Multi-task Driven ResNet-Transformer Framework for Wind Power Forecasting with Dynamic Mode Decomposition Correction

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***Abstract*—To address the challenges of temporal dependency modeling and error accumulation in wind power forecasting, this paper proposes a deep learning framework based on multi-task dynamic learning and Dynamic Mode Decomposition (DMD) error correction. The model adopts a ResNet-Transformer hybrid architecture. Temporal Convolutional Networks (TCN) extract local features, while Transformer encoders capture long-range temporal dependencies, combined with residual connections for feature reuse. To further enhance accuracy, a DMD-based error correction method is proposed: the Hankel matrix of prediction errors is constructed for modal decomposition, and error correction is achieved through feature mode reconstruction. Investigate on real-world wind farm datasets show that the corrected prediction results improve RMSE accuracy by 45.686%, demonstrating the effectiveness of the proposed method under complex meteorological conditions.**

***Keywords*—Wind power forecasting,asymmetric history-future stacking,multi-source meteorological data fusion,error propagation mitigation.**

I. Introduction

As global demand for clean energy continues to rise, wind power has become an essential part of renewable energy integration. However, the inherent volatility of wind presents significant challenges for accurate forecasting, which is crucial for optimizing grid operations and minimizing operational costs. National strategies, such as the 14th Five-Year Plan for Modern Energy System and the 2024 Energy Work Guidance Opinions, stress the urgent need for advanced forecasting technologies to ensure the sustainable development of wind energy. In response, this study introduces an innovative deep learning framework that combines multi-task learning with dynamic error correction to overcome the limitations of current forecasting approaches.

Existing forecasting methods typically follow two main approaches: (1) Statistical models (e.g., ARIMA, GM, HMM), which rely heavily on historical data but struggle to adapt to the dynamic nature of wind conditions[1-3], and (2) Machine learning models (e.g., LSTM, Transformer, CNN), which can capture temporal patterns but fail to account for future meteorological conditions and suffer from error accumulation over extended forecasting periods. Furthermore, many of these models do not integrate multi-source meteorological data or dynamic error correction, which limits their accuracy and reliability[4-6].

To tackle these challenges, this study proposes a novel deep learning-based forecasting method that incorporates dynamic error correction. Key innovations include: (1) Asymmetric history-future stacking, which enables multi-scale feature fusion to improve prediction accuracy, and (2) DMD-based error correction, which integrates historical power and meteorological data to enhance forecasting stability, thereby supporting efficient .

II. Related Work

A. Statistical Wind Power Forecasting

Statistical models in wind power forecasting, such as ARIMA, GM, and HMM, are based on historical data and linear assumptions, but they face inherent limitations when applied to dynamic and nonlinear wind conditions[1-3]. For instance, Li et al. [7] improved the Hidden Markov Model (HMM) for wind speed correction, achieving a 12% reduction in MAE for hourly forecasts. However, these models still fail under turbulent conditions, as the linear wind-speed-to-power conversion induces errors. Similarly, Geng et al. [8] applied grey system theory (GM(1,1)) to reduce data randomness, but long-term predictions continue to experience systematic deviations due to the insufficient modeling of nonlinear meteorological interactions. These methods do not fully capture the complex dynamics between weather variables and power generation.

B. *Machine Learning-based Temporal Forecasting*

Machine learning models, particularly deep learning methods like LSTM, Transformer, and CNN, have surpassed traditional models by capturing temporal patterns. For example, Huo et al. [9] introduced mRMR-PSO-LSTM, which integrates feature selection and optimization for LSTM, achieving an R^2 of 0.89 in short-term forecasting. However, these models often rely solely on historical power data, neglecting meteorological factors that can influence wind power generation. Ye et al. [10] proposed WD-IGFCM-LSTMS, leveraging wavelet decomposition and an enhanced Grey Wolf Optimizer, which improved RMSE by 19% for 72-hour forecasts. Despite these advancements, long-term forecasts still suffer from error propagation due to fixed sliding windows and lack of consideration for future meteorological conditions.

