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EcoForecast: An interpretable data-driven approach for short-term macroeconomic forecasting using N-BEATS neural network

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ABSTRACT

It will be beneficial to devise an effective approach for short-term macroeconomic forecasting. Existing traditional statistics-based macroeconomic forecasting mainly focuses on exploring feasible methods for improving the accuracy of long-term predictions. However, the performance of short-term predictions was far less impressive under the impact of unexpected incidents. Furthermore, some deep learning-based approaches can achieve fine-grained variable frequency forecasting and preliminarily demonstrate effective results, but the interpretability is still controversial. Therefore, how to consider both the performance and the interpretability has already become a universal concern and an urgent unsolved problem. In this paper, we identified the above issue and proposed an interpretable data-driven approach, named EcoForecast[1], for short-term macroeconomic forecasting based on the N-BEATS (neural basis expansion analysis for interpretable time series forecasting) neural network. To the best of our knowledge, EcoForecast is the first interpretable purely data-driven unified normative scheme for macroeconomic forecasting that achieves variable forecast frequencies and prediction domains, surpassing traditional statistics-based and deep learning-based approaches in performance or interpretability.

EcoForecast used a three-level hierarchical signal encoding, including the fully connected neural network (FCNN) level, the block level, and the stack level. The FCNN level implemented both forecast and backcast information extraction for the temporal prediction and parameter learning of context. Block levels were connected by residuals so that the block's backcast could be sequentially filtered on the input. The stack level was used to form the top-level system of EcoForecast, where each stack was constrained to specialize in different inductive functions. To some extent, EcoForecast can balance effectiveness, efficiency, generalizability and interpretability while conditions such as forecast frequency and time window change, even when unexpected incidents occur. Based on the actual macroeconomic data for China from 1992 to 2022, the data-driven EcoForecast demonstrated high stability in different sequence learning scenarios and the accompanying high-accuracy performance. This stability was reflected in smaller prediction error expectation and variance, tolerance of fewer input samples, and robustness across prediction domains. The experimental results indicated that EcoForecast improved the accuracy up to 3.94 times compared with the traditional BVAR. In the robustness test, EcoForecast required only a quarter of the data to achieve 2.51 times smaller forecast errors than the BVAR while also improving the accuracy of varied macroeconomic indicators such as the Purchasing Managers' Index (PMI) and national electricity generation (ELEC)forecasting by 2.38 and 1.45 times. EcoForecast had a high sensitivity to the emergence of economic inflection points and adapts quickly when the economic environment changes, thus demonstrating a performance that exceeds traditional solutions in GDP forecasting during epidemics and PMI forecasting during economic turmoil. Interfacing with traditional economics research, the interpretable EcoForecast can uncover the trends and cycles of economic change, from which the conclusions are validated with the actual economics practice in China. Our findings can provide a new possible research direction for short-term macroeconomic forecasting.

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[1] The code and data are available at https://github.com/navfour/ecoforecast.

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1. Introduction

Forecasting the country's macroeconomy has always been an important research area in sequence learning since macroeconomic trends are the critical basis for state policy regulation and enterprises' financing decisions. With the rapid development of information technology, the quantity and dimensionality of data collection have increased significantly, posing a challenge to traditional macroeconomic forecasting methods based on theory and statistics. First, the statistics-based forecasting method lacks scalability to factor since an increasing number of external variables that significantly impact economic trends (Law et al., 2019) should be incorporated into the model. Second, traditional methods fail to support cross-scale dimensionality and accuracy prediction (Salinas et al., 2019; Ostad-Ali-Askari and Shayannejad, 2021; de Jesús Rubio, 2020; de Jesús Rubio et al., 2021; Chiang et al., 2019; de Jesús Rubio et al., 2022; Mújica-Vargas, 2021), such as fine-grained indicator prediction in thousands of dimensions. Third, statistics-based methods fail to maintain stable accuracy at varying forecast frequencies (Barbaglia et al., 2020). Especially in a globally interconnected world, changes in one economy may be rapidly transferred to other economies, making real-time information throughput and high-frequency forecasting necessary. However, traditional statistics-based macroeconomic forecasting mainly focuses on exploring feasible methods for improving long-term prediction accuracy, and their short-term prediction performance is far less impressive under the impact of unexpected incidents. Finally, the structured approach lacks cross-domain mobility. On the one hand, traditional macroeconomic forecasting methods have high sensitivity to model specification and high data requirements (Diebold, 1998). On the other hand, structured models have a dependence on expert knowledge, making it difficult to perform a transfer of forecast indicators and domains (Smalter Hall and Cook, 2017). In contrast, nonstructural approaches are data-oriented rather than model-oriented, focusing on specific properties of the data itself and thus providing the proper model structure or methods for the prediction (Lucas et al., 1976).

Deep learning, a data-driven unstructured approach, has been proposed to solve these new challenges. However, deep learning methods have not been able to replace traditional methods in terms of accuracy and interpretability. According to the M4 Competition (Makridakis et al., 2020b), pure machine learning methods perform weaker than the naive-2-benchmark, which stems from their large number of parameters and the lack of a standardized approach (Makridakis et al., 2020a). In addition, the macroeconomic field has requirements for the interpretability of forecast results, making sequence learning methods based on deep learning untrustworthy.

N-BEATS (Oreshkin et al., 2019) is the first pure deep learning using no time-series specific components while outperforming well-established statistical approaches on the M3, M4 and TOURISM datasets. N-BEATS uses a stack of residuals from several multilayer perceptron (MLP) layers for univariate prediction. Each block in N-BEATS takes the output of the previous block as input and learns information about the data (called backcast) while making predictions. However, macroeconomic indicator forecasting has more requirements and constraints than other forecasts, including maintaining stability across multiple indicators and remaining robust to changes in forecast frequency and sliding time windows, providing economic interpretability that is lacking in N-BEATS models.

Although deep learning methods such as N-BEATS have made progress in univariate forecasting, the field of macroeconomic forecasting is still dominated by traditional statistics-based economic methods. We propose EcoForecast, a data-driven macroeconomic forecasting method that applies the state-of-the-art univariate forecasting model N-BEATS to macroeconomic forecasting for the first time, surpassing traditional statistics methods with a pure deep learning approach. The main contributions of this paper include the following:

- ***We propose an interpretable data-driven approach, EcoForecast, for short-term macroeconomic forecasting based on the N-BEATS neural network.*** Demonstrating the feasibility of the current SOTA univariate forecasting model N-BEATS for applications in macroeconomics, EcoForecast may serve as a standard data-driven solution that meets the application requirements needed in the macroeconomic field, such as maintaining generality among multiple forecasters and robustness when conditions such as forecast frequency and time windows change. EcoForecast, as a new forecasting paradigm, provides a new possible research direction for short-term macroeconomic forecasting.
- ***Real Chinese macroeconomic data from 1992 to 2022 are used for training and testing to enhance the performance of EcoForecast.*** We designed five sets of experiments focusing on different aspects, covering forecasting performance, varying period forecast robustness, adaptability to different economic indicators, and interpretability. EcoForecast's performance far exceeds that of the traditional economics forecasting method BVAR in actual data, both in terms of forecast accuracy and forecast stability. In particular, during the COVID-19 outbreak, when macroeconomic data fluctuated significantly, EcoForecast still achieved high accuracy at the abnormal inflection points.
- ***To a certain extent, the EcoForecast model can be interpretable.*** With the addition of interpretability constraints, EcoForecast can be interpretable while maintaining high accuracy, as it reduces the mean error in the economic indicators GDP, PMI, and ELEC by 3.94, 2.38 and 1.45 times, respectively, compared to the statistics-based method. Even when reducing EcoForecast's data sliding window to 3, it has 2.51 times smaller forecast errors compared to the statistics-based method with a window of 12, which presents solid short-term forecast robustness. Interfacing with traditional economics research, the interpretable EcoForecast can uncover the trends and cycles of economic change, from which the conclusions are validated with the actual economics practice in China.

