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Inflation Prediction: A Hybrid Time-Series Approach

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Abstract

Accurately forecasting inflation is a vital aspect of economic strategy. However, it presents challenges due to its complex and often nonlinear nature, which is influenced by a range of external factors. This study explores an integrated modelling framework that leverages both traditional time series analysis and modern techniques to improve inflation prediction. Using economic data from Ireland and the United Kingdom, four hybrid models were developed by combining Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) with machine learning and deep learning algorithms, namely, Random Forest, Support Vector Regression, and Long Short-Term Memory networks. Among these, the Seasonal Autoregressive Integrated Moving Average with Exogenous Variables and Long-Short Term Memory (SARI-LSTM) model delivered the most consistent performance across key evaluation metrics, Mean Absolute Estimate (MAE), Root Mean Square Estimate (RMSE), and Mean Absolute Percentage Estimate (MAPE), effectively capturing both seasonal trends and sequential patterns in the data. The results highlight the benefit of combining traditional statistical techniques with modern modelling approaches to produce more reliable and interpretable forecasts. This method offers policymakers and economists valuable insights for managing the uncertainties of inflation.

Keywords: Inflation (Finance); Economic Forecasting; Deep Learning (Machine Learning); Time-series Analysis, Neural Networks (Computer Science)

1 Introduction

Inflation refers to the sustained increase in the general price level of goods and services over time, which consequently reduces the purchasing power of money (Investopedia, n.d.). According to Khan Academy (n.d.), the Consumer Price Index (CPI) is commonly used to monitor this change.

Inflation plays a significant role in shaping economic conditions and influences household spending, business investment, and central bank policies. While moderate inflation can sometimes signal a healthy economy, rapid price increases can lead to financial instability. One key factor affecting inflation is immigration. According to the immigration-disinflation theory, increased immigration can help lower inflation by expanding the labour supply, which may put downward pressure on wages (Arthur, 2024). However, this perspective may overlook the fact that immigrants also increase demand in the economy when they spend their earnings, which can counteract the disinflationary effect (Card, 2004).

Many economists, including those at the Federal Reserve, support this theory. For example, Fed Chair Jerome Powell has stated that immigration can lead to slightly higher unemployment and lower wage growth, even in a strong economy. This is because an increase in migrants expands the labour supply, which can place downward pressure on wages and reduce inflation in the short term (Arthur, 2024).

To better understand inflation, it is essential to examine the effects of both supply and demand. Data from the UK show that from the mid-1990s to 2015, the share of working-age immigrants rose from under 8% to over 13%, during which time house prices also surged (Office for National Statistics, 2015). In the same period, Ireland saw a sharp rise in its immigrant population from around 6% to over 17%, accompanied by notable growth in housing costs, reflecting heightened demand and constrained supply (Central Statistics Office, 2024). These examples underscore the interconnectedness of demographic trends, housing markets, and inflation and highlight the importance of considering multiple macroeconomic dimensions when analysing inflationary patterns.

Much of the existing literature on inflation forecasting tends to focus on either single-country studies or broad global models, often overlooking specific external influences such as changes in immigration patterns or fluctuations in housing markets. To address this gap, this research conducts a comparative analysis of Ireland and the United Kingdom, two countries with close geographic and historical ties but distinct economic structures, allowing for an examination of how these external factors may affect inflation dynamics differently across similar yet non-identical economies. The choice of Ireland and the UK as case studies is particularly relevant given their geographical proximity and shared historical context, yet they exhibit distinct economic characteristics and external influences (Coyle, 2018).

Traditional time series forecasting methods, such as Autoregressive Integrated Moving Average (ARIMA), have known limitations when dealing with the nonlinear and multifactorial nature of modern economic data. Therefore, this study introduces a hybrid modelling strategy combining the strengths of conventional statistical approaches with advanced techniques in machine learning, Random Forest (RF) and Support Vector Regression (SVR), which are capable of modelling complex, nonlinear relationships between macroeconomic variables (Geurts et al., 2006). This makes them well-suited for analysing the effects of external factors, such as immigration, on inflation dynamics. In addition, these methods can handle large datasets and capture intricate dependencies that may be overlooked by more rigid traditional models (Hastie et al., 2009).

