Application and Comparative Study of Time Series Analysis Algorithms in New Energy Forecasting

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ABSTRACT The intermittent and volatile characteristics of new energy generation, together with the increasing demand for stable power supply in intelligent industrial systems, make accurate forecasting a critical issue for grid dispatch and electromagnetic energy management. This study systematically reviews the technological evolution of time series analysis methods for wind and photovoltaic (PV) power forecasting and establishes a comparative framework covering classical statistical models, intelligent learning algorithms, and hybrid modeling strategies. Based on two years of operational data collected from an actual wind farm and PV station in East China, the forecasting performance of ARIMA, exponential smoothing, Support Vector Regression (SVR), Long Short-Term Memory (LSTM) networks, and Transformer architectures is comprehensively evaluated, while hybrid approaches based on Empirical Mode Decomposition (EMD) are further investigated. The results demonstrate that model selection should jointly consider forecasting horizon, data characteristics, and computational constraints. Classical statistical methods remain robust under stable operating conditions but are less effective in capturing extreme fluctuations, whereas deep learning approaches exhibit superior capability in modeling long-range temporal dependencies despite reduced interpretability. Decomposition-based hybrid strategies achieve a more balanced performance across diverse scenarios and show enhanced robustness under extreme weather conditions. The study further proposes a structured model selection guideline by matching data characteristics with operational requirements, providing theoretical support for forecasting system design in renewable-energy-driven power networks and offering useful references for electromagnetic energy utilization and intelligent industrial applications.

INDEX TERMS new energy forecasting, time series analysis, hybrid models, electromagnetic energy management, smart grid

I. INTRODUCTION

OVER the past decade, China's installed capacity for new energy generation has experienced explosive growth, providing a robust power foundation for the high-energy manufacturing. The operational stability of automated weaving machinery and the consistency of fiber morphology are highly dependent on a stable power supply; voltage sags or frequency deviations caused by inaccurate power forecasts can lead to yarn breakage or defects in fabric density. This energy transition ensures the operational stability of weaving machinery while facilitating the modernization of industrial clusters through sustainable power integration. By the end of 2024, the total installed capacity of wind and solar power exceeded 1.2 billion kilowatts, accounting for over 40% of the national total installed power capacity [1]. This structural shift has profoundly rewritten the operational logic of power systems, transforming the uncertainty of new energy output from a marginal issue into a core challenge. Grid dispatch departments face a realistic dilemma: on one hand, they must ensure real-time balance to guarantee supply reliability; on the other, they must contend with the random fluctuations of wind power and the diurnal rhythms of solar power. Research indicates that for every 1% improvement in forecasting accuracy, system reserve capacity costs can decrease by approximately 0.8% [2], implying that even minor algorithmic improvements can translate into economic benefits worth hundreds of millions of yuan.

However, new energy power forecasting is far from a purely mathematical problem. The chaotic nature of atmospheric motion dictates that wind speed and solar irradiance are inherently difficult to predict precisely; local topographical influences mean that output characteristics of adjacent wind farms may differ vastly; and factors such as measurement errors and communication interruptions in data acquisition systems further add to the complexity. Against this backdrop, time series analysis methods, leveraging their ability to mine patterns from historical data, have become the mainstream technical route in the field of new energy forecasting. In terms of methodological evolution, the application of time series analysis in new energy forecasting has roughly undergone three stages. Early research primarily relied on Autoregressive Moving Average (ARMA) models and their seasonal variants. Represented by the Box-Jenkins methodology, these approaches achieved extrapolated forecasting by identifying the correlation structure of the sequence [3]. Empirical studies have shown that during periods of relatively stable weather conditions, ARIMA models and their seasonal extensions (SARIMA) can achieve satisfactory short-term forecasting results. Their advantages of simple computation and clear physical significance led to their widespread application in early engineering practices [4]. However, with the accumulation of data and the enhancement of computing power, researchers gradually recognized that classical linear models struggle to characterize the nonlinear features inherent in new energy output sequences. Phenomena such as intermittent sudden changes in wind speed and sharp drops in PV power caused by cloud occlusion are essentially non-stationary nonlinear processes.