The rest of this paper is organized as follows. In Section 2, we introduce related work, including macroeconomic forecasting using deep learning and BVAR, and the impact of N-BEATS. In Section 3, the structure of EcoForecast is described in detail, including the mathematical representation of the model, the algorithmic pseudocode, and the model architecture. In Section 4, the performance of EcoForecast is tested, including the forecast accuracy and stability of the model, structural optimization, robustness to transition forecast frequencies and forecast indicators, and interpretability tests. In Section 5, conclusions and future work are described.

2. Related work

As an essential sequence learning task, the discussion on improving macroeconomic forecasting performance has been ongoing, and short-term forecasting with high accuracy has become one of the research difficulties. Zarnowitz found that (Zarnowitz, 1991) the accuracy of US GDP forecasts in 1953–89 did not improve. Heilemann analyzed Germany's GDP growth rate forecast from 1967 to 2010 (Heilemann and Stekler, 2013) and found that the forecast performance in 2010 had not improved but degraded to the level of 1970. To make matters worse, the authors analyze that several GDP forecast improvements over the last forty years are not methodological improvements but are due to the decline in growth and inflation variance over this period. The United States, the United Kingdom, and Germany have experienced stagnation in economic forecasting performance, with forecasting methods failing to anticipate the economic crises of 1975, 1981/82, 1993, 2001, and 2008 and failing to sense the economic upturns of the late 1960s, early 1990s, and 2010. Fildes predicted that advances in macroeconomic theory are unlikely to lead to improvements (Fildes and Stekler, 2002) and that accuracy will be challenging to improve unless there is a significant innovation in the structure of forecasting models. Experts in the field also have offered suggestions for improving the performance of macroeconomic forecasting. The first suggestion is to use real-time data more extensively (Döpke, 2001), to provide higher frequency data for accurate short-term forecasts (Sims, 2002) and to provide model enhancements (Braun, 1990; Corrado and Greene, 1988; Fuhrer and Haltmaier, 1988; Howrey et al., 1991; Parigi and Schlitzer, 1995) for data processing at different frequencies. The second is that the model should have a sensitive response to macroeconomic inflection points (Schuh et al., 2001). The emergence of inflection points may have a high degree of randomness, and the model needs to quickly capture the structural transitions taking place in the macroeconomy and analyze their possible impacts.

The Bayesian Vector Autoregressivevector autoregressive (BVAR) model is currently the primary method used in macroeconomic forecasting (Curry et al., 1995). The BVAR model can not only overcome the shortcomings of the general simultaneous equation model that requires the strict distinction between endogenous and exogenous variables (Hui et al., 2011) but also has a good fit when faced with the problems of insufficient data (Xinguang and Shuozhi, 2014), which is applicable to make high-accuracy short-term forecasts of Chinese financial data (Wenlin and Hui, 2020). In this paper, we chose BVAR as the traditional control method for the experiment.

Many empirical studies have verified the potential of deep learning for economic forecasting (Wen et al., 2017; Rangapuram et al., 2018; Haotian, 2020; Bandara et al., 2020), with outstanding advantages in long memory pattern learning (Montero-Manso and Hyndman, 2021; Pirnazar et al., 2018), nonlinear system modeling (Ostad-Ali-Askari et al., 2017; Ostad-Ali-Askari and Shayan, 2021), latent correlation (Smyl, 2020), scalability (Kapgate, 2022; Roy, 2022), and data sparsity (Chen et al., 2020). Combining synergetics with neural networks (Haken, 2004) opened the trend of deep learning to carry out economic forecasting. Zhang found that the shorter the prediction period is, the better the prediction performance of neural networks compared to other networks (Zhang and Hu, 1998). Huang concluded experimentally that neural networks could better fit policy and market changes (Zhigang and Guozhong, 2021). Kamalov used a deep learning approach for stock price forecasting and achieved a validation and test mean absolute error of 0.0148 (Kamalov et al., 2020). Mining exogenous multiscale data, Derakhshan and Beigy (2019) implemented stock price movement prediction based on a graphical user opinion extraction model, and Wang et al. (2020) introduced Google search volume index (GSVI) to construct a crude oil price prediction model. Wang implemented the exchange rate forecast of the RMB based on the hybrid copula function by introducing the theory of exchange rate determination (Yang et al., 2021). Maté analyzed the impact of hyperparameters in the interval multilayer perceptron model on foreign exchange market forecasting performance (Maté and Jimeńez, 2021).

However, in the field of macroeconomic forecasting, deep learning does not bring higher accuracy than traditional statistical methods (Stekler, 2007). There is still a lack of a unified normative scheme for macroeconomic forecasting that balances generality and accuracy. In contrast, hybrid approaches that utilize both statistical and ML features show superior performance (Clemen, 1989; Makridakis, 1989; Timmermann, 2006; Kolassa, 2011; Athanasopoulos et al., 2017; Petropoulos et al., 2018; Kourentzes et al., 2019). Li (2021) implemented the filtering decomposition and production function integration based on the Grey Model, which reduced the MAPE error of Short-Term prediction to 1.6264. Chen et al. (2021) used the Differential Autoregressive Integrated Moving Average and Long Short-Term Memory models to forecast the agricultural futures index, reducing the root mean square error to 2.1287. Alaminos et al. (2021) used quantum computing-based SVRQBA, QBM, QNN, deep learning-based DRCNN, DBN, DNDT, and DSVR to build a GDP growth forecasting model for 70 countries (emerging, developing, and a global sample of countries) and reduced the root mean square error to 0.21. Leon-Gonzalez et al. (2021) uses Dynamic model averaging (DMA) to support predictors with different lengths and frequencies, and the root-mean-square-error of economic growth forecasts for Thailand and the Philippines are reduced to 0.1655 and 0.1257, which are 8.34% and 8.04% lower than BVAR. However, the combination approach loses much transfer flexibility in the prediction domain compared to pure deep learning.

