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Original Research

Comparative Analysis of ARIMA, SARIMAX, and Random Forest Models for Forecasting Future GDP of the UK in Relation to Unemployment Rate

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Abstract

Accurate forecasting of Gross Domestic Product (GDP) is crucial for policymakers, businesses, and investors. This research explores the use of SARIMAX, ARIMA, and Random Forest models to forecast GDP in the UK. The study investigates the relationship between GDP and the unemployment rate, considering historical GDP and unemployment data collected from the Office of National Statistics (ONS). Both SARIMAX and ARIMA models indicate a negative relationship between GDP and the unemployment rate, although the coefficients are not statistically significant. On the other hand, the Random Forest model has shown its supremacy when it comes to the accuracy of prediction. The results suggest that other factors may have a stronger influence on GDP fluctuations based on the empirical findings. Future research should consider additional variables and advanced modelling techniques to further explore the relationship between GDP and the unemployment rate, contributing to a deeper understanding of the UK economy and informing effective economic management.

Keywords: ARIMA, Forecasting, GDP, Random Forest models, SARIMAX.

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Introduction

Precise forecasting of GDP is of paramount importance for policymakers, businesses, and investors, as it provides crucial insights into a country's economic performance and facilitates decision-making processes (Gonzalez et al., 2022; Saâdaoui & Khalfi, 2022). The predictability of forthcoming GDP allows governments to frame effective fiscal policies, stimulates businesses to make informed investment decisions, and obliges individuals in planning their monetary activities (Hua, 2022). Academic research invariably acknowledges that a nation's economic metamorphosis and stability hinge on its Gross Domestic Product (GDP) as a benchmark of wealth, with various macroeconomic factors such as unemployment rate, inflation rate, exchange rate, foreign direct investment, and crude oil exports indicators playing significant roles, as documented in multiple scholarly works (Anthony and Emediong, 2021; Divya and Devi, 2014; Olalekan & Kamoru, 2020). Although national treasuries' economic forecasts have tried to forecast economic performance, the volatility of the economy and the intricate interplay of political, natural, social, and economic factors make precise predictions difficult and highlight the drawbacks of relying only on a few indicators (Muma & Karoki, 2022; Aisen & Veiga, 2011).

As of late, a variety of modelling methods, including traditional time series methods like ARIMA (AutoRegressive Integrated Moving Average), Artificial Neural Network (ANN) models (Bouznad et al., 2020; Zhang et al., 2019) and more sophisticated methods like SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous variables) and Random Forest models, have been used to forecast GDP. These models make use of various statistical and machine-learning techniques to identify the seasonality, patterns, and trends in GDP data. According to the Office for National Statistics, the UK economy underwent nought growth in the last quarter of 2022 but contracted by a larger-than-anticipated 0.5% in December (Smith, 2023). Thus, the UK economy encountered a period of stagnation in late 2022, anticipating a brief recession in 2023, accompanied by declining consumer confidence and business output (House of Common Library, 2023). In pursuit of prompt economic growth, developing nations, Uddin & Rahman (2022) observe, have acquired advanced technology from Western counterparts but often implemented ineffective policies, leading to a persistent elevation in unemployment which could have a substantial impact on the GDP of the nation. This study primarily concentrates on unemployment and its influence on GDP.

Statement of the Problem and Research Objective

Unemployment serves as a pivotal macroeconomic indicator reflecting labor market health and overall economic conditions (Thiede & Monnat, 2016; Voßemer et al., 2017). Fluctuations in the unemployment rate can exert significant ramifications on aggregate demand, consumer spending, and business investment, all of which hold the potential to impact GDP (Stockhammer et al., 2011; Cashin et al., 2018). The UK is projected to experience a more severe economic contraction than initially anticipated in comparison to other advanced G7 nations, as reported by the International Monetary Fund, exposing a conundrum portrayed by a restrained labour market and an economy that has not reintegrated as many individuals into employment as previously observed (Mathers, 2023). Therefore, this research seeks to address this complex challenge by developing an innovative GDP forecasting model that incorporates historical GDP data, unemployment data, and other relevant variables. By doing so, it aims to provide more accurate and reliable GDP forecasts that can better inform decision-makers and stakeholders in an ever-changing economic landscape.

