INFLATION PREDICTION: A HYBRID TIME SERIES APPROACH

Tonia Ojochide Ameh[1] and Alexander Okhuese Victor[2]
[1] School of Information Technology Dublin Business School, Ireland
[2]Dublin Business School, Ireland
20029980@mydbs.ie

Abstract. Inflation forecasting is critical for effective economic planning and policy formulation. However, predicting inflation is challenging due to multiple external factors such as housing market trends and immigration. This study explores a hybrid modelling approach to enhance inflation prediction by combining the strengths of traditional statistical methods and advanced predictive techniques. Using time series data for Ireland and the United Kingdom, this research integrates Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) with other models, including Random Forest, Support Vector Regression, and Long-Short-Term Memory. Four hybrid models SARI-SVR, SARI-RF, RF-SVR and SARI-LSTM were developed and evaluated based on their ability to capture linear patterns and complex nonlinear relationships in the data. The findings demonstrate that the SARI-LSTM model consistently outperformed the others, achieving the lowest Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) for Ireland and the UK. This model's ability to combine SARIMAX's seasonal trend analysis with LSTM's strength in handling sequential dependencies makes it particularly effective for inflation forecasting. By leveraging hybrid modelling, this study provides a comprehensive framework for addressing the complexities of inflation prediction. The results highlight the potential for improved forecasting accuracy, offering valuable insights for policymakers and economists.

Keywords: SARIMAX, LSTM, Hybrid, Inflation, Forecasting, Evaluation, Prediction.

1 Introduction

Inflation, defined as the general rise in prices of goods and services, reduces the purchasing power of money and is measured using the Consumer Price Index (CPI). It significantly affects economies by influencing consumer behaviour, investment, and monetary policy. While moderate inflation can have positive and negative effects, rapid inflation leads to economic instability. In the context of external factors influencing inflation, the immigration-disinflation theory posits that an increased labour supply from immigration helps curb inflation by limiting wage growth. However, this perspective is incomplete, neglecting how immigrants' spending can boost demand, potentially driving economic growth (Federal Reserve, 2020). Therefore, a comprehensive understanding of inflation dynamics must consider both the supply-side effects and the demand-side implications of immigration. Recent trends in the United Kingdom and Ireland illustrate the complex relationship between immigration, housing markets, and inflation. In the UK, the proportion of working-age immigrants grew from less than 8% in the mid-1990s to over 13% by 2015, accompanied by a significant rise in average house prices, according to the Office of National Statistics (2015). Similarly, Ireland experienced a marked increase in immigration, with the proportion of immigrants rising from 6% to over 17%, and house prices escalating sharply, reflecting increased demand and limited housing supply, as reported by the Central Statistics Office (2024). These dynamics highlight the need for a nuanced approach to understanding inflation, considering macroeconomic and demographic factors.

Existing studies on inflation prediction often focus on single-country analyses or global models that overlook specific external factors like immigration and housing market fluctuations. This research addresses the gap by conducting a cross-country comparative analysis of inflation in Ireland and the UK, examining the impact of immigration and housing pressures. These countries' geographical proximity, shared history, and distinct economic characteristics make them ideal for studying the interplay between external factors and inflation (Coyle, 2018). While traditional forecasting methods, such as ARIMA, have limitations in capturing the complex influences of external factors like immigration, this research proposes a hybrid approach, integrating traditional models with machine learning (e.g., RF, SVR) and deep learning techniques (e.g., LSTM), to handle nonlinear relationships and temporal dependencies better (Geurts et al., 2006; Hastie et al., 2009).

