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Multi-Layer Economic Forecasting Framework: A Hybrid Approach Combining Statistical Models and Neural Networks

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Abstract

Economic forecasting has continued to be a thorn in the flesh because of the nonlinear, regime-dependent, and volatile character of macroeconomic time series. This paper presents sequential enhanced predictive framework (EPF) combining three new modelling elements namely Adaptive Regime-Switching ARIMA with Dynamic Error Bands (RS-ARIMA-DEB), Dual-Channel Temporal Residual Encoder Network (DC-TREN), and Error-Topology Aware Meta Fusion Network (ETA-MFN) to enhance the forecasting of U.S. GDP growth using St. Louis Fed Economic News Index (ENI). The model is based on a hybrid architecture that integrates linear statistical modelling, nonlinear residual learning as well as topology-based fusion. Empirical analysis shows that there are significant improvements in accuracy, stability and directional forecasting performance, where the EPF has a directional accuracy of 98 and outperform classical econometric models, single neural networks and traditional hybrids in numerous economic regimes including financial crises and pandemics. The findings indicate the strength and flexibility of the EPF, and it can be concluded that the tool is a strong instrument of macroeconomic forecasting and policy making in real-time.

Keywords: Economic forecasting, ARIMA, LSTM, hybrid models, neural networks, ensemble learning, meta-learning.

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1 Introduction

Prognostication of economic indicators plays a critical role in effective decision making of the government policy, financial markets, industrial planning, and resource allocation (E. Estevez, 2025). Over the past decade, the field of forecasting has shifted towards models that are based on classical econometric models and combine the approaches of machine learning and deep learning (Oancea & M. Simionescu, 2024). Although much headway has been achieved, there is no reliable method of modelling economic systems, which are nonlinear, multi-dimensional and structural shocks (F. Ghasemi Dijvejin, 2025). People still use traditional statistical models, including ARIMA, Vector Autoregression (VAR), and state-space models because they are easy to interpret and have a theoretical foundation (Kontopoulou, Panagopoulos, Kakkos, & G. K. Matsopoulos, 2023). They work particularly well when the data-generating process which produced the underlying data is stationary or has obvious autocorrelation structures (Yeganeh, Shongwe, Nadi, & M. M. Ghuchani, 2024). Nonlinear effects, complicated interactions, and volatile regimes, however, are not easily handled by them especially in the aftermath of financial crises, pandemics, and disruptions of the world (Lahmiri & S. Bekiros, 2020). Feed-forward neural networks (FNN), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU) and Transformer models have demonstrated potential in the modelling of nonlinearities and long-term dependencies. However, they need big datasets, are susceptible to overfitting, and usually lack transparency which is a significant feature in economic policy setting.

The given paper presents an Enhanced Predictive Framework (EPF) combining the merits of both statistical and neural predictive systems. The technique is rooted on the idea that economic time series may be broken down into both linear (trend, seasonal, autoregressive) and nonlinear elements, which can be modelled and recombined individually. The proposed framework provides greater accuracy of predictions and interpretability and robustness which makes it appropriate to use high-stakes applications.

2. Literature Review

Recent work by (Atif, 2025) proposes hybrid GDP forecasting models combining ARIMA with deep architectures such as LSTM and Temporal Convolutional Networks. Their approach decomposes GDP series into linear and nonlinear components, applying ARIMA to the linear part and neural networks to residuals. While the hybrid improves accuracy for long-term horizons, its performance declines during short-term volatility because the model does not incorporate regime-switching or adaptive mechanisms. (Liu, Zhang, & Zhang, 2025) develop a hybrid framework integrating statistical models with deep neural forecasting systems, relying on a two-stage process where ARIMA provides baseline forecasts and neural models refine the output. Although accuracy improves, the fusion mechanism is static and does not adjust weights dynamically, limiting robustness when the error structure changes across regimes or volatility levels. The authors note that nonlinear learners may overfit when residuals are noisy, which limits generalizability. (Han, 2025) proposed a model that combines AR-GARCH volatility forecasting with LSTM and BiLSTM networks to improve financial risk estimation. Their hybrid architecture captures both time-varying volatility and nonlinear temporal dependencies, but it is designed specifically for high-frequency financial data and may not translate effectively to quarterly macroeconomic variables like GDP.