The proposal of N-BEATS, a SOTA deep learning model for time-series forecasting, brings the possibility of innovation in the structure of forecasting models. After the deep learning approach N-BEATS was proposed, it was applied in various directions, such as business (Anderer and Li, 2021) and electricity load (Oreshkin et al., 2021). Although N-BEATS is the first pure deep learning model with prediction accuracy exceeding that of traditional statistical methods, there is a lack of research on its cross-domain applications and scheme optimization. NBEATSx (Olivares et al., 2021) is proposed as a domain-specific application scheme for N-BEATS with enhancements in exogenous variables. However, NBEATSx has only been applied only in electricity pricesprice prediction, and no other application directions have been considered. To date, no pure deep learning model with such high prediction accuracy as N-BEATS has been applied to macroeconomic forecasting.

In summary, although many experts and scholars have explored the issues of macroeconomic forecasting from different perspectives and have achieved a series of achievements, there is still much room for improvement in purely data-driven short-term high-precision forecasting. Deep learning-based approaches can exploit the potential of massive data information and achieve fine-grained variable frequency forecasting, but they cannot meet the requirements of interpretability. Hybrid approaches that combine statistical and ML features achieve performance gains but at the expense of purely data-driven and transfer flexibility in the prediction domain. To the best of our knowledge, EcoForecast is the first interpretable purely data-driven unified normative scheme for macroeconomic forecasting that achieves variable forecast frequencies and prediction domains, surpassing traditional statistics-based economic methods in performance.

3. Problem formulation

From an overall point of view, EcoForecast uses a three-level hierarchical signal encoding, which includes the fully connected Neural Network (FCNN) level, the block level, and the stack level, as shown in Fig. 1. The FCNN level implements both forecast and backcast information extraction for the temporal prediction and parameter learning of context. Block levels are connected by residuals so that the block's backcast can be sequentially filtered on the input. The stack level is used to form the top-level system of EcoForecast, where each stack is constrained to specialize in different inductive functions, such as trend and seasonal functions.

This subsection aims to provide the necessary notation to describe EcoForecast. X characterizes the macroeconomic data time series being forecasted, such as GDP and PMI. At the FCNN level, the outputs of two types of information sequences, forecast and backcast, are denoted as X^f and X^b, respectively, with lengths of H and L. Specifically, the length of X^b is the lag available as classic autoregressive features in the backcast model, while the length of X^f characterizes the range of predictions, which is 1 in the following experiments. (See Table 1.)

At the FCNN level, each block receives one set of inputs and produces two sets of outputs. Taking the lth block as an example, the inputs are x^b_{l-1}, and the outputs are $\hat{y}^b_l$ and $\hat{y}^f_l$. The input data are processed by the forked fully connected neural network stack h_l to produce the forward and backward predictors of expansion coefficients θ^b_l and θ^f_l. The next step is the lth block based on the next step to obtain the transformation components $\hat{y}^b_l$ and $\hat{y}^f_l$ based on the linear transformation of the basis vectors v_l.

The postprocessing of $\hat{y}^b_l$ and $\hat{y}^f_l$ is implemented at the block level using double residual stacking. The former implements the sequential

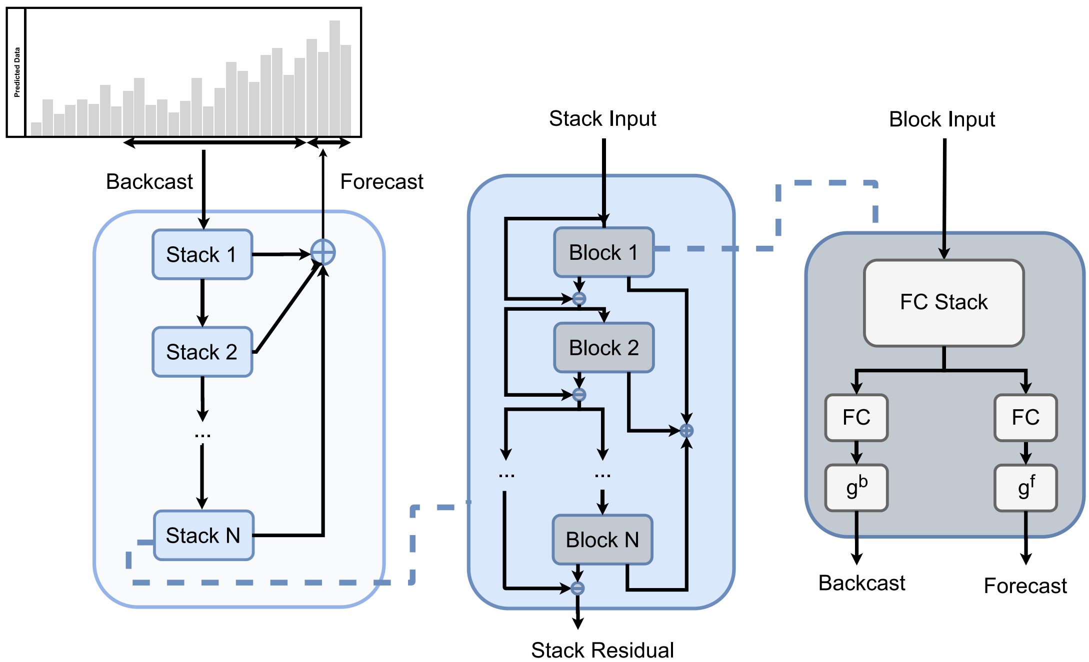

Fig. 1. The main structure of EcoForecast.

Table 1
Features definitions.

Features for stacks and blocks		
X	Forecasted macroeconomic data series	
X^f	Forecast window vector of X	The forecast window is of length H
X^b	Backcast window vector of X	The backcast window is of length L
h_l	Hidden units of the lth block	$h_l = FCNN_l(x^b_{l-1})$
θ_l	Predictors of expansion coefficients from h_l	$\theta^b_l = Linear^b\ (h_l)$ $\theta^f_l = Linear^f\ (h_l)$
v_l	Basis vector of the lth block	
$\hat{y}_l$	Transformation components of the lth block	$\hat{y}^b_l = \sum_{i=1}^{\lvert\theta^b_l\rvert} \theta^b_{l,i} v^b_{l,i}$ $\hat{y}^f_l = \sum_{i=1}^{\lvert\theta^f_l\rvert} \theta^f_{l,i} v^f_{l,i}$
T	Time vector	$T = [t_0, t_1, t_2 ..., t_{H-2}, t_{H-1}]$

decomposition of the processed signal by residual subtraction, while the latter integrates partial predictions, as shown in Eqs. (1)–(2).

$$x^b_l = x^b_{l-1} - \hat{x}^b_{l-1} \tag{1}$$

$$\hat{x}^f = \sum_{l=1}^{number\ of\ blocks} \hat{x}^f_l \tag{2}$$

The mechanism of the partial forecasts makes the interpretable model implementation possible. Since EcoForecast is applied to macroeconomic forecasting, the interpretable-basic-function decomposition and economic analyzability of the model become necessary. EcoForecast provides the design of constrained decomposition, which transforms the stack function into interpretable forms (Cleveland et al., 1990) such as polynomial and harmonic functions, as described in Eqs. (3)–(4). For instance, Eq. (4) constrains the output transformation components $\hat{y}$ to be in Fourier series form to construct the periodic function by setting the basis v to the vector of sinusoidal waveforms, which satisfies the regular, cyclical fluctuation requirement. The decomposition design allows macroeconomic forecasting to explain economic changes from the perspectives of economic trends and economic cycles.