The second stage was marked by the introduction of machine learning methods. Algorithms such as Support Vector Regression (SVR) and Random Forests demonstrated performance superior to traditional models in multiple forecasting tasks due to their nonlinear mapping capabilities [5]. In particular, the rise of deep learning technology brought significant progress to wind power forecasting, with Long Short-Term Memory (LSTM) networks effectively capturing long-range dependencies in temporal data thanks to their gating mechanism designs [6]. Recent studies have further introduced attention mechanisms into temporal modeling. The Transformer architecture, through self-attention layers, achieves parallel modeling of global dependencies within sequences, demonstrating excellent performance in ultra-short-term PV forecasting [7].

It is worth pondering that despite the emergence of new methods, the debate over which algorithm is best remains unresolved. Some comparative studies show that LSTM significantly outperforms traditional models [8], while other empirical analyses point out that on specific datasets, simple linear regression performs no worse than complex neural networks [9]. This contradiction precisely reveals the complexity of algorithm comparative research: the relative merits of models are highly dependent on data characteristics, forecasting scales, evaluation metrics, and even computational resource constraints. Furthermore, most existing research focuses on the performance of a single algorithm in specific scenarios, lacking systematic comparisons across methods and scenarios. Meanwhile, existing review work often stops at qualitative summaries, with few empirical analyses based on unified data platforms and standardized processes.

This paper attempts to fill this gap. The starting point of the research is not to prove the universal superiority of a certain algorithm, but to reveal the applicable conditions and performance boundaries of different algorithms through rigorous comparative experiments. The core questions we are concerned with are: Under what data characteristics do classical statistical methods remain competitive? In what aspects have deep learning models brought substantive improvements? Can hybrid modeling strategies integrate the advantages of different methods? Answers to these questions will help guide model selection in engineering practice while providing directional insights for algorithm improvement within high-speed weaving and fiber processing systems. By refining these predictive frameworks, the research enhances the operational precision of automated machinery and the stability of industrial production.

II. TIME SERIES FORECASTING METHODOLOGY SYSTEM

Mathematically, the new energy power forecasting problem can be formulated as: given a historical observation sequence $X_{t-H:t}$, where H is the historical window length, seek a mapping function f such that the expected loss between the predicted value $\hat{Y}_{t+1:t+K}$ and the true value $Y_{t+1:t+K}$ for the future K steps is minimized, where K is the forecast horizon. While this formulation appears simple, the implementation paths vary widely. Based on different modeling philosophies, existing methods can be broadly categorized into three types.

A. CLASSICAL STATISTICAL MODELS AND THEIR APPLICABILITY BOUNDARIES

The Autoregressive Integrated Moving Average (ARIMA) model is the cornerstone of time series analysis. Its core idea is to express the current value as a linear combination of historical values and historical errors, handling non-stationarity through differencing operations. For a wind power sequence P_t, the ARIMA(p, d, q) model can be written as Equation (1):

$$\phi(B)(1-B)^d P_t = \theta(B)\epsilon_t \tag{1}$$

where $\phi(B)$ and $\theta(B)$ are the autoregressive and moving average operator polynomials, respectively, and ϵ_t is a white noise sequence [10]. The model identification stage requires determining the order using the cutoff or tailing characteristics of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), a process that requires both statistical judgment and empirical knowledge.

