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A Hybrid Source–Load Power Forecasting Model for Distribution Networks with High Penetration of Renewable Energy

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Abstract

INTRODUCTION: High renewable energy penetration introduces significant uncertainties in distribution networks, posing challenges for source-load power forecasting and voltage management.
OBJECTIVES: This study aims to enhance forecasting accuracy and address voltage control difficulties caused by distributed generation and load fluctuations using a novel integrated framework.
METHODS: A hybrid model combining Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN), Temporal Convolutional Network (TCN), and DLinear is proposed. First, CEEMDAN decomposes source-load and meteorological data into stable Intrinsic Mode Functions (IMFs) to reduce non-stationarity. Subsequently, TCN captures short-term dependencies, while DLinear extracts multi-scale features by decomposing IMFs into trend and residual components. The final forecast is derived by aggregating the reconstructed subsequence predictions.
RESULTS: Extensive simulations validate that the proposed method significantly outperforms conventional benchmarks, such as BiGRU and TCN-BiGRU. It achieves higher forecasting precision and effectively mitigates the adverse effects of data uncertainty.
CONCLUSION: The proposed CEEMDAN-TCN-DLinear framework demonstrates consistent superiority in handling complex data patterns, offering a robust solution for distribution network voltage control under high renewable penetration scenarios.

Keywords: distributed power sources and loads, uncertainty; DLinear model, complete ensemble empirical mode decomposition with adaptive noise, time convolutional network

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1. Introduction

With the continuous advancement of global "carbon peaking" and "carbon neutrality" strategies, accelerating the development of renewable energy and deepening energy substitution initiatives have become critical pathways for transforming the global energy structure and building a new clean-energy system [1]. In recent years, the renewable energy industry worldwide has maintained rapid growth. In 2024, the global installed capacity of renewable energy continued to expand, reaching approximately 4,448 GW by the end of the year [2], driven largely by the fast deployment of wind power and photovoltaics. Among these technologies, photovoltaic generation has emerged as the primary contributor, accounting for nearly three-quarters of the newly added renewable capacity [3]. Meanwhile, the share of distributed photovoltaic systems on the energy consumption side has continued to increase, becoming a significant force in promoting the global transition toward green and low-carbon energy [4].

Although distributed generators (DGs) possess adjustable capability and flexibility, their significant uncertainty affects the accuracy of reactive power regulation in practical applications [5]. For example, the reactive power output of a DG is constrained by its active power, while the active power is strongly coupled with environmental conditions; thus, its actual regulating capability exhibits stochastic variation during operation. Therefore, incorporating and accurately characterizing the uncertainties of both source and load sides can enhance the accuracy and effectiveness of voltage control in distribution networks [6]. Renewable energy power forecasting—particularly wind and solar forecasting—is essential for ensuring efficiency, reliability, and secure operation of power systems [7,8], as it mitigates the adverse impacts of strong uncertainty from both the source and load sides on voltage stability, power quality, operational security, and economic performance in distribution networks [9,10].

In recent years, researchers worldwide have carried out extensive studies on renewable power forecasting and load forecasting. The mainstream approaches include mathematical-model-based methods, artificial intelligence techniques, and hybrid forecasting models [11,12]. Existing source–load forecasting methods can be mainly categorized into three types: time series–based methods, regression-based methods, and neural network–based methods [13].

Time series–based approaches primarily utilize periodic dependencies in historical data. They feature low computational cost and high computational efficiency, but are highly sensitive to data quality and typically ignore meteorological factors affecting source–load power [14,15]. Pełka applied ARIMA, ETS, Prophet, and other statistical time-series models to analyze and forecast monthly electricity demand, focusing on periodicity, trends, and random fluctuations [16]. Sun et al. also validated the applicability and limitations of time-series models in short-term load forecasting using purely historical data [17]. Yu and Ge integrated a broad learning system with variational mode decomposition to forecast electric vehicle charging loads, demonstrating that decomposing historical data patterns can improve prediction accuracy [18].

Regression-based approaches aim to forecast load by establishing mathematical relationships between load data and influential factors [19]. Li et al. considered meteorological variables and combined multivariate regression with support vector machines for load forecasting [20]. Ugbehe et al. conducted a systematic review of regression-based methods, summarizing their applications and limitations in real power systems [21]. Although regression methods are simple and computationally efficient, they remain constrained by historical data quality and exhibit limited generalization capability.