The hybrid model enhanced prediction accuracy by leveraging the strengths of each method, particularly during volatile economic periods influenced by factors such as housing market dynamics and immigration trends. This study developed and evaluated a hybrid model for predicting inflation using time series data. This research involved comparing the predictive accuracy of traditional forecasting models, such as ARIMA, with machine learning and deep learning techniques, including SVR, RF, and LSTM, for inflation prediction while incorporating external factors like housing market dynamics and immigration trends. A hybrid model was created by integrating traditional forecasting methods with machine learning and deep learning approaches to enhance prediction accuracy and model robustness. The performance of the hybrid model was evaluated in terms of accuracy and resilience under volatile economic conditions, particularly during periods of high inflationary pressure. Additionally, the study provided insights into the influence of external factors on inflation dynamics and offered recommendations for improving inflation forecasting in complex and dynamic macroeconomic environments. By integrating traditional and modern techniques, this research addressed limitations in existing models and contributed to more accurate inflation forecasting, which is vital for economic stability. Understanding external factors like housing and immigration provides a comprehensive view of inflation drivers, aiding policymakers, financial analysts, and businesses in making informed decisions. Improved inflation forecasting informs better monetary and fiscal policies, benefiting policymakers, economists, financial analysts, and businesses. The findings also benefit the real estate sector and the public by providing insights into inflation trends and drivers.

This report begins with an overview of the models used, covering traditional, machine learning, and deep learning approaches and the development of hybrid models. It then details the methods employed in the study, including data collection and modelling techniques. The results and findings are presented next, comparing the performance of different models in predicting inflation for the UK and Ireland. This is followed by a discussion on the implications of these findings, particularly the influence of external factors such as immigration and housing market dynamics. It concludes with a summary of key insights and recommendations for future research to enhance inflation forecasting models.

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 the long-term performance of the electricity sector by incorporating seasonal and exogenous factors, as demonstrated in a study focused on Saudi Arabia's power sector from 2021 to 2050. This approach significantly enhances forecasting accuracy compared to simpler models, effectively handling various dataset sizes. By addressing future planning and performance analysis challenges, SARIMAX provides a reliable forecasting technique crucial for modern energy systems (Alharbi & Csala, 2022). Additionally, SARIMAX was evaluated for predicting Covid-19-related deaths, highlighting its strengths and limitations alongside other models, and 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 crucial 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) emphasised RF's effectiveness in capturing complex economic interactions during volatile periods, such as the COVID-19 pandemic, underscoring its importance in providing accurate inflation forecasts.

In the context of a solar-assisted liquid desiccant air-conditioning system, Daghigh et al. (2024) assessed RF and SVR for predicting key performance indicators like mass removal rate, efficiency, and effectiveness. The study found that SVR with an RBF kernel was the best predictor for effectiveness, while RF was evaluated for its predictive capabilities. The inclusion of timestamps as model inputs significantly improved prediction accuracy, a factor often overlooked in previous research. This highlights the potential of RF and SVR in accurately modelling complex systems by considering influential factors such as ambient temperature and solar radiation.

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, concluding that LSTM and its variants provide higher accuracy than traditional approaches, underscoring their superiority in handling complex, time-dependent data.

2.4 Hybrid Model

Hybrid models have gained popularity for enhancing forecasting accuracy by integrating the strengths of both traditional and advanced methodologies. M.A. et al. (2023) demonstrated this by applying a hybrid ensemble learning approach that combines 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 LSTVAR-ANN hybrid model to analyze monetary policy effects and improve inflation forecasts by leveraging different economic dynamics across business cycles.

While advanced ML 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 generalizable forecasts. Marinho et al. (2021) highlighted the limitations of ARIMA in capturing nonlinear trends and proposed an optimized 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, providing a strong foundation for the hybrid approach.

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

Where:

- p, d, q: Non-seasonal order parameters for ARIMA
- P, D, Q: Seasonal order parameters.
- m: The number of observations in a seasonal cycle ($m = 52$ weeks for weekly data).
- X: 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 minimize overfitting. It aggregates predictions from all 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 generalization and reducing overfitting risks. It optimizes the trade-off between model 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. LSTM's architecture, 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 overall predictive performance. SARIMAX addresses seasonal and external factors, while RF and SVR handle complex nonlinearities and LSTM captures sequential dependencies. This layered approach ensures that each model contributes uniquely to refining the prediction, addressing 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, we leverage their strengths to better predict inflation. 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 SVR's robustness 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 Random Forest 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.