$$\hat{x}^{trend}_l = \sum_{i=0}^{H-1} \theta^{trend}_{l,i}\ t_i \tag{3}$$

$$\hat{x}^{seasonality}_l = \sum_{i=0}^{[H/2-1]} \theta^{seasonality}_{l,i} \cos(2\pi i t) + \theta^{seasonality}_{l,i+[H/2]} \sin(2\pi i t) \tag{4}$$

The basis vector serves as the interpretable constraint for the block, which makes the seasonal-trend decomposition for time-series data prediction possible. Algorithm 1 shows the generation of the basis parameter vector corresponding to the trend and seasonal blocks. Algorithm 2 demonstrates the training process and model structure of EcoForecast, where serial processing by block and residual connection constitutes the model. It should be emphasized that the cost function of EcoForecast training is MAPE's criteria, and the optimization method is adaptive momentum estimation (ADAM). In the practical training process, data augmentation is adopted to compensate for the data sparsity of macroeconomic forecasting, and reinforcing adaptive learning rate decay is simultaneously performed to derive convergence.

4. Experimental evaluation and discussion

4.1. Performance on GDP forecasts

This section focuses on forecasting GDP(gross domestic product) data using EcoForecast and the traditional economic method BVAR. The training data are China's GDP data for each quarter, with the time sliding window of both BVAR and EcoForecast set to 12, i.e., the forecast output is made by analyzing the GDP information of the previous three years. Fig. 2 shows the comparison of GDP forecasting curves between the EcoForecast and BVAR models, with EcoForecast having an advantage in macroeconomic trend and cycle fitting. Specifically,

Algorithm 1: Generate the basis parameter vector for trend and seasonal blocks

Input: h, p, b, f
// h for harmonics used in S
// p for polynomials used in T
// b for backcast is the length of the data window
// f for forecast is the output data window length of the forecast
Output: $forecast\_basis\_S$,
$backcast\_basis\_S$,
$forecast\_basis\_T$,
$backcast\_basis\_T$
Initialization of basis vector $B = [0, 1, \dots\dots b-1]$, $F = [0, 1, \dots\dots f-1]$;
$H = [0, h, h+1, \dots\dots (h \div 2) \times f - 1]$;
$H' = (H/h)$; $//H' = [0, 1, 1+\frac{1}{h}, 1+\frac{2}{h}, \dots\dots \frac{f}{2} - \frac{1}{h}]$
$B' = (B/b)^T$; $//B'\ is\ the\ transpose\ of\ [0, \frac{1}{b}, \frac{2}{b}, \dots\dots \frac{b-1}{b}]$
$F' = (F/f)^T$; $//F'\ is\ the\ transpose\ of\ [0, \frac{1}{f}, \frac{2}{f}, \dots\dots \frac{f-1}{f}]$
$backcast\_basis\_S = concat[cos(H' \times (-2\pi) \times B'),\ sin(H' \times (-2\pi) \times B')]$;
$forecast\_basis\_S = concat[cos(H' \times (-2\pi) \times F'),\ sin(H' \times (-2\pi) \times F')]$;
while i<p **do**
  $B' = \frac{B}{b^i}$; $//\ B' = [0, \frac{1}{b^i}, \frac{2}{b^i}, \dots\dots \frac{b-1}{b^i}]$
  $F' = \frac{F}{f^i}$; $//\ F' = [0, \frac{1}{f^i}, \frac{2}{f^i}, \dots\dots \frac{f-1}{f^i}]$ $backcast\_basis\_T = Concatenate\ each\ B'\ generated\ in\ the\ loop$;
  $forecast\_basis\_T = Concatenate\ each\ F'\ generated\ in\ the\ loop$;
  $i{+}{+}$;
return $forecast\_basis\_S, backcast\_basis\_S, forecast\_basis\_T, backcast\_basis\_T$;

Algorithm 2: Training EcoForecast

Input: $Dataset\ X$ //Macroeconomic sequence data
$b, f, epochs$ $//b$ for backcast data window, f for forecast data window
$forecast\_basis\_S$, $backcast\_basis\_S$,
$forecast\_basis\_T$, $backcast\_basis\_T$
$s = shape(forecast\_basis\_S)[0]$, $t = shape(forecast\_basis\_T)[0]$;
while $epoch < epochs$ **do**
  $index = [random(0 - len(Dataset\ X), b)]$;
  $x = X[index]$; //using index as a pointer
  $y = X[index + f][-f]$;
  $forecasts = x$, $residuals = x$;
  while $i < number\ of\ blocks$ **do**
    if $block == S$ **then**
      $theta = FCNN(residuals)$;
      $block\_forcast = theta[:\ s] * forecast\_basis\_S$;
      $block\_backcast = theta[s\ :] * forecast\_basis\_S$;
    if $block == T$ **then**
      $theta = FCNN(residuals)$;
      $block\_forcast = theta[:\ t] * forecast\_basis\_T$;
      $block\_backcast = theta[t\ :] * forecast\_basis\_T$;
    if $block == G$ **then**
      $theta = FCNN(residuals)$;
      $block\_forcast = theta[:\ f]$;
      $block\_backcast = theta[b\ :]$;
    $residuals = (residuals - block\_backcast)$;
    $y' = residuals + block\_forecast$; //the prediction result
    $i{+}{+}$;
  $Get\ cost\ function\ of(\ y', y\ )$; //cost function using MAPE
  $Backpropagation$;
  $epoch{+}{+}$;

EcoForecast has significantly improved the prediction accuracy of the economic growth rate and inflection point position compared with the traditional economic method. In addition, under extreme economic conditions, when there are significant fluctuations and epidemic turbulence, EcoForecast shows much better performance than the BVAR, such as the GDP forecasts for 2020 and 2021.

To statistically quantify the accuracy of the forecasts, three types of errors, SMAPE, MAPE, and MASE, are measured, as shown in Eqs. (5)–(7). Fig. 3 shows the box plots of the three error measures. EcoForecast has a lower error expectation, and its forecasting accuracy reflects higher stability relative to the traditional economics scheme.

$$SMAPE = \frac{200}{H} \sum_{i=1}^{H} \frac{\left|y_{T+i} - \hat{y}_{T+i}\right|}{\left|y_{T+i}\right| + \left|\hat{y}_{T+i}\right|} \tag{5}$$

$$MAPE = \frac{100}{H} \sum_{i=1}^{H} \frac{\left|y_{T+i} - \hat{y}_{T+i}\right|}{\left|y_{T+i}\right|} \tag{6}$$

$$MASE = \frac{1}{H} \sum_{i=1}^{H} \frac{\left|y_{T+i} - \hat{y}_{T+i}\right|}{\frac{1}{T+H-m} \sum_{j=m+1}^{T+H} \left|y_j - y_{j-m}\right|} \tag{7}$$

The average errors of the EcoForecast prediction results based on the three evaluation methods SMAPE, MAPE, and MASE are 0.009654416, 0.01912634, and 0.063727964, which improved the accuracy by 3.147, 3.153, and 3.442 times, respectively, compared to the traditional BVAR. EcoForecast can maintain advantages in the accuracy and stability of GDP forecasts relative to the BVAR, the influential traditional macroeconomic forecasting method.