Neural networks have become a dominant technique due to their powerful ability to extract nonlinear features from data [22]. Eren et al. provided a systematic survey of deep learning methods for short-term load forecasting (STLF), comparing the performance of CNN, RNN/LSTM, and Transformer models, and discussing feature engineering, external meteorological/calendar factors, and the trend toward probabilistic forecasting [23]. Jing et al. employed an artificial neural network (ANN) combined with scheduling optimization for load forecasting, demonstrating effective modeling of complex nonlinear relationships [24]. Liu et al. proposed a highly optimized single-model forecasting method for short-term load prediction [25]. However, single-model approaches often fail to capture diverse data characteristics. Hybrid models integrate multiple algorithms to leverage complementary advantages and improve forecasting accuracy [26]. Zhang proposed a DenseNet–LSTM model enhanced by an attention mechanism to extract long-term dependencies in time-series data and improve prediction performance [27]. Dong et al. developed a hybrid model combining LSTM and fully connected blocks, introducing an online correction mechanism to adapt to load variations [28]. Salman et al. investigated multi-model combinations of CNN, LSTM, and Transformer architectures for solar power forecasting, effectively capturing temporal correlations and power fluctuations. With the large-scale integration of photovoltaic and wind power, forecasting complexity has further increased [29]. Alrashidi and Rahman combined SVR and ANN with a meta-heuristic optimization algorithm for short-term PV power forecasting [11]. Cavus et al. used deep learning to extract spatiotemporal features of distributed PV systems under high penetration conditions [30]. Lu and Chen integrated Transformer networks with multivariate features to forecast short-term load in high-renewable-penetration scenarios [31]. Xie proposed a data-driven distributed PV forecasting approach incorporating meteorological and temporal features, effectively improving prediction accuracy [32].

Existing literature indicates that the high penetration of distributed renewables, driven by the "dual carbon" goals, poses growing challenges to conventional voltage control methods due to intensified uncertainties. Source-load power forecasting, as a key technology to address these uncertainties and support precise voltage control, has become a focal point of current research. Existing forecasting approaches commonly used encompass time series analysis, regression models, and neural networks. Time series analysis is computationally efficient but relies heavily on data quality and struggles to effectively incorporate external factors such as meteorological conditions. Regression analysis is structurally simple and highly interpretable, but has limited generalization capability and falls short in capturing complex nonlinear relationships. Although neural network methods excel in feature extraction and nonlinear fitting, single models often fail to adequately capture the multi-scale and non-stationary characteristics of source-load power. As a result, hybrid forecasting models have gradually emerged as the mainstream approach, significantly improving forecasting accuracy and robustness by integrating the advantages of multiple methods.

To address the strong uncertainty of source-load power in distribution network voltage management under high penetration of renewable energy, this paper proposes a hybrid forecasting method based on CEEMDAN, TCN, and DLinear. Firstly, the CEEMDAN algorithm is used to decompose non-stationary source load power and meteorological data into multiple stable IMF subsequences. Subsequently, a TCN DLinear hybrid model was constructed to capture short-term temporal features through TCN, and combined with DLinear's trend residual decomposition mechanism to explore global patterns, achieving multi-scale feature fusion. By reconstructing the subsequences, the final predictions achieve substantially enhanced power forecasting accuracy. The main contributions of this work are as follows (1) Multi-scale feature extraction and sequence decomposition. This study introduces a decomposition of the original power sequences and multi-variable factor sequences into stable subsequences. By integrating Temporal Convolutional Network (TCN) and DLinear neural network models, the approach effectively captures dynamic features of power data across different time scales, thereby addressing the non-stationarity and uncertainty issues in source-load power under high penetration of renewable energy integration. (2) Hybrid deep learning prediction model architecture. Innovatively integrating TCN's long-term dependence on capture capability and DLinear's advantages in linear time series modeling, a multi-scale feature fusion prediction model is built, significantly improving the prediction accuracy of high volatility new energy power, and overcoming the defect of traditional single models' insufficient fitting of complex time series relations. (3) Robust optimization for high-penetration renewable energy integration. By integrating diverse environmental variables (e.g., meteorological conditions and load variations) and decomposing stable subsequences for joint modeling, the proposed method markedly enhances forecasting robustness against noise and outliers while reducing prediction errors versus conventional LSTM and GRU models, thereby offering a more reliable basis for distribution network voltage control.

2. Input feature selection for the source load prediction model

The core of distributed generation and load power forecasting lies in using mathematical or deep learning models to process historical data and, combined with specific conditions, reveal the inherent laws of power generation and load changes. Based on these patterns, short-term predictions can be made for the source load power during a certain period in the future. Accurate forecasting relies on a comprehensive comparison and analysis of extensive high-precision historical data on source and load. Both distributed generation and load prediction are affected by multiple factors—such as meteorological conditions, seasonal variations, calendar types, and unforeseen incidents—introducing significant uncertainty and nonlinearity into the forecasting process. It is therefore essential to thoroughly investigate the diverse factors influencing distributed generation and load fluctuations, and to identify those key variables that are most strongly correlated with short-term forecasting performance.