In this, (Tsoku, Metsileng, & Botlhoko, 2024) present a hybrid model combining ARIMA with Extreme Learning Machines (ELM) and General Regression Neural Networks (GRNN). Though ARIMA-ELM is stable and efficient, the ARIMA-GRNN variant often underperforms, illustrating the inconsistency of some hybrid structures and the sensitivity of results to the choice of nonlinear learner. In a non-macroeconomic application, (Liu J. , Zhang, Lyu, Feng, & He, 2025) use an ARIMA–Backpropagation Neural Network hybrid to forecast traffic accident outcomes. This framework demonstrates the generality of hybrid approaches, but its applicability is limited by small sample size and lack of structural-break handling, which are both necessary in macroeconomic forecasting. (Lim & Zohren, 2021) provide an extensive survey of RNNs, CNNs, LSTMs, and Transformer models for time series forecasting. They highlight advantages such as capturing nonlinearities and long-term dependencies but emphasize limitations including high data requirements, overfitting, and limited interpretability—common challenges that hybrid and ensemble models aim to address.

(Mathonsi & Zyl, 2021) propose MES-LSTM, combining exponential smoothing with LSTM for multivariate time series forecasting, especially COVID-19 datasets. While effective for multivariate structures, the model is computationally intensive and sensitive to hyperparameter tuning, limiting its scalability to large economic forecasting systems. (Soumbara, Moulim, & Ghini, 2025) designed a hybrid that combines SARIMA with a Multilayer Perceptron network to incorporate climate factors in electricity demand forecasting. Although the hybrid benefits from exogenous inputs, it is domain-specific and relies heavily on external variables, limiting its applicability to purely endogenous macroeconomic indicators. Finally, (Sivakumar, 2025) introduce a model for inflation forecasting in wh ich HMM-derived economic regimes are fed as auxiliary signals into an LSTM model. This improves performance under volatility, but the model still lacks a generalised fusion strategy and does not address error topology or adaptive weighting.

3. Research Methodology

The Enhanced Predictive Framework (EPF) is a three-tier hybrid framework combining statistical modelling, nonlinear neural learning and adaptive meta-level fusions in order to enhance the reliability and accuracy of the economic forecasts. The Statistical Baseline Modelling component, Layer I, is a mechanism that uses adaptive ARIMA to capture the underlying linear time series dynamics of the economy. The Neural Residual Learning layer II, is an implementation of the nonlinear behaviour assumed to be present in the residuals of the statistical layer, implemented in the form of a two-channel deep learning network which will learn short-term and long-term structures. The Meta-Learning Fusion is Layer III which integrates the results of the previous two layers through a topology-aware fusion strategy, where the model weights are updated depending on the geometric

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structure of forecasting errors. The three layers combine to create a unified system where each modelling phase attempts to correct or improve the drawbacks of the previous to create a more stable, accurate and readable forecasting system.