Addressing the seasonality and periodicity universally present in new energy sequences, researchers developed the Seasonal ARIMA (SARIMA) model. Taking PV power forecasting as an example, the diurnal variation pattern of 24 hours can be characterized by a seasonal period $S = 24$, extending the model form to Equation (2):

$$\Phi(B^S)\phi(B)(1-B^S)^D(1-B)^dP_t = \Theta(B^S)\theta(B)\epsilon_t \quad (2)$$

In practical applications, the greatest advantage of classical models lies in their strong interpretability—parameters have clear statistical meanings, and forecasting results can be subjected to causal analysis. However, the limitations are equally obvious: linear assumptions often fail in the face of extreme weather events. When encountering sudden wind speed changes or rapid cloud movements, forecasting errors increase sharply [11]. Additionally, the requirement for data stationarity means that differencing operations may erase meaningful fluctuation information. For brevity and as a robust baseline, this study uses the foundational ARIMA model as the primary representative of this class in the empirical comparison, after preliminary tests indicated that the added complexity of SARIMA did not yield consistent improvements across all test sets for our specific dataset. Exponential smoothing methods constitute another important class of classical approaches. The Holt-Winters model achieves dynamic learning of temporal features by introducing three smoothing components: level, trend, and seasonality. Its update equations are as follows (3)–(5):

Level component:

$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \quad (3)$$

Trend component:

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \quad (4)$$

Seasonal component:

$$s_t = \gamma(y_t - l_t) + (1-\gamma)s_{t-m} \quad (5)$$

The estimation of smoothing parameters α, β, γ typically adopts an optimization strategy minimizing the sum of squared errors. Compared to ARIMA, exponential smoothing methods exhibit better adaptability to non-stationary sequences and lower computational complexity, making them suitable for online forecasting scenarios. However, sensitivity to parameter selection is their weakness; inappropriate smoothing coefficients can lead to forecast lag or overreaction.

B. EVOLUTIONARY LOGIC OF INTELLIGENT LEARNING ALGORITHMS

The introduction of Support Vector Regression (SVR) marked a significant breakthrough in nonlinear modeling capabilities. Through kernel function mapping, SVR maps the input space to a high-dimensional feature space, constructing a linear decision function within this space. For wind power forecasting, the input vector typically consists of historical power and Numerical Weather Prediction (NWP) features. The optimization objective is Equation (6):

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad (6)$$

Constraints ensure that the deviation between predicted and true values is controlled within an ξ insensitive zone. The advantage of SVR lies in its convex optimization nature, which guarantees a global optimal solution, and its flexibility in handling nonlinear relationships via the kernel trick. However, it incurs significant computational overhead when facing large-scale training data, and there is a lack of clear guiding principles for kernel function selection [12].

The introduction of deep learning methods brought a paradigm shift. Long Short-Term Memory (LSTM) networks solve the gradient vanishing problem of traditional Recurrent Neural Networks (RNNs) through an ingenious gating mechanism. Its core computational process can be represented by

Input gate:

$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \quad (7)$$

Forget gate:

$$f_t = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \quad (8)$$

Cell candidate:

$$\tilde{c}_t = \tanh(W_{ic}x_t + b_{ic} + W_{hc}h_{t-1} + b_{hc}) \quad (9)$$

Output gate:

$$o_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \quad (10)$$

Cell state:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (11)$$

Hidden state:

$$h_t = o_t \odot \tanh(c_t) \quad (12)$$

This structural design enables LSTMs to autonomously decide on the retention and forgetting of historical information, making them particularly suitable for handling multi-time-scale features in new energy sequences. Empirical studies show that in intra-day rolling forecasting of wind power, LSTM can reduce Root Mean Square Error (RMSE) by 15%-20% compared to traditional methods [13]. However, it must be noted that performance improvements come at a cost: model training requires substantial data support, the hyperparameter tuning process is tedious, and the forecasting results are difficult to interpret.