4.2. Structure optimization

In this section, the structural optimization of EcoForecast is tested. EcoForecast can provide different fitting paradigms by different stack function constraints, and the final prediction results are obtained by accumulating the outputs of the stack functions in series. By adjusting the composition and combination order of different stack functions, EcoForecast can be adapted to different information characteristics of the predicted data. In the GDP prediction experiment, EcoForecast adopts the model structure combination of S-T-G, which can be further improved by structure optimization (S denotes the seasonal harmonic function, T denotes the trend polynomial function, and G denotes the generic deep learning network).

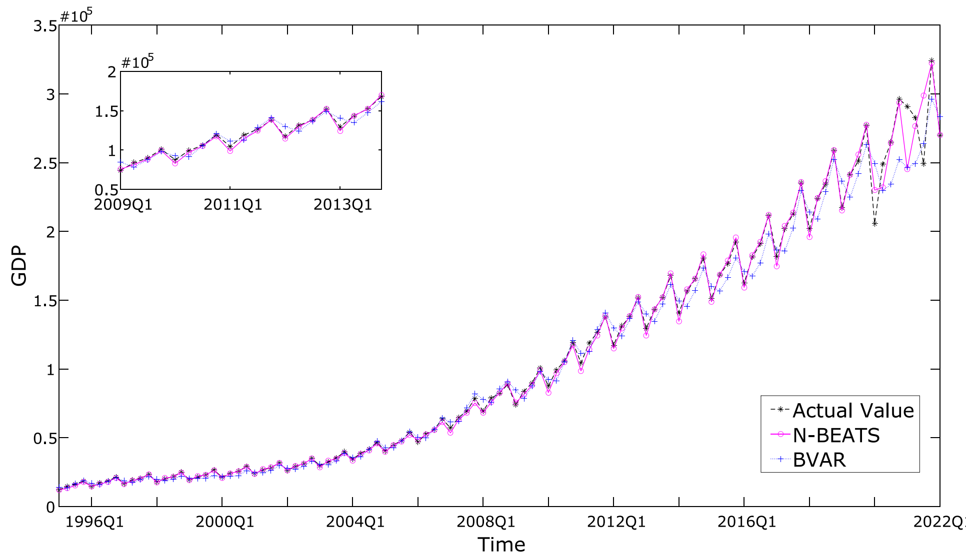

Fig. 2. Comparison of the forecasting curves of EcoForecast and BVAR for GDP.

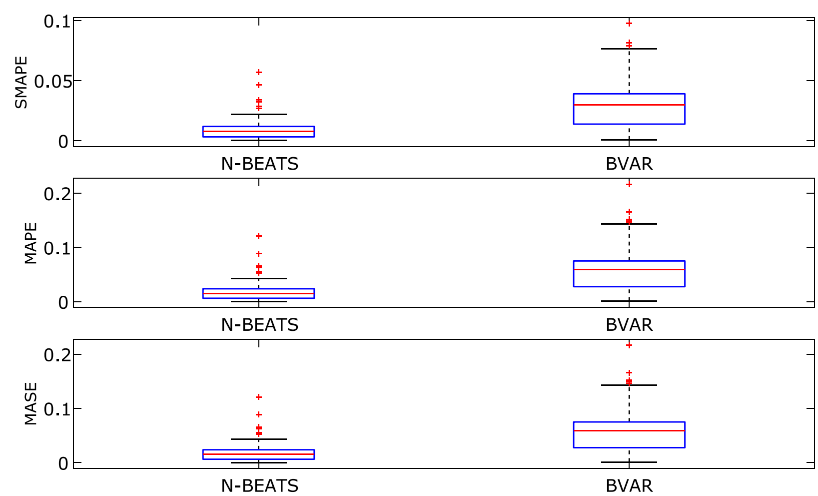

Fig. 3. Prediction error of EcoForecast and BVAR for GDP data.

Fig. 4 shows the performance of different model structures of EcoForecast in GDP forecasting based on the SMAPE error. Structural optimization can lead to improvements in forecasting accuracy and stability, or both, as in the case of the STGG structure. It needs to be emphasized that although the EcoForecast approach is based on a deep learning model, the depth of the model is not necessarily positively correlated with the forecasting performance, which can be derived from the fact that the stacking of multiple generic deep learning networks does not achieve optimal performance.

EcoForecast's search-based structure optimization could further improve the GDP forecasting performance, and in experiments, the SMAPE error could be reduced to 0.007734261 after optimization, which improved the accuracy by 3.94 times compared with the BVAR. This fully automated structure search optimization method results in a smaller prediction error, higher prediction stability, and fewer prediction outliers.

4.3. Robustness of transition forecast frequencies

The forecast frequencies need to be flexibly adjusted in the actual forecasting task, and thus the forecast results need to maintain high accuracy for different forecast frequencies, i.e., the robustness of transition forecast frequencies. Economics believes that adaptability to high-frequency inputs such as real-time data and improving sensitivity to macroeconomic inflection points are two development paths worth considering for macroeconomic forecasting models. At the same time, realistic demand may be possible using only a small sliding time window, and the extent to which information loss affects prediction performance is an essential indicator of model structure.

Fig. 5 illustrates the variation in the forecast result error by reducing the forecast time window from 15 to 3. Fig. 6 shows the prediction error of EcoForecast under the transition-forecast frequencies robustness experiment, which proves that EcoForecast has higher accuracy and stability than BVAR at various forecast frequencies. The different models show diverse robustness of transition-forecast frequencies, but even with reducing the data sliding window to 3, the EcoForecast scheme has twice the forecast error than the BVAR model with a window of 12. In other words, the EcoForecast scheme requires only a quarter of the data information to achieve twice the prediction performance of the BVAR model.

4.4. Robustness to forecast indicators

Although GDP can be used as a relatively comprehensive scorecard to measure a country's economic health, other important macroeconomic indicators exist, and they often have different data characteristics. Since EcoForecast aims to build a purely data-driven approach

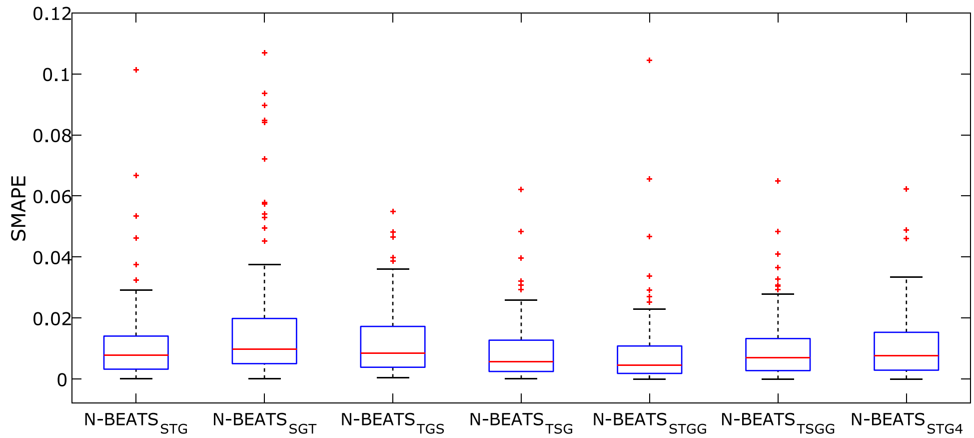

Fig. 4. Performance of different model structures of EcoForecast in GDP forecasting.