2.1. Wind power impact factor

The theoretical value of wind power output P_{wind} is

$$P_{\text{wind}} = 1/2\eta\rho\pi R^2 V^3 \tag{1}$$

In the formula, R is the generator fan blade (m); ρ is air density (kg/m3); η is turbine efficiency; V is wind speed (m/s). ρ varies with temperature T, humidity, and air pressure, while air pressure decreases with increasing altitude

$$\rho = \frac{P}{0.2869 \times (T + 273.1)} \tag{2}$$

Although wind power is influenced by multiple factors, inputting all meteorological factors into the wind power prediction model can result in data redundancy and overfitting of the model. Therefore, it is necessary to screen out key factors that are highly correlated with wind power. Assuming two mutually influential variables $M = (m_1, m_2, \ldots, m_n)$ and $K = (k_1, k_2, \ldots, k_n)$, the correlation coefficient e between the two variables is

$$e = \frac{n\sum_{i=1}^{n} m_i k_i - \sum_{i=1}^{n} m_i \sum_{i=1}^{n} k_i}{\sqrt{n\sum_{i=1}^{n} m_i^2 - \left(\sum_{i=1}^{n} m_i\right)^2}\sqrt{n\sum_{i=1}^{n} k_i^2 - \left(\sum_{i=1}^{n} k_i\right)^2}} \tag{3}$$

The magnitude of the correlation coefficient |e| reflects the strength of the relationship between sequences M and K. The sign of e denotes the direction, with positive values indicating a positive correlation and negative values a negative one. The correlation strength increases as |e| approaches 1. This study computes the correlation coefficients between wind power and various meteorological factors, including wind speed, temperature, precipitation, and air density. The results, presented in Figure 1, demonstrate that wind speed exhibits the strongest influence on power output. Consequently, wind speed and power are selected as input variables for the wind power prediction model in this work.

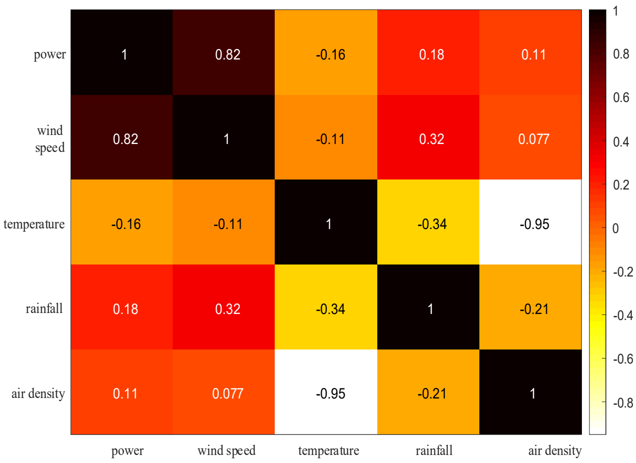

Figure 1. Heat map of the correlation coefficient between wind power and meteorological factors

2.2. Photovoltaic power influencing factor

The output power P_{PV} of a photovoltaic system is produced through the conversion of sunlight by PV modules and is highly dependent on solar irradiance intensity. The corresponding formula is provided below

$$P_{\mathrm{PV}} = \eta_{\mathrm{PV}} S I \left[1 - 0.005\left(t_{out} + 25\right)\right] \tag{4}$$

Where, η_{PV} is the conversion efficiency of photovoltaic modules; S is the area of the photovoltaic module, unit m2; I is irradiance, unit kW/m2; t_{out} is environmental temperature, unit ℃.

According to equation (4), for deterministic photovoltaic modules, their output power is related to irradiance and ambient temperature. Under certain circumstances, the stronger the irradiance, the greater the output power of the photovoltaic module. Meanwhile, rising irradiance increases the temperature of photovoltaic modules, consequently adversely affecting their efficiency.

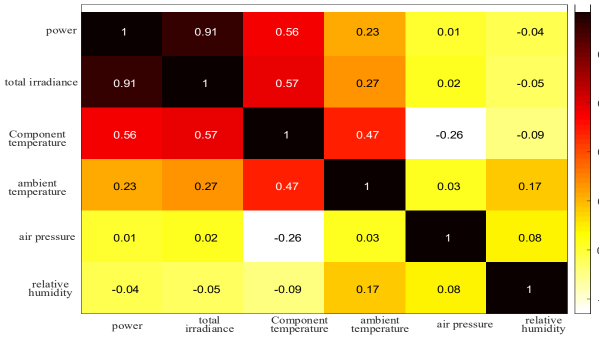

Figure 1. Photovoltaic Power-Meteorological Factor Correlation Heatmap

As shown in Figure 2, which presents the correlation c oefficients between photovoltaic power and various meteor ological factors, total irradiance and component temperature are identified as the key influencing factors. Therefore, tota l irradiance and component temperature can be used as inpu t features for photovoltaic prediction models.