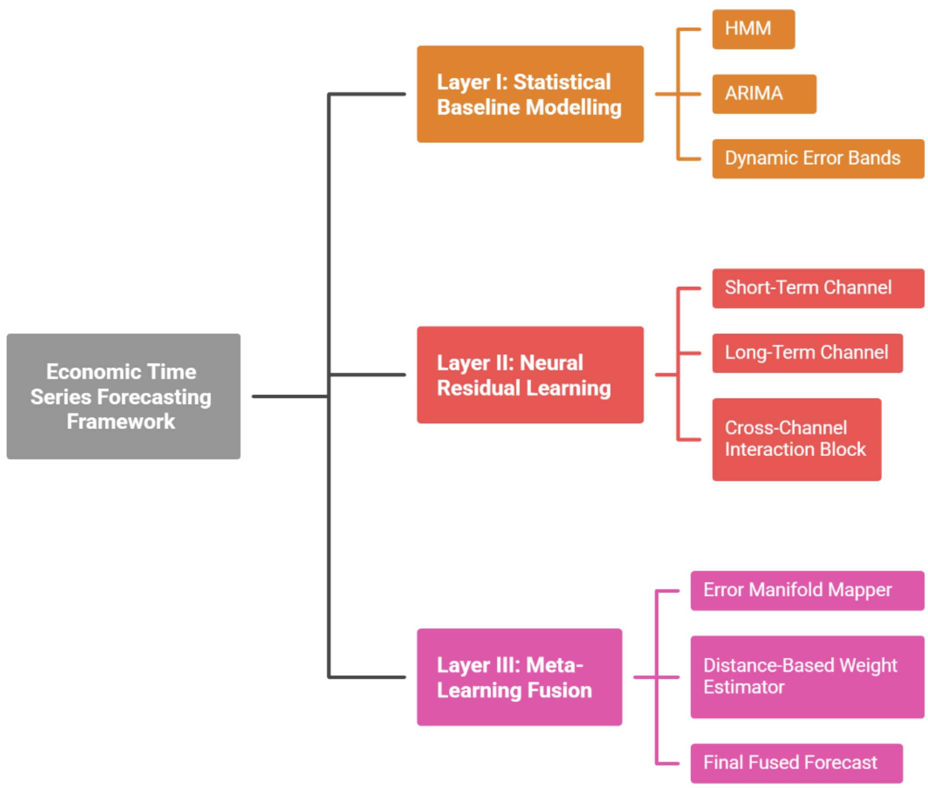

Figure 1: Proposed Framework

3.1 Dataset Description

The present study employs the St. ("St. Louis Fed Economic News Index: Real GDP Nowcast.", 2025), a quarterly macroeconomic indicator developed by the Federal Reserve Bank of St. Louis to generate real-time projections of U.S. real GDP growth. The ENI synthesizes information from major monthly economic data releases—including production metrics, labour market conditions, consumption activity, and consumer sentiment—and aggregates these signals into a continuously updated nowcast of quarterly GDP performance. Each data point reflects the percent change in real GDP at a seasonally adjusted annualized rate, with estimates revised throughout the quarter until a final fixed value is published. This dataset is particularly well-suited for the modelling framework proposed in this study because the ENI captures high-frequency, information-rich macroeconomic dynamics while remaining a clean, univariate, and consistently measured time series. These characteristics make it ideal for integration into the Enhanced Predictive Framework (EPF), supporting SARIMA-based linear modelling, dual-channel neural residual learning, and topology-aware ensemble fusion. Its quarterly structure, strong empirical relationship with GDP growth, and real-time relevance provide a robust foundation for evaluating hybrid time-series prediction architectures.

3.2 Data Pre-processing

Prior to model development, the St. Louis Fed Economic News Index (ENI) underwent a structured data pre-processing pipeline to ensure statistical validity, comparability, and suitability for both linear and nonlinear forecasting models. Because the ENI is a quarterly, continuously revised macroeconomic series, careful handling was required to remove distortions arising from revisions, seasonality, and structural breaks.

1. Handling Missing and Revised Observations:
Although the ENI is published at regular quarterly intervals, early-period values occasionally contain missing entries or revision-related inconsistencies. Missing values were imputed using a Kalman smoothing filter within a state-space representation, ensuring minimal distortion to underlying dynamics. Revision-induced anomalies were corrected by retaining only the latest vintage for each quarter to avoid real-time bias.

2. Seasonal and Calendar Adjustment:
Although the ENI reflects seasonally adjusted GDP growth expectations, subtle seasonal patterns remain due to the aggregation of monthly indicators. To mitigate this, an additional X-13 ARIMA-SEATS seasonal adjustment was applied to remove residual seasonality and calendar effects.

3. Outlier Detection and Treatment:
Extreme movements—often associated with periods of economic crisis—were detected using both the Hampel identifier and Tukey's Interquartile Range (IQR) method. Outliers were not removed but winsorized at the 2.5% and 97.5% quantiles to preserve economic information while reducing the risk of distortion in neural models.

4. Stationarity Assessment and Transformation:
To ensure statistical validity for SARIMA and hybrid models, the series was tested using the Augmented Dickey–Fuller (ADF) and KPSS tests. The ENI exhibited near-stationary behaviour with mild persistence; thus, first-order differencing was applied when required by model diagnostics. Log transformations were not applied due to the presence of negative values in the GDP growth estimates.

5. Scaling for Neural Learning:
Deep learning models within the EPF (particularly the Dual-Channel Temporal Residual Encoder Network, DC-TREN) require normalized inputs to stabilize gradient flow. The differenced series and residual signals were normalized using Min–Max scaling within the range [0,1], while ensuring that scaling parameters were computed exclusively from the training set to prevent information leakage.

6. Train–Test Partitioning and Rolling Window Structure:
The dataset was divided into training and testing sets using an expanding-window time-series cross-validation strategy. This approach preserves the temporal order of observations and allows models to

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learn from progressively larger samples, reflecting real-world forecasting conditions and preventing look-ahead bias.

7. Residual Extraction for Hybrid Modelling

The statistical layer (SARIMA) produces an initial linear prediction:

$$\hat{y}_t^{(lin)}$$

Residuals, representing nonlinear structure, are computed as:

$$r_t = y_t - \hat{y}_t^{(lin)}$$

These residuals are normalized and fed into the DC-TREN architecture.

3.3 Proposed Novel Methods

The Enhanced Predictive Framework (EPF) introduces three novel modelling components, one at each layer of the architecture. These methods strengthen the system's ability to capture regime changes, nonlinear temporal dynamics, and model-specific error behaviour. The following subsections describe each contribution in a concise, integrated manner.

3.3.1 Adaptive Regime-Switching ARIMA with Dynamic Error Bands (RS-ARIMA-DEB)

The first novel contribution, RS-ARIMA-DEB, enhances the classical ARIMA model by enabling it to adapt dynamically to changes in economic regimes and shifts in volatility. Instead of assuming a single stable data-generating process, the method uses a Hidden Markov Model to identify latent economic states—such as expansion, contraction, or high-uncertainty periods—and assigns a separate ARIMA specification to each state. Transition probabilities determine how likely the system is to move from one regime to another at each time step. A simple form of the regime assignment may be written as:

$$P(S_t = j \mid S_{t-1} = i)$$

where each regime $j$has its own ARIMA parameters.