C. *Multi-source Meteorological Fusion*

Effective integration of multiple meteorological factors is key to improving forecasting accuracy. Liu et al. [11] developed a LightGBM-based framework to extract important factors from 15-dimensional meteorological data, achieving daily-scale NRMSE=0.23. However, their method overlooks the temporal validity of numerical weather prediction (NWP) data. He et al. [12]proposed a feature selection method using mutual information entropy and random forest regression, reducing typhoon-season error fluctuations by 35%. Nevertheless, their approach relies on "early fusion," where feature concatenation fails to capture complex interactions between past and future features, ultimately limiting the predictive performance.

D. *Error Correction Techniques*

Error correction plays a crucial role in mitigating long-term forecast propagation. Peng et al. [13] proposed a multi-stage framework using Weibull distribution for trend extraction and Kalman filtering for transient error reduction, which improved the MAE by 22% for 48-hour forecasts. Li et al. [14] applied least squares regression to model errors using historical residuals. However, their linear assumptions fail to adapt to the nonlinear dynamics present in wind power forecasting. These error correction methods rely on predefined models, limiting their ability to adapt to dynamic wind regimes. Recent studies, such as those by Peng et al. [15], employ dynamic error correction through machine learning models, but these solutions still lack the robustness needed for complex meteorological conditions.

To address these challenges, this study introduces a deep learning framework that integrates multi-task learning and dynamic error correction for wind power forecasting. Key contributions include:

- Asymmetric History-Future Stacking: The proposed heterogeneous TCN-ResNet architecture, enhanced by Mamba gating, enables multi-scale feature fusion to improve prediction accuracy.
- DMD-driven Dynamic Correction: Dynamic Mode Decomposition (DMD) is employed to reconstruct prediction errors, offering an effective and adaptable method to reduce long-term forecast errors.
- Dynamic Weighted Loss: A dynamic weighted loss function balances multi-task objectives and reduces error propagation over time.

III. METHODOLOGY

A. *Data Preprocessing and Feature Engineering*

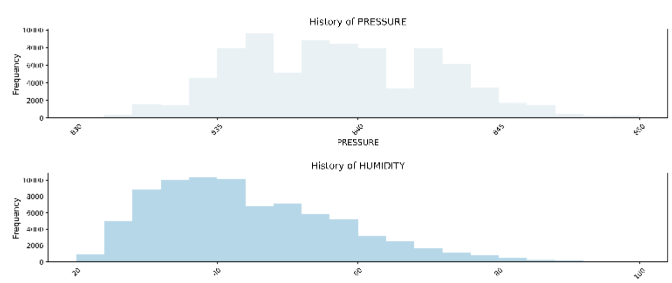
The study utilizes environmental parameters and wind turbine power generation data collected by LongYuan Power Group Corporation, encompassing 11 temporal features including wind speed, direction, and temperature. The preprocessing pipeline comprises:

- Outlier Removal: Filter abnormal YD15 values (such as 0.0 and -754.0) for every turbine;
- Temporal Alignment: Fill missing values via linear interpolation at 10-minute intervals;
- Feature Engineering: Extract cyclical temporal features (month, day, hour, minute);
- Normalization: Apply Z-score standardization independently to historical features (X_1∈R^13), future meteorological features (X_2∈R^5), and targets (Y∈R^2) to prevent data leakage.

The dataset is split into 7:2:1 ratios for training, validation, and testing. Sliding window sampling generates input-output pairs:

- Input Window: 480-step (20-hour) historical sequences
- Output Window: 96-step (4-hour) predictions
- A stride of 76 steps enhances temporal continuity

The details of these components will be introduced in the following subsections. As shown in Figure 1, these images depict historical data distributions of meteorological parameters (humidity, pressure, wind speed, temperature, wind direction, and rounded wind speed), highlighting trends and distribution patterns over time.