2.3. Power load impact factor

Electricity price is an important factor affecting users' electricity consumption, mainly manifested in the policy of peak and off-peak electricity prices, which can not only increase the load rate, but also suppress the load growth during peak hours of electricity consumption. Electricity pricing influences the utilization rate of grid equipment and, by setting rational peak-valley tariffs, can reduce the peak-valley difference, thereby achieving energy conservation and peak shaving.

The impact of meteorological factors on electricity load is particularly evident, such as cold and high temperatures, which can significantly increase electricity load. Taking temperature and humidity as an example, in cold winter weather, the extensive use of heating equipment such as air conditioning and electric heating can lead to an increase in electricity demand and a significant increase in load. The high or low humidity can also affect people's comfort, indirectly affecting the power load.

Date type is also an important factor affecting power load. Compared with weekdays, industrial load decreases on weekends and holidays, while residential and commercial load increase. In addition, date types can also cause load data to exhibit a certain periodicity, which is particularly significant between different weeks, mainly due to significant differences in user electricity consumption patterns between workdays and rest days.The date type features are converted into numerical features for model input through one-hot encoding: working days are encoded as [1,0,0], weekends as [0,1,0], and holidays as [0,0,1], which effectively quantifies the periodic characteristics of load caused by date type differences.

All the key features screened by the correlation coefficient method in Sections 2.1-2.3 are preprocessed by z-score standardization before being input into the model, which eliminates the dimensional difference between different features and improves the convergence speed and prediction accuracy of the deep learning model.

3. Source load prediction model based on CEEMDAN TCN DRinear

This article considers the high degree of oscillation and instability in the source load raw data and meteorological factor sequences, which makes learning the power curve susceptible to interference. Therefore, CEEMDAN is first used to decompose it into more stable subsequences, enabling the feature extraction model to better learn temporal trends. Then, TCN is used to encode the subsequences and extract relevant feature information. DLinear further explores the multi-scale features of the sequences and finally reconstructs the prediction results of different subsequences to achieve complete power prediction.

3.1. Fully adaptive noise ensemble empirical mode decomposition

Building upon Empirical Mode Decomposition (EMD), the Fully Adaptive Noise Ensemble Empirical Mode Decomposition (CEEMDAN) method introduces adaptively adjusted Gaussian white noise into the input signal. Through repeated decomposition, it generates multiple distinct Intrinsic Mode Functions (IMFs) that capture the local characteristics of the original sequence. The detailed procedure is as follows

Step 1: Add Gaussian white noise of standard normal distribution to the original feature sequence to obtain a new signal.

$$y_i(t) = y(t) + \varepsilon_0 \omega_i(t), \quad t = 1, 2, \cdots, n; i = 1, 2, \cdots, I \tag{5}$$

Where, $y(t)$ is the original feature sequence; ε_0 is the initial amplitude of Gaussian white noise; $\omega_i(t)$ is Gaussian white noise; n - sample size; l - number of experiments.

Step 2: Use EMD to decompose $y_i(t)$ and extract the residual $r_i(t)$ corresponding to the first modal components $C_1(t)$ and $y_i(t)$.

$$C_1(t)=\frac{1}{I}\sum_{i=1}^{I}C_1^I(t) \tag{6}$$

$$r_1(t)=y_i(t)-C_1(t) \tag{7}$$

Step 3: Decompose the newly constructed (k+1) to obtain the second modal component $C_{k+1}(t)$ and residual $r_{k+1}(t)$.

$$C_{k+1}(t)=\frac{1}{I}\sum_{i=1}^{I}E_1\left[r_k(t)+\varepsilon_k E_k\left(\omega_i(t)\right)\right] \tag{8}$$

$$r_{k+1}(t)=r_k(t)-C_k(t) \tag{9}$$

Step 4: Obtain the final decomposition sequence.

$$x(t)=\sum_{k=1}^{K}C_k(t)+r_k(t) \tag{10}$$

Where, K is the total number of modal components.

3.2. Time Convolutional Neural Network

Compared with conventional recurrent neural networks, TCN employs multi-layer convolutional structures to capture long-range temporal dependencies while avoiding gradient vanishing issues. It demonstrates strong modeling capacity, high computational efficiency, and adaptable input handling in time series analysis, making it a widely adopted method in the field. As illustrated in Figure 3, the TCN architecture integrates dilated causal convolutions with residual connections to form the complete network model.