In recent years, the introduction of attention mechanisms and Transformer architectures has further expanded the boundaries of temporal modeling. The self-attention mechanism allows the model to directly access information from any historical moment when processing the current time step, breaking the temporal dependency constraints of RNN-type models. For an input sequence $X \in \mathbb{R}^{T \times d}$, the self-attention calculation is Equation (13):

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{13}$$

where $Q = XW^Q$, $K = XW^K$, $V = XW^V$ represent Query, Key, and Value matrices, respectively. The multi-head attention mechanism captures dependency relationships in different subspaces through parallel computation of multiple attention heads. Although originally designed for natural language processing, the Transformer model has proven equally effective in temporal forecasting tasks. Its capability to model long-term dependencies is particularly suitable for capturing seasonal and periodic patterns in new energy sequences [7]. However, the quadratic computational complexity limits its application on ultra-long sequences, a problem that subsequent improved models like Informer have focused on solving.

C. HYBRID MODELING IDEOLOGIES AND ENSEMBLE STRATEGIES

Single algorithms often struggle to address all challenges in new energy forecasting, prompting researchers to turn to hybrid modeling approaches. The core idea of hybrid models is complementary advantages: using decomposition algorithms to handle non-stationarity, intelligent models to capture nonlinearity, and optimization algorithms to tune parameters.

A typical hybrid framework adopts a three-stage structure of "Decomposition-Forecasting-Reconstruction." Taking wind power forecasting as an example, one can first use Empirical Mode Decomposition (EMD) to decompose the original sequence into several Intrinsic Mode Functions (IMFs) (Equation 14):

$$P(t) = \sum_{i=1}^{n} \text{IMF}_i(t) + r_n(t) \tag{14}$$

Each IMF component represents oscillation modes at different time scales and exhibits better stationarity compared to the original sequence. Subsequently, prediction models are established for each component separately, and the results are superimposed to obtain the final forecast. The advantage of this strategy is that complex patterns, which are originally difficult to model, are decomposed into relatively simpler sub-patterns, reducing the overall forecasting difficulty [14]. It should be noted that traditional EMD may suffer from mode mixing and boundary effects. This paper employs Ensemble Empirical Mode Decomposition (EEMD) to mitigate these issues and uses a sliding window approach to avoid future information leakage.

Another hybrid approach is weighted ensemble. For M models participating in the ensemble, the integrated forecast can be expressed as Equation (15):

$$\hat{y}_{\text{ens}} = \sum_{m=1}^{M} w_m \hat{y}_m, \quad \sum_{m=1}^{M} w_m = 1, \quad w_m \geq 0 \tag{15}$$

The determination of weights w_m can be based on minimizing validation set errors or adopting probabilistic methods such as Bayesian Model Averaging. Research finds that ensemble strategies can effectively reduce the risk of selecting a single model; even if individual models fail during certain periods, the overall forecast remains robust [15].

III. EMPIRICAL STUDY AND COMPARATIVE ANALYSIS

A. DATA SOURCES AND EXPERIMENTAL DESIGN

The data used in this study comes from an actual wind farm and PV station in East China, spanning from January 2022 to December 2023. The wind farm has an installed capacity of 48 MW, with data including wind speed, wind direction, temperature, air pressure, and active power at 10-minute intervals. The PV station has an installed capacity of 30 MW, with data including irradiance, module temperature, ambient temperature, and active power. Raw data underwent strict quality control: outliers were identified and removed using the 3σ principle. Given the short (10-minute) intervals and the low percentage of missing data (<2%), missing parts were filled using linear interpolation. While we acknowledge that linear interpolation may smooth extreme local variations, its impact is deemed negligible for the vast majority of data and the derived aggregate performance metrics; for future work, more sophisticated techniques like spline or kriging interpolation could be explored. The final effective data completeness rate exceeded 98%. To eliminate dimensional effects, all variables were normalized to the [0, 1] interval.