By integrating these techniques, the hybrid framework was able to deliver improved forecasting accuracy, even under volatile economic conditions shaped by housing pressures and immigration trends. The study involved developing and testing multiple models using time-series data from both Ireland and the UK, comparing their predictive performance across several metrics. This approach allowed for an in-depth evaluation of how external variables influence inflation and demonstrated that hybrid models can provide more stability and precision during periods of economic uncertainty.

Beyond technical evaluation, this research offers broader insights into how macroeconomic and demographic variables interact. The findings have practical implications for policymakers, economists, analysts, and stakeholders in sectors such as real estate and public finance. Enhanced inflation forecasts can support better decision-making in monetary and fiscal policy.

The report outlines the modelling strategies used alongside the data collection process and methodology. Results are then presented and compared, followed by a discussion on the role of immigration and housing markets in shaping trends in inflation. The study concludes with key insights and practical recommendations to support future research aimed at improving inflation forecasting models in dynamic economic contexts.

2 Overview of Advanced Forecasting Models

2.1 Seasonal Autoregressive Integrated Moving Average with Exogenous Factors (SARIMAX)

The SARIMAX model is a powerful tool for forecasting long-term performance in the energy sector by incorporating seasonal and exogenous factors; this is demonstrated in a study forecasting Saudi Arabia's electricity sector from 2021 to 2050, where SARIMAX improved accuracy relative to simpler models (Alharbi & Csala, 2022). Additionally, SARIMAX has been evaluated against other models for predicting

COVID-19-related deaths, offering insights for future epidemic prediction (Sulistijanti & Khotimah, 2024).

2.2 Random Forest and Support Vector Regression

The evolution of machine learning has significantly advanced time-series forecasting, with models like Random Forest (RF) and Support Vector Regression (SVR) playing important roles. Messaoudi and Khouidmi (2024) demonstrated RF's superior performance in predicting economic growth, highlighting its accuracy and reliability over traditional methods. Similarly, Das and Das (2024) emphasise RF's effectiveness in capturing complex economic interactions during volatile periods such as the COVID-19 pandemic, showing its importance in providing accurate inflation forecasts.

In the context of a solar-assisted, liquid desiccant air-conditioning system, Daghigh et al. (2024) applied RF and SVR to predict key performance indicators, including mass removal rate, efficiency, and effectiveness. The study concluded that SVR with a Radial Basis Function (RBF) kernel provided the most accurate predictions for effectiveness, while RF demonstrated strong predictive performance for other indicators. Additionally, incorporating timestamps as model inputs significantly enhanced prediction accuracy, highlighting the importance of considering temporal and environmental factors, such as ambient temperature and solar radiation, when modelling complex systems.

2.3 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks, a type of deep learning model, have shown significant value in managing sequential data with long-term dependencies. Abuein et al. (2024) demonstrated the effectiveness of LSTM in forecasting stock market trends, where it outperformed SVR and enhanced trading strategies through improved predictive accuracy. Similarly, Foroutan and Lahmiri (2024) conducted a comparative analysis of deep learning models for predicting commodity prices and concluded that LSTM and its variants provide higher accuracy than traditional approaches, showing their superiority in handling complex, time-dependent data.

2.4 Hybrid Models

Hybrid models have gained popularity for enhancing forecasting accuracy by integrating the strengths of both traditional and advanced methodologies. (Mohammed, Arokiaraj and Roobini, 2023)demonstrated this by applying a hybrid ensemble learning approach, combining LSTM with other methods, to forecast the Indian Consumer Price Index, achieving greater accuracy than single models. Similarly, Aldabagh et al. (2023) developed a hybrid model using Convolutional Neural Networks (CNN) and LSTM to predict crude oil prices, showing superior performance over standalone models. Chojnowski (2023) introduced the Linear Smooth Transition Vector Autoregression (LSTVAR-ANN) hybrid model to analyse monetary policy effects and improve inflation forecasts by leveraging different economic dynamics across business cycles.