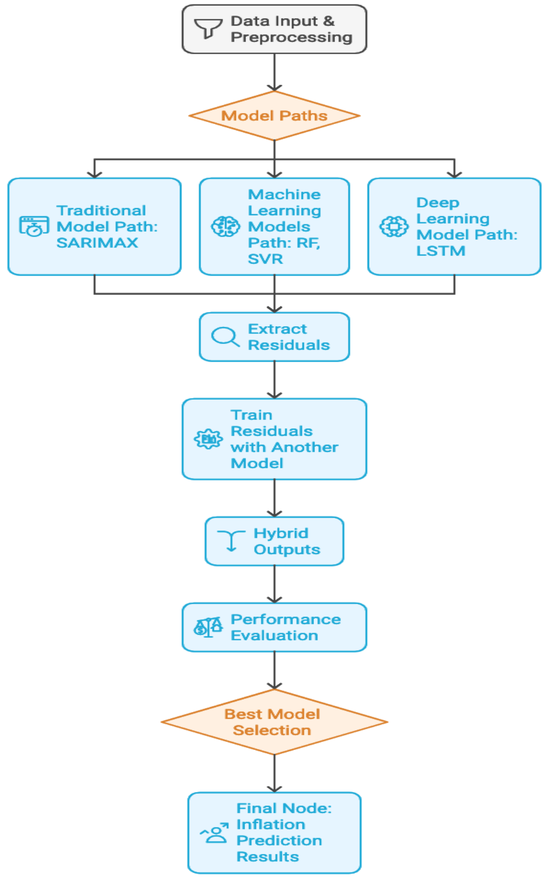

Fig 5: Proposed Structure of the Hybrid Model

4 Evaluation Metrics

Various metrics are utilised to evaluate the models' performance 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, useful for gauging model performance with smaller variance data.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |yi - \hat{y}i| \tag{10}$$

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

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (yi - \hat{y}i)^2 \tag{11}$$

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

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (yi - \hat{y}i)^2} \tag{12}$$

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.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{yi-\hat{y}i}{yi}\right|\times 100 \tag{13}$$

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

5 DATASET DESCRIPTION, EVALUATION AND DISCUSSIONS

5.1 Datasets Description

The research follows a quantitative, data-driven approach, utilising historical inflation data for evidence-based analysis. This ensures a structured framework for analysing inflation trends using well-defined mathematical and statistical techniques.

Data was collected from multiple reputable sources to capture macroeconomic variables affecting inflation in Ireland and the UK from 2000 to 2024. These include Inflation rates, Interest rates, stock indices, GDP, Exchange rates, Unemployment, Immigration, and Housing price index. Notably, Stock data was scraped from Yahoo Finance using Python, inflation and economic variables from the UK Data Service, Irish housing trends from the Central Statistics Office, and UK housing data from the HM Land Registry were incorporated. Immigration data was sourced from the Migration Policy Institute to understand demographic pressures.

Data preprocessing was crucial to ensure consistency and accuracy across all variables. Quarterly data was interpolated to weekly intervals, achieving uniformity for analysis. Standard scaling was applied to standardise features, ensuring no single variable dominated the models due to differences in scale.

Advanced feature engineering techniques were employed to enhance model accuracy and interpretability. Initial correlation analysis identified potential multicollinearity among macroeconomic variables. The Fourier Transform was used to decompose time series data into frequency components, revealing patterns such as seasonality and trends while filtering out noise. This process informed the application of Spectral Principal Component Analysis (Spectral PCA), which reduced dimensionality while preserving the most significant frequency-based features for modelling.