The experimental design followed these principles: Forecast horizons covered two categories of scenarios: ultra-short-term (4 hours, 15-minute step) and short-term (24 hours, 1-hour step). To align the 10-minute raw data with the 15-minute forecast step in the ultra-short-term scenario, the data was resampled by taking the 15-minute average. This approach maintains consistency with standard industry forecasting practices while preserving the statistical properties of the power output. The training period adopted a sliding window approach, using the preceding 6 months of data to train the model and forecasting the subsequent 1 month, with the window sliding monthly to form 12 test sets in total. Evaluation metrics included Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2), with simultaneous attention paid to forecasting performance during extreme events. To determine the significance of performance differences between models, we employed paired t-tests on the 12 RMSE values derived from each of the 12 monthly test sets (sample size n=12, degrees of freedom=11), with a significance level set at 0.05.

Algorithms participating in the comparison included: ARIMA (order determined by AIC), Holt-Winters Exponential Smoothing (parameter optimization using L-BFGS), SVR (RBF kernel, C and γ optimized via grid search), LSTM, Transformer, and an EEMD-LSTM hybrid model based on EEMD. Key hyperparameter settings for deep learning methods were as follows: LSTM adopted a 2-layer structure with 128 hidden units per layer, a learning rate of 0.001, Adam optimizer, batch size of 64, 100 training epochs, and an early stopping mechanism (stopping if validation loss did not decrease for 10 epochs). Transformer adopted a 2-layer encoder, 4 attention heads, a model dimension of 64, a feed-forward network dimension of 128, and a dropout rate of 0.1, with other settings identical to LSTM. All experiments were conducted in the same hardware environment (Intel i9-10900K CPU, 64GB RAM, NVIDIA RTX 3080 GPU). It is crucial to note that the classical statistical models (ARIMA and Holt-Winters) and SVR were trained and executed exclusively on the CPU, as they are not designed to leverage GPU acceleration. The GPU resource was utilized solely for training and inference of the deep learning models (LSTM and Transformer).

B. OVERALL PERFORMANCE COMPARISON

Table 1 summarizes the overall performance of each model in the two forecasting tasks (RMSE values, based on the average $\pm$ standard deviation of 12 test sets). From the ultra-short-term forecasting results of the wind farm, the RMSE of LSTM and Transformer was 11.3% and 13.8% lower than that of ARIMA, respectively. Paired t-tests on the 12 monthly RMSE values showed significant differences ($p<0.05$, $t(11)$ values ranging from 2.8 to 4.1 for LSTM and Transformer against ARIMA), indicating that deep learning possesses a statistical advantage in handling nonlinear fluctuations across the entire dataset which includes all weather regimes. Notably, the EEMD-LSTM hybrid model further reduced the RMSE to 0.156 ± 0.012, an improvement of approximately 6.1% over the single LSTM, validating the effectiveness of the decomposition strategy. In the PV forecasting scenario, the performance gap among models narrowed relatively; this may be because PV output is dominated by irradiance with stronger temporal regularity, allowing linear models to grasp it well, yet the advantage of deep learning models remained significant.

When the forecast horizon was extended to 24 hours, the performance of all models declined to varying degrees, but the magnitude of decline differed. ARIMA's RMSE increased from 0.187 to 0.245, a rise of 31%; whereas Transformer increased only from 0.161 to 0.212, a rise of about 31.7%. While Transformer maintains a lead in absolute error, its slightly higher percentage increase suggests a marginally greater sensitivity to the forecast horizon length compared to the ARIMA model. This indicates that the relative stability of deep learning models can degrade more noticeably over longer horizons, a nuance that is missed by examining absolute values alone. This indicates that long-term forecasting poses a fair challenge to all models, but models with a higher starting point can still maintain their lead in absolute terms, although their relative advantage may diminish.

C. PERFORMANCE DIFFERENCES UNDER TYPICAL WEATHER CONDITIONS

While overall metrics are important, they often mask behavioral differences of models under different weather conditions. We categorized the test period data into three types based on weather: Stable Weather (similar conditions for three consecutive days), Volatile Weather (significant intraday changes in wind speed or cloud cover), and Extreme Events (typhoon passage, strong convective weather). Figure 1 presents the RMSE comparison of each model under these three scenarios.