While advanced machine learning and deep learning models require substantial computational resources and may struggle with less volatile or smaller datasets, hybrid models address these challenges by providing more robust and generalizable forecasts. (Pereira et al., 2021) Highlight the limitations of ARIMA in capturing nonlinear trends, and its authors propose an optimised hybrid model using SVR and ARIMA to enhance prediction performance. This trend towards combining traditional and machine learning models reflects an effective strategy for tackling the complexities of modern economic landscapes.

3 Methodology: Advancing Hybrid Model Techniques for Improved Forecasting

3.1 Residual-Based Model Training (RMT) and Integration

A comprehensive modelling approach enhances inflation forecasting by integrating traditional, machine learning, and deep learning models. The process begins with the SARIMAX model, which extends the traditional ARIMA approach by incorporating exogenous variables. This makes it suitable for data with significant seasonal components and external influences, such as housing market trends and immigration data. SARIMAX effectively captures these patterns and provides a foundation for a hybrid approach:

$$SARIMA(p, d, q)(P, D, Q, m) + X(1) \tag{1}$$

where:

- p, d, q are non-seasonal order parameters for ARIMA.
- P, D, Q are seasonal order parameters.
- m refers to the number of observations in a seasonal cycle ($m = 52$ weeks for weekly data).
- X are exogenous variables (e.g. housing index and immigration data).

After fitting the SARIMAX model, the residuals representing the unexplained variance are used to train additional models. This residual-based training approach allows subsequent models to focus on capturing patterns and relationships not addressed by SARIMAX.

In the machine learning domain, both RF and SVR models are employed. RF, an ensemble learning algorithm, constructs multiple decision trees to improve prediction accuracy and minimise overfitting. It aggregates predictions from all decision trees to produce a final output, effectively handling complex, nonlinear relationships in the data. SVR, adapted for regression tasks, focuses on fitting the best line within a margin of tolerance, enhancing generalisation and reducing overfitting risks. It optimises the trade-off between the model's complexity and error tolerance, making it suitable for inflation prediction.

The deep learning component employs LSTM networks, which are known for handling sequential dependencies in time-series data. The multivariate LSTM model incorporates various input features such as the housing index, immigration data, stock indices, and macroeconomic variables, with inflation as the target variable. The architecture of LSTM, including forget, input, and output gates, allows it to capture long-term dependencies and trends influenced by multiple factors over time.

The hybrid framework leverages the residuals from SARIMAX to train RF, SVR, and LSTM models, leveraging their complementary strengths and enhancing the overall predictive performance. SARIMAX addresses seasonal and external factors, while RF and SVR handle complex nonlinearities; LSTM captures sequential dependencies. This layered approach ensures that each model contributes uniquely to refining the prediction, addressing both straightforward and complex trends in inflation data.

3.2 Hybrid Model Integration

Building on the residual-based model training approach, this study further enhances inflation forecasting by integrating various models into hybrid configurations. By combining different forecasting models, their strengths cause better inflation prediction. We developed four hybrid models, each designed to handle straightforward and complex inflation data trends.

1. SARI-SVR: This model combines SARIMAX's ability to handle seasonal and linear patterns with the robustness of SVR in high-dimensional spaces. It effectively captures both periodic trends and complex nonlinear influences. It builds on the residuals from SARIMAX to refine predictions with SVR's precision.
2. SARI-RF: This model integrates SARIMAX with RF and addresses both structured temporal patterns and nonlinear interactions. SARIMAX manages linear trends and seasonality, while RF captures complex variable relationships, using the residuals to enhance its predictive power.
3. RF-SVR: This combination leverages the nonlinear predictive strengths of SVR and RF, providing a nuanced approach to modelling complex, multidimensional relationships between predictors and the target variable. Focusing on the residuals enhances the model's ability to capture intricate patterns.
4. SARI-LSTM: This model pairs SARIMAX with LSTM networks to effectively address short-term seasonality and long-term trends. LSTM captures extended temporal patterns influenced by macroeconomic variables, using the residuals to improve its sequential dependency handling.