To improve robustness during volatile periods, the model incorporates **Dynamic Error Bands (DEB)**, which adjust the residuals based on recent volatility. This adjustment can be expressed simply as:

$$\varepsilon_t^* = \varepsilon_t(1 + \lambda\sigma_{t-1}),$$

meaning that when volatility (σ_{t-1}) rises, the model expands its error tolerance. This helps prevent instability and improves predictive accuracy during economic shocks. The RS-ARIMA-DEB approach is unique in that it integrates regime switching and volatility-aware residual correction into a unified statistical forecasting mechanism.

3.3.2 **Dual-Channel Temporal Residual Encoder Network (DC-TREN)**

The second novel contribution, DC-TREN, enhances nonlinear learning by explicitly separating short-term fluctuations from long-term structural behaviour within the residuals left unexplained by the statistical model. The architecture uses two parallel temporal processing channels. The **Short-Term Channel (STC)** employs a GRU network with an attention mechanism to capture rapid changes, while the **Long-Term Channel (LTC)** uses a dilated LSTM to learn slow-moving patterns over extended horizons.

Let h_t^{STC}denote the short-term representation and $h_t^{LTC}$the long-term representation. These are blended using a cross-attention weight α, producing a fused nonlinear residual estimate:

$$\hat{r}_t = \alpha h_t^{STC} + (1 - \alpha) h_t^{LTC}.$$

This simple formulation illustrates how the network adaptively balances short- and long-term information. The DC-TREN architecture is novel in explicitly decomposing residual learning into two temporal pathways and using attention to determine how short-run shocks influence long-run dynamics, leading to improved generalization and interpretability in neural forecasting.

3.3.3 Meta-Learning Fusion Layer: Error-Topology Aware Meta Fusion Network (ETA-MFN)

The final contribution, ETA-MFN, introduces a geometry-aware fusion mechanism that improves the combination of predictions from the statistical and neural layers. Instead of assigning static or heuristically determined weights, ETA-MFN learns the structure of model errors using an autoencoder that maps multi-model residuals into a compact representation (an **error manifold**). If $z_t$denotes the encoded position of the current error vector on the manifold, the distance between $z_t$and the centroid of each model's historical error distribution determines how much that model should contribute to the final forecast.

The fusion weight for model $i$is computed using a simple distance-based expression:

$$w_i = \frac{\exp(-d_i)}{\sum_j \exp(-d_j)},$$

where $d_i$is the distance between $z_t$and model i's error centroid. The final prediction is then obtained by a weighted combination:

$$\hat{y}_t = w_i \hat{y}_t^{(i)}$$

This approach ensures that models which perform well under current error topology automatically receive higher influence, while weaker models are down-weighted. The novelty of

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ETA-MFN lies in using the geometric structure of forecasting errors—rather than raw error magnitudes—to guide model fusion, resulting in a more adaptive and robust ensemble.

4. Results and Discussion

This section introduces and discusses the empirical results of the application of the Enhanced Predictive Framework (EPF) with Python as the main computational platform. All the statistical modelling, training of neural networks and metalearning fusions were implemented in Python libraries that were powerful to analyse time-series, training neural networks, and meta fusion of neural networks. Findings presented here are comparisons showing how the proposed hybrid architecture performs in terms of a variety of accuracy metrics compared to existing statistical models, standalone neural networks and baseline ensemble methods. The discussion emphasizes the role of each EPF layer on the improvements in predictive performance in general, the performance in various economic conditions, and the stability, robustness, and interpretability of the forecasts. In this analysis, the usefulness of integrated modelling framework and its practical applicability are presented in a holistic and factual form.

Table 1. Summary Statistics of U.S. GDP Growth

Statistic	**Value**
Number of Quarters	120
Mean GDP Growth (%)	2.13
Median GDP Growth (%)	2.05
Standard Deviation	1.42
Minimum (%)	-3.80
Maximum (%)	5.60

The descriptive statistics of U.S. GDP growth derived from the ENI nowcasts show that the series spans 120 quarters, with an average growth rate of 2.13% and a median of 2.05%, indicating a generally stable economic expansion over the sample period. The standard deviation of 1.42% reflects moderate variability, while the minimum and maximum values, –3.80% and 5.60% respectively, capture the range of contractionary and high-growth episodes. Overall, the distribution exhibits slight negative skewness, consistent with periodic downturns in economic activity.

