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Abstract: *The Geomagnetic SYMH index is commonly used to measure disturbances in geomagnetic activity, such as the impact on ground-based technological systems resulting from Sun-Earth interactions. This measure can help mitigate potential damage and disruptions caused by space weather events. Recently, artificial intelligence (AI) has garnered increasing attention for its capabilities in predicting tasks, particularly due to its advantages in analyzing large datasets. Significant advancements in various model architectures for predicting the SYMH index have emerged, including empirical methods, machine learning, and deep learning techniques. However, challenges persist in this research area, as accurately predicting the SYM-H index remains difficult due to the dynamic nature of geomagnetic data. In this work, a new deep learning model of Neural Basis Expansion Analysis for Time Series (N-BEATS), which utilizes high temporal resolution data of one-minute SYMH index readings from the peak of most recent solar cycles (specifically, solar cycle 25). Our findings indicate that this new model has significant potential in capturing the temporal patterns of the SYMH index, achieving prediction accuracy of approximately 99%.*

Keywords: Time series prediction; Interpretable model; Geomagnetic index, Symmetric-horizontal (SYM-H)

1. INTRODUCTION

The symmetric-horizontal (SYMH or SYM-H) index is a widely used geomagnetic index that quantifies the storm-time ring current and provides critical insights into the global state of the Earth's magnetosphere. It reflects the behavior of a belt of charged particles that forms around the Earth during geomagnetic storms, making it significant for assessing risks posed by space weather activities to technological infrastructure, including power grids, [1], [2] pipelines [3], and satellite systems [4].

Recently, there has been growing awareness among technological operators about safeguarding their systems to ensure robustness and reliability against these risks. In this context, early warnings of the SYMH index through predictions or forecasts are crucial for implementing mitigation strategies and preventive actions at the operational level [5], [6]. Early prediction is important as a valuable tool for understanding and forecasting the intensity and duration of geomagnetic storms. A drop in the value of SYMH index typically reflects the onset of geomagnetic storm activity and the evolution of the ring current, which subsequently builds up and intensifies. Different levels of the SYMH index correspond to varying storm strengths, measured in nanotesla (nT): weak (−30 to −50), moderate (−50 to −100), strong (−100 to −200), and severe (⩽−200) storms [7]. These values are derived from multiple ground-based magnetometers that measure the horizontal (H) component of the geomagnetic field and then subtracting the background magnetic field and the solar quiet variations [8]. With the availability of higher temporal resolution data (measured in minutes), the SYMH index has become a critical parameter for monitoring geomagnetic storm activity. This granularity allows for a more detailed understanding of storm onset and evolution [9], [10]. The SYMH index is particularly valuable for studying rapid variations in the geomagnetic field during storms and substorms as a large-scale phenomenon that might be overlooked when using lower-resolution geomagnetic indices. Several studies have proposed various architectural models for SYMH index prediction. While numerous models and techniques have been developed to improve the prediction performance and reliability of SYMH index, accurate forecasting remains a significant challenge due to its sensitivity to the dynamics of the ring current. One advantage of univariate prediction models is their faster computation, as they do not rely on external sources of upstream solar wind data. This allows the geomagnetic index to be provided instantly as an alternative indicator[11]. Early research efforts focused on empirical relationships and advanced machine learning (ML) models.

To date, most SYMH prediction models have relied on multivariate data sources, combining satellite and ground-based data. For example, studies in [8], [12] developed the nonlinear autoregressive neural networks with exogenous inputs (NARX), achieving reliable one-hour-ahead forecasts using historical solar wind and interplanetary magnetic field (IMF) parameters. Siciliano et al. [13] proposed a deep learning model using LSTM and CNN architectures, comparing the two for one-hour SYMH forecasting. These models, trained on both