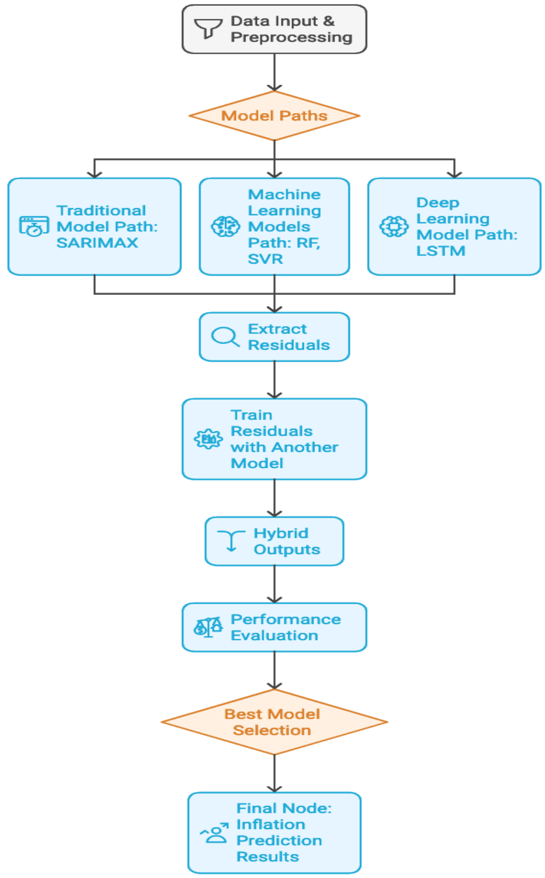

Figure 1. Proposed structure of the hybrid model

4 Evaluation Metrics

Various metrics are utilised to evaluate the models' performances in forecasting inflation, each offering a unique perspective on accuracy and reliability:

1. Mean Absolute Error (MAE): Provides an average measure of errors without regard to their direction; it is useful for gauging model performance with smaller variance data.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |yi - \hat{y}i| \tag{2}$$

2. Mean Squared Error (MSE): Emphasises larger errors, making it suitable for models like RF and SVR to assess their stability in volatile conditions by penalising significant deviations.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (yi - \hat{y}i)^2 \tag{3}$$

3. Root Mean Squared Error (RMSE): Converts MSE to the same units as the target variable to offer a more interpretable measure of average prediction error. It is particularly beneficial for analysing LSTM and hybrid model performance on long-term trends.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \quad (4)$$

4. Mean Absolute Percentage Error (MAPE): Expresses errors as a percentage, allowing for a relative comparison of prediction accuracy across different inflation rates and providing insight into nonlinear dependency handling.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{yi-\hat{y}i}{yi}\right| \times 100 \quad (5)$$

In these equations, n represents the total number of data points, yi the actual inflation rate for the data point, and $\hat{y}i$ the predicted inflation rate. Collectively, these metrics offer a comprehensive view of each model's effectiveness in capturing inflation trends, rendering their respective strengths and weaknesses visible.

5 Dataset Description, Evaluation, and Discussion

5.1 Datasets

This research adopts a quantitative approach, using historical data to analyse inflation trends in Ireland and the UK from 2000 to 2024. It integrates a wide range of macroeconomic variables, including inflation and interest rates, GDP, exchange rates, unemployment, immigration figures, and housing prices and stock indices. These indicators were selected to capture both economic and demographic factors that influence inflation.

Data was obtained from reputable sources such as the UK Data Service, CSO (Ireland), HM Land Registry, Yahoo Finance, and the Migration Policy Institute. These sources provided reliable and up-to-date information to support robust analysis. Where necessary, data were collected through direct extraction and supplemented with publicly available records. To ensure consistency across datasets, pre-processing steps were applied. Quarterly data were interpolated to weekly intervals to allow for uniform time-series modelling. Standard scaling techniques were used to normalise features, preventing larger-scale variables from disproportionately influencing the model outcomes. These steps helped establish a clean and structured dataset suitable for developing and evaluating forecasting models.

To support more accurate and reliable predictions, several engineering steps were taken. The process started with examining relationships between key economic indicators to check for multicollinearity, which could affect the model's performance. Then, the Fourier transform was applied to break down the time series into different frequency components. This helped uncover important seasonal patterns and long-term trends while reducing random noise. Based on this, Spectral Principal Component Analysis (PCA) was used to simplify the data by focusing on the most meaningful features, making the modelling process more efficient and focused.