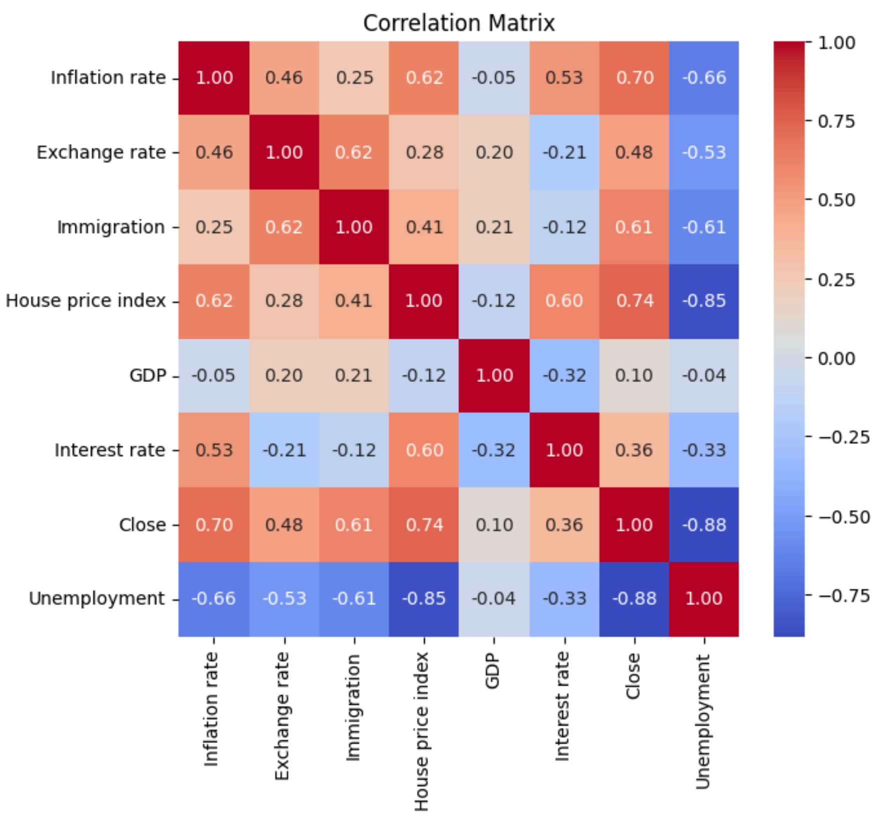

Fig 4: Correlation matrix heatmap

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 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, which combines SARIMAX and 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, standalone models like RF and LSTM showed higher error rates, highlighting their limitations in this context.

In contrast, standalone models like 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. Standalone models like LSTM and RF had higher error metrics, indicating challenges in capturing the UK's inflation dynamics. Overall, the results underscore the importance of hybrid models in enhancing prediction accuracy, particularly when dealing with complex inflation trends influenced by external factors and nonlinear relationships.

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. Standalone models like LSTM and RF had higher error metrics, indicating challenges in capturing the UK's inflation dynamics.

Overall, the results underscore the importance of hybrid models in enhancing prediction accuracy, particularly when dealing with complex inflation trends influenced by external factors and nonlinear relationships.

Method	Search Parameters	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
	- learning_rate	0.001	0.001
Hybrid	- Combination of SARIMAX residuals and LSTM	Aggregation by addition	Aggregation by addition

Table 1: Parameter values used in the search process for all methods

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: UK 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**

Table 2: Ireland evaluation metrics result

5.5 Discussion on Predictive Accuracy

The SARI-LSTM model demonstrates superior predictive accuracy for inflation in both Ireland and the UK. By combining SARIMAX's ability to capture seasonal and linear patterns with LSTM's strength in modelling long-term dependencies and nonlinear influences, SARI-LSTM emerges as the most effective model. While SARIMAX alone provides robust predictions, the hybrid approach enhances overall accuracy.

MAPE offers insights into relative error but can be misleading when low values in the time series skew results, as seen with Ireland's SARI-LSTM model. Despite a high MAPE, shown in both Table 2 and 3 moderate MAE and RMSE values suggest a need to interpret MAPE alongside other metrics for a balanced evaluation.

5.6 Predictive Analysis of Inflation

For Ireland, the forecast indicates initial stability followed by a rise in inflation, as shown in Figure 6. This increase may be attributed to economic shocks or external influences, suggesting a need for strategies to manage future inflation spikes. Factors such as supply chain disruptions and fiscal policy changes should be considered in planning.