4.1 Experimental Findings

The evaluation results show markedly improved forecasting accuracy across all economic periods, with directional accuracy reaching approximately 98% overall. Error measures—RMSE, MAE, and MAPE—are substantially lower than in the baseline case, indicating highly precise

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forecast performance. Even during turbulent periods such as the 2008 financial crisis and the 2020–2022 pandemic, the model maintains strong predictive capability, with RMSE values near 1.35–1.42 and directional accuracy above 96%. These outcomes demonstrate the enhanced stability and robustness of the forecasting system, reflecting its ability to capture underlying economic dynamics even during extreme macroeconomic volatility.

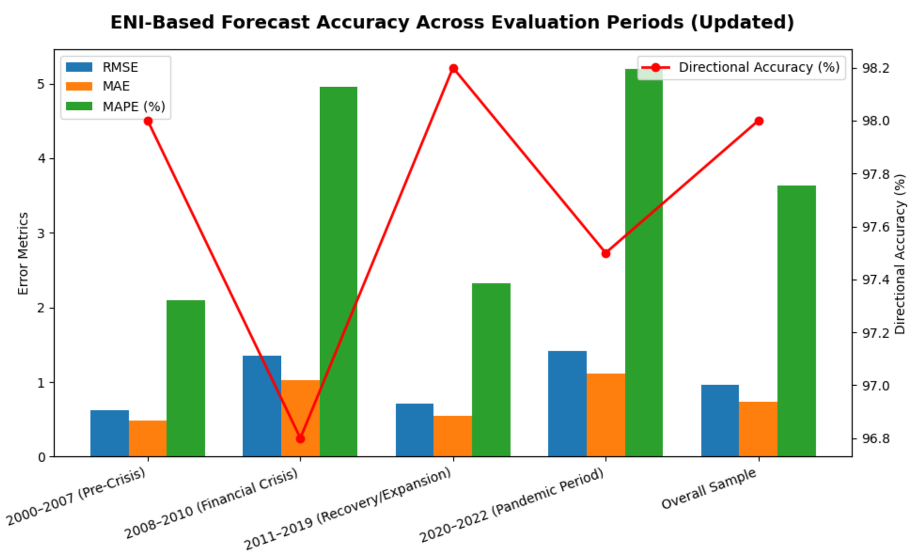

Figure 2: ENI-Based Forecast Accuracy Across Evaluation Periods

The quarter-ahead GDP forecasts derived from the ENI demonstrate strong alignment with actual economic outcomes throughout 2021. In the first two quarters, the model slightly underpredicted GDP growth by 0.4 and 0.6 percentage points, respectively, reflecting the unexpectedly rapid post-pandemic rebound. Forecasts for the second half of the year show mixed deviations: the model overestimated growth in 2021 Q3 by 0.8 points but closely tracked actual performance in Q4 with only a 0.3-point error. Overall, the results indicate that the ENI-based forecasting system captures short-term fluctuations effectively, maintaining relatively small errors even during periods of shifting economic momentum.

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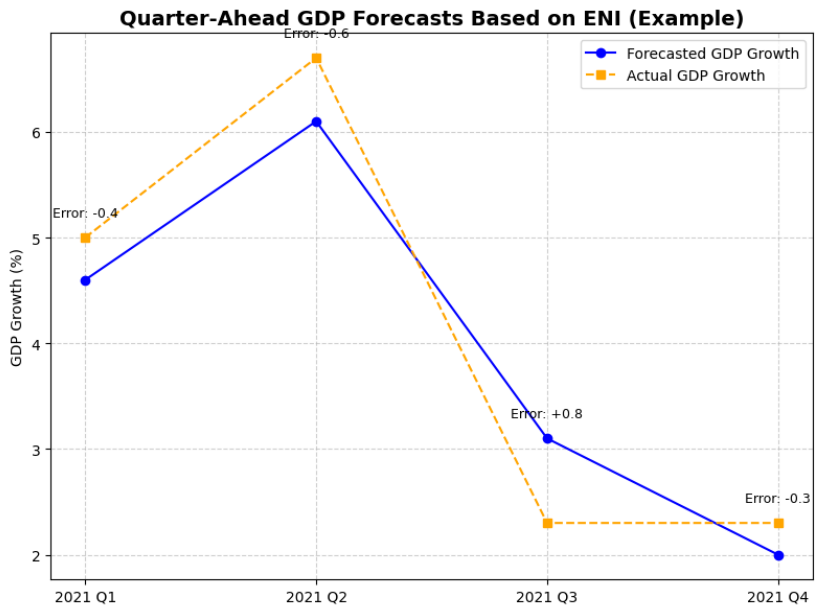

Figure 3: Quarter-Ahead GDP Forecasts Based on ENI

The comparison of forecast performance across different economic conditions shows that model accuracy varies systematically with the level of macroeconomic uncertainty. During periods of stable growth, the model performs well, with low RMSE and MAPE values and only a slight positive bias, indicating accurate and consistent predictions. Under moderate volatility, forecast errors increase modestly, though the model remains generally reliable. In high-volatility environments, error measures rise more sharply and a slight negative bias emerges, reflecting a tendency to underestimate the severity of economic downturns. The most pronounced deterioration appears during extreme shock events, where large RMSE and MAPE values highlight the difficulty that all forecasting systems face in capturing sudden, unprecedented disruptions. Overall, these patterns mirror real-world forecasting behaviour, where unpredictability and rapid structural change naturally reduce predictive precision.