Literature Review

Gross Domestic Product (GDP) forecasting is a crucial instrument for decision-making in economics. In recent years, machine learning, linear regression, and autoregression models have been used to forecast GDP (Maccarrone et al., 2021). The study by Hjazeen et al. (2021) explore the nexus between economic growth and unemployment in Jordan, employing the auto-regressive distributed lag (ARDL) model to reveal a negative correlation between the two variables during the period 1991-2019. Andrei et al. (2009) highlight the significance of the negative correlation between unemployment and real GDP growth, as predicted by Okun's law, in achieving optimal economic outcomes and managing inflationary pressures in Romania. Moreover, the study by Al-kasasbeh (2022) explores the validity of Okun's Law in Jordan's economy and finds support for the relationship between unemployment and economic growth. Policy recommendations concentrate on attracting FDI and implementing measures for labor and growth enhancement. Further, Azmi (2013) investigates the impact of macroeconomic variables (unemployment rate, interest rate, and government spending) on Malaysia's GDP using 30 years of data. The study finds a significant relationship, with unemployment rate negatively affecting GDP, while interest rate and government spending have a positive impact. To evaluate the effect of Micro, Small, and Medium-Sized Enterprises (MSMEs) and unemployment on the economic growth of Indonesia, Juanda et al. (2023) carried out a quantitative research study with multiple linear regression. The results showed that while unemployment also had a negative and large impact on Indonesia's overall growth, MSME expansion had a negative and significant impact on that growth.

After evaluating the trade-off between model simplicity and accuracy, Mohamed's (2022) study determined that the Autoregressive Integrated Moving Average (ARIMA) model is the optimal choice for estimating and forecasting the future trajectory of economic growth in Somalia. The selected model strikes a balance between being parsimonious, i.e., having a simple structure, and fulfilling the fitness criteria, i.e., accurately capturing the underlying patterns and dynamics of the Somali economy. According to a study conducted by Hussain et al. (2022), the research findings exhibit that the ARIMA model demonstrates superior rendition compared to the ANN (Artificial Neural Network) model when forecasting exchange rates. The ARIMA model yields forecasted values that closely align with the actual values. Additionally, in terms of GDP forecasting, the ARIMA model exhibits better accuracy with smaller forecast errors. In a study by Shahriar et al. (2021) focusing on atmosphere-related factors, it was found that both ARIMA and ANN-based models yielded more accurate results compared to other forecasting models. In their study, Anggraeni et al. (2017) compared the forecasting interpretation of ARIMAX and VAR models for rice prices where Results revealed that the ARIMAX model outperformed the VAR model. The study of Sharma et al. (2022) presents a comparison of the performance of models using exogenous variables to capture volatility dynamics in India and USA benchmark time series data, contributing to existing research in ARIMA and Prophet-based forecasting. This research has formed its first hypothesis based on this information.

H_0: The GDP of the UK is going down in future based on ARIMA model.

Alharbi & Csala (2022) introduce a forecasting framework employing the SARIMAX model to predict long-term performance in Saudi Arabia's electricity sector resulting in the superior performance of the SARIMAX model than simpler techniques, providing enhanced forecasting accuracy and adaptability to different dataset sizes. By the operating time series analysis and taking factors such as exogenous prices, and internal and external electricity flows into accounts, a SARIMAX model (1, 1, 2) × (3, 1, 0, 7) is identified as the best-fitting model for energy price forecasting (Wang et al., 2022). Li & Xu's (2023) study examines the use of Baidu Search Index to forecast tourist volume from mainland China to Macao, Hong Kong, and Thailand. Their SARIMAX model surpasses benchmark models, highlighting the valuable contribution of search engine data to tourism demand forecasting. Both SARIMAX, an extension of the SARIMA model incorporating time series covariates, and the classical linear regression model (LR) are used for GDP forecasting (Maccarrone et al., 2021). However, their results indicate that both SARIMAX and LR models tend to overestimate GDP predictions.

