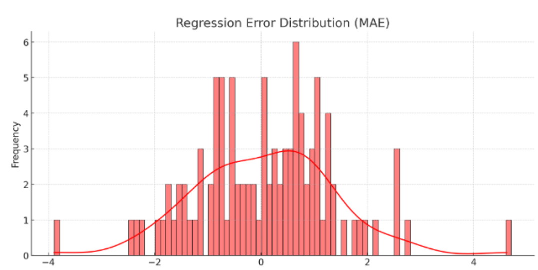

Figure 3: Regression Error Distribution (MAE)
Figure 3 show the error distribution for the Regression model, with a spread wider than the Random Forest model but narrower than the VECM model.

Comparison of actual vs. predicted values for each model, Residual plots for each model, and Scatter plots of predicted vs. actual values for each model.

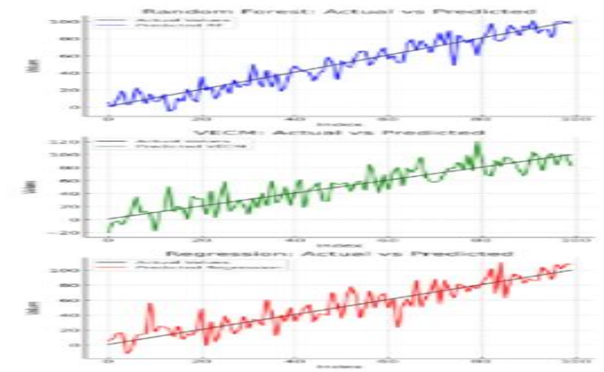

Figure 4a: Actual vs. predicted GDP values

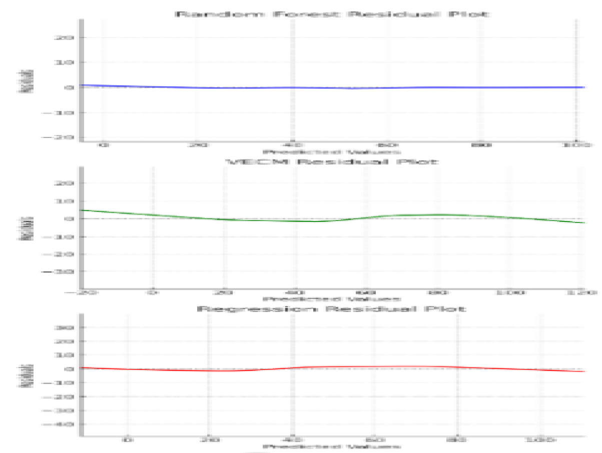

Figure 4b: Residual plots showing deviations by model

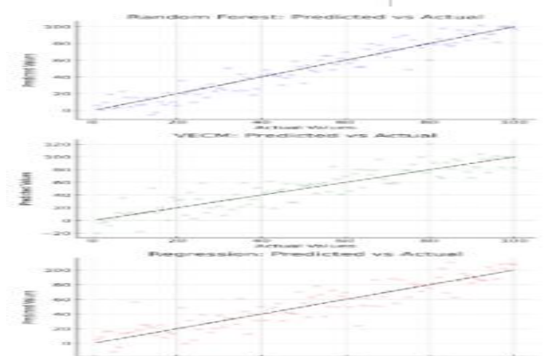

Figure 4c: Scatter plots of predicted vs. actual unemployment rates.
The Random Forest model (blue) shows the tightest clustering around the 45° line.