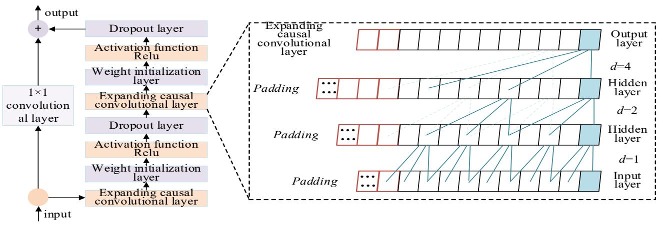

Figure 2. TCN Structure Diagram

In TCN, causal convolution is a specialized form of convolution that exclusively incorporates features from previous time steps during computation, preventing any leakage of information from future time steps. This design preserves the temporal causality of the sequence, ensuring that predictions at any given time are not influenced by future data.

Assuming the filter function is $F=(f_1,f_2,\ldots,f_N)$, N is the number of filters, and the time series $X==(x_1,x_2,\ldots,x_J)$, J is the number of sequences, to ensure that the sequences can be evenly divided by the size of the convolution kernel, the padding $(\cdot)$ function is used to fill 0 at the end of the time series before convolution. The causal convolution at the subsequence x_j is

$$(F\times X)_{x_j}=\sum_{n=1}^{N}f_n x_{j-N+n} \tag{11}$$

Where, x_j - the jth sequence; f_n - nth filter function; x_{j-N+n} - the j-N+nth sequence.

Dilated convolution in TCN expands the network's receptive field by incorporating a dilation factor into the convolutional kernel. This technique achieves broader coverage without adding computational cost, which improves long-range dependency capture and enhances time series forecasting accuracy. The output G of the dilated convolution at sequence element s for an input sequence X and a filter F is defined as

$$G(s)=(x*df)(s)=\sum_{i=0}^{c-1}f(i)\cdot X_{s-d\cdot i} \tag{12}$$

Where, * - Convolution operation; c - Convolutional kernel size; d - Expansion coefficient; $f(i)$ - i-th convolution kernel; S-d i - the direction of the past.

To mitigate the issues of gradient attenuation and vanishing caused by causal and dilated convolutions, a residual module is incorporated after the dilated causal convolution layer. The specific implementation is described as follows

$$g=\text{Activation}(X+U(X)) \tag{13}$$

Where, $U(X)$ - convolution; Activation - activation function.

3.3. DLinear model

DLinear is a high-precision linear time series prediction model with a simple structure consisting of only one decomposition method and two direct prediction linear networks. However, it can effectively aggregate historical information, learn time series trends, avoid error accumulation effects, and solve the problems of time series prediction models with Transformer architecture and recursive architecture. The internal structure of DLinear is shown in Figure 4.

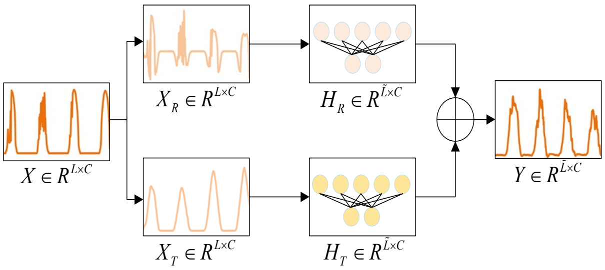

Figure 3. Structure diagram of DLinear

In the prediction process, DLinear first decomposes the original sequence of source load power and meteorological historical data into residual and trend components. Secondly, use two directly predicted linear networks to output the prediction results. Finally, the outputs of the two linear layers are linearly added to obtain the final prediction result $Y \in R^{L_y \times C}$

$$\begin{cases} H_T = X_T W_T \\ H_R = X_R W_R \\ Y = H_R + H_T \end{cases} \tag{14}$$

Where, $X_T \in R^{L_x \times C}$ - Trend component; $X_R \in R^{L_x \times C}$ - Residual component; C - Feature dimension; $H_T \in R^{L_y \times C}$ - Trend item prediction results; $H_R \in R^{L_y \times C}$ - Residual term prediction result; W_T 、 W_R - Linear prediction network for trend and residual terms.

The local temporal features extracted by TCN are first flattened into a one-dimensional feature vector, and then directly concatenated with the trend/residual feature vectors decomposed and extracted by DLinear in the feature dimension to form a fused high-dimensional feature tensor, which is input into the subsequent linear prediction layer for joint prediction, realizing the effective fusion of short-term local features and global trend/residual features.

The overall architecture of the source-load power forecasting model introduced in this study, which integrates CEEMDAN, TCN, and DLinear, is depicted in Figure 5.