In the UK, the SARI-LSTM model predicts stable inflation initially, with a sharp increase anticipated in late 2025, as shown in Figure 7. This reflects LSTM's ability to detect complex patterns while maintaining SARIMAX's stability. The forecast suggests potential economic shifts influenced by immigration trends, housing price fluctuations, and other global developments.

These insights highlight the importance of addressing structural issues to maintain economic stability and protect purchasing power.

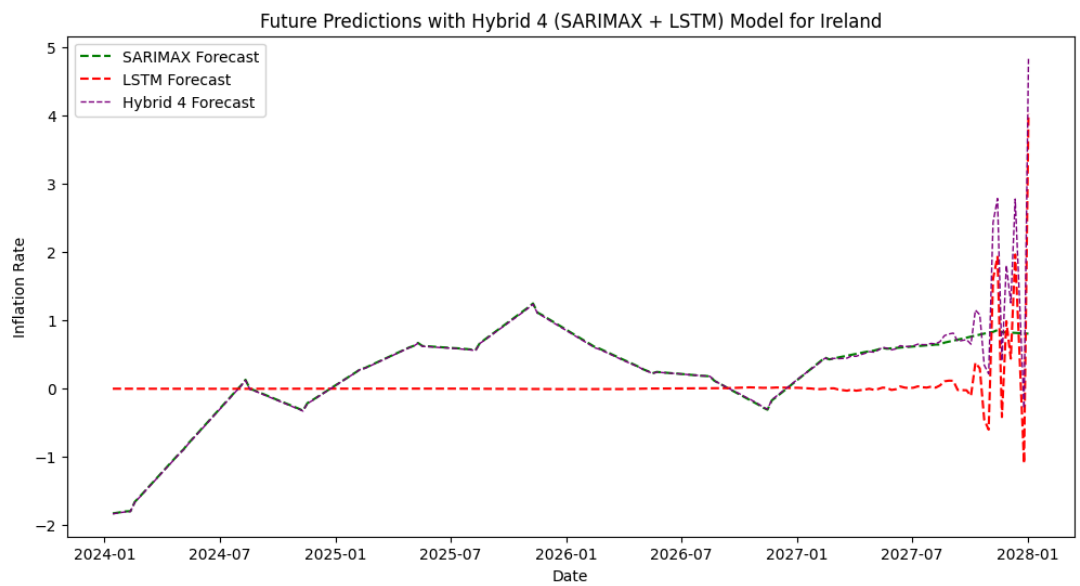

Fig 6: Forecasts of Inflation predictions in Ireland by the hybrid model

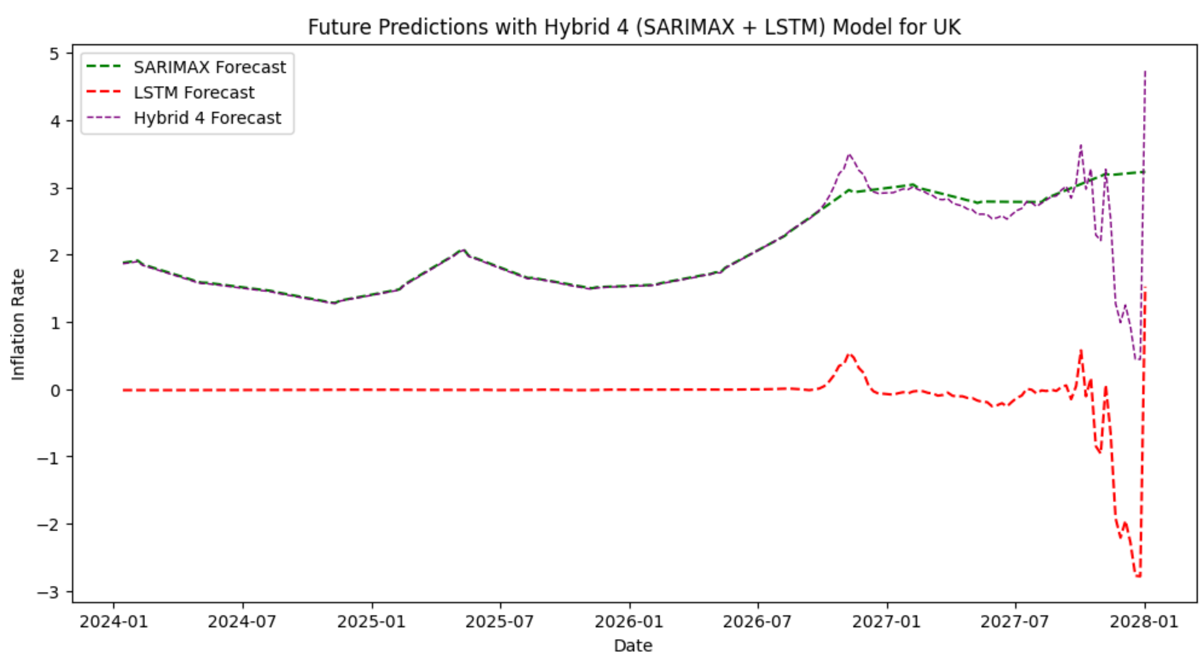

Fig 7: Forecasts of Inflation predictions in the UK by the hybrid model

The forecast suggests potential economic shifts influenced by immigration trends, housing price fluctuations, and other global developments. These insights underscore the importance of addressing structural issues to maintain economic stability and protect purchasing power.

6 CHALLENGES, CONCLUSION AND FUTURE WORK

6.1 Challenges of Hybrid Modelling

Inflation prediction is a complex but crucial task for economic planning. This dissertation demonstrates that hybrid modelling approaches, particularly the SARI-LSTM model, significantly enhance the accuracy of inflation forecasts by capturing both linear patterns and nonlinear dependencies. The integration of traditional statistical methods with advanced machine learning and deep learning techniques shows great potential for accurate inflation forecasting. However, the unpredictable nature of factors influencing inflation, such as the COVID-19 pandemic, highlights the limitations of forecasting models and the necessity for continuous adaptation and refinement.

However, This research encountered limitations, including slow server processing speeds that affected model training and evaluation, especially for computationally intensive models like LSTM. Additionally, reliance on historical data may overlook unforeseen future economic events, impacting predictive accuracy.

6.2 Conclusion

Although the results are encouraging, predicting inflation is complex and unpredictable. This means that models need to be continuously improved and updated to ensure they remain accurate and useful as economic conditions change.

