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Multi-Horizon Short-Term Residential Load Forecasting Using Decomposition-Based Linear Neural Network

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Abstract. Short-Term Load Forecasting is crucial for grid stability and real-time energy management, particularly in residential settings where consumption is highly volatile and influenced by behavioral and external factors. Traditional models struggle to capture complex, non-linear patterns. This study proposes a forecasting framework based on the DLinear model, which decomposes time series data into trend and seasonal components using a simple linear neural network architecture. Designed for multi-horizon forecasting, the model predicts electricity demand across several future time points simultaneously. Experimental results show that DLinear performs best at a 24-hours prediction length, achieving the lowest mean absolute error of 5.11, indicating improved accuracy with longer horizons. These results confirm DLinear's robustness in modeling residential electricity patterns and support its use in adaptive energy management within smart grid systems. DLinear shows strong potential for multi-horizon forecasting, offering a lightweight and efficient alternative to both traditional single-horizon models and computationally intensive transformer-based approaches.

Keywords: DLinear, Time Series Forecasting, Multi-Horizon Forecasting, Energy Management, Smart Grid

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1. Introduction

Short-Term Load Forecasting (STLF) plays an important role in energy management, with residential electricity demand presenting significant forecasting challenges due to its non-stationary nature, strong behavioral dependencies, and temporal volatility among households Click or tap here to enter text. [1], [2], [3], [4]. STLF aims to predict electricity demand over short time horizons, typically from minutes to a few hours ahead. It is essential for maintaining grid stability, balancing supply and demand, and enabling real-time energy dispatch [5]. While traditional STLF has focused on aggregated demand, forecasting at the individual household level presents a new set of challenges due to the high variability and uncertainty inherent in residential consumption. Household electricity usage is strongly influenced by personal behaviors, daily routines, and irregular appliance usage patterns, making the load profiles highly volatile and challenging to model with conventional statistical methods [6]. These uncertainties lead to prediction errors, particularly in capturing peak loads, which are further amplified by phenomena such as the double penalty effect, where early or late errors in predicting demand spikes are penalized equally.

STLF is classified within the group of time-series problems. There are two categories of approaches to solving the STLF problem, which can use classical methods and machine learning methods [7] [8]. Classical methods such as Auto-Regressive Integrated Moving Average (ARIMA) method are widely adopted for STLF as they require only historical load data and make no additional assumptions [9], [10]. However, Amin et al. [10] found that ARIMA shows limited performance in short-term load forecasting applications due to its inability to effectively model nonlinear data patterns. On the other hand, Support Vector Regression (SVR) provides better accuracy than ARIMA as it can predict electricity consumption patterns, which ARIMA fails to predict. Machine learning methods are a more reliable solution to implement compared to classical methods, as they can better capture more complex non-linear relationships [11], [12], [13], [14], [15]. Nevertheless, SVR is limited to forecasting only one step ahead by default, so it cannot be used for multi-horizon forecasting [16], [17] compared Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) for short-term load forecasting.

Multi-horizon forecasting allows a model to predict several future time steps simultaneously, offering significant benefits over traditional single-step models that predict only one time point at a time. This approach improves the accuracy of forecasting by capturing the underlying temporal dependencies over multiple horizons, thus reducing errors, especially when predicting peak loads, which are often challenging due to their volatility [18]. Transformer models, on the other hand, are designed to handle multi-horizon forecasting more effectively by using attention mechanisms to focus on relevant past time steps, which allows them to better capture long-range dependencies [19]. However, transformers are computationally expensive and require significant resources, making them less suitable for real-time applications or environments with resource constraints [20]. LSTM can be adapted for multi-horizon forecasting by learning patterns across multiple time steps, but they often face challenges in capturing long-term dependencies and maintaining performance over extended horizons. This results in performance degradation as the forecast horizon increases.