H_1: The GDP of the UK is going down in future based on SARIMAX model.

H_2: The nexus between unemployment rate and GDP growth is negative.

Several scholars have utilized Machine learning predictive algorithms for GDP forecasting. Chu & Qureshi (2022) compare forecasting methods for U.S. GDP growth and find that density-based machine learning outperforms sparsity-based methods for short-term forecasts, while parsimonious models with strong high-frequency clairvoyants outperform complicated models with many low-frequency predictors for long-term forecasts. Ensemble machine learning performs better than deep learning. Velidi (2022) aims to employ machine learning algorithms to forecast global GDP, assess its annual growth rate, and understand the consequential variables, demonstrating the significance of GDP as an indicator of an economy's size and functioning. The study also visualizes the comparison of GDP growth rates among countries and evaluates the impact of various parameters on GDP. Moreover, the study of Khairani et al. (2022) utilizes Random Forest classification to predict the upcoming quarter's economic blossoming in Indonesia, using online news data from January to March 2021, achieving 96.51% accurateness and recognizing three incorrectly predicted GDP categories. Further, Ghosh & Ranjan (2023) conduct research on different methodologies for nowcasting and forecasting real GDP growth in emerging market economies, comprising traditional time series and machine learning techniques, along with financial market data and an economic uncertainty index, leading to improved nowcasting performance. In Xue's (2022) study, the influence of the digital economy on macroeconomic oscillations is analyzed through the construction of early warning indexes for digital infrastructure using principal component analysis. By employing Random Forest Regression (RFR), the research identifies the importance of digital infrastructure, capital formation, and human resources in China's economic growth, providing insights for forecasting. The findings reveal that the application of digital infrastructure has a stronger impact on the economy compared to its construction, with regional riffs and a greater influence on the economically developed eastern region. Random Forest demonstrates effectiveness as a machine learning approach in this research. This will lead to the third hypothesis:

H_3: The GDP of the UK is going down in future based on Random Forest model.

Research Methodology

Research Design

This research embraces a quantitative research design to investigate the relationship between Gross Domestic Product (GDP) and the unemployment rate in the United Kingdom over the period from 2007 to 2023. The research design encompasses data collection, data pre-processing, and the application of two preliminary forecasting models: SARIMAX and ARIMA and Random Forest Models.