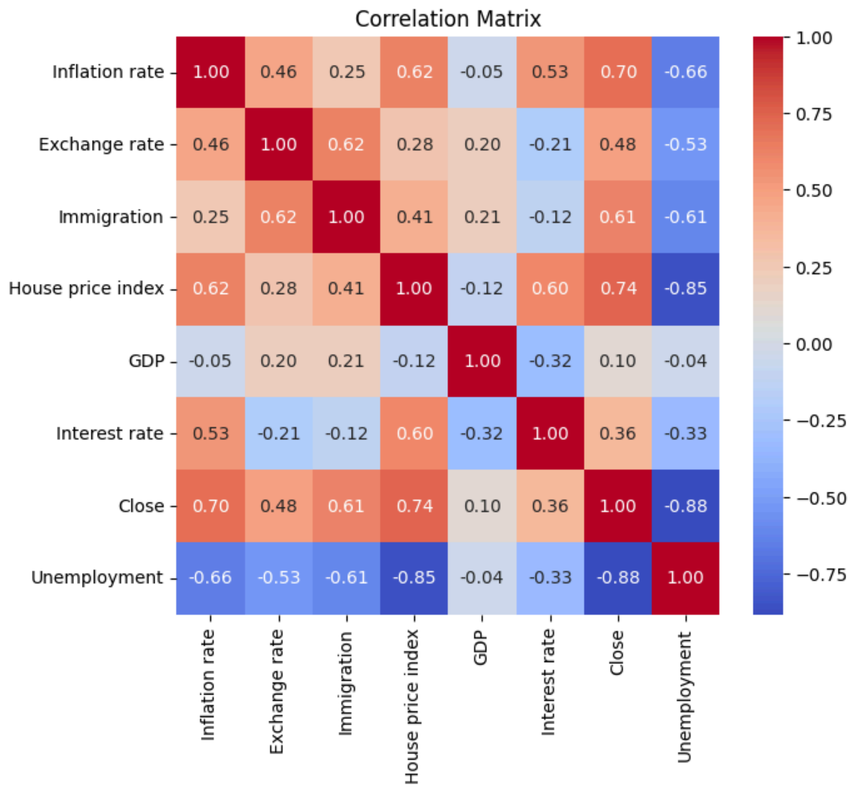

Figure 2. Correlation matrix heatmap

5.2 Evaluation of Core and Advanced Learning Models

Optimising the performance of inflation forecasting models for the UK and Ireland required careful tuning of hyperparameters for SARIMAX, RF, SVR, LSTM, and hybrid models. Table 1 shows the hyperparameters selected to enhance the model's performance.

5.3 Ireland: Model Performance Analysis

In Ireland, SVR emerged as the most effective standalone model, achieving low error metrics, as shown in Table 2. This indicates its capability to accurately capture inflation patterns. Among hybrid models, SARI-LSTM performed best. This model effectively integrated SARIMAX's seasonal forecasting with LSTM's ability to capture long-term dependencies and nonlinear patterns, providing a comprehensive understanding of inflation dynamics. In contrast, RF and LSTM showed higher error rates, highlighting their limitations in this context.

5.4 United Kingdom: Model Performance Evaluation

In the UK, hybrid models generally outperformed standalone models, as shown in Table 3. SARI-LSTM again stood out, achieving the lowest error metrics and demonstrating its strength in combining SARIMAX's linear and seasonal capabilities with LSTM's nonlinear modelling. This integration effectively handled both short-term and long-term inflation trends. Other hybrid models, such as SARI-SVR and SARI-RF, showed competitive performance but did not fully exploit nonlinear patterns as effectively as SARI-LSTM. The LSTM and RF models had higher error metrics, indicating challenges in capturing the UK's inflation dynamics. Overall, the results show the importance of hybrid models in enhancing prediction accuracy, particularly when dealing with complex inflation trends influenced by external factors and nonlinear relationships.