Previous research on short-term residential electricity load forecasting has shown various limitations. LSTM shows that performance is influenced by the number of lookbacks, which represent historical hours before the current hour. When the lookback used is fewer than 10, the accuracy of the model increases. However, when using 10 lookbacks the accuracy decreases and error increases. It shows that short-term load forecasting using LSTM only provides better accuracy if using less than 10 lookbacks [20]. Residential electricity that is influenced by social activities, weather, and day needs an accurate model to capture dynamic patterns and improve forecasting accuracy. In order to capture those dynamic patterns, Neethu et al. [21] used Dynamic Mode Decomposition (DMD) that shows DMD is adaptive to multiple seasonal and cyclic patterns. Adaptability suited for short-term residential electricity load forecasting is influenced by many external factors. The consequence of the existence of dynamic patterns is the emergence of trend change patterns that are characteristic in time series forecasting in terms of STLF. The handling of these trends can be achieved through DLinear approach [22]. DLinear is more accurate in capturing trends in time series data, because this model specifically processes the trend components [23]. In addition, DLinear has a simple structure and can better extract trends and seasonal features through time decomposition that are suitable for residential electricity that is influenced by external factors [24].

The main contribution of this work is a forecasting framework that addresses the challenges of short-term residential electricity prediction across multiple time horizons by integrating time series decomposition with a linear neural network structure through DLinear model. In this context, multi-horizon refers to multi-step predictions, where the model forecasts electricity demand at several future time points simultaneously. The proposed approach enables accurate long-range short-term forecasting while remaining lightweight and robust in handling the volatility of household-level consumption. This design allows flexible control over prediction length, making it adaptable to various operational requirements in residential energy management.

2. Methods

DLinear is a time series forecasting approach designed to address the limitations of traditional Transformer-based models, particularly in terms of computational efficiency and the ability to capture long-term temporal trends. While the Transformer architecture has proven highly effective for natural language processing tasks, it tends to perform poorly when applied to time series data due to difficulties in modeling smoothly increasing or decreasing trends over time. Moreover, the complex structure of Transformers, originally built for sentence-level semantic understanding, results in excessive computational overhead when used for time series analysis [25].

To overcome these issues, DLinear applies a simple yet effective strategy by decomposing the input time series taken from a lookback window of length L into two separate components: trend and remainder. The trend component is extracted using a moving average, capturing the long-term behavior of the signal, while the remainder component represents short-term fluctuations and noise. Each component is then passed through its own linear layer, then the final prediction is obtained by summing up the outputs of both linear projections. This separation allows the model to learn different temporal dynamics using lightweight linear operations that enabling better interpretability and faster inference compared to other deep neural networks.

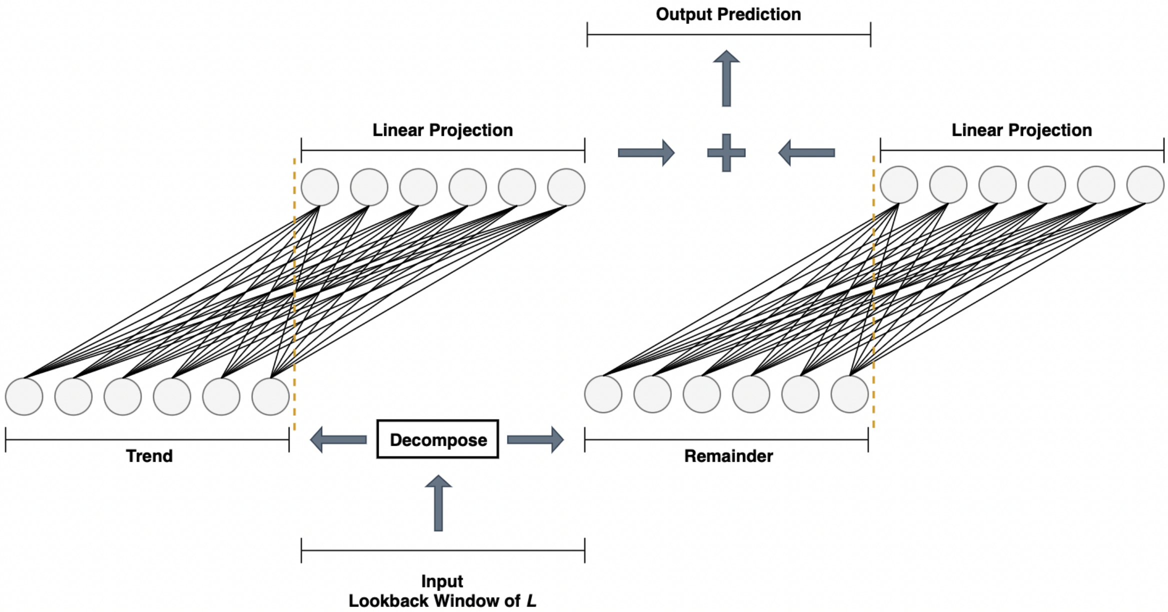

Figure 1. Architecture of DLinear showing the input-output mapping. The model takes a lookback window of length L from historical time series data as input, which is decomposed into two components: the trend (capturing long-term patterns) and the remainder (representing short-term fluctuations). Each component is processed independently through a linear projection layer. The outputs from both projections are then summed to generate the final prediction.