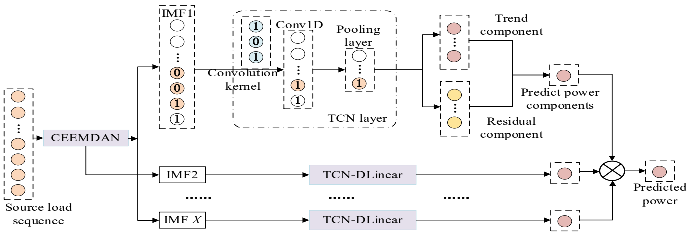

Figure 4. Overall framework of the source load prediction model

Firstly, CEEMDAN is used to decompose photovoltaic and meteorological historical data into a set of subsequences, to eliminate volatility features, and obtain intrinsic mode functions that better reflect the trend of sequence fluctuations. Different subsequences are then fed into TCN DLinear. Secondly, using TCN to extract temporal features of input features effectively captures local dependency relationships in sequence data, achieves long-term dependency modeling, and constructs feature tensors containing local and long-term temporal trends. Then, using DLinear, the feature tensor is decomposed into trend and residual terms, and direct prediction is achieved through a linear network. Finally, reconstruct each predicted subsequence and obtain the final prediction result.

RMSE and MAE evaluated the accuracy of the proposed method by quantifying the deviation between predicted and actual values. Their calculation formulas are provided below.

$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(y_t - \hat{y}_t\right)^2} \tag{15}$$

$$\mathrm{MAE} = \frac{1}{T}\sum_{t=1}^{T}\left|y_t - \hat{y}_t\right| \tag{16}$$

Where, T - evaluation duration; y_t - True value; $\hat{y}_t$ - Model predicted value.

4. Discussion

This article selects the IEEE 33-node distribution network structure for source load prediction case analysis. The distribution network includes distributed photovoltaics (PV), wind power (WT), gas turbines (GT), and energy storage systems (ESS), and their entry points in the distribution network are shown in Figure 6. Table 1 lists the capacity of each device.

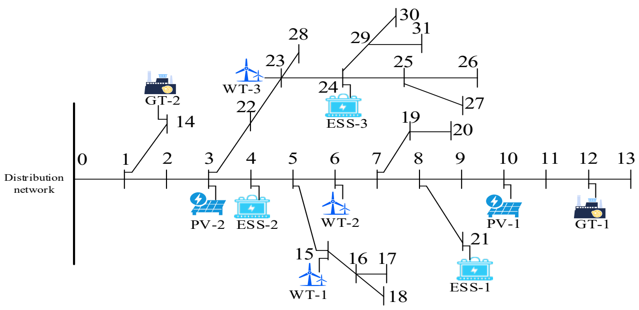

Figure 5. IEEE 33 Node Structure Diagram of Active Distribution Network

Table 1. Capacity of Distributed Power Sources and Energy Storage

Equipment	Capacity	Access node
Wind Turbine No. 1	500kW	Node 15
Wind Turbine No. 2	600kW	Node 6
Wind Turbine No. 3	500kW	Node 23
Distributed Photovoltaic No.1	400kW	Node 10
Distributed Photovoltaic No.2	500kW	Node 3
Energy storage device No.1	300kWh	Node 21
Energy storage device No.2	300kWh	Node 4
Energy storage device No.3	200kWh	Node 24
Gas Turbine No.1	100kW	Node 12
Gas Turbine No.2	100kW	Node 14

Firstly, CEEMDAN is used to perform modal decomposition on the input features of source load power prediction. Taking photovoltaic prediction as an example, CEEMDAN is used to decompose the irradiance sequence in photovoltaic prediction into 16 IMFs, as shown in as shown in figure 7. The number of IMFs (16 for irradiance) is automatically generated by the CEEMDAN algorithm according to the fluctuation and stationarity characteristics of the input signal, rather than a manually set parameter. For different input sequences such as wind speed and power load, the number of IMFs will change adaptively depending on signal complexity. All IMFs are retained without manual screening to ensure complete multi-scale information is preserved for forecasting, .Although inputting all 16 IMF components will slightly increase the number of model input features, the CEEMDAN-decomposed IMF components are low-dimensional and mutually independent stable subsequences, which will not cause a significant increase in model computation load; at the same time, inputting all IMFs can fully retain the multi-scale characteristic information of the original non-stationary sequence, avoid the loss of valid information caused by screening partial IMFs, and maximize the improvement of the model's feature learning and prediction ability. Considering that both the TCN layer and the DLinear layer can achieve multidimensional feature interaction and extract cross dimensional feature correlations through embedding, the method proposed in this paper inputs all IMF obtained by decomposing multivariate meteorological sequences into the model, learns the temporal features of subsequences and the dimensional features between subsequences, fully utilizes the information potential of multivariate sequences, enhances feature learning ability, and effectively improves prediction accuracy.