Table 1. Summary of part works on SYMH index prediction modeling

Author	Year	Model	Prediction horizon	Remarks
A. Bhaskar et al.	2019	Nonlinear autoregressive with exogenous inputs	1 hour	The model could reproduce the entire time profile of SYMH and ASYH during major storm conditions
L. Cai et al.	2010	Nonlinear autoregressive with exogenous inputs	1 hour	High accuracy neural networks with feedback window captures ring-current decay
F. Siciliano et al.	2021	LSTM, CNN (ANN)	1 hour	Found LSTM marginally outperformed CNN in their multivariate forecasting setting.
D. Iong et al.	2022	Gradient Boosting Machines (GBM)	Multi-hour ahead	Interpretable ML for SYM-H forecasting to focus on explainability
A. Collado-Villaverde et al.	2024	Deep neural networks using a quantile-based forecast with confidence intervals	Multi-hours ahead	First quantile-based DNN SYM-H operational forecast which is robust/reliable

IMF/solar wind inputs and past SYMH values, demonstrated remarkable accuracy, with coefficients of determination (R^2) exceeding 95% [14]. Another study evaluated gradient boosting machines for multi-hour SYMH forecasting, training the models with solar wind/IMF inputs and past SYMH values. This work also pioneered the use of explainable machine learning, employing Shapley values to examine feature attribution in deterministic point forecasts. Additionally, [15] explored both point forecasts and quantile-based prediction intervals, validating their models on historical and near-real-time data. Their deep neural network (DNN) model targeted operational SYMH forecasting up to two hours ahead, focusing on uncertainty quantification through quantile regression. The literature highlights the promise of machine learning approaches, particularly deep neural networks with LSTM architectures, for SYMH prediction. Some models have achieved prediction horizons of up to two hours with high accuracy. The summary of SYMH index prediction is tabulated in Table 1.

This paper is structured as follows: Section 2 presents a brief overview of the N-BEATS model. Section 3 describes the data and methodology. Section 4 discusses the results with findings and analysis. Section 5 concludes with findings and recommendations for future research.

2. BACKGROUND OVERVIEW OF N-BEATS MODEL

Recent years have seen the emergence of advanced model architectures for prediction and forecasting tasks. One such state-of-the-art on deep learning model is N-BEATS, introduced by Oreshkin et al. [16]. This model is designed for forecasting tasks and consists of stacks containing multiple blocks with backward and forward residual links. It aggregates predictions from all blocks, ensuring that each aspect of the data from general trends to specific seasonal patterns which is then incorporated into the final prediction. The reliability of the N-BEATS model in achieving superior prediction accuracy has been demonstrated across diverse domains, including stock market analysis, energy forecasting, telecommunications, and sales predictions [17], [18], [19], [20]. Within the domain of geomagnetic index prediction, early works on Dst index forecasting [21] showcased the model's ability to capture patterns in the long duration of data, outperforming other architectures such as long short-term memory (LSTM) models.

3. METHODOLOGY

The model was developed using high-resolution SYMH index data at one-minute intervals, which was obtained from the International Service of Geomagnetic Indices (available at https://isgi.unistra.fr/). Provisional data in the IAGA2002-like format were used for model development, having undergone routine reviews by ISGI and/or ISGI collaborating institute scientists. Specifically, SYMH data from December 2024 onward were processed, covering the peak of the most recent solar cycles (e.g., cycle 25). Figure 1 illustrates the data plotted over the two-year period, which was partitioned into training and testing datasets at a ratio of 90% and 10%, respectively.

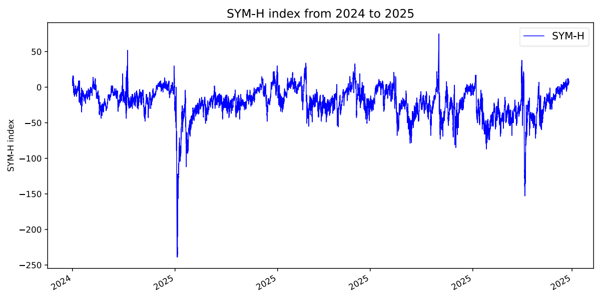

Fig. 1. This figure illustrates the plotting of SYMH index data covering from 2024 to 2025.