Table 1. Hyperparameter values used in the search process for all methods

Method	Search Hyperparameters	Ireland Values Used	UK Values Used
SARIMAX	*p*, *d*, *q* (ARIMA order)	(1, 1, 1)	(1, 1, 1)
	P, *D*, *Q*, *m* (Seasonal order)	(1, 1, 0, 12)	(0, 1, 1, 12)
	exogenous variables	Housing market data, immigration trends	Housing market data, immigration trends
Random Forest	n_estimators	300	300
	max_depth	10	10
	min_samples_split	10	10
	min_samples_leaf	4	4
SVR	C	1	0.1
	epsilon	0.3	0.3
	kernel	RBF	RBF
	gamma	auto	scale
LSTM	units	150	50
	dropout	0.3	0.3
	epochs	50	150
	batch_size	32	64

Method	Search Hyperparameters	Ireland Values Used	UK Values Used
	learning_rate	0.001	0.001
Hybrid	Combination of SARIMAX residuals and LSTM	Aggregation by addition	Aggregation by addition

Table 2. UK evaluation metrics result

Model	MAE	MSE	RMSE	MAPE
SARIMAX	1.360110457	3.427871656	1.84604216	40.0943852
SVR	1.873443877	8.270713431	2.875884808	40.83583922
RF	3.36597387	14.78348406	3.844929656	109.8109715
LSTM	3.77986103	13.64671376	3.694145877	100.0038479
SARI-SVR	1.357690659	3.35017913	1.830349456	40.65696842
SARI-RF	1.359932724	3.407853513	1.846037246	40.07446789
SVR - RF	2.023507394	8.849290413	2.974775691	46.86965143
SARI - LSTM	1.352255128	3.406692443	1.825722743	40.08913071

Table 3. Ireland evaluation metrics result

Model	MAE	MSE	RMSE	MAPE
SARIMAX	2.625656958	12.74533084	3.570060342	128.9773971
SVR	1.623683273	3.153826733	1.775901668	225.5405491
RF	2.490958831	9.124049783	3.020604208	159.5756332
LSTM	2.232144997	8.472941007	2.910831669	129..88208445
SARI-SVR	2.613142561	12.62117638	3.552629503	129.9081105
SARI-RF	2.613142561	12.62117638	3.552629503	129.9081105
SVR - RF	2.884829137	4.187982727	4.046456139	287.000321
SARI- LSTM	2.122272559	12.068813	3.0508424	128.4045034

5.5 Discussion on Predictive Accuracy

The SARI-LSTM model demonstrated the highest predictive accuracy for both Ireland and the UK. By combining SARIMAX's ability to model seasonal and linear trends with LSTM's capacity to capture long-term dependencies, the hybrid approach outperformed the standalone models. While SARIMAX offered reliable baseline forecasts, the integration of it with LSTM improved performance by accounting for more complex patterns.

As shown in Tables 2 and 3, the SARI-LSTM model produced the lowest MAE and RMSE values across both countries. However, the MAPE metric for Ireland appeared relatively high. This is largely due to low inflation values during certain periods, which can distort percentage-based errors. Despite this, the overall performance remained strong, and the model's reliability is better understood when multiple evaluation metrics are considered together.

5.6 Predictive Analysis of Inflation

In Ireland, the inflation forecast (see Figure 3) indicates a period of relative stability followed by an upward trend. Including both sharp downward and upward trends, according to the LSTM and hybrid models. This projected increase may be influenced by recent economic pressures such as supply chain disruptions, changes in government spending, or residual effects from the COVID-19 pandemic. The pattern suggests the importance of preparedness in fiscal and monetary policy to cushion against inflation surges.

For the UK, the forecast (see Figure 4) illustrates a significant divergence among models regarding future price stability. While the traditional SARIMAX forecast indicates a relatively stable outlook slightly above the 2% target, the LSTM and Hybrid forecasts project considerable volatility near the end of the forecast period.

Specifically, the LSTM and Hybrid models show sharp downward spikes immediately followed by pronounced upward spikes around 2028. This rise likely reflects the influence of structural factors, including housing market pressures, rising demand due to immigration, and broader global economic developments. The ability to anticipate such shifts provides a valuable insight for policy and planning aimed at maintaining price stability and protecting purchasing power. The forecast suggests shifts influenced by immigration, housing, and global trends, emphasising the need for proactive economic planning to preserve stability and protect consumers.