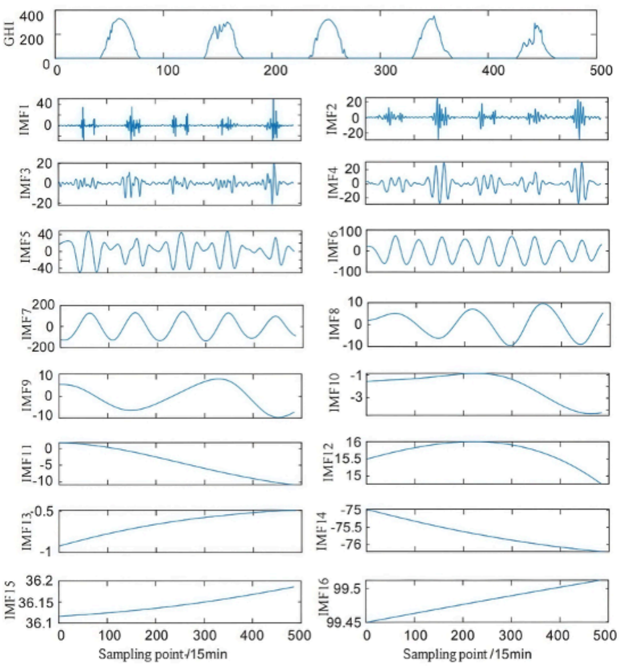

Figure 6. Irradiance decomposition results of photovoltaic prediction

Using the method proposed in this article, along with Bidirectional Gated Recurrent Unit (BiGRU) and TCN BiGRU, short-term power predictions were made for distributed photovoltaics, wind power, and loads in the example. BiGRU and TCN-BiGRU are selected as benchmark models because they are classical and widely adopted recurrent and hybrid networks for power forecasting and time-series prediction. In addition, the proposed model is also compared with mainstream methods in recent studies, including GRU, TCN, and Transformer. The proposed CEEMDAN-TCN-DLinear shows better performance in dealing with non-stationary, volatile source-load power sequences under high renewable penetration. The prediction results are shown in Figure 8,Figure 9, andFigure 10, respectively. Considering that the photovoltaic power generation during nighttime is basically zero, the photovoltaic forecasting period is from 7 am to 5 pm, the wind power and load forecasting period is 24 hours, and the time interval for short-term forecasting is 15 minutes.

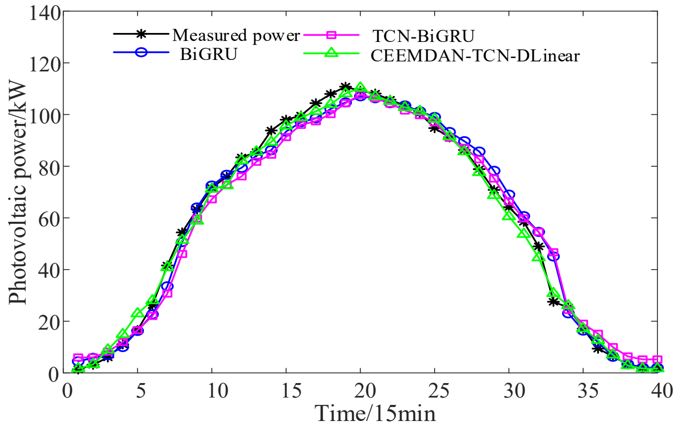

Figure 7. Comparative Analysis of Short-Term Photovoltaic Power Forecasting Models on Typical Days (7:00–17:00)

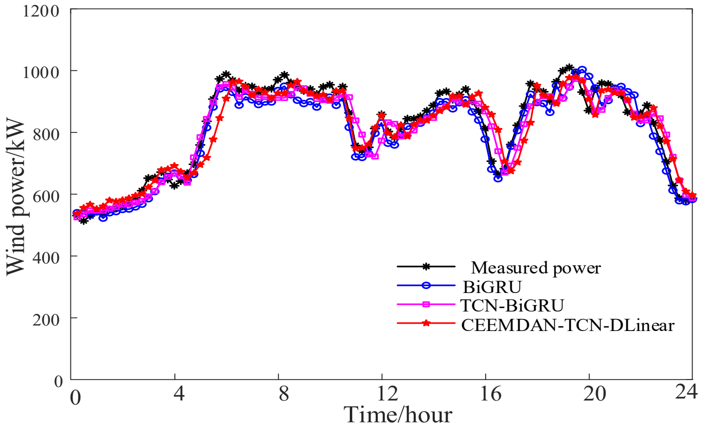

Figure 8. A Comparative Study of Short-Term Wind Power Forecasting Models

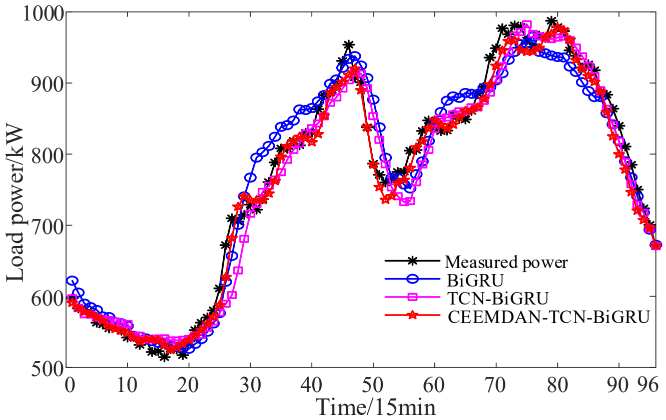

Figure 9. Comparison of Short-term Load Power Forecasting Results for Different Models