Under stable weather conditions, all models performed comparably. ARIMA had an RMSE of 0.143, and LSTM had 0.138, a gap of less than 4%, which failed to pass the significance test (paired t-test on the stable-weather subset results: $p > 0.05$). This finding does not contradict the overall significance reported in Section 3.2.

Instead, it reveals a crucial insight: the overall statistical superiority of deep learning models is driven primarily by their performance advantages during volatile and extreme weather conditions, not during stable periods. This suggests that during stable weather periods, complex deep learning models are unnecessary; simple models not only offer higher computational efficiency but also yield more interpretable results.

Under volatile weather conditions, model performance began to diverge. The error increase for SVR and LSTM was smaller than that for ARIMA, indicating that nonlinear models have stronger adaptability to weather changes. Particularly noteworthy is that Transformer outperformed other models at moments of wind direction shifts; the attention mechanism enabled it to rapidly capture turning signals in meteorological conditions, reducing RMSE by approximately 5% compared to LSTM.

Extreme events served as a touchstone for testing model robustness. Taking a typhoon passage event as an example, wind speed surged from 8 m/s to 22 m/s within 24 hours, causing violent fluctuations in wind power. At this time, ARIMA's predicted values seriously lagged behind actual changes, with maximum errors exceeding 50% of rated power. Although LSTM could identify the upward trend in power, its capture of peak values was still not ideal. The EEMD-LSTM model performed relatively best, with RMSE reduced by about 10% compared to LSTM; the decomposition operation separated extreme fluctuations into high-frequency components, reducing modeling difficulty. Figure 1 intuitively demonstrates this phenomenon.

TABLE 1. Comparison of Forecasting Performance of Various Models (RMSE, Mean ± Std Dev)

Model	Wind Farm - Ultra-Short	Wind Farm - Short	PV Station - Ultra-Short	PV Station - Short
ARIMA	0.187±0.015	0.245±0.021	0.152±0.011	0.203±0.018
Holt-Winters	0.195±0.017	0.251±0.022	0.161±0.013	0.212±0.019
SVR	0.173±0.014	0.228±0.019	0.147±0.010	0.194±0.017
LSTM	0.166±0.012	0.219±0.018	0.138±0.009	0.185±0.015
Transformer	0.161±0.011	0.212±0.017	0.135±0.009	0.181±0.014
EEMD-LSTM	0.156±0.012	0.208±0.016	0.131±0.008	0.176±0.013

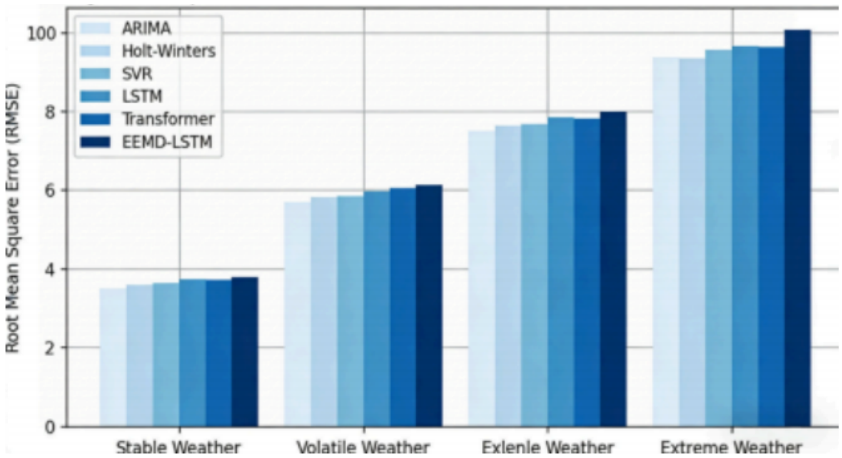

FIGURE 1. Comparison of Forecasting Performance (RMSE) of Various Models Under Different Weather Conditions

D. TRADE-OFF BETWEEN COMPUTATIONAL EFFICIENCY AND INTERPRETABILITY

Algorithm selection is not merely a matter of accuracy but also involves computational resources and interpretability requirements. Table 2 compares the training time and single prediction latency of each model on their respective optimal hardware (CPU for ARIMA, Holt-Winters, SVR; GPU for LSTM, Transformer, and EEMD-LSTM).