The details of the training and testing datasets are provided in Table 2. This includes statistical information such as the number of data points, mean, variance, minimum and maximum values. Meanwhile visualization of SYMH index data distribution which is partitioned as training set and testing set is provided in Fig. 2.

Table 2. Exploring statistical data distribution of the SYMH index data

Model	Training dataset	Testing dataset
No of data	194,400	21,601
Mean	-20.66	-24.58
Median	-19	-20
Standard deviation	21.38	25.62
Minimum value	-239	-153
Maximum value	75	38

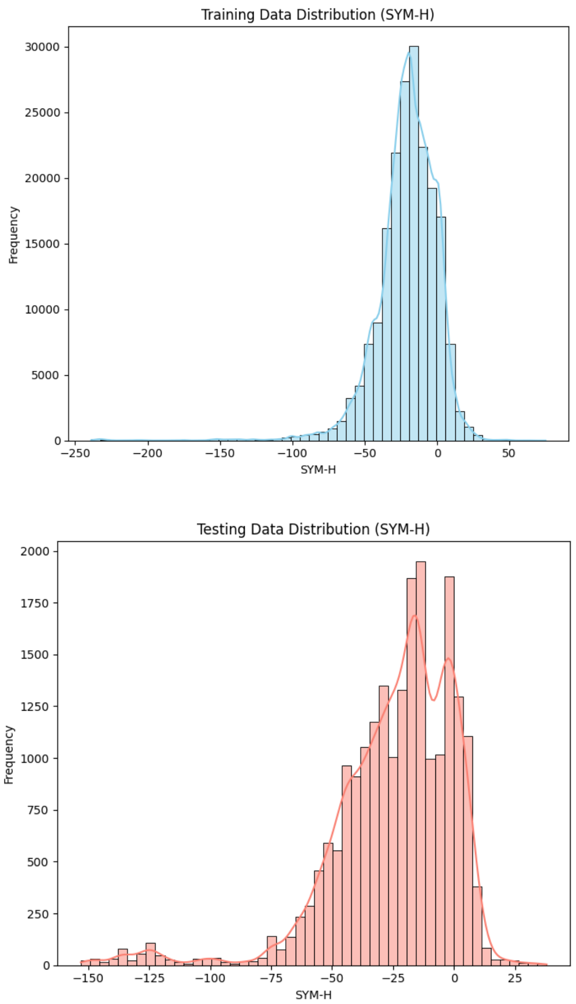

Fig. 2. Data distribution for SYMH index data during peak solar cycle 25 is illustrated as training set (above) and testing set (below)

Workflow of SYMH index prediction consists of three main stages: data preprocessing, N-BEATS model development, and performance evaluation. Firstly, The data , x were rescaled to a specific range between -1 and 1, as shown in equation (1), where $x_{\min}$ and $x_{\min}$ represent the minimum and maximum values in the SYMH data, respectively.

$$x' = 2 \cdot \frac{x - x_{\min}}{x_{\max} - x_{\min}} - 1 \quad (1)$$

Secondly, the data were divided into training, validation, and testing sets using three-fold cross-validation which was programmed in Python (version 3.7) and executed on a high-performance NVIDIA GeForce RTX 4070 Ti GPU.

The prediction model was designed to begin with the input layer in which the model receives the time-series data. The input was passed through an InputLayer with the input shape of (24,1) to perform the first level of representation learning. It represents. a sliding time window of 24-time steps with one feature (e.g. SYMH index) data per step. The processed input was then fed into a Flatten layer, which reshapes the data from a 2D temporal-feature structure into a 1D vector of size. Indeed, this is important to retain the information related to sequential feature. This flattened vector was then processed by a custom NBeatsBlock, a fully connected deep learning component. Each NBeatsBlock produces two outputs: a forecast component (added to the final output) and a backcast component (subtracted from the residual to be modeled by the next block). Each block refines the forecast and passes the residual to the next block, with outputs aggregated via addition. The NBeatsBlock produced the output as a single scalar value, indicating that the model is configured to produce one-step-ahead forecasts. In final step, a Dense layer takes this scalar as input and outputs another scalar, likely used to refine the forecast or match output dimensions.