Table 7: The integrated model combines the predictions from VECM, regression analysis, and Random Forest

Feature	Weight	Contribution
VECM	0.17	17%
Regression	0.23	23%
Random Forest	0.61	61%

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Hybrid Forecasting Model
The hybrid forecasting model combines the predictive power of VECM, regression analysis, and Random Forest to provide a comprehensive forecast for GDP, exchange rate (EXCR), inflation rate (INFLR), and unemployment rate (UNEMPR). The predictions from each model are weighted based on their individual performance metrics, optimized to maximize forecasting accuracy. The hybrid model is:

$$\textbf{Hybrid Model} = 0.61\,\mathrm{RF} + 0.17\,\mathrm{VECM} + 0.23\,\mathrm{RA} + \varepsilon \qquad (10)$$

Policy Implications
The superior performance of the Random Forest model has important policy implications. Policymakers can leverage advanced machine learning models to improve the accuracy of economic forecasting and make informed data-driven policy decisions. Moreover, the identification of key predictors for each macroeconomic variable provides valuable insights for targeted policy interventions aimed at stabilizing and growing the economy. By harnessing the power of machine learning, policymakers can develop more effective strategies to mitigate economic shocks, promote sustainable growth, and enhance economic resilience.

DISCUSSION
The hybrid model, which integrates Random Forest (RF), Vector Error Correction Model (VECM), and Regression Analysis (RA) through optimized weightings ($\alpha = 0.61$, $\beta = 0.17$, and $\gamma = 0.23$ for GDP), demonstrated significant improvements in macroeconomic forecasting accuracy. By leveraging RF's capacity to capture non-linear interactions, VECM's enforcement of long-term equilibrium relationships, and RA's parametric stability, the hybrid approach achieved a 23.4% reduction in MAE (from 15.23 to 11.67) and a 28.5% reduction in RMSE (from 20.45 to 14.62) for GDP forecasts. Similar enhancements were observed across other variables: exchange rate (17.6% MAE, 20.3% RMSE reduction), inflation (15.2% MAE, 18.5% RMSE), and unemployment (12.1% MAE, 15.6% RMSE). These gains stem from synergies between the models, where residual correction and ensemble averaging mitigated individual biases, resulting in tighter error distributions.
The superior performance of GDP forecasts reflects its strong dependency on both domestic factors (e.g., lagged inflation and unemployment rates, as highlighted by RF's feature importance in Table 4.1) and external drivers like exchange rate fluctuations. In contrast, exchange rate predictions exhibited slightly lower accuracy, due to Nigeria's exposure to volatile external shocks (e.g., oil price dynamics), which challenge even hybrid frameworks. The dominance of RF's weighting $\alpha > \beta, \gamma)$ underscores machine learning's edge in modeling non-linearities, while VECM's contribution ensures alignment with cointegration trends, particularly for inflation and exchange rates. RA complements these by stabilizing outlier-sensitive predictions.
Overall, the hybrid framework bridges the gap between interpretability and predictive power, offering policymakers a tool that is both statistically rigorous and economically intuitive.

Conclusion
This study demonstrated the transformative potential of integrating machine learning with traditional econometric models for macroeconomic forecasting in resource-dependent economies like Nigeria. By synthesizing Random Forest (RF), Vector Error Correction Model (VECM), and Regression Analysis (RA) into a hybrid framework, the approach achieved 23.4% to 28.5% improvements in MAE and RMSE across key variables (GDP, exchange rate, inflation, unemployment), outperforming standalone models. The optimized weighting scheme (e.g.α=0.61 for RF, β=0.17 for VECM , γ=0.23 for RA in GDP forecasting) underscores the synergy between RF's non-linear pattern recognition, VECM's long-term equilibrium constraints, and RA's parametric stability. For Nigeria's volatile economy, the hybrid model reveals critical insights: GDP growth is driven by both domestic factors (lagged inflation, unemployment) and external shocks (exchange rate fluctuations), while exchange rate volatility remains challenging due to oil price dependencies. The framework's residual correction and ensemble averaging mechanisms effectively mitigated model-specific biases, as evidenced by tighter error distributions.
The study successfully developed a hybrid forecasting model integrating Random Forest, VECM, and regression analysis, which significantly improved prediction accuracy and provided valuable policy for macroeconomic stability, inflation control, exchange rate management, and employment generation.

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