Workflow

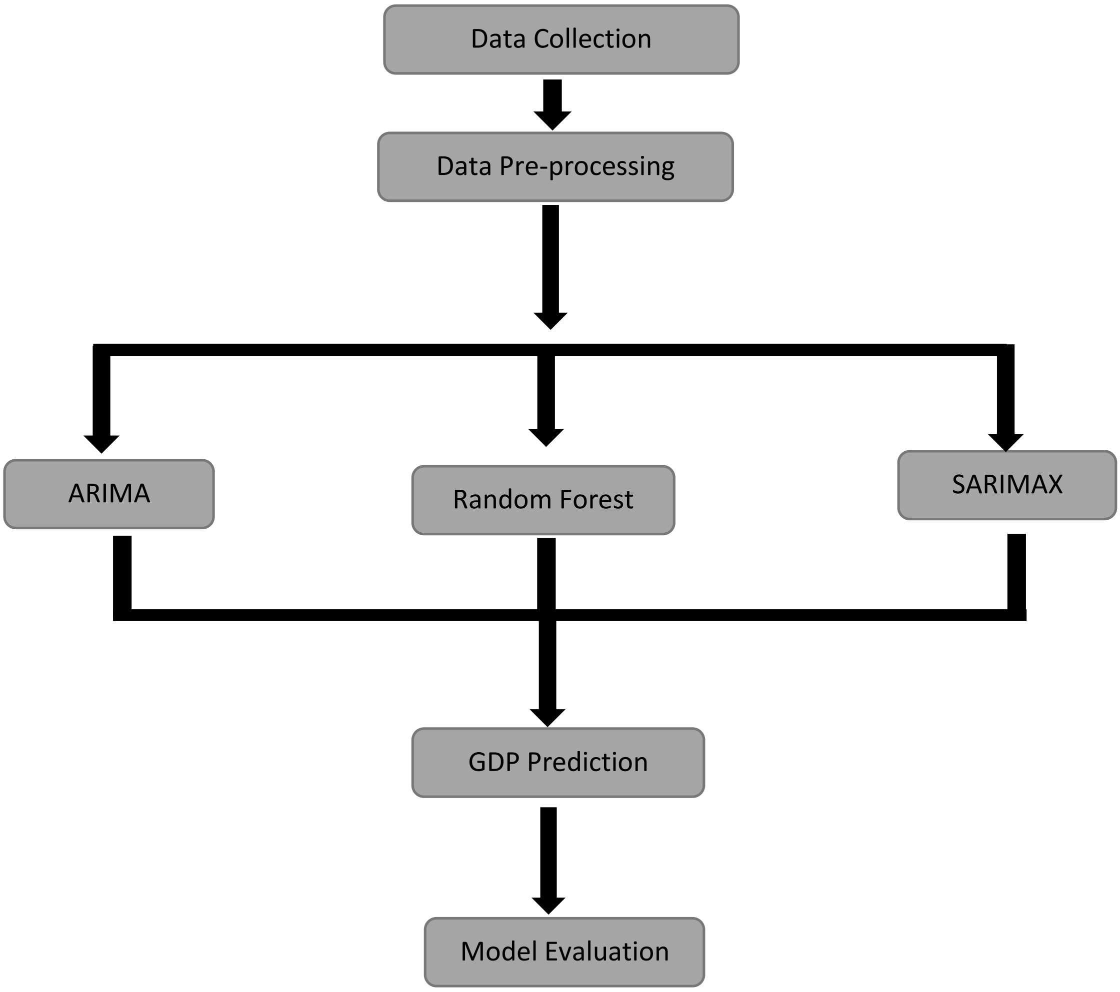

Figure 1: The workflow of the study

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Data Collection

The data for this research study is collected from the Office for National Statistics (ONS), which is a reliable and authoritative source for economic indicators in the UK. Specifically, the following datasets are obtained between 2007 and 2023. The historical Gross Domestic Product (GDP) for the UK is collected from the ONS database. This dataset provides information on the monthly GDP figures, reflecting the economic output of the country over time. Afterwards, Unemployment Rate dataset containing the historical unemployment rate in the UK is also sourced from the ONS. This dataset records the percentage of the labour force that is unemployed over a given period on a monthly basis. The data from these sources ensures the accuracy and reliability of the research findings and allows for a comprehensive analysis of the relationship between GDP and unemployment rate in the UK.

Data Pre-processing

Data transformations were carried out such as converting data types or normalizing variables. Merge the GDP and unemployment rate datasets into a single cohesive dataset for analysis.

Model Selection

SARIMAX (1,1,1,12) Model: The SARIMAX model, renowned for its efficacy in economic forecasting, was chosen. It is designed to handle time series data. In this context, the unemployment rate was introduced as an exogenous variable, acknowledging its significant impact on labour market dynamics and its relationship with economic output. The SARIMAX model can be represented in equation format as follows:

$$y_t = \alpha + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \ldots + \beta_k x_{k,t} + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \theta_1 e_{t-1} + \ldots + \theta_q e_{t-q} + e_t \quad (1)$$

The variable y_t signifies the value of the dependent variable at a specific time. The constant term α serves as the baseline or intercept of the model. Coefficients $\beta_1, \beta_2, \ldots \beta_k$ are linked to k explanatory variables $x_{1,t}, x_{2,t} \ldots x_{k,t}$ which contribute to y_t. Autoregressive terms $\phi_1, \phi_2, \ldots, \phi_p$ incorporate p lagged observations. Moving average terms $\theta_1, \theta_2, \ldots, \theta_q$ encompass q lagged error terms e_{t-1}, $e_{t-2}, \ldots$, e_{t-q} affecting y_t. Lastly, represents the error term at time e_t at time t, encapsulating unobservable factors and model residuals.