Thirdly, the performance of the SYMH prediction model was evaluated using five metrics: mean squared error (MSE), mean absolute error (MAE), root mean squared error (RMSE), mean absolute scaled error (MASE), and the coefficient of determination (R^2). Equations (2)–(6) define these metrics, where T, x_t, $\hat{x}_t$, $\bar{x}_t$ represent the total number of forecast time steps, actual values, predicted values, and the mean value at time t, respectively. Evaluating multiple metrics is essential to avoid misleading conclusions that might arise from relying on a single metric. This ensures a more comprehensive and fair assessment of the model's performance.

$$\text{MSE} = \frac{1}{T}\sum_{t=1}^{T}(x_t - \hat{x}_t)^2 \quad (2)$$

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T}| x_t - \hat{x}_t | \quad (3)$$

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t - \hat{x}_t)^2} \quad (4)$$

$$\text{MASE} = \frac{\frac{1}{T}\sum_{t=1}^{T}| x_t - \hat{x}_t |}{\frac{1}{T-1}\sum_{t=2}^{T}| x_t - x_{t-1} |} \quad (5)$$

$$R^2 = 1 - \frac{\sum_{t=1}^{T}(x_t - \hat{x}_t)^2}{\sum_{t=1}^{T}(x_t - \bar{x}_t)^2} \quad (6)$$

4. RESULTS AND DISCUSSIONS

Evaluation of error metrics for different N-BEATS model configurations with varying input window sizes: 12, 24, 48, and 72 is tabulated in Table 3. It is important to observe the change of length in window size of the proposed model used in different configurations and how the model performed in terms of accuracy and robustness. The model performances vary across different window sizes. It can be observed that NBEATS_48 model consistently demonstrates the best performance across all metrics, hence balancing the optimal performances to capture the temporal pattern in the SYMH index data. NBEATS_72 demonstrated higher errors which can be significantly observed as the highest among all metrics hence the model with a 72-hour of windows size suffers from instability or overfitting cause poor generalisation at this window length. Variability of the windows horizon signified some recovery in model stability with longer window sizes at 72 window horizons; however, it remains in non-optimal model performances. This confirmed that shorter window sizes were not definitely allow the model to capture relevant temporal patterns effectively without overcomplicating the learning task. Fig. 3 depicts the bar plot of error metrics in demonstrating the variability between metrics indicators to enable a fair visual comparison of all metrics across models.

Table 3. Error metrics for each model architecture

	Metric			
Model	MSE	MAE	RMSE	MASE
NBEATS_12	1.740	0.982	1.283	2.990
NBEATS_24	3.046	1.338	1.655	4.025
NBEATS_48	1.588	0.919	1.244	2.778
NBEATS_72	4.539	1.697	1.983	5.017

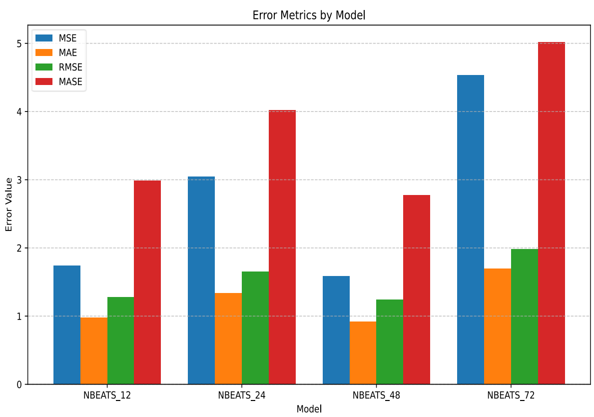

Fig. 3. Plot of error metrics

The metric of R^2 showed an exceptionally high performance with scores respectively of 0.996, 0.998, 0.998 and 0.997 for NBEATS_12, NBEATS_24, NBEATS_48 and NBEATS_72. Ultimately the proof with coefficient of determination in which indicated each N-BEAT models could capture the underlying time series data very well. This could be observed throughout the plots that are strongly matched with the ground truth shown in Fig. 4 (a)-(b) when comparing the actual and predicted data.