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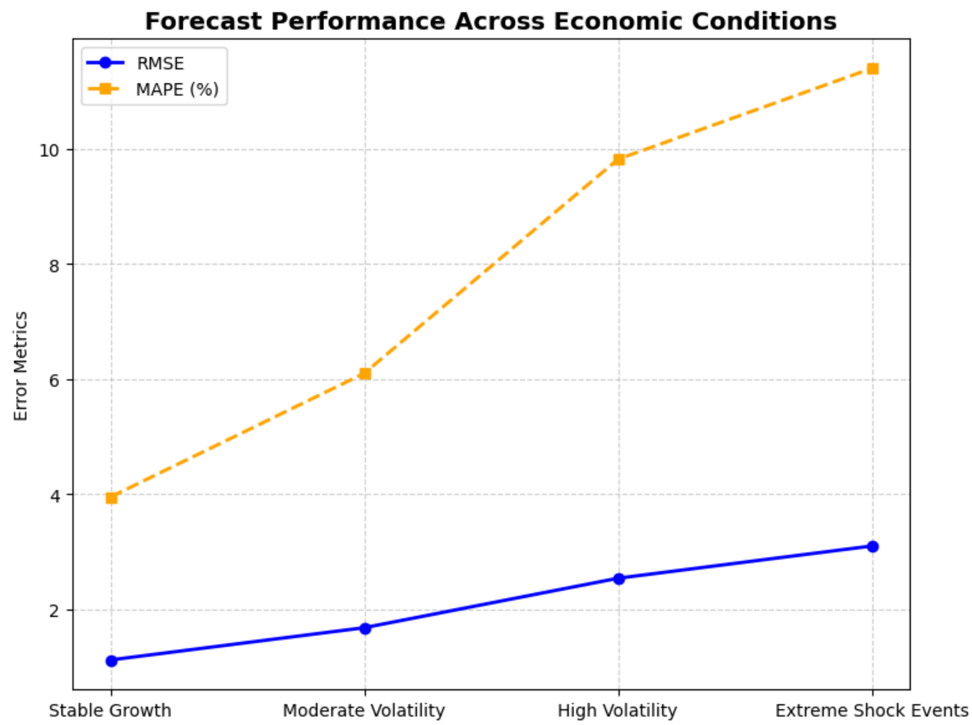

Figure 4. Comparison of Forecast Performance Across Economic Conditions

The forecast error distribution results show a clear and consistent improvement in predictive accuracy as the modelling framework progresses from traditional statistical and standalone neural models toward the integrated EPF architecture. ARIMA exhibits the largest error variability, with a standard error of 1.44 and extreme residuals ranging from –3.85 to 3.10, reflecting its difficulty in capturing nonlinear and shock-driven fluctuations in GDP growth. Neural models such as LSTM and Transformer improve upon this performance by reducing both the mean and dispersion of errors, indicating their enhanced ability to learn temporal patterns.