6.3 Recommendation

To enhance inflation forecasting, a hybrid approach combining traditional models like SARIMAX with advanced techniques such as LSTM is recommended. Future research should explore alternative hybrid models and incorporate advanced feature engineering techniques. Investigating additional macroeconomic indicators, utilizing frequency-based feature extraction, or experimenting with emerging machine-learning algorithms could provide new insights and improve forecasting accuracy.

REFERENCES

1. Aldabagh, H., Zheng, X., & Mukkamala, R. (2023) 'A Hybrid Deep Learning Approach for Crude Oil Price Prediction', Journal of Risk and Financial Management, 16(12), pp. 503.
2. Alharbi, F.R. and Csala, D., 2022. A seasonal autoregressive integrated moving average with exogenous factors (SARIMAX) forecasting model-based time series approach. Inventions, 7(4), p.94.
3. Blanchard, O. & Johnson, D.R. (2013) Macroeconomics. 6th ed. Upper Saddle River, NJ: Pearson.
4. Central Statistics Office (CSO). (2024) Key Findings Population and Migration Estimates, April 2024.
5. Chojnowski, M. (2023) 'Enhanced Forecasting with LSTVAR-ANN Hybrid Model: Application in Monetary Policy and Inflation Forecasting', in Hamoudia,
6. Coyle, D. (2018) The Economics of Enough: How to Run the Economy as If the Future Matters. Princeton, NJ: Princeton University Press.
7. Daghigh, R., Arshad, S.A., Ensafjoe, K. and Hajialigol, N., 2024. A data-driven model for a liquid desiccant regenerator equipped with an evacuated tube solar collector: Random forest regression, support vector regression and artificial neural network. Energy, 295, p.130932.
8. Das, P.K. and Das, P.K., 2024. Forecasting and Analyzing Predictors of Inflation Rate: Using Machine Learning Approach. Journal of Quantitative Economics, 22, pp.493–517.
9. Dixon, H., Mendez, C. & Rosenberg, C. (2020) ‘Regional economic integration and inflation: A cross-country analysis’, Journal of Economic Policy, 12(3), pp. 345-368.
10. Federal Reserve Bank of Dallas, 2024. *Immigration and its impact on labour markets and inflation*.
11. Foroutan, P. and Lahmiri, S., 2024. Deep learning systems for forecasting the prices of crude oil and precious metals. Financial Innovation, 10, p.111.