Figure 1 shows the architecture of DLinear that was used in this study. The DLinear architecture combines time series decomposition with linear modeling for effective forecasting. The model uses a lookback window of length L from historical data, which is decomposed into two components: the trend (capturing long-term patterns) and the remainder (representing short-term fluctuations). Each component is processed separately using a linear projection, and their outputs are summed to produce the final prediction. This approach allows DLinear to capture both trends and noise with fewer parameters than complex deep learning models.

For preprocessing, we apply standard scaler normalization based on the training data range, with validation and test subsets following the same range. We then use a sliding window approach, where the window size is L, and the window shifts by one time step at a time to generate the features for forecasting.

3. Results and Discussion

The proposed method was evaluated using the OpenEI dataset. This dataset contains hourly residential load demands from a variety of cities and states across the United States. For this study, one-year load data from a selected region in 2012 is used. For this study, we selected the NY subset, which is publicly available and includes data from 24 individual households, and is commonly used in prior research for its widespread adoption. The model's performance was assessed using Mean Absolute Error (MAE), in Equation (1). MAE calculates the average of the absolute differences between predicted and actual values, treating all errors equally regardless of their magnitude, thus providing a more interpretable and balanced view of overall prediction accuracy. MAE provides a straightforward understanding of the typical size of prediction errors.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Y_i - \hat{Y}_i| \quad (1)$$

where n is the total household number, Y_i is the ith actual value, and $\widehat{Y_i}$ is ith predicted value.

The configuration outlined in Table 1 provides insight into how the model is optimized during training. The model is set to run for a maximum of 100 epochs, with a batch size of 32, allowing it to process 32 samples at a time for each update step. A patience value of 3 is implemented as part of an early stopping strategy, meaning that training will cease if the validation loss does not improve for 3 consecutive epochs, helping to prevent overfitting and reduce unnecessary training time. As shown in Table 2, the model is evaluated under three different prediction lengths 6-hours, 12-hours, and 24-hours to assess its performance across various forecasting horizons. The actual number of epochs completed before early stopping varies depending on the prediction length: training halts at the 13th epoch for the 6-hour forecast, at the 11th epoch for the 12-hour forecast, and once more at the 13th epoch for the 24-hour forecast. These results indicate that the model typically converges relatively quickly, and the early stopping mechanism effectively prevents overtraining by identifying when the model's performance has plateaued.

Table 1. Hyperparameter Settings

Name	Value
The number of times the entire experiment is repeated	3
Epochs	100
Batch size	32
Patience	3
Learning rate	0.0001
Loss function	mean absolute error

We evaluate the performance of DLinear using a lookback and prediction window of 6-hours, 12-hours, and 24-hours. Our findings indicate that the model's performance generally improves with longer lookback and prediction windows, with a notable increase in accuracy observed at a 24-step configuration, consistent with these findings. As shown in Table 2, the MAE consistently decreases as the lookback and prediction windows increase, with the most pronounced improvement observed at 24-hours. These results suggest that DLinear performs satisfactorily in short-term load forecasting tasks. However, the risk of overfitting becomes more evident with longer lookback windows, warranting careful consideration in practical applications.

Table 2. Mean Absolute Error Result of the DLinear Model for Three Different Prediction Lengths Compared to Other Models

Model	Value for each prediction length		
	6-hours	12-hours	24-hours
LSTM	6.15	6.49	8.64
Transformer	6.20	6.12	6.24
DLinear	5.78	5.68	5.11

When comparing DLinear to other models, such as LSTM and Transformer, it consistently outperforms both in terms of MAE across all prediction horizons. Specifically, at the 24-hours prediction horizon, DLinear achieves the lowest MAE of 5.11, significantly outperforming LSTM (MAE of 8.64) and Transformer (MAE of 6.24). This superior performance highlights DLinear's efficiency, reliability, and robustness in handling multi-horizon forecasting tasks, where capturing long-term dependencies and fluctuations is critical. The lower MAE observed in DLinear suggests it is better at generalizing across multiple horizons, especially when handling the inherent volatility of residential electricity demand. Furthermore, DLinear's simplicity and computational efficiency make it a highly viable solution for real-time applications, in contrast to the more complex and computationally expensive Transformer model, which, although powerful, requires significantly more resources.