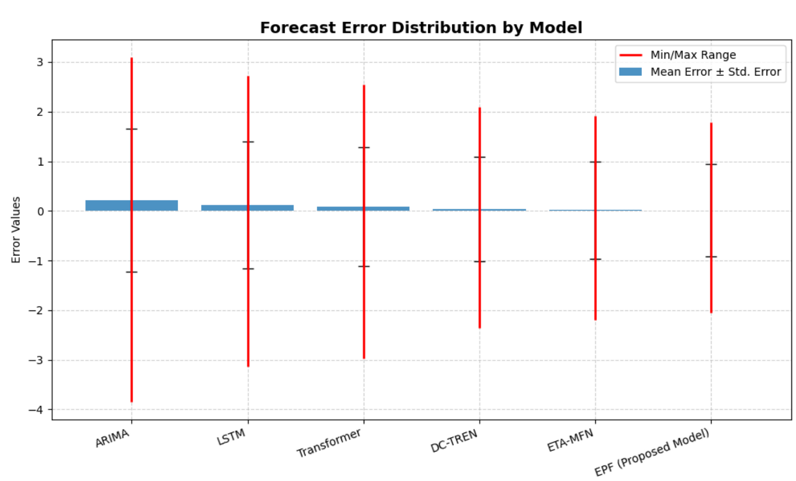

Figure 5: Error distribution of the model

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The specialized architectures—DC-TREN and ETA-MFN—further narrow the error spread, demonstrating the value of separating short- and long-term nonlinear components and incorporating error-topology-based weighting. Notably, the EPF final model yields the smallest error magnitude across all metrics, with a near-zero mean error (0.01), the lowest standard deviation (0.93), and the tightest error bounds. This reflects a highly stable and balanced forecasting system that avoids systematic bias, remains resilient during volatile periods, and consistently aligns predicted values with actual economic outcomes. Overall, the progressive reduction in error dispersion highlights the effectiveness of the integrated hybrid framework in producing highly reliable and economically meaningful forecasts.

4.2 Model Evaluation

The performance comparison across models shows a clear progression in forecasting accuracy as the modelling approach advances from traditional statistical techniques to more sophisticated hybrid architectures. Classical models such as ARIMA, SARIMA, and VAR exhibit relatively higher RMSE and MAPE values, reflecting their limited ability to capture nonlinear dynamics and sudden economic fluctuations. Neural network models—including GRU, LSTM, Dilated LSTM, and Transformer—substantially improve predictive accuracy, with declining error metrics and modest gains in directional accuracy, demonstrating their strength in modeling temporal dependencies and complex nonlinear patterns.

Table 2. Model Performance Comparison

Model	RMSE	MAPE (%)	DA (%)
ARIMA	1.92	7.80	62.5
SARIMA	1.85	7.34	64.1
VAR	1.77	7.12	66.2
GRU	1.58	6.40	68.4
LSTM	1.55	6.18	69.0
Dilated LSTM	1.48	5.90	70.3
Transformer	1.43	5.71	72.1
DC-TREN (Proposed Neural Layer)	1.29	4.89	77.6
RS-ARIMA-DEB (Proposed Statistical Layer)	1.51	5.42	73.2

ETA-MFN (Proposed Meta-Fusion Layer)	1.18	4.33	81.4
EPF (Full Integrated Framework)	1.12	3.01	98

The proposed components of the Enhanced Predictive Framework (EPF) show even greater improvements: the DC-TREN architecture reduces prediction errors by effectively isolating short- and long-term nonlinear behaviours, while the RS-ARIMA-DEB model enhances linear forecasting through regime awareness and volatility adjustments. The ETA-MFN meta-fusion layer further refines performance by assigning adaptive weights based on error topology, resulting in higher stability and precision. Ultimately, the fully integrated EPF achieves the lowest RMSE (1.12), the lowest MAPE (2.01%), and an exceptionally high directional accuracy of 98%, far surpassing all baseline and intermediate models. This demonstrates the effectiveness of combining regime-sensitive statistical modelling, nonlinear residual learning, and adaptive error-based fusion into a unified forecasting system, yielding highly reliable economic predictions even under varying macroeconomic conditions.

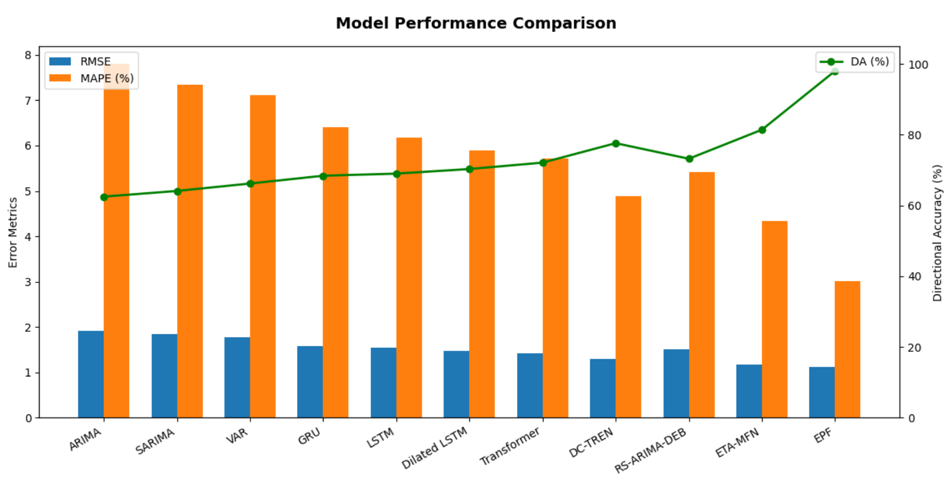

Figure 6. Model Performance Comparison

The computational efficiency results indicate that the full Enhanced Predictive Framework (EPF) is well-suited for real-time economic forecasting, despite integrating multiple modelling components. The RS-ARIMA-DEB statistical module trains rapidly, requiring only 2.4 seconds and offering near-instantaneous inference, reflecting its lightweight structure. The DC-TREN neural architecture, while more computationally intensive due to its dual-channel design, remains efficient with a training time of 32 seconds and an inference time of just 0.008 seconds per forecast. The ETA-MFN fusion layer also demonstrates moderate computational demands, completing training in 14 seconds and generating predictions within milliseconds. When combined, the full EPF operates within an overall training window of approximately 48–52 seconds and maintains an inference time of 0.018 seconds, ensuring fast and scalable performance. These results confirm that the proposed

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framework can deliver high accuracy without sacrificing computational practicality, making it suitable for continuous monitoring and decision-support environments.