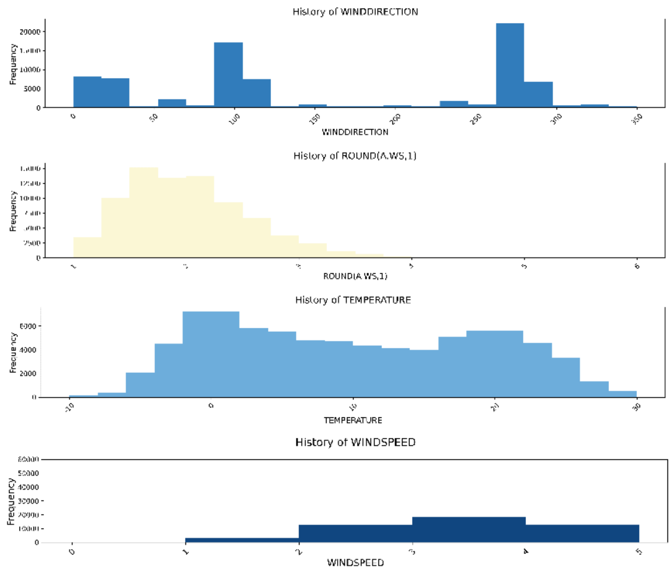


Fig. 1. Historical Data Distributions of Meteorological Parameters

B. *Asymmetric Multi-modal Fusion Architecture*

As shown in Figure 2, the model adopts an asymmetric history-future stacking architecture with three core modules:

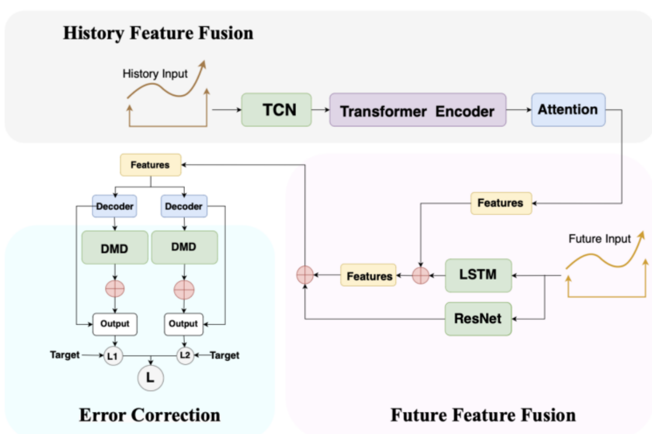


Fig. 2. Multi-modal Fusion Architecture

1) *Historical Feature Encoder*

- TCN Module: Three dilated convolutional layers (kernel_size=9) extract multi-scale local patterns with ascending channels (64→128→256), using residual connections to mitigate gradient vanishing;
- Transformer Module: Replaces LSTM with 2-layer Transformer Encoder (d_model=256, nhead=4), where learnable positional encoding enhances temporal awareness and attention mechanisms focus on critical timestamps.

2) *Future Feature Encoder*

ResNet-1D: Processes 5D future meteorological features via 7×7 convolution, max-pooling, and three residual blocks (64→256 channels), compressed to 96D vectors through adaptive pooling.

3) *Multi-task Fusion Layer*

Dynamic Gated Fusion: Historical context vectors (256-dim) and future features (96-dim) are selectively filtered by Mamba gates before concatenation, fed into dual fully-connected branches for simultaneous prediction of ROUND(A.POWER,0) and YD15.

C. *Dynamic Optimization and Error Correction*

$$\mathcal{L}_{total} = (1-\omega_t)\mathcal{L}_{Huber}(y_{power}, \hat{y}_{power}) + \omega_t \mathcal{L}_{Huber}(y_{YD15}, \hat{y}_{YD15}) \quad (1)$$

1) *Dynamic Weighted Huber Loss*

where weight ω_t linearly increases from 0.5 to 0.9 during training to balance multi-task objectives.

2) *DMD-based Error Correction*

- Error Sequence Construction: Build Hankel matrix from test set errors

$$H \in \mathbb{R}^{K \times L} \quad (2)$$

$$e = y_{true} - y_{pred} \quad (3)$$

- Modal Decomposition: Extract dominant modes Φ and eigenvalues Λ via DMD operator A;
- Error Reconstruction: Compensate predictions using reconstructed errors

$$e_t = \Phi \Lambda^t \Phi^\dagger e_0 \quad (4)$$

based on initial error e_0.