Example of prediction results in 6-hours, 12-hours, and 24-hours shown in Figure 2. The plots compare the actual load values (ground truth) with the predicted values at each time step using solid black and dashed blue lines, respectively. In the 6-hours forecast (Figure 2a), the model demonstrates reasonable accuracy, capturing the general trend of the actual data, although it slightly underestimates the magnitude of the load. The predictions are relatively close to the ground truth, indicating that the model performs well in the very short term.

As the prediction horizon extends to 12-hours (Figure 2b), the accuracy of the model begins to decline. While the model still captures some overall trends, the predicted values begin to diverge more noticeably from the ground truth. This is typical in time-series forecasting, where uncertainty increases with time. In the 24-hours forecast (Figure 2b c), the performance further deteriorates. The predicted curve shows a smoothed version of the actual data, failing to capture some of the more abrupt changes and exhibiting both under- and over-estimations. This suggests that while the model retains some awareness of the general load pattern, it becomes less sensitive to fluctuations as the prediction window widens. Overall, the analysis indicates that the model is effective for very short-term forecasts (up to 6 hours) but less reliable for longer horizons, which is a common limitation in STLF tasks. These findings are important for applications such as smart grid operation, demand response, and energy management, where accurate short-term forecasting is critical for operational efficiency and stability.

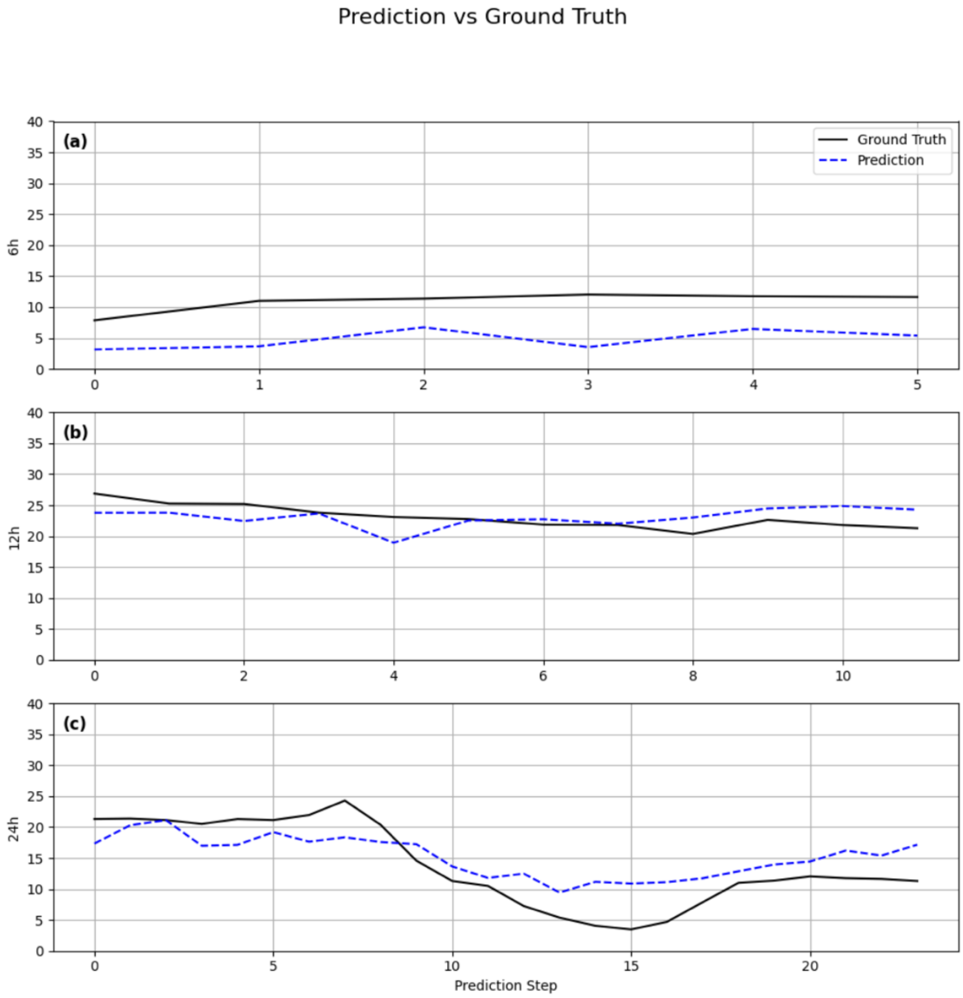

Figure 2. Example of Ground Truth vs Prediction in (a) 6-hours, (b) 12-hours, and (c) 24-hours