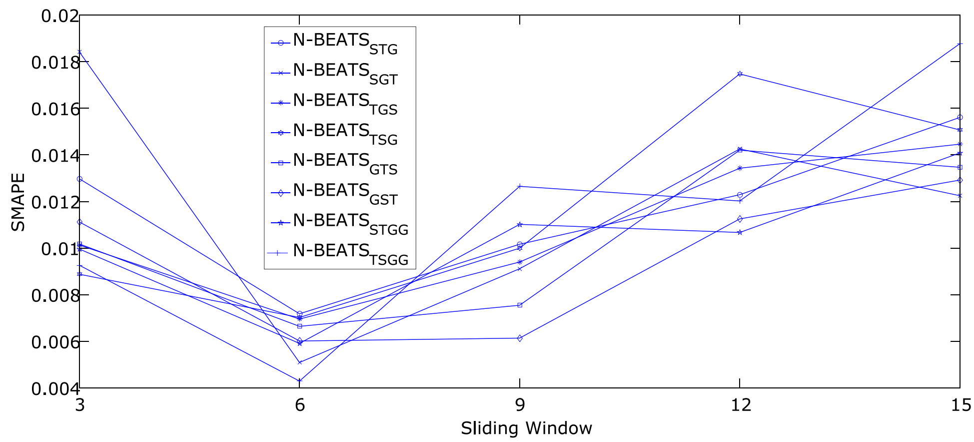

Fig. 5. Robustness of transition forecast frequencies for different structures.

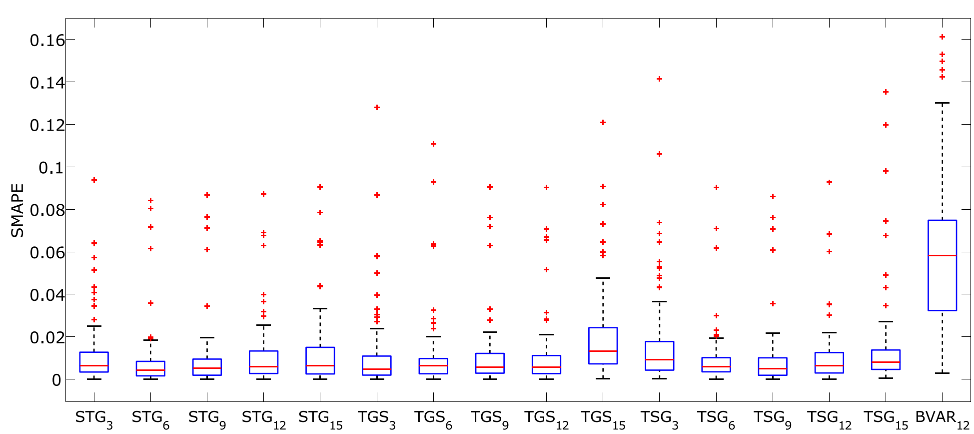

Fig. 6. Comparison of the transition forecast frequencies robustness of EcoForecast and BVAR.

to general economic forecasting, this section will test the robustness of EcoForecast for different indicators by forecasting macroeconomic indicators other than GDP. We chose two typical indicators as tests, the Purchasing Managers' Index (PMI) and national electricity generation (ELEC). PMI, a nationwide survey index of purchasing managers, reflects the level of optimism of companies about the economy. Electricity generation (ELEC) is an essential indicator of industrial production activity and the operating rate of factories. These two typical indicators correspond to economic confidence and industrial base in macroeconomics, respectively.

As shown in Fig. 7, both EcoForecast and BVAR can make relatively accurate forecasts of PMI. EcoForecast is more sensitive to real-time data, while BVAR's forecast has a significant lag compared to the actual data. In addition, in 2020, when economic optimism received significant fluctuations due to the epidemic, EcoForecast significantly outperformed traditional economics methods in analyzing sudden abnormalities and predicting subsequent evolutions. It is important to emphasize that the PMI threshold of 50% separates expansion from contraction, representing the trend of the country's economy. If this value is below 50%, it represents the concern of recession, and above 50%, it represents the signal of economic expansion. This threshold

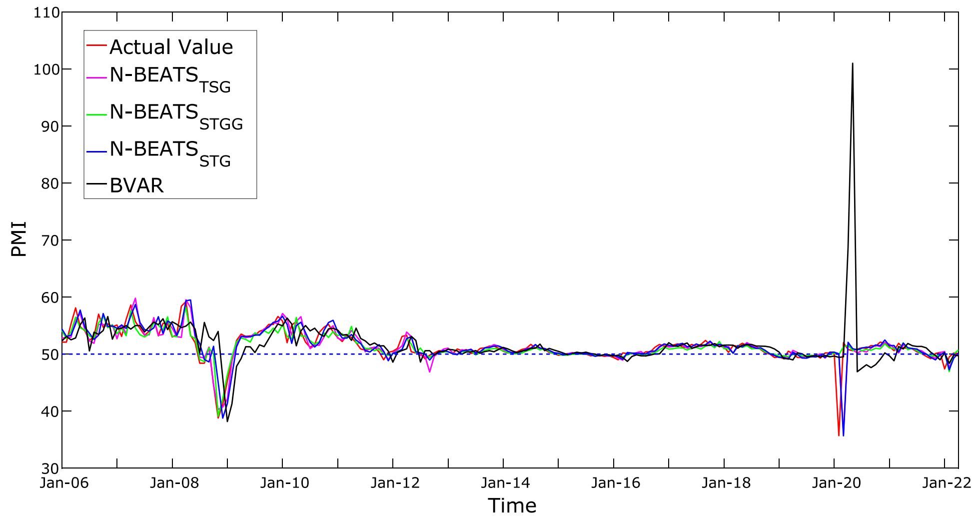

Fig. 7. Comparison of the forecasting curves of EcoForecast and BVAR for PMI.