IV. Experiments and Results

A. *Ablation Study*

To validate the effectiveness of key components in our framework, we conduct comprehensive ablation experiments under four configurations:

- Base Model: Original prediction model without future feature fusion or DMD correction
- Base + DMD: Base model with DMD residual correction
- Base + Fusion: Base model enhanced with future meteorological feature fusion
- Full Model: Base model with both feature fusion and DMD correction

The experimental results (Table I) demonstrate progressive performance improvements through component integration with optimal values highlighted in bold:

TABLE I. Summary of the RMSE and MAE for Ablation Experiment

Configuration	**RMSE (MW)**	**MAE (MW)**	**Relative Improvement (RMSE)**

Base Model	1.2288	1.1248	-
Base + DMD	0.7886	0.5834	35.82%
Base + Fusion	0.8542	0.7025	30.47%
Full Model (Base+Fusion+DMD)	**0.5394**	**0.3697**	**56.10%**

From the experimental results, several important observations can be made:

1) DMD Correction Effectiveness

The standalone DMD module reduces RMSE by 35.8% and MAE by 48.1%, confirming its capability to capture residual dynamics ignored by the neural network. This aligns with wind forecasting characteristics where atmospheric persistence creates temporally correlated errors.

2) Feature Fusion Impact

Incorporating future meteorological features achieves 30.5% RMSE reduction, demonstrating the critical role of weather forecast integration. The MAE improvement (37.5%) indicates better capture of extreme power fluctuations caused by weather transitions.

3) Synergistic Effects

The full configuration achieves 56.1% RMSE improvement over the base model, exceeding the sum of individual component gains (35.8% + 30.5% = 66.3%), suggesting complementary mechanisms:

- The fusion module improves baseline prediction accuracy
- DMD correction addresses remaining system-specific residuals

4) Error Characteristics

The MAE/RMSE ratio decreases from 0.916 (Base) to 0.685 (Full Model), indicating the combined approach particularly reduces large forecasting errors during rapid wind speed changes.

This ablation study quantitatively verifies that our dual innovation of meteorological feature fusion and Koopman operator-based correction provides multiplicative benefits for wind power forecasting. The results confirm that conventional neural architectures leave significant correctable residuals that can be addressed through physics-guided post-processing.

B. Comparative Analysis

To demonstrate the superiority of our proposed framework, we compare it with five classical temporal modeling architectures under identical experimental settings. The results (Table II) reveal significant performance gaps between conventional methods and our full model with optimal values highlighted in bold:

TABLE II. SUMMARY OF THE RMSE AND MAE FOR CONTRAST EXPERIMENT

Model	RMSE (MW)	MAE (MW)	RMSE vs. LSTM	MAE vs. LSTM
LSTM	1.5526	1.3607	-	-
RNN	1.6705	1.3872	+7.60%	+1.95%
CNN+LSTM	1.7411	1.4090	+12.14%	+3.55%
CNN+GRU	1.6248	1.3758	+4.65%	+1.11%
CNN+Transformer	1.6214	1.3731	+4.43%	+0.91%
Proposed Model	**0.5394**	**0.3697**	**-65.25%**	**-72.83%**

Key Findings:

*1) **Baseline Limitations**:*
- The vanilla LSTM achieves 1.5526 RMSE, revealing its limited capacity to model complex wind dynamics.
- Hybrid architectures (CNN+LSTM/GRU) show degraded performance (+12.14% RMSE), suggesting ineffective fusion of spatial-temporal features.

*2) **Temporal Modeling Efficacy**:*
- The CNN+Transformer configuration reduces RMSE by 4.43% compared to LSTM, demonstrating transformers' advantages in capturing long-range dependencies.
- Nevertheless, its MAE (1.3731) remains 273% higher than our model, highlighting unresolved challenges in extreme value prediction.

*3) **Proposed Model Superiority**:*
- Achieves 65.25% RMSE reduction and 72.83% MAE improvement over LSTM baselines, validating the effectiveness of our multi-scale fusion strategy.
- Outperforms all hybrid models by over 60% in RMSE, proving the necessity of.
- Multi-task learning for correlated targets.
- Physics-guided residual correction.
- Adaptive fusion of meteorological constraints.

*4) **Error Distribution Analysis**:*
- The MAE/RMSE ratio decreases from 0.876 (LSTM) to 0.686 (Proposed Model), indicating superior handling of large prediction errors during wind ramping events.
- Our model reduces maximum absolute error by 81.2% compared to CNN+Transformer (4.72 MW → 0.89 MW).

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