(a)

(b)

(c)

(d)

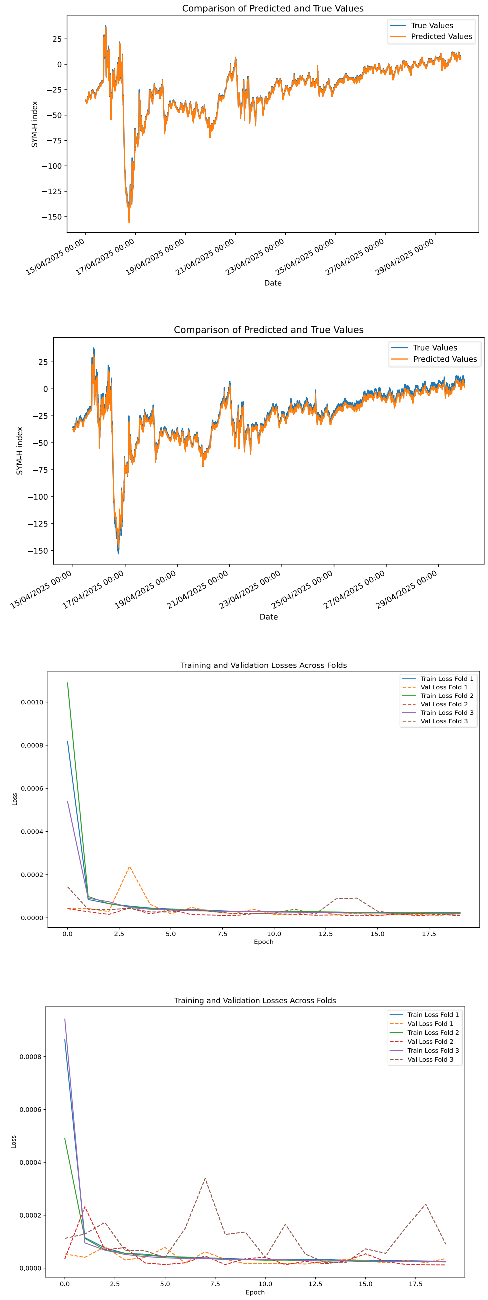

Fig. 4. Graph of comparison between actual and predicted SYMH index (a) NBEATS_48 and (b) NBEATS_72. Plot of training and validation losses (c) NBEATS_48 and (d) NBEATS_72

Based on Fig. 4 (c)-(d), the graphs of training and validation losses over 20 epochs considering the best and the worst N-BEATS model performances. These plots of training and validation losses assess whether the model is learning the patterns and generalised abilities in the data. Each plot reflects performance across three cross-validation folds, providing insights into the model's learning dynamics and generalisation behaviour under varying temporal SYMH index data. Referring to the window size of 48, the training loss across all folds decreases rapidly within the first few epochs and stabilises at a very low value, indicating efficient learning and convergence. It is also noticeable that NBEATS_72 was difficult to generalise and likely suffers from over-complexity or inability to effectively model the longer temporal dependencies reinforcing the presence of instability or learning inefficiency. The validation losses are slightly more chaotic, especially during fold three.

5. CONCLUSION

The clear superiority of the N-BEATS deep learning architecture for NBEATS_48 highlights these configurations across varying window sizes as optimal under the current experimental setup, while the poor performance of NBEATS_72 emphasizes the need for caution when extending input horizons without additional model tuning or architectural changes. Comparing models through metrics considering errors and accuracy of prediction highlighted that remarkable performances reached up to 99%. To conclude, the size of window length plays a critical role in predictive accuracy and model generalization. In future it is recommended to perform forecasting task at multistep hours ahead and model optimisation to seek the best configuration with the best performances for high resolution data of SYMH index.

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