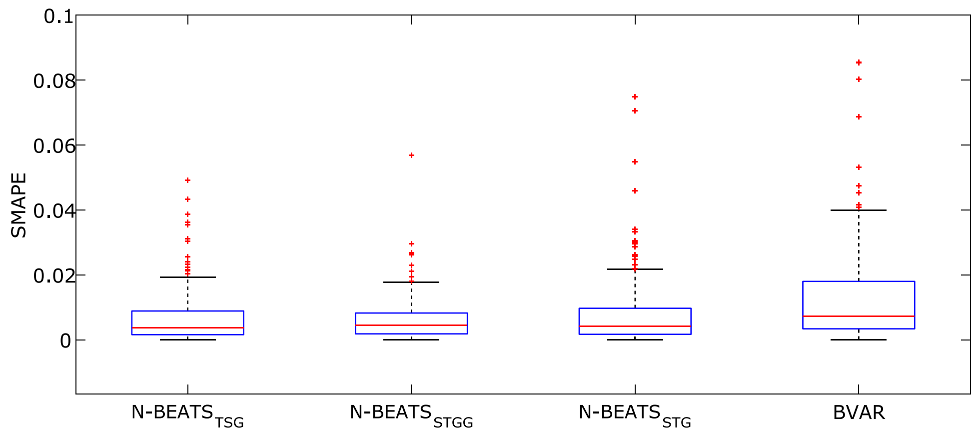

Fig. 8. Prediction error of EcoForecast in PMI forecasting.

implies the sensitivity of the forecasts; compared to EcoForecast, the statistical-based BVAR approach gave judgments contrary to reality in 2008, 2012, and 2020, which is fatal for forecasting.

Fig. 8 shows the errors of different EcoForecast model structures for PMI forecasting. The mean error of EcoForecast for PMI forecasts is similar to that of BVAR, but the stability is significantly more prominent. For a volatile index such as PMI, BVAR has significantly more high-error forecast outliers than EcoForecast.

Fig. 9 shows the forecasting curves of EcoForecast and BVAR for electricity generation (ELEC). When ELEC shows high stability, both methods can achieve relatively high accuracy, and EcoForecast is superior. However, when irregular fluctuations of the indicators occurred in recent years, the predictions of both methods were distorted. Fig. 10 shows the prediction errors of EcoForecast for ELEC with different structures. The EcoForecast prediction is more stable, with a smaller mean prediction error than that of BVAR. The average SMAPE error of EcoForecast for the PMI and ELECT forecasts is 0.007048448 and 0.014860746, which improves the accuracy by 2.38 and 1.45 times compared to BVAR, respectively.

To summarize, the data-driven EcoForecast demonstrates high stability in different sequence learning scenarios and the accompanying high-accuracy performance. This stability is reflected in a smaller prediction error expectation and variance, tolerance of fewer input samples, and robustness across prediction domains. Due to the search-based structural optimization and the paradigm design of short-term forecasting, EcoForecast has a high sensitivity to the emergence of economic inflection points and adapts quickly when the economic environment changes, thus demonstrating a performance that exceeds traditional solutions in GDP forecasting during epidemics and PMI forecasting during economic turmoil.

4.5. Interpretability

Purely data-driven deep learning models are often “black boxes”, and EcoForecast has developed interpretable features for forecasting, taking into account the needs of applications in the macroeconomic domain.

The interpretable function is developed based on the stack-based model structure of EcoForecast. Interpretability is achieved by constraining the stack to interpretable functions and implementing model decomposition after training is completed, as shown in Fig. 11. T, S, and G are the constraint functions of the stack, where T is fitted with the trend method for economic change, S is fitted with the period method, and G is fitted with a deep neural network.

Leveraging the function-fitting capabilities of machine learning to discover patterns and formulate of reasonable conjectures has proven to be an effective solution for advancing the discipline (Davies et al., 2021). EcoForecast’s interpretability allows it to contribute to the development of economics in a more far-reaching way. Specifically, it has four main implications:

- First, in engineering terms, the decomposition of the EcoForecast forecast curve into STG means that we add “constraints” to

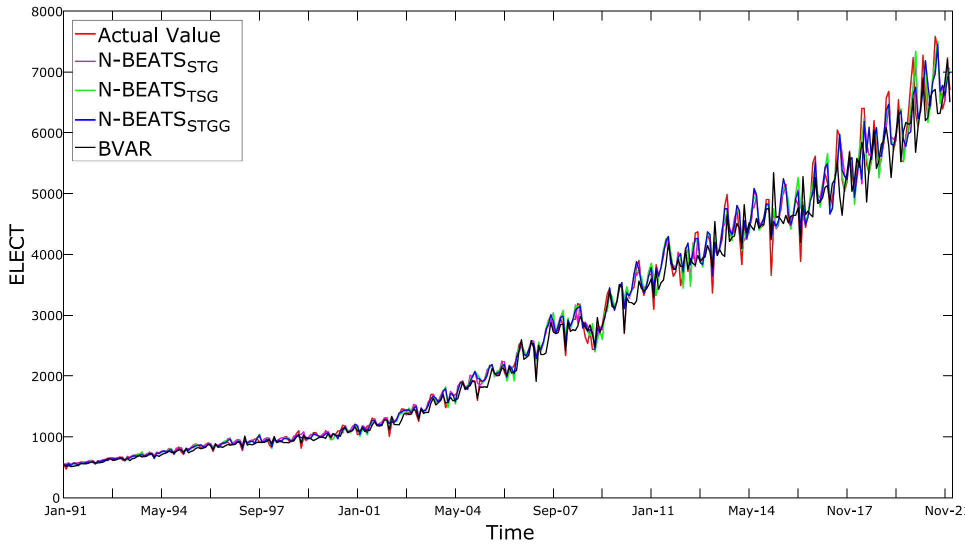

Fig. 9. Comparison of the forecasting curves of EcoForecast and BVAR for ELEC.

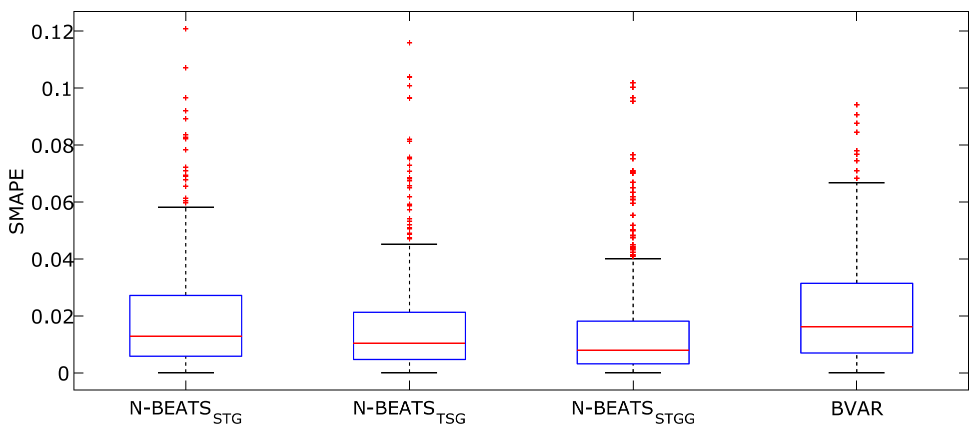

Fig. 10. Prediction error of EcoForecast and BVAR for ELEC.

the deep learning network, such as the need to use polynomial functions to fit, and these constraints are often interpretable (e.g., periodic and polynomial functions).