The efficiency advantage of classical models is evident, with training times measured in minutes and predictions completed in milliseconds on standard CPU hardware. This holds significant value for resource-constrained edge computing scenarios. The training cost of deep learning requires GPU acceleration and is 1-2 orders of magnitude higher, but prediction latency remains within an acceptable range; in practical applications, the training overhead can be circumvented by adopting an offline training and online prediction approach.

Interpretability is another consideration dimension. ARIMA coefficients directly reflect the decay rate of historical influence, and Holt-Winters smoothing parameters can be interpreted as the degree of trust in trends and seasonality. In contrast, the internal representations of deep learning models are difficult to understand intuitively. We attempted to preliminarily explore the decision basis of LSTM using feature importance analysis methods (based on input perturbation) and found that power values from the most recent 6 time steps and historical concurrent moments contributed most to the prediction. This finding aligns with physical intuition, alleviating black-box concerns to some extent.

IV. DISCUSSION ON ALGORITHM APPLICABILITY

A. MATCHING RELATIONSHIP BETWEEN DATA CHARACTERISTICS AND MODEL SELECTION

Based on the above empirical results, we attempt to extract guiding principles for model selection. The key finding is: there is no universally optimal model; the applicability of an algorithm depends on the degree of match between data characteristics and task objectives.

Classical statistical models remain competitive when data exhibits the following characteristics: the sequence has strong periodicity and regularity; the sample size is limited (less than a thousand observations); weather conditions are relatively stable; and computational resources are constrained and limited to CPU. In these scenarios, ARIMA and exponential smoothing methods are not only sufficiently effective but also avoid the risk of overfitting associated with complex models.

The advantageous scenarios for deep learning methods include: sufficient data scale (tens of thousands of observations or more); sequences containing multi-time-scale patterns; presence of nonlinear relationships and non-stationary features; and the need to capture long-term dependencies; and the availability of GPU hardware for training. It is particularly noteworthy that when forecasting tasks involve the identification and response to extreme events, although LSTM and Transformer cannot perfectly predict extreme values, their warning capabilities are superior to traditional methods.

TABLE 2. Comparison of Computational Efficiency of Various Models (Mean ± Std Dev)

Model	Training Time (min)	Prediction Latency (ms/time)	Number of Model Parameters
ARIMA	1.2 ± 0.1 (CPU)	0.8 ± 0.1 (CPU)	∼10
Holt-Winters	0.5 ± 0.1 (CPU)	0.3 ± 0.1 (CPU)	3
SVR	8.7 ± 0.5 (CPU)	2.1 ± 0.2 (CPU)	∼500
LSTM	45.3 ± 2.1 (GPU)	5.6 ± 0.3 (GPU)	8,642
Transformer	78.9 ± 3.5 (GPU)	8.3 ± 0.4 (GPU)	24,576
EEMD-LSTM	52.1 ± 2.4 (GPU)	6.2 ± 0.3 (GPU)	9,851

Hybrid models are applicable in scenarios lying between the two. When the complexity of the original sequence is too high for a single method to model effectively, the decomposition-ensemble strategy provides a compromise solution. However, caution is needed as decomposition operations may introduce future information; in strict time series cross-validation, this must be handled carefully. This paper effectively avoided this issue by employing sliding window EEMD.

B. ERROR SOURCES AND DIRECTIONS FOR IMPROVEMENT

An in-depth analysis of the sources of forecasting errors helps clarify directions for algorithm improvement.