4. Conclusion

This study introduces a decomposition-based linear neural network framework, DLinear, designed for multi-horizon short-term residential load forecasting. By integrating time series decomposition into trend and remainder components, DLinear effectively addresses the volatility and irregularity of household electricity consumption while maintaining a lightweight and interpretable structure. Evaluation on the OpenEI dataset demonstrated the model's strong performance across different prediction horizons, with accuracy improving for longer prediction windows, particularly at 24 hours. These findings confirm DLinear's ability to adapt to varying operational demands in energy management.

However, while promising accuracy improvements were observed with longer prediction windows, the potential trade-off with overfitting suggests the need for further tuning and validation. We also acknowledge several limitations in our work. First, the use of data from a single region may limit generalizability to other areas with different consumption behaviors. Second, the exclusion of external factors, such as weather and occupancy, reduces the model's ability to adapt to broader real-world scenarios.

For future research, we plan to explore the generalization of DLinear to multi-regional datasets and incorporate external contextual features like weather conditions and demographic data. Additionally, we aim to investigate hybrid architectures combining decomposition with lightweight attention mechanisms to further enhance model performance.

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References

[1] W. Lin, D. Wu, and M. Jenkin, "Electric load forecasting for individual households via spatial-temporal knowledge distillation," IEEE Trans. Power Syst., 2024, doi: 10.1109/TPWRS.2024.3393926.

[2] S. Gao, Y. Liu, J. Wang, Z. Wang, X. Wenjun, R. Yue, R. Cui, Y. Liu, and X. Fan, "Short-term residential load forecasting via transfer learning and multi-attention fusion for EVs' coordinated charging," Int. J. Electr. Power Energy Syst., vol. 164, 2025, Art. no. 110349, doi: 10.1016/j.ijepes.2024.110349.

[3] R. Kaur and D. Gabrijelčič, "Behavior segmentation of electricity consumption patterns: A cluster analytical approach," Knowl.-Based Syst., vol. 251, 2022, Art. no. 109236, doi: 10.1016/j.knosys.2022.109236.

[4] A. A. Peñaloza, R. C. Leborgne, and A. Balbinot, "Comparative analysis of residential load forecasting with different levels of aggregation," Eng. Proc., vol. 18, no. 1, 2022, doi: 10.3390/engproc2022018029.

[5] T. Kataray et al., "Integration of smart grid with renewable energy sources: Opportunities and challenges – A comprehensive review," Elsevier Ltd., Aug. 1, 2023, doi: 10.1016/j.seta.2023.103363.

[6] F. Rodrigues, C. Cardeira, J. M. F. Calado, and R. Melicio, "Short-term load forecasting of electricity demand for the residential sector based on modelling techniques: A systematic review," Energies, May 1, 2023, doi: 10.3390/en16104098.

[7] J. Li et al., "A novel hybrid short-term load forecasting method of smart grid using MLR and LSTM neural network," IEEE Trans. Ind. Inform., vol. 17, no. 4, pp. 2443–2452, Apr. 2021, doi: 10.1109/TII.2020.3000184.

[8] H. Tantyoko, D. Nurjanah, and Y. Rusmawati, "Utilizing sequential pattern mining and complex network analysis for enhanced earthquake prediction," Adv. Sustain. Sci. Eng. Technol., vol. 6, no. 4, 2024, doi: 10.26877/asset.v6i4.1003.

[9] K. S., V. Margaret, and K. Balaraman, "Hybrid short term load forecasting using ARIMA-SVM," in Proc. IPACT, Apr. 2017, doi: 10.1109/IPACT.2017.8245060.

[10] M. A. Al Amin and Md. A. Hoque, "Comparison of ARIMA and SVM for short-term load forecasting," in Proc. IEMECONX, 2019, doi: 10.1109/IEMECONX.2019.8877077.