- Second, the existence of T and S provides an interface between the model and the economy, e.g., by extracting the parameters of S from the fitted S model, the cycle of macroeconomic change can be inferred, and by fitting the T model, the primary trend of the country's economic change can be inferred.
- Third, EcoForecast can analyze the dominant macroeconomic terms by decomposition, such as how much growth trends and economic cycles play a role in the country's economic changes. In the example in Fig. 11, China's GDP curve is decomposed into the effects of economic trends and cycles, which provides an intuition for economists' further research.
- Fourth, EcoForecast also provides the possibility of introducing economics knowledge, such as setting the function constraint to a specific economic formula, to improve the accuracy of EcoForecast forecasting continuously.

EcoForecast's interpretable decomposition analysis approach can constitute cross-validation with economics practice. Since the 1990s, China has adopted a series of reform measures, such as accession to the WTO, reform of state-owned enterprises, divestiture of nonperforming assets, and listing of state-owned banks as well as cultivation of the real estate market, which brought economic growth to a cyclical high in 2008 (Ba, 2022). An economic downswing followed this due to the industrial structure imbalance (Sarygulov et al., 2022) and subprime mortgage crisis (Yang et al., 2022), which can be unearthed under the cover of the sustained growth GDP curve, as shown in the seasonality and generic decomposition curves in Fig. 11.

5. Conclusion and future work

Macroeconomic forecasting requires a new paradigm to adapt to the current information development. However, existing traditional statistics-based macroeconomic forecasting mainly focuses on exploring feasible methods for improving the accuracy of long-term predictions, and their performance with short-term predictions was far less impressive under the impact of unexpected incidents. Although many experts and scholars have explored the issues of macroeconomic forecasting from different perspectives and have achieved a series of achievements, there is still much room for improvement in purely data-driven short-term high-precision forecasting. The typical deep learning scheme cannot meet the requirement of interpretability in economic forecasting and still lacks a unified normative scheme for macroeconomic forecasting that balances generality and accuracy in terms of performance.

We proposed EcoForecast, a data-driven macroeconomic forecasting method based on the N-BEATS neural network. EcoForecast demonstrates the feasibility of the current SOTA model of univariate forecasting, N-BEATs, surpassing traditional economics methods with a pure deep learning approach for macroeconomics applications for the first

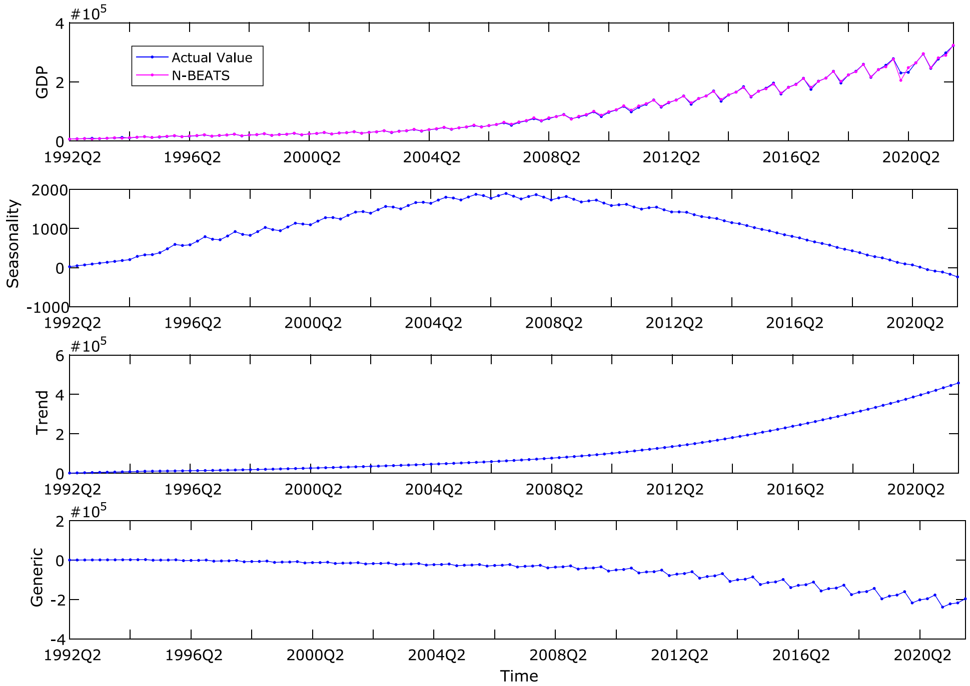

Fig. 11. EcoForecast decomposition and interpretability.

time. EcoForecast, as a new forecasting paradigm in macroeconomic forecasting, can maintain generalizability across multiple forecast indicators and robustness when conditions such as forecast frequency and time window change, providing a new possible research direction for short-term macroeconomic forecasting. It should be emphasized that the EcoForecast model is interpretable, and its performance is verified by actual macroeconomic data for China from 1992 to 2021.

To test the performance of EcoForecast, experiments focusing on five aspects of its forecasting performance, robustness, and interpretability were implemented.

- Three types of errors, SMAPE, MAPE, and MASE, were chosen to measure the GDP forecasting ability of EcoForecast, and the average errors were obtained as 0.009654416, 0.01912634, and 0.063727964, which improved the accuracy by 3.147, 3.153, and 3.442 times, respectively, compared to the traditional BVAR. To further improve the GDP forecasting performance of EcoForecast, a structure optimization test was used, and the SMAPE error could be reduced to 0.007734261 after optimization, which improved the accuracy by 3.94 times compared with the traditional method. Structure optimization results in a smaller prediction error, higher prediction stability, and fewer prediction outliers.
- By reducing the data sliding window, EcoForecast's robustness of transition forecast frequencies was tested. It was found that EcoForecast has strong robustness, i.e., even with reducing the data sliding window to 3, the EcoForecast scheme has 2.51 times smaller forecast errors compared to the BVAR model with a window of 12. In other words, the EcoForecast scheme requires only a quarter of the data information to achieve twice the prediction performance of the BVAR model.
- Considering the application needs in the macroeconomic domain, testing for the interpretability and generalizability of EcoForecast among multiple forecast indicators is implemented. The average SMAPE error of EcoForecast for the PMI and ELECT forecasts is 0.007048448 and 0.014860746, which improves the accuracy by 2.38 and 1.45 times compared to BVAR, respectively. Finally, interpretable decomposition of GDP forecasts from EcoForecast can provide forecasting analysis from economic trends and cycles.
- EcoForecast's interpretable decomposition result is consistent with the actual economics practice in China, and this approach can analyze the dominant terms in economic changes, which provides an intuition for economists' further research.

Although EcoForecast has achieved high forecasting performance, the model also has network structure limitations, and the input interface for external information has not yet been developed. Specifically, production and sales information may provide supporting data for GDP forecasts, while richer inductive biases such as convolutional and recurrent neural networks will accommodate a broader range of forecast types. Future work includes building multichannel data-driven interfaces and extending multi-network structure selections, followed by in-depth testing of EcoForecast's adaptability to different regions, macroeconomic indicators, and external variable selections.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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