The proposed method achieves the highest source-load power forecasting accuracy and demonstrates superior real-time performance over other deep learning approaches, as evidenced particularly during abrupt power fluctuations.This advantage is reflected in the absence of noticeable lag at extreme variation points, enabling rapid response to power changes and more accurate forecasting.

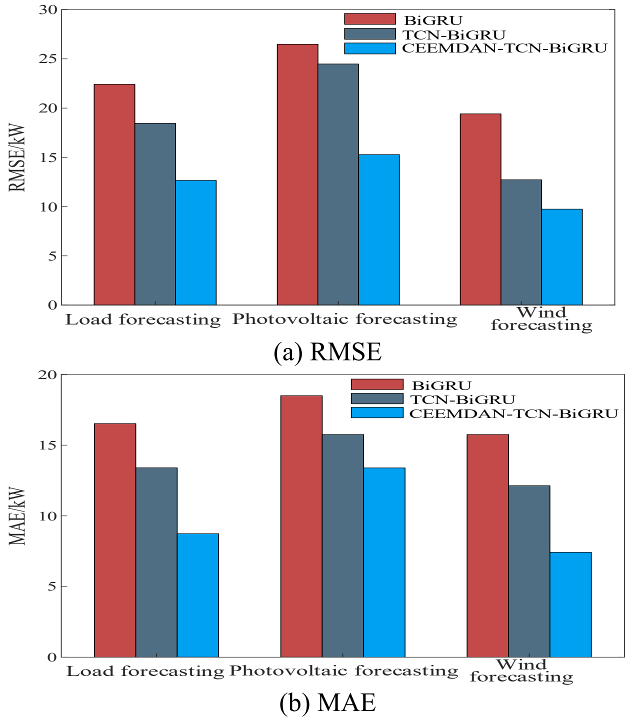

Figure 10. Comparison of source load power prediction errors for different models

The prediction errors, quantified by RMSE and MASE (Figure 11), were significantly reduced by the proposed model. For instance, in load forecasting, it achieved MAE reductions of 18.5% and 16.6% compared to the BiGRU and TCN-BiGRU models, respectively. These results demonstrate its superior capability in feature extraction and overall predictive accuracy.

5. Conclusions

This study addresses the short-term power forecasting problem for distributed photovoltaic, wind power, and load by proposing a hybrid forecasting method based on CEEMDAN-TCN-DLinear. First, the irradiance and other meteorological sequences are adaptively decomposed into multiple Intrinsic Mode Functions (IMFs) using CEEMDAN, effectively extracting multi-scale features from non-stationary sequences. Subsequently, all IMFs are fed into the TCN-DLinear hybrid model, which leverages the strengths of TCN in extracting local temporal features and DLinear in decomposing global trends, achieving cross-dimensional feature interaction and multi-scale information fusion.

This study innovatively integrates the CEEMDAN signal decomposition technique with a TCN-DLinear hybrid model for short-term power forecasting. The proposed method accurately tracks rapid power fluctuations, significantly reduces prediction errors and latency, and effectively enhances the accuracy and robustness of power forecasting in distributed energy scenarios.

Experimental results demonstrate that the proposed method delivers outstanding performance in forecasting photovoltaic, wind power, and load power. Particularly during periods of rapid power fluctuation, the approach accurately tracks extreme value variations and significantly reduces prediction lag, reflecting strong real-time capability and adaptability. Error analysis shows that, compared to BiGRU and TCN-BiGRU models, the proposed model achieves a notable reduction in key metrics such as Mean Absolute Error (MAE). For instance, in load forecasting, MAE is reduced by 18.5% and 16.6%, respectively, confirming its superior prediction accuracy and robustness. In summary, the CEEMDAN-TCN-DLinear method effectively integrates the advantages of signal de-composition and deep learning techniques, thoroughly mining the temporal patterns and cross-dimensional correlations of input features. It provides a reliable solution for source-load power forecasting in high-penetration renewable energy environments, thereby contributing to enhanced stability and reliability in distribution grid operation and control.

The proposed model ignores critical external factors like extreme weather, local microclimates, and future electricity prices. This omission could cause its prediction ac-curacy to deteriorate in complex real-world applications. Future research will prioritize probabilistic forecasting for uncertainty management and synergistic modeling of interconnected multi-energy systems across regions.

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