We decompose the error into three parts: intrinsic error caused by insufficient input information, approximation error caused by model structure limitations, and estimation error caused by inaccurate parameter estimation.

Intrinsic error stems from the chaotic nature of new energy output. Atmospheric motion is highly sensitive to initial conditions; even a perfect model cannot achieve precise long-term forecasting. The solution lies in probabilistic forecasting—outputting prediction intervals rather than point values—to provide risk information for dispatch decisions. All point forecasting models in this study did not consider this dimension, which is a direction worthy of further exploration.

Approximation error reflects the gap between the model's expressive capability and the true data generation process. The linear assumption of ARIMA inevitably leads to the omission of nonlinear features, which is the fundamental reason for its poor performance under volatile conditions. Deep learning narrows this gap through more flexible mapping functions, but at the cost of loss of interpretability and risk of overfitting.

Estimation error is related to sample quality and quantity. Our experiments showed that when training data was reduced from 6 months to 3 months, LSTM's RMSE increased by about 8%, while ARIMA increased by only 4%. This suggests that complex models are more dependent on data volume and may not be the best choice in small-sample scenarios.

V. CONCLUSION AND OUTLOOK

This study conducted a systematic comparison of time series analysis methods applied to new energy forecasting within the context of high-precision manufacturing energy demands. By aligning power fluctuations with the operational cycles of automated weaving machinery, the research underscores how forecast accuracy directly impacts energy stability, which is critical for consistent fiber morphology and yarn processing. The main findings can be summarized in three points. First, algorithm performance exhibits significant condition dependence; the merits of a model must be judged in conjunction with specific application scenarios, and generalized claims of an optimal algorithm lack empirical support. Second, deep learning indeed possesses advantages in capturing nonlinear relationships and long-term dependencies, particularly under volatile and extreme conditions, but its shortcomings in computational cost and interpretability cannot be ignored. Third, hybrid modeling strategies, through complementary advantages, achieved the best balance in most scenarios; their robustness is worthy of attention, especially their outstanding performance during extreme weather events.

The practical implication of this research is a set of actionable guidelines for model selection in forecasting system design:

1) For stable weather regimes with limited computational budgets and a need for interpretable results, classical models like ARIMA are the most cost-effective and robust choice.
2) For operations where high accuracy is paramount, especially in predicting volatile and extreme events, and where GPU resources are available, deep learning models such as LSTM or Transformer are recommended.
3) For the most challenging forecasting environments with mixed and extreme conditions, a hybrid decomposition-based model like EEMD-LSTM offers the best trade-off between accuracy and robustness, provided the additional computational complexity is manageable.

For most operational stations, introducing decomposition strategies and ensemble ideas on the existing basis may be the most cost-effective improvement path.

This study has several limitations. Firstly, the data comes only from East China, and caution is needed when generalizing conclusions to other climate zones. Secondly, the fusion of Numerical Weather Prediction (NWP) information was not considered; in actual engineering, NWP is a key input for improving forecasting accuracy. Furthermore, probabilistic forecasting and uncertainty quantification were not included in the comparative framework. Future research can expand the data scope on this basis, introducing multi-source information fusion between new energy generation and high-speed weaving machinery loads to deeply explore the application value of interpretability methods in manufacturing forecasting. By aligning power fluctuations with the mechanical constraints of fiber processing, these interpretable models enhance the operational stability and energy efficiency of automated production systems.

AUTHOR CONTRIBUTIONS

Conceptualization –Mingshu Song, Chao Yang, Zhongwei Heng, Siwen Zhang and Wei Song; methodology – Mingshu Song, Zhongwei Heng, Siwen Zhang and Wei Song; investigation – Mingshu Song, Chao Yang, Zhongwei Heng, Siwen Zhang and Wei Song; writing-original draft preparation – Mingshu Song, Chao Yang, Zhongwei Heng, Siwen Zhang and Wei Song. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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