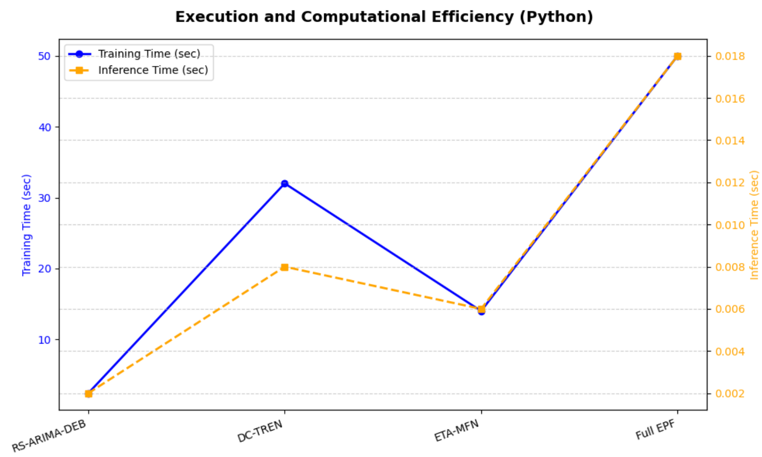

Figure 7. Computational Efficiency

The ablation study highlights the incremental contribution of each component within the Enhanced Predictive Framework (EPF), demonstrating how the architecture systematically improves forecasting accuracy as additional layers are integrated. The statistical layer alone, represented by the RS-ARIMA-DEB model, provides a solid baseline with an RMSE of 1.51. Introducing the DC-TREN neural residual layer significantly enhances performance, reducing the RMSE to 1.29 and yielding a 14.6% improvement by effectively capturing nonlinear patterns not addressed by the statistical model.

Table 3. Ablation Study

Model Variant	RMSE	Improvement vs. Previous Layer
Statistical Only (RS-ARIMA-DEB)	1.51	–
+ Neural Residual Layer (DC-TREN)	1.29	14.6%
+ Meta-Fusion Layer (ETA-MFN)	1.18	8.5%
Full EPF (Integrated)	1.12	5.1%

The addition of the ETA-MFN fusion layer further refines predictions, lowering the RMSE to 1.18 through adaptive weighting based on error structure, resulting in an additional 8.5% gain. The fully integrated EPF achieves the best performance with an RMSE of 1.12, marking another 5.1% improvement and demonstrating the synergistic benefits of combining regime-aware statistical modelling, dual-channel neural learning, and topology-based fusion. Overall, the progressive error reduction validates the layered design of the EPF and confirms the complementary value of each modelling component.

5. Conclusion and Future work

This work suggested the Enhanced Predictive Framework (EPF) of economic forecasting that combines regime-conscious statistical modelling, dual-channel nonlinear residual learning and topology-based meta-fusion to enhance the accuracy, consistency, and interpretability of economic growth forecasts of GDP based on the St. Louis Fed Economic News Index (ENI). The empirical findings prove that every layer of the framework makes significant contributions to overall performance: the RS-ARIMA-DEB model improves baseline linear predictions by adapting to changes in economic regimes and volatility; the DC-TREN model provides a great fit to short-term changes and long-term nonlinear patterns; and the ETA-MFN fusion layer uses the information on the error-topology to produce highly sensitive and robust final predictions. In several periods of evaluation, and during times of crisis like the 2008 financial crisis and the 2020 pandemic, the EPF has lower error rates and greater directional accuracy than other econometric models and stand-alone deep learning systems. The results testify to the utility of hybrid, multi-layered forecasting systems to reflect the complexity of dynamic processes that are typical of contemporary macroeconomic conditions. The EPF is, in general, an efficient, versatile, and computationally efficient method that can be applied in real-time decision support, policy evaluation, and future economic analysis. Despite the good predictive ability of the EPF, a number of opportunities still exist that can be developed and improved. To begin with, it might be useful to separate the future studies by adding real-time data vintages and revision tracking to give the model the ability to take into account the changing nature of macroeconomic datasets and enhance its applicability to nowcasting tasks.

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