[11] S. K. Agarwal and P. V. Manitha, "Comparative analysis of feedforward neural network and LSTM model for load forecasting," in Proc. ICSES 2024, pp. 1354–1359, 2024, doi: 10.1109/ICSES63445.2024.10763070.

[12] D. Wu and W. Lin, "Efficient residential electric load forecasting via transfer learning and graph neural networks," IEEE Trans. Smart Grid, vol. 14, no. 3, pp. 2423–2431, May 2023, doi: 10.1109/TSG.2022.3208211.

[13] Z. Tan, J. Zhang, Y. He, Y. Zhang, G. Xiong, and Y. Liu, "Short-term load forecasting based on integration of SVR and stacking," IEEE Access, vol. 8, pp. 227719–227728, 2020, doi: 10.1109/ACCESS.2020.3041779.

[14] D. Wu, B. Wang, D. Precup, and B. Boulet, "Multiple kernel learning-based transfer regression for electric load forecasting," IEEE Trans. Smart Grid, vol. 11, no. 2, pp. 1183–1192, Mar. 2020, doi: 10.1109/TSG.2019.2933413.

[15] K. Chen, K. Chen, Q. Wang, Z. He, J. Hu, and J. He, "Short-term load forecasting with deep residual networks," IEEE Trans. Smart Grid, vol. 10, no. 4, pp. 3943–3952, Jul. 2019, doi: 10.1109/TSG.2018.2844307.

[16] M. F. Azam and M. S. Younis, “Multi-horizon electricity load and price forecasting using an interpretable multi-head self-attention and EEMD-based framework,” IEEE Access, vol. 9, pp. 85918–85932, 2021, doi: 10.1109/ACCESS.2021.3086039.
[17] M. F. Ainuri, Sarjiya, and I. Ardiyanto, “Short-term load forecasting with long short-term memory: A case study of Java-Bali system,” in Proc. ICITEE 2020, Yogyakarta, Indonesia, Oct. 2020, doi: 10.1109/ICITEE49829.2020.9271763.
[18] X. Liu and W. Wang, “Deep time series forecasting models: A comprehensive survey,” Mathematics, vol. 12, no. 10, 2024, doi: 10.3390/math12101504.
[19] S. F. Stefenon, L. O. Seman, L. S. A. da Silva, V. C. Mariani, and L. dos S. Coelho, “Hypertuned temporal fusion transformer for multi-horizon time series forecasting of dam level in hydroelectric power plants,” Int. J. Electr. Power Energy Syst., vol. 157, 2024, Art. no. 109876, doi: 10.1016/j.ijepes.2024.109876.
[20] D. Ageng, C. Y. Huang, and R. G. Cheng, “A short-term household load forecasting framework using LSTM and data preparation,” IEEE Access, vol. 9, pp. 167911–167919, 2021, doi: 10.1109/ACCESS.2021.3133702.
[21] N. Mohan, K. P. Soman, and S. S. Kumar, “A data-driven strategy for short-term electric load forecasting using dynamic mode decomposition model,” Appl. Energy, vol. 232, pp. 229–244, Dec. 2018, doi: 10.1016/j.apenergy.2018.09.190.
[22] A. Zeng, M. Chen, L. Zhang, and Q. Xu, “Are transformers effective for time series forecasting?,” 2023. [Online]. Available: www.aaai.org
[23] Y. Chen, Y. Zhao, S. Pan, L. Ye, and M. Pei, “Short-term wind power prediction based on DLinear-CrossFormer considering error correction,” in Proc. ACPEE 2024, pp. 2727–2731, 2024, doi: 10.1109/ACPEE60788.2024.10532762.
[24] S. G. Zhao, Y. Cen, and L. C. G. Yongjiang, “Energy demand and renewable energy generation forecasting for optimizing dispatching strategies of virtual power plants using time decomposition-based DLinear,” in Advances in Systems Engineering, H. Selvaraj, D. G., and Z. Chmaj, Eds., Cham: Springer Nature Switzerland, 2023, pp. 3–11.
[25] H. Fan, "Enhancing Long-Term Time Series Forecasting via Hybrid DLinear-PatchTST Ensemble Framework," *Applied and Computational Engineering*, vol. 142, pp. 145–150, 2025. doi: 10.54254/2755-2721/2025.KL22290.