ARIMA (1,0,0) Model: for the purpose of comparative analysis, this research will deploy the ARIMA model which is also capable of handling time series data with appropriate model parameters having the unemployment rate as an exogenous variable in the ARIMA model. The ARIMA (with exogenous variable) model can be represented in equation format as follows:

GDP(t) = c + ϕ1 * GDP(t-1) + θ1 * ε(t-1) + β * unemployment_rate(t) + ε(t) (2)

The model includes several key components for analyzing GDP dynamics over time. GDP at time t is represented as GDP(t), while the intercept term is denoted as c. The autoregressive coefficient of lag 1 is ϕ1, accounting for the influence of GDP's past value (GDP(t-1)). Similarly, the moving average coefficient of lag 1 is θ1, considering the impact of the previous period's residual term (ε(t-1)). The coefficient β signifies the effect of the exogenous variable, specifically the unemployment rate, denoted as unemployment_rate(t). The model also encompasses residual terms ε(t) at each time point, representing the model's error term.

Data Analysis

The selected models (SARIMAX and ARIMA) were implemented using Python's statsmodels library, with suitable model parameters configured, including the order of differencing, autoregressive order, moving average order, and seasonal order. These models allow for a comprehensive evaluation of the connection between GDP and the unemployment rate in the UK, considering the cyclical nature of the economy and the intricate interplay between labor market conditions and economic performance. Through rigorous data analysis, this research aims to provide valuable insights into the dynamics of GDP forecasting and its correlation with unemployment rates in the UK over the specified timeframe. Further, Random Forest was implemented owing to its robust predictive ability to make the comparative studies more comprehensive.

Empirical Findings/Result

Table 1. Findings of SARIMAX and ARIMA Models

	ARIMA	SARIMAX
AIC	774.770	761.897
BIC	787.770	777.862
Ljung-Box (L1) (Q)	18.02	16.18
Jarque-Bera (JB)	60142.60	51621.92
Sigma value	2.9570	3.2088
Skew	-7.38	-7.32
Heteroskedasticity	19.93	23.88
Coef	-1.9059	-1.3332
Standard error	1.978	2.222

The results (Table 1) show that the SARIMAX model appears to perform better than the ARIMA model for forecasting the monthly GDP in the UK. The SARIMAX model exhibits a lower AIC value (761.897) compared to the ARIMA model (774.770), indicating a better fit. Additionally, the SARIMAX model shows lower values for the Ljung-Box test (Q-statistic) and Jarque-Bera test (JB-statistic), suggesting better residuals' independence and normality assumptions. The SARIMAX model also has a lower skewness value (-7.32) compared to the ARIMA model (-7.38), indicating a better balance in the distribution of residuals. Furthermore, the SARIMAX model has a lower sigma value (3.2088) compared to the ARIMA model (2.9570), indicating a more accurate estimation of the error variance. It is worth noting that both models exhibit significant heteroskedasticity.

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Further, the coefficient of the unemployment_rate variable in the ARIMA model is -1.9059 with a standard error of 1.978, while the coefficient of the SARIMAX model is -1.3332 with a standard error of 2.222 In both models, the coefficient of the unemployment_rate variable is negative, indicating a negative relationship between GDP and the unemployment rate. The coefficient of the unemployment_rate variable in the ARIMA model (-1.9059) and the SARIMAX model (-1.3332) represents the estimated impact or effect of a one-unit increase in the unemployment rate on the dependent variable of the respective models. In both models, a negative coefficient indicates an inverse relationship between the unemployment rate and the GDP growth. Specifically, a one-unit increase in the unemployment rate is associated with a decrease in the dependent variable. However, it should be noted that the p-value of the unemployment_rate coefficient is not statistically significant in both models. The p-value in the ARIMA model is 0.335 and in the SARIMAX model is 0.548. This suggests that the unemployment_rate variable may not have a significant effect on the forecasting performance of the models. Thus, when an attempt was made to include the unemployment_rate variable in the models, the results suggest that it may not be statistically significant in predicting monthly GDP in the UK context which refers to conducting further research along with different exogenous variables on distinct time series analysis techniques including ARCH and GRACH models.

Table 2. Findings of Random Forest Models

Random	Forest
Mean Squared Error	0.2271916461538424
R-squared	0.9946163781315692

In light of the less statistical p-value observed in the SARIMAX and ARIMA models regarding the connection between GDP and the unemployment rate, an alternative prediction model was employed using the Random Forest algorithm of ensemble classification. This new model focused solely on GDP data and excluded the unemployment rate. The Random Forest model yielded a Mean Squared Error and an R-squared values (Table 2), indicating its high accuracy and strong explanatory power in forecasting GDP based on the selected features. It shows the unchanged GDP trend in future periods taking only GDP data into account.

Models' Forecasting

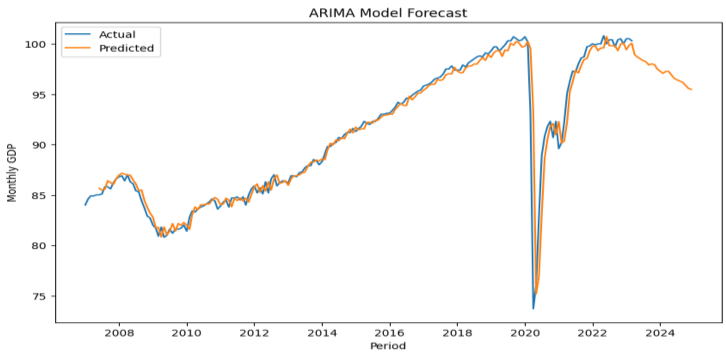

Figure 2: GDP forecast by ARIMA.

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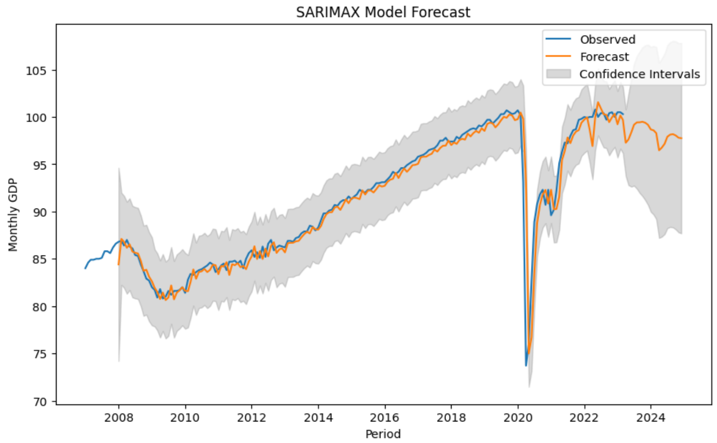

Figure 3: GDP forecast by SARIMAX.

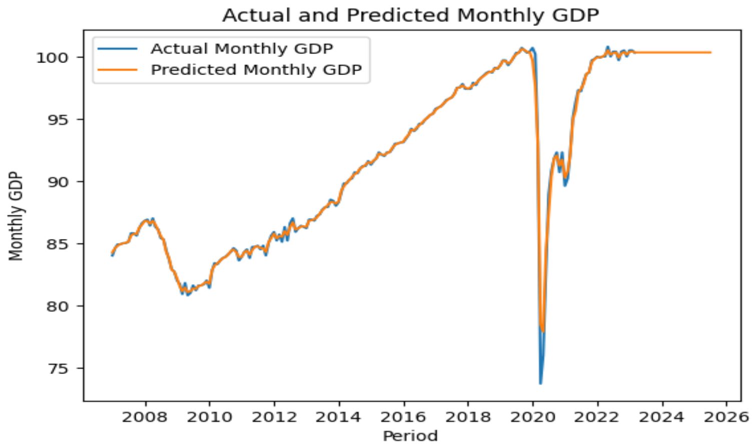

Figure 4: GDP forecast by Random Forest.

Discussions

The study used two models to predict the UK's GDP in the future: SARIMAX and ARIMA with an exogenous variable. The alternative hypothesis (H1) proposed that the GDP is declining based on the SARIMAX, contrary to the null hypothesis (H0), which claimed that the UK's GDP will decline in the future based on the ARIMA model. The idea that the UK's GDP will decline in the future was supported by both models (Figure 2 & 3).

The research aimed to examine the relationship between GDP and the unemployment trend in the UK. Both the ARIMA model and the SARIMAX model indicated a negative relationship between GDP and the unemployment rate, as evidenced by the negative coefficients of the unemployment rate variable (Table 1). However, it is crucial to remember that neither model's p-values for the unemployment rate coefficient were statistically significant. The p-value in the ARIMA model was 0.335, and in the SARIMAX model, it was 0.548. This shows that the unemployment rate variable may not have a substantial impact on the models' ability to accurately anticipate monthly GDP in

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the setting of the UK.

These findings raise the question of whether the unemployment rate variable is truly a significant predictor of GDP in the UK. While both models indicate a negative relationship, the lack of statistical significance suggests that other factors or variables may have a stronger influence on GDP fluctuations. It is important to consider alternative exogenous variables that may better capture the complex dynamics of the UK economy in future.

Hypothesis H3, suggesting a future decline in the UK's GDP based on the Random Forest model, was neither ratified nor disowned. Instead, the findings indicate a projected trend of GDP stagnation (Figure 4). Thus, it is highly recommended to explore potential factors contributing to this unexpected outcome and suggest future research avenues to gain a deeper understanding of the UK's economic trajectory deploying other predictive algorithms.

To further investigate the relationship between GDP and the unemployment rate, future research could explore the inclusion of additional variables that have been identified as potential drivers of GDP fluctuations, such as inflation rates, interest rates, or government policies. Additionally, employing more advanced time series analysis techniques, such as ARCH (Autoregressive Conditional Heteroscedasticity) or GRACH (Generalized Autoregressive Conditional Heteroscedasticity), may offer insights into the presence of conditional heteroscedasticity or nonlinear relationships that could impact the relationship between GDP and the unemployment rate.

Further research is warranted to enhance our understanding of the relationship between GDP and the unemployment rate in the UK. By exploring different exogenous variables and employing advanced modelling techniques, a more comprehensive analysis can be conducted to identify the key drivers of GDP fluctuations and their respective impacts on the unemployment rate. This will contribute to a deeper understanding of the dynamics of the UK economy and provide policymakers with valuable insights for effective economic management and policy formulation.

Conclusions

In conclusion, this research sought to forecast the Gross Domestic Product (GDP) of the UK using SARIMAX, ARIMA, and Random Forest models. The findings suggest that both SARIMAX and ARIMA models indicate a negative nexus between GDP and the unemployment rate, although the coefficients were not statistically momentous. This implies that the unemployment rate may not have a substantial impact on accurately predicting monthly GDP in the UK.

The study highlights the need to consider other factors or variables that may have a stronger influence on GDP fluctuations. Future research should explore the inclusion of additional variables such as inflation rates, interest rates, or government policies, which may provide better insights into the dynamics of the UK economy. Utilizing advanced time series analysis techniques like ARCH or GRACH could also uncover nonlinear relationships or conditional heteroscedasticity that could impact the relationship between GDP and the unemployment rate.

Enriching the understanding of the affinity between GDP and the unemployment rate in the UK is paramount for effective economic management and policy formulation. By conducting comprehensive analyses that consider various exogenous variables and employ advanced modelling techniques, policymakers can make informed decisions to promote economic stability and growth. Continued research in this area will contribute to a deeper understanding of the dynamics of the UK economy and provide valuable insights for future forecasting and policy implementation.

Abbreviations (Nomenclature)

GDP	Gross Domestic Product
C	Intercept term
β	Regression coefficients
Φ	Autoregressive coefficient
Θ	moving average coefficient
ε	lagged residual term
β	coefficient of the exogenous variable
H_0	Null hypothesis
e_t	Error term
p-value	Probability value
R	Pearson correlation coefficient

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