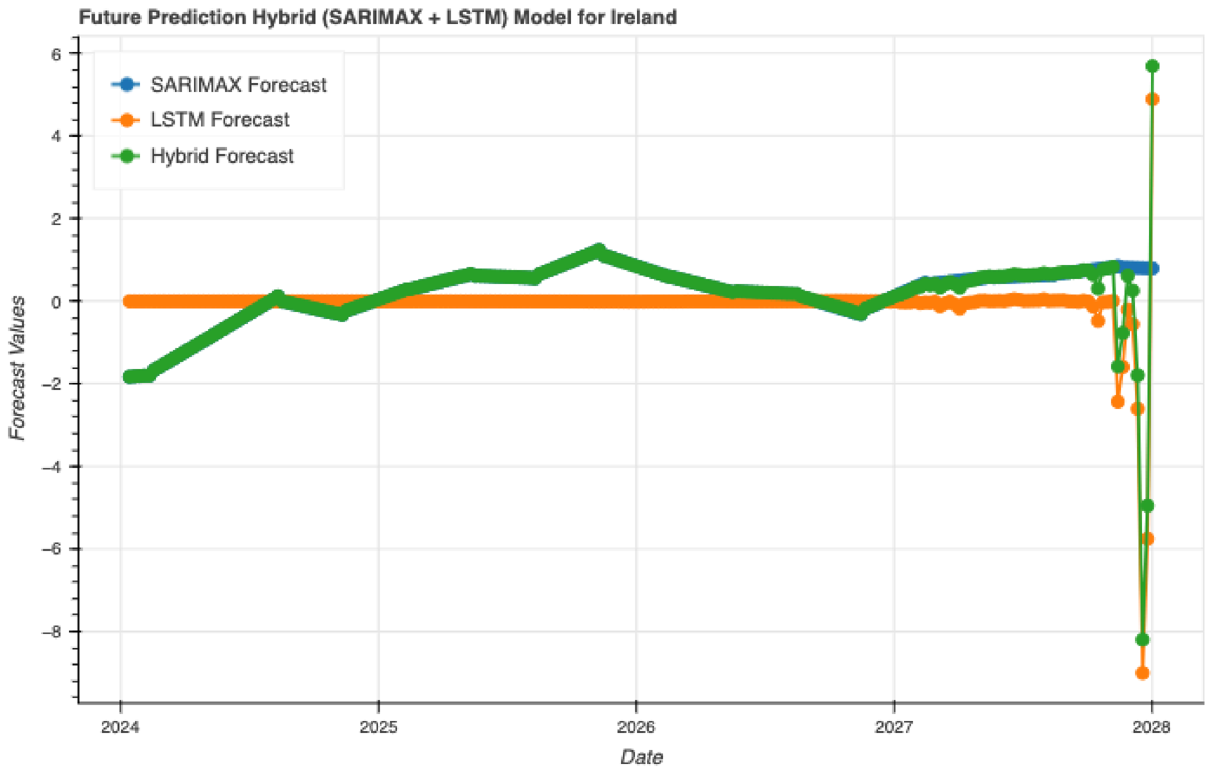

Figure 3. Forecasts of inflation predictions in Ireland by the hybrid model

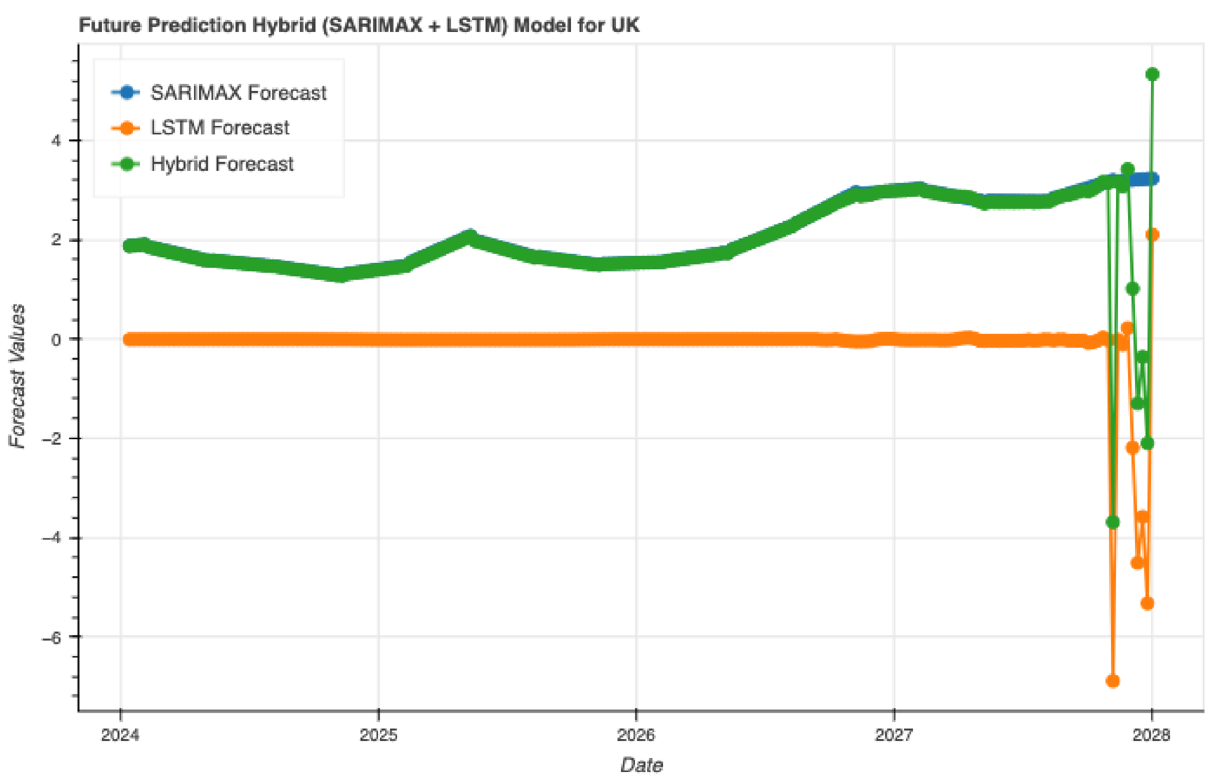

Figure 4. Forecasts of inflation predictions in the UK by the hybrid model

6 Challenges, Conclusion, and Recommendations

6.1 Challenges of Hybrid Modelling

Inflation forecasting is a complex but essential aspect of economic planning. This study demonstrates that combining different modelling techniques – such as traditional time series methods with more flexible, data-driven approaches – can enhance the accuracy of forecasts by capturing both consistent seasonal patterns and more irregular trends. In particular, the SARI-LSTM model outperformed the others in identifying shifts in inflation dynamics across different periods.

However, several challenges were encountered during the modelling process. A key limitation was the slow processing speed of available systems, which affected the training and evaluation of more computationally demanding models. This restricted the depth of experimentation and the number of model variations that could be tested. Another significant challenge was the reliance on historical data, which may not fully account for sudden, disruptive events. For instance, the COVID-19 pandemic had far-reaching economic impacts that were difficult to anticipate using past trends. Such events highlight the limitations of static forecasting models and reinforce the need for regular updates and flexible frameworks that can adapt to evolving conditions.

6.2 Conclusion

Although the results of this study are promising, inflation forecasting remains a challenging task due to the constantly shifting nature of economic variables and external influences. This research shows the potential of combining traditional time-series models with more advanced techniques to better capture both linear and nonlinear patterns. The strong performance of the SARI-LSTM model suggests that integrated modelling approaches can offer improved predictive accuracy. However, as economic conditions evolve, forecasting models must be regularly reviewed, updated, and adapted to maintain their relevance. It is also important to ensure that models used for policy decisions remain transparent and interpretable, particularly when incorporating more complex methodologies.

6.3 Recommendations

To further strengthen inflation forecasting, future research should continue to explore hybrid models that bring together established statistical approaches with more flexible methods capable of learning from patterns in economic data. Efforts should also be made to include a broader range of macroeconomic indicators and apply more advanced feature engineering techniques to extract meaningful signals from noisy data. Additionally, improving the clarity and explainability of complex models is essential, particularly when they are used to inform public policy. Future research should also consider the development of models that can update forecasts in real time as new data becomes available, offering more responsive and practical tools for economic planning.

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