12. Gamber, E. & Hung, J., 2001. Has the rise in globalisation reduced U.S. inflation in the 1990s? *Economic Inquiry*, 39(1), pp.58-73.
13. Gikungu, S.W., Waititu, A.G., and Kihoro, J.M. (2015) 'Forecasting inflation rate in Kenya using SARIMA model', *American Journal of Theoretical and Applied Statistics*, 4(1), pp. 15–18.
14. Gür, Y. E. (2024). 'Forecasting the Euro Exchange Rate Using Deep Learning Algorithms and Machine Learning Algorithms', İstanbul Ticaret Üniversitesi Sosyal Bilimler Dergisi, 23(49), 1435-1456.
15. Hyndman, R.J. & Athanasopoulos, G. (2018) Forecasting: Principles and Practice. 2nd ed. OTexts.
16. International Monetary Fund (n.d.) Inflation: Prices on the Rise. Available at: www.imf.org (Accessed: 21 October 2024).
17. Investopedia (n.d.) Inflation. Available at: www.investopedia.com (Accessed: 31 December 2024).
18. Khan Academy (n.d.) Lesson summary: Price indices and inflation. Available at: www.khanacademy.org (Accessed: 21 October 2024).
19. Mankiw, N.G. (2016) Principles of Economics. 7th ed. Boston, MA: Cengage Learning.
20. McKinsey & Company (n.d.) What is inflation: The causes and impact. Available at: www.mckinsey.com (Accessed: 21 October 2024).
21. Office for National Statistics (ONS). (2015) International migration: a recent history.
22. PIMCO (n.d.) Understanding Inflation. Available at: www.pimco.com (Accessed: 31 December 2024).
23. Quicken Loans (n.d.) 5 Effects of Inflation on the Economy. Available at: www.quickenloans.com (Accessed: 21 October 2024).
24. Saz, G., 2011. The efficacy of SARIMA models for forecasting inflation rates in developing countries: The case for Turkey. International Research Journal of Finance and Economics, 62, pp.111-142.
25. Şimşek, A. İ. (2024) ‘Use of machine learning and deep learning methods in housing price index estimation: an analysis on Ankara and Istanbul’, Fırat Üniversitesi Sosyal Bilimler Dergisi, 34(3), pp. 1345-1353.

26. Strike (n.d.) 14 Positive and Negative Effects of Inflation. Available at: www.strike.money (Accessed: 21 October 2024).
27. Sulistijanti, W. and Khotimah, N., 2024. Comparing Time Series Predictions of COVID-19 Deaths Using SARIMAX, Neural Network, and XGBoost. Asian Journal of Engineering, Social and Health, 3(12), pp.2751-2758.
28. Sun, Y., Li, G., Zhang, J. and Qian, D., 2019. Prediction of the strength of rubberised concrete by an evolved random forest model. Advances in Civil Engineering, 2019(1), p.5198583.
29. Taylor, J.B. (2019) 'The importance of inflation forecasting', The Economists' Voice, 16(2), pp. 24-28.
30. Van Otten, N. (2024) Structure of support vector regression. Data Science, Machine Learning. Published on 8 May.
31. Wang, W., Ma, B., Guo, X., Chen, Y. & Xu, Y., 2024. A Hybrid ARIMA-LSTM Model for Short-Term Vehicle Speed Prediction. *Energies*, 17(15), p.3736.