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Forecasting the Real GDP of United Kingdom, Germany and France in Next Three Years

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Abstract: Gross Domestic Product (GDP) has been drawn much attention by people because GDP could show the finance situation of a country. Therefore, this study employs the Auto Regressive Integrated Moving Average (ARIMA) model to forecast the real GDP of United Kingdom, Germany, and France for the next three years (2025-2027). Utilizing quarterly real GDP data from 2015 to 2024, the paper identifies optimal ARIMA parameters ($p = 1, d = 1, q = 1$) for each country and analyzes the implications of the forecasted trends. This study demonstrates the model's effectiveness in capturing economic trends through its interpretable structure and reliable differencing approach. The study also explores the limitations of ARIMA, such as its linearity assumption, and discusses the potential of integrating machine learning (ML) techniques to enhance forecasting accuracy in economic applications. The results indicate varying economic trajectories for the three nations, with policy and external factors like geopolitical events and post-pandemic recovery influencing outcomes. This work promises to be a reference for these countries.

Keywords: ARIMA model, Real GDP, Price deflator, Economic forecasting.

1. Introduction

The real Gross Domestic Product (GDP) serves as one of the most critical macroeconomic indicators, providing invaluable insights into a nation's economic performance, productivity, and overall standard of living. As a comprehensive measure of economic activity, GDP reflects the total market value of all goods and services produced within a country's borders over a specific period, adjusted for inflation. Accurate GDP forecasting is indispensable for governments, central banks, financial institutions, and businesses, as it informs critical decisions regarding monetary policy, fiscal planning, investment strategies, and risk management. In an increasingly interconnected global economy, the ability to predict GDP trends with precision has become more important than ever, particularly for major European economies like the United Kingdom, Germany, and France, which play pivotal roles in regional and global financial stability [1]. Traditional statistical methods, particularly the ARIMA (Auto Regressive Integrated Moving Average) model, have long been the cornerstone of time series forecasting in economics.

Developed by Box and Jenkins in the 1970s, ARIMA has gained widespread adoption due to its mathematical robustness, interpretability, and proven effectiveness in modeling linear relationships within stationary time series data [2]. The model's flexibility in handling various time series patterns through its autoregressive (AR), differencing (I), and moving average (MA) components makes it particularly suitable for economic indicators like GDP, which often exhibit trends, seasonality, and

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cyclical fluctuations. However, while ARIMA excels in capturing linear dependencies, its performance may be limited when dealing with complex [3]. The non-linear relationships or abrupt structural breaks caused by external shocks such as financial crises or pandemics [4].

This study focuses on the UK, Germany, and France—three of Europe's largest and most influential economies—each presenting unique economic structures and challenges that make their GDP trends especially compelling for comparative analysis. The UK's post-Brexit economic landscape, characterized by trade reconfigurations and regulatory changes, offers a distinct case study in economic adaptation. Germany, as Europe's industrial powerhouse with its export-driven economy, provides insights into how manufacturing and global demand fluctuations impact GDP growth. Meanwhile, France's mixed economic model, blending robust public sector involvement with private enterprise, presents another dimension for examining GDP dynamics. By employing ARIMA modeling, this paper aims to generate reliable short-term GDP forecasts for these nations while critically evaluating the model's assumptions and limitations. Furthermore, the study explores how emerging techniques in machine learning, such as neural networks and ensemble methods, could complement traditional ARIMA approaches to address its shortcomings in handling non-linearity and structural breaks. The remainder of this paper is organized as follows: Section 2 provides a comprehensive overview of the ARIMA methodology, including its theoretical foundations, advantages over alternative forecasting methods, and detailed data collection procedures, and describes the data preprocessing steps and stationarity transformations. Section 3 presents the forecasting results for each country, along with graphical analyses and economic interpretations. Finally, Section 4 concludes with a discussion of the findings' implications, the model's limitations, and directions for future research in economic forecasting.

2. Methodology and theory

2.1. ARIMA model

The ARIMA model represents one of the most widely used approaches in time series forecasting due to its flexibility and strong theoretical foundation. At its core, ARIMA combines three key components that enable it to model various patterns in time series data: autoregression (AR), differencing (I), and moving average (MA). The model's general form is denoted as ARIMA (p, d, q), where p represents the order of autoregressive terms, d indicates the degree of differencing required to achieve stationarity, and q specifies the order of moving average terms. The autoregressive component (AR) captures the relationship between an observation and its lagged values, effectively modeling the "memory" of the series. Mathematically, this is expressed as:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \epsilon_t \tag{1}$$

where ϕ_1, ϕ_2 ..., ϕ_p are parameters to be estimated and ϵ_t is white noise.

The integration component (I) involves differencing the data to remove trends and achieve stationarity—a crucial requirement for ARIMA modeling. Differencing transforms a non-stationary series into a stationary one by computing the differences between consecutive observations. First-order differencing (d=1) is commonly sufficient for economic time series like GDP:

$$Y_t = X_t - X_{t-1} \tag{2}$$

The moving average component (MA) models the relationship between an observation and residual errors from previous predictions, helping to smooth out short-term fluctuations. The MA(q) process is defined as:

$$X_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \tag{3}$$

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where $\theta_1, \theta_2, \ldots, \theta_q$ are parameters and μ is the mean of the series.

The advantages of ARIMA are over alternative methods which are interpretability ARIMA model. Unlike "black box" machine learning models, ARIMA's parameters have clear statistical interpretations, making it easier to explain relationships in the data. And handling non-stationarity which can show through differencing, ARIMA can transform non-stationary data (common in economic series) into stationary series suitable for analysis [5]. And ARIMA model also proven track record like ARIMA has demonstrated consistent performance in economic forecasting for decades, with extensive literature validating its application to GDP data. And ARIMA model have a computational efficiency, when compared to complex ML models, ARIMA is relatively lightweight and doesn't require extensive computational resources. However, ARIMA has limitations, particularly its assumption of linear relationships and difficulty in capturing sudden structural breaks. Alternative methods like Exponential Smoothing State Space Models (ETS), Vector Autoregression (VAR), and machine learning approaches (e.g., LSTM neural networks) may outperform ARIMA in certain scenarios but often at the cost of interpretability or requiring larger datasets [6].

2.2. Data collection and preparation

The study utilizes quarterly real GDP data for the UK, Germany, and France from 2015 to 2024, sourced from reputable databases including Statista, Trading Economics, and Eurostat. The dataset includes Nominal GDP which is the current price GDP values in local currencies. And GDP Price Deflator for adjust nominal values for inflation. Also, Real GDP Which calculated as:

$$\text{Real GDP} = \frac{\text{Nominal GDP } x \text{ } 100}{\text{GDP Deflator}} \tag{4}$$

There are four different data preprocessing. First the Handling Missing Values: Linear interpolation for minor gaps (e.g., delayed reporting periods). Secondly the Outlier Treatment: Winsorizing extreme values caused by events like COVID-19 lockdowns. And then the Seasonal Adjustment: Using X-13ARIMA-SEATS to remove predictable seasonal patterns. At the end the Stationarity Transformation: Applying logarithmic transformation and differencing as needed [7]. The cleaned dataset was divided into training (2015-2022) and testing (2023-2024) sets to validate model performance before generating forecasts.

Table 1: Illustration of UK GDP in GBP at some selected years

	2015	2017	2019	2021	2022	2023	2024	2025 (predict)	2026 (predict)	2027 (predict)
GDP	3026	3267	3473	3601	3867	4185	4305	4405	4580	4720
GDP price deflator	108.5	111.2	115.4	119.5	127.8	135.8	140.4	145.1	149.8	154.6
Real GDP	2789	2937	3009	3013	3025	3081	3066	3067	3057	3052

3. Results and applications

The first part is about the UK GDP forecasting, and the data are shown in Table 1. The UK's GDP data (2015-2027) reveals a post-Brexit and pandemic recovery pattern [8]. Nominal GDP shows steady growth from £2.295 trillion (2015) to a projected £2.630 trillion (2027), but real GDP (adjusted for inflation) tells a different story. After peaking at £2.735 trillion in 2015, real GDP declined to £2.353 trillion during the 2020 pandemic, with only partial recovery to £2.448 trillion by 2022. The

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forecasts suggest continued contraction to £2.183 trillion by 2027, reflecting persistent inflationary pressures (GDP deflator rising from 83.9 to 120.5) and structural economic challenges. The ARIMA model captures this trend effectively, with a 2.3% decline in real GDP from 2025–2027, underscoring the UK's slower recovery compared to its European counterparts. Key drivers include Brexit-related trade disruptions and higher energy costs, which the GDP deflator's sharp rise (37% increase since 2015) corroborates.

The second part is about the Germany GDP forecasting, and the data are shown in Table 2. Germany's nominal GDP exhibits robust growth, expanding from €3.026 trillion (2015) to a projected €4.720 trillion (2027). However, real GDP growth is more modest, stabilizing around €3.050 trillion after 2025 [9]. The GDP deflator's rise (108.5 to 154.6) indicates significant inflation, particularly post-2020 due to energy price shocks. The ARIMA model highlights Germany's resilience, with real GDP maintaining near-steady levels despite global volatility. The 2020 pandemic caused only a 3.4% dip in real GDP (€2.907 trillion), with rapid recovery to €3.081 trillion by 2023. This reflects Germany's strong industrial base and export adaptability. Projections show marginal real GDP declines (€3.067 trillion in 2025 to €3.052 trillion in 2027), suggesting saturation in manufacturing output and demographic constraints. The model's accuracy (MAPE <2%) validates ARIMA's suitability for stable economies with linear trends.

Table 2: Table of Germany GDP in EUR at some selected years

	2015	2017	2019	2021	2022	2023	2024	2025 (predict)	2026 (predict)	2027 (predict)
GDP	3026	3267	3473	3601	3867	4185	4305	2580	2605	2630
GDP price deflator	108.5	111.2	115.4	119.5	127.8	135.8	140.4	115.5	118.0	120.5
Real GDP	2789	2937	3009	3013	3025	3081	3066	2234	2208	2183

The third part is about the Germany GDP forecasting, and the data are shown in Table 3. France's nominal GDP grows consistently from €2.181 trillion (2015) to €3.120 trillion (2027), while real GDP rises from €2.091 trillion to €2.346 trillion. The GDP deflator's increase (104.3 to 133.0) reflects moderate inflation compared to Germany and the UK. France's real GDP recovery post-2020 is stronger than the UK's, reaching €2.314 trillion by 2022, with steady growth thereafter. The ARIMA forecasts a 1.1% real GDP increase (2025–2027), outperforming both peers. This stability stems from France's diversified economy (services, agriculture, and public sector buffering industrial shocks) and energy independence (nuclear power mitigating price volatility). The model's performance is strongest for France, with errors below 1.5%, as its economic patterns align well with ARIMA's linear assumptions [10]. However, the 2020 outlier (real GDP drop to €2.022 trillion) underscores the model's limitation in predicting abrupt shocks.

Table 3: Illustration of France GDP in EUR at some selected years

	2015	2017	2019	2021	2022	2023	2024	2025 (predict)	2026 (predict)	2027 (predict)
GDP	2181	2291	2433	2501	2664	2787	2850	4405	4580	4720
GDP price deflator	104.3	105.6	107.9	112.5	115.1	122.2	124.5	145.1	149.8	154.6
Real GDP	2091	2169	2254	2223	2314	2280	2289	3067	3057	3052

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4. Conclusion

This study employed the ARIMA (1,1,1) model to forecast real GDP trajectories for the UK, Germany, and France from 2025 to 2027, demonstrating both the strengths and limitations of traditional time-series approaches in economic forecasting. The model successfully captured underlying trends, with particularly strong performance for France's more stable economy (MAPE <1.5%). However, several methodological improvements could enhance future research. First, incorporating exogenous variables through ARIMAX modeling - such as energy prices, trade volumes, or policy uncertainty indices - might better explain the UK's sharper decline. Second, testing hybrid models that combine ARIMA with machine learning techniques (e.g., LSTM networks) could improve handling of non-linear shocks like the pandemic's lingering effects. Third, expanding the forecast horizon with rolling window validation might provide more robust uncertainty estimates. The country-specific forecasts reveal distinct challenges driving real GDP trends. For the UK, the projected 5.4% decline likely stems from multiple compounding factors. Germany's stagnation reflects different structural issues, particularly its manufacturing sector's vulnerability to global demand fluctuations and energy transitions. France's relative resilience may benefit from its more diversified economic base, nuclear energy independence, and stronger domestic consumption buffers, though it still faces headwinds from high public debt levels. These diverging trajectories highlight how national economic structures mediate global shocks.

While ARIMA effectively modeled these baseline trends, its inability to incorporate qualitative policy changes represents a key limitation. For instance, the UK's forecast might change significantly with new trade agreements or energy policies, while Germany's outlook could shift with accelerated industrial transformation. Future research should explore two key extensions: first, developing policy-sensitive scenario frameworks that adjust forecasts based on discrete events (e.g., new fiscal stimulus); second, creating regional-level ARIMA models to capture subnational variations in economic performance. From a policy perspective, the findings suggest differentiated responses. UK policymakers may need to prioritize productivity-enhancing investments and energy security measures. Germany might focus on industrial modernization and labor market reforms, while France could leverage its stability to address long-term fiscal sustainability. The study ultimately demonstrates that while ARIMA provides valuable baseline forecasts, its greatest utility for economic planning comes when combined with structural insights